

## INVESTIGATIONS INTO TRAINABLE PICTURE PROCESSING SYSTEMS

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by

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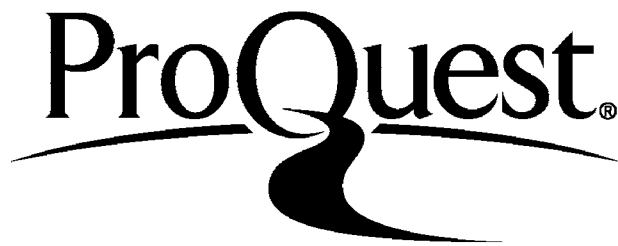
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ABSTRACT

This work concerns the development of a new type of picture processing system for images represented as digital arrays of pixels. This is a synthesis of two established ideas, already under independent investigation. The first of these is picture processing by look-up tables. This is a fast method of generating pixel outputs as a result of input pixels accessing a particular region of a look-up table, pre-loaded with the required data. The second idea is the use of RAMs as learning machines. Here, RAM elements are connected together so as to be alterable in data content by training stimuli in a coherent manner. This results in a system able to exhibit definite responses to later test stimuli, and thus identify these stimuli unambiguously.

The methods used for bringing these two concepts together are described here. A practicable picture processor results, which can be trained by examples. That is, it can perform a picture transformation simply by presenting to the machine (in a prior training phase) examples of the process. From this, the machine deduces the information necessary to be able to perform the same transformation on unseen patterns.

Experiments have been performed on a wide range of variations on this theme. Different types of machines acting on different data and tasks have been tried, under various conditions. A description is given of these machine variations, together with a generalized system for describing such variations more formally. The machines were simulated in practice on a microcomputer system. The simulation software used in these investigations is also described.

Finally, the implications and limitations of such machines are discussed with reference to their ultimate performance and possible applications in fields other than picture processing.



"Contrariwise," continued Tweedledee, "if it was so, it might be;  
and if it were so, it would be; but as it isn't, it ain't.  
That's logic."

Lewis Carroll

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## CHAPTER 1

## LEARNING PICTURE PROCESSORS

1.1 Introduction

The advent of data processing that followed the development of the digital computer brought with it many entirely new disciplines. Amongst these is a set of applications that requires deductive and intuitive processing, related to the processes of reasoning and perception in the brain. One of the more important examples of this is concerned with visual image processing and classification, an area that has been ever more closely studied over the last two decades.

1.2 Applications

There are many applications of machines able to process and classify pictures, and several examples of these will be given here.

Optical character recognition is of great use in the world of business - many types of document formerly read by human operators can be read and subsequently processed entirely by machine (69,10). In medical applications, image analysis may take many different forms (75), including X-ray screening (34), cancer cell scanning (18) and radiograph analysis (36). These all exhibit characteristic patterns, enabling subsequent diagnosis of symptoms - also by machine (56). A combination of OCR and the medical field results in

practical blind reading aids (54).

Military and space applications are also under investigation (29), although such applications may be classified and consequently difficult to research. Automatic identification and tracking of objects is often the goal here, for the purpose of targetting weapons automatically (39). Space satellites send picture data in need of considerable processing in the form of filtering (eg. for noise removal) or other transformations (eg. to remove distortions, blurring or compression and expansion for the extraction of the maximum information (44) ). Video images (of any subject) can make use of filtering operations or even modifications for special effects. The present generation of video effects mixers used on broadcast television are examples of this. Security systems make use of automatic monitoring of CCTV systems for alarm situations, and subsequent matching and identification of faces or fingerprints that may be recorded (17,62).

Scientific laboratories can make use of machine scanning of signals (often comprising vast quantities of data) in a search for a particular pattern or feature (68,67). The type of features sought are often abstract, to the extent that even human observers can sometimes be unsure of identification.

Many industrial applications also exist - a robot assembly device can benefit from visual input (3,8,46). This must be suitably processed to give the relevant information to help it as a capable and, more important, general-purpose tool. This can be extended to transportation, where visual inputs to an autonomous vehicle can greatly aid its

movements in unknown territory (33). This can be applied across a wide range of complexities - from manoeuvring fork lift trucks to piloting aircraft.

There is obviously considerable scope in the choice of a problem to be tackled. Unfortunately this may give rise to a multitude of attempts at solutions - often 'tuned' to a particular application. While this undeniably extracts the maximum potential from a solution, many are left very specific and over-adapted to a particular application. They become no longer suited to a range of users. There are vast numbers of alternatives to be explored even within each attempt at a solution.

### 1.3 Alternatives in Picture Processing

At every level of the search for a picture processing solution, there are alternatives to be considered. This may slow the progress of research by directing it towards a 'tuned' solution, specific to a problem. It can also be cited as a reason for assuming that no general solution exists. It is in an attempt to generate at least a partially general picture processing solution that the work described in this thesis has been carried out. While it is necessary to make several specific choices before any form of picture processing can commence, it will be shown here that a single, simple machine can readily perform a relatively large range of tasks without further specialisation.

### 1.3.1 Alternatives in the Representation of Picture Data

The alternatives that exist in picture processing begin with the data. The data are in some form of organised, reproducible representation of visual images, with a large number of alternative storage methods available. Analogue storage has been used (37) in the days before the advent of cheap digital devices, yet today the latter method is used almost exclusively.

Digital pictures are most often represented as two-dimensional arrays of picture elements (pixels). The number of elements and their spatial relationship are some of the first alternatives to be specified in such picture processing machines. Once the number of pixels per picture and the tessellation have been defined, the quantity of information per pixel is to be decided. The representation can vary from simple binary (black and white) to a full range of colours at each point. Subsequently, if the picture is to represent a moving image, a frame repetition rate must be specified. Frequently, a single static picture is used in experimentation, but ultimately many of the applications mentioned above would require the use of moving pictures. This is for two reasons:

- 1 many pictures change in time (which must be recorded),
- 2 much potentially useful information can be gathered from the manner of these changes.

Normal TV video rates are often used as a standard, to suggest some values for these variables. This rate is equivalent to approximately 12 bits per pixel, 625 by 833 pixels per frame and 25 frames per second for a full colour,

moving television quality image. This is equivalent to a gross data rate of  $\sim 10^8$  bits per second, and is cited as a goal for many current devices (78). Alternative data rates are well-known and documented in many books on the subject (7,15).

### 1.3.2 Global or Local Processing of Data

Broad alternatives also exist in the processing carried out on the data. The choice to be made is between local and global approaches. In the former case, processed areas of the picture are solely a function of the local area in the picture before processing. Global processing allows any processed picture area to be a function of any or all of the regions in the unprocessed picture. Global operations lend themselves well to transform processing - possibly by optical means (47). At present this method has enormous advantages in speed over discrete processing, being effectively instantaneous. However, when implemented on serial processors, global processing is necessarily much slower than local processing. This is the predominant factor accounting for the emphasis on the latter in much of the image processing literature.

### 1.3.3 Sequential or Parallel Processing

In the case of local processing of discrete pixel arrays, there exists the alternative of parallel or sequential processing (63). In the former, all localities are processed simultaneously (either actually or effectively). Each resultant new local area is created in a

different picture space from the original picture. Several hardware devices have been created with architecture to implement this type of processing (16,26,28).

In sequential processing, each locality is processed to finality before the process is applied to the next area in an ordered scan. The processed results are inserted back into the original picture space. This results in the input to the processor being part processed, part unprocessed pixels. This has important implications in many types of picture processing where topological variables such as connectedness are involved (70).

#### 1.3.4 The Choice of the Size of the Locality

The size of the locality or neighbourhood mentioned above is related to the overall picture size and the number of pixels within it. This 'window' size is a major factor in such processing and is chosen subject to two constraints: with a large window there is the potential for more powerful processing, yet the smaller the window the faster and simpler the process.

#### 1.3.5 The Choice of Algorithms

The final choice, and possibly the most important of all in picture processing is that of the actual algorithm employed. At this point it is interesting that a distinction can be drawn between an underlying strategy and the device-dependent algorithm, giving rise to yet further alternatives in approach.

Here is considerable scope for what is often a rather arbitrary variation. Algorithms are generated by introspective analyses of how the process should be done, and thereafter evaluated on the results of their application. Comparisons between man and machine have been made (57), which are inclined to suggest man's methods as a suitable, if not the only source of solutions. Consequently, this is the area of picture processing most subject to 'ad hoc' solutions, and is thus where the main thrust of this thesis is aimed. A successful search will be made for a method of generating algorithms not based on such 'ad hoc' solutions. This will rely on examples of processed pictures alone, rather than premeditated methods of achieving these processed pictures.

#### 1.4 Basic Problems in Picture Processing

The alternatives above lead to considerable problems in finding picture processing solutions. These may be summarized generally into three aspects:

- 1 there are vast quantities of information to be stored and processed,
- 2 the time taken to process pictures in real time must be controlled,
- 3 the processes to be executed are not known.

The ideal solution sought here will have to be fast, efficient and capable of generating its own algorithms.

The problem of speed cannot be overlooked in many applications which, once divorced from the laboratory, must

ultimately work in real time. This requires efficient algorithms capable of working quickly to generate outputs from inputs: yet even this is usually insufficient. Special purpose hardware is currently necessary to approach the data processing rates required. Early attempts at reducing the execution times of processors resulted in parallel machines (79,80) as an approach to speeding up the hardware. The current generation of programmable general purpose computers is still far too slow to cope with the video data rates cited above as a standard. The hardware that must be produced is often grossly restricted in its adaptability to even closely related problems. This may result in forced simplifications of the algorithms that can be implemented in the chosen application area.

Look-up tables are examples of such systems used for pixel value transformations (1). Shift register delay lines are examples that allow the processing of windows of pixels that are spatially adjacent, but temporally distant in serial data streams (42,74).

The solution proposed here will be based on a novel use of look-up tables in a writing mode, as well as a reading mode.

Apart from speed, the other major problem is that the algorithms required are unknown. That is, while the results required of the picture processor can be defined (perhaps by examples) there are no clues to the methods of solution. Attempts at finding the human methods employed here (31,71) have not been easily translatable into machine form. The usual approach is to break down the process into a set of 'primitives' - that is, a set of relatively well-defined



tasks capable of at least some successful intuitive solutions. These range from the trivial (such as inversion, or the removal of 'salt and pepper' noise) to the complex (such as thinning or object identification). These are often combined in a particular sequence to produce the overall image transformation required for a particular application.

Laudable attempts have been made at organising the tools to search for these algorithms. Examples of these are the VICAR software package developed at JPL, California (15); and the SUSIE package at Southampton (9). These command type languages relieve the researcher from the mundane aspects of picture processing, allowing concentration on the actual image processing techniques under investigation. A similar type of language has also been developed for pattern recognition: JANSYS at Brunel University (55).

However, solutions proposed as a result of these and other methods are further complicated by the choices highlighted in Section 1.3 above. This often confuses the pursuit of a good solution. Good proposals can be lost in an unfortunate combination of parameters (such as size, type of picture, etc.) thus obscuring the way ahead. As Groh stated in 1978 (32), it is for these reasons that "technical picture processing is still in its infancy".

In an attempt to avoid this arbitrariness in the cycle from problem definition to problem solution, the work in this thesis is proposed. Indeed, the broad range of solutions covered in several recent review papers (64,81) illustrates the fact that no genuinely 'best' strategies have crystallized.

### 1.5 The Need to Avoid 'ad hoc' Development

An example of where this 'ad hoc' nature of the art has resulted in an inefficient collection of algorithms is in the task of thinning. Thinning here is defined as the successive erosion of the edges of a figure until a unit width, connected skeleton remains along the figure's limbs (22). The algorithms that have been generated in the past (70,10) are not generally guaranteed to work. They may break the figure, or not discriminate between noise and limbs, or simply produce inaccurate skeletons. This record of bad performance has stimulated the generation of new, complex or arbitrary algorithms; but unfortunately these are not derived evolutionarily from earlier solutions (43). There is a need for algorithms to be 'guaranteed' to do the job, and one aid to achieve this is to define a 'requirements specification' before attempting to find a solution to meet it. Thereafter any proposed solutions can be tested to ensure they meet these specifications.

Thinning has arisen as a non-trivial problem that has been continually attempted because of its potential use, and actual implementation, in many practical applications. It has been used in printed circuit board manufacture (59), inspection of fibres on air filters (24), fingerprint classification (60) and chromosome analysis (38). The requirements can be specified as a capability to simplify the image by a reduction in limb width for subsequent analysis or data compression purposes. The difficulty is that this is a global problem where long-range features have to be taken into account, and is thus not strictly solvable with the often proposed local solutions.

To define the problem explicitly, a set of requirements can be expressed about the required thinning algorithm.

- 1 It must transform the image to a unit width skeleton.
- 2 It must maintain connectedness.
- 3 It must retain any line ends that it locates.
- 4 It must modify the image isotropically.
- 5 It must complete its task in a reasonable length of time.

Algorithms have been developed under these conditions, yet still found lacking, by breaking limbs (23), being over-complex and hence slow, or having other shortcomings. Although it is somewhat artificial to separate these properties in this manner, this can focus attention on the minimum requirements. Algorithms are usually proposed as complete solutions - and failure to identify sub-tasks or constraints properly is often the fundamental problem. Indeed, an attempt to meet all the requirements simultaneously usually results in not meeting some at all. However, acceptance criteria are highly desirable for quantifying the usefulness of a given algorithm. This may also tend to generate algorithms designed from the 'top down', with the advantage that they can be tailored to applications by re-adjustment of requirements at the design stage. Different tessellations, noise characteristics and noise levels are but three examples of variations that might invalidate a given algorithm. Ideally an algorithm should be readily modifiable to meet the new conditions. The only requirement is to produce a skeleton of predictable accuracy under given conditions. Until recently (22), there has been

no mention of such skeleton accuracy standards in the literature.

Davies and Plummer (22) have approached the problem with this methodology. A family of algorithms has been proposed that can be guaranteed to generate a skeleton rigorously defined as 'adequate'. These algorithms can be adapted to a range of conditions and thus are no longer 'ad hoc' solutions, but transportable between applications.

This structured approach to image processing is preferable - execution of a cycle of requirement specification, solution development, and validation. However, an alternative is proposed in this thesis, which even avoids the need to generate a solution by intelligent considerations. If the requirements can be specified formally, a device can in principle be created capable of generating its own algorithms directly from these specifications. The method used here for specifying the problem is the provision of examples of processed data. Additionally, this no longer restricts the task to thinning, or any picture processing task. The device is capable of performing any task that can be specified by the examples, and is not subject to any 'ad hoc' proposals of solutions. A device capable of such action will be described in the following sections.

#### 1.6 RAMs as Processors in Learning Machines

It has been suggested that the present work will try to avoid any arbitrariness in finding solutions. Thus one of the most suitable sources of information available to define

the requirements is a set of examples. A picture set exists (or can be created) to illustrate the processes to be performed. The problem has consequently been modified to the creation of a machine capable of responding coherently to these examples, such that it can later copy the process onto new data. The example data themselves are used to drive the machine, to re-order it internally in such a way that it can reproduce the picture processing task on which it was trained.

RAMs have been identified as universal devices capable of emulating any logic circuit (2). In particular, RAMs have been examined in considerable depth by Aleksander et al. : as 'n-tuple' learning machines for pattern recognition (4,82,83). Such machines can be trained to respond to a pattern/class pair, such that they can later generate correct classes from unseen patterns (11,72,77). It will be shown here that a similar type of machine can be created that will react to a pair of examples, consisting of a raw picture input, together with a processed picture input. Such a machine will generate 'correct' output pictures from unseen inputs, and should fulfil the requirements above for avoiding arbitrary designs of algorithms.

The machine should be general in the sense that it will be:

- 1 task-independent,
- 2 capable of handling different tasks with a change of examples rather than re-programming,
- 3 able to handle different task complexities,
- 4 able to process different picture formats and
- 5 capable of generalisation.

This last point is of fundamental importance to any intelligent machine. In this context, the property of generalisation can be defined as the ability to process, correctly, pictures not previously seen as examples. For a learning picture processor to be of any use, this is vitally important. The question of whether the performance is 'sufficient' to be useful is to be investigated here.

### 1.7 The Proposed Learning Picture Processing Machine

The characteristics of the machine proposed herein are summarized below. This is an attempt at finding an optimum solution to producing an output picture data set, correctly transformed from an input picture data set. Assuming that examples of these data sets are available for training, a machine is proposed that can generate the required algorithm autonomously. This machine will be implemented in RAM devices used as modifiable look-up tables. This will be shown to result in fast operation - as seen elsewhere with this type of device (1,61,62). A practical version of the machine will be described, which makes use of currently available hardware technology.

### 1.8 A Summary of the Following Chapters

Chapter 2 will introduce the methods by which practical learning machines may be organized to process digital pictures, having learnt to do so only by example.

Chapter 3 will document preliminary practical experiments on such systems, and illustrate the results with

some proposals for modifications and improvements.

Chapter 4 will show a structured approach to the generation and categorisation of variations on the basic theme, and will propose a 'general machine'.

Chapters 5 and 6 represent the bulk of the experimental work which investigates a number of variations by experiment. The evaluation of the results leads to a convergence onto some general rules regarding such systems' behaviour.

Chapter 7 documents the simulation process used throughout these experiments, for creating and operating this range of learning picture processors on a conventional digital computer.

Chapter 8 will conclude by summarizing the implications of the systems proposed here, in the light of the current position of image processing; and also make some specific suggestions for further work. Some rather more general conclusions will also be drawn regarding the applications of learning machines in the future.

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While this work addresses itself to the practical aspects of two-dimensional pattern learning, there already exists a considerable body of work on theoretical one-dimensional learning - grammatical inference. This shows the potential power of a negative sample, (ie. training indicating what not to do) which has interesting implications for the work presented here. The following reference will serve as an introduction to this sphere :

Feldman J. 'Some Decidability Results on Grammatical Inference and Complexity.' Information and Control Vol 20 pp244-262 1972.

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## CHAPTER 2

## RAM DEVICES AS LEARNING PICTURE PROCESSORS

2.1 The General RAM Logic Device

It has long been known that practical pattern recognition machines must incorporate RAM nets. These can form the storage elements within machines utilising techniques such as n-tuples (13), nearest neighbours (19), feature extraction (41) and template matching (37) for pattern recognition. Machines can also be constructed entirely of RAM nets - possibly of many layers - in a closer analogy to a living neural net. These randomly interconnected devices can form nets with considerable information processing abilities. This type of machine is used in the multi-layer net (MLN) approach to pattern recognition (21).

The use of RAM nets in various configurations for pattern recognition comes from the fact that RAMs are universal logic devices. This is a development of earlier work on universal logic circuits using RAMs or RAM-like devices in single layer net (SLN) structures (2).

To illustrate the generality of RAMs, consider any combinational logic block with  $n$  binary inputs and  $m$  binary outputs. For any given  $n$ -bit input word, the block generates an  $m$ -bit output word. Now consider a RAM element with an  $n$ -bit addressing input and an  $m$ -bit data output. This too can generate any combination of  $m$ -bit output words when fed with  $n$ -bit input words. Evidently the RAM has to be



programmed with the correct data initially to perform this emulation properly. However, it can still in principle perform any of the  $(2^m)^{2^n}$  functions that an n-bit input logic device can exhibit at its m-bit output. Hence a RAM loaded with the correct data can emulate any other combinational logic block.

While this has been shown to be possible in theory, the large value of  $2^n \cdot m$  - the number of storage bits required in the RAM block - would be impossibly large for a machine of any useful size (4). In addition, the time taken to program it would be inordinately long. However, techniques can be applied to enable practically-sized RAM nets to be used successfully in pattern recognition. These techniques usually involve some form of reduction of the input data resulting in realisable sizes of machine.

## 2.2 RAM Nets in Picture Processing and Pattern Recognition

The reduction of input data necessary for practical pattern recognition machines usually involves the extraction of subsets or functions from the input data (25,13). Common examples of these subsets are n-tuples and local or global features, which may possibly be combined into feature vectors. These machines are internally composed of identical sections arranged in parallel - one for each class of pattern to be identified. This results in the size of a pattern recognition machine being directly proportional to the number of classes it is capable of resolving. The input pattern passes through all these parallel channels simultaneously and a decision is made as to the most appropriate class label for the pattern.

A process closely allied to pattern recognition is picture processing, where a picture (possibly destined for eventual classification) is transformed into an improved, extended or otherwise modified version of itself. The purpose of this is, typically, to facilitate later processing the picture may undergo - whether by man or machine. However, it is important to note that in the present context when comparing picture processing with pattern recognition, a processor is a single channel device, whereas a classifier is a multi-channel device.

Thus, it may be predicted that such a machine would be smaller in general than an equivalent classifier designed to handle the same type of pictures. A picture processing RAM machine would be of a size comparable with a single class channel of a classifier. This will later be shown to be the case in practice (see Section 2.7).

### 2.3 The Need to Train RAM Machines

As mentioned in Section 2.1, a RAM machine can emulate any combinational logical device, provided it is programmed with the correct data initially. This pre-programming or 'training' phase is vitally important, as the performance of the RAM machine - whatever its task - depends heavily on the quality and quantity of training received.

For any RAM machine to perform usefully it must generate some dependant output variable that is a definite function of an independent input variable. In training, the machine is presented simultaneously with examples of the input variable ( $A_{tr}$ ) and the corresponding output variable (B) - generated by the function (f) to be learnt

(ie  $B=f(A_{tr})$  ). In this manner, the RAM machine will learn the function it is to perform on any input variable presented to it in future.

Thus, if the training is adequate the RAM should be able to show coherent performance in a test period. Here, it will be presented with only a new input variable ( $A_{te}$ ), enabled to read, and expected to generate the new output variable ( $C$ , where  $C=f(A_{te})$ ,  $f$  being the function learnt earlier).

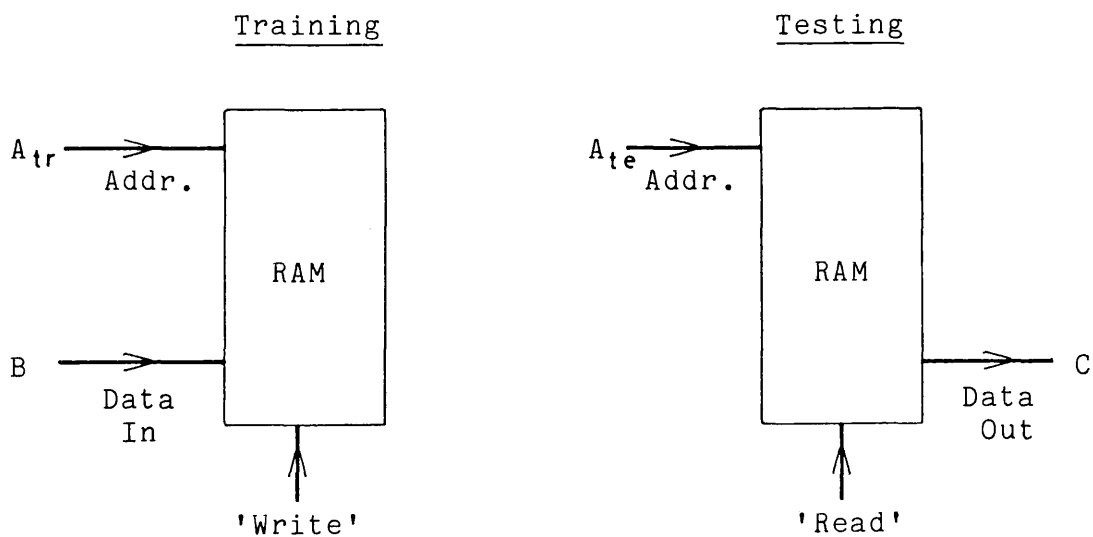


Fig 2.1 Training and Testing Phases of a Learning RAM Device

The usual meanings of the data types  $A_{tr}$ ,  $A_{te}$ ,  $B$  and  $C$  are given below in Fig 2.2 for pattern recognition: this figure also shows a possible set of interpretations for the case of image processing.

Process	Training	Testing
Pattern Recognition	<p><math>A_{tr}</math> I/P Input Picture (Example of Classification Given Below)</p> <p>B I/P Example of Class Label of Above</p>	<p><math>A_{te}</math> I/P Input Picture (To be Classified by Machine)</p> <p>C O/P Class Label of Above, Generated By Machine</p>
Picture Processing	<p><math>A_{tr}</math> I/P Input Picture (Example of Processing Given Below)</p> <p>B I/P Example of Processed Version of Above</p>	<p><math>A_{te}</math> I/P Input Picture (To be Processed by Machine)</p> <p>C O/P Processed Version of Above, Generated by Machine.</p>

Fig 2.2 Meanings of Inputs and Outputs for RAM Pattern Recognition and Picture Processing Machines

#### 2.4 The Use of a Scanning Window to Reduce Data Input

There is a need in picture processing, as in pattern recognition, to reduce the amount of storage required from that used by the 'brute-force' method shown above. For pictures comprising  $n$  bits of data, the storage requirement would be  $2^n \cdot n$  bits for such a brute-force picture processing machine. Using practically sized pictures ( $n=256$  or more) this value reaches  $10^{78}$  bits of storage - an obviously impractical value.

The methods used for storage reduction in pattern classification are not necessarily the best or even suitable for doing the same job in picture processing. This is due to the fundamentally different natures of the tasks to be learnt. The former relies primarily on global features and

is not concerned with the exact spatial relationship between adjacent points in the input picture.

(This fact is to some extent justifiable, since if a pattern recognition method is to remove the maximum amount of redundant information from a picture in one major process, in order to classify it, it must retain features that are as nearly as possible uncorrelated. Hence pattern recognition tends to be less concerned with what is happening in local neighbourhoods of a picture.)

Picture processing however, depends on these local features and short range patterns in the input picture. This equal dependence on local patterns - wherever they originate in the picture space - would suggest the use of a small scanning window as a suitable method of reducing the data derived from the input picture.

The application of a scanning window extractor to an  $n$ -bit input picture results in the generation of a  $w_i$ -bit window for each stage of the scan. This value ( $w_i$ ) is much less than the number of bits contained in the whole input picture ( $n$ ); hence a large reduction in the storage requirements can be expected. (It has been assumed in this early discussion that each picture element or pixel is composed of a single binary digit to simplify the analysis.)

To cover the entire picture, this window extractor requires two co-ordinate parameters ( $x,y$ ) as input to define the current position of the window to be extracted. One complete run will involve the extraction of  $n$  separate windows while cycling through all possible values of ( $x,y$ ) once (Fig 2.3).

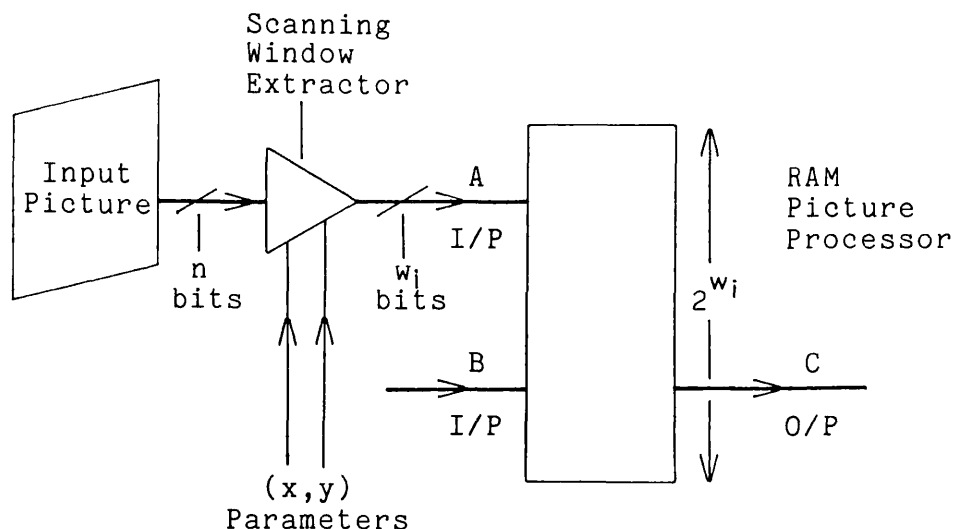


Fig 2.3 Application of a Scanning Window Extractor To the Input Picture

This reduction in the number of inputs at A considerably reduces the storage requirements - by a factor  $(2^{w_i}/2^n)$ , which is very small. (It should be recalled that  $w_i < n$  thus  $2^{w_i} \ll 2^n$ .)

The use of a scanning window on the input picture suggests further opportunities to reduce storage, and also to reduce irrelevant data in the example picture at input B. This irrelevant data is the part of the example picture that is not inside the window being currently extracted from the input picture. This stems from the earlier realisation of the fact that a picture processor deals only with local operators, so that only the region of the example picture near  $(x,y)$  is of any use in determining the processing operation to be performed on the region near  $(x,y)$  in the input picture (Fig 2.4).

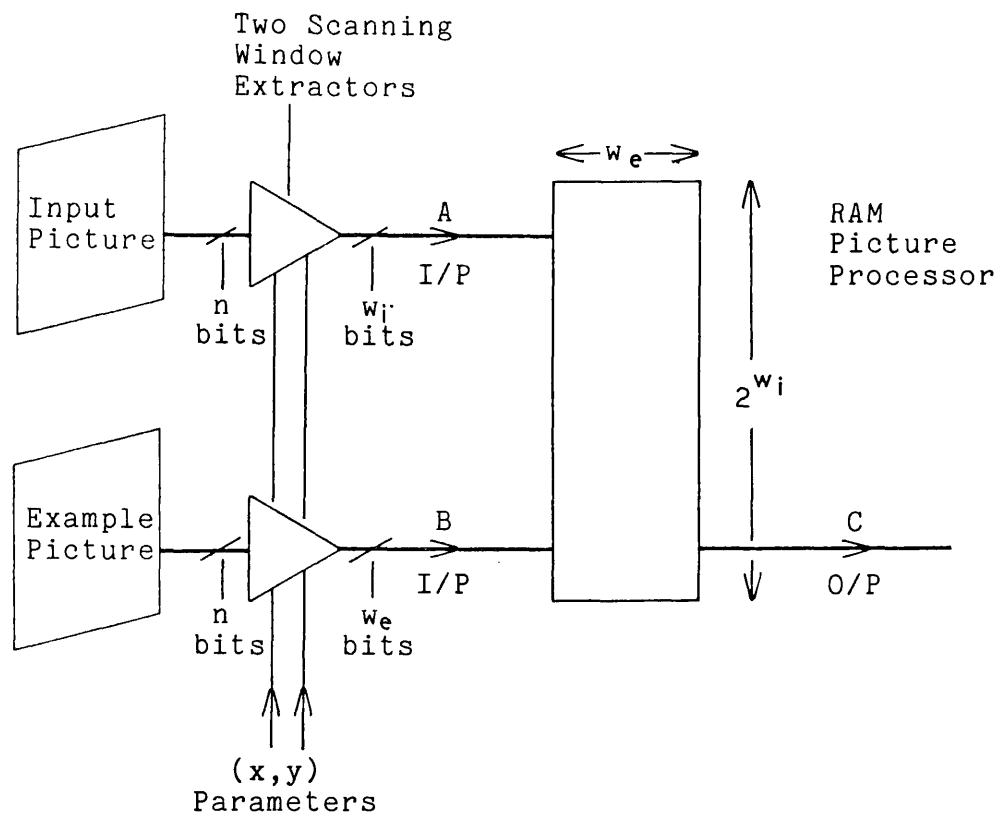


Fig 2.4 The Use of Two Synchronised Scanning Window Extractors on the Input and Example Pictures

This suggests a method of generating the output picture. In training the machine scans the pair of input pictures sequentially. In testing it can similarly scan the input picture to be processed, while synchronously generating the output picture. This can be seen as re-creating a large ( $n$ -bit) output picture from the smaller ( $w_o$ -bit) data output derived from the RAM memory matrix.

The machine described above uses three synchronized scanning window devices - although only two (shown as I and II below) are used in training, and two (shown as I and III below) are used in testing (Fig 2.5):

Device	Type	Function
I -	( Window )	sequentially extracts
	( )	$w_i$ - (or $w_e$ -) bit windows from
II -	( Extractors )	an $n$ -bit input (or example) picture
III -	( Picture )	sequentially generates
	( )	an $n$ -bit output picture from
	( Generator )	successive $w_o$ -bit windows

Device I acts on the Input Picture in training and testing;

Device II acts on the Example Picture in training only;

Device III acts to form the Output Picture in testing only.

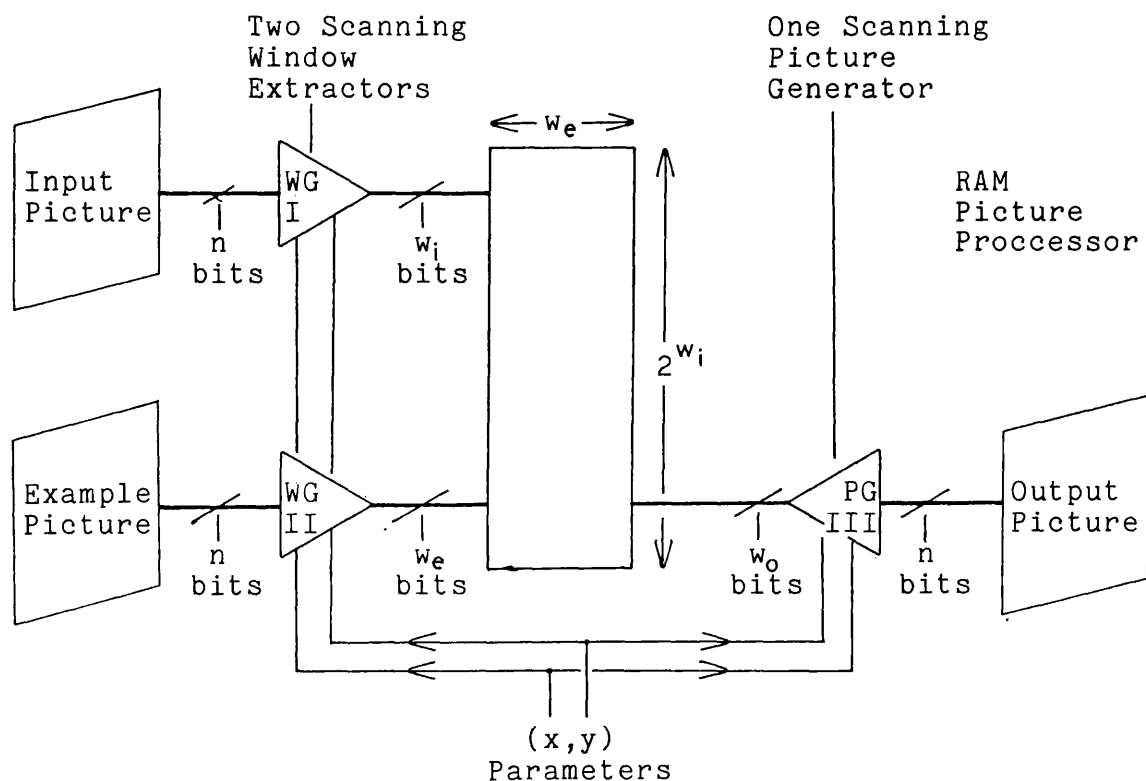


Fig 2.5 The Use of Three Scanning Devices to Read Inputs and Generate Outputs in a RAM Picture Processor

### 2.5 The Advantages of Using a Scanning Window

This use of a scanning device means that not only is the storage requirement much reduced, but also the training



received from a single pair of input pictures  $A_{tr}$  and  $B$  is much increased. This is because the number of training sets received from each single pair of pictures is increased to  $n$  sets of values. Since the machine receives many more training sets of data from each pair of pictures and can effectively intermix such feature subsets to recreate whole patterns, it can begin to generalize. That is, it gains the ability to be able to process pictures in the testing phase not seen previously in the training phase. This is as opposed to the brute-force machine seen earlier (in Section 2.3) where there is no opportunity to generalize over pictures. Here, each  $n$ -bit picture would have addressed one unique cell in the memory matrix, chosen from the  $2^n$  cells present. This machine could not process pictures not seen before, as the memory matrix cells corresponding to those as yet unseen pictures would not have been set before. This property of generalisation is one of the fundamental reasons for using such an architecture, as it is an essential requirement for any practical picture processor, just as it is for any practical pattern recognition machine.

## 2.6 Processing within the RAM Picture Processing Machine

The actual use made of the incoming data by the RAM machine will now be considered. It has been shown (Section 2.4) that this decrease in the RAM storage requirement results from two causes: the reduction in the incoming data width from  $n$  to  $w_i$  bits in the case of the input picture, and from  $n$  to  $w_e$  bits for the example picture. This implies the simplest and, as will be shown later, completely practicable arrangement for processing the

incoming data.

The window extracted from the input picture forms the address lines of the RAM, and the window extracted from the example picture in training forms the data input lines of the RAM. Consequently, the data output lines of the RAM will be used to form the window for generating the output picture during testing (Fig 2.6).

This implies that  $w_o \leq w_e$ , and the simplest and again practical arrangement is to have  $w_o = w_e$ . That is, the output window used to generate the output picture uses the whole of the original example window stored in training.

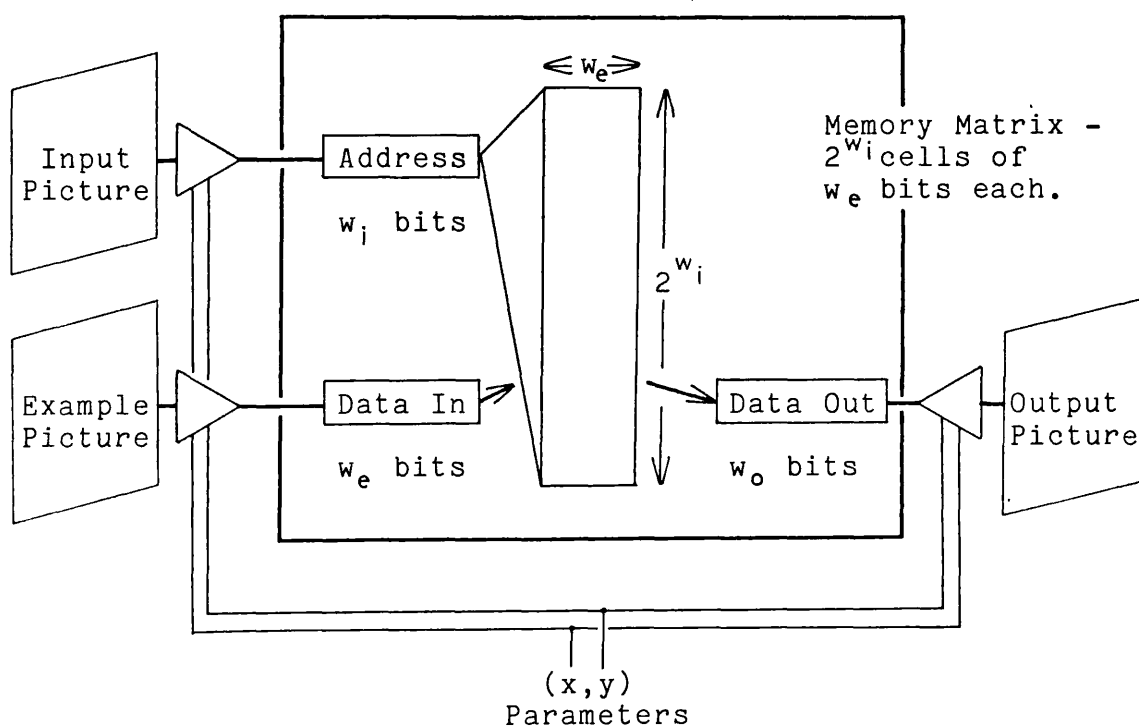


Fig 2.6 Data Handling in a Practical RAM Picture Processing Machine

## 2.7 Practical RAM Picture Processor Layout

In order to facilitate understanding of the machine in this and the next section, some numerical values for the variables introduced so far are given in Fig 2.7. This will illustrate the layout and operation in actual learning and application of a picture processing task with real data. These numerical values are by no means optimum, but are practical and have been shown to work. (A fuller treatment of the type and range of possible values will be given later in Chapter 4.)

This hardware layout results in the following features:

### Window Extractor I

This uses a 256-bit input pattern and a pair of 4-bit (x,y) co-ordinates to define a 9-bit output window. The latter contains the centre point value at (x,y) and its surrounding 8 nearest neighbours. This 9-bit word is used to address one of the 512 ( $=2^9$ ) locations in the memory matrix of the RAM.

### Window Extractor II

This similarly takes a 256-bit example pattern and the two 4-bit co-ordinates to define a 1-bit output window, containing only the centre point value at position (x,y). This is used as the data input for the RAM during training.

### The RAM

This has 9 address lines, and 1 data input line, giving a store size of 512 1-bit words. The control line defines the mode of operation as being either 'write' or 'read' in training or testing respectively.

Variable	Function	Value	Comment
n	no.of pixels in picture field	256	( $=16^2$ ) : a coarsely digitized two dimensional picture
$w_i$	no.of pixels in window extracted from input picture	9	( $=3^2$ ) : i.e. 3x3 pixel window with a centre point and eight neighbours (implies a rectangular grid)
$w_e$	no.of pixels in window extracted from example picture	1	the centre point value only, with the same x,y values as above
$w_o$	no.of pixels in window used to generate output picture	1	a single point is inserted in the output picture at x,y (recall : $w_o=w_e$ )
x,y	length of side of digitized picture	16,16	a square picture ( $n=xy$ )
b	no.of bits per pixel	1	a binary (black and white) picture

Fig 2.7 Numerical Values of Variables in a Practical LPP Machine

### Picture Generator III

This takes a 1-bit data output from the RAM and two 4-bit co-ordinates (x,y) to gradually define a 256-bit output pattern in testing. The pixel value supplied is inserted in the picture field at position (x,y).

### (x,y) Co-ordinate Generator

This cyclically scans through all values of x (from 0-15) and for each value of x scans through all values of y (0-15). This covers the entire 256-bit picture

systematically, and 'drives' the above Devices I, II and III.

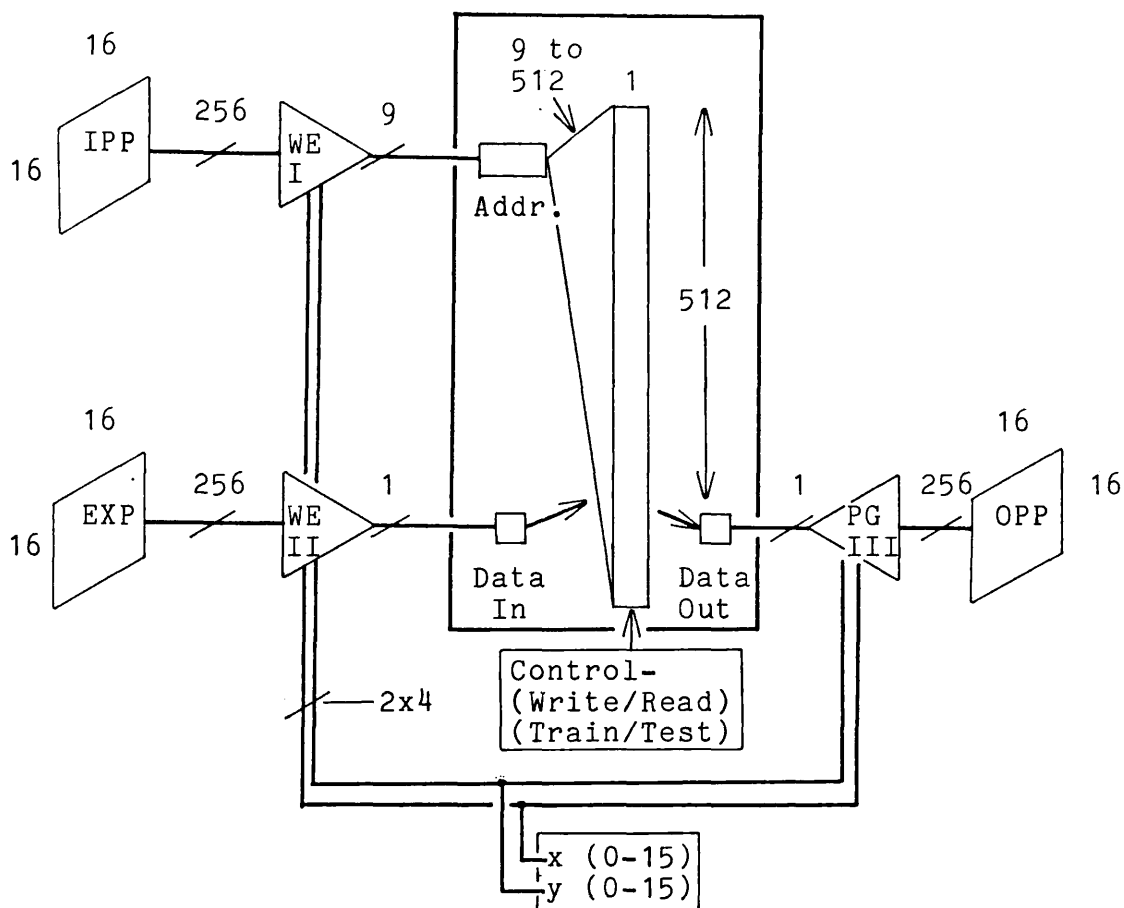


Fig 2.8 Hardware of a Practical RAM Picture Processor

### 2.8 Mode of Operation

The operation of the machine described above will be described in two phases of operation, training and testing.

#### Training

The machine is presented simultaneously with two 256-bit pictures - the input pattern (IPP) and the example pattern (EXP). (The example pattern should be a transform of the input pattern, modified according to the processing task

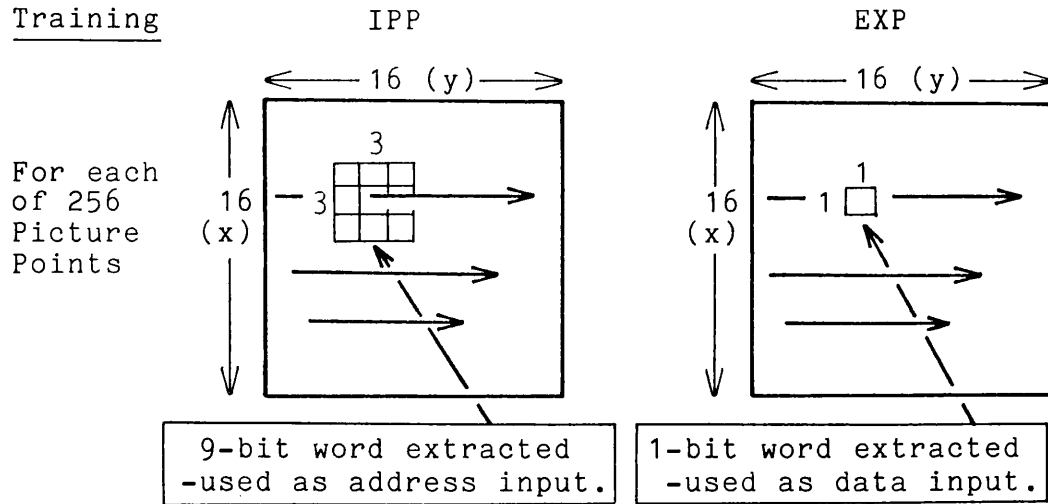
the machine is to learn.) From each point in the input picture the machine extracts a (3x3) window. This is used to form the address, defining one of 512 locations in a 512 by 1-bit RAM array. A single data bit point is simultaneously extracted from the corresponding position in the example picture. This value is written into the RAM location now selected. This process is repeated for each pixel in the pattern field, and then possibly for further pairs of pictures, if the training is to involve more than one pair of pictures.

### Testing

The machine is presented with a single 256-bit picture, the input pattern (IPP), and is expected to produce one 256-bit picture - the output pattern (OPP). (This output pattern should ideally be a correctly transformed version of the input pattern, modified according to the process learnt earlier.) For each point in the picture, the machine again extracts a (3x3) window from the input pattern, and uses this to address one of the 512 locations in the 512 by 1-bit RAM array. A 1-bit word is read from this location and is inserted into the picture space of the output pattern at a position corresponding to the current position of the window. The output pattern is correspondingly built up as all points are scanned sequentially.

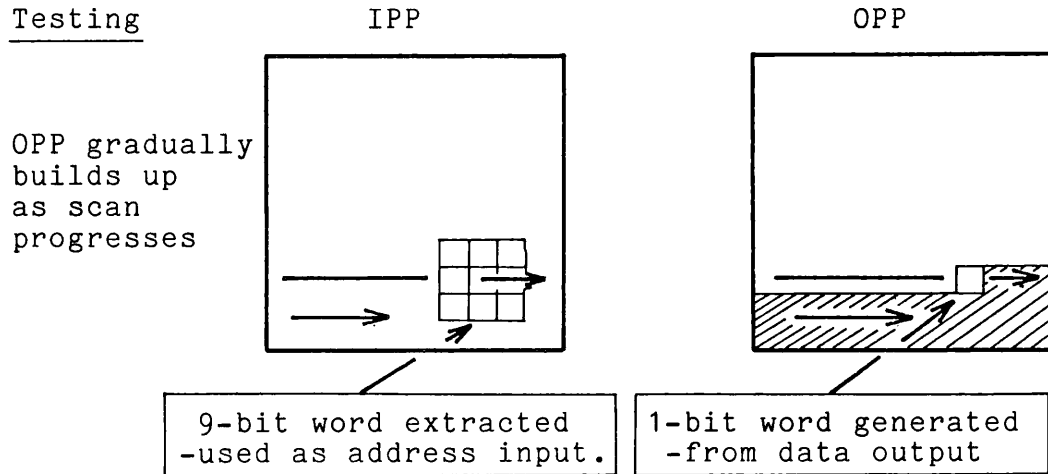
As stated earlier, it is probable that there will be more than one pair of training examples presented to the machine in the training phase. It is also probable that in the testing phase more than one picture will be presented to the machine for processing, which will in turn be expected to generate a set of output pictures. Thus, in both the

Training



IPP and EXP scanned synchronously as RAM is loaded with data - trained.

Testing



IPP and OPP scanned synchronously as RAM reads out data - tested.

Fig 2.9 Mode of Operation on Picture Pairs

training and testing phases, the machine will be presented with a set of pictures, each set being operated upon as in Fig 2.9. This is shown in Fig 2.10.

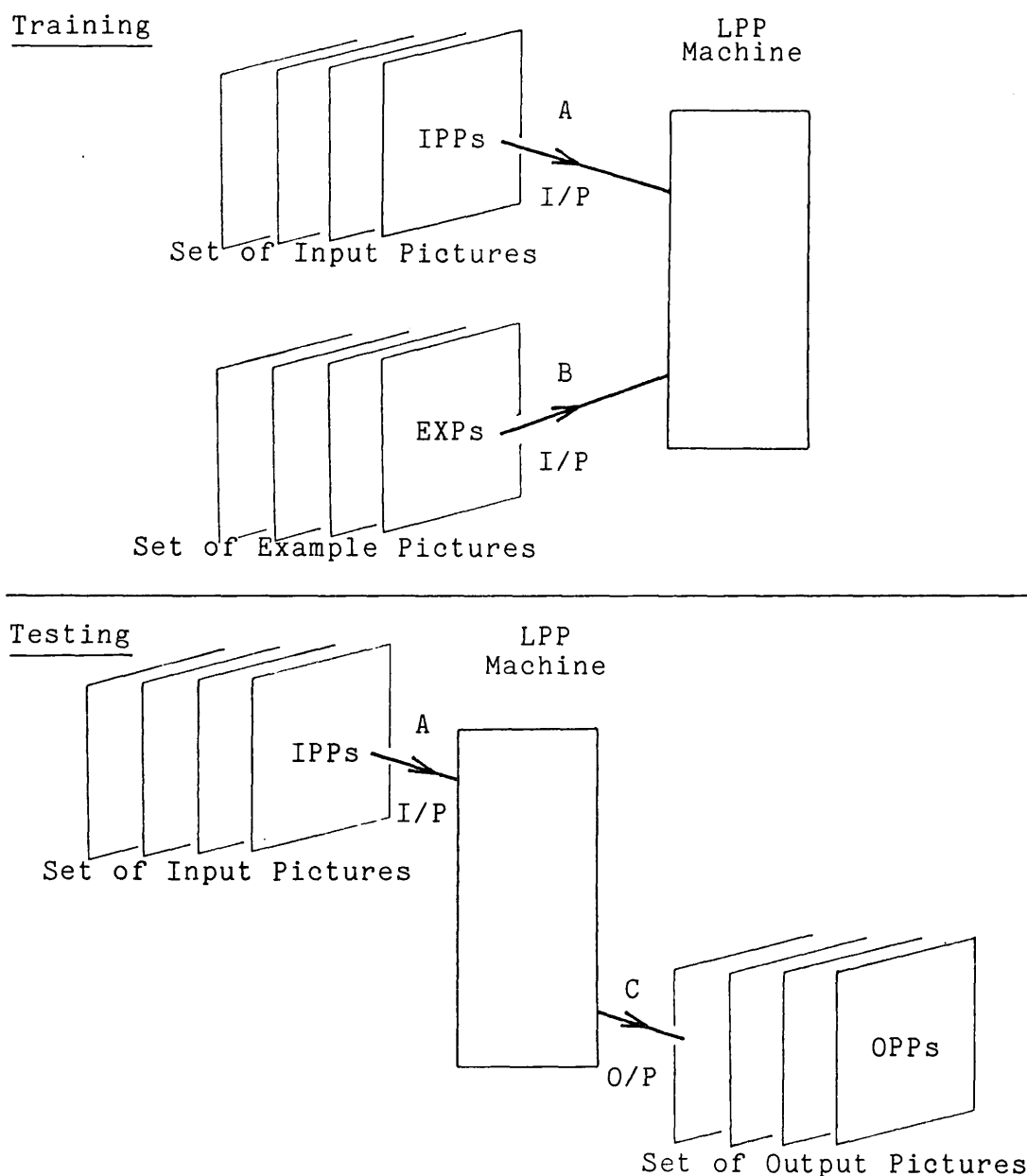


Fig 2.10 Mode of Operation on Sets of Pictures

## 2.9 Preliminary Conclusions about RAM Picture Processors

This RAM learning picture processor can be interpreted as a simple look-up table of all possible variations in a 9-bit binary window. This is a perfectly valid interpretation, although four additional points should be noted:



1 The look-up table can be written into selectively, and hence it can be generated by examples in training. Thus there is no need to determine how to express the picture processing algorithm analytically in terms of the input window. If examples are available to illustrate the process, this is now a sufficient condition to enable machine processing to be carried out.

2 In addition, the machine's memory matrix, once trained by example, will represent the algorithm that has been used to transform the picture. Thus even if an algorithm is not known, use of such a RAM learning picture processor will generate an expression for this algorithm in terms of a window look-up table. Subsequent analysis of this internal state of the machine will give insight into this initially unknown algorithm.

3 The memory matrix of the machine can also be trained directly, as opposed to being trained by example. If the picture processing algorithm is known analytically, then the memory matrix locations can be loaded directly with the correct data. The machine then operating in the testing phase would perform this picture processing algorithm as if it had been learnt earlier by example. This procedure would have the particular advantage of rapid processing of known algorithms (see below).

4 The Learning Picture Processor can in principle operate extremely rapidly, since the only processing time required is the generation delay for a window (usually a simple extraction of a subset of data from the input set), coupled with the access time of the RAM, for each point in the

picture. To take the simple example of the binary picture used earlier with 256 ( $16^2$ ) picture points and a RAM having an access time of 200ns, then a picture could be processed in approximately 50 $\mu$ s. Picture points are often generated serially (as in, for example, a video system) and can be fed into a shift register type processor, that effectively extracts windows from high speed serial data in a 'shift delay' period. If this delay period is less than or equal to the access time of the RAM, then a processing time of 50 $\mu$ s would become realisable in practice.

## CHAPTER 3

## EXPERIMENTS WITH BASIC LPP MACHINES

3.1 An Introduction to the Experimental Work

The hardware layout and mode of operation of a small, simple Learning Picture Processor (LPP) have been described in Sections 2.7 and 2.8. It will be appreciated that this layout is neither the only possible nor even an optimum one. It is evident that a very large number of variations is possible. A simple layout was chosen merely to serve as a workable example of an LPP machine. This particular layout will be used in the following experiments to show the concept of machine learning of picture processing to be practicable. Similarly, the mode of operation described is one of the simplest possible, and will serve to show the machine as described performing actual picture processing operations.

Both these aspects can be considerably extended and ultimately improved. These improvements will stem from :

- 1 theoretical considerations of the processes occurring in the machine, which will suggest layouts and operating modes more efficient in terms of speed, performance, flexibility and quantity of hardware used,

- 2 results of practical experiments which will confirm or suggest new methods of improving the machine.

As the preliminary experiments are run, improvements will gradually be incorporated into the machine and their results noted. Eventually, a global view of the machine in its most general form will emerge and will be fully discussed in Chapter 4. More ambitious variations in the layout and operation of an LPP machine will then be investigated in the further experiments in Chapters 5 and 6.

### 3.2 Picture Processing Tasks for the Simple LPP Machine

In order to attempt picture processing with the LPP machine, it is necessary to consider first the range of tasks the machine should be able to tackle. Some physical constraints are apparent with the machine as described in Section 2.7. It is only within these limitations that the machine can be expected to perform usefully. There are essentially two such constraints :

- 1 The use of a binary digitized picture; ie. only two grey levels are used to define the brightness at each picture point (most conveniently labelled 'black' and 'white'),

- 2 only the centre point and its immediate eight connected neighbours on a rectangular lattice will be used to define and execute the picture processing algorithm.

These constraints could well be relaxed later on: until then several useful picture processes are still possible.

Examples of such operations are:

#### Inversion

The swapping of the two brightness values to form a 'negative' image, ie. white objects on a black background. (Here, and in what follows, an initial picture is assumed to be composed of black objects on a white background.)

#### Cleaning

The removal of small isolated black (or white) specks from a contrasting white (or black) background. This is a well known operation which improves the picture by the removal of 'salt and pepper' noise (66).

#### Shrinking

The removal of a single outer layer of black points from black objects, often with a view to removing black objects entirely below a certain size.

#### Expanding

The removal of a single outer layer of white points from white objects, often to remove white holes entirely below a certain size. Shrinking and expanding are sometimes applied consecutively to remove both black and white objects and holes (65).

#### Shifting

The movement of objects in a given direction with respect to their (stationary) background. This serves as an aid to subsequent position dependent analysis of objects (45).

### Edge Finding

The location and marking of points on the boundary between black and white areas resulting in the outline of the objects - a useful aid in classification and scene analysis (69).

### Convex Hull Determination

The transformation of black objects into their minimum enclosing convex shapes by the addition of black points into concavities. This resulting convex hull can then be used in certain methods of pattern recognition and shape description (53).

### Location of Objects

The identification and marking of objects of a particular shape or size within the field.

### Thinning

The production of a unit width black skeleton from a black object with variable width limbs, whilst maintaining limb ends and connectivity. This is a well known aid to pattern analysis (70,10).

This list is clearly not exhaustive: it is limited to include only those picture processing tasks that the LPP machine described earlier could perform. However, it contains examples of varying complexity from such trivially simple tasks as inversion and cleaning, up to more involved tasks such as the location of objects or thinning. (These may require several passes through a small-windowed and thus diameter-limited machine (50), performing the process gradually on successive passes.)

One important point should be mentioned at this stage regarding the concept of a Learning Picture Processor and the tasks it can perform. The above list of picture processing tasks contains a range of well-defined separate operations that may be of use in transforming a picture for subsequent classification or identification. These tasks have already been compartmentalized in that each one has been graded in complexity and does a specific, limited job: some suggestion has even been made of the algorithm that might be used to do this job.

One of the predominant features of a Learning Picture Processor to be demonstrated here is its generation of its own processing algorithms when presented with examples of an original and transformed picture. This transformation need not be simple nor even immediately reducible to any of the picture processing operations listed above. Provision of examples showing the required transformation is sufficient to train the machine, without recourse to direct investigation of that transformation itself.

### 3.3 An Outline of the Computer LPP Simulator

An LPP machine was first constructed by software simulation of the hardware on a small general purpose digital computer. Since large-scale changes to the ultimate layout were envisaged as the experimental investigation proceeded, simulation had many advantages over actual construction of working hardware. These included development time, effort, flexibility, ease of connection to existing picture handling peripherals and the possibility of

including some form of rudimentary operating system. This facilitated the handling of data and the automation of some repetitive processes.

The software package developed to fulfil these requirements was written in Assembly Language for a Motorola M6800-based microcomputer (49,52). This use of a local machine was aimed at making the maximum use of available image input and output devices. A low level language was used to maximize the machine's effective size and speed. The program proceeds as a series of interactive exchanges between the computer and the operator, taking the form of machine prompts, operator responses and machine processing.

This description of the simulation software has been provided here to facilitate understanding of how the following experiments were performed in practice. A more complete description is given in Chapter 7.

### 3.4 Experiment 1 : Proving Run

As an initial run using an LPP machine for the first time, a simple picture processing task was attempted. This task was the thinning down of a character with limbs of three to five units width to limbs of two to three units. It should be remembered that no precise definition of the operation is necessary, as the provision of examples is itself sufficient definition.

#### Data

The original letters used as the input patterns (IPPs) in these early experiments were hand-written block capital letters collected from volunteers and digitized on a binary



16x16 matrix. Details of the collection of these data is given in (58). The example patterns (EXPs) were produced by subsequent manual editing of these pictures to remove noise points and generally thin the limbs down to an approximately constant width by eye. This produced a set of non-rigorously transformed data - suitable for testing a LPP machine's learning ability.

### Training

The input pattern (IPP) and example pattern (EXP) presented to the machine are shown in Fig 3.1. The EXP can be seen as a thinned version of the IPP. This one pair of pictures is presented to the machine and the RAM is enabled to write - ie. it is trained. This occurs separately for every pixel, as training occurs in parallel for such a machine.

### Testing

To test the performance, another input pattern (IPP 1) is presented to the machine and the RAM is enabled to read, thus generating an output pattern (OPP 1) as the machine scans through the picture field. This similarly occurs in the parallel mode, as the machine builds up OPP 1 in a different picture space from IPP 1. (Later experiments in Chapter 6 will also use the sequential mode of operation.) This testing IPP 1 is shown together with the resultant OPP 1 in Fig 3.2.

### Results

The machine can be seen to have transformed the testing IPP 1 in generally the same manner as the training IPP was transformed - it has reduced the thick object to a thinner

Training Set : 1x(IPP+EXP) pair presented to the machine

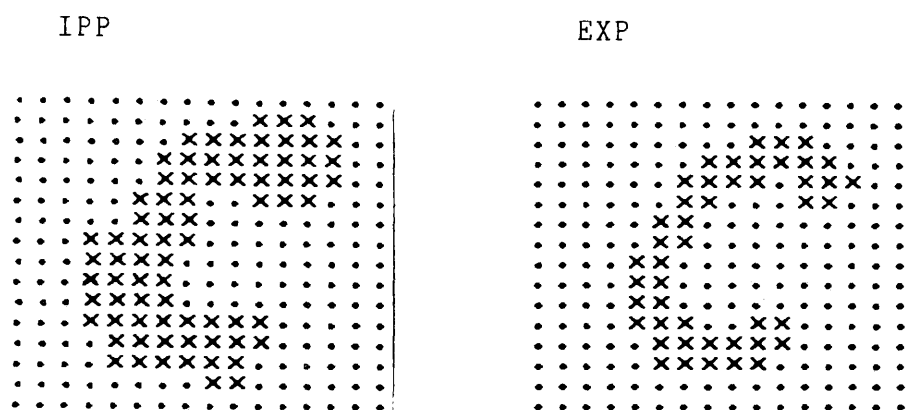


Fig 3.1 Experiment 1 : Training Patterns

Test Set : IPPs 1-2 presented to machine,  
which generates OPPs 1-2 respectively

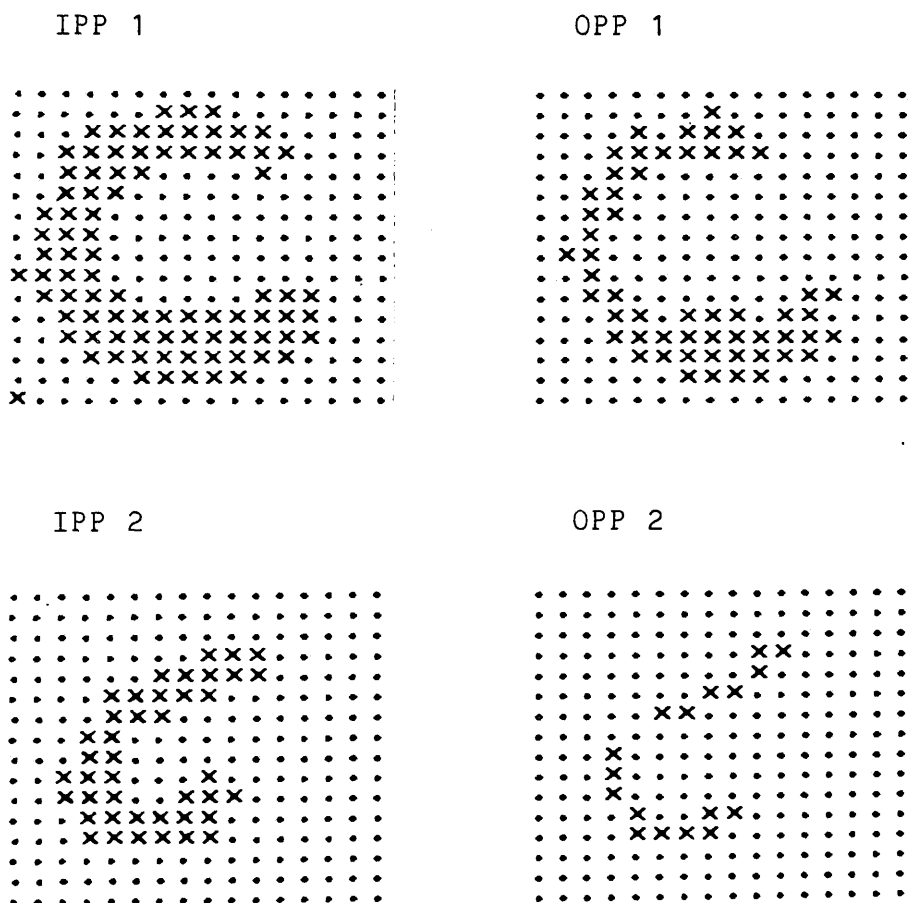


Fig 3.2 Experiment 1 : Testing Patterns

one. This been achieved after the use of only one pair of training examples. The fact that the machine responded correctly after only one such training pair is an important point and will be referred to later.

### Discussion

Despite the success in producing a thinning effect as trained, there are some shortcomings in the performance obvious from even a cursory inspection. The OPP 1 now has erratic shape and limb widths when compared with the original. Although the average limb width has decreased, it now ranges from one to four units. This would appear to be due to 'under-training' - ie. not all bits in the memory matrix were actively set or reset by the training patterns. The memory matrix was arbitrarily cleared (all bits set to '0') before training. This means that bits actively cleared to '0' by training are indistinguishable in testing from bits initially cleared to '0' and thereafter not accessed in training. Thus if, in testing, IPP 1 presents a (3x3) window feature not seen before in training, this will address a cell in the memory matrix not accessed since pre-training initialisation. Consequently it will contain (and hence read out) a '0' into this position of OPP 1. These additional '0' points in OPP 1 can thus be attributed to insufficient training. This will be investigated further in Section 3.6, Experiment 3.)

As a further demonstration of the inadequacy of the training received, an already thin pattern was also used to test the same machine. This pattern IPP 2 and the machine's output OPP 2 are shown in Fig 3.2.

The resultant broken limbs again suggest insufficient training. The machine has never seen patterns with features like those in IPP 2 before, and consequently cannot be expected to produce correct transformations of such patterns. This is exactly analogous to the well-known RAM pattern recognition machine that might exhibit poor classification ability due to insufficient or unrepresentative training. This results in too few discriminators calling a co-incidence with the unfamiliar pattern and hence an unreliable (and probably wrong) result occurs. Attempts have been made to avoid this in established recognition systems, involving choices of 'optimum' internal arrangements (12).

In the case of the LPP machine, the wrong result takes the form of the introduction of excessive '0' values into the output picture space, here totally breaking the original object.

### 3.5 Experiment 2 : Training Set Size

In an effort to improve the performance of the LPP machine, it has been noted that it requires sufficient examples in training to enable it to generalize over a greater range of pictures in testing. This can be effected in two ways :

- 1 The training patterns themselves can be altered to contain more varied features, in an attempt to train more memory matrix cells per pattern. Every training pattern of  $n$  pixels each effectively constitutes  $n$  training patterns, as  $n$   $w_i$ -bit windows are extracted from each one.

This explains the apparently reasonable picture processing ability found after just one pair of training patterns in the previous experiment. The single training pair generated  $n$  (256) training patterns on scanning the input picture, pausing at each of the 256 points. So, if as many different features as possible (of all  $2^9$  possible window features) can be introduced into a single training pair, then that pair will train the machine to a far greater extent than one with less variation. (This approach to increasing the training will be attempted in Experiment 13.)

2 More training patterns can be used, in the hope that more patterns will be likely to contain a wider variation of features. This simple and obvious method of increasing the amount of training will be tried here.

### Training

A set of eight pairs of thick patterns (IPPs 1-8) and corresponding thin patterns (EXPs 1-8) is presented to the machine for training. These are shown in Figs 3.3 and 3.4. The memory matrix of the RAM is initially cleared before training such that all bits are reset to '0'.

### Testing

Again, the parallel mode of operation is used to generate the OPP set. The test IPPs are shown together with their corresponding OPPs in Fig 3.5; as are the two outputs generated by the machine in Experiment 1 - to facilitate comparison between these two machines with differing amounts of training. This test set (IPPs 1-4) contains the original two characters used to test the machine in Experiment 1 (a thick and thin letter 'C') and also two letters of a

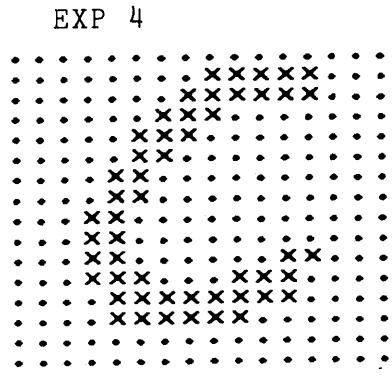
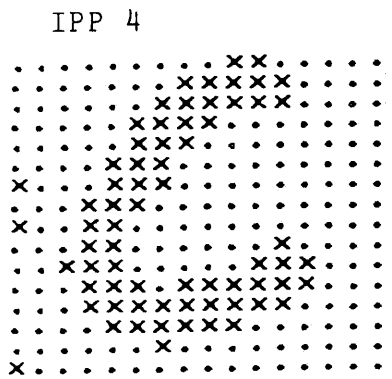
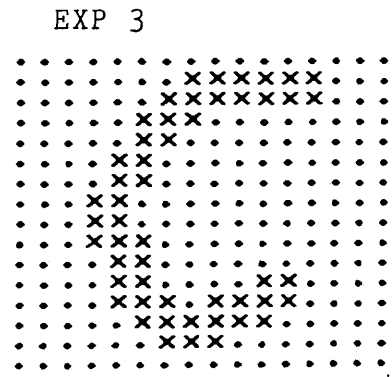
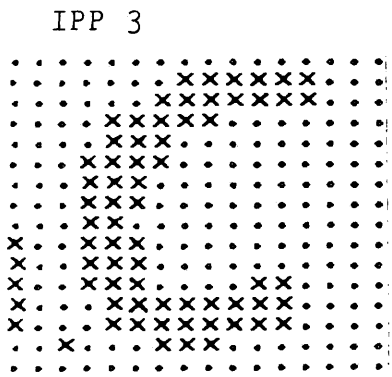
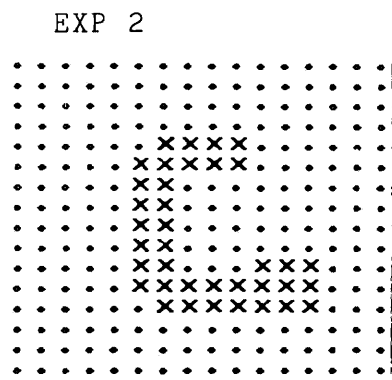
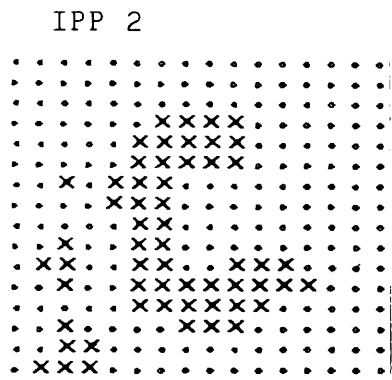
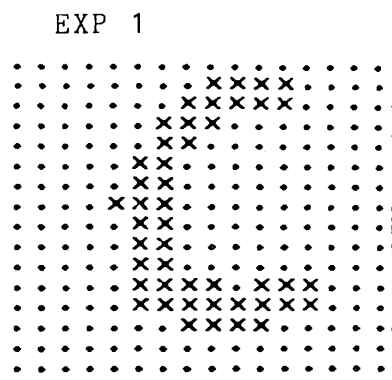
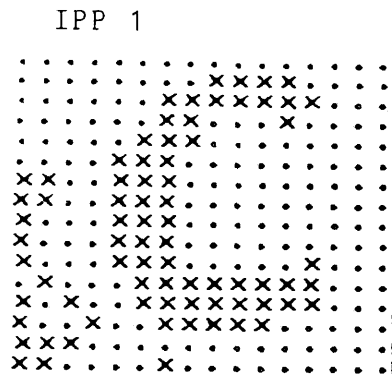


Fig 3.3 Experiment 2 : Training Patterns 1-4

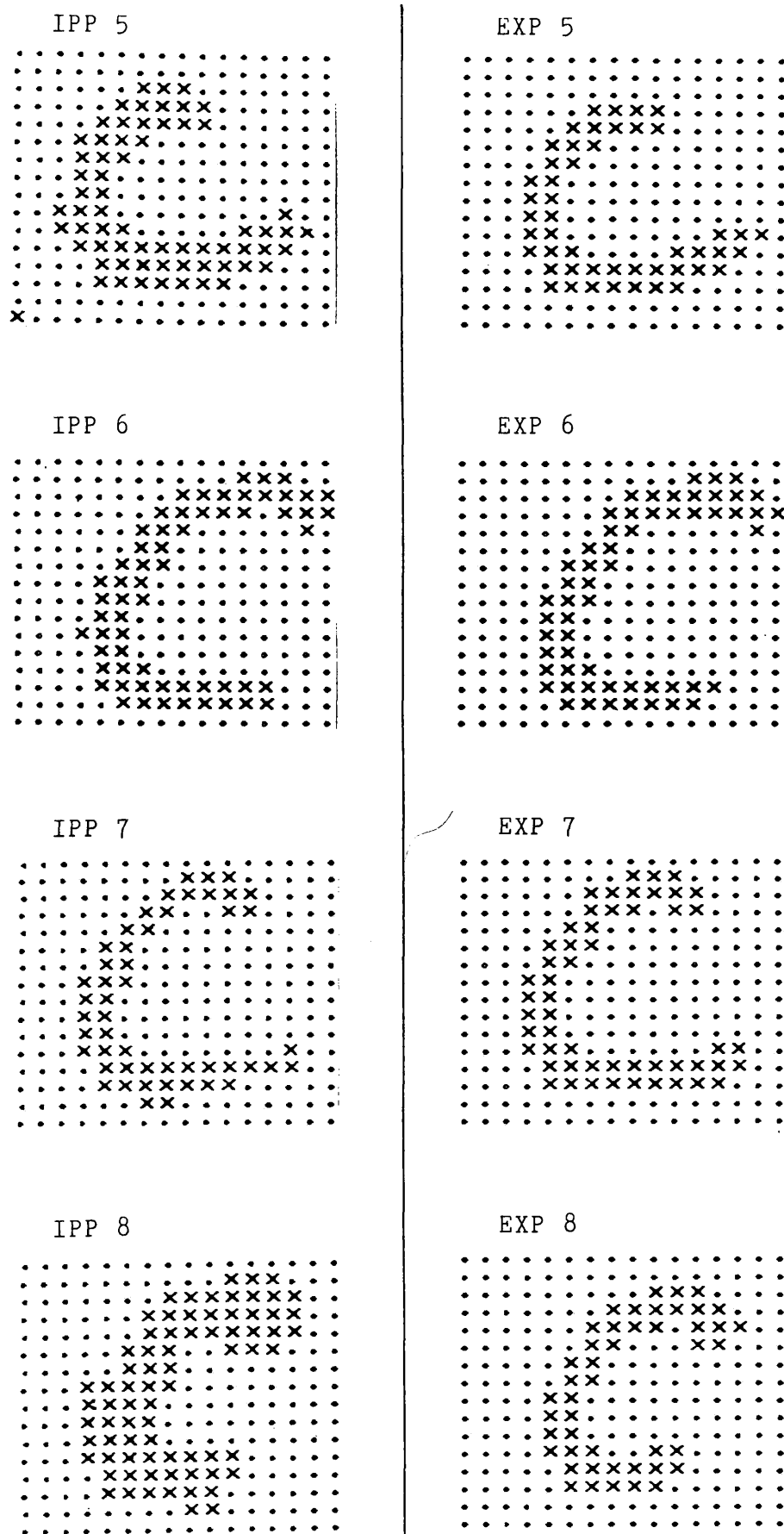
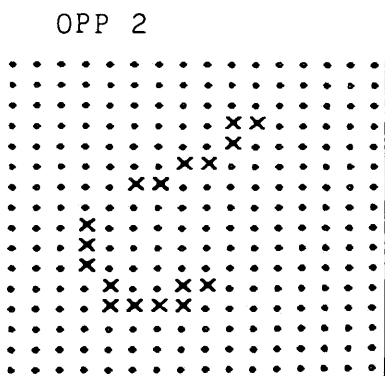
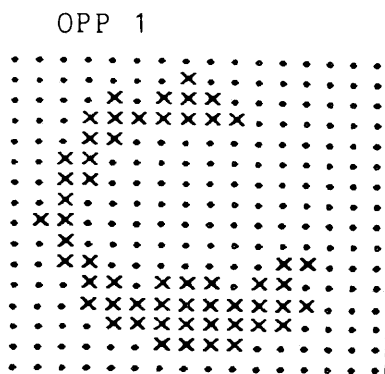
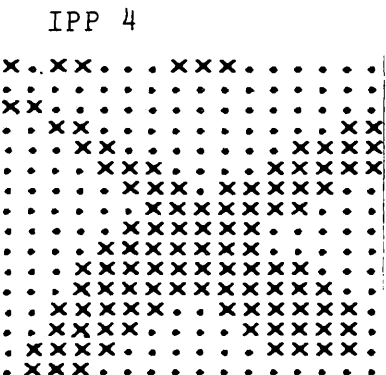
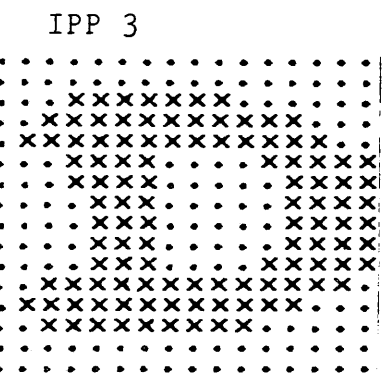
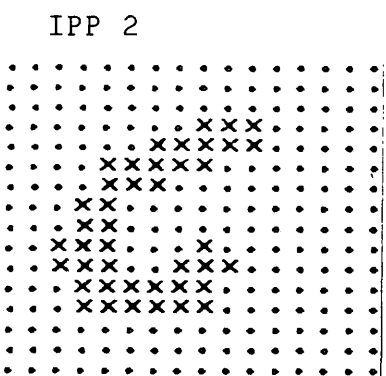
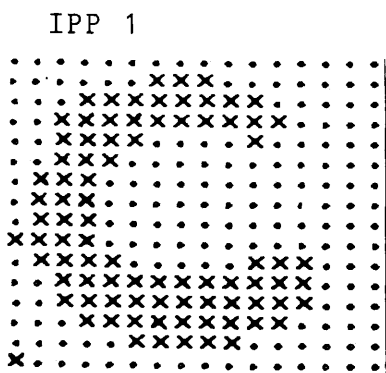


Fig 3.4 Experiment 2 : Training Patterns 5-8

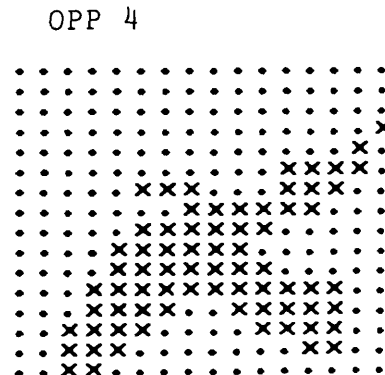
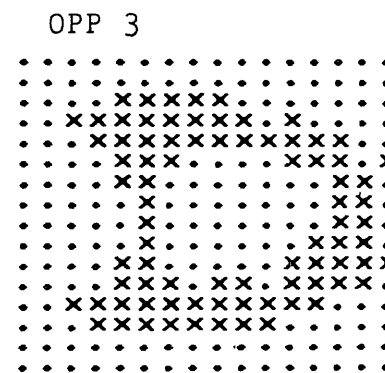
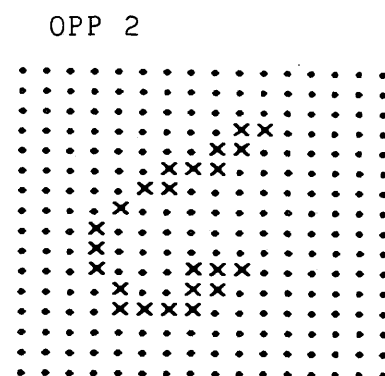
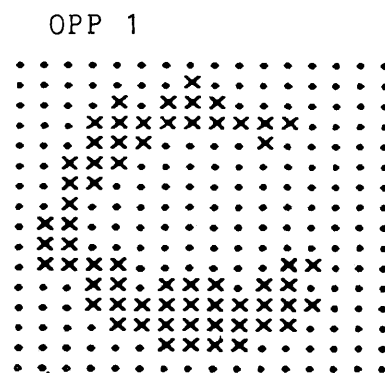
Outputs of Exp 1 -  
Machine Trained  
by ONE pair only :



Inputs to both  
Machines :



Outputs of Exp 2 -  
Machine Trained  
by EIGHT pairs :



Machine tested on  
Patterns of  
Different Class,  
but Same Style as  
Training Patterns

Machine tested on  
Patterns of  
Different Class,  
and Different Style  
from Training  
Patterns :  
'Thin Limbed'

Fig 3.5 Experiments 1 and 2 : Comparison of Test Results



different alphabetic class - the letters 'D' and 'X'.

### Results

The OPPs 1-2 (Fig 3.5) generated by this machine (in the right hand column of the diagram) are to be compared with the OPPs 1-2 generated by the same machine in Experiment 1 (left hand column of diagram). In both these cases the same IPPs 1-2 were used (centre column), the only variation being the quantity of training received.

### Discussion

It can be seen that in the case of IPP 1 both machines produced a thinner version of the object. This is to be expected, since both machines are now being tested with the same type of data (ie. thick letter 'C's) as those on which they were trained. However, when the second test patterns are examined (IPP 2 to OPP 2) for both these machines, a thinner object being presented as a test, the two results begin to show the differences in training. The machine trained on only one pair has broken the limbs completely at one point, but the machine trained on eight pairs has retained connectedness throughout the object, producing a thinned, but not broken skeleton.

As a further test of this machine's ability, it was tested with an object of a different class (IPP 3) : the letter 'D'. The resultant output (OPP 3) shows that the machine is capable of processing objects of a class different from that on which it was trained. In hindsight, this is to be expected since the machine as described relies only on local features as a small (3x3) window is used. Since there is no dependence on similarity between global

features in the training and test set the machine is 'blind' to any large scale shapes of objects: it is essentially 'diameter-limited' (50).

A final test was made to find the limit of useful performance of this machine. An object (IPP 4 : the letter 'X') containing limbs of varying thickness, from one to five units width, was presented to the machine. This and the resultant OPP 4 are shown in Fig 3.5. The machine removed the narrow limb entirely, illustrating that although it has been more thoroughly trained than that of Experiment 1, it is still deficient. In fact there are still some memory matrix cells unset, as not all the possible 512 ( $=2^9$ ) window features have been seen in training.

### 3.6 Experiment 3 : Initialisation

The fact that the training given to the LPP machines was insufficient in the above two cases has been stated without proof. To furnish proof, the following experiment was performed.

The LPP machine was set up exactly as for Experiments 1 and 2, except that the memory matrix cells were all initialised before training commenced to contain the value '1' rather than '0'.

#### Training

The training given was exactly the same as that in Experiment 2 so that a comparison of the ultimate results can be drawn.

### Testing

For ease of comparison with the results of Experiment 2, the same four picture objects are used again here. These IPPs 1-4 are reproduced in the centre column of Fig 3.6, with the corresponding OPPs 1-4 in the right hand column. (The output of Experiment 2 (OPPs 1-4) is reproduced in the left hand column of the same diagram.)

The only difference between this and the previous experiment lies in the initial states of the machines - training and testing being identical. This means that any difference in the final outputs must be due solely to the accessing of cells in testing that were not accessed at all in training, and hence would be still in their (different) initial states. The position and extent of these differences will indicate the cells in the memory matrix not trained by the training set.

### Results

An examination of Fig 3.6 reveals the expected differences in the OPPs of the two Experiments 2 and 3. The differing pixels have been 'boxed' in the diagram.

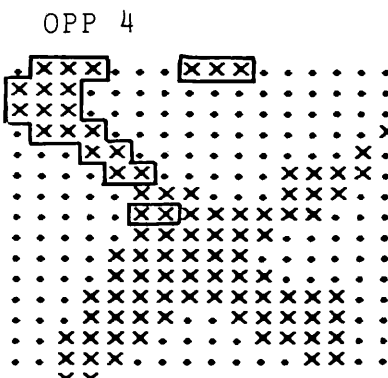
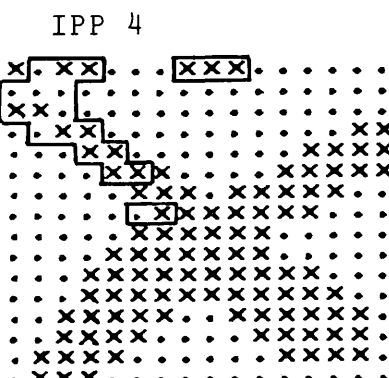
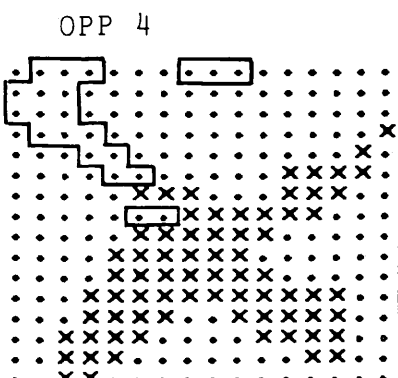
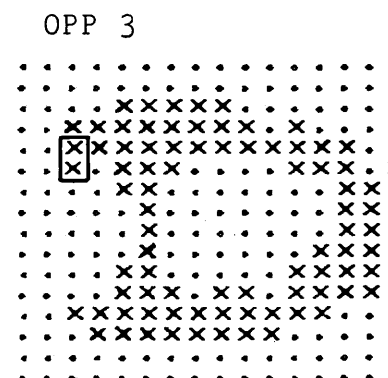
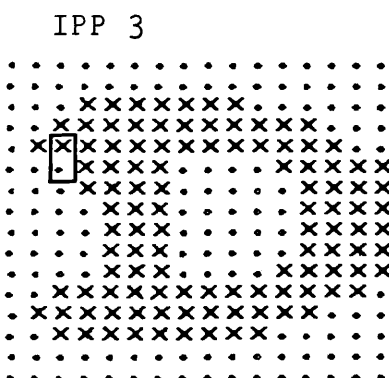
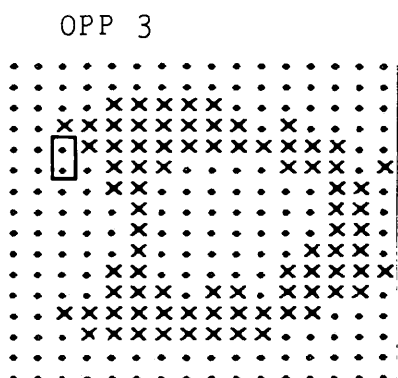
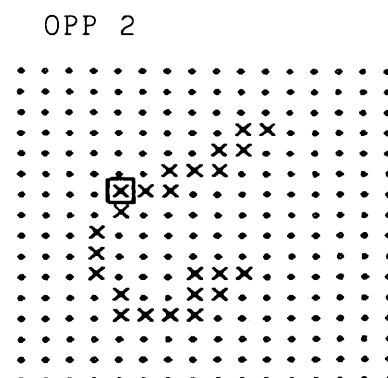
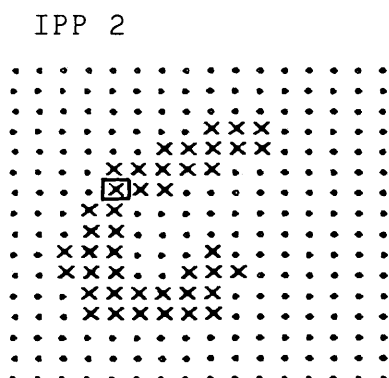
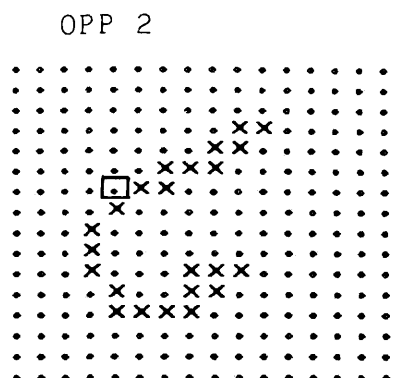
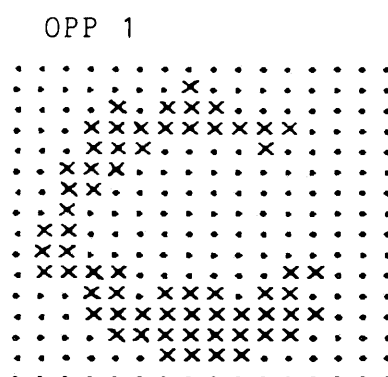
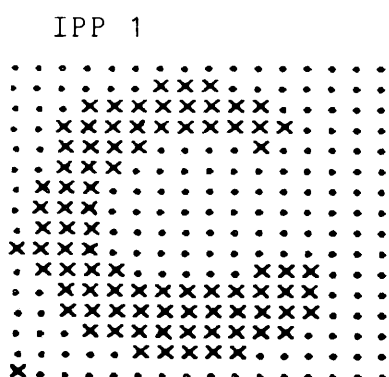
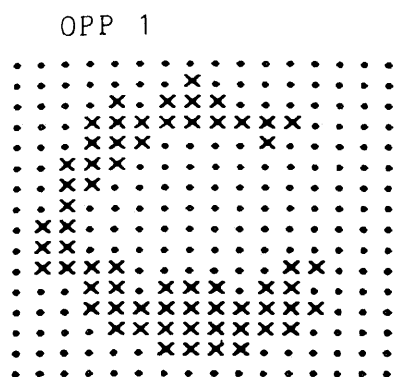
### Discussion

If these boxed regions are examined on the test IPPs (centre column of Fig 3.6) they show that the very regions where the OPPs differ is where the IPPs contain the type of features not seen before in training. This leads to the conclusion that the chosen training set is inadequate in the sense that it has now been shown to have insufficient variation (ie. range of features) to enable the machine to generalize correctly. At least, the machine can generalize

Outputs of Exp 2 -  
Machine Initialised  
To Contain '0's :

Inputs to  
Both Machines :

Outputs of Exp 3 -  
Machine Initialised  
To Contain '1's :



Differences in OPPs are 'boxed' on corresponding patterns

Fig 3.6 Experiments 2 and 3 : Comparison of Test Results

to a limited extent - to include IPPs 1-3 which are broadly similar to the original training set, but not IPP 4 which contains features (viz. thin limbs) not found at all in the training set.

Thus, it can be seen that while increasing the training set size demonstrably increases the quantity of training received, the resultant machines could still be even more fully trained. Experiment 3 has also shown how the machine's performance is heavily dependent on the initialisation of the memory matrix before training. To be specific, if the machine is not fully trained (in that the training set does not contain all possible features) then it will generate its initialisation value when attempting to process an unseen feature. This can have a considerable effect of the overall appearance of an output when the test input varies greatly from the training inputs.

### 3.7 Variations in the Memory Matrix Format

The previous experiments have shown how the performance of the machine depends on a change in the initialisation of the two-state memory cells. This raises the question of which of the many possible internal arrangements of such a machine is optimal.

A brief description of the format used in the experiments performed so far will be given as an aid to the suggestion of variations on this arrangement.

The LPP machine used so far has consisted of a set of bistable memory cells which are addressed by the contents of binary windows extracted from the input picture IPP. In

training, the memory matrix cells thus addressed assume the binary values in the corresponding centre point positions in the example picture EXP. This occurs for every point in the picture field. In testing, windows from a new IPP address memory matrix cells whose contents are placed in the output field OPP in the positions corresponding to the current IPP window.

These memory matrix cells have only two possible states and so once a cell has been set, there can be no further reaction by that cell to any further setting stimuli received in training thereafter. Similarly, a cleared cell cannot respond to further clearing stimuli. The cells may oscillate if the stimuli received set and clear the cells alternately, but this condition only shows inconsistent training. Repeated stimuli in the same sense contain valuable information that a common feature has been found. This information is effectively being lost.

A better LPP machine might well record this as the number of sightings of each particular feature. This would require the storage of a multi-level variable in the memory matrix, as opposed to the present two-level system.

In training, the binary centre point value extracted from EXP could be used to cause a fixed small increase (if this point is '1') or decrease (if '0') in the current value of the memory matrix cell being addressed by the IPP window. These cells can be initialised to contain some intermediate value, and the increment or decrement could be made small compared to the maximum range of the values in the cells. The machine should then be able to record relatively accurately the number of times each cell has been accessed,

at the same time taking note of the polarity of the training stimulus.

In testing, the cells addressed by the windows extracted from IPP now effectively contain analogue variables. These are high if a large number of positive stimuli (EXP point = '1') were received or low if a larger number of negative stimuli (EXP point = '0') were received. A simple process to produce the required binary output would compare the cell content with a threshold value and output a '0' pixel (into OPP) if the contents are lower than this threshold or a '1' pixel otherwise.

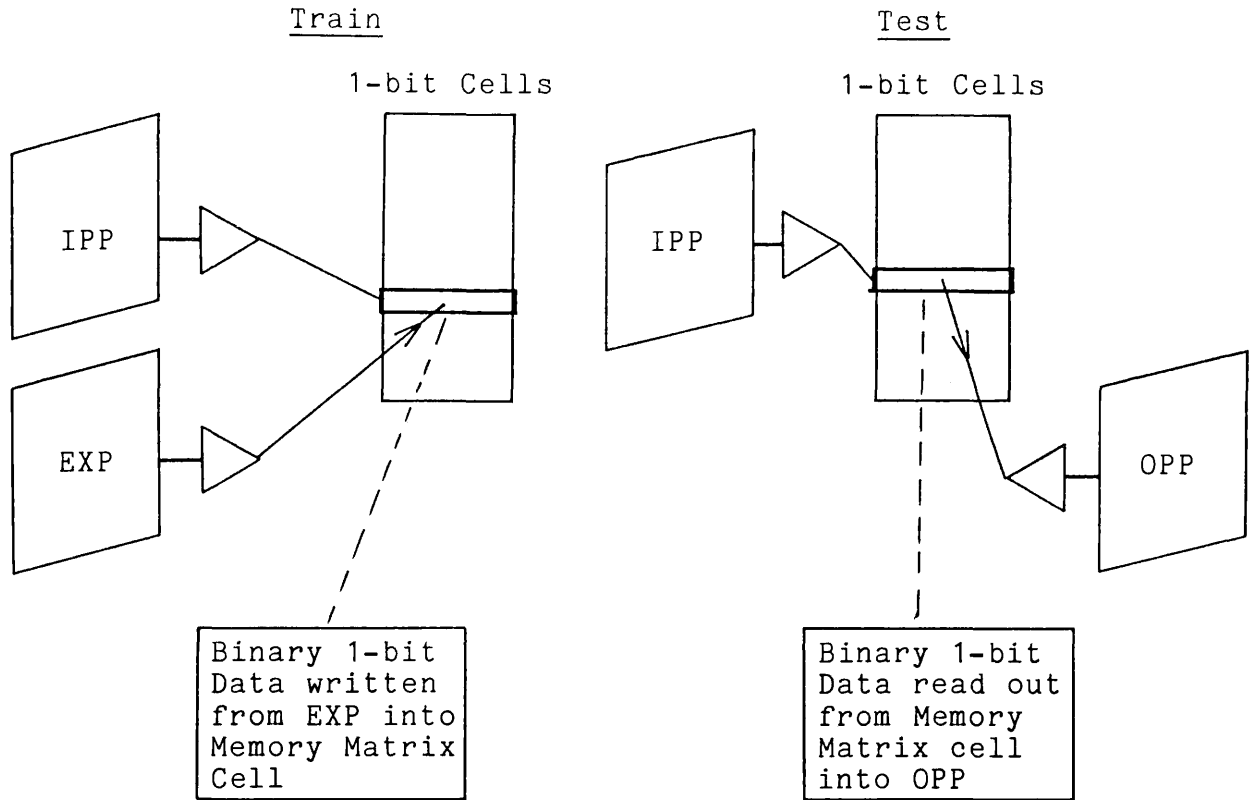
A summary of this new internal arrangement (which will be labelled 'Format 2' for future reference) is compared with the arrangement used earlier ('Format 1') in Fig 3.7. This new Format 2 introduces four more parameters that must be chosen before a working system is simulated :

1 The new size of the memory matrix cell. As an eight-bit computer was used for the simulation and eight bits give a range of 256 levels, this was deemed a suitable starting point for the investigations.

2 The effect of the EXP centre point value in training. The increment or decrement chosen by the polarity of the training stimulus causes a change in the cell contents of one level. This is the obvious choice in this case.

3 The initialisation value of the cells. So that each cell should be able to record a change in both directions an intermediate value ('127') was chosen. This would stop cells from reaching either the maximum ('255') or minimum ('0') levels prematurely. (If these levels are reached, the

Format 1



Format 2

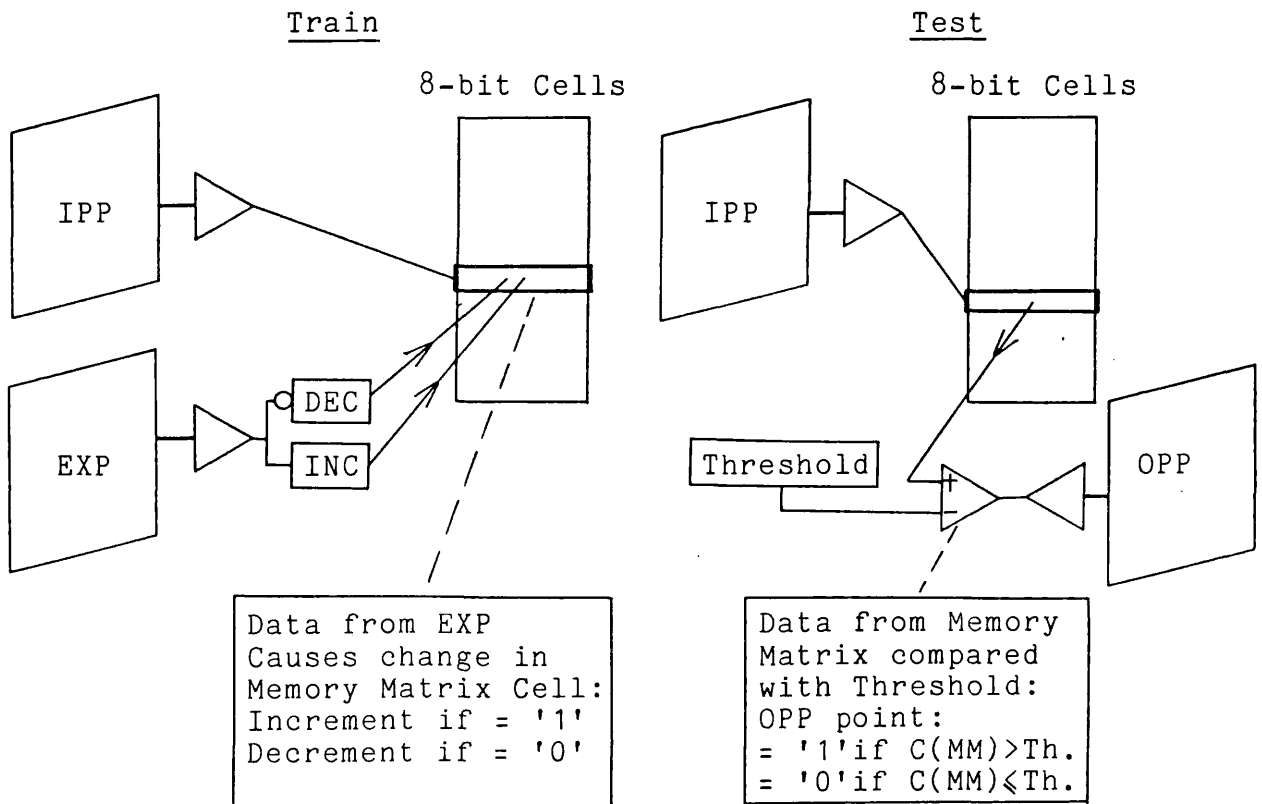


Fig 3.7 Comparison of Internal LPP Formats 1 and 2



machine would not respond to further stimuli in the direction of the limiting.)

4 The threshold level at which, in testing, a choice is made of the binary OPP value to be generated. This was originally set equal to the initial value of the cells, such that any stimuli in either direction, however small, would show up as a resultant change in output.

### 3.8 Experiment 4 : Two and Many Valued M.M. Cells

This experiment will investigate the relative performances of the two types of LPP machine formats now introduced :

#### Format 1 (hereinafter referred to as 'F1')

where the memory matrix cells have just two levels, and the cells are set to equal the binary training stimuli received from EXP in training; and are output directly to generate OPP in testing,

#### Format 2 ('F2')

where the memory matrix cells have 256 levels and are incremented or decremented by one level according to the polarity of each binary stimulus received from EXP in training; and are 'thresholded' to produce a binary output to generate OPP in testing.

#### Training

To ensure that neither the F1 nor F2 LPP machines is undertrained, a large training set size of 200 pairs was used. This should ensure that the majority of the cells in

the F1 machine each receive some training, such that few are left in their 'initialisation' state which can have a large effect on the results (see Experiment 3). This should also allow cells in the F2 machine to assume values widely distributed in the range of '0-255' levels.

Both machines received the same training set of 200 pairs of IPP and EXP patterns - again drawn from the stock of manually thinned and cleaned characters, similar to those in Fig 3.3. The exact character set used contained 100 pairs of the letter 'C' and 100 pairs of the letter 'D' and are not reproduced here. As each pair effectively generates 256 actual training pairs, it is assumed that the resultant 51200 (=256x200) sub-patterns would fully train the 512 cells in both memory matrices. The danger of 'overtraining' - a common problem in RAM pattern recognition nets - should not arise here. This is because unlike many pattern recognition systems, these cells can repeatedly be set and cleared (F1) or adjusted (F2) to reflect ever more accurately the training stimuli received. The nature of the problem is also different: in picture processing an attempt is being made to maximise the response, whereas in pattern recognition a differential response between discriminators is being sought.

### Testing

The same test set (IPPs 1-12) was used to test both machines, and is shown in the centre columns of Figs 3.8 to 3.10. The OPPs 1-12 generated by the F1 machine are shown in the left hand columns, and the OPPs 1-12 of the F2 machine on the right. A relatively large test set of various character fonts was used in an attempt to show up any

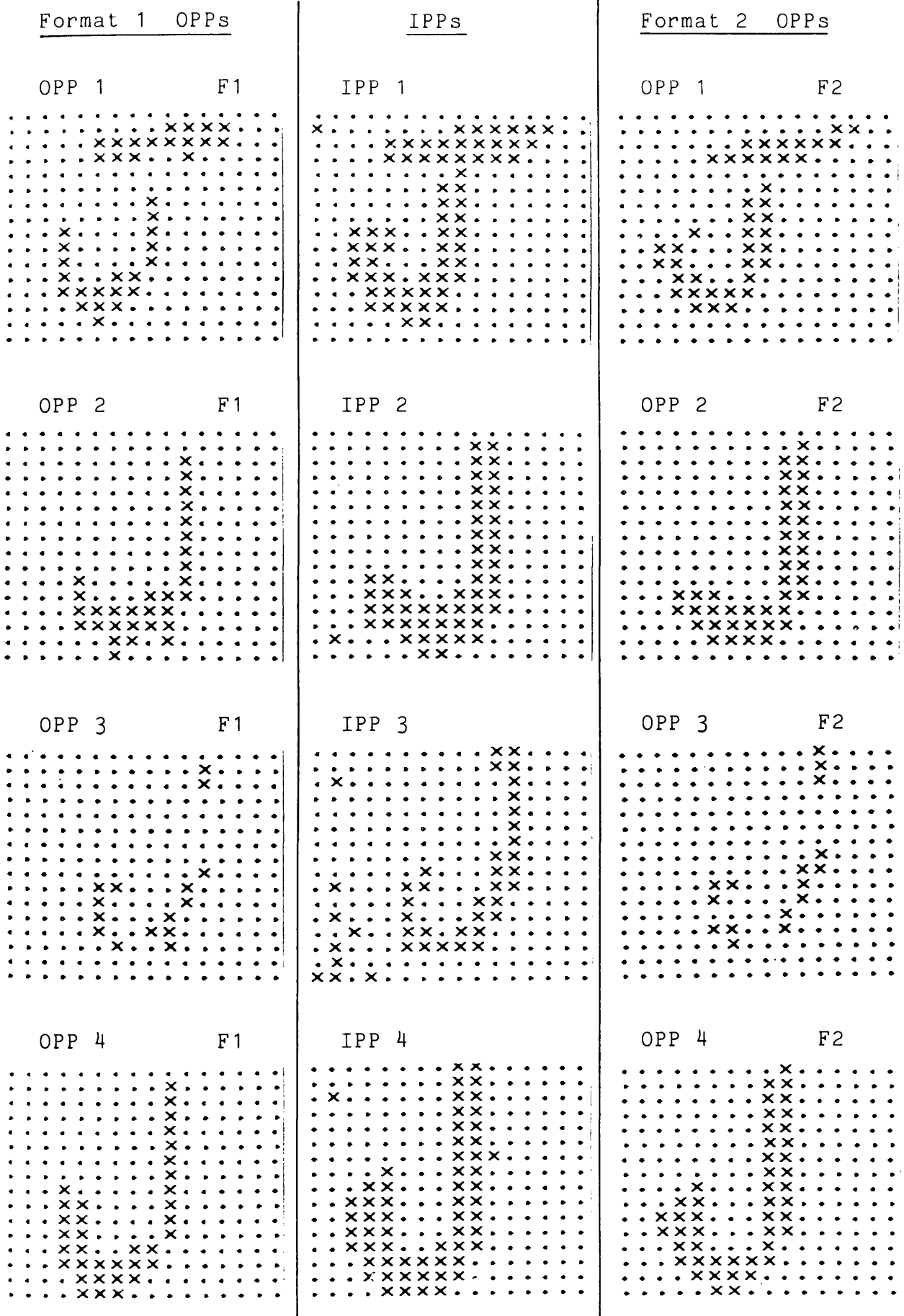


Fig 3.8 Experiment 4 Test Patterns 1-4

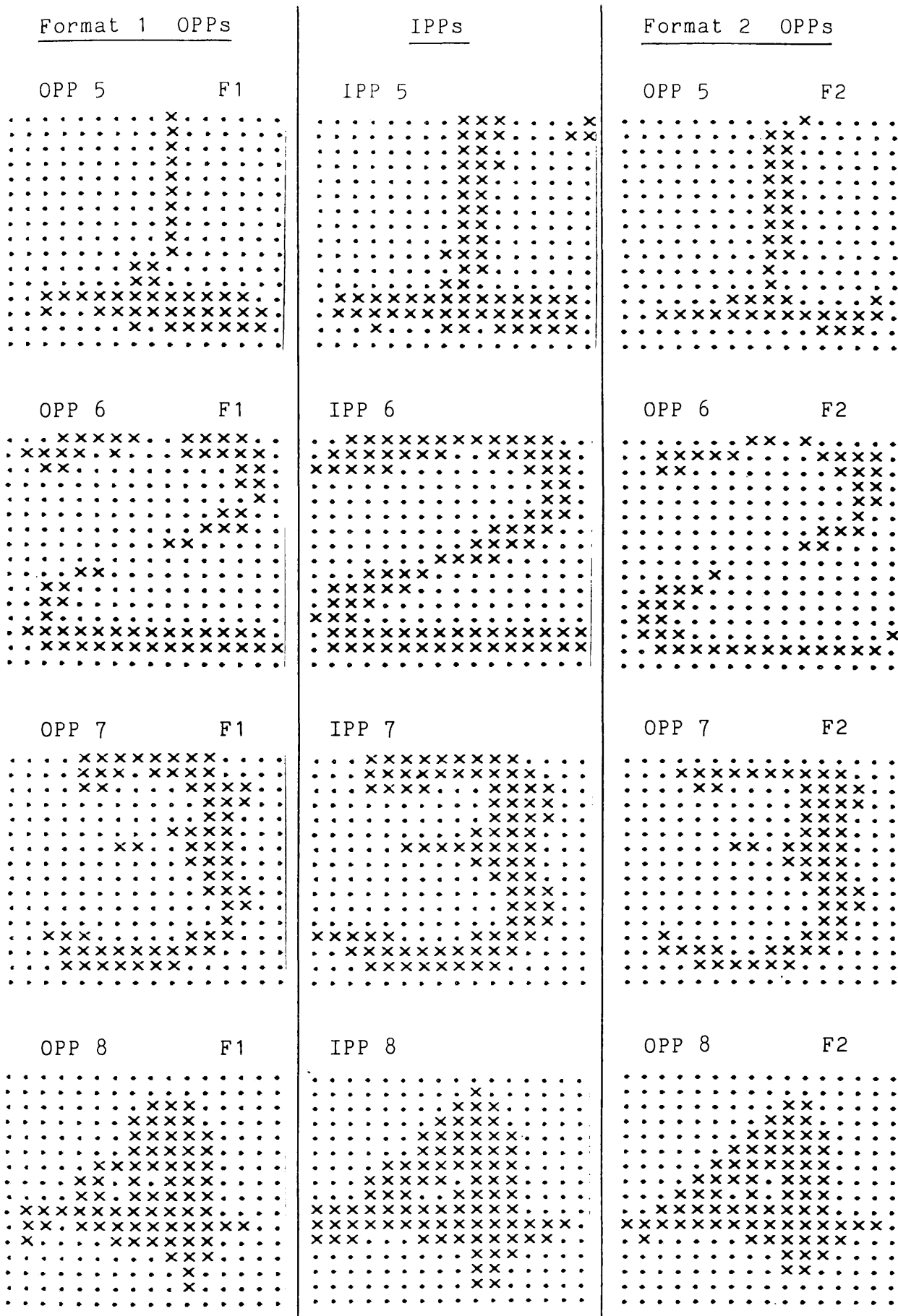


Fig 3.9 Experiment 4 Test Patterns 5-8

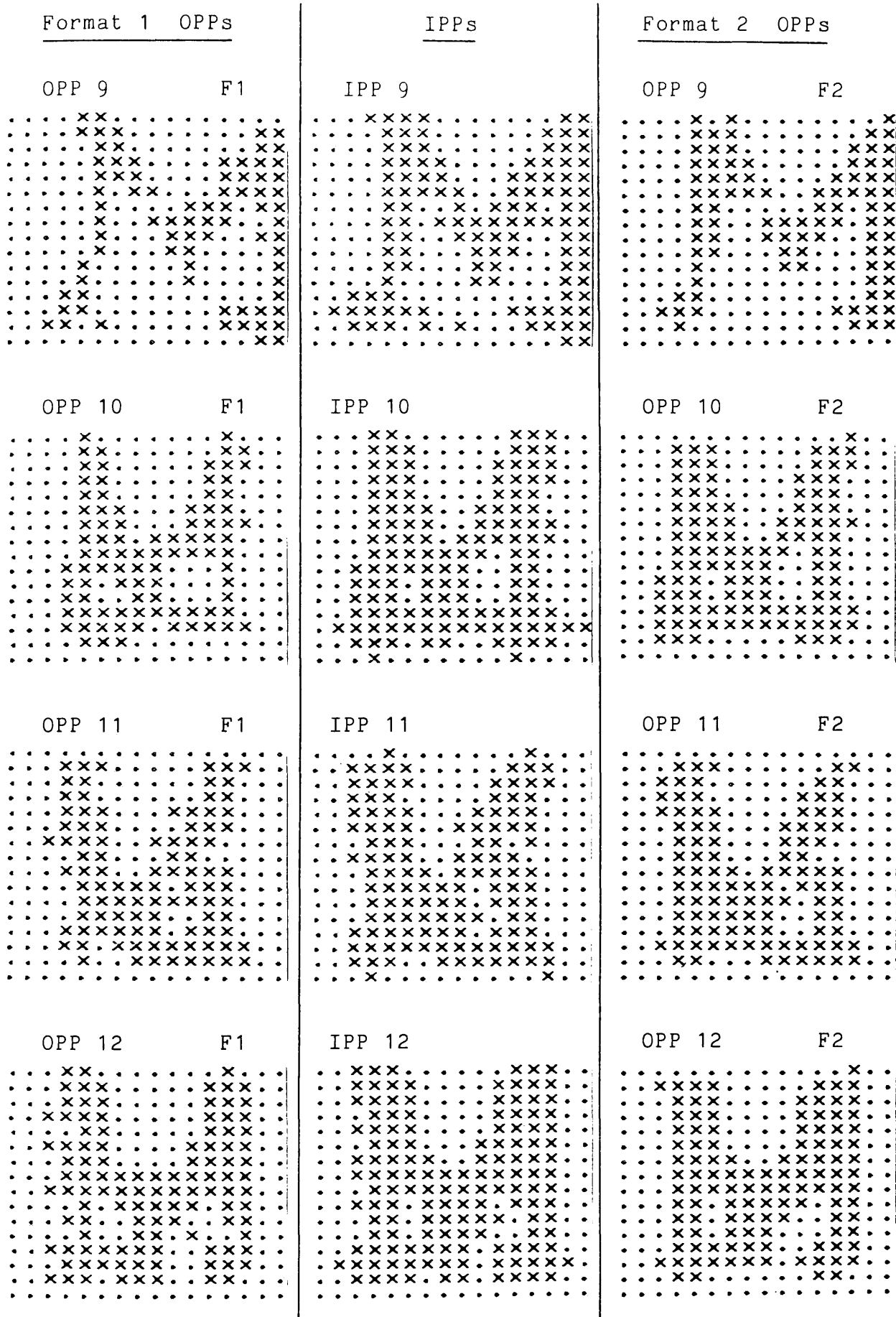


Fig 3.10 Experiment 4 Test Patterns 9-12

significant differences in the performance of the two machines. The test set was composed of three character styles :

1 Four hand-drawn letters 'J' - collected in the same manner as the training set of 'C' and 'D' letters. (IPPs 1-4 in Fig 3.8)

2 Four type-written numerals '1', '2', '3', and '4'. These were collected by the Post Office from actual type-written mail for use in pattern recognition research work (54). (IPPs 5-8 in Fig 3.9)

3 Four type-written letters 'M' from the same Post Office source as the above numerals. These were chosen for their 'unclean' appearance and dissimilarity from the training set to act as a test of the machines' generalisation abilities. (IPPs 9-12 in Fig 3.10)

The output threshold used in the F2 machine in this experiment was set at the mid-range value of '127'. This resulted in a pixel output of '0' if the addressed cell contained '127' or less, or '1' if '128' or more.

### Results

A comparison of the left hand (F1) and right hand (F2) columns in Figs 3.8 to 3.10 reveals the variations in performance of the two machines. The most immediately obvious feature of the comparison of the two results is that they appear broadly similar. Both machines do generally thin and clean the characters fed to them in test. This indicates that both F1 and F2 are practicable and perform coherently. (This is a new result with the F2 machine.)

However, on closer inspection it becomes obvious that there are differences which are systematic and repeated between the results of the two formats. These differences are analysed in detail below.

(It should be noted that considerable caution has to be exercised in analysing differences in performance of the two machines, since they are not performing rigorous algorithms; but rather they have been trained on the same rather ad hoc set of characters. Thus, though the results are comparable, it is not possible to place an absolute 'figure of merit' on either performance.)

### Discussion

References will be made to specific examples in the test set to illustrate the point being made in the following discussion, although all of the points below generally apply to all of the test patterns.

The F2 machine can be seen to follow the original shape of the object more faithfully and to preserve its outline through the thinning process. This can be seen in IPP 4 and IPP 8 and their respective outputs. In the case of the hooked end of the letter 'J' in IPP 4, this hooked appearance is retained in OPP 4 - F2 but not OPP 4 - F1. The sloping edge of IPP 8 has been stripped back and thinned well, maintaining a straight edge in OPP 8 - F2 unlike that of OPP 8 - F1.

An interesting variation in performance is seen in the handling of vertical lines of two units width. The F1 machine produces single width lines (centred on the right hand of the two original lines); the F2 machine retaining the whole double width line. This can be seen in

IPPs 2, 4, and 5.

The F2 machine also produces smoother vertical edges - resulting in a straighter line, as opposed to the F1 machine's introduction (or retention) of small spurs and nicks in such edges. Examples of these can be seen on the left hand vertical side of IPPs 11 and 12. This does not happen with the right hand edges (IPP 10) where both machines produce a similar result. This discrepancy must be a result of the particular training set used, and hence supplies little useful information regarding the relative performances of the two machines.

Both the machines are capable of breaking a thin character (IPPs 3 and 6) - again as a result of the training set not containing 'correct' examples. As before, the fact that both machines perform essentially identically on this feature conveys little information about their relative merits.

A further point of this type where the machines both act similarly is the removal of noise points, as seen in IPPs 3 and 5.

The F1 machine can be seen to thin features to a considerable degree (often to a unit width limb) whilst retaining the original limb length; whereas the F2 machine appears to strip off the outer layers of such limbs, resulting in thinner but shorter features. This can be seen in the lower limb of IPP 8, and in the bottom of the centre 'V' in IPP 9. In both cases, the F1 machine retained the full length with a single width result, the F2 machine losing some length and not thinning to such a great extent.



These results show that there are some demonstrable improvements in performance when using an F2 machine as opposed to an F1 machine. This difference is primarily due to the fact that the F1 machine simply remembers the last stimulus, giving equal preference to isolated 'bad' examples as to the many 'correct' stimuli. The F2 machine essentially ignores such noise points. However, the improvements in performance are not large, and on the evidence of the present data, it seems safest to conclude that the outputs are 'broadly similar'. The small difference must be viewed in the light of the cost of the more complex machine. This cost can be divided into three categories :

#### 1 Memory Size

The F2 machine uses eight times the amount of memory of the F1 machine. Recall that the F1 machine uses 512x1-bit cells and the F2 machine uses 512x8-bit cells. While it is debatable whether all 256 ( $=2^8$ ) levels are necessary, any machine with even a few levels will require several times the storage capability of the simpler F1 machine.

#### 2 Processing Complexity

The simple F1 machine reads data derived from the EXP directly into the memory matrix cells. These data are later read out - without further processing - to generate OPP. The F2 machine tests the data derived from EXP, and as a result of this test either increments or decrements the contents already contained within the cell. The data, when later read out, has to be compared with a threshold value and the result of this comparison is used to generate the output value used to generate OPP.

### 3 Processing Speed

As a result of the increased processing required by the F2 machine, the time taken to process a picture will be necessarily longer, both in training and testing.

In the light of these considerations, the overall efficiency of the F2 machine compared with that of the F1 machine is debatable. While some processing improvements have been seen, these have been made at a cost of considerable increase in the processing requirements in terms of size, complexity and time. A compromise solution may, however, be more efficient, wherein more than one threshold is used simultaneously to give more than two output levels. This will be attempted later in Section 5.3 Experiment 7.

#### 3.9 Experiment 5 : Variable Output Threshold and Grey Level Output

The OPPs 1-12 generated by the F2 machine in the previous experiment were all generated using a constant threshold in the testing phase. That is, the contents of each memory matrix cell addressed were compared with a fixed value, the result of this comparison being used to determine the polarity of the output pixel. This threshold was set to the initial value stored in each cell to show a response to as little training as possible.

Direct examination of the internal state of this machine (after training as described previously) reveals that the spread of memory matrix cells extends over all possible values (0-255). Thus, a single threshold value is

not capable of extracting all the information from the memory matrix. This distribution of cells over the possible values before and after training is tabulated in Fig 3.11. For each value, the number of cells containing that value is recorded.

It follows from this spread, that those cells with values far removed from the initial value (ie. values near '0' or '255') have received a larger amount of training than those close to the initial value ('127'). Consequently, the features corresponding to these particular cells have been seen many times in training. As a result, these cells are likely to be reliably set, reflecting accurately the picture processing task being taught to the machine. This measure of 'reliability' of any cell is related to the difference in the cell value before and after training.

The data in Fig 3.11 can be expressed as a histogram to clarify the reliability distribution. (See Fig 3.12.)

From this figure it can be seen that the majority of cells lie close to the original initial value ('127') as they have received few or no stimuli in training. They are therefore likely to be unreliable indicators of the picture processing algorithm taught to the machine. The reverse applies for the two peaks at the extremities of the range. As a result they are likely to be reliable and the corresponding features are also more likely to occur in testing. This is a pointer to the setting of the threshold value in the test period.

The criteria for setting the threshold value is to obtain the maximum information from the most reliable cells. This is apparently not possible with a single threshold,



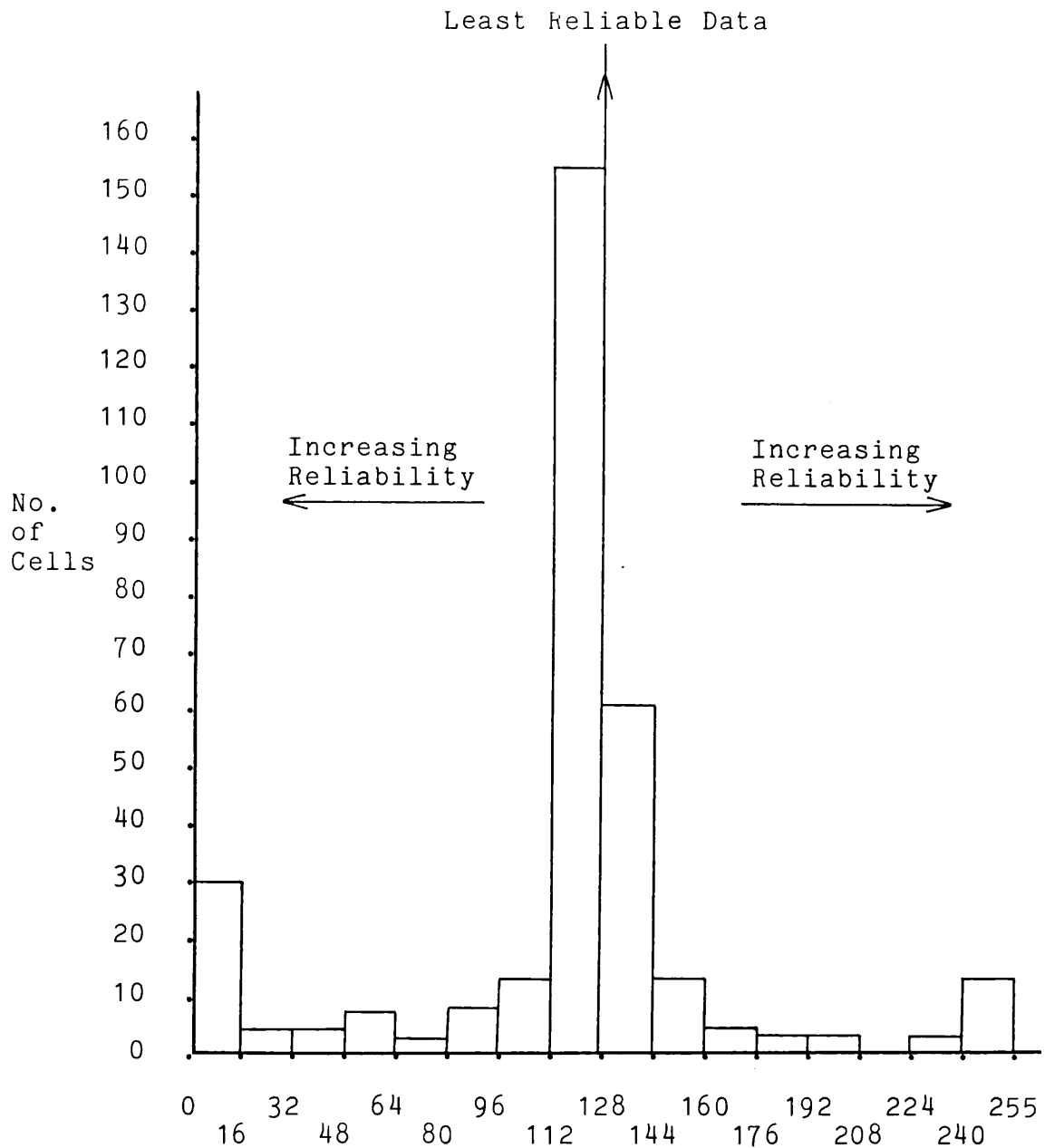


Fig 3.12 Reliability Distribution of Memory Matrix Cells

since there are two maxima of 'reliable' cells either side of a maximum of 'unreliable' cells. Hence a variable threshold was applied in the following experiment to determine the effect on the output. This threshold was swept across the entire range of cell values.

There are two conflicting considerations when attempting to predict the result of sweeping through the

cell values. The first is that the major change in output may be expected when the threshold traverses the central maximum. This is due to the very large proportion of memory matrix cells located in that area, that will change their output as the threshold passes them.

However, on further consideration, a second point emerges, that a large number of these cells are in general unlikely to be accessed at all in testing. As they have not moved far from their original value they were obviously not accessed much in training - the corresponding features were relatively uncommon in the training set. If the test set is similar it will also contain few features that will access these cells remaining near the initial value. As a result, the movement of the threshold causing these cells to output different pixels may not affect the final result greatly. Most of the change in output could be expected at the extremities of the cell value range (around '0' and '255') as these are common cells and are likely to be used more in generating the OPP. Nonetheless, it is important to determine whether there are any configurations that are common, yet appear in the centre of the range, reflecting inconsistent training.

### Experiment

An F2 machine was trained on 200 pairs of manually thinned and cleaned 'C's and 'D's, as in Experiment 4. The resultant memory matrix is that which has been examined above. A single test pattern was used - a letter 'J' from the same set of hand drawn characters. The tests were repeated with this pattern several times; each time using a different output threshold. The threshold was swept through

the cell values in steps of 32 (ie. 16,48,80,112,144, 176,208,240). The test IPP 1 together with the resultant set of OPPs '16-240' are shown in Fig 3.13.

### Results

Examination of these OPPs reveals that there is a gradual change in output as the threshold scans across the memory matrix values. The largest change in the ratio of cells outputting '0' and '1' pixels occurs as the threshold moves between 112 and 144, the respective outputs being OPPs '112,144' in Fig 3.13. However, these pattern outputs not vastly dissimilar. This would confirm the infrequent occurrence of these cells' features in the test set. The changes here are comparable with the changes in OPPs as the threshold moves to the extremes at the cell values (OPPs '16 to 48'; and OPPs '208 to 240'). In all these cases there are only a few pixels difference between each adjacent pair of pictures.

Fig 3.14 presents the degree of change in the output pictures and the number of memory matrix cells on either side of the threshold as it moves. These quantities are recorded for OPPs '16-240' taken in pairs, the difference in adjacent pairs of pictures being measured in terms of the hamming distance between them.

Examination of these data reveals the following facts about an F2 machine : the degree of change in output (as exhibited by actual patterns under test) is in no way related simply to the number of memory matrix cells on either side of the output threshold. The large number of memory matrix cells clustered near the initial value must, for this data, all represent rarely or never found features.

OPPs Produced  
with a Threshold  
Varying from

16 - 240

in Steps of  
32 units

IPP 1 Original

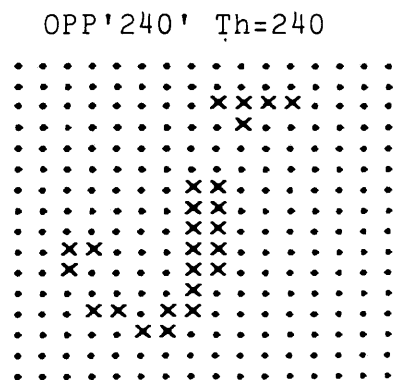
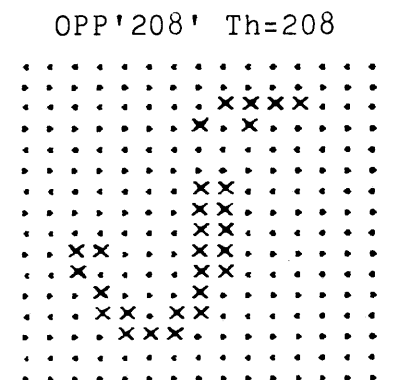
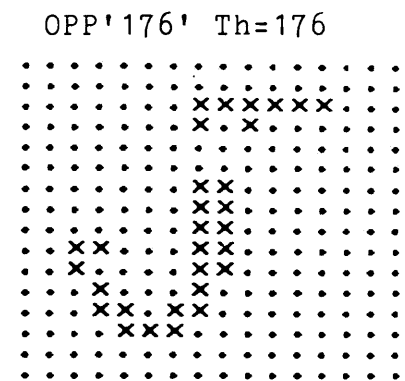
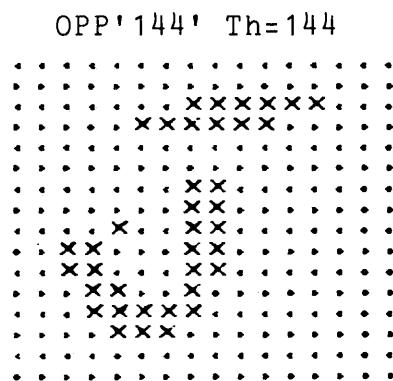
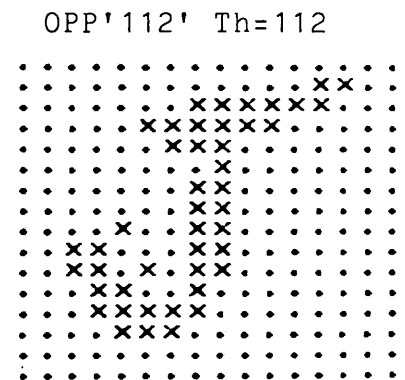
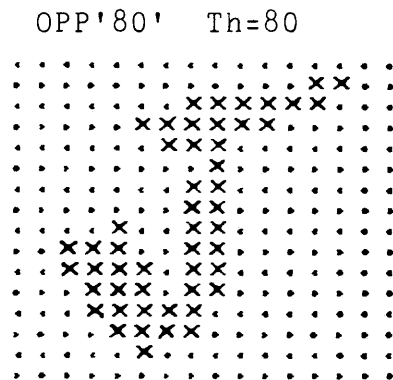
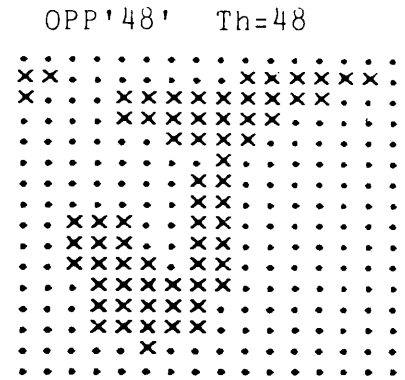
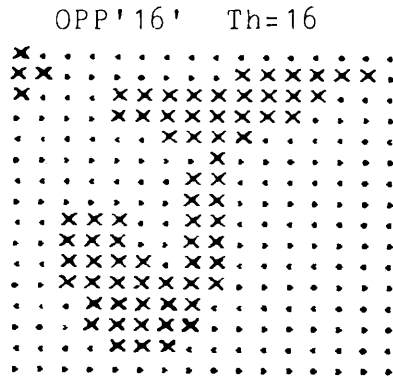
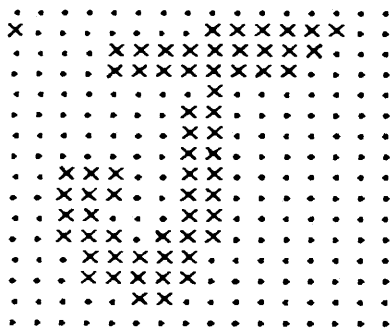


Fig 3.13 Experiment 5 IPP 1 and OPPs '16-240'



OPP Pair (Threshold)	16, 48	48, 80	80, 112	112, 144	144, 176	176, 208	208, 240
No.M.M.Cells Moving Across Threshold	6	8	20	313	16	4	2
Hamming Distance Between OPPs	5	16	6	7	8	2	3

Fig 3.14 Table of OPP Changes against M.M Cells Crossing Threshold

The converse is also true : the small number of cells with values far removed from the initial value are likely to predominate in the outputs, as they represent common features. This indicates that a greater variation could be expected by increasing the amount of training than by moving the threshold.

#### Continuous (Grey Scale) Output

Examination of the OPPs '16-240' in Fig 3.13 will reveal that this series of binary patterns, generated using an increasing threshold, effectively constitutes a single grey scale pattern. The F2 machine can be used to generate many-valued output pixels in testing, by removing the threshold and comparator of Fig 3.7. In this mode, the binary input pattern addresses cells in the memory matrix which contain digitally continuous values, which are output directly. Examples of such pseudo-grey-scale OPPs are illustrated in Fig 3.15, together with the corresponding (binary) IPPs displayed in the same format. (This format depicts grey levels as '00' for white, 'FF' (hexadecimal) for black, '7F' as the initial value, and intermediate



levels as intermediate numerical values.) The inputs are the same as those used earlier in Experiment 4 (IPPs 5-7, Fig 3.9) as was the training received.

If the two effective grey-levels used in the case of the binary patterns are assumed to lie at the extremities of the grey-scale (pure black and pure white) then this processing constitutes a form of low-pass spatial filtering. As such, it may be of use in certain picture processing and scene analysis applications (40). It is effectively the inverse transformation of 'thresholding' in the normal sense when applied directly to a grey-scale digitized pattern.

This production of thinned and cleaned grey-scale pictures, from a machine having been trained only on binary inputs forms an interesting investigation. Similar techniques using 'fuzzy logic' have been employed elsewhere to handle grey scale pictures with binary processes (30).

### 3.10 Summary of Experiments 1 - 5

The preliminary experiments described in this chapter have shown an LPP machine to be a workable proposition. While this has been distinctly encouraging, and a spur to further investigation, the results have not always been clear cut, and the rather simple experiments tried have not yet revealed final answers as to how to set up LPP machines. For this reason Chapter 4 analyses the underlying theory and possibilities in some detail, and Chapters 5 and 6 describe further, more rigorous experiments on LPP machines. These later chapters also move towards real applications by employing pictures with rather more than  $16^2$  resolution. In

addition, sequential as well as parallel processing will be attempted.

## CHAPTER 4

## THE GENERAL LEARNING PICTURE PROCESSOR

4.1 An Introduction to the Development of a General  
LPP Machine

The experimental work performed so far on the learning picture processor has suggested some departures from the original machine as conceived in Chapter 2. These changes have been in response to the need for improvements in performance, but have been arbitrary. It is possible to create a more formalized and structured concept of a general learning picture processor. This framework will also aid the generation of new variants, as a large family of machines can be proposed. Evidently, the resulting large numbers of machines cannot all be analysed by experiment within the confines of one thesis. However, predictions of performance can be made, based on theoretical considerations and extrapolations from the modest machines described in earlier chapters. There are several levels of development in this general machine. These include :

- 1 Variations in the internal data processing of a single, simple LPP machine
- 2 Different modes of operation of such variants in terms of the handling of test picture data
- 3 The use of feedback around a single stage machine
- 4 The cascading of machines

These may in principle all be combined to produce large and complicated machines. Such machines would be exceptionally complex to analyse, and as such may well illustrate the limit of the trainable picture processor type of machine. The following sections discuss these levels of development in more detail.

#### 4.2 Variations in the Internal Data Processing of the LPP Machine

This section proposes a generalized system by which a LPP machine may operate. Implied by such a generalized system are variations in the means by which :

- 1 useful information is extracted from the training patterns;
- 2 this data is used to modify a memory matrix to reflect the task to be learnt;
- 3 data in the memory matrix is used to generate subsequent output pictures in testing.

#### Examples of Data Transformation through 'Function Modules'

At each internal stage of such a machine, there is a transformation of data. Some examples would be :

- 1 The extraction of a window of pixels according to the input picture and the current values of the x and y co-ordinates,

2 The transformation of this window into an address of a cell in the memory matrix.

From these, it can be seen that the data processing occurs as a series of transformations which can be represented as a series of interconnected 'function modules'. Each module takes data inputs and performs a particular function upon them, thus generating output data. In the case of the above two modules, their functions could be represented as :

$$\begin{array}{l} 1 \quad W = f_a(IPP, x, y) \\ 2 \quad A = f_b(W) \end{array}$$

where : IPP represents the binary input picture,  
 $x, y$  the cartesian co-ordinates of the window,  
 $W$  the window contents,  
 $A$  the memory matrix address,  
 and  $f_a$  and  $f_b$  the functions to be performed on the arguments above.

It is a change in these functions ( $f_a$  and  $f_b$  above) that represents a design change in the machine in general terms. Fig 4.1a shows how such function modules will be represented both algebraically (as above) and diagrammatically below.

#### Function Module Representation of the General LPP Machine

The whole internal operation of the machine can be represented as a set of these function modules. Such a machine is illustrated in Fig 4.2, nomenclature being as defined in Fig 4.1b.

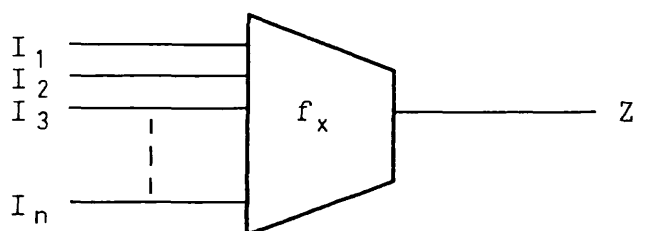
(a) Function Modules :Function expressed algebraically as

$$Z = f_x(I_1, I_2, I_3 \dots I_n)$$

where :  $f_x$  is the function

$I_1$  to  $I_n$  are the independent input variables

and  $Z$  is the dependent output variable

Functions will be expressed diagrammatically in Fig 4.2 as :(b) Nomenclature of Variable Names to be used in Fig 4.2 :

IPP	Complete Input Picture (to be processed)
EXP	Complete Example Picture (used in Training)
OPP	Complete Output Picture (generated in Testing)
x	Horizontal ) Cartesian Co-ordinates of
y	Vertical ) Current Scan Position
W	Window Contents Extracted from IPP
A	Address of Memory Matrix Cell
MM	Original Complete Memory Matrix
mm(A)	Original Single Memory Matrix Cell addressed by A
mm'(A)	Updated Single Memory Matrix Cell addressed by A
MM'	Updated Complete Memory Matrix
P0	Centre point pixel in Window defined by x , y
P1-P8	Immediate eight-connected neighbours of P0

Fig 4.1 General Function Module Description  
and Variable Nomenclature



Algebraic Representation :

- 1  $W = f_1(IPP, x, y)$  Input Window Extractor
- 2  $A = f_2(W)$  Address Calculator
- 3  $mm(A) = f_3(MM, A)$  Cell Extractor
- 4  $EXP/PO = f_4(EXP, x, y)$  Example Window Extractor
- 5  $mm'(A) = f_5(EXP/PO, mm(A))$  Cell Modifier
- 6  $MM' = f_6(mm'(A), MM)$  Cell Replacer
- 7  $OPP/PO = f_7(mm(A))$  Output Pixel Generator
- 8  $OPP = f_8(OPP/PO, x, y)$  Output Picture Generator

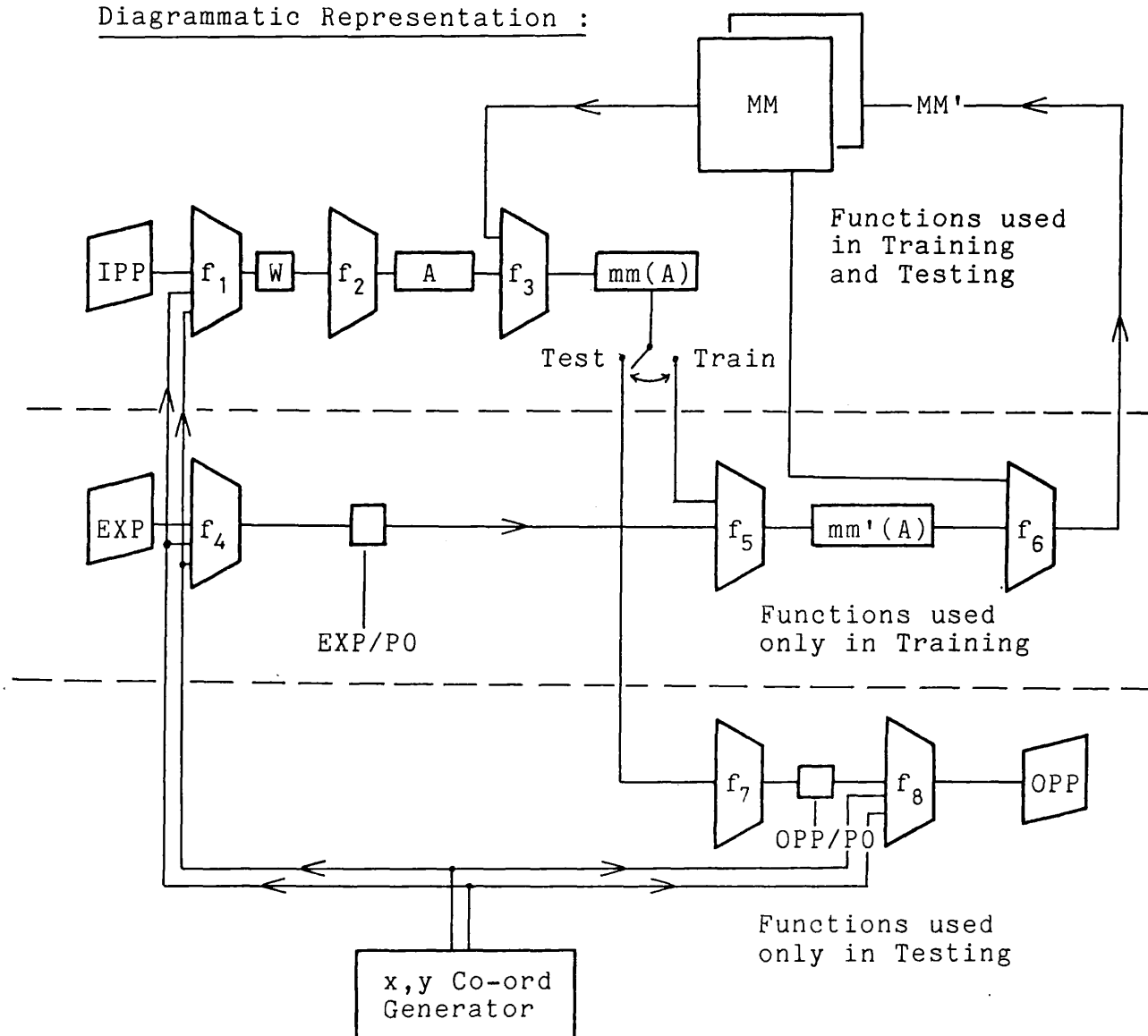
Diagrammatic Representation :

Fig 4.2 Internal Function Modules in a General LPP Machine

When the functions themselves are specified, the machine is transformed from a general one to a particular variant. To illustrate this, the definition of the F1 machine of Chapter 2 will be considered.

### Specific Definitions of General Functions for F1 Machine

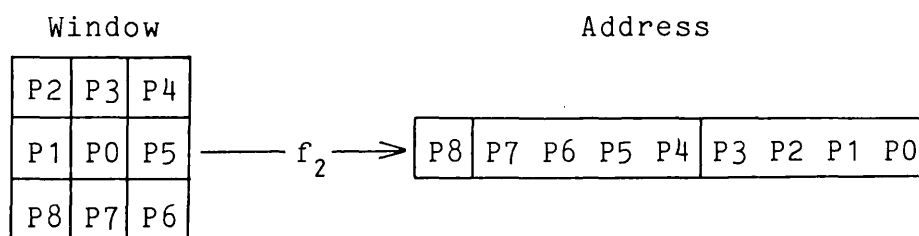
For each of the eight functions in Fig 4.2, there follows a general explanation and a specific definition related to the F1 machine described earlier :

#### 1 Input Window Extractor $W = f_1(IPP, x, y)$

This is effectively the scanning window extractor (WE I) of Fig 2.8 acting on the input picture. This device takes a pair of co-ordinates  $x, y$  in the range 0-15 to define a centre point and its adjacent eight-connected neighbours in the input picture. These nine pixels (P0-P8) form the window contents  $W$ .

#### 2 Address Calculator $A = f_2(W)$

This function re-arranges the window contents  $W$  to form the 9-bit binary address - in this case the exact format of the re-arrangement is arbitrary, but follows the pattern below :



(Both 9-bit binary variables)

This function (in this example) merely re-formats the data.

3 Cell Extractor  $mm(A) = f_3( MM , A )$

This function extracts the single memory matrix cell pointed to by the address generated above. This is simply the accessing of a particular bit of storage in a table of 512 bits.

4 Example Window Extractor  $EXP/P0 = f_4( EXP , x , y )$

This is the scanning window extractor (WE II) of Fig 2.8. This extracts the centre point P0 from the example picture according to the current value of the x and y co-ordinate generator. This pixel becomes EXP/P0. (This function only operates in training.)

5 Cell Modifier  $mm'(A) = f_5( EXP/P0 , mm(A) )$

This is the modification of the addressed cell according to the value of the centre point extracted from EXP/P0. This produces the new cell value, which, in this simple example is set equal to EXP/P0. (This function is also only active during training.)

6 Cell Replacer  $MM' = f_6( mm'(A) , MM )$

This is the updating of the memory matrix as a whole, after each training stimulus has been received into the particular cell. Here, this is simply the replacing of the cell (with its modified contents) into the table in its correct position - the writing back into the RAM. (Training only.)

7 Output Pixel Generator  $OPP/P0 = f_7( mm(A) )$

This is the generating of a new output pixel from the cell contents, for insertion into the OPP field. In the simple example taken this OPP/P0 is set equal to the value

of the addressed cell. (This operates only in the testing phase.)

8 Output Picture Generator  $OPP = f_8( OPP/P0 , x , y )$

This represents the picture generator (PG III) of Fig 2.8 and is the generation of OPP, pixel by pixel, as each value is computed by the LPP machine. (Testing only.)

This completes a description of the internal functions of the machine when applied to a particular variant - the F1 machine. To facilitate the description of how other variants are defined by changes in these eight functions, they are tabulated for two machines (F1 and F2) in Fig 4.3 below. (It will be noticed that they differ only in functions  $f_5$  and  $f_7$ ).

If Fig 4.3 is examined in conjunction with Fig 4.2 it will be seen that these functions define the two machines whose internal formats were illustrated in Fig 3.7.

#### Further Possibilities for Variations

A set of more complex machines may be devised by a systematic examination of the above functions and speculation of the range of possibilities available at each stage. Even the arrangement between these functions shown in Fig 4.2 can be altered to give yet more variations.

For example, a system could be envisaged where the scanning window does not move over the input picture in a regular manner. The window could follow some feature of the pattern itself : eg. an edge that has been defined as the 'driving' data, directing the generation of the x and y co-ordinates of the window. The values x and y would then

General Function	Particular Functions	
	F1 machine	F2 machine
$W=f_1(IPP,x,y)$ Input Window Extractor	W becomes equal to the 9 pixel values at points in IPP defined by $x\pm 1,y\pm 1$ , ie. centre point and its eight immediate neighbours	
$A=f_2(W)$ Address Calculator	A formed by stacking two dimensional binary window into a one dimensional binary address	
$mm(A)=f_3(MM,A)$ Cell Extractor	mm(A) becomes equal to cell in MM with address A	
$EXP/PO=f_4(EXP,x,y)$ Example Window Extractor	EXP/PO becomes equal to pixel value at point in EXP defined by x,y	
$mm'(A)=f_5(EXP/PO,mm(A))$ Cell Modifier	$mm'(A)=EXP/PO$	if $EXP/PO=1$ , $mm'(A)=mm(A)+1$ ; if $EXP/PO=0$ , $mm'(A)=mm(A)-1$
$MM'=f_6(mm'(A),MM)$ Cell Replacer	new cell contents written into MM on top of old contents, remainder of MM unaltered	
$OPP/PO=f_7(mm(A))$ Output Pixel Generator	$OPP/PO=mm(A)$	if $mm(A)>Threshold$ , $OPP/PO=1$ ; if $mm(A)\leq Threshold$ , $OPP/PO=0$
$OPP=f_8(OPP/PO,x,y)$ Output Picture Generator	OPP/PO inserted into OPP field at position defined by x,y, remainder of pattern unaltered.	

Fig 4.3 Functions ( $f_1 - f_8$ ) defined for F1 and F2 Machines

themselves be a function of IPP, rather than cycling through all possible values autonomously as at present.

This could be formalized as :

$$\begin{array}{ll} x = f_9( IPP ) & x \text{ Co-ordinate Generator} \\ y = f_{10}( IPP ) & y \text{ Co-ordinate Generator} \end{array}$$

This would obviously affect all the other functions defined so far, as x and y appear in these functions either implicitly as independent variables, or explicitly by substitution.

For a coherent operation of the scanning window extractor, the above functions  $f_9$  and  $f_{10}$  could be formulated in a machine programming style as suggested below. The function  $f_9$  might adjust the value of x such that the window always produced a 'crossing number' of two. A similar, and interacting function  $f_{10}$  might generate y such that the window scanned along the edges of objects in the field of view.

This is a somewhat simplified suggestion of a rather more complex development of the internal workings of the LPP machine. It serves to illustrate that although the above formulation of LPP variants is comprehensive, it is not exhaustive. It provides one example of a framework upon which a system of machine variants can be built.

#### Down-loading the Memory Matrix

An important variation that can be expressed in terms of these functions is the down-loading of the memory matrix contents directly from a host machine. The LPP machine is trained by direct injection of data into all of the memory matrix cells, rather than by the generation of these cells

through training by example.

The functions above used in training ( $f_4, f_5$  and  $f_6$ ) are no longer implemented, and the variable MM - the contents of the complete memory matrix - is introduced from an external source into the system as a set of constants. For the value of MM to be meaningful, it is necessary to be aware of how the functions used in testing ( $f_7$  and  $f_8$ ) will operate. An example of this use of a down-loaded memory matrix is shown later in Experiment 12.

#### 4.3 The Handling of Picture Data in the Testing Phase

All the machines described so far have been parallel (as described earlier in Section 1.3.3). The possibility of testing 'sequentially' also exists: the two methods of generating the OPP are illustrated in Fig 4.4.

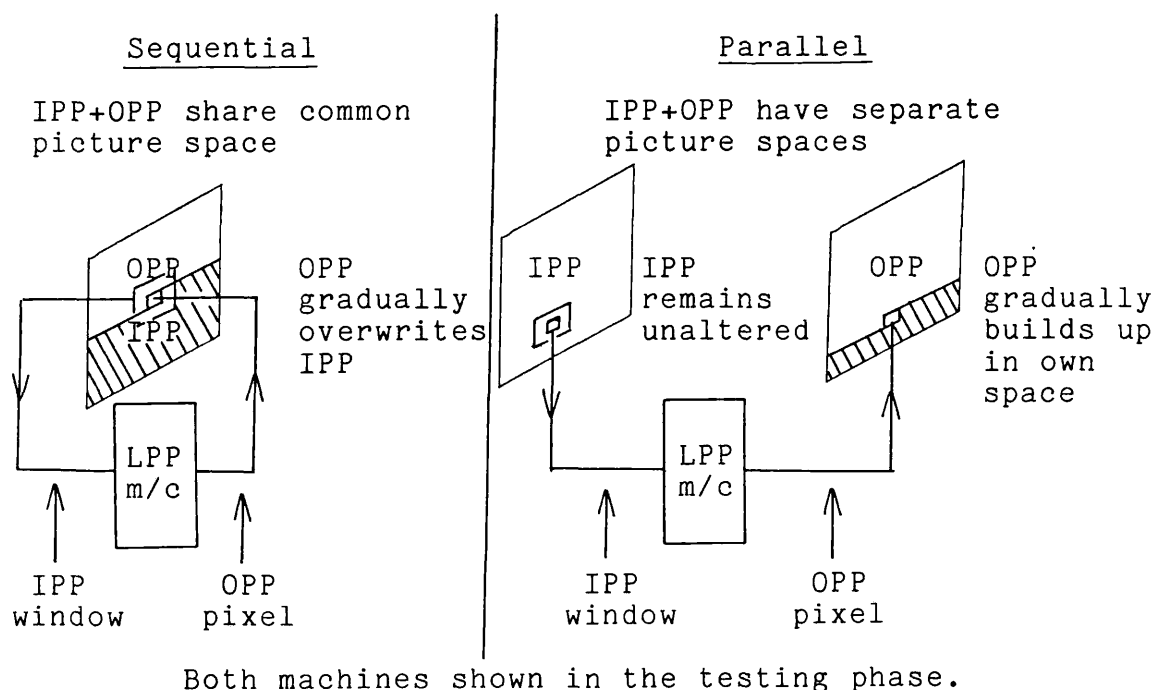


Fig 4.4 The Operation of a Picture Processor in Sequential and Parallel Modes

### The Effect of the Different Modes

The difference in effect of these two modes of operation can vary depending on the actual picture processing operation to be carried out. For example, if a simple operation such as inversion is attempted, both modes are likely to generate similar results. However, if a process such as thinning (which is intended to preserve connectedness) is attempted with the same training algorithm, the results are likely to be significantly different. The difference occurs because pixels are processed individually, and would not be removed if doing so would break the connectedness of a limb. In the parallel mode, as all pixels are processed simultaneously and independently, connectedness might well be broken by removal of pixels from a limb of two units width. As a 'limb-pixel' is processed, it is assumed to still have a neighbouring line of pixels and hence it is correctly removed, but this being true for those neighbouring pixels as well, the entire limb may be removed. Hence the result may be quite different for sequential and parallel modes of operation. The two modes will be compared later on the LPP machine in Experiment 13.

### 4.4 Feedback around a Single Machine

The concept of feedback of pictures round these machines may be usefully employed. The 'single pass mode' in both training and testing has been implied so far, as illustrated earlier in Fig 2.10. Here, each picture passes through the machine only once. The use of feedback, where



pictures are repeatedly passed through the machine, may be employed in the testing phase.

Assuming a LPP machine is already trained then the test operation, which results in the generation of one output picture from one input picture, lends itself well to this mode of operation. The diameter-limited restriction (see the discussion in Section 3.5) can be lifted also, or at least partially relaxed, dependent on the number of feedback passes to be made. That is, the machine can react to and process features that are spread over a distance greater than that seen by a single window at once. For example, if the machine is attempting to find the centres of objects larger than the window size, this could not be effected by a single pass through the machine. However, multiple passes could progressively strip the outer layers from the objects until the machine is finally left with the centre points as required.

The operation of the feedback mode in testing is illustrated in Fig 4.5. The number of passes made through the machine may clearly vary from one upwards without limit.

There are several criteria by which it could be deemed that sufficient passes have been made. A fixed number of passes could be made (known by previous experience to be sufficient) or the pattern could be passed continually through the machine until no further changes occur in the resultant output. Both these approaches have been employed experimentally (see Chapter 6).

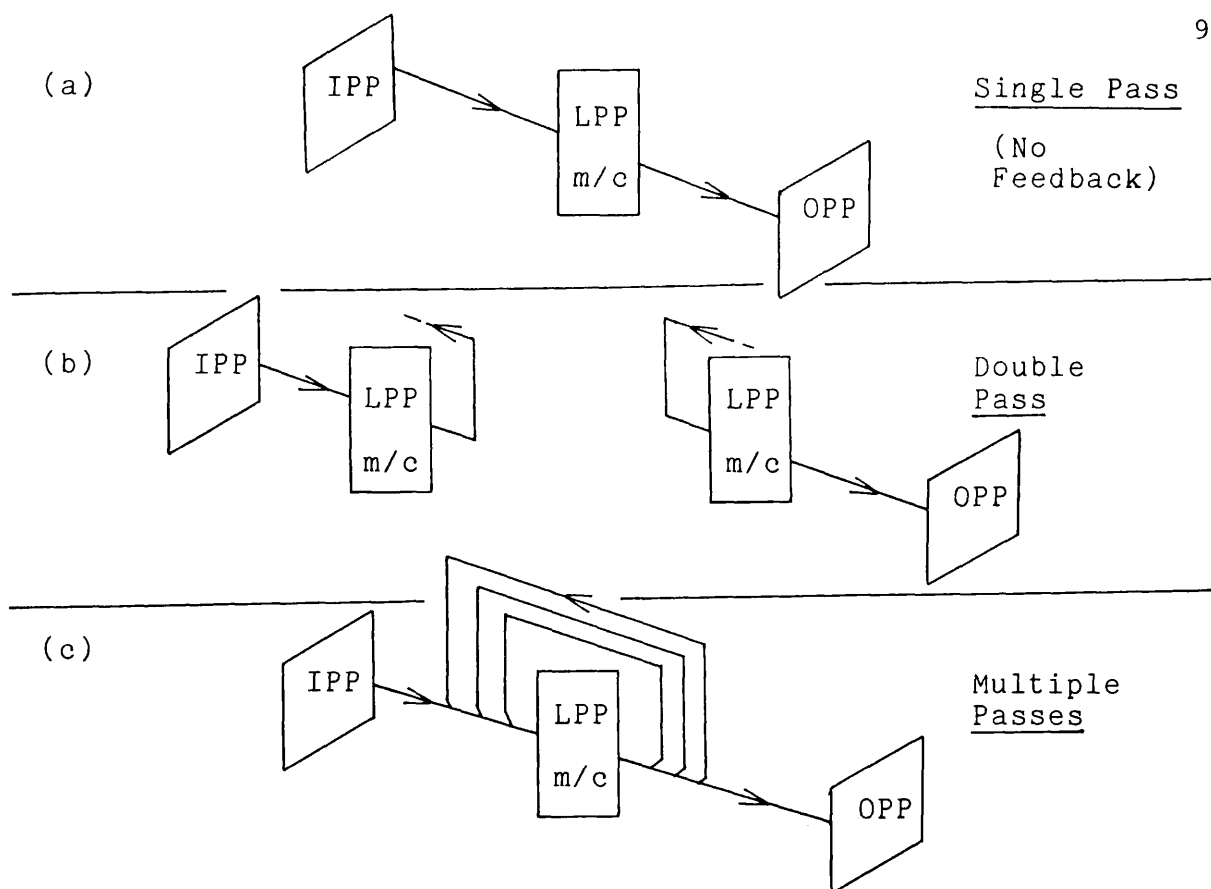


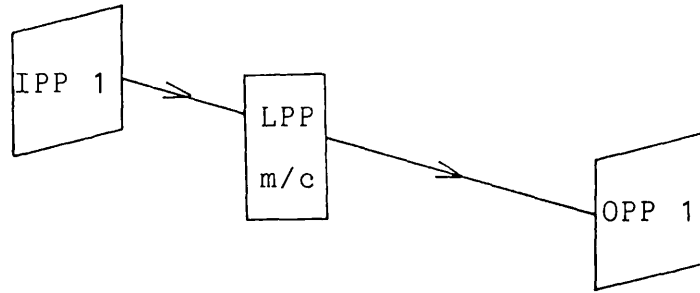
Fig 4.5 Feedback in Testing

#### 4.5 Cascaded Machines

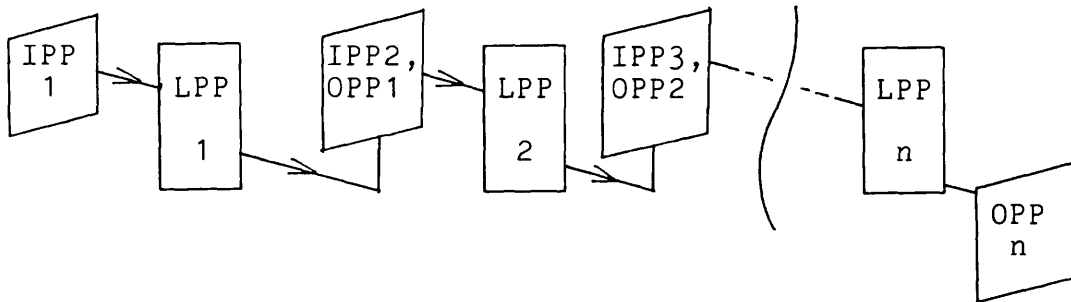
As with any machine that produces output data in the same format as the input data, a set of LPP machines can be cascaded. That is, the output of one machine can be fed into the input of the next, the complete set of machines now being regarded as the whole picture processor. This is illustrated in Fig 4.6b.

Again, as with the case of feedback, this mode of operation may only usefully be employed in the testing phase, where the machine stages each produce an output. In training, as each stage requires two inputs and produces no output there is no obvious method of cascading the machines. Such cascaded stages must therefore be trained independently from each other, and can only be cascaded to commence

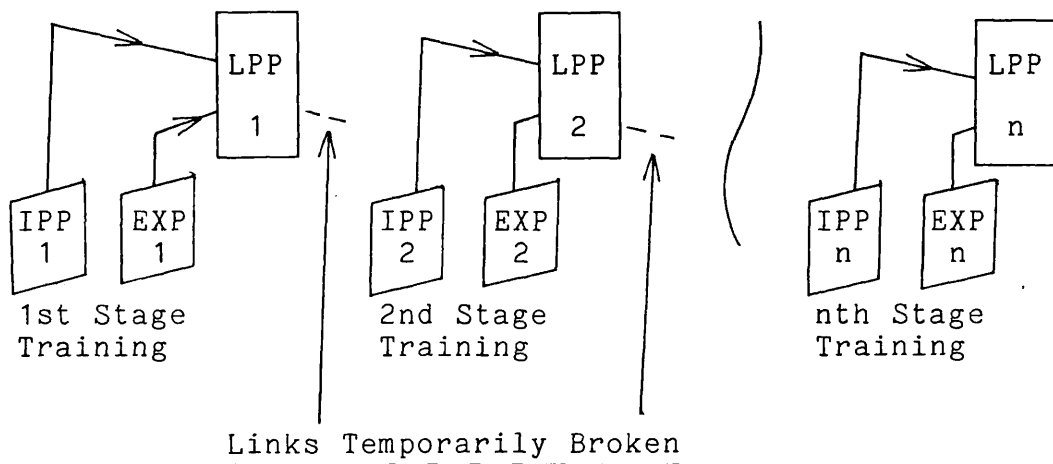
(a) Testing - Single Stage Machine



(b) Testing - Cascaded Machines



(c) Training - Cascaded Machines



Each Stage (1,2 and n shown) represents a particular section of the Transformation from IPP 1 to OPP n

Fig 4.6 Testing and Training of Cascaded Machines

testing. Consequently, the training of each stage must represent the particular (and probably different) process required at each stage of the transformation. This requirement is illustrated in Fig 4.6c.

#### 4.6 Compounded Variants : The Problems of Complex

##### LPP Machines

It has been shown in the above sections how variations can be introduced and to some extent formalized in the LPP machines. These variations have been broadly divided into four major classes :

- 1 internal data processing,
- 2 parallel or sequential mode of operation on pictures,
- 3 the use of feedback around a machine, and
- 4 the cascading of machines.

These last two classes together introduce the idea of compounded machines, where feedback need not only occur around single stages but possibly around more than one stage.

In principle, feedback of data can occur any number of times around any number of stages, and this represents the compounded machine both cascaded and with feedback. If the individual stages are capable of assuming any of the internal or mode variations described earlier, then this represents a more general machine.

However, this concept of the large and general machine is of questionable practical use. A machine that exploited all of these options simultaneously might be impossibly

complex to analyse by experiment. Thus it appears reasonable to let such complexities evolve as necessity dictates.

In the experiments that follow, the machines used are thus generally simple variants, to enable meaningful comparisons of performances. At this early stage in the development of trainable picture processing systems, these experiments are aimed at producing results that can be extrapolated to more complex systems later.

## CHAPTER 5

## EXPERIMENTS WITH MORE ADVANCED LPP MACHINES

5.1 An Introduction to Further Experimental Work

As a result of the preliminary experiments in Chapter 3 some practical modifications have been suggested for the basic LPP machine. A general set of theoretical modifications has been described in the previous chapter, and some more experimental variations will be attempted here.

It will be noted that this is not primarily an investigation of the picture processing tasks themselves, rather an investigation into how the LPP machine performs such tasks, and the effect of design and operational changes on this performance. Hence a fixed range of picture processing tasks will often be retained over several of the experiments to permit comparative judgements of the results.

In performing these experiments it will be appreciated that there is no easy way of accurately or rigorously measuring the performance. Consequently, there will be a heavy reliance on visual examination of the picture outputs for assessment of the results.

5.2 Experiment 6 : A Range of Picture Processing Tasks

In the experiments performed so far, only one picture processing task has been attempted. This was the manual 'tidying up' of alphabetic characters involving cleaning and

thinning. To exercise the system on other tasks, an LPP machine was trained to perform four different tasks. These were : cleaning, inverting, thinning and thickening of characters.

The machines used so far have operated on  $16^2$  patterns as these were adequate to show up the points raised regarding the LPP system. However, in the following experiments the picture resolution will be doubled - 32 samples will be taken in each direction. The  $16^2$  machine was defined as format 'F1'; the  $32^2$  machine is referred to as the 'F3' machine. It is otherwise identical internally, with two-levelled memory matrix cells - initially set to '0'.

#### Train/Test Cycle

One IPP+EXP pair of patterns was found here sufficient to train the machine, and one test IPP pattern sufficient to establish the performance in general terms. This is because each  $32^2$  pattern effectively generates 1024 training patterns when used with a scanning window device and consequently trains the machine to a considerable extent.

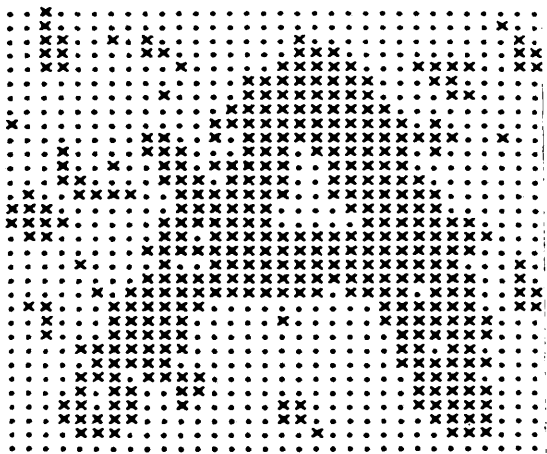
For each of the four tasks to be learnt : clean, invert, thin, thicken; this IPP+EXP pair is shown at the top of a block of 4 patterns in Figs 5.1 to 5.4. Below these two patterns are shown the test IPP and the resultant OPP generated by the machine working in the parallel mode.

#### Results

The OPPs in Figs 5.1 to 5.4 illustrate that this machine can learn different tasks. While there is an unavoidable requirement of greater frame storage, the actual Learning Picture Processor is internally the same size for

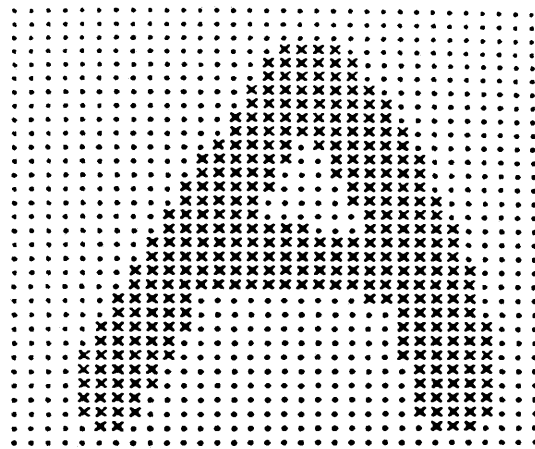
IPP Train

F3



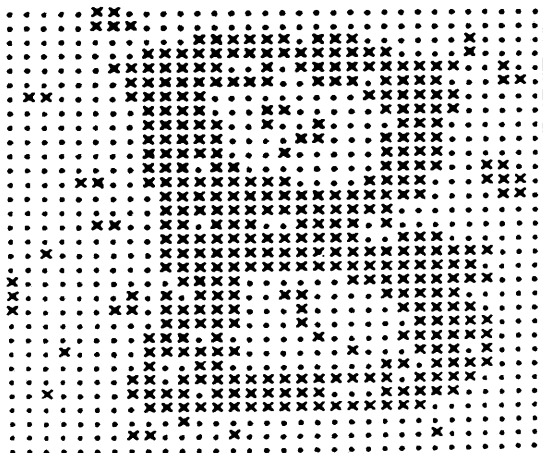
EXP Train

F3



IPP Test

F3



OPP Test

F3

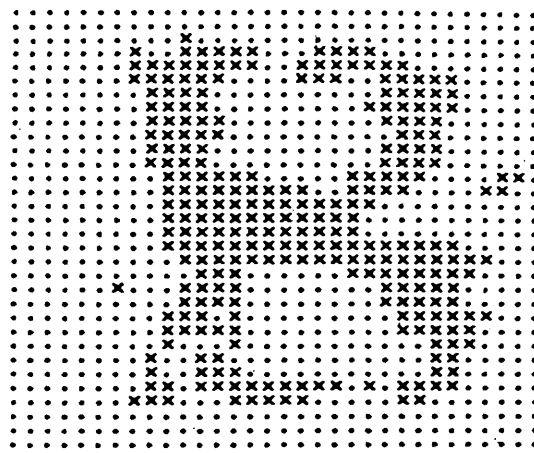
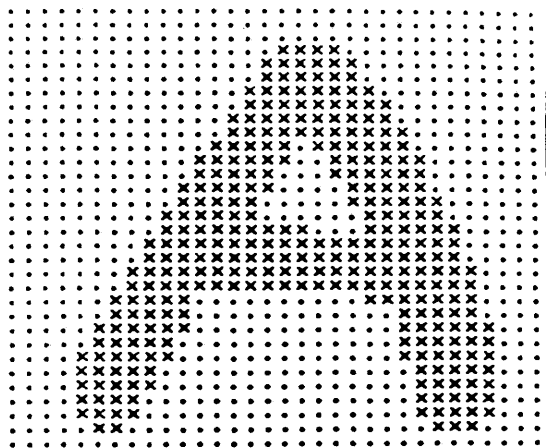


Fig 5.1 Experiment 6 Task : CLEAN



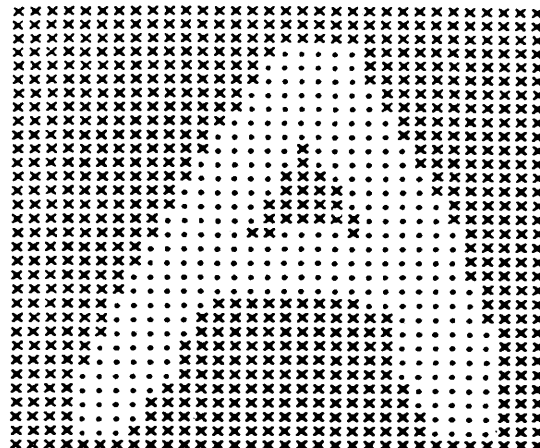
IPP Train

F3



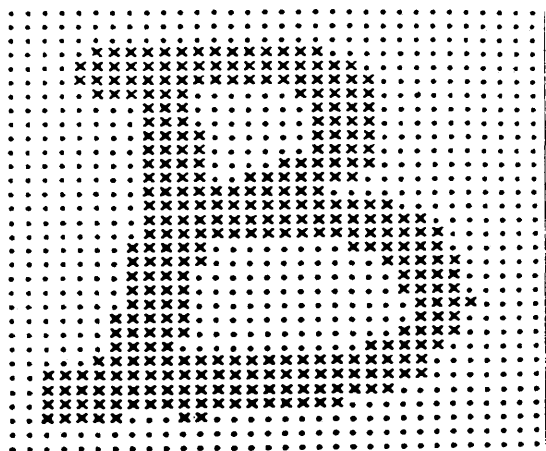
EXP Train

F3



IPP Test

F3



OPP Test

F3

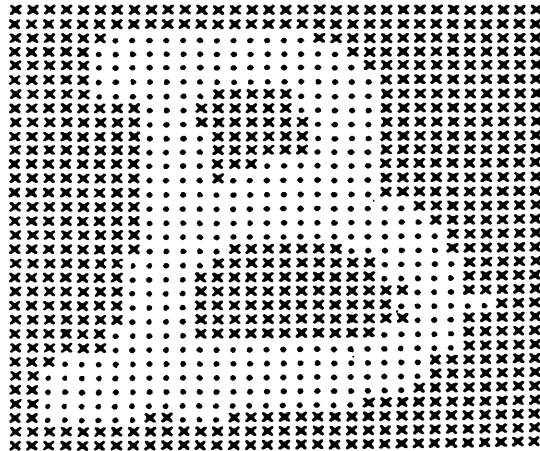


Fig 5.2 Experiment 6 Task : INVERT

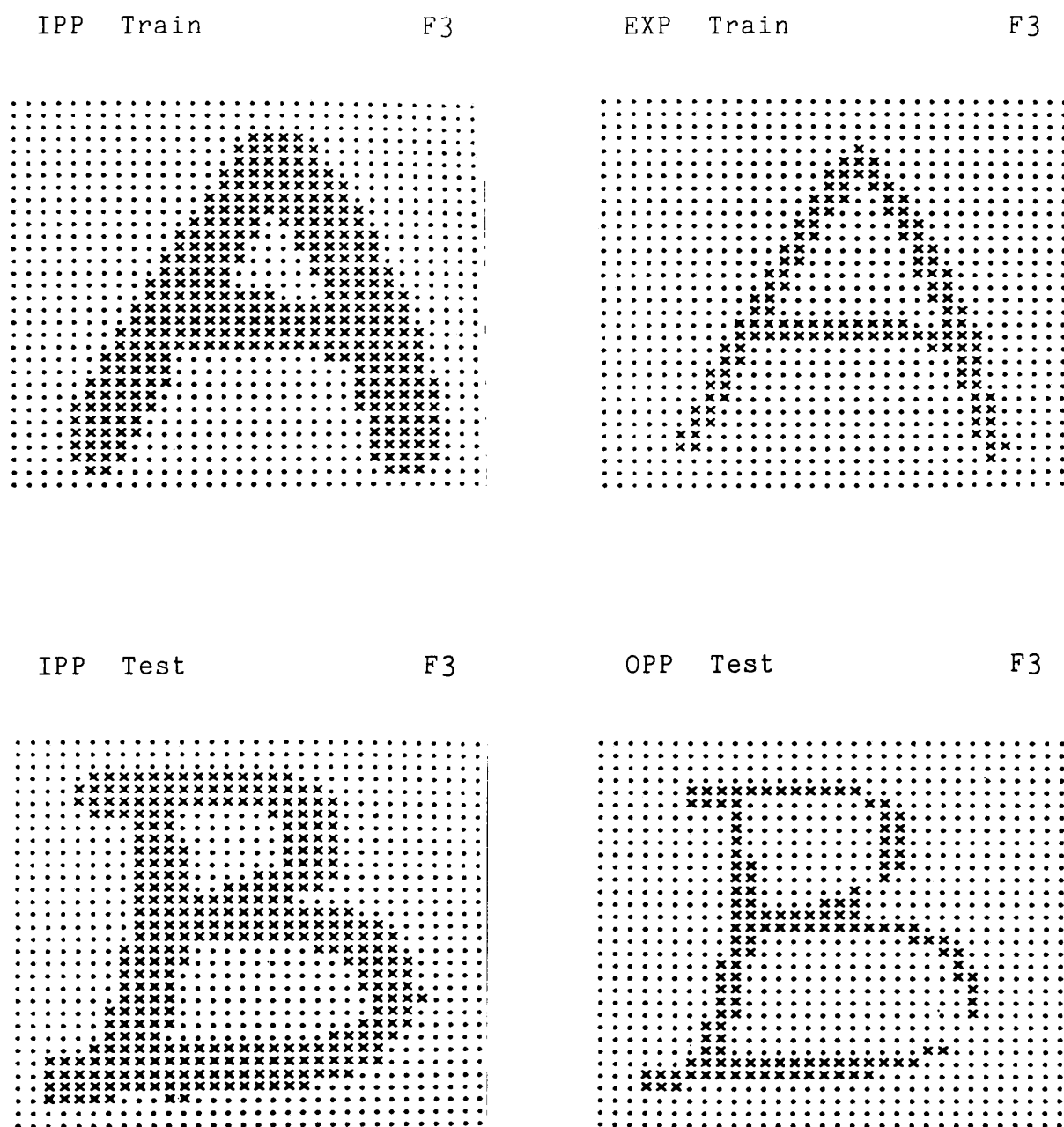


Fig 5.3 Experiment 6 Task : THIN

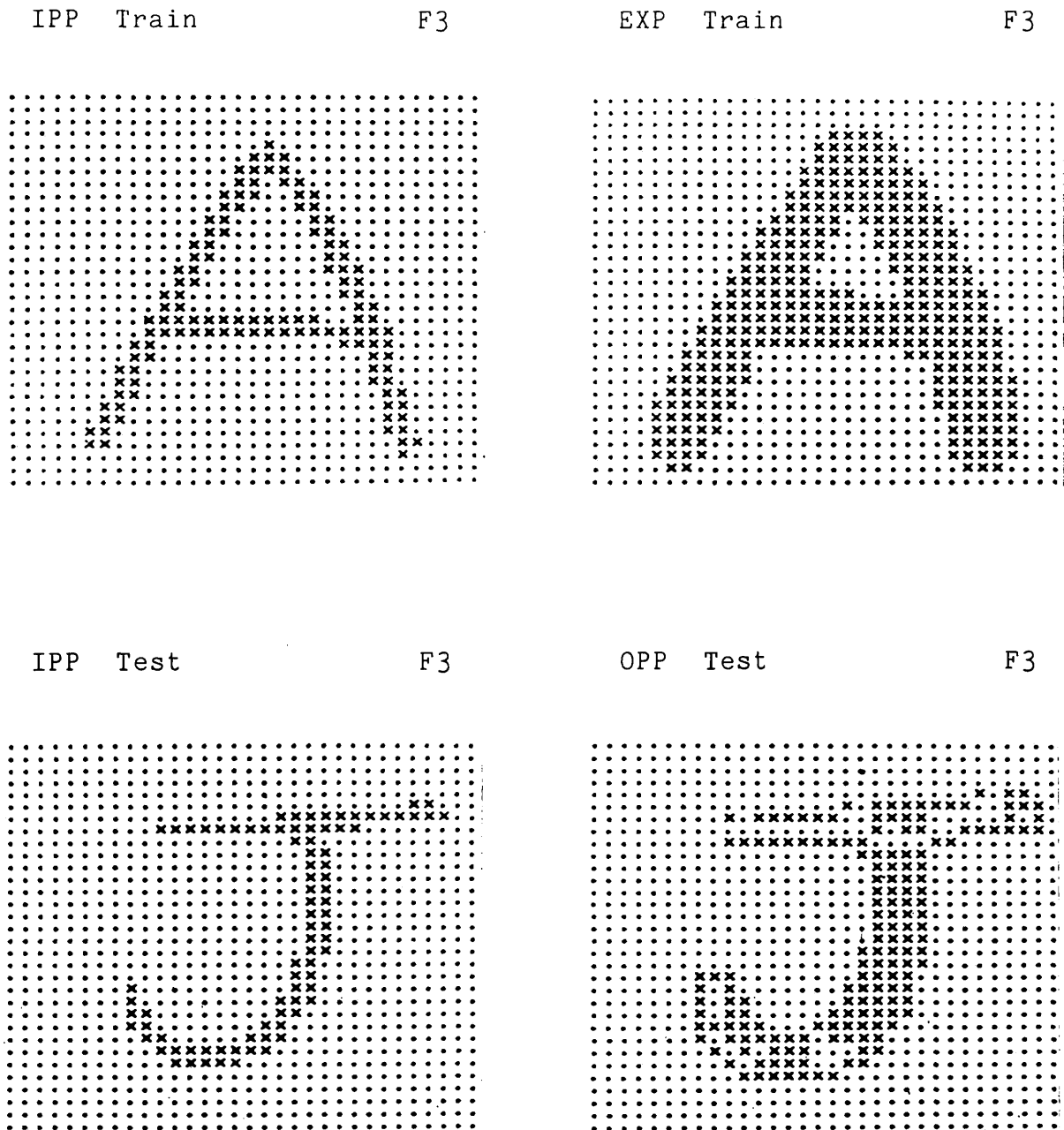


Fig 5.4 Experiment 6 Task : THICKEN

both the  $16^2$  and  $32^2$  formats. This is an important point - since both machines use a scanning window, which effectively serializes the input picture; a machine of fixed size could process a picture of any size given sufficient time.

In the experiments that follow, the  $32^2$  picture is taken as the current standard for the LPP machine, which has here been shown capable of learning different picture processing tasks as a result of re-training alone.

### 5.3 Experiment 7 : Tri-state/Bi-state Memory Matrix Cells

It has been noted in Experiment 5 that the use of multi-valued memory matrix cells (the F2 machine) may lead to possible improvements in performance, by extracting more of the useful information from the memory matrix. However, with the F2 machine suggested earlier, the complex internal processing is an expensive price to pay for the apparently small gains in performance.

A compromise should be possible with the use of a smaller range of memory matrix cell values. Ideally, this could also simplify the processing requirement and hence further improve the machine's efficiency.

It is suggested here that just three cell values would retain in the memory matrix most of the useful information available in the training set. Referring to Fig 3.11 it can be seen that the largest single group of memory matrix cells remains at the initialisation value - even after the machine has received considerable training. The only useful information contained within these cells is that the features they represent have not been seen in training. If a

test pattern selects one of these untrained cells, by presenting a feature not seen before, it would be advantageous if the resultant output pixel could indicate this lack of training. The resultant F4 machine would operate in the following manner.

Before training, all cells are preset to the initialisation value, represented as '?'. During training, the stimuli received from the training set cause the cells addressed to be either set to '1' or reset to '0'. In testing, those cells that have not been trained at all (and hence still contain '?') can now be distinguished from those that have been trained and contain either '0' or '1'. An appropriate output can then be made into each OPP pixel to reflect this. Repeated training in the same cell, but in the opposite sense will immediately overwrite the old cell contents with the new value, without re-entering the '?' state.

The operation of the F4 machine is represented in Fig 5.5 in terms of the response of the memory matrix to training stimuli. The F4 machine's response is shown compared to that of the F3 machine as used earlier. (The F3 response is shown for the two possible initialisation values.)

It is clear from Fig 5.5 that the F4 (Tri-state) memory matrix will retain all the information regarding the training stimuli that is found in both cases of the F3 machine's initialisation.

#### Experiment

This situation is illustrated by the test run shown in Fig 5.6 comparing these machines. This test was run in the

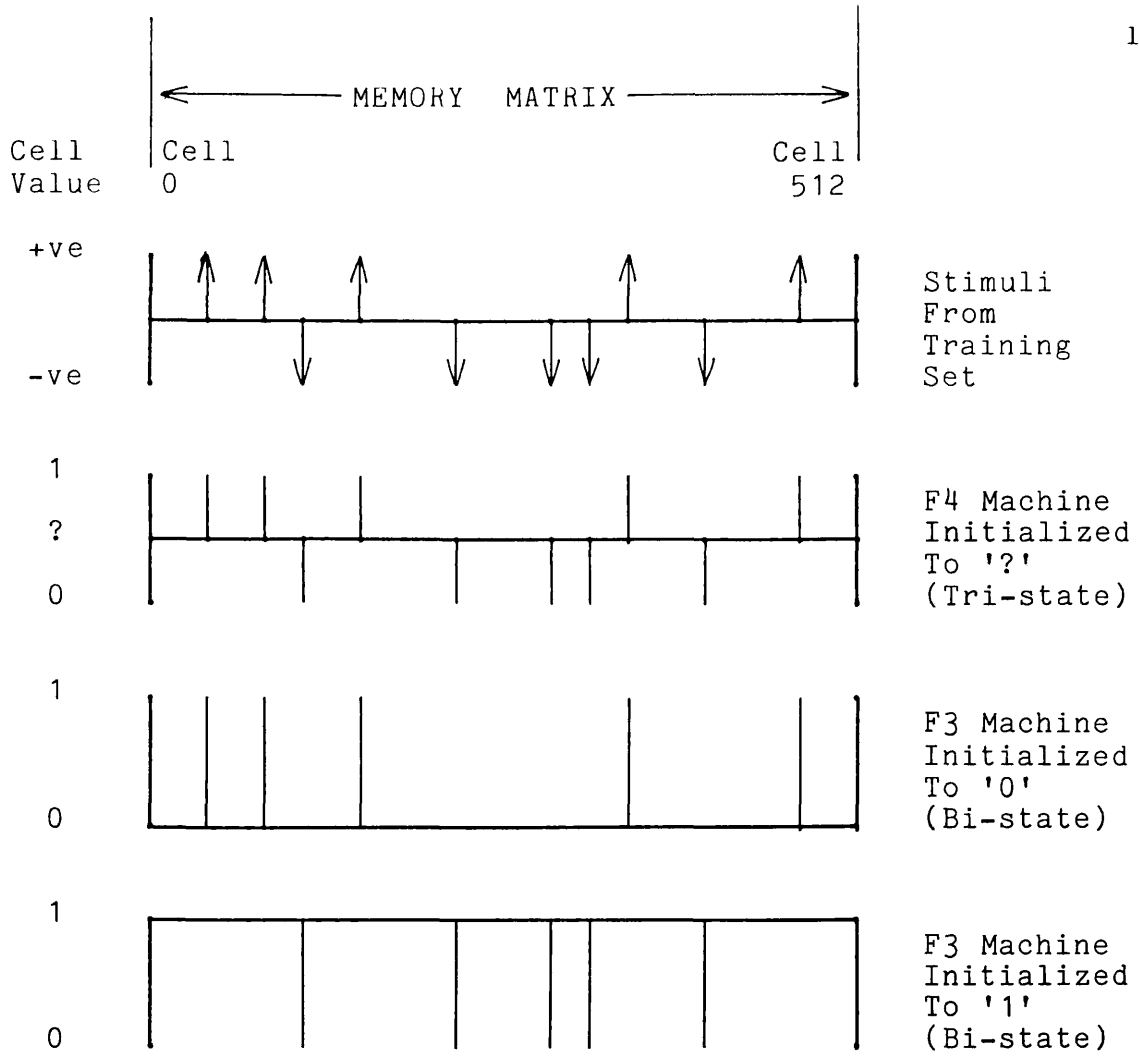


Fig 5.5 Effect of Training Stimuli on Memory Matrices

parallel mode, and the three pixel values are depicted as :

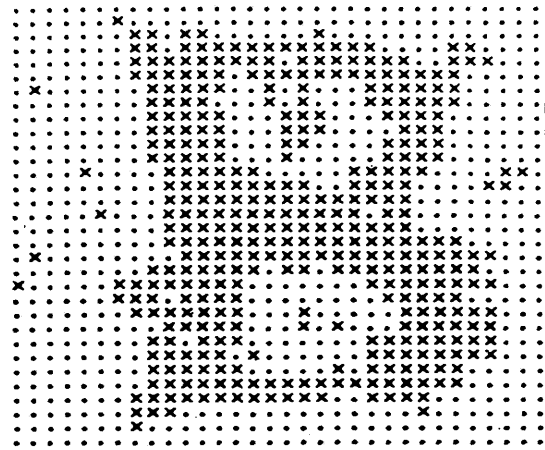
X if cell value = 1  
 ? if cell value = ?  
 . if cell value = 0

(The training was shown in the top row of Fig 5.1).

Results

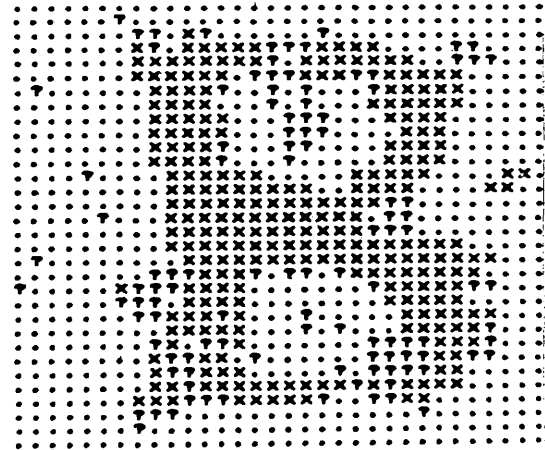
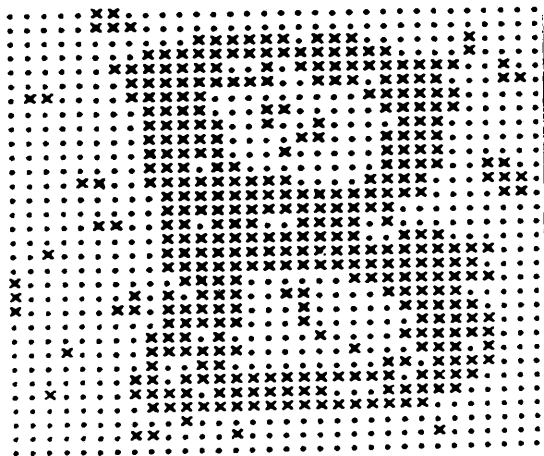
The OPP generated by the F4 machine in the centre row can be seen to differentiate between the regions of the test patterns over which it can legitimately generalize. This

OPP F3 Bi-state m/c Init=1



IPP All Machines

OPP F4 Tri-state m/c Init=?



OPP F3 Bi-state m/c Init=0

Operation : CLEAN

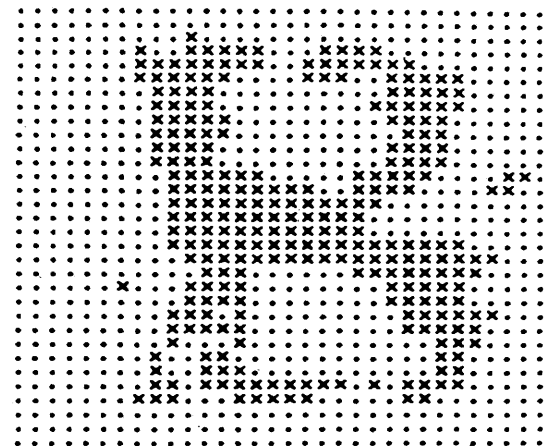


Fig 5.6 Comparison of Bi-state/Tri-state Machines' OPPs

gives an indication of how suitable and complete was the training received earlier.

### Discussion

The F4 machine requires no more internal processing than the F3 machine. The only changes involve the storage and handling of potentially three-valued as opposed to two-valued variables. This involves a slight increase in storage by a factor  $(\log_2 3 / \log_2 2)$ .

### Testing on Four Tasks

A more complete test of the performance of the F4 machine was run. The range of picture processing tasks (clean, invert, thin, thicken) attempted in Experiment 6 with an F3 machine was repeated with the new variant.

The training received in both cases was identical, and corresponds to the top rows of IPP+EXP patterns in Figs 5.1 to 5.4. The test IPPs and two OPPs (one from each machine) are shown for each of the four tasks in Figs 5.7 and 5.8.

The F4 machine can be seen to generate '?' pixels in regions where the training has been insufficient to allow the machine to generalize. Since neither machine is able to generate reliable information in these areas, more useful data is conveyed to the OPP field if this distinction between 'reliable' and 'unreliable' pixels is displayed. Thus, in the experiments that follow this tri-state memory matrix will be used predominantly as the new standard machine layout.



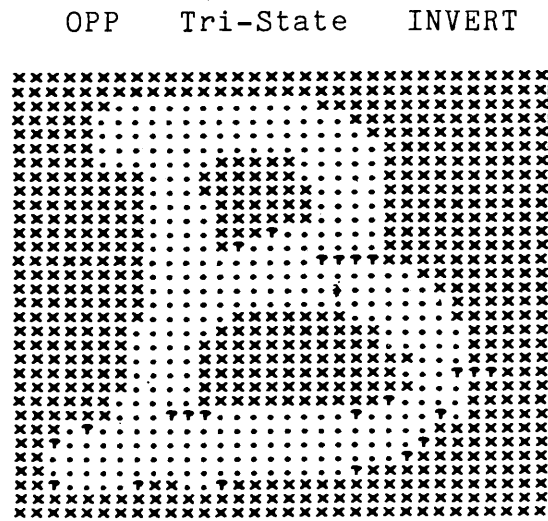
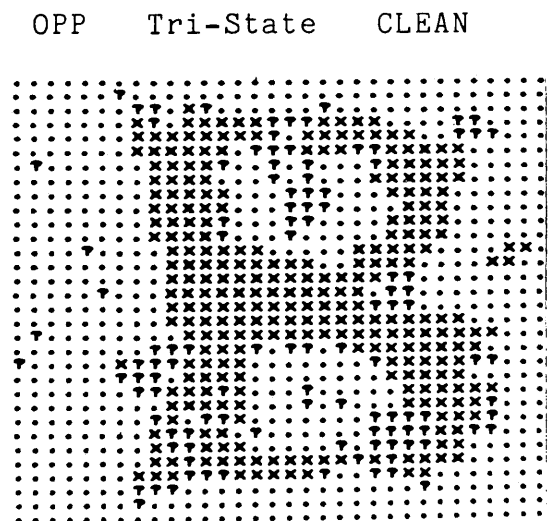
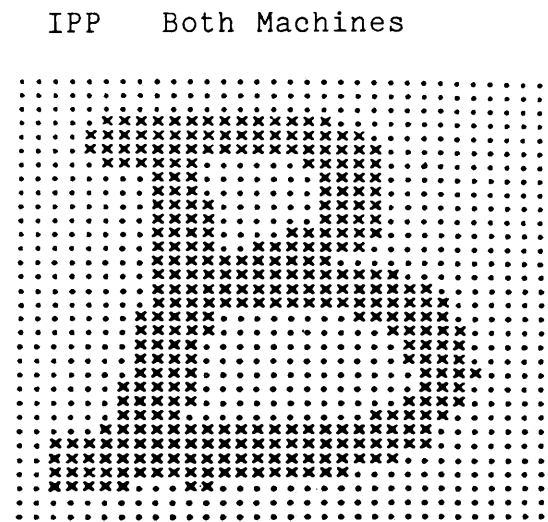
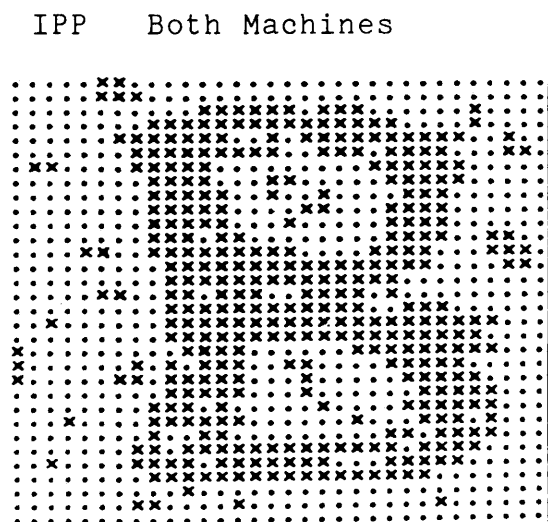
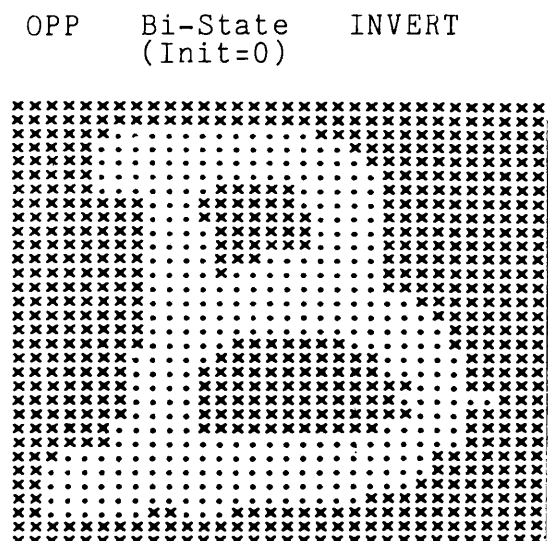
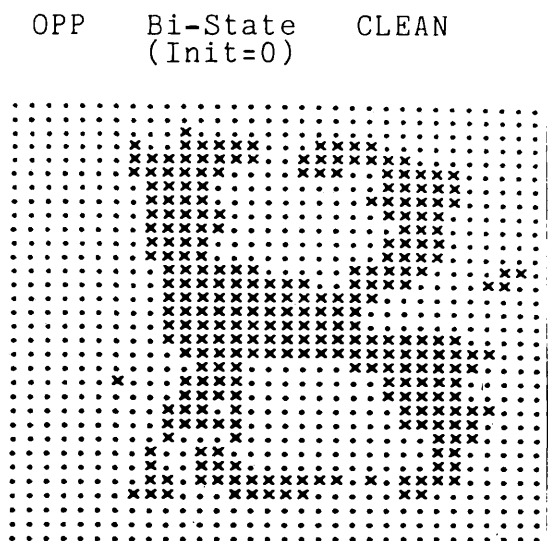


Fig 5.7 Experiment 7 : Bi/Tri-State MM : CLEAN,INVERT

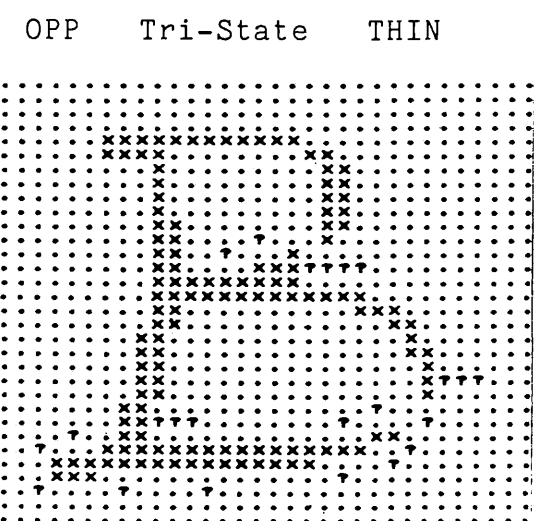
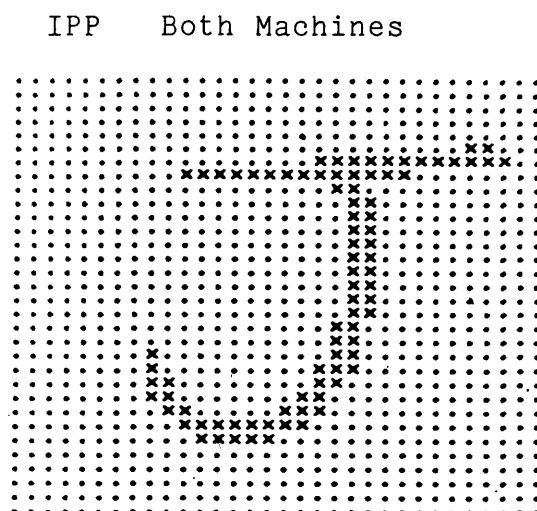
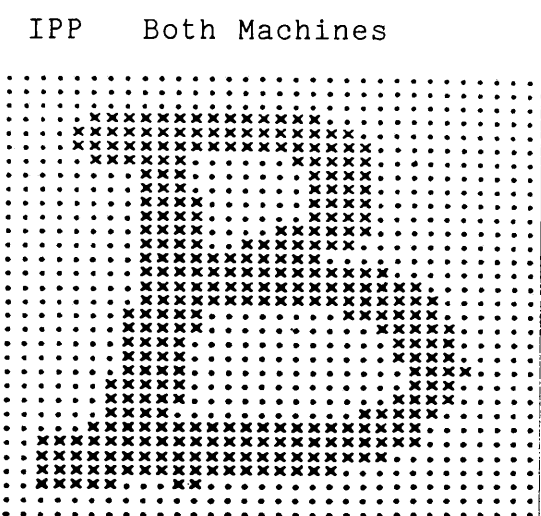
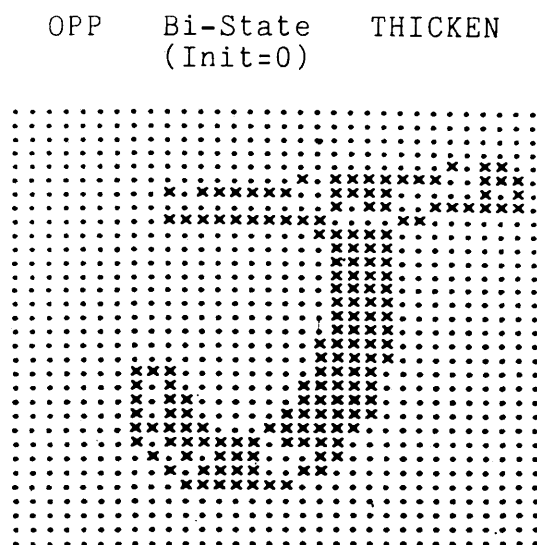
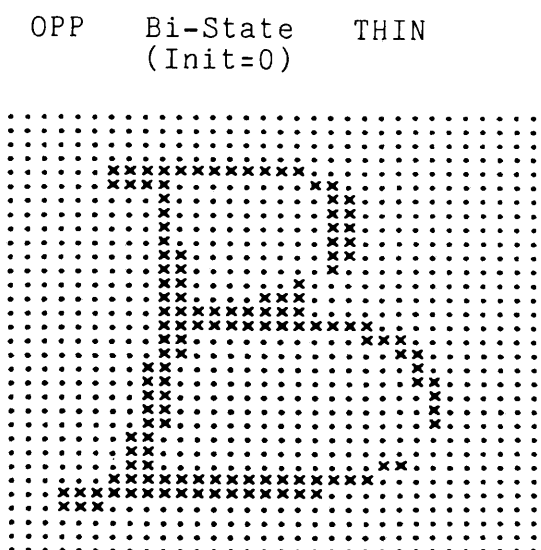


Fig 5.8 Experiment 7 : Bi/Tri-State MM : THIN, THICKEN

#### 5.4 The Concept of a 'Trained Percentage'

The fact that a F4 machine uses tri-state memory matrix cells can be used to generate a measure of the amount of training received by the machine. This is primarily because cells that are unaffected by training stimuli are now distinguishable from those that have been set or cleared by such stimuli. Consequently, the number of cells remaining in the initial ('?') state after training can be compared with the number of cells that have been altered (to contain '0' or '1'). This ratio can be expressed as :

$$\frac{(\text{ number of trained cells })}{(\text{ total number of cells })} \times 100 \% = \text{Percentage of Trained Cells}$$

and will be referred to as the 'trained percentage'. In a system of tri-state cells, it can be seen equivalent to :

$$\frac{(\text{ number of cells = 0 or 1 })}{(\text{ total number of cells })} \times 100\%$$

or :

$$\frac{(\text{ total number of cells }) - (\text{ number of cells = ? })}{(\text{ total number of cells })} \times 100\%$$

The F3 (bi-state) machine cannot be used to calculate simply this trained percentage, but the F4 machine can give it directly. Fig 5.9 shows these measurements being taken from these machines (F3 in two cases, and F4). The data used

Before Training :	% Cells set to 0	% Cells set to ?	% Cells set to 1
F3 Machine Init=1	0	-	100
F4 Machine Init=?	0	100	0
F3 Machine Init=0	100	-	0
After Training :			
F3 Machine Init=1	21.9	-	78.1
F4 Machine Init=?	21.9	64.4	13.7
F3 Machine Init=0	86.3	-	13.7
Key to Histograms			

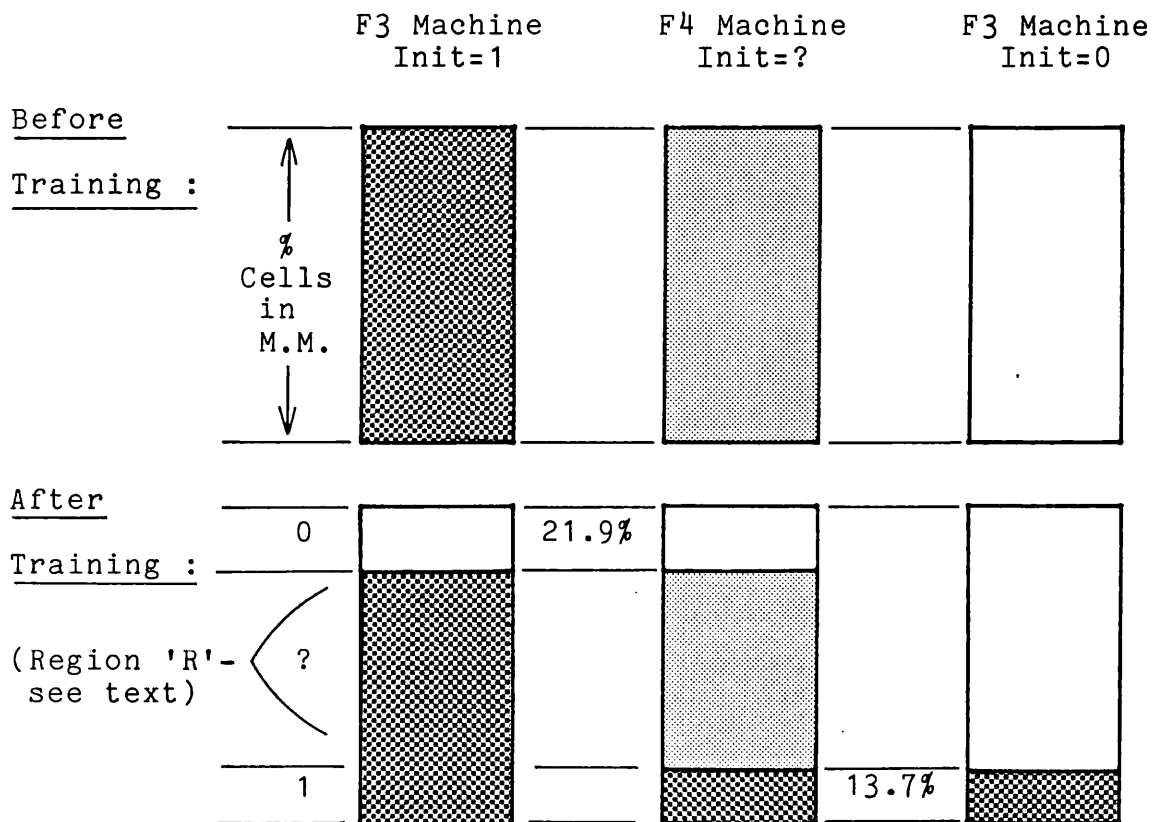


Fig 5.9 Percentage Totals of Memory Matrix Cells

in this figure were obtained by examination of the memory matrices after training in the first part of Experiment 7 (the pattern results having been shown in Fig 5.6).

### Analysis

From Fig 5.9 it can be seen that the operation represented in Fig 5.5 is occurring - where there is a central band of residual cells in the machines which remain in the arbitrary initialisation state. (These are marked as 'Region R' in Fig 5.9.) If this state is distinguishable from the '0' and '1' states then the number of cells in this state can be measured directly. Thus the trained percentage can be most easily found from the F4 machine and is equal to :

$$( 100 - 64.4 ) \% = 35.6 \%$$

This means that 35.6% of the cells were affected by the training set, which in this case was the IPP+EXP pair shown in the top row of Fig 5.1.

Prior to the use of this trained percentage value ('TP'), the only meaningful measure of the performance was a subjective evaluation of the resultant test OPPs. Now a more exact measure has been developed, although it must be noted that it only refers directly to the training quantity and only indirectly to the testing performance (ie. it reflects those cells whose value should have become either '0' or '1', but gives no indication which of these values is the more appropriate).

It should also be noted that this TP value can be a misleading figure of merit as it has a limiting value of 100%, and ultimately cannot be proportional to any

performance figure. A LPP machine with a TP of 100% ('fully trained') may still not give optimal picture processing performance. This only means that every cell has been accessed by the training set, but not that this training was necessarily correct. It will be shown later in Experiment 11 that while TP increases with a larger training set, again it is not a proportional increase. There is an asymptotic limit dependant on the quality of the training received.

Although these three factors : the quantity of training, TP value and the test performance are all related, and increase together, their relationship is neither linear nor readily quantifiable. However, relative changes in TP can give clear indications of the effect of varying parameters in the LPP machine's operation. In this capacity, the TP value will be found a useful measure.

#### TP and the Memory Matrix Size

It has been noted that TP depends on the size of the memory matrix. This relationship may be more fully expanded. For an input window of  $w_i$  bits, there are  $2^{w_i}$  cells in the memory matrix (assuming the cell addresses are formed by the simple stacking of binary pixels). When the machine is trained on a pattern of  $n$  bits,  $n$  accesses are made to the memory matrix. These will access any number (up to  $n$ ) of different cells. The exact number depends on the variation in features in the training pattern. On a random data model of the input pattern, we have:

$$\begin{aligned} \text{Number of training examples per pattern} &\leq n \\ \text{Number of memory matrix locations} &= 2^{w_i} \end{aligned}$$

thus: Addition to TP value per pattern  $\leq \frac{n.100\%}{2^{w_i}}$

for 'N' pictures in a training set:

Total TP value after receiving N patterns  $\leq$

$$\frac{N.n.100\%}{2^{w_i}} = \frac{\text{Total training received}}{\text{Memory Matrix Size}}$$

(The inequality simply illustrates that pictures generally contain a limited and repeated subset of all possible  $2^{w_i}$  features.)

The TP value will remain constant for a variation in N, n or  $w_i$  if the expression

$$N.n / 2^{w_i}$$

remains constant. As an example, four extra binary pixels could be added to the  $w_i$  bit feature window. This would require a training picture with sixteen times the number of pixels, or alternatively sixteen times the number of training pictures to reach the same TP value.

While this analysis contains gross assumptions regarding the lack of redundancy in such training patterns, it illustrates the problems that would be encountered if very large windows were used. Enormous quantities of training would be required to maintain a significant TP value in the bigger memory matrix. The fact that the memory matrix grows exponentially with the window size results in two limiting factors on this arrangement of a LPP machine: the storage needed and the training requirements.

### The Use of TP in Analysing Experimental Results

In this subsection, an analysis is made of how the TP varies with the picture processing task being learnt. The TPs for the memory matrices (trained to perform four separate tasks) in the latter half of Experiment 7 are given in Fig 5.10. Also shown are the distributions of cells set to the three possible states.

From these data, it can be seen that the TP value for the tri-state machine (F4) is more or less task independent - thin and thicken tasks have similar TP but widely differing numbers of cells set to alternately '0' or '1'. This means that the F4 machine is not muddled by pictures that are mostly '0's or mostly '1's, and TP can be a valid measure of training.

However, the exact value of TP in this machine depends only on the number of different 3x3 bit window features seen in the training IPP. In the case of the tasks invert and thin, the training IPP was the same. (See Figs 5.2 and 5.3 - the left patterns in the top rows are identical : a solid, thick letter A.) Consequently, these patterns accessed exactly the same memory matrix cells in both cases, even though the different EXPs then caused different data to be loaded into these cells. As a result, the TPs for these two tasks are identical, even though the number of cells equal to '0' and '1' differ, reflecting the different training. This highlights that TP is not, therefore, an ideal measure in all respects.



TASK	No. of Cells=0	No. of Cells=?	No. of Cells=1	No. of Trained Cells
Clean	112 (21.9%)	330 (64.4%)	70 (13.7%)	182 (35.6%)
Invert	32 (6.2%)	450 (87.9%)	30 (5.9%)	62 (12.1%)
Thin	61 (11.9%)	450 (87.9%)	1 (0.2%)	62 (12.1%)
Thicken	1 (0.2%)	436 (85.2%)	75 (14.6%)	76 (14.8%)

Histogram of Above Data :

(Key as in Fig 5.9)

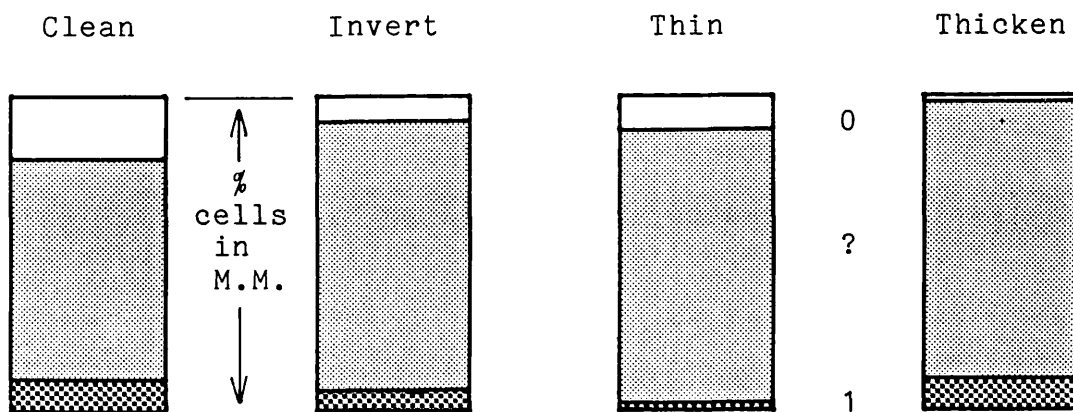


Fig 5.10 Distribution of Exp 7 F4 Machines Memory Matrix Contents

### 5.5 Experiment 8 : Augmenting Training by Window Symmetry Operations

It has been noted how the effectiveness of the training set can be measured by examining the TP value after training. In an effort to increase this TP value it was recognised that many of these feature cells correspond to effectively identical features.

For example, many tasks show no dependence on the feature direction in the pattern field. This results in independence from rotation and reflection of the input window in isotropic picture processing. The features shown in Fig 5.11 should all generate identical OPP pixels.

```

. . X      X . .      X . X      . . .
. . .      . . .      X . .      X . .
. X X      X X .      . . .      X . X

X X .      . X X      . . .      X . X
. . .      . . .      . . X      . . X
X . .      . . X      X . X      . . .

```

Fig 5.11 Example Features requiring the same OPP Pixel under any Combination of Rotation and Reflection

This indicates that more useful information could be extracted from the training set, if this principle of rotation and reflection of the feature window is utilised. A reduction in the memory matrix size would be an alternative as a number of cells are equivalent and hence redundant.

An 'F5' machine was devised to take advantage of such rotation and reflection symmetries. This is similar to the earlier F4 version, changed only in the function 'f<sub>2</sub>' which generates the address from the window contents (see Fig 4.2). Each window extracted will be used to generate up to eight addresses and these will all be used to train the memory matrix repeatedly. These eight addresses will be generated by the rotation and reflection of the window in accordance with the layout shown in Fig 5.12.

P2 P3 P4	P8 P1::P2	P6 P7 P8	P4 P5 P6
::	::		
P1::P0 P5	P7 P0 P3	P5 P0::P1	P3 P0 P7
		::	::
P8 P7 P6	P6 P5 P4	P4 P3 P2	P2::P1 P8
P8 P7 P6	P2::P1 P8	P4 P3 P2	P6 P5 P4
	::		
P1::P0 P5	P3 P0 P7	P5 P0::P1	P7 P0 P3
		::	::
P2 P3 P4	P4 P5 P6	P6 P7 P8	P8 P1::P2

Fig 5.12 Eight Possible Rotations and Reflections  
Of a 3x3 Pixel Window

The memory matrix cells corresponding to these eight features will all be trained by the centre point value derived from the EXP pattern. Some of these permutations will generate identical addresses, dependent on the symmetry of the feature involved. (Some cells may be trained more than once with the same data, but the above method is used as it saves processing and rationalises the operation for any input window, whatever its symmetry. In any case, this cannot give misleading results, as once a cell is set,

setting it again has no additional effect with this machine. Another important point is that the overhead of checking to reduce the effort of such repeated training, might well itself consume more effort than it saves.)

The retention of all 512 cells also simplifies the test procedure, which is carried out exactly as in the F4 machine. The test IPP windows address the relevant cells (which may now have been trained by equivalent, rather than identical features) and the contents are output as the new OPP pixels.

### Experiment

The same four tasks used for training the F4 machine in the previous experiment were used again here for comparison. (This training data was shown at the top of Figs 5.1 to 5.4). The test IPPs and OPPs from both the F4 and F5 machines are compared in Figs 5.13 and 5.14. The TP values are tabulated in Fig 5.15.

### Discussion

Examination of the data in Fig 5.15 reveals the expected increase in TP as a result of rotating and reflecting the input window from the training pattern. This shows in testing as an improvement in the OPPs from the F5 machine which have generally fewer '?' pixels, indicating improved generalisation ability. This is most notable in the case of the cleaning task, where there is a large reduction in the undefined pixels - the TP value changes from 35.6% to 65.8% .

Also shown in Fig 5.15 are the average TPs for the two

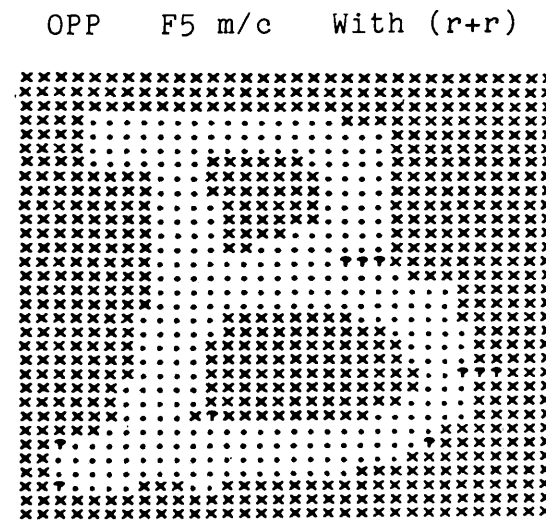
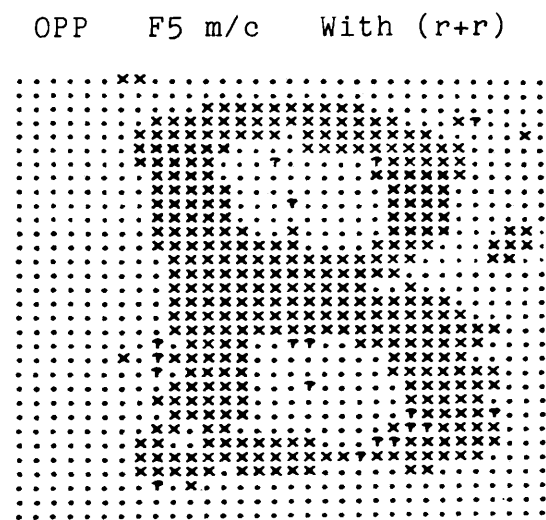
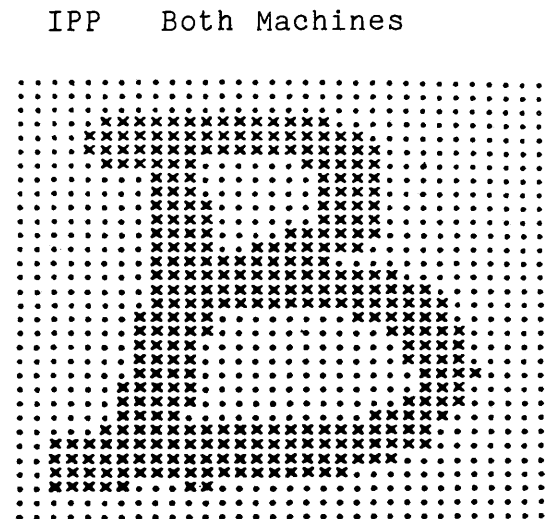
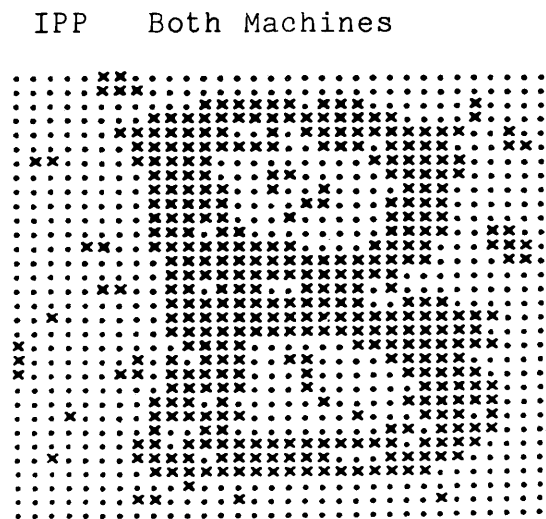
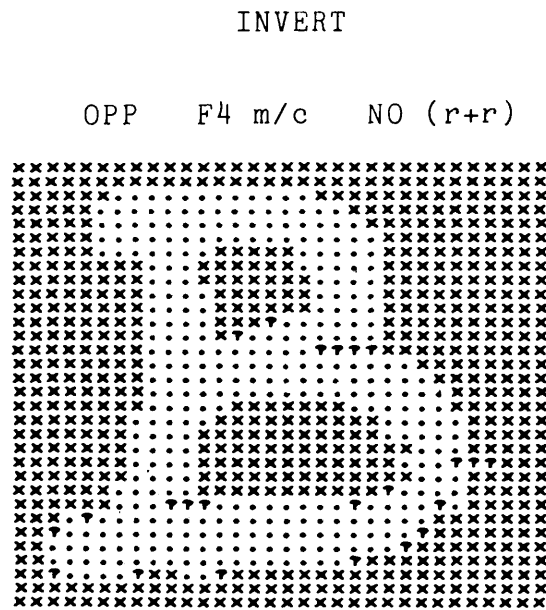
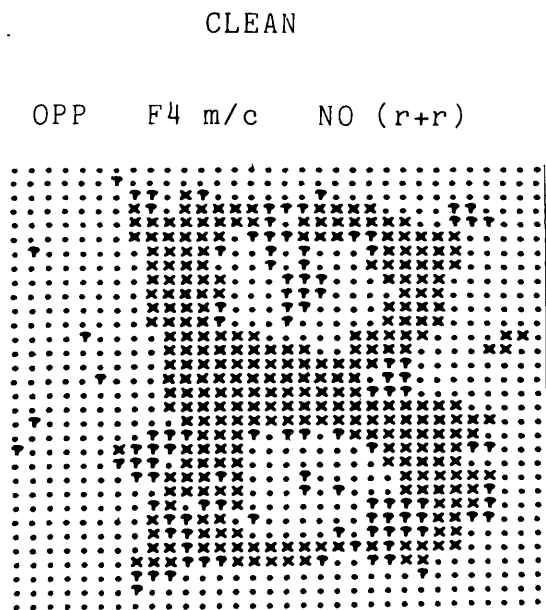


Fig 5.13 Experiment 8 : Test Results Comparison  
With/Without (r+r) : Tasks : CLEAN , INVERT

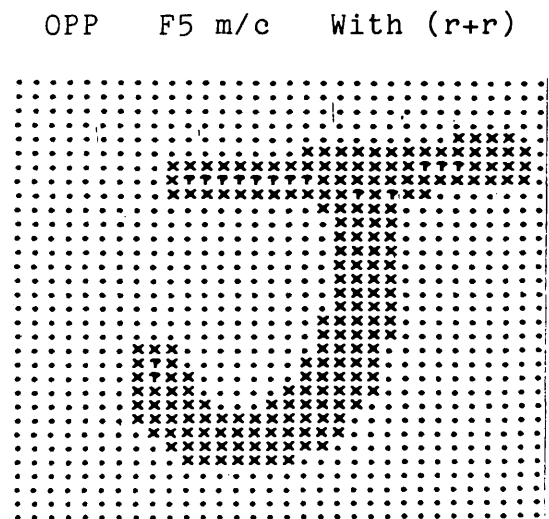
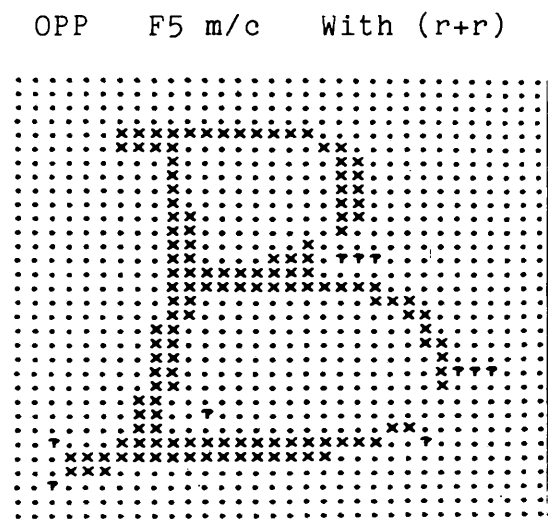
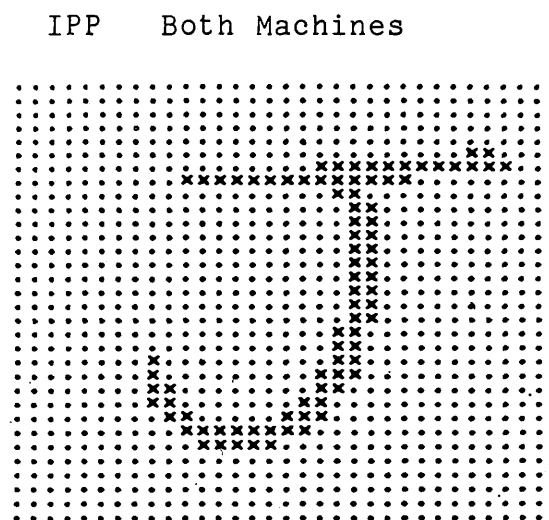
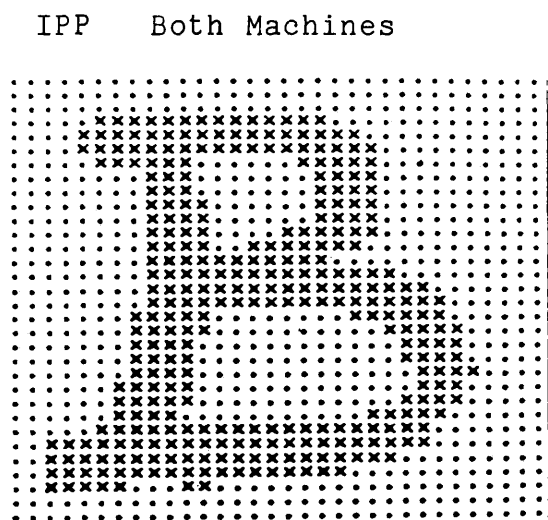
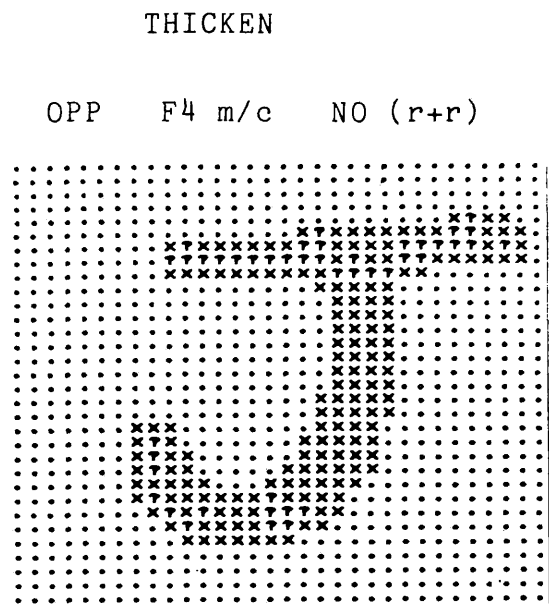
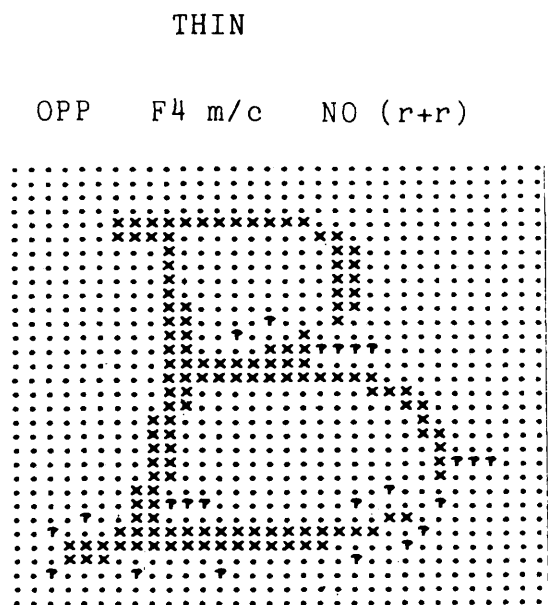


Fig 5.14 Experiment 8 : Test Results Comparison  
With/Without (r+r) : Tasks : THIN , THICKEN

	F4 m/c NO (r+r)				F5 m/c with (r+r)			
TASK	Cells % = 0	Cells % = ?	Cells % = 1	T P (0+1)	Cells % = 0	Cells % = ?	Cells % = 1	T P (0+1)
Clean	21.9	64.4	13.7	35.6	35.7	34.2	30.1	65.8
Invert	6.2	87.9	5.9	12.1	7.2	84.0	8.8	16.0
Thin	11.9	87.9	0.2	12.1	15.8	84.0	0.2	16.0
Thicken	0.2	85.2	14.6	14.8	0.2	70.9	28.9	29.1
	Average TP F4 m/c = 18.6				Average TP F5 m/c = 31.7			

Histograms of Above Data :

(Key as in Fig 5.9)

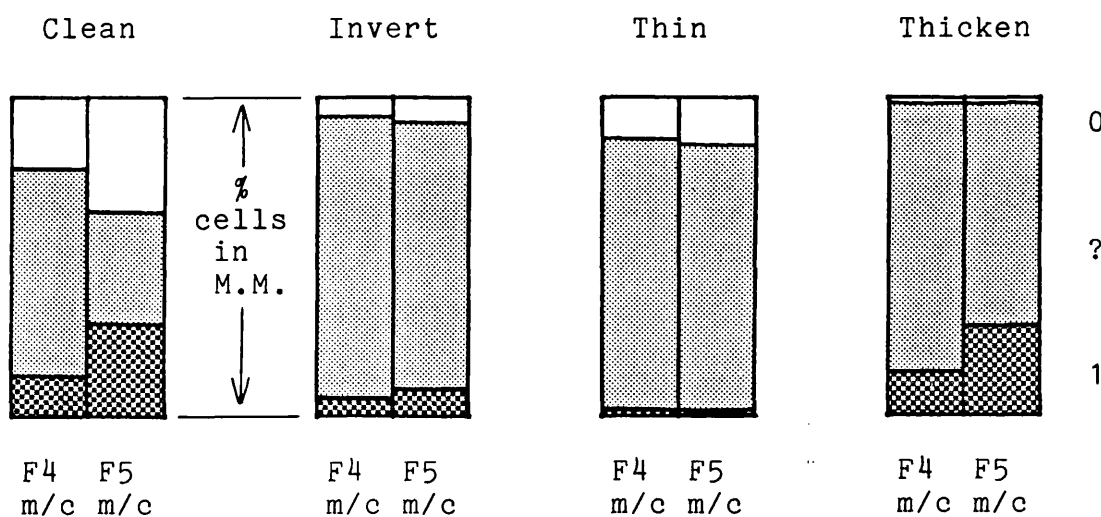


Fig 5.15 Comparison of F4 and F5 Machines' Memory Matrix Contents : With/Without (r+r)

cases of machines - with and without rotation and reflection. These are respectively 31.7% and 18.6% and represent a 1.7 fold increase in TP as a result of using this technique.

There is an important value that can be derived from the theory to predict this effective increase in training quantitatively. It refers to the change in number of different possible 3x3 window features with and without rotation and reflection. Consequently, this factor of 1.7 will be compared later (Section 5.7) with this maximum possible theoretical increase (viz.  $512/102$ ).

#### 5.6 Experiment 9 : The Effect of Scan Direction on an Anisotropic Picture Processing Task

The above use of symmetry, which extracts more information from the training set, relies on an isotropic picture processing task for coherent results. All four tasks used above were of this type and exhibited an increase in TP on the adoption of window rotations and reflections. However, the use of an anisotropic task (such as 'shift laterally') illustrates how the machine's output depends on the following :

- 1 the relationship between the direction of movement of the scanning window in training and the direction defined by the anisotropic task (eg. shift direction),
- 2 the use or not of rotation and reflection of the input window giving respectively incoherent or coherent results.



The combined investigation of these two effects gives four combinations of outputs to be examined experimentally. These are :

- |   |   |                                   |
|---|---|-----------------------------------|
| 1 | Scan in a given direction<br>(eg. against the direction of shift) | - use of (r+r)<br>(F5 machine)    |
| 2 | Scan in a given direction   | - NO use of (r+r)<br>(F4 machine) |
| 3 | Scan in opposite direction<br>(with the shift direction)          | - use of (r+r)<br>(F5 machine)    |
| 4 | Scan in opposite direction  | - NO use of (r+r)<br>(F4 machine) |

These four cases will be attempted below.

To facilitate execution of this experiment an alternative, but equivalent, method of effectively reversing the direction of scan will be used. Rather than physically reversing the scan direction - which has so far been arbitrarily set as left to right, top to bottom - the direction of the shift will be reversed. That is, cases 3 and 4 above will be run with a shift task in the opposite direction (viz. towards bottom right) to that used in cases 1 and 2 (towards top left). This method of effectively reversing the direction of scan when using an anisotropic picture processing task is used because it is simple to implement - requiring only the interchange of the IPP and EXP pair during training.

### Experiment

The four cases specified above were run, using training and test characters from the same stock of hand-drawn,

binary  $32^2$  patterns used in the previous experiment. These are illustrated in Figs 5.16 and 5.17.

### Results

The resultant OPPs generated in these four cases can all be seen to be quite different and will be briefly described here.

#### Case 1 - Scan in opposite direction to shift, F5 machine

This results in very few pixels left in OPP 1, only a few isolated points set to '1' or '?'. The object is essentially removed entirely from the field.

#### Case 2 - Scan in opposite direction to shift, F4 machine

The OPP 2 generated is a shifted version (towards top left) of the test IPP as required. However, some breaks in the limbs can be seen at junctions.

#### Case 3 - Scan in same direction as shift, F5 machine

This results in a generally unshifted and 'ragged' OPP 3 with many holes and spurs over the entire pattern in all directions.

#### Case 4 - Scan in same direction as shift, F4 machine

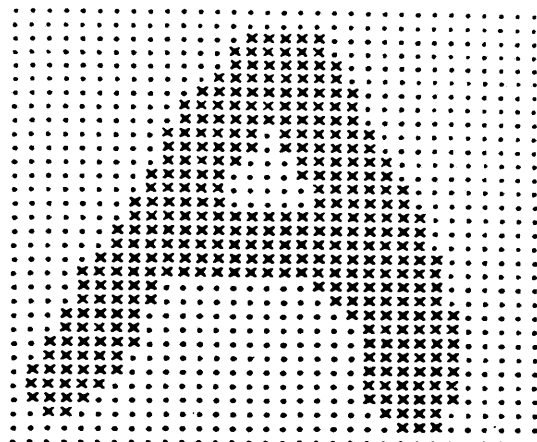
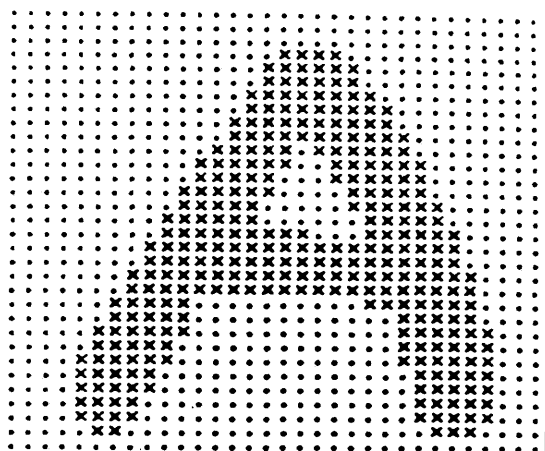
The OPP 4 is a correctly shifted version of IPP, towards the bottom right.

### Discussion

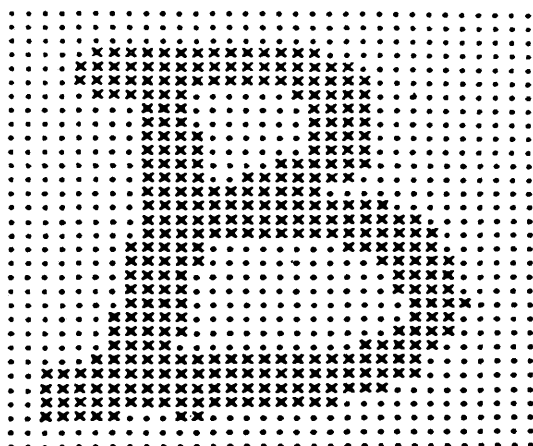
The training of a F4 machine on an anisotropic task such as shift is relatively insensitive to the direction of shift compared to that of scan. That is, cases 2 and 4 above performed coherently as trained and shifted the test IPP in the required directions.

IPP Train

EXP Train (Shift T.L.)

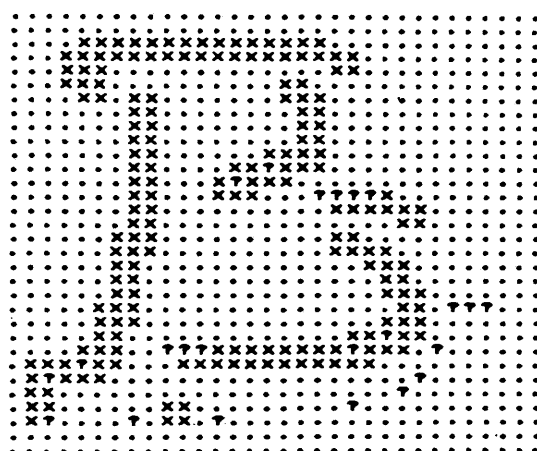
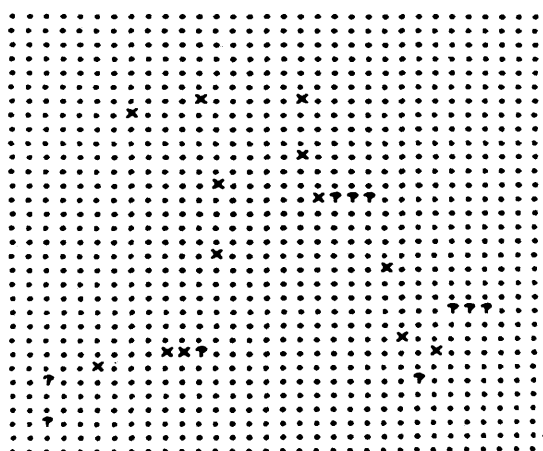


IPP Test (All Cases)



OPP 1 F5 m/c with (r+r)

OPP 2 F4 m/c NO (r+r)



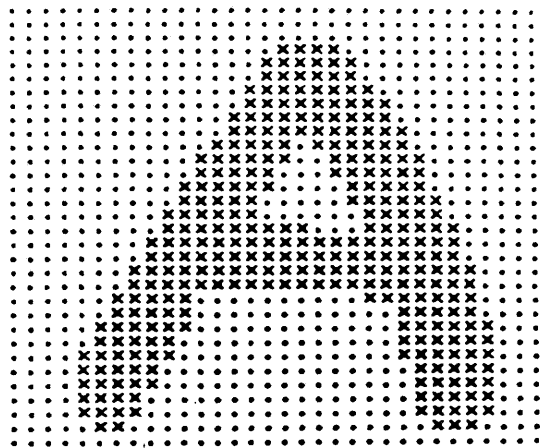
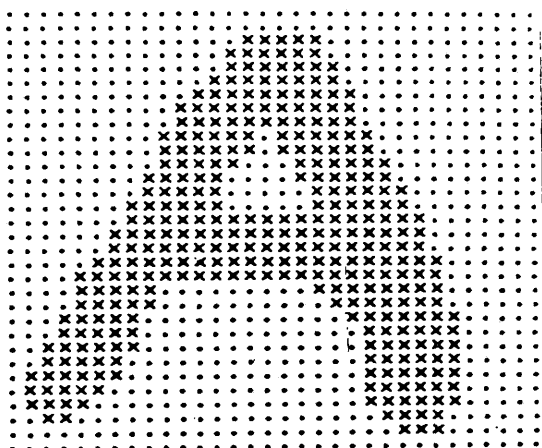
CASE 1

CASE 2

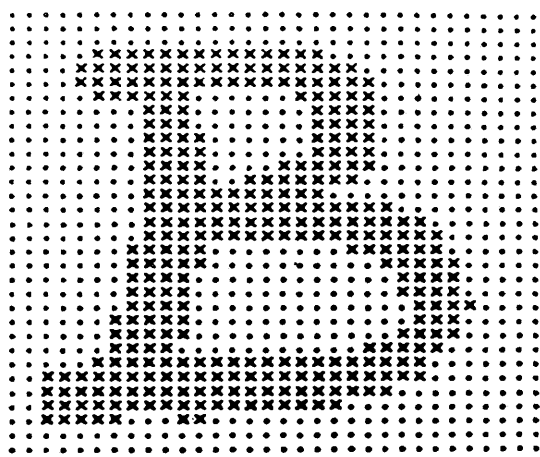
Fig 5.16 Experiment 9 : Cases 1 and 2 : SHIFT Top Left

IPP Train

EXP Train (Shift B.R.)

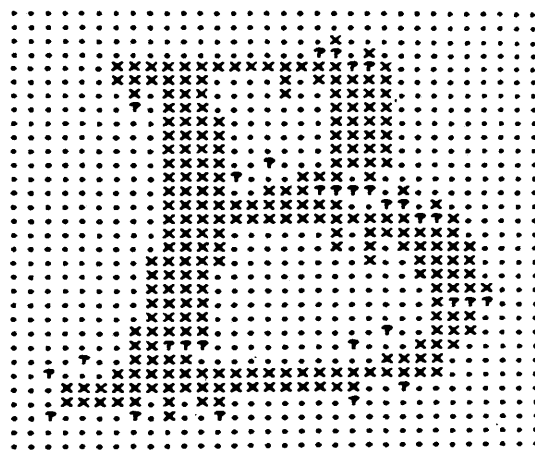
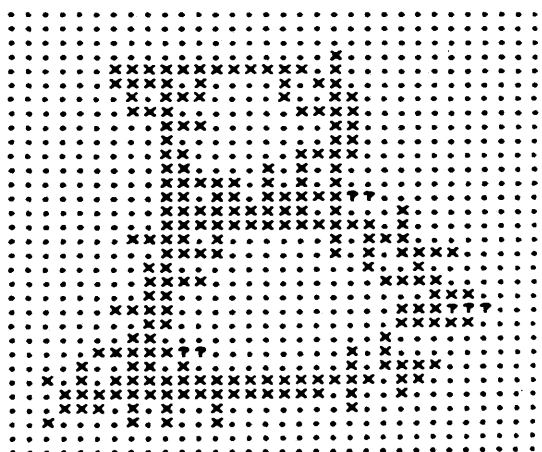


IPP Test (All Cases)



OPP 3 F5 m/c with (r+r)

OPP 4 F4 m/c NO (r+r)



CASE 3

CASE 4

Fig 5.17 Experiment 9 : Cases 3 and 4 : SHIFT Bottom Right

However, in cases 1 and 3 - the F5 machine - the attempt at utilizing rotation and reflection has resulted in widely differing results dependent on the shift direction. This behaviour can be explained by the following considerations.

In the case of the shift direction being in the opposite direction to the scan direction (Case 1), the effect of the training set on the memory matrix must be examined. It must be remembered that this is a temporal process as patterns are scanned sequentially. The memory matrix is gradually built up by successive applications of the input and example window extractors ( $f_1$  and  $f_4$  of Fig 4.2) to the training pair. Consequently, the stimuli received towards the end of the scan will have the more recent effect than those at the beginning. Normally this is unimportant as in the case of isotropic tasks, the training would be consistent - wherever it originated in the training pair, and hence - whenever it was received in the scan period. However, in the case of an anisotropic task ('shift top left') the stimuli from the top of the picture (beginning of scan) is different from that at the bottom of the picture (end of scan). The stimuli could be formalized in general terms as follows :

- (a) stimuli from the top of the picture cause the machine to generate '1' pixels,
- (b) stimuli from the bottom of the picture cause the machine to generate '0' pixels.

The rotation and reflection of the input window removes the possibility of dependence on orientation of the features

and hence no dependence on left, right, upper or lower edges can remain. The stimuli are reduced simply to generate '0' or '1' pixels from symmetrical features. That is, the training is inconsistent and generates a state of dynamic equilibrium in the memory matrix, where the contents at any point are indeterminate.

This is illustrated in Fig 5.18a where the training pair IPP+EXP are shown with sample windows extracted towards both the beginning and end of the scan period. The stimuli can be seen to vary from 'generate 1 pixels' to 'generate 0 pixels' as the scan proceeds in this case. Consequently, as the later stimuli predominate, the test run in the experiments just performed reveals a memory matrix trained to generate predominantly '0' pixels. This can be seen in the lower left pattern of Fig 5.16 (Case 1).

The reverse is true in the case of the opposite shift direction (Case 3). As shown in Fig 5.18b the training stimuli received later in the scan result in the generation of '1' pixels, resulting in a OPP (lower left of Fig 5.17) that is generated by a memory matrix trained in this manner. It should be noted that although this OPP is generally full of spurs and holes, it is not shifted in any particular direction. (The 'noisy' result is due to this inconsistent training received from the beginning and end of the characters, for they are not symmetrical.)

This experiment has demonstrated clearly that these machines rely most heavily on the most recent information received in training. This means, in the case of a sequential scan, the 'end' of a picture will predominate. If this differs from the transformation seen at the beginning

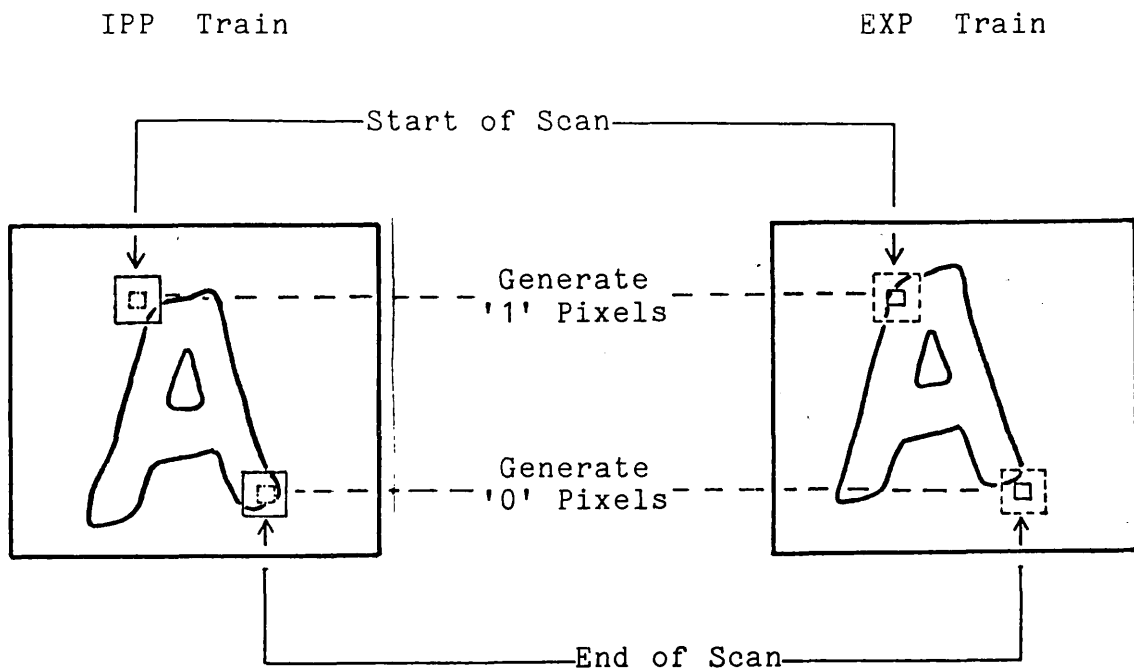
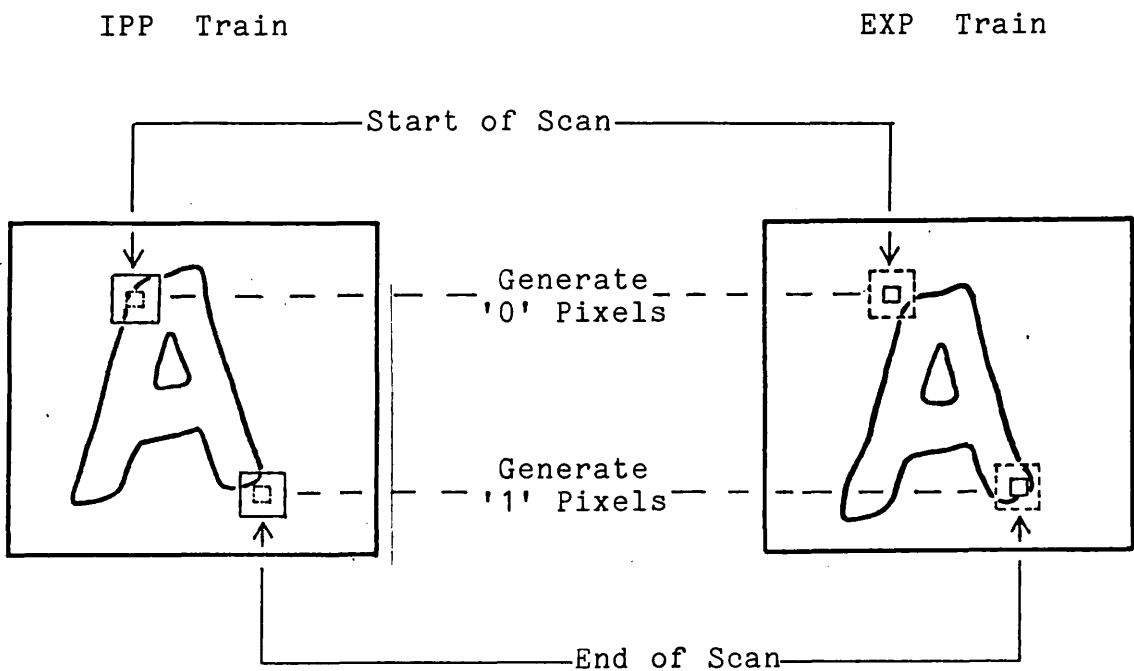
(a) SHIFT Towards Top Left(b) SHIFT Towards Bottom Right

Fig 5.18 Training Stimuli Received at Start and End of Scans for Two Shift Operations

of the picture, the machine is subject to 'neurosis' - it cannot resolve the inconsistency. (This 'neurotic' aspect of behaviour is covered in some depth in Experiments 16 and 17.)

### 5.7 Experiment 10 : 5-bit Window and the Direct Examination of the Memory Matrix

It has been mentioned in earlier sections that the memory matrix can be examined directly after training as an aid to understanding how the LPP machine operates. This direct examination of the memory matrix cells' contents has not yet been implemented. Only the integrated totals of numbers of cells set equal to particular values have been examined so far, producing the type of data seen earlier in Figs 5.9 and 5.10.

However, the interrogation of the LPP simulator will supply these cell data contents directly, albeit in a rather unwieldy form - a table of 512 tri-state variables. In order to appreciate these data, it will be helpful to temporarily change the format of the LPP machine. This will result in less bulk data to be examined, and will facilitate later understanding of a larger (512 cell) memory matrix.

#### The 5-bit Window Format

The 9-bit window used so far will now temporarily be replaced by a 5-bit window, consisting of a centre point and its immediate four-connected neighbours on a rectangular lattice. This is transformed by the address calculator ( $f_2$  of Fig 4.2) into a 5-bit binary address in the range 0-31.





M.M. Addresses, 5-bit Features and Cell Contents for  
the Four Tasks : Clean, Invert, Thin, Thicken.

CELLS 00 - 15

M.M. Address		Feature	Cell Contents trained to :			
Dec	Binary		CLEAN	INVERT	THIN	THICKEN
00	00000	. . . . .	.	X	.	.
01	00001	. X . . .	.	?	?	?
02	00010	X . . . .	.	X	.	X
03	00011	X X . . .	X	?	?	X
04	00100	. . . X .	.	X	.	X
05	00101	. X . . .	.	?	?	X
06	00110	X . . X .	.	.	.	X
07	00111	X X . . .	.	.	.	X
08	01000	. . . X .	.	X	.	X
09	01001	. X X . .	.	?	?	?
10	01010	X . . X .	.	?	?	?
11	01011	X X X . .	X	?	?	X
12	01100	. . . X .	X	X	.	X
13	01101	. X X . .	X	.	.	X
14	01110	X . . X .	X	X	.	X
15	01111	X X X . .	X	.	.	X

( 0 = .    ? = ?    1 = X )

Fig 5.20 Memory Matrix Listing for F6 Machine - Part 1

M.M. Addresses, 5-bit Features and Cell Contents for  
the Four Tasks : Clean, Invert, Thin, Thicken.

CELLS 16 - 31

M.M. Address		Feature	Cell Contents trained to :			
Dec	Binary		CLEAN	INVERT	THIN	THICKEN
16	10000	. . X	.	.	.	X
17	10001	. X X	.	?	?	X
18	10010	. X X	.	X	.	X
19	10011	. X X	.	.	.	X
20	10100	X . X	.	?	?	?
21	10101	X . X	X	?	?	?
22	10110	X X X	X	?	?	?
23	10111	X X X	X	.	.	X
24	11000	. . X	.	X	.	X
25	11001	. X X	.	X	.	X
26	11010	X . X	X	?	?	?
27	11011	. X X	X	.	.	X
28	11100	X . X	X	?	?	?
29	11101	X . X	X	.	.	X
30	11110	X X X	X	?	?	?
31	11111	X X X	X	.	.	X

( 0 = .    ? = ?    1 = X )

Fig 5.21 Memory Matrix Listing for F6 Machine - Part 2

below in Fig 5.22, with data taken from Figs 5.20 and 5.21 in accordance with the formulae in Section 5.4.

For the sake of completeness, the test OPPs actually generated by this 5-bit F6 machine are shown in Figs 5.23 and 5.24, compared with the OPPs generated by the 9-bit F4 machine in Experiment 7. These two machines have received the same training and test inputs, and consequently the outputs differ only as a result of the window size being reduced. It is interesting to note that in the case of the 'thin' task the training appears too coarse for a smaller 5-bit window, yet the other tasks show reasonable results from both machines. (It is to be remembered that these results were obtained with a memory matrix of only 32 tri-state variables.)

With the above data, it can be seen how the F6 machine reacted to its training, and consequently generated the OPPs shown in Figs 5.23 and 5.24. An examination of each pixel in the test IPPs, together with its four neighbours, will indicate (from the look-up table of Figs 5.20 and 5.21) the corresponding OPP pixel.

For the 9-bit window machine, the equivalent look-up table is, of course, sixteen times larger and hence a direct examination of the full memory matrix would be excessively tedious. Methods for effectively reducing the number of cells to be examined are thus desirable.

#### Reduction in Memory Matrix size by Rotation and Reflection

Neither the F4 or F6 machines used above made use of rotation or reflection of the input window. However, this has already been achieved with the F5 machine. In addition to an effective increase in the training to be gained from a

F6 m/c Tri-state M.M.				
TASK	No. of Cells=0	No. of Cells=?	No. of Cells=1	No. of Trained Cells
Clean	17 (53%)	0 (0%)	15 (47%)	32 (100%)
Invert	10 (31%)	13 (41%)	9 (28%)	19 (59%)
Thin	19 (59%)	13 (41%)	0 (0%)	19 (59%)
Thicken	1 (3%)	9 (28%)	22 (69%)	23 (72%)

Histogram of Above Data :

(Key as in Fig 5.9)

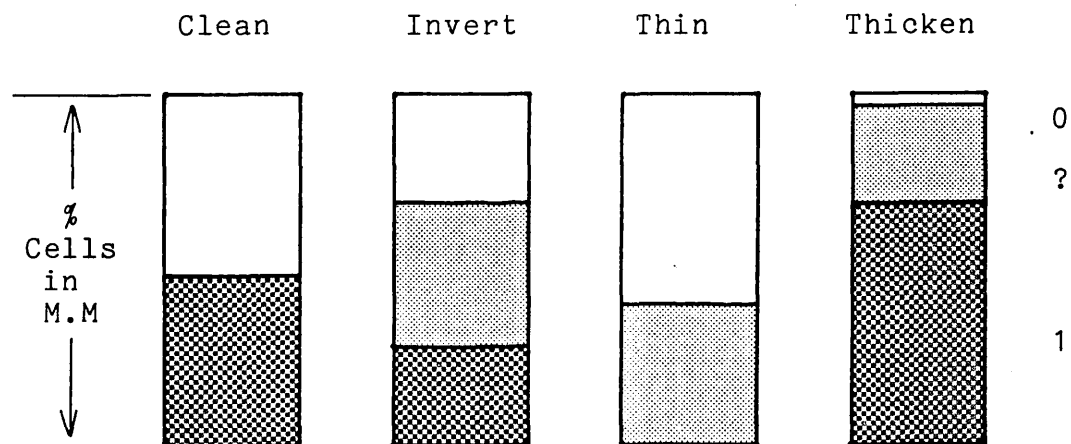
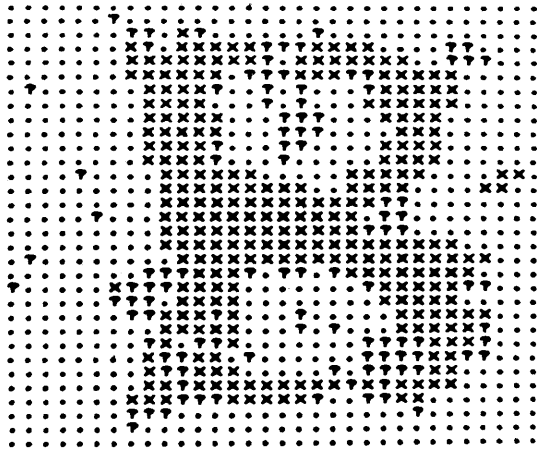


Fig 5.22 Distribution of M.M Contents of F6 Machine As Trained in Experiment 10

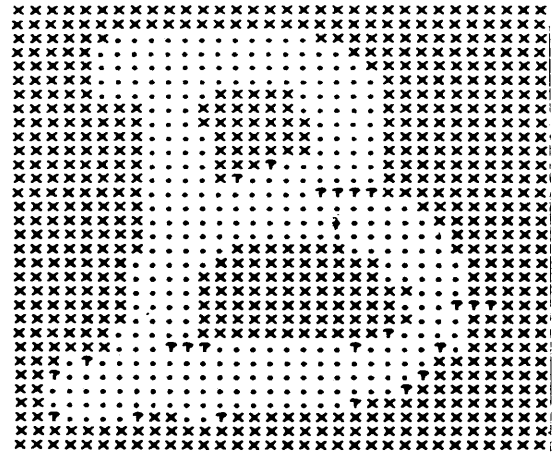
CLEAN

OPP F4 m/c 9-bit Window

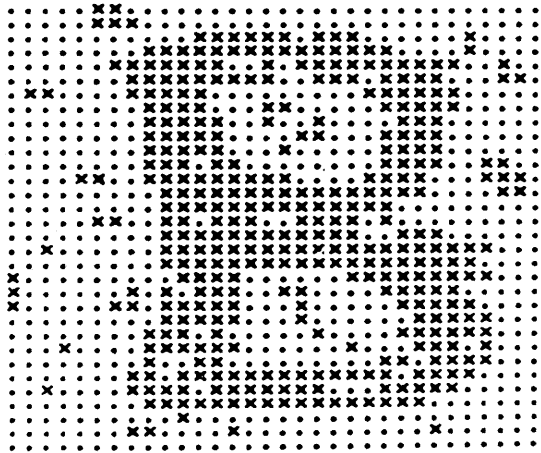


INVERT

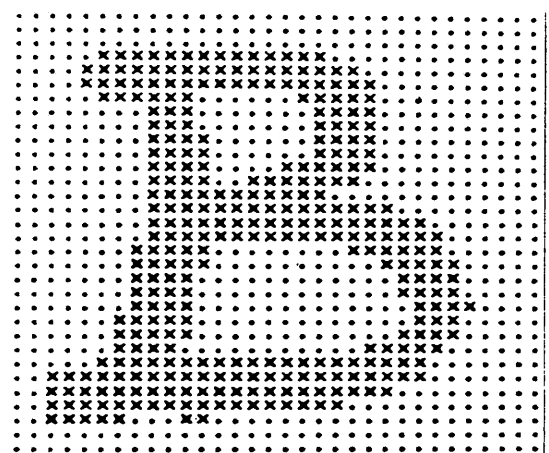
OPP F4 m/c 9-bit Window



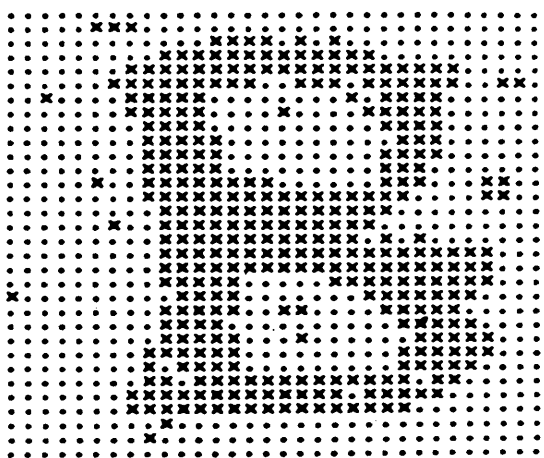
IPP Both Machines



IPP Both Machines



OPP F6 m/c 5-bit Window



OPP F6 m/c 5-bit Window

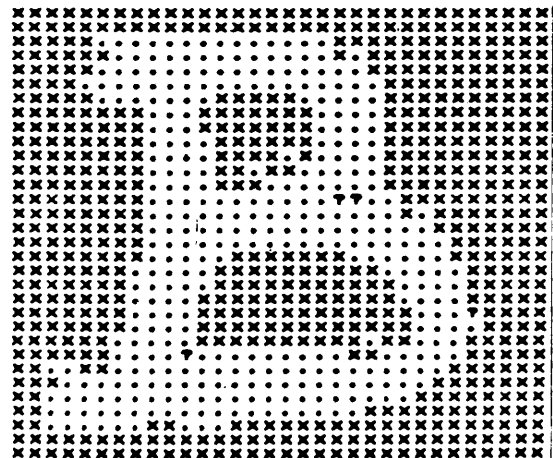


Fig 5.23 Experiment 10 : Tests Results : F4/F6 m/cs  
Tasks : CLEAN , INVERT

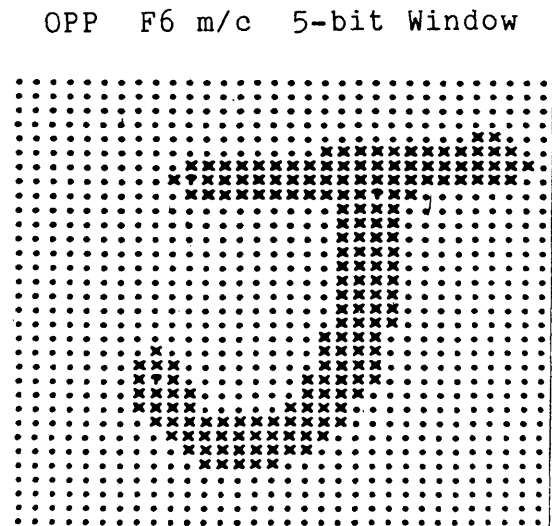
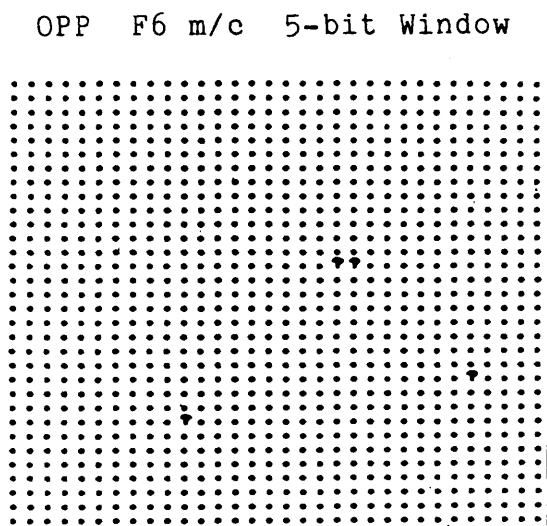
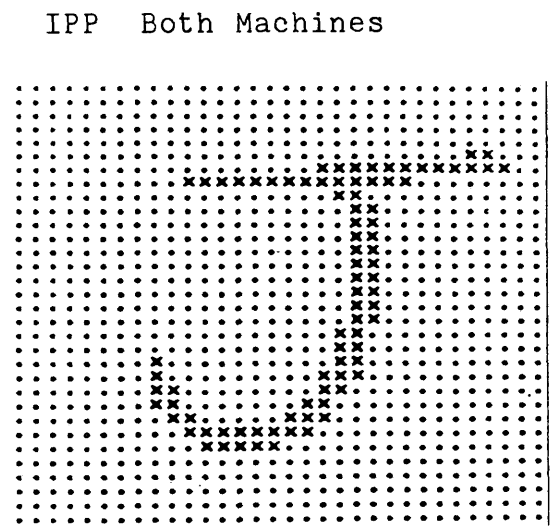
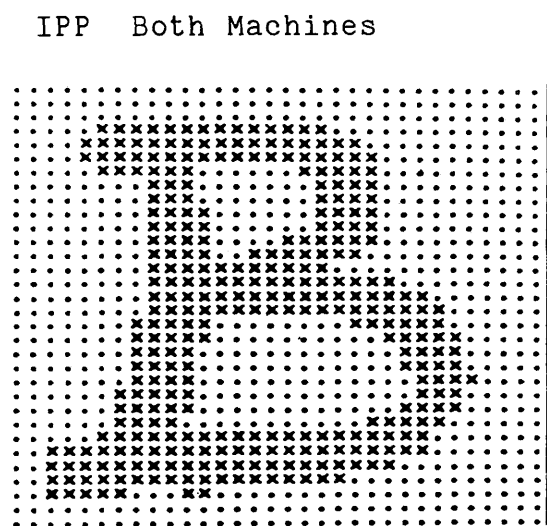
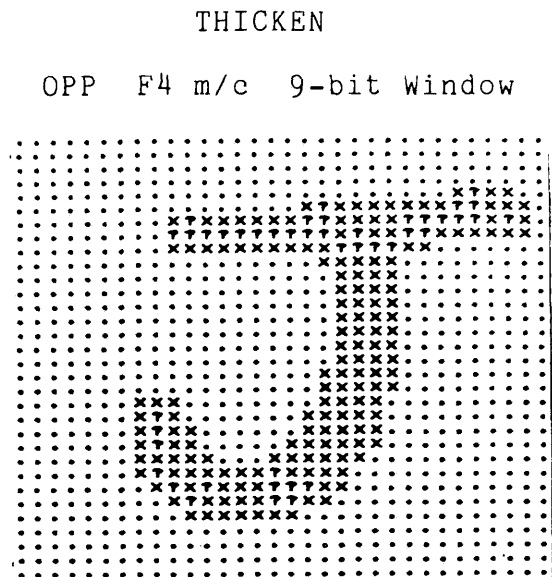


Fig 5.24 Experiment 10 : Tests Results : F4/F6 m/cs  
Tasks : THIN , THICKEN

given set, this can also effectively reduce the number of cells in the memory matrix. Many features (and hence cells) are equivalent and consequently redundant. Only a relatively small proportion of the cells - corresponding to a 'preferred subset' of all possible features - need be retained. To illustrate this subset of features, consider again the 5-bit window as used above.

In this format, there is a maximum total of 32 unique features, all shown in Figs 5.20 and 5.21. However, if any feature that becomes redundant under rotation or reflection is removed from this list, the number of different cells drops to 12, as shown in Fig 5.25. These 12 features constitute the subset of 'preferred locations' in the memory matrix of this machine, and could in principle perform by themselves any isotropic picture processing task as competently as the full set of 32 cells.

It should be noted that these preferred features are in pairs. That is, each adjacent pair of features has the same neighbours, differing only in the centre point P0. If the dependence on P0 can be removed without detrimental effect on the test performance, then the number of cells required is halved - leaving only 6 distinct windows from the original 32. (It should be mentioned that this argument applies to the original 'full set' of features also - independence from P0 halves any memory matrix size.)

#### 9-bit Window Memory Matrix Listing

In the case of the 9-bit F4 machine, the use of rotation and reflection of the input window (producing the F5 machine) reduces the total number of cells in the memory matrix from 512 to 102 preferred locations. A listing of all



'Preferred' Location Subset		'Non-preferred' Locations
Address	Feature	Equivalent Features obtained by Rotation and Reflection
00	. . .	
01	. X .	
02	X . .	04 . X . .
03	X X .	05 . X . .
06	X X .	12 . X . .
07	X X .	13 . X X .
10	X . X	20 . X . .
11	X X .	21 . X . .
14	X X .	28 . X X .
15	X X .	29 . X X .
30	X X .	
31	X X .	

Fig 5.25 5-bit Window 'Preferred Features' and Equivalents

these cells and their corresponding features appears in Appendix 2a.

In Appendix 2a, these data are laid out in the following manner. Each of the 512 cells in the memory matrix is assigned a hexadecimal address in the range 000-1FF. These are listed with the corresponding 3x3 bit window feature shown beneath in accordance with the re-formatting arrangement already described in Section 4.2. The preferred subset of features are 'boxed' throughout the listing. Examination of the 'unboxed' features reveals that all these features can be generated by rotation or reflection of those boxed, and consequently the former are redundant in isotropic picture processing. Again, note how these boxed features occur in pairs throughout the listing. This is because the addresses are organised with the least significant bit corresponding to P0 - the centre point value. Hence, the pairs of boxed features are identical apart from this central point.

In the F5 machine devised earlier, all 512 cells were retained despite the rotation and reflection of the input window. This was because of the resultant minimal changes required in the software simulator in the training phase. The machine rotated and reflected each input feature in training to one, two, four or eight equivalent features (dependent on its degree of symmetry) and modified all these cells. The testing phase looked up a single cell in the normal manner. The maintenance of the complete memory matrix (512 two-bit words) is a justifiable extravagance in this case, in the light of the advantages of this approach.

This software compatibility between machines with and without rotation and reflection extends to the listing of the addresses and data contents of the memory matrix. A sample listing of the cell data contents of the F5 machine as trained in Experiment 8 to 'thin' is shown in Appendix 2b. The format follows that of the window feature listings in Appendix 2a, and consists of each address listed above the corresponding cell contents : one of '.', '?' or 'X'. The preferred subset of cells are again boxed to aid interpretation. This is expanded upon below.

### 5.8 Interpretation of LPP Machine Algorithms

It has been noted in Section 2.9 that the examination of the memory matrix constitutes an attempt to interpret the machine's method of processing. The memory matrix contains the information derived from the training set, although it is in a form more suitable for assimilation by machine than man. However, it does represent the algorithm generated by the machine for processing pictures. This leads to two important possibilities :

- 1 the examination of the memory matrix contents (albeit hampered by their volume) gives insight into picture processing algorithms that come directly from a source of such processes - some examples. This is done without intervention by man and a consequent bias on how such a task should 'best' be performed. The algorithm contained in the memory matrix should reflect the training exactly, in the sense that it was produced autonomously by machine. If these data can be interpreted correctly, they may well represent a

definitive, rather than arbitrary, algorithm. This is ultimately what research into picture processing by machine is seeking to achieve. This problem has thus been reduced to :

- (a) the provision of suitable examples,
- (b) the correct interpretation of the resultant internal state of the machine.

2 the possibility of examining all possible algorithms with such a machine is approaching. With a machine that does not use rotation or reflection of a binary 9-bit window there are  $2^{512}$  ( $\sim 10^{150}$ ) possible different algorithms. It is obviously impossible to test these by automatic generation of all these algorithms. However, on using rotation and reflection this number falls to  $2^{102}$  ( $\sim 10^{30}$ ). This is still an impossibly large number, yet by selective additional restraints it can be reduced further to a practicable, although still large, number. Such restraints could be generated by considering the task attempted. The process of 'thinning' for example, need only be restricted to regions of the pattern (and hence windows) with a crossing number of two. That is, a window straddling an edge of an object has two changes of polarity of the neighbours surrounding the centre point when examined as a ring. The 20 pairs of features in a 9-bit window that fulfil this condition are indicated with an asterisk in Appendix 2a. If the dependence on the centre point P0 can again be removed (which again halves the number of features involved) the number of possible different features drops to 20 single examples. These are shown in Fig 5.26 below with P0 thus removed.

. . .	X . .	X . .	* X .
X . .	. . .	X . .	X . .
. . .	. . .	. . .	. . .
X X X	* X X	* X *	X X *
. . .	X . .	X X .	. X .
. . .	. . .	. . .	. . X
* X *	* X *	(P0 has been removed)	
X . X	X . X		
. . X	X . X	* - 'Don't care'	

Fig 5.26 20 9-bit Windows with Crossing Number of Two

This leaves only  $2^{20}$  ( $\sim 10^6$ ) possible different algorithms, hence it would be feasible to attempt all these cases by automatic generation and testing of these memory matrices. Other such restraints on the features to be examined could be tried for other picture processing tasks. This would similarly enable the testing of an exhaustive set of memory matrices as a step towards interpretation of such machine generated algorithms.

### 5.9 Experiment 11 : The Variation of TP with Training Set Size

The Trained Percentage value (TP) has been used in Experiments 7 and 8 to determine how the changes in operation and format of the LPP machine alter the effective training received. Here the effect of a change in the

training set size on TP will be examined, and how this relates to the change in output when the machine is tested on actual patterns.

### Experiment

An F5 machine was set up, with a tri-state memory matrix and a 9-bit window rotated and reflected in training. It was trained on a varying number of hand-drawn characters, taken from the set used earlier in Experiment 2. (These were digitised in a  $32^2$  format here, and not  $16^2$  as used earlier.) The example pictures were manually cleaned and thinned to a uniform limb width as described earlier. Five training runs were made, with training sets of 1, 4, 16, 32 and 100 pairs of patterns. After each training session, the memory matrix was tested with a fixed test IPP, thus generating a set of OPPs.

### Results

The data collected from the five memory matrices are shown in Fig 5.27 as a table and histogram in the manner of Fig 5.9. A graph of TP against 'Ntr' (the number of pairs of patterns in the training set) is also included. The test IPP and the five OPPs produced are shown in Fig 5.28.

The TP shows a rapid rise as Ntr changes from 1 to 16, but levels off as Ntr exceeds 16. This is reflected in the OPPs - the 'quality' of processing increases rapidly as Ntr reaches 16, but thereafter remains relatively constant.

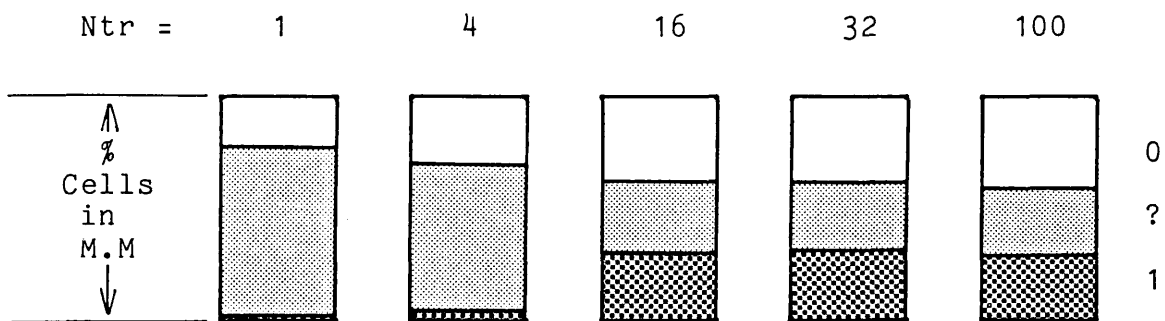
### Discussion

The set of OPPs shows machine behaviour that becomes self-explanatory in the light of the TP data collected. The increase in TP reflects an increase in performance seen in

Ntr	% Cells = 0	% Cells = ?	% Cells = 1	T.P.
1	22.3	76.7	1.0	23.3
4	30.0	64.5	5.5	35.5
16	37.9	31.6	30.5	68.4
32	37.9	30.1	32.0	69.9
100	41.0	29.3	29.7	70.7

Histogram of Above Data :

(Key as in Fig 5.9)



Graph of T.P against Ntr :

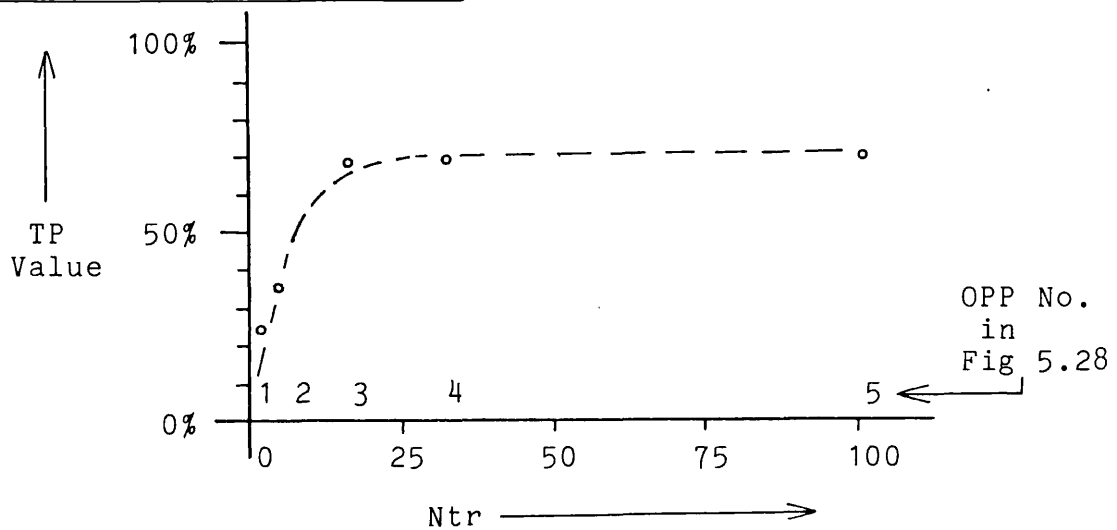


Fig 5.27 Distribution of M.M Contents of F5 Machine Trained in Experiment 11 with Different Ntr

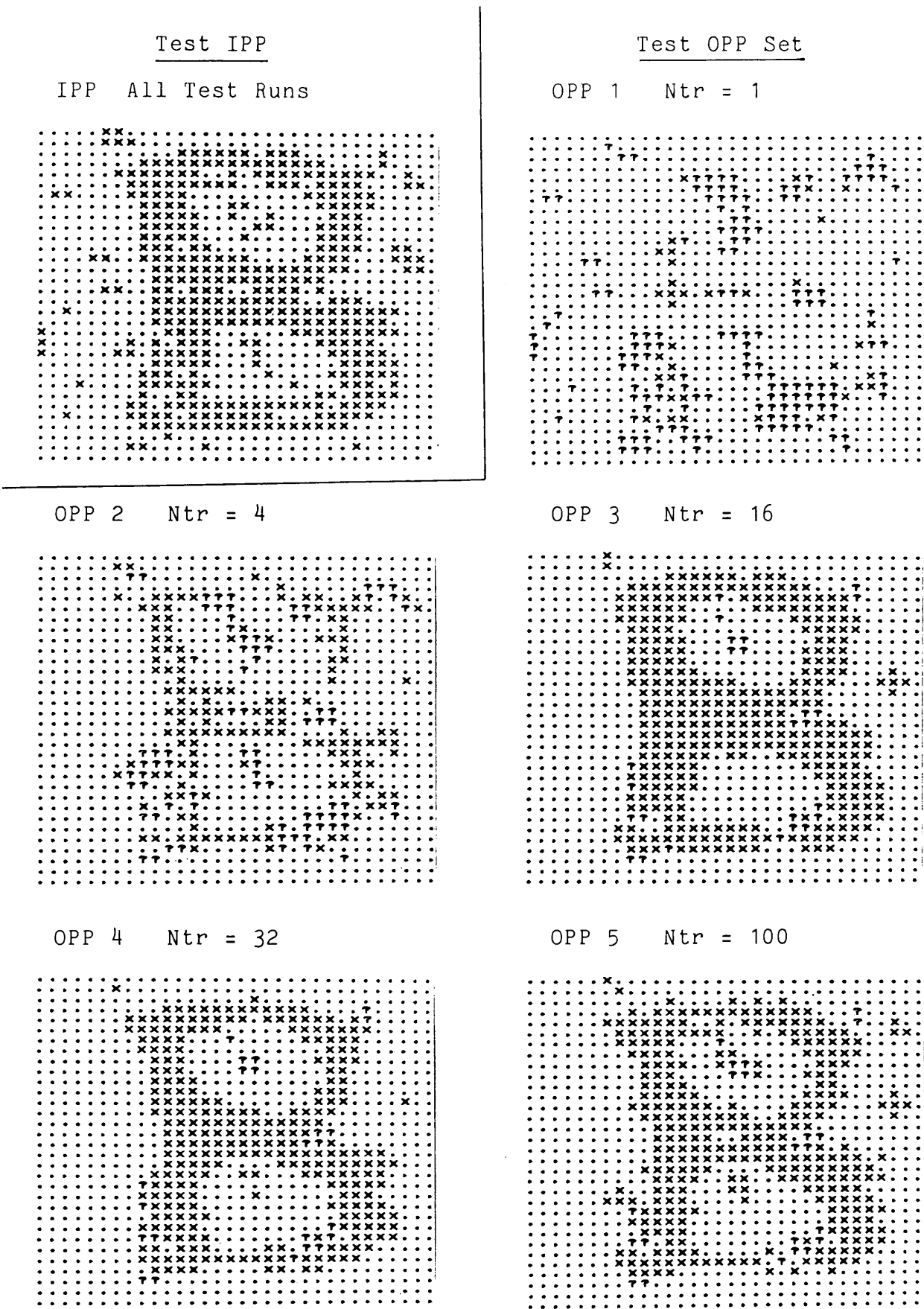


Fig 5.28 Experiment 11 : F5 Machine  
Trained on 1, 4, 16, 32, 100 Pairs



the first three cases. Similarly, a relatively constant TP appears as a constant processing performance in the last three cases.

There only remains a need to explain the 'knee' in the curve in the graph of Fig 5.27. This can be attributed to the fact that of the 102 possible different features under rotation and reflection, there is a large variation in the likelihood of a particular feature occurring within a particular processing application. For example, those features having a large crossing number represent small width, multi-limbed junctions. These are obviously uncommon in this character set, and hence no amount of training is ever likely to set those memory matrix cells corresponding to such features. Since the TP curve levelled off around 70%, it may be inferred that 30% of the possible features are 'uncommon' in this character set. The memory matrix contents (after training with 100 characters) are listed in Appendix 2c. Examination of this listing reveals that those cells still in the initialisation state '?' after training with 100 characters (boxed in this listing) do represent uncommon features in the training set, as expected.

#### 5.10 Experiment 12 : Down-Loaded Memory Matrix

It has been mentioned in Section 5.8 that an automatic generation of memory matrix contents could be used to test all possible picture processing algorithms. An alternative to this is the production of a single set of cells, generated externally and down-loaded into the LPP machine. The machine may then be tested in the normal manner to

reveal how this matrix performs.

### The 'Keyin' Facility of the Simulator

This acts by initially clearing the memory matrix of the machine, then prompting the operator with each of the 102 preferred cell features. (This use of the subset of cells greatly reduces the effort required, without detracting from the essential features of this method.) The operator replies with the data cell contents (one of '0', '?' or '1') to be placed in that cell corresponding to the feature presented. This reply is inserted into that cell, and also into all the equivalent cells under rotation or reflection. In this manner, all 512 cells are filled with data as the machine proceeds through the preferred subset. The resultant memory matrix may then be stored permanently, before testing begins.

### Experiment

The 'keyin' facility was used to create a memory matrix designed to locate the edges or outlines of objects. This was done by consideration of each of the features presented to the operator, then responding with the new pixel that would ultimately leave only the edge of objects. That is, if the feature would be centred on an edge point, the '1' reply was made; if not, '0' was specified. Appendix 2d shows the resultant memory matrix - the cells prompted (the preferred subset) are shown 'boxed' together with the operator's replies of cell contents. Examination of Appendix 2d and the listing of the corresponding features (Appendix 2a) will show how the operator responded to each feature, in an attempt to generate the 'edgeing' function. (This LPP

machine was consequently to bypass the usual training period.)

The machine was tested in parallel with three objects illustrated on the left of Fig 5.29 to ascertain its performance. The resultant OPPs are shown on the right of the diagram.

### Results

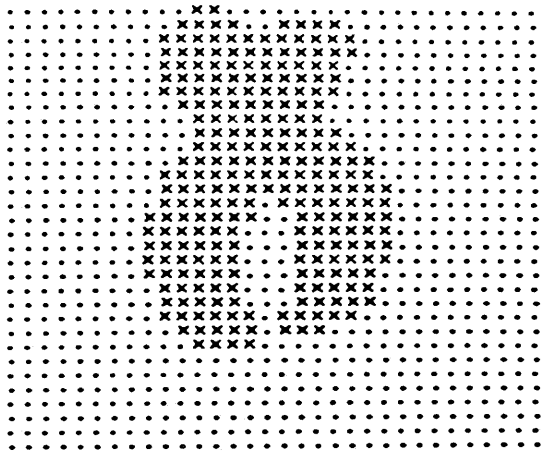
The 'keyed in' memory matrix can be seen to have correctly 'edged' the test IPPs - resulting in a single width line located on the outermost edge of the objects. (Interestingly, an 'error' has occurred at the bottom of OPP 3, shown boxed in Fig 5.29. This is generated from the input feature 'OBD' in IPP 3. Examination of this cell in Appendix 2d reveals that it does indeed contain an erroneous '0', fed in by the operator.)

### Discussion

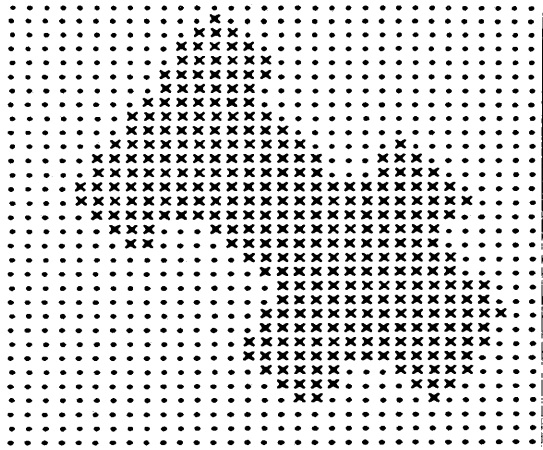
It has been shown that manually generating a memory matrix for a specific task is a practical alternative to training by example. The edging operator is chosen as particularly simple to implement, but serves as a suitable illustration of the principle. However, it requires the intelligence of the operator to supply the ability to process pictures. This procedure does not constitute machine learning in any useful sense, as the machine is being used simply as a tool for executing the process defined by the operator. Consequently, this avenue of research will not be developed further here. It will merely be recorded as an alternative mode of operation in which no machine learning or trainability is exploited.

Test IPPs

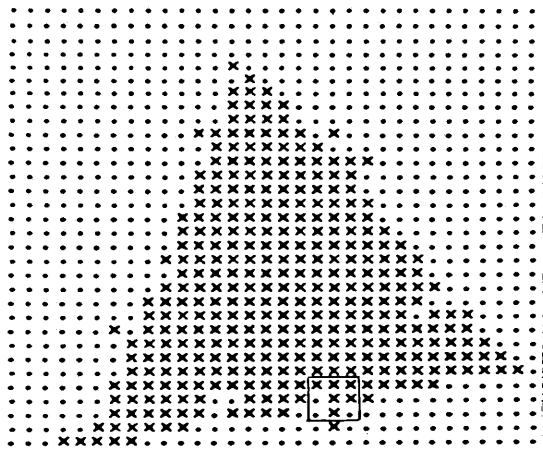
IPP 1



IPP 2

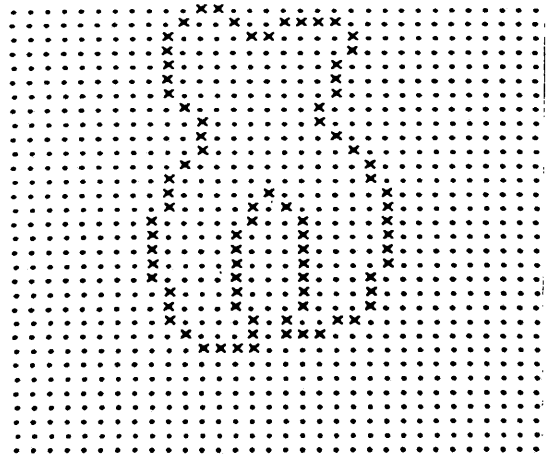


IPP 3

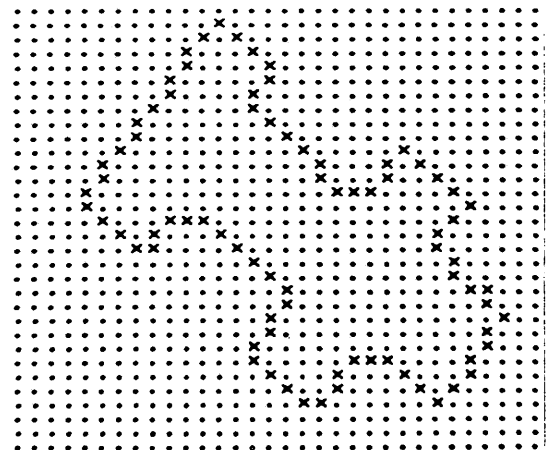


Test OPPs

OPP 1



OPP 2



OPP 3

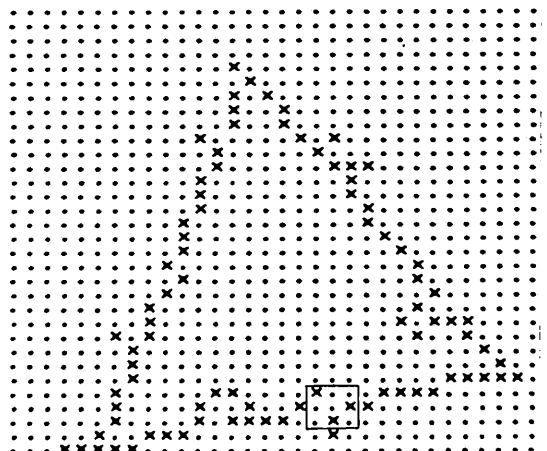


Fig 5.29 Experiment 12 : Memory Matrix  
Keyed In by Operator to EDGE FIND

## 5.11 Summary of Experiments 6 - 12

To consolidate the results achieved in this second experimental chapter, there follows a brief summary of the main conclusions. It should be noted that all the algorithms described in this chapter have employed parallel processing in the testing phase.

A higher resolution ( $32^2$ ) LPP machine was used in Experiment 6, with an otherwise identical internal format. This confirmed that such a machine can perform a set of different tasks by re-training alone.

Tri-state memory matrix cells were used in Experiment 7, enabling the machine to produce results which illustrate not only the algorithm, but also the adequacy of the training received. A 'trained percentage' (TP) was defined which served as a measure of training quantity.

Rotation and reflection of the input window in training resulted in an effective increase in training and thus in performance (Experiment 8). However, this is only of use in symmetrical picture processing. In Experiment 9 an assymetrical operation was attempted with such an arrangement - and illustrated behaviour heavily dependent on factors such as the scanning window direction. That is, the LPP is shown to retain recent training. If the training varies the machine is being 'asked to do the impossible' and hence becomes 'neurotic'. This will be examined later in Experiments 16 and 17.

In Experiment 10 a 5-bit window was used to allow the generation, and hence examination of a small (32 cell) memory matrix. This direct examination gives considerable insight into how the memory matrix reflects the training,

the use of the TP value, and the effect of rotation and reflection of the input window. This leads to the possibility of limited interpretation of the full sized (512 cell) memory matrix generated with a 9-bit window.

The effect of varying the training set size is examined in Experiment 11, where the OPP results and TP values were viewed in the light of this change.

Experiment 12 illustrated the possibility of downloading the memory matrix, rather than training by example. This alternative produces good results, yet relies on a prior knowledge of the operation and layout of the machine.

Further experimental investigations will be made in the following chapter.

## CHAPTER 6

## EXPERIMENTS EMBODYING SPECIAL TRAINING TECHNIQUES

6.1 Experiment 13 : Training by Specially PreparedExamples

Two possible methods of increasing the quantity of training received by the machine were suggested in Section 3.5. The first was the increasing of the size of the training set, as demonstrated in Experiment 11 above. The second was the creation of special training characters to increase the number of different features found in each training pair. This latter course will be attempted here.

This problem can be reduced to providing special examples which illustrate the task to be performed more comprehensively than random example characters. These characters will ideally contain a larger proportion of all possible features, together with correct examples of the task as applied to these features.

Examination of the memory matrix after training on randomly chosen example characters will show the features for which training could be improved. These features not trained correctly invariably cause the generation of '?' or erroneous pixels in testing. So, a training example pair containing these features - shown processed correctly - should result in enhanced test performance. This will be attempted in the following experiment.

This experiment will also be used as an opportunity to attempt several other developments in machine layout and

operation. The high quality of training, as a result of using these specially prepared characters, allows changes to the machine in other areas without poor training masking the results.

### 6.1.1 The 'Thinning' Task

The task of thinning was chosen as a suitably non-trivial task, revealing a great difference between machines trained on random and specially created examples. This task was attempted by an F5 machine trained on random examples in Experiment 8. This same machine format will be used here. The training examples were shown at the top of Fig 5.3, and the test results in Fig 5.14. The most serious shortcoming was the breaking of characters' limbs, which occurred when an already thin limb was processed. This was to be expected, since such thin limbs were not present in the training IPP - and hence the machine was not trained to process such features. The essence of the approach to be attempted here is to create a training set containing examples of all possible features shown correctly processed, such that the machine can learn to deal with any test IPP presented to it.

#### The Creation of Special Characters as Thinning Examples

The characters to be created should contain features shown processed as below, to train the machine to 'thin' correctly :

- (a) Wide limbs (that is, edges that extend beyond the range of a single 3x3 window) should be stripped back - both convex and concave edges,



- (b) Narrow limbs should be thinned down only as far as single width limbs,
- (c) Single width limbs (including single width junctions) must be left unbroken.

(It is this last condition upon which earlier attempts at thinning have failed.)

Later developments within this experiment will show a further condition to be of interest :

- (d) Ends of lines should be maintained.

The training pair created contains examples of all the above conditions (a) to (c), and a second pair includes the (d) condition also. These will illustrate how, with the proper training, it is possible to be quite specific regarding the exact picture processing task required of the LPP machine.

Initially, only the former case, with the three requirements (a) to (c) will be examined. The equivalent picture processing task may be summarized as :

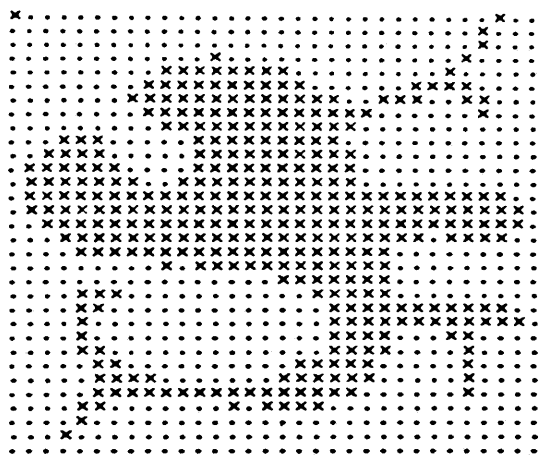
'Thin, whilst maintaining connectedness,  
but losing line ends.'

The example characters were created by hand to illustrate this task, using the picture editing facility of the LPP simulator (see Chapter 7), and are shown in Fig 6.1a. These characters do not represent any particular pattern type, nor are they necessarily representative of the expected test set. They were designed solely according to the criteria (a) to (c) above. That is, IPP 1 contains thick

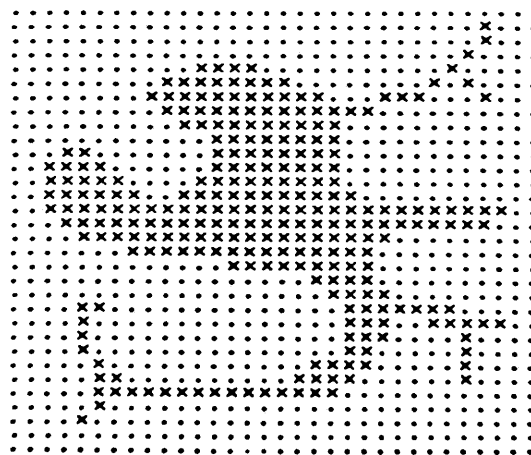
(a) Training Pair Specially Created to :

'Thin, Maintain Connectedness, but LOSE Line Ends'

IPP 1 Train



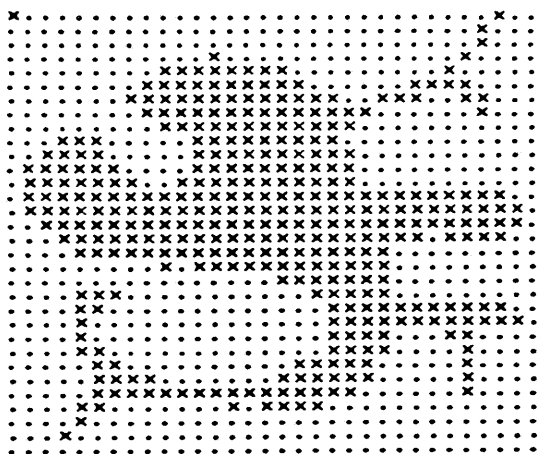
EXP 1 Train



(b) Training Pair Specially Created to :

'Thin, Maintain Connectedness, and KEEP Line Ends'

IPP 1 Train



EXP 2 Train

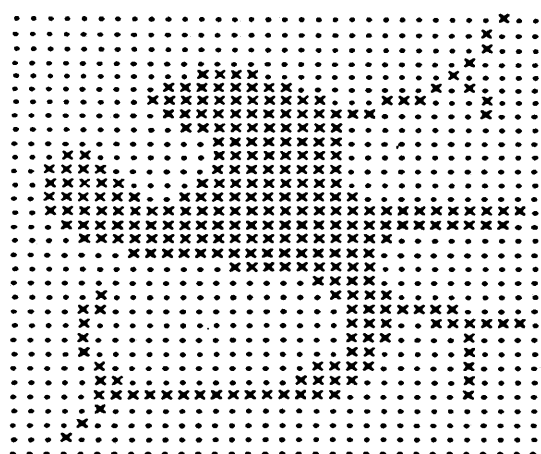


Fig 6.1 Training Characters Specially Created  
For Experiments 13 (a-f)

limbs, concave and convex edges, narrow limbs, line ends, single width limbs and junctions, all shown correctly processed in EXP 1.

### 6.1.2 Experiment 13a : Initial Run

An F5 machine was trained to 'thin, maintain connectedness and lose line ends' using the pair of patterns shown in Fig 6.1a. The machine was then tested in the parallel mode with a set of three characters shown on the left of Fig 6.2. The resultant OPPs are shown on the right of this figure.

#### Results

The machine can be seen to have thinned these three characters, although the last two have been broken. This has occurred in several places, where the original limbs were two units wide. This is apparently in conflict with the training stimuli, which did not show any examples of such behaviour.

#### Discussion

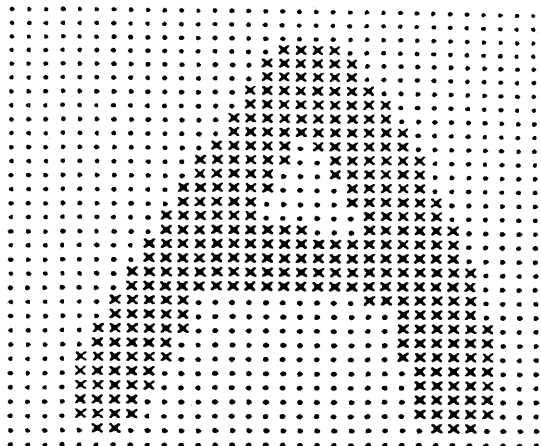
The reason for the breaking of the characters lies in the fact that these breaks only occur on double width limbs, the wider and narrower width limbs all remaining intact. This suggests that the breaks are due to the machine's thinning of these limbs simultaneously from both sides (as this particular testing was implemented in parallel), resulting in a zero width (broken) section. The machine correctly recognized a single width limb as a feature not to be further thinned from either side. The problem lies in the fact that the machine is effectively operating simul-

Test Inputs

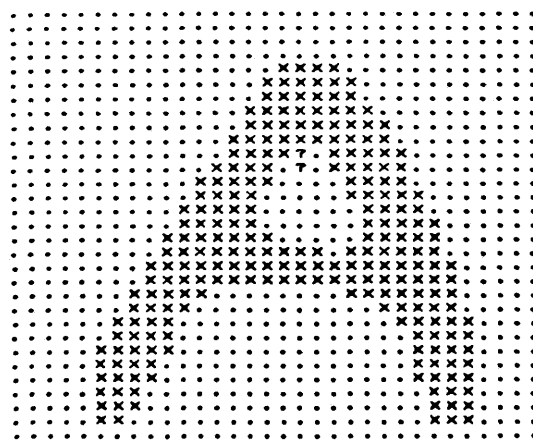
F5 Machine

Test Outputs

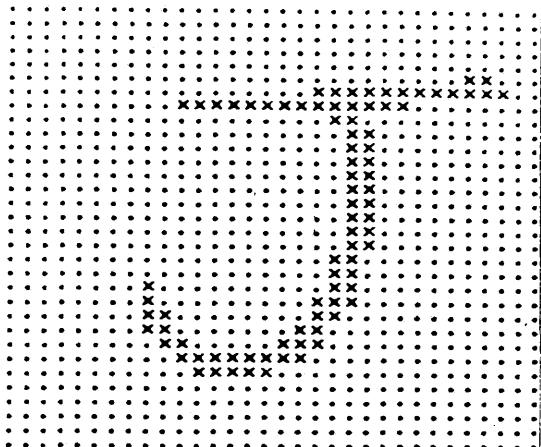
IPP 1



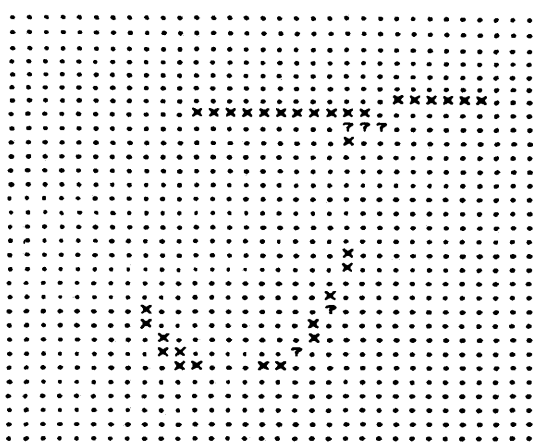
OPP 1p



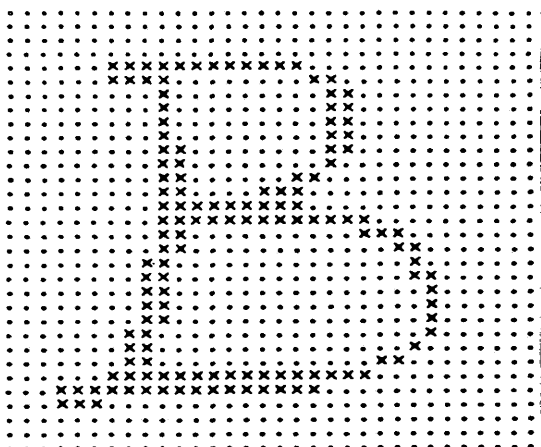
IPP 2



OPP 2p



IPP 3



OPP 3p

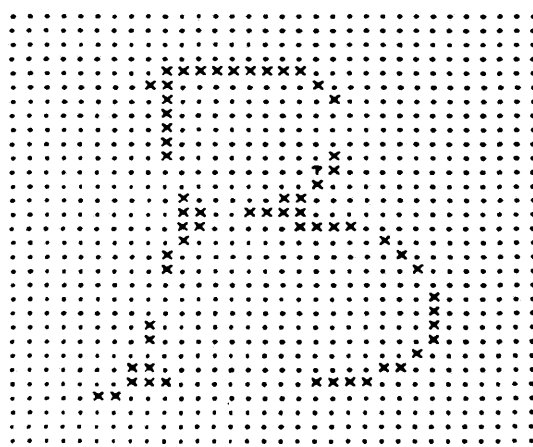


Fig 6.2 Exp 13a : Test Results after Training With Special Characters (One Pass, Parallel Mode)

taneously on all pixels in IPP, not that the training is necessarily incorrect. This breaking of a double width limb is a well-known problem when a picture processing machine is applied in this 'parallel' mode, as here (73,6). The alternative 'sequential' mode of operation was described in Section 4.3, and is attempted experimentally below.

### 6.1.3 Experiment 13b : Sequential Mode of Operation

The above experiment was repeated with all parameters and data kept constant, except that in testing, the LPP machine was applied sequentially to the test IPPs, to generate a new set of OPPs in Fig 6.3.

#### Results

Here, the machine has again thinned the characters, including double and single width limbs, to a minimum of one unit width resultant limbs. However, in the case of the letter 'J' the upper left limb has been removed entirely, as has the upper left serif of the letter 'B'. The thick limbs of the letter 'A' have been thinned to a varying degree, leaving vertical left hand edges where areas of the object are 'shadowed' from the downward moving scan direction.

#### Discussion

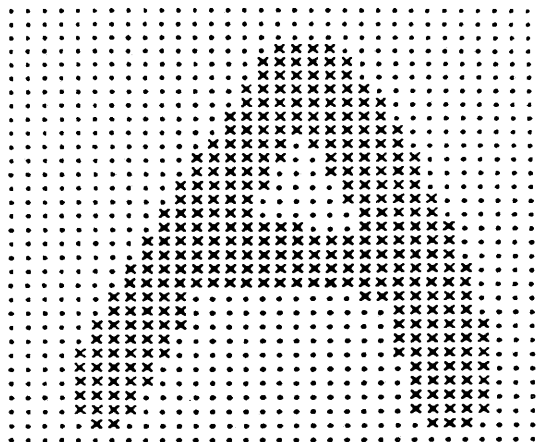
The sequential mode of operation has disabled the machine from breaking limbs. There are no breaks anywhere in the OPP set. However, the removal of entire limbs that point into the direction of scan is the apparent result of this sequential application. As the scan proceeds along a limb, it repeatedly removes points, as it has been trained to 'lose line ends'. This proceeds until either a junction is

Test Inputs

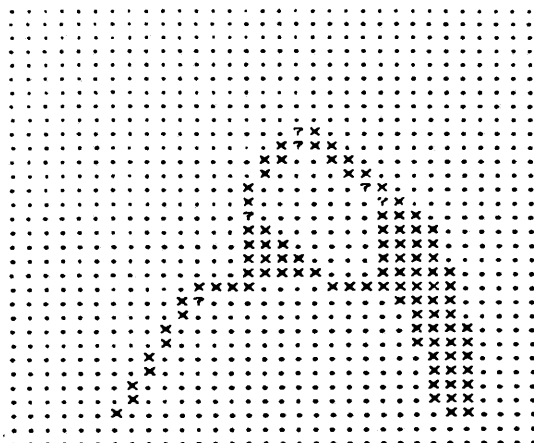
F5 Machine

Test Outputs

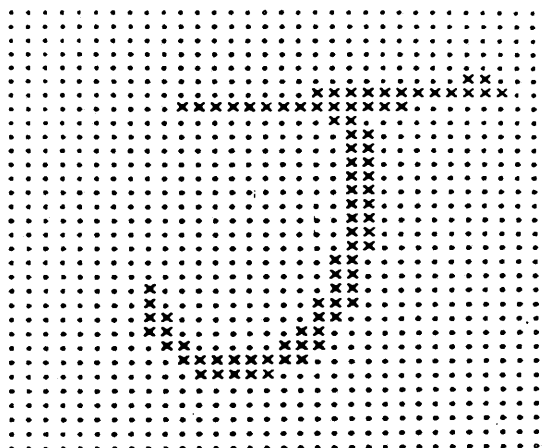
IPP 1



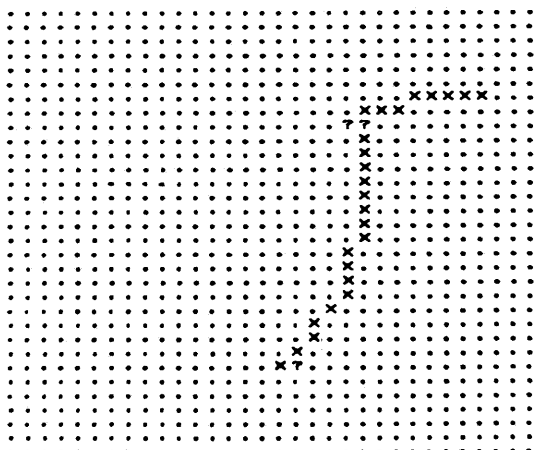
OPP 1s



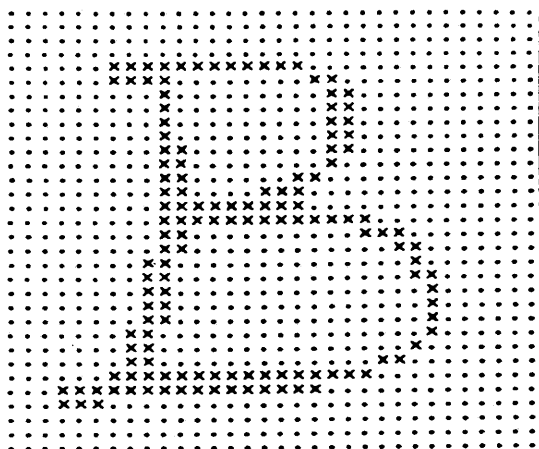
IPP 2



OPP 2s



IPP 3



OPP 3s

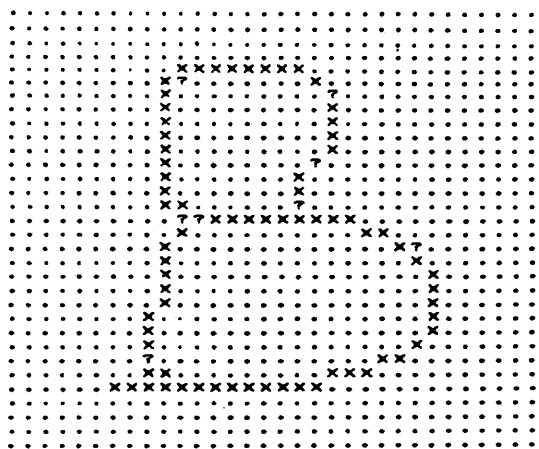


Fig 6.3 Exp 13b : Sequential Application of Machine Trained on Special Characters (One Pass)

encountered, or the scanning centre leaves the limb behind. It should be noted that while the limbs pointing into the direction of scan are removed entirely, the other limbs are only shortened by a small amount, as the machine 'loses a line end' on one occasion - when the scan is centered on this line end point.

This process of losing line ends, either by degrees or completely in one pass, indicates that the machine would eventually entirely remove any limbs with ends if allowed to repeatedly act on such patterns. This will be verified below.

#### 6.1.4 Experiment 13c : The Use of Feedback in Testing

The F5 machine as trained above, is applied to the IPP set repeatedly until the OPPs show no further change. That is, feedback passes in testing will be made, as described in Section 4.4. The sequential mode of operation will be used again. The same IPPs are used, and the OPPs generated after each pass are illustrated in Figs 6.4 (letter 'A') and 6.5 (letters 'J,B').

#### Results

The letter 'A' is rapidly thinned to a unit width 'skeleton' after 4 passes through the machine. Thereafter, each pass removes a unit length from the lower limbs. The upper loop does not break at any time, although the junctions between this loop and the lower limbs contain '?' pixels. After 13 passes, the lower limbs have been removed entirely, leaving only the static single width upper loop.

The letter 'J' has its upper left hand limb removed

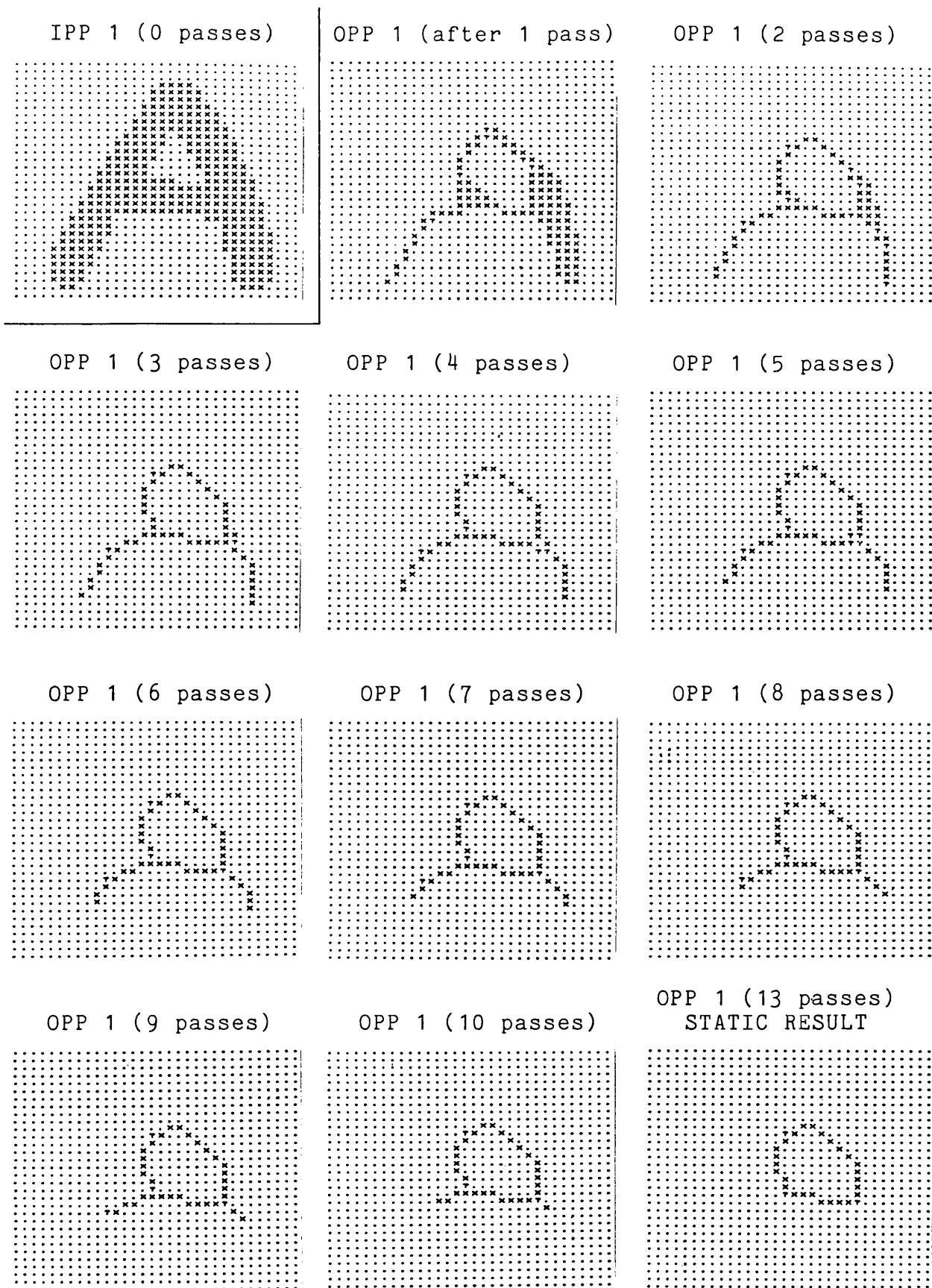


Fig 6.4 Exp 13c : Feedback Stages Applied  
To IPP 1 in the Sequential Mode



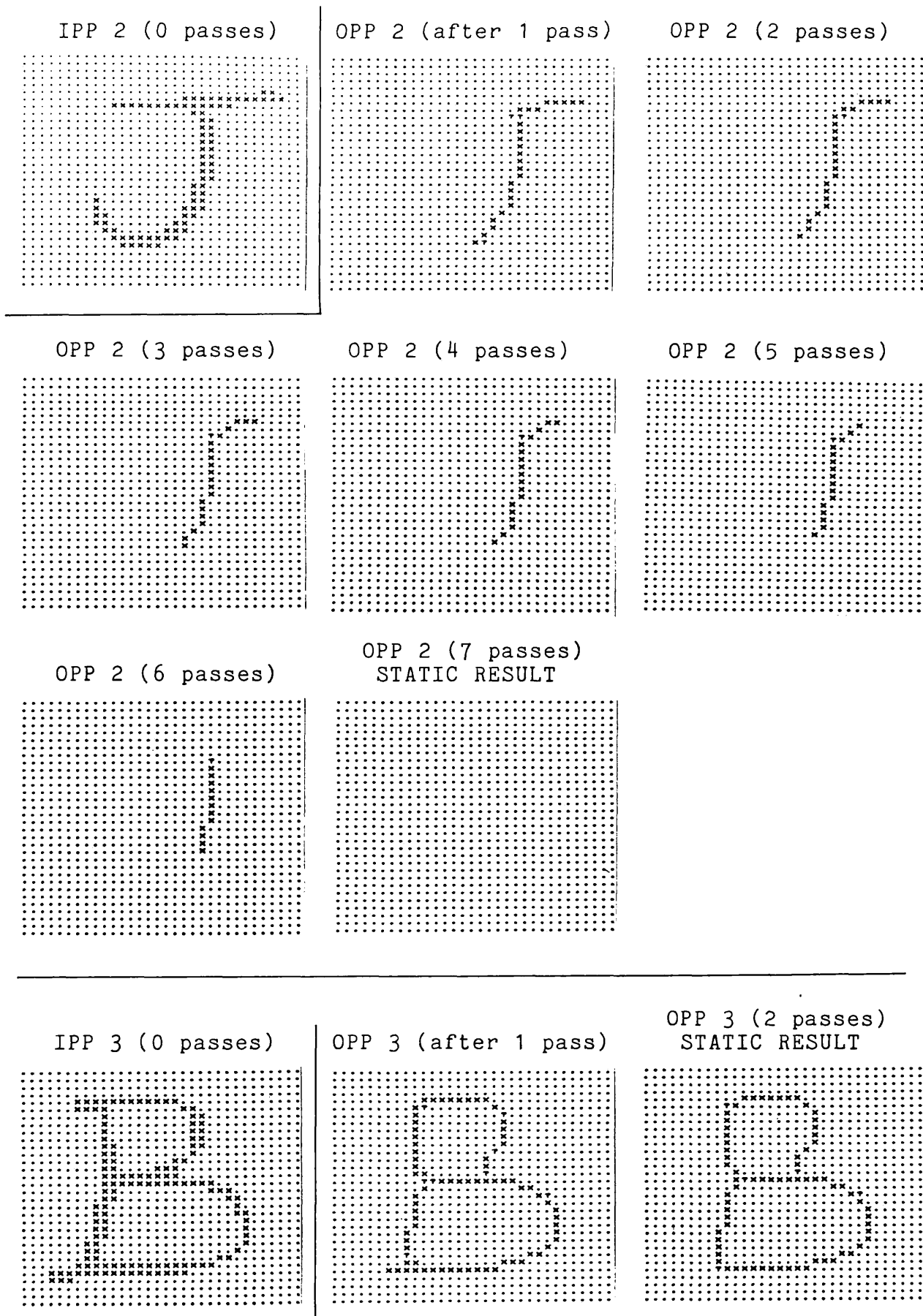


Fig 6.5 Exp 13c : Feedback Stages Applied To IPPs 2 and 3 in the Sequential Mode

immediately after one pass. Thereafter the other limb ends are gradually cut back on each successive pass, until finally the direction of the upper right limb changes from horizontal to diagonal. This enables its complete removal in the next pass, and the consequent removal of the entire remaining vertical limb in the pass after that, leaving a null field.

The letter 'B' is quickly transformed into a single width skeleton, and after two passes such 'limbs' that do exist (the serifs) are removed. This leaves a static single width skeleton composed of two attached closed loops.

#### Discussion

As expected, by inference from the previous experiment, the repeated passing of patterns through this machine will eventually lose any features except closed loops. These will be reduced to single width loops, which are never broken. These loops are centered on the right hand lower edges of wide limbs due to the scanning direction effect, and hence are not ideal skeletons, which would be centered along the middle of such limbs. However, the process acts reliably and predictably, after training on just one specially produced pair of examples. The loss of line ends is to be expected as the training contained examples of this. The training will be modified in this respect below.

#### 6.1.5 Experiment 13d : Modification to Training Set

In this section, condition (d) above is included - the retention of line ends - in order to produce a more conventional thinning algorithm. A pair of training patterns

was produced (Fig 6.1b) representing the algorithm :

'Thin, maintain connectedness, and KEEP line ends.'

On re-training the F5 machine, the same test set was presented to the machine. Again, the results were fed back repeatedly through the machine operating in the sequential mode, until the OPP results were static. The IPP letter 'A' and its set of OPPs at each pass are shown in Fig 6.6, the letters 'J,B' and their OPPs in Fig 6.7.

### Results

A comparison of these OPPs with those produced in the previous experiment (Figs 6.4 and 6.5) show two main differences :

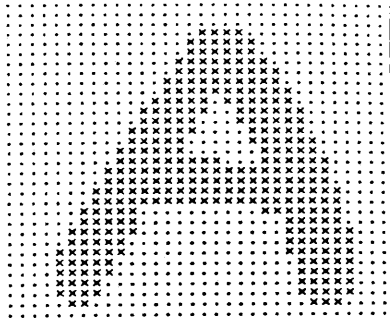
- 1 The retention of limbs at their full original length
- 2 The fewer number of passes required to reach a static result

In all three cases in this experiment a static, single width skeleton, with all limbs retained completely, was produced after a small number of passes through the machine.

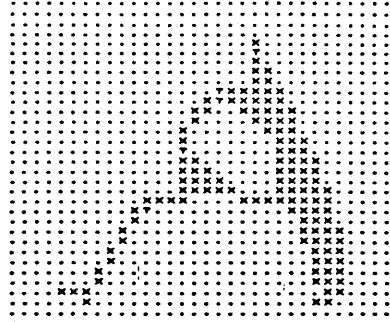
### Discussion

The modification to the training made in this experiment to retain line ends has manifested itself in the test phase as a retention of full length skeletons. This successful production of a unit width skeleton is well-known to be of great value in picture processing (51).

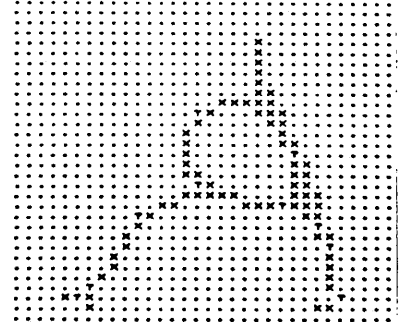
IPP 1 (0 passes)



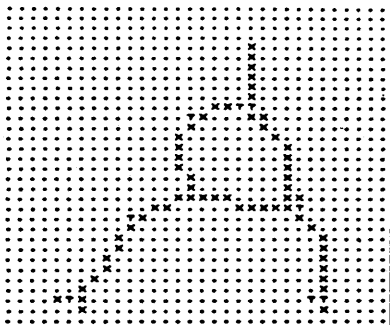
OPP 1 (after 1 pass)



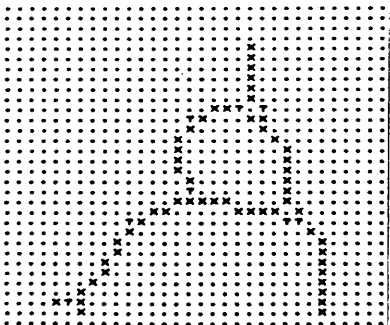
OPP 1 (2 passes)



OPP 1 (3 passes)



OPP 1 (4 passes)



OPP 1 (5 passes)

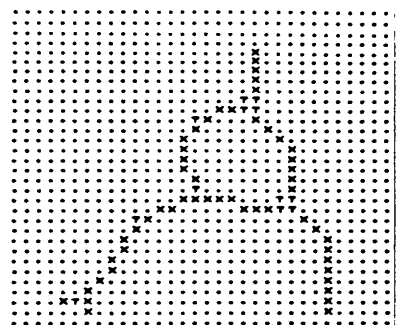
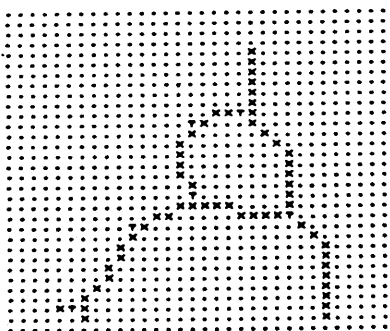
OPP 1 (6 passes)  
STATIC RESULT

Fig 6.6 Exp 13d : Machine Trained To 'Keep Line Ends'  
Feedback Passes Applied Sequentially to IPP 1

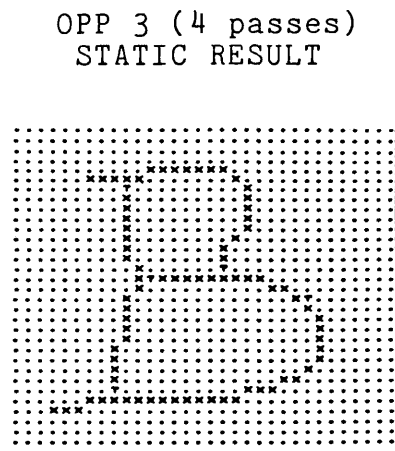
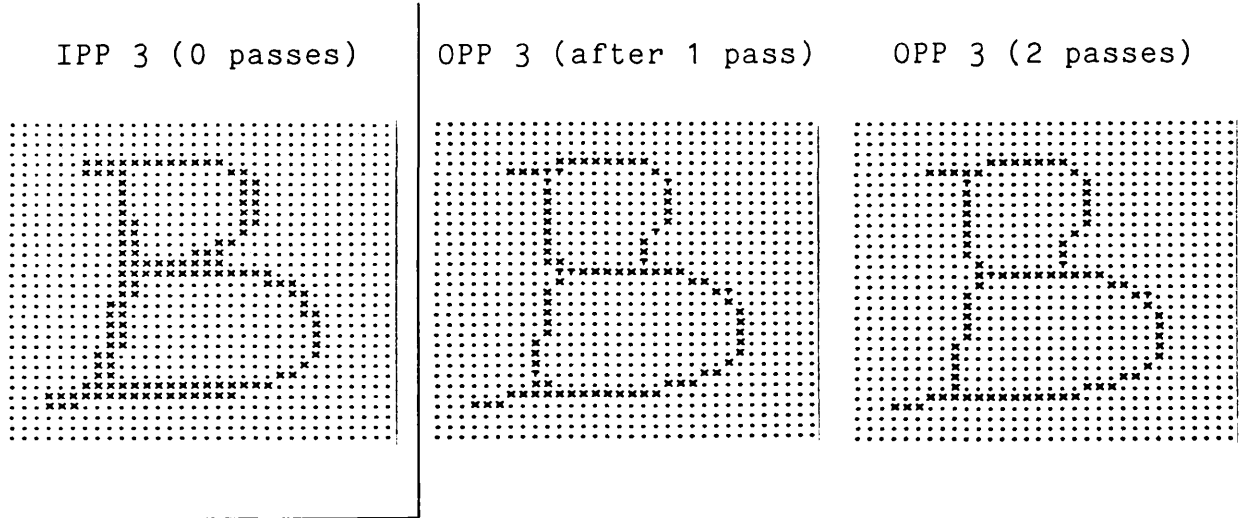
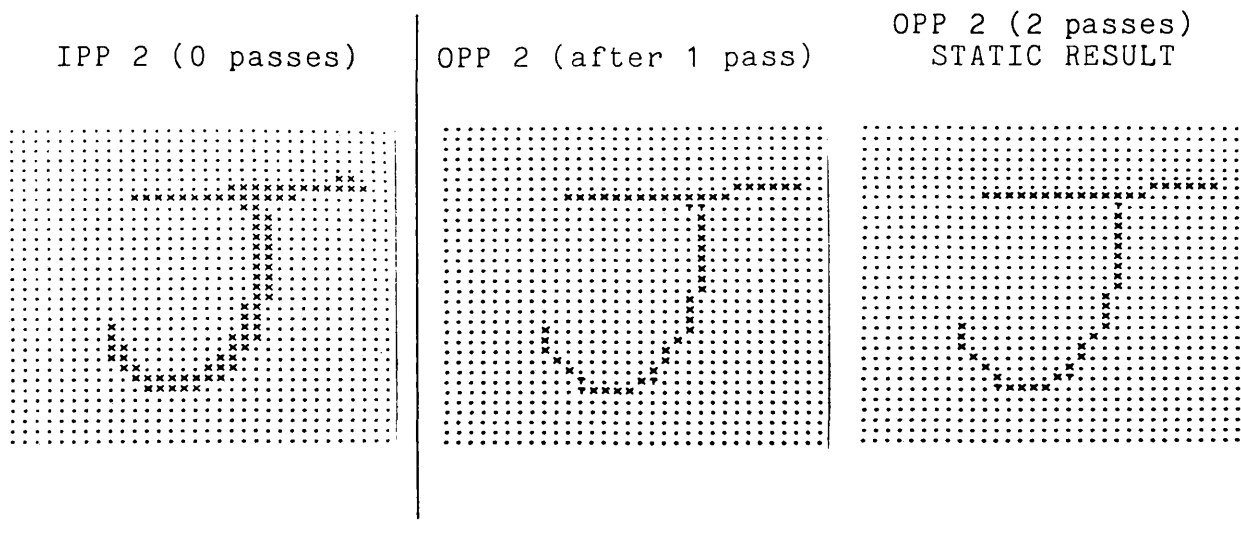


Fig 6.7 Exp 13d : Machine Trained to 'Keep Line Ends'  
Feedback Passes Applied Sequentially To IPPs 2 and 3

### 6.1.6 The Examination of the Memory Matrices after Training with Special Purpose Examples

It has been illustrated above how it is possible to be quite specific - by training alone - regarding the exact picture processing task required of a LPP machine. In the cases above, the training has been adjusted to represent the two tasks :

- 1 'Thin, maintain connectedness, lose line ends' and
- 2 'Thin, maintain connectedness, keep line ends'

The two memory matrices after training with these tasks were examined as in the previous analysis; the resultant totals of cells set to '0', '?' and '1' being shown in Fig 6.8a as a table and histogram.

It should be noted that the TP value in both cases is 42.8% - a high value, compared to the TP value obtained in Experiment 8 (Fig 5.15) for the corresponding 'thin' task of 16.0%. This latter figure was obtained on training with a pair of non-specially prepared characters seen in Fig 5.3. This suggests that the training pairs used here (Fig 6.1) contain a much larger proportion of all possible 3x3 bit window features.

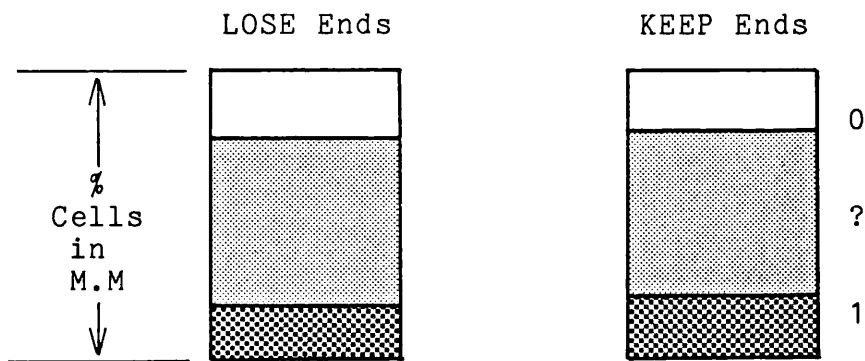
The fact that the two TP values for the two cases of different training here are exactly equal is to be expected. As seen before (Section 5.4), both pairs of training patterns used identical IPP patterns (on the left of Fig 6.1), it is only the EXPs that differ. IPP addresses the memory matrix, and if identical IPPs are used in different training phases they will still address exactly the same (and hence same number of) memory matrix cells in each case.

(a) Totals of M.M Cell Contents after Training :

TASK	No. of Cells=0	No. of Cells=?	No. of Cells=1	No. of Trained Cells
Thin, Maintain Connectedness, LOSE Line Ends	122 (23.8%)	293 (57.2%)	97 (19.0%)	219 (42.8%)
Thin, Maintain Connectedness, KEEP Line Ends	106 (20.7%)	293 (57.2%)	113 (22.1%)	219 (42.8%)

Histogram of Above Data :

(Key as in Fig 5.9)



(b) Feature Differences in M.M. Cell Contents :

Preferred Features	. X . . X . . . .	. . X . X . . . .	. X X . X . . . .
No. of Equivalent Cells (Total=16)	4	4	8
Cell Data Contents	LOSE Ends	.	.
	KEEP Ends	X	X

Fig 6.8 Totals and Differences in Memory Matrices Trained in Two Cases in Experiment 13

As a result, the TP values will be identical. This can be seen in the totals of Fig 6.8a, where the number of cells left equal to '?' (untrained) is equal in both cases to 293 out of 512.

#### Differences in Memory Matrices Reflecting Different Tasks

The differences in the memory matrices after training on the two different tasks can be found by direct examination of the two cell contents' listing similar to those in Appendices 2b to 2d. The two complete memory matrices from this experiment are not reproduced here, but merely their differences. These differences occur in 16 cells, as may be deduced from the differences in totals in Fig 6.8a of cells equal to '0' or '1'. It should be recalled that the F5 machine was used, which rotates and reflects the input windows, and so these 16 cells correspond (in this case) to just three preferred cells or features. These features are shown in Fig 6.8b.

These differences are consistent with the training, in that the features where the training differs represent line ends. In the first case '0' pixels would be generated in testing (losing line ends) and, in the second '1' pixels are specified (keeping line ends).

This illustrates how the creation of special characters for training can generate quite specific memory matrices. In these two cases, the memory matrices differ in only 16 out of 512 cells (-3%), yet the resultant test OPPs generated show significant and predictable differences.



### 6.1.7 A Summary of Parallel/Sequential Processing Applied To Lose/Keep Line Ends

The experiments performed so far have given insight into the use of an LPP machine trained on two alternative sets shown in Fig 6.1 and operated in two alternative modes - parallel and sequential. Together with more exhaustive experiments not reproduced here, this has enabled some general conclusions to be drawn regarding these variations in operation and their resultant test performances.

The four cases of operation to be compared are :

- 1 Parallel operation - trained to lose line ends,
- 2 Parallel operation - trained to keep line ends,
- 3 Sequential operation - trained to lose line ends,
- 4 Sequential operation - trained to keep line ends.

In all cases the OPPs are repeatedly fed back to the inputs in testing to observe the processing develop to its ultimate result.

#### Experimental Investigations

Experiments 13c and 13d have respectively examined cases 3 and 4 above, and further experiments (not reproduced here) have examined cases 1 and 2. These results from cases 1 and 2 may also be deduced from the behaviour seen in Experiments 13a, and will be summarized below. Examples of cases 2 and 4 (processed to a static result) will be compared later in Experiment 13f.

## Comparison

The summary of the behaviour of the four cases appears in Fig 6.9. This includes a description of the changes in test patterns as they pass repeatedly through the machine, and hand-drawn sketches of OPP sets illustrating the process.

From this diagram, the test performances in the four cases can be summarized as follows :

### 1 Parallel operation - trained to lose line ends

Breaks character, then loses resultant line ends, finishes with a null field from any starting object shape.

### 2 Parallel operation - trained to keep line ends

Breaks character, but retains resultant line ends, finishes with possible short breaks in an otherwise complete unit width skeleton.

### 3 Sequential operation - trained to lose line ends

Cannot break character, but loses line ends if any, finishes with only closed loops remaining as unit width rings.

### 4 Sequential operation - trained to keep line ends

Cannot break character or lose line ends, finishes with a complete unit width skeleton; often over-elaborate as 'limbs' are produced to corner points of original thick limbs or noise spurs.

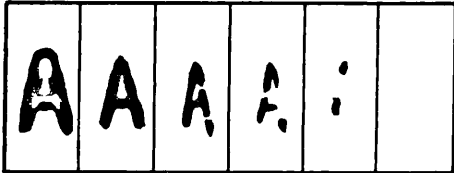
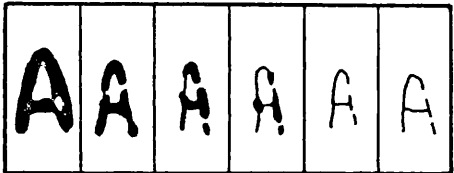
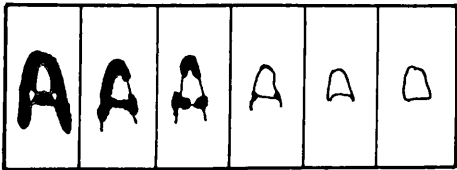
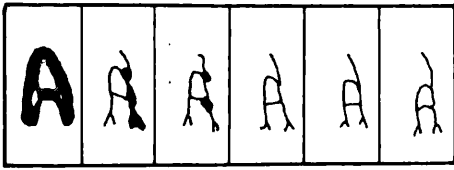
M O D E	M/c Trained to : Thin, while <u>LOSING</u> Line Ends	M/c Trained to : Thin, while <u>KEEPING</u> Line Ends
P A R A L L E L	<p>Parallel operation, hence double width lines CAN be broken as machine strips away two sides simultaneously.</p> <p>Most lines eventually ARE broken, and ends that result are then gradually trimmed back on successive passes.</p> <p><u>Result:</u> NULL Field.</p> <p>In general, objects fragment, then line ends retreat:</p> 	<p>Parallel operation also, hence breaks CAN occur as at left.</p> <p>However, line ends that result on either side of such breaks are retained once they (and other) limbs reach unit width.</p> <p><u>Result:</u> Skeleton correct but for short breaks</p> <p>Objects thin to a broken skeleton:</p> 
S E Q U E N T I A L	<p>Sequent. operation means NO breaks. No loops or limbs are broken, but once limbs are of unit thickness, they disappear (QUICKLY if pointing into the scan direction, SLOWLY if pointing away from the direction of scan.)</p> <p><u>Result:</u> single width loops with no limbs. Characters without loops result in NULL field.</p> <p>Skeleton produced, limbs disappear :</p> 	<p>Sequent. operation means NO broken limbs possible. Once unit width reached, (often after first pass) ends retained. Hence, over-elaborate skeleton produced with limbs to corners and noise spurs.</p> <p><u>Result:</u> full-length complete skeleton centred on lower right edges of original.</p> <p>Objects quickly reach elaborate skeleton :</p> 

Fig 6.9 Comparison of Machine Operations in Parallel or Sequential Mode, Trained to Lose or Keep Line Ends

### 6.1.8 Experiment 13e : Direction of Limbs Affecting Processing Time

It has been stated in Fig 6.9 that in the case of a sequential LPP machine trained to lose line ends (case 3 above), the direction of the limbs compared with that of the window scanning direction affects the time taken to remove these limbs. This will be examined here.

An F5 machine was trained on the pair of patterns in Fig 6.1a ('lose line ends') and then repeatedly applied sequentially to a test IPP. This test pattern was composed of two objects in the same field, essentially identical apart from their orientation. The objects each consisted of a thick closed loop with a thick limbed spur projecting from it - upwards in one case (into the scan direction) and downwards in the other (with the scan direction).

This IPP 4 is shown in the top left hand corner of Fig 6.10. The resultant OPPs after successive passes through the machine are shown in the remainder of the diagram.

#### Results

The thick limb pointing upwards is removed entirely after just one pass through the machine. The remaining two loops are reduced to unbroken single width static rings after three passes. The lower limb is gradually removed, at the rate of one pixel each pass, and finally disappears completely after nine passes, leaving only the two static loops.

#### Discussion

The immediate removal of the upward pointing limb is a result of a sequentially applied algorithm, continually

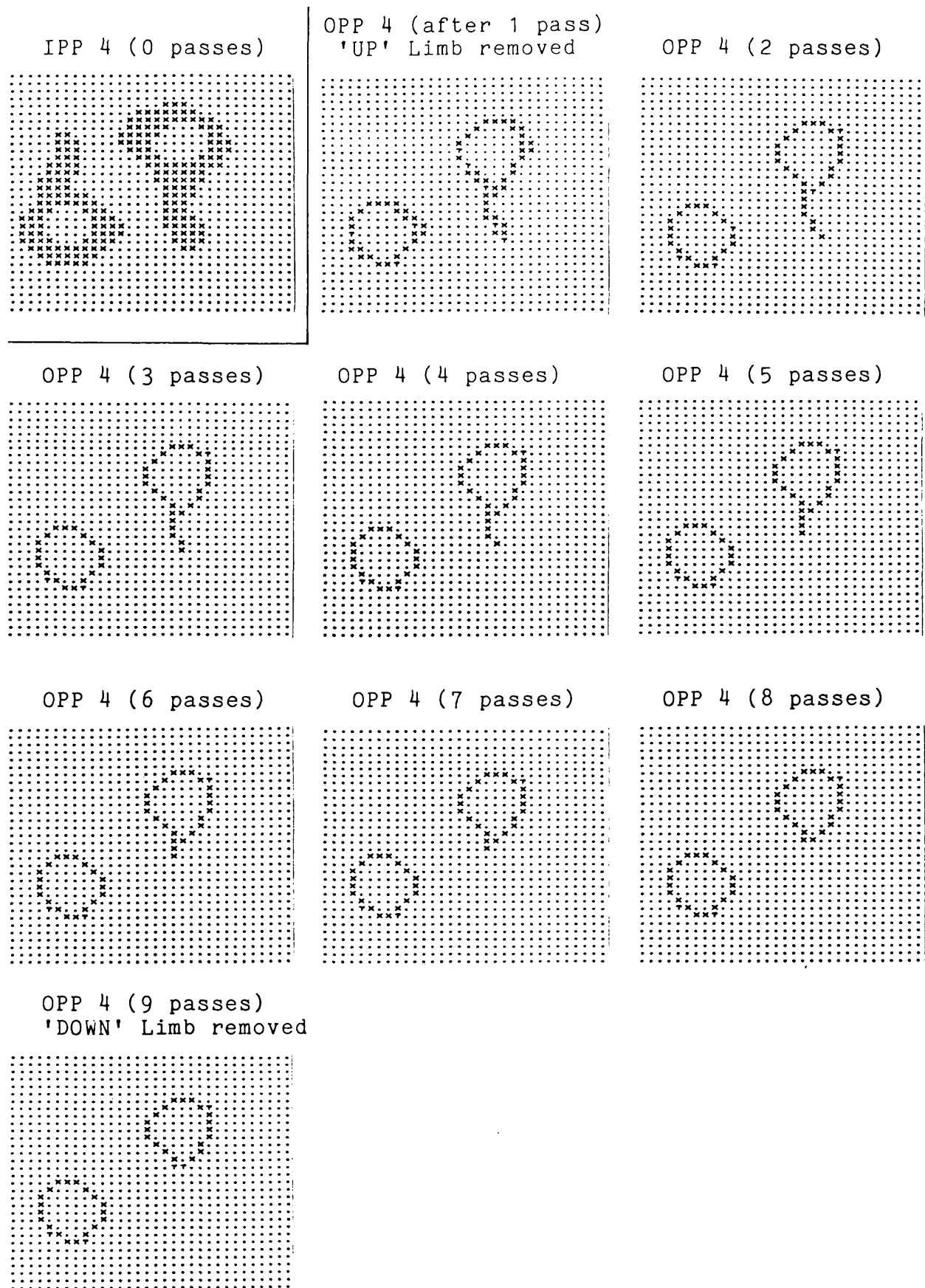


Fig 6.10 Exp 13e : Limb Direction Affecting Removal Speed

removing the line end, then on the next line scan (within the same field scan) removing the already retreating line end. This process repeats until the entire limb is removed in one frame scan - that is, in one pass through the machine. The downward pointing limb loses only a small end portion on each pass, as the scan only covers the line end once in each field scan or pass.

This result confirms the performance behaviour claims made in Fig 6.9 regarding the case 3 machine. This dependence on the scan direction suggests that a picture processor could take advantage of a reversible scan.

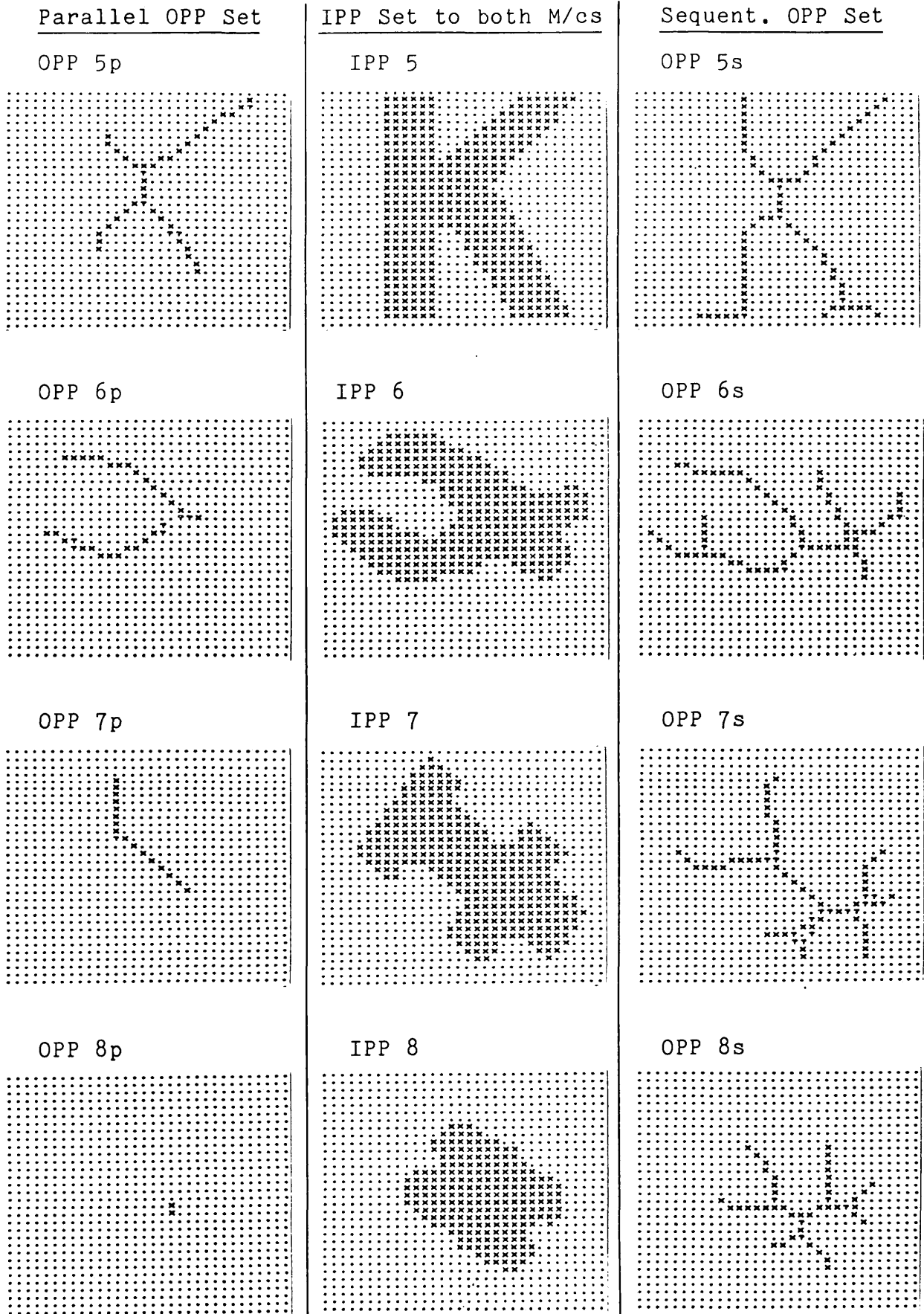
#### 6.1.9 Experiment 13f : Parallel/Sequential Behaviour

##### Exhibited With a LPP Machine

To confirm the claims made in Section 6.1.7 regarding the behaviour of sequential and parallel machines, this final section of this experiment was run.

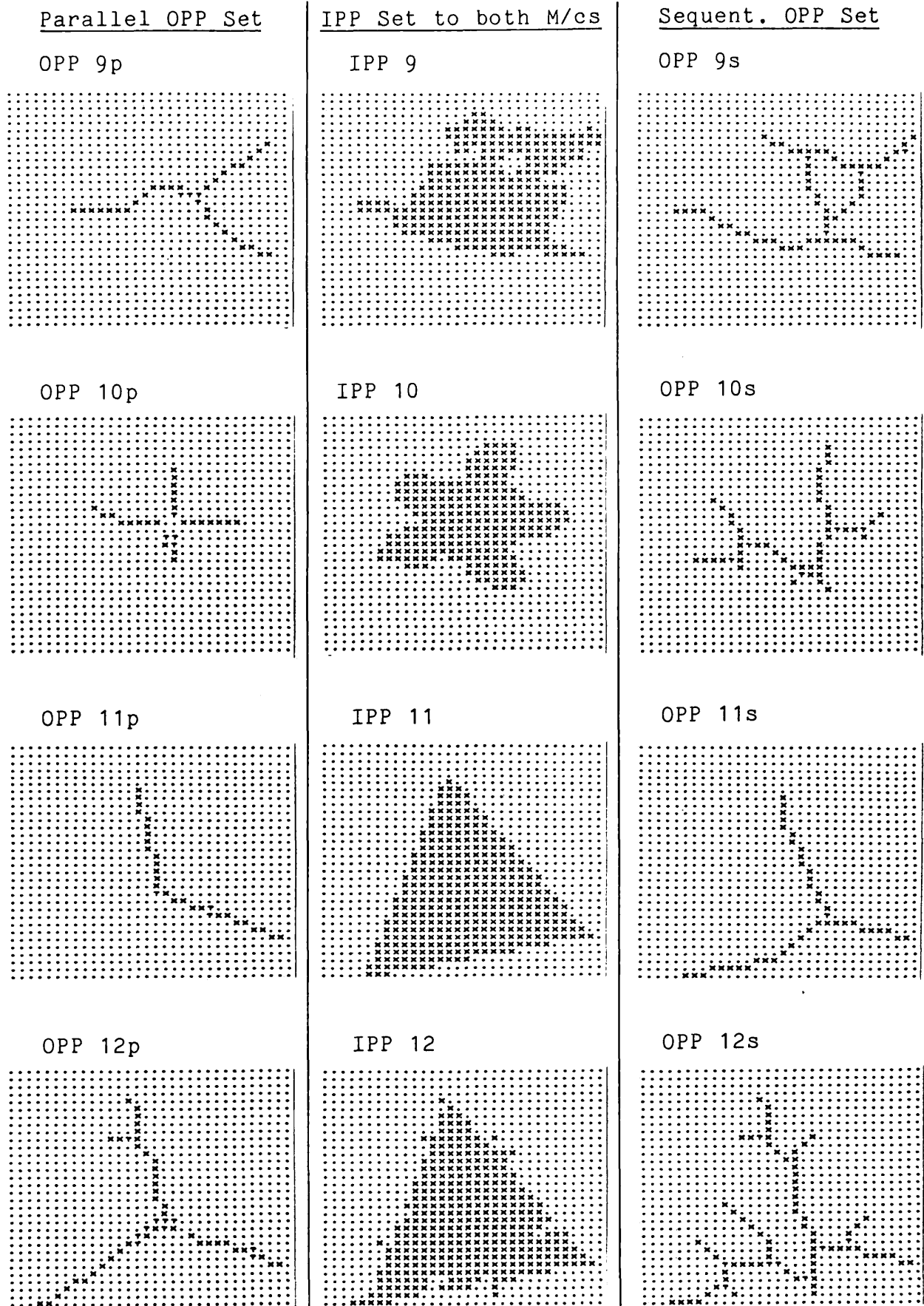
##### Experiment

A LPP machine was trained to 'thin and keep line ends' then applied in the sequential and parallel modes to a set of test inputs. These test inputs are shown in the centre columns of Figs 6.11 and 6.12. The results were produced using repeated feedback, the outputs being continually passed back into the machine until essentially static results were obtained. The OPPs produced using the sequential mode are reproduced on the right of Figs 6.11 and 6.12, and the parallel mode results on the left.



(All patterns passed 16 times)

Fig 6.11 Exp 13f : Comparison of Parallel/Sequential Applications with Feedback to IPPs 5-8



(All patterns passed 16 times)

Fig 6.12 Exp 13f : Comparison of Parallel/Sequential Applications with Feedback to IPPs 9-12



## Results

The comparison of the results confirms the LPP machine behaviour as summarized in Fig 6.9 above. These characteristic differences are already well-known (20) and are not only a consideration restricted to trainable systems such as these.

## Conclusion of Experiment 13

This concludes Experiments 13a to 13f, which have investigated the use of specially prepared training characters. This has shown how training may be adjusted to be quite specific in the tasks required (for example, 'keep or lose line ends') and can be improved to such an extent that other, more subtle effects on the test performance may be investigated. These investigations may also be further aided by the use of feedback in testing, to accentuate the processing behaviour. These machines have also been shown to exhibit the usual effects of parallel and sequential applications to test inputs.

## 6.2 Experiment 14 : Variations in the Addressing Function

In the previous experiments, the Address Calculator Function, as represented by ' $f_2$ ' in Section 4.2, has remained a simple binary word re-formatting function. That is, this function, which acts on a binary input  $W$  to form a binary output  $A$  ( $A = f_2(W)$ ), does not perform any calculation or processing to generate its result. A processing function will now be attempted.

Consideration of the ways in which a binary input window may be transformed into a binary address leads to an

infinite variety of possible functions. These more sophisticated functions fall broadly into two groups - those that reflect the 'brightness' of the window, and those that are dependent on the 'structure' of the pattern contained within the window. (The function used earlier was more rudimentary, to the extent that it did not rely implicitly on either of the above characteristics of the window to generate the address.)

An example of a function of the former type would be a total or average value of black (or white) pixels in the window. This is obviously closely related to the brightness, but independent of the structure within the window. A function dependent on the structure might represent the concavity, convexity or limbs in the window pattern.

An address calculator function that relies on such features will be considerably more costly in processing time and complexity than the earlier simple re-stacking. However, it is likely to be more efficient in the size of the memory matrix required, as there is a necessarily smaller combination of characteristic features possible than the maximum possible number of windows (512) used earlier.

#### The F7 Format

The retention of a small (3x3) bit window extractor function results in a very small number of possible features of the type discussed above. Consequently, a single new address calculator function was created that made use of both types of characteristics - brightness and structure.

Consider the ring of eight-connected neighbours around the window centre point  $P_0$ . A function that relies on the 'brightness' of such a ring is the simple total number of

pixels ('t') set equal to '1'. Here, this value 't' may range from 0 to 8.

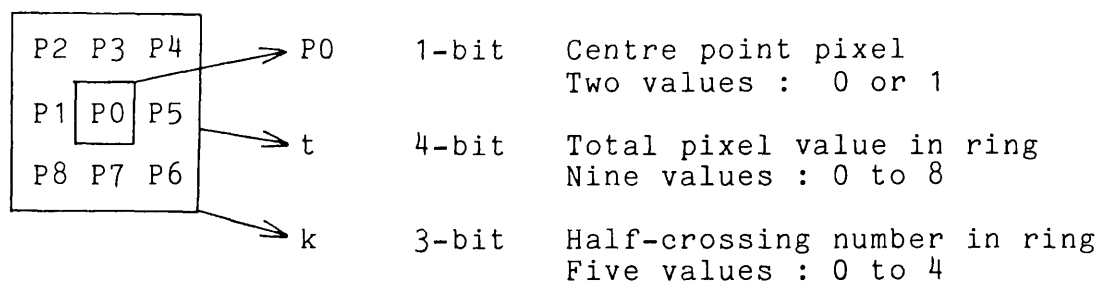
A function that depends on the structure within this window may be generated by calculation of the crossing number around the ring of immediate neighbours of the centre point. The crossing number ( X ) is defined as the number of transitions between black and white as the pixels around the centre point are examined in a ring. 'X' is necessarily an even number, and hence the value 'k' ( $=X/2$ ) will be used to avoid redundancy. Clearly, k is the number of limbs connecting to the centre point of the window and may range from 0 to 4 on this rectangular lattice.

Dependence on this centre point value P0 is retained as a single bit in the address. This address calculator function is thus composed of these three characteristics, the values 'k,t,P0' arranged as in Fig 6.13 below.

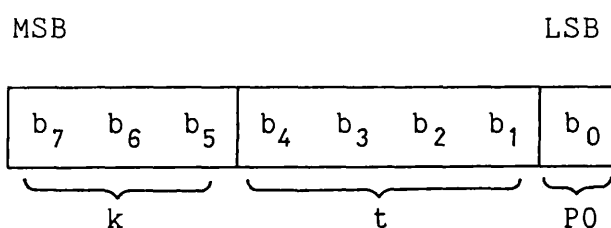
(This change in the LPP machine format is effected by a single subroutine change, as described later in Section 7.5. The original subroutine 'CADDR' which corresponds to the 'Address Calculator ( $f_2$ )' is listed in Appendix 1a (lines 5000 to 5510 for the F5 LPP machine format. The new version of 'CADDR' for this F7 format simply replaces the original subroutine.)

### Experiment

The F7 LPP machine as described above was set up in the software simulator and trained on the pair of specially prepared patterns used in the previous experiment. That is, the pair of patterns shown in Fig 6.1b was used, designed to illustrate the task :

9-bit I/P Window : W

These are combined to form :

8-bit Memory Matrix Address : A

Hence M.M in practice uses 256 ( $=2^8$ ) cells,  
although less than 90 ( $=2 \times 9 \times 5$ ) are accessible.

Fig 6.13 F7 Machine Address Calculator Function

'thin, maintain connectedness and keep line ends.'

This use of a training set known to be effective was to focus the investigation on the changes in performance due to the changes in machine format alone - to avoid the problem of poor training masking this effect. Consequently, the same test IPPs, modes of operation (parallel and then sequential) and number of feedback passes (ie. 16) were all used here, as in part of the previous Experiment 13f shown in Fig 6.11. The four test IPPs and the corresponding OPPs generated by the parallel and sequential modes (all with feedback applied

to ensure completion of the process) are shown in Fig 6.14. These are to be compared directly with the F5 machine results in Fig 6.11.

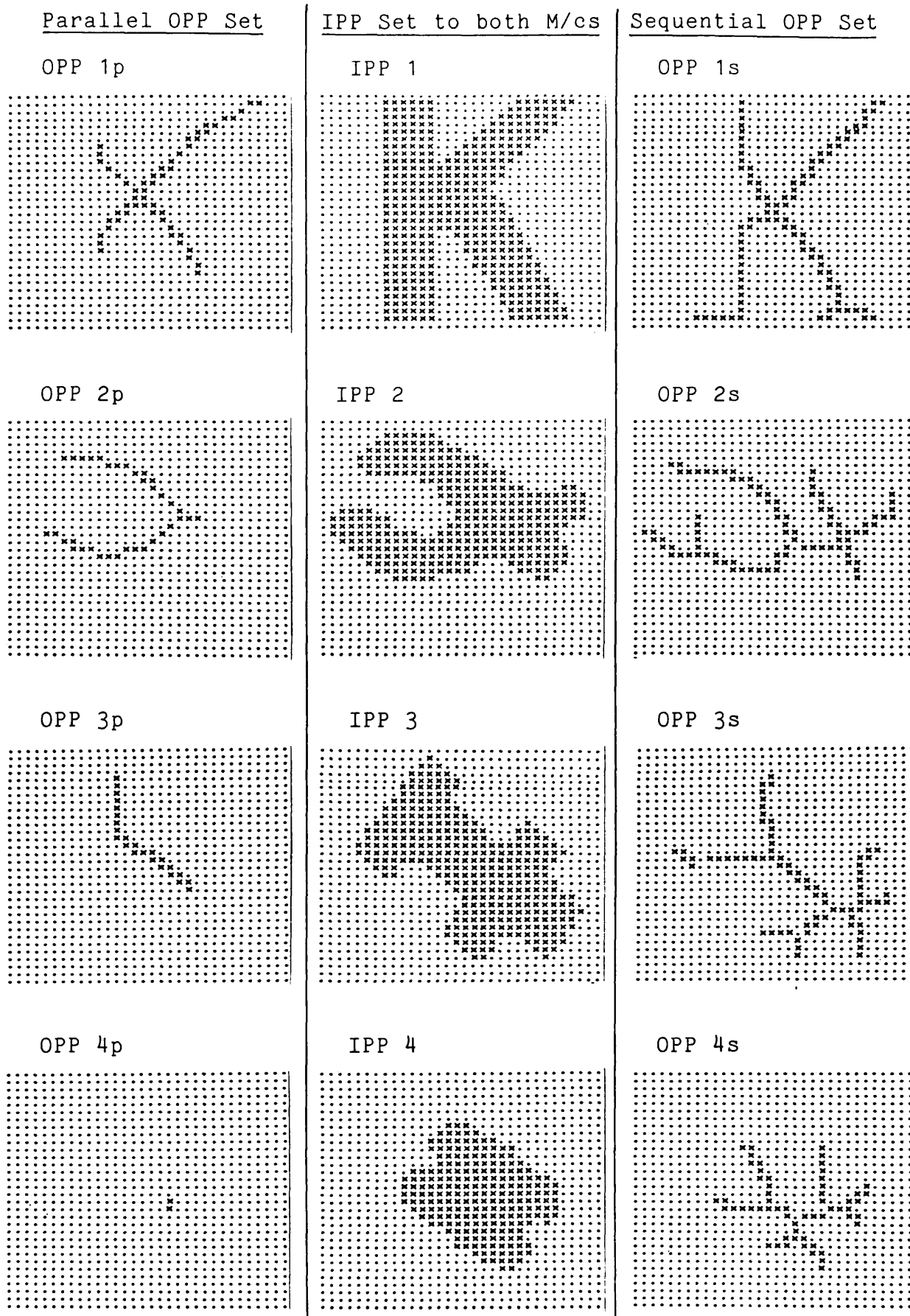
### Results

The results obtained here with the F7 machine are broadly similar to those obtained earlier with the F5 machine. That is, the IPPs have all been thinned to a unit width skeleton on repeated application of the thinning algorithm. The expected variation in performance seen between parallel and sequential processing has occurred again, further confirming the earlier analysis of this behaviour.

However, there are some interesting non-random differences between the results of the F5 and F7 machines. The skeletons produced by the F5 machine were single width and generally eight-connected. The corresponding single width limbs from the F7 machine are four-connected, the difference being especially apparent in diagonal lines. This difference is illustrated below in Fig 6.15.

It will also be noted that there are no '?' pixels, as the machine was preset to contain '1' pixels. This is necessary for the reasons explained in the discussion below. (The alternative of presetting the machine to '0' pixels before training makes little difference to the outputs.)

The results with the parallel mode of operation produced static results after 16 feedback passes, whereas the sequential mode of operation produced results that were often in a small local state of stable oscillation. That is, on each pass a local transformation on a particular feature produced an output that was eventually transformed back into



(To be compared with Fig 6.11)

Fig 6.14 Experiment 14 : Test Results

Single Width Connected Limbs :

```

. . . . .
. . . . .
X X X X X . . . . .
. . . . . X . . . . .
. . . . . X . . . . .
. . . . . X . . . . .
. . . . . X . . . . .
. . . . . X . . . . .
. . . . . X . . . . .
. . . . . X . . . . .
. . . . . X . . . . .
. . . . . X . . . . .

```

Eight-connected  
Skeletal Limbs

(Similar to those in  
Fig 6.11 : F5 m/c.)

```

. . . . .
. . . . .
X X X X X . . . . .
. . . . . X X . . . . .
. . . . . X X . . . . .
. . . . . X X . . . . .
. . . . . X X . . . . .
. . . . . X X . . . . .
. . . . . X X . . . . .
. . . . . X X . . . . .
. . . . . X . . . . .
. . . . . X . . . . .
. . . . . X . . . . .

```

Four-connected  
Skeletal Limbs

(Similar to those in  
Fig 6.14 : F7 m/c.)

Fig 6.15 Differences Between Eight and Four-connected  
Limbs as Exhibited by F5 and F7 Machines

the original feature. The particular cycle that occurred is illustrated in Fig 6.16 below. These errors are due to inadequate training, where such patterns have not occurred in the training set. Unlike the F5 machine, the F7 machine must necessarily output definite values on each pass, hence the possibility of oscillatory behaviour.

```

X . . . . X . . . . X . . . . X . . . .
. X . . . . X . . . . . X . . . . . X . . . .
. X X X X . . X X X . . . X X . . X X X X etc...
. X . . . . X . . . . . X . . . . . X . . . .
X . . . . X . . . . X . . . . X . . . .

```

F7 Machine (trained on patterns in Fig 6.1b) produces this cyclic behaviour on this feature on each successive feedback pass in the sequential mode of operation.

Fig 6.16 Local Stable Oscillatory Behaviour

Discussion

It is difficult to relate the reasons for the differences in results to the structure of the F5 and F7 machines. The more complex address calculator function (F7) means that not only is intuitive analysis difficult, but so is an analysis based on statistical examination of the machine's internal state. Neither an analysis of the TP value (derived from examination of cell totals) nor a physical listing of the memory matrix cells (as in Appendix 2 - albeit in a different format) is of much interpretive use.

However, it is interesting to note that such a machine, with this complex addressing function, not only works but works relatively well. Certainly the test performance compared with the F5 machine reveals similar picture processing ability having been trained by the same experiences only. It should also be noted that the memory matrix size has been reduced from 512 to less than 90 cells, yet comparable results have been produced.

(Less than 90 cells are actually used for the following reason. Although the three variables ( $k, t, P_0$ ) may take 5, 9 and 2 values respectively, suggesting their product as the total number of cells required, several cells are never used. This is because they represent impossible combinations. For example, it is obvious that  $t$  and  $8-t$  must be greater than or equal to  $k$  for consistency, resulting in several cells' addresses never arising, and the corresponding use of considerably less than 90 cells in the memory matrix.)



The major repeatable difference in testing is seen as a variation in dealing with the structure of the pattern within the 3x3 window. This is not unexpected as the F7 machine relies on this structure in a totally different manner from the F5 machine, and hence reacts differently in testing. This sensitivity to structure is in some sense an improvement in performance.

There are three further points to discuss concerning this specific machine, which arise from theoretical considerations rather than experimental results.

#### 1 Rotation and Reflection

The more complex address calculator function generating  $k$  and  $t$  effectively replaces the requirement used in previous formats to rotate and reflect the input windows in training. These new cell addresses are invariant under rotation and reflection and thus implement this function automatically. Consequently, in building this new format in the simulator, not only was the 'CADDR' subroutine changed as described above, but also the routine to rotate and reflect the input window was removed from the software.

#### 2 Memory Matrix Preset Value

The value to which the memory matrix cells are preset before training must be examined closely in conjunction with the mode of operation in which the machine will be run. Specifically, the preset value must depend on whether or not the machine will be tested with feedback. This is because if the memory matrix cells are preset to '?' as before, the subsequent feedback of OPPs containing '?' pixels cannot be easily resolved into a consistent value for  $k$  or  $t$ . These

totals ideally should be generated from binary (not trinary) variables. The conflict occurs in the former case ( k ) in deciding whether :

$$\begin{array}{c} \text{'?'} \\ \text{pixels} \end{array} = \begin{array}{c} \text{'0'} \\ \text{pixels} \end{array} \text{ or } \begin{array}{c} \text{'1'} \\ \text{pixels} \end{array}$$

in the comparison to define the changes of state as the ring of neighbours is examined, and in the latter case ( t ) deciding whether '?' pixels should be regarded as 'black', 'white' or something in between. This problem was resolved in this experiment by presetting the cells in the memory matrix to contain '1' pixels. (The alternative of presetting the cells to '0' made little experimental difference.)

### 3 Memory Matrix Effective Size

The effective size of the memory matrix of the F7 machine has been reduced from 512 to less than 90 cells, compared with a reduction from 512 to 102 with the F5 machine. While this reduction is comparable in this case, much larger reductions could be envisaged when larger windows are used with an F7-like machine in future.

### Interpretations of Variations in the Addressing Format

The above experiment varied the memory matrix addressing format used from the earlier simple 9-bit pixel stack address. This leads to the question as to the theoretical optimum memory matrix addressing mode that may be generated from a 9-bit binary input window.

The address calculator function (  $A=f_2(W)$  ) that takes a 9-bit argument and simply re-formats this to a 9-bit binary result loses no information at all in this process. That is, the F5 machine's memory matrix must be potentially

the most capacious in terms of the ultimate information storage. However, this is obviously to be weighed against the more efficient alternatives that may store the same information in less space. The F7 format would seem to be such a candidate from the results of these experimental observations. There is an added complication to be weighed in the search for the optimum performance - the computational cost of such a calculating function. This acts against the information storage efficiency, and again, each potential system must be evaluated with this in mind.

Unfortunately, in this imprecise field of training a picture processor by examples (which themselves must be imprecise if they are to represent practical data, gathered from realistic situations) the only method of ascertaining the performance is by pragmatic examination of test results. This too will be imprecise, but in many such complex systems this is often the most efficient method of searching for a justifiable conclusion on performance.

#### Other Window Formats

This change in the addressing format illustrates how a more memory efficient machine may be produced which is still capable of processing pictures when viewed through a 3x3-bit window. Changes in the window itself are also possible; that is, in the Input or Example Window Extractors as represented in Section 4.2 as :

$$\begin{array}{ll}
 W = f_1(IPP, x, y) & \text{Input Window Extractor} \\
 EXP/PO = f_4(EXP, x, y) & \text{Example Window Extractor}
 \end{array}$$

Examples of variations in the input window can be simple extensions of the size (beyond 3x3, or even below 3x3

as in Experiment 10) to encompass a feature size more closely suited to the type of processing envisaged. The resolution of pixels need not be constant over the window, if such a system were found efficient. An example of this type is illustrated in Fig 6.17 below, where a reduction in resolution away from the centre point results in a 'local pyramid' type of configuration. This use of such pyramids over a local window is an extension of the already established use of such quadrees and pyramidal data structures as picture descriptors over the entire field (5,27,76). Here, within a local window, the full pixel resolution is retained at the centre point, yet the next three layers of pixels are 'averaged' to generate a single-bit brightness value for each of the eight surrounding groups of pixels.

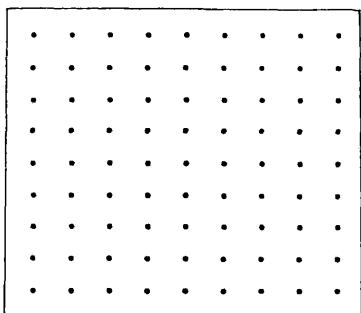
Such a window format would take detailed account of the centre point and its immediate neighbours, and depend less on a broader spread of pixels. This may be a better compromise than an equivalent system where full resolution is retained over the entire input window.

This system could be extended indefinitely, reducing resolution as more neighbours are encompassed. It is suggested here as a possibly more efficient method of processing local windows by such trainable systems; but has not been attempted experimentally in this work.

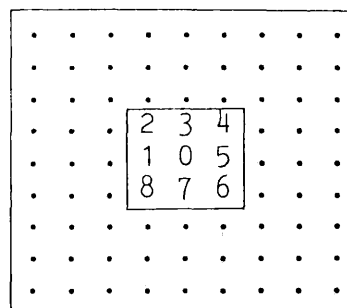
### 6.3 Experiment 15 : Locating and Tracking of Objects

A short experiment in this series was performed to examine how a trainable picture processing system would

9x9 bit Window  
in the Input Picture



Full Resolution Maintained  
in the Centre Pixels



10	11	12		
9	2	3	4	13
	1	0	5	
	8	7	6	
16	15	14		

The next layers of pixels can be arranged as eight groups of nine pixels each, and their average brightness only recorded.

→ Each averaged to one bit value

This results in a 17 bit window with resolution high near centre point and lower as distance from centre increases.

Fig 6.17 An Example of a Pyramidal Type of Representation  
As a Variation in Window Format

tackle a task somewhat different from the 'shape analysis' range attempted above. This task was the location and tracking of objects within the field of view. Location of objects by such a machine could be accomplished by simply marking the object desired in the field, and tracking could possibly move or modify the desired object in the desired manner. The location task was attempted first.

### Experiment

The training of a F5 machine was accomplished using a field containing a large object among several smaller objects as IPP (to represent 'a target against a noisy

background' for example). The EXP was a lone marker centred on the larger object, thus defining the task as 'produce a marker on the desired object'. A set of eight such hand-drawn pairs were used to train the F5 LPP machine, three of which are illustrated in Fig 6.18. Examination of these patterns will show clearly the task attempted.

The memory matrix contents, as they changed throughout the training period were 'totalized' after each training pair was applied, and the TP value at each stage calculated. These data are shown in Fig 6.19 as a table and histogram.

The machine was tested in parallel on a set of input patterns shown in the left hand column of Fig 6.20. These can be seen to represent such 'target' pictures with an increasingly noisy background. The resultant set of OPPs are shown on the right of this figure.

### Results

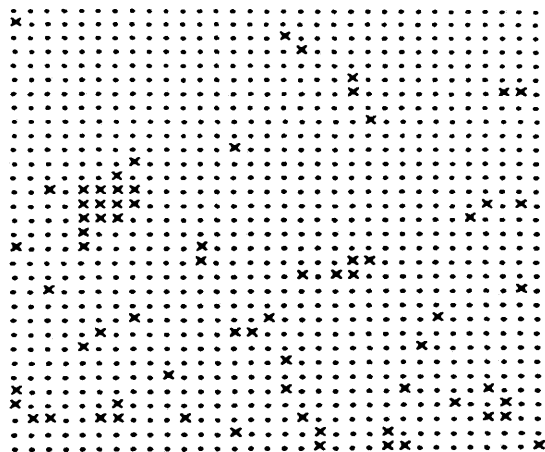
The test inputs with little or no noise are correctly processed to give a single marker appearing in the output centred on the object to be located. As the noise in the input increases, the machine eventually starts to react to this by generating marker outputs at the position of the larger noise objects in addition to the required object.

### Discussion

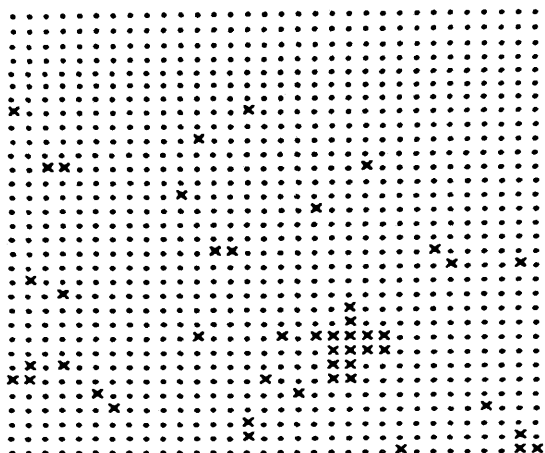
The ability to locate objects correctly in the face of moderate noise indicates successful operation of the LPP machine in these cases. The greater noise producing spurious results is to be expected, in that the machine is obviously reacting to the size of objects only, not any other intrinsic properties such as shape or orientation.

Training IPPs

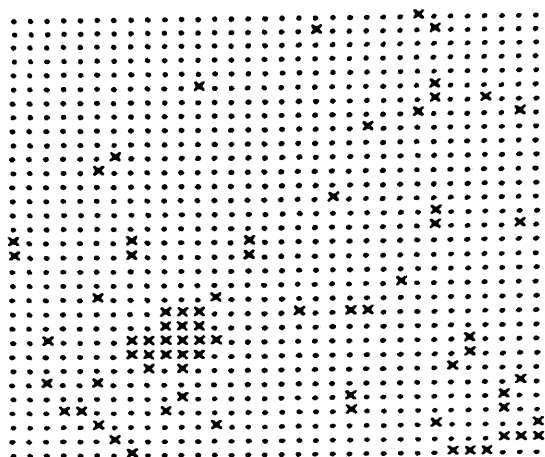
IPP 1



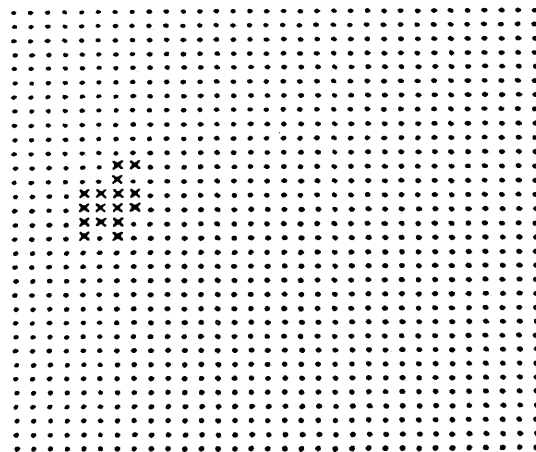
IPP 2



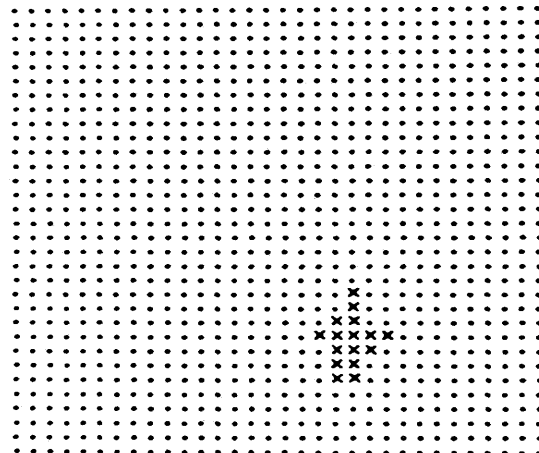
IPP 3

Training EXPs

EXP 1



EXP 2



EXP 3

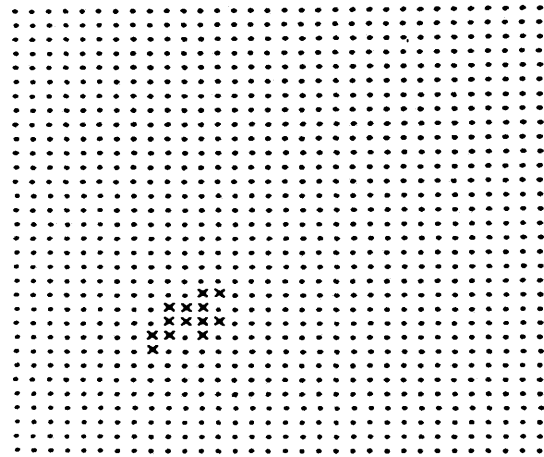


Fig 6.18 Experiment 15 : 3 of 8 Pairs from Training Set

No. of Training Patterns Received	No. of Cells=0	No. of Cells=?	No. of Cells=1	No. of Trained Cells
0	0 (0%)	512 (100%)	0 (0%)	0 (0%)
1	142 (27.8%)	313 (61.1%)	57 (11.1%)	199 (38.9%)
2	158 (30.8%)	285 (55.7%)	69 (13.5%)	227 (44.3%)
3	207 (40.4%)	249 (48.6%)	56 (11.0%)	263 (51.4%)
4	238 (46.5%)	215 (42.0%)	59 (11.5%)	297 (58.0%)
5	230 (44.9%)	191 (37.3%)	91 (17.8%)	321 (62.7%)
6	234 (45.7%)	183 (35.7%)	95 (18.6%)	329 (64.3%)
7	246 (48.1%)	163 (31.8%)	103 (20.1%)	349 (68.2%)
8	234 (45.7%)	147 (28.7%)	131 (25.6%)	365 (71.3%)

Histogram of Above Data :

(Key as in Fig 5.9)

No. of Patterns :

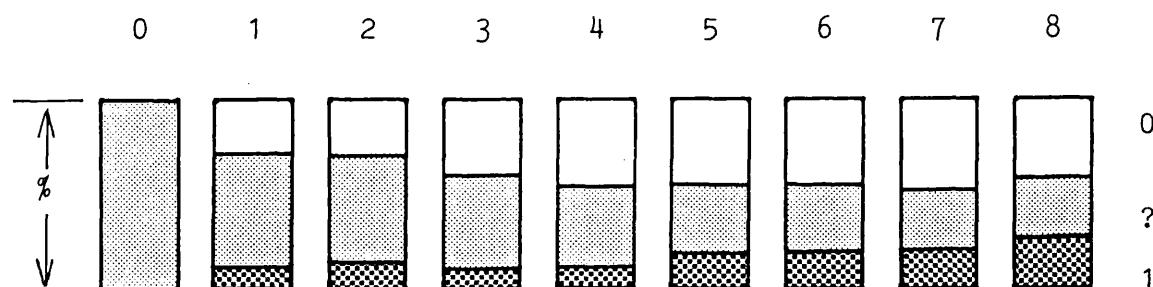


Fig 6.19 Exp 15 : Development of M.M Contents During Training Phase



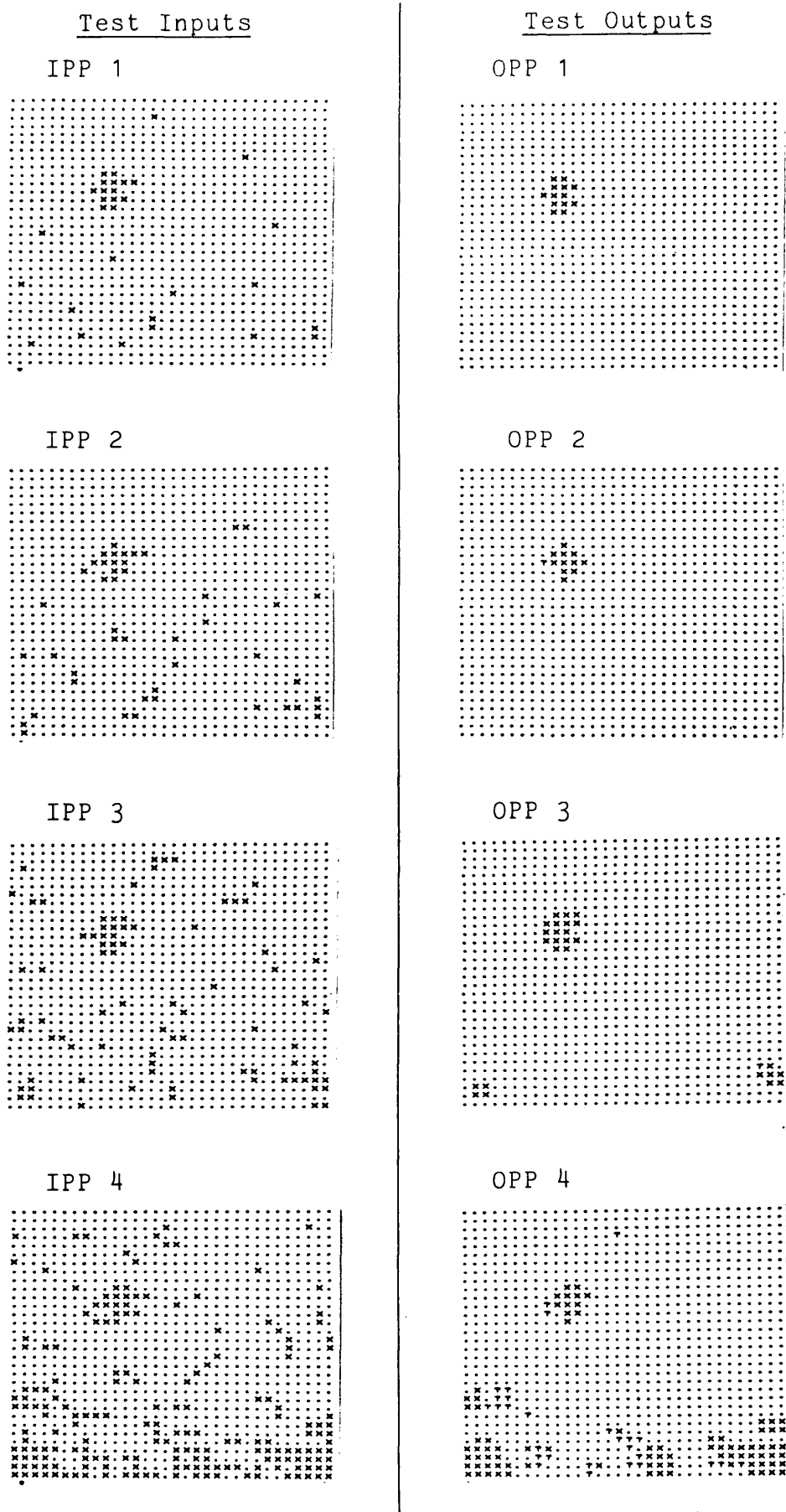


Fig 6.20 Experiment 15 : Test Results

Thus, the test results confirm the training was as thorough as is possible with such a machine; indeed, the TP value obtained of 71.3% (see Fig 6.19) confirms that the quantity of training was ample.

For the machine to be able to differentiate between the desired object and noise (or any other objects) it must be trained on information that is 'visible' through the (in this case) 3x3 bit window. Such a small window used here precludes the use of any intricate structure or design in the required object as a distinguishing feature to which the machine may react. Consequently, 'size' compared to the 3x3 window is the only feature available to the machine trained in this manner, thus accounting for its behaviour.

This determination of size using a small window is encouraging, given the usual limitations of such windows. However, this size is strictly limited to that directly comparable with the window.

The task of 'tracking' (in which an object may have its motion on two temporally successive frames predicted) is frustrated by this small window also. (This has been verified by experiments not described fully here, where the outputs showed no coherent response.) It would be necessary to distinguish between the 'front' (advancing) and 'back' (receding) edges of the required object for the machine to be able to predict the next frame showing the direction of motion of the object. Such distinguishable features are just conceivable on a 3x3 window, but these would not represent realistic, distorted features, such as would be received 'off-camera' in any real situation.

### The Need for Bigger Windows

The limit of possible processing in this task (and others) with this small window has been reached. Further investigations must make use of larger windows - large enough to enable detailed structure of pictorial objects to be contained within a single window. The use of a larger window should also be accompanied by the corresponding increase in overall frame size (that is, greater than  $32^2$ ) to enable a field of view much larger than the window extracted. The combination of these two requirements may be stated alternatively by stipulating that a far greater overall resolution or finesse should be used in defining discrete pixels in the original digitisation process.

### 6.4 Experiments 16 and 17 : LPP Machine 'Neurosis'

There is a need to develop a more generalised approach to understanding these LPP machines. Experiments have been performed that give performances of specific machines in specific applications. It has emerged that this performance is predominantly dependent on the training received, and to a lesser extent on the machine format and operation.

It is wished to shift the experimental emphasis from the investigation of particular cases to the development of a more useful tool in assessing the potential for picture processing by learning machines. The quality of training is known to be paramount, and so a more penetrating analysis of this quality is highly desirable. This will not necessarily lead to better ultimate performance, but certainly to a better understanding of the capabilities of these machines.

An LPP Machine sensitive to Neurosis : the F8 Machine

As it happens, a relatively simple variant of the LPP machines already developed gives much of this type of information, previously lost. The 'F8' machine was created, which is capable of recording a 'neurotic' memory matrix cell - one that has been trained to different values on different occasions - ie. inconsistently trained. This is done by introducing a fourth possible state for the cells. The state transition diagrams for responses to the various stimuli are shown in Fig 6.21 to explain this. A comparison is made with the most similar F5 machine.

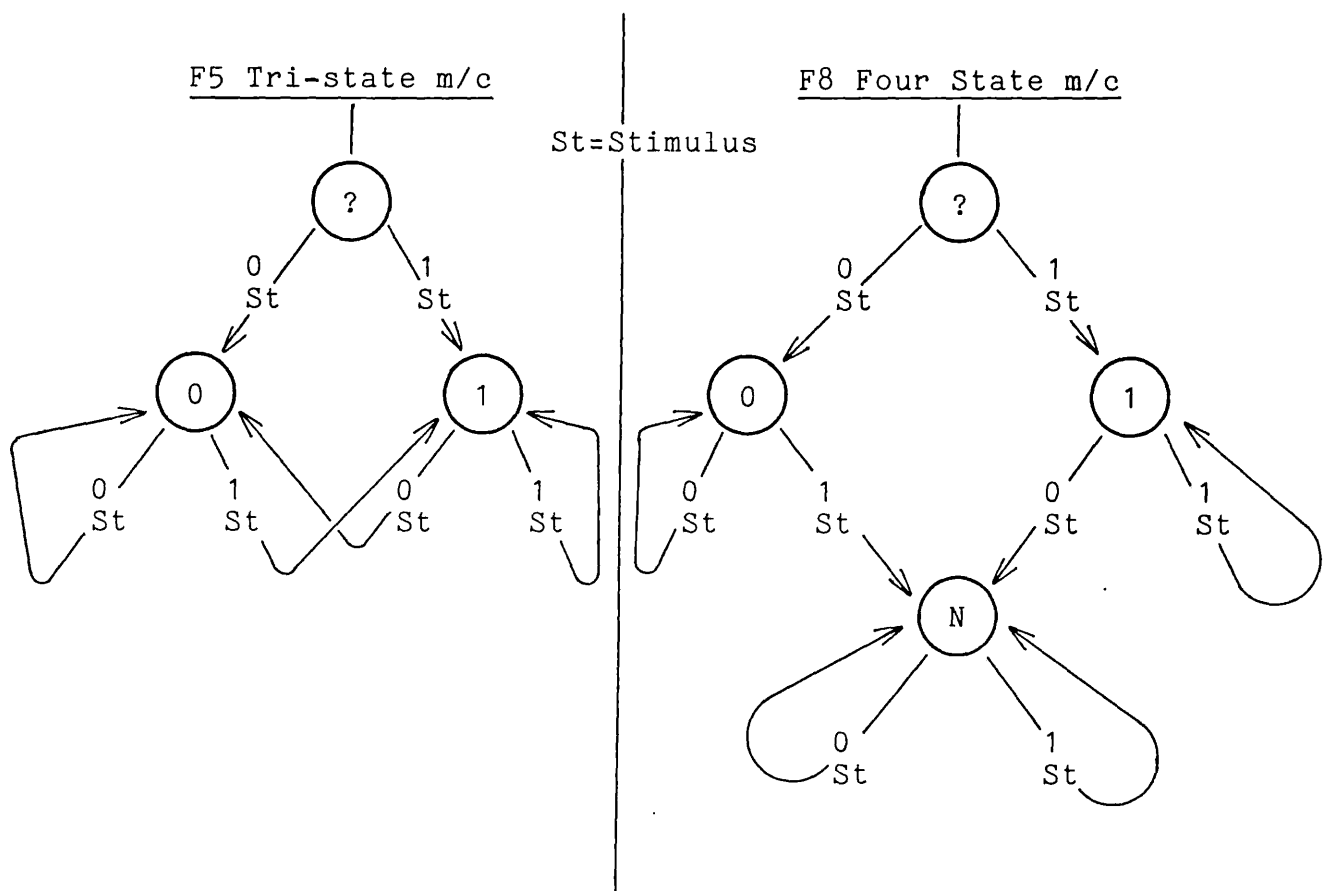


Fig 6.21 State Transition Diagrams for F5 and F8 Machines

It can be seen that any attempt at inconsistent training with the F8 machine will result in a cell being set

to 'N' permanently.

Experiment 16

As a practical exercise for this F8 machine, it was trained on the second training set used in Experiment 13 (see Fig 6.1b). The results (which now show the extent of 'neurotic' memory after training) are shown in Fig 6.22, again compared with the original results from Experiment 13 using the F5 machine.

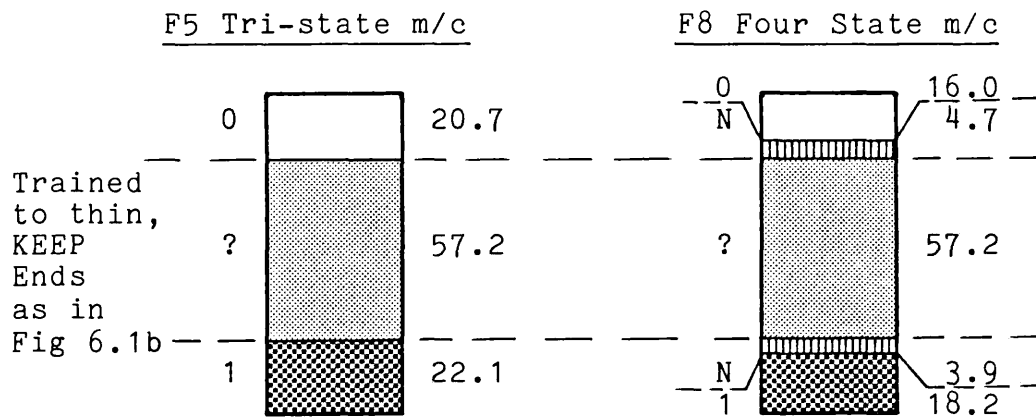


Fig 6.22 Exp 16 : Memory Matrices of F5 and F8 Machines

(Although only one type of 'N' cell is detectable after training, comparison of the F5 and F8 results allow the separation of the 'N' cells into two bands - those that were ultimately left equal to '0' in the F5 machine, and those left equal to '1'. Hence the two bands of 'N' cells in the F8 machine result.)

Results

The use of the F8 machine shows a result of 8.6% neurotic cells after training. This must be classed as

'good' training, as the remainder of Experiment 13 showed to be the case.

### Discussion

This short demonstration serves to illustrate the potential now available for assessing the quality of training. This is a considerably more powerful measure than the TP value developed earlier, which merely measured the quantity of training, both consistent and inconsistent.

Before a full discussion of the implications of this type of investigation, a further short development is made below, generating an even more powerful tool for LPP machine behaviour analysis.

### The F9 Machine

A final variant (F9) machine was set up with the following response in each memory matrix cell to training stimuli. Each cell contains two counters, one to count the number of '0' stimuli received, the other to count the number of '1' stimuli. Both counters are initially set to zero before training and saturate if they reach their maximum value. (In this implementation, these are two four-bit binary counters, and thus each has a range of 0-15.)

### Experiment 17

The F9 machine was again trained on the set used in Experiment 13 (Fig 6.1b). A second training session was also implemented to provide further data for investigation. This training used the set in Experiment 15, three of the eight pairs used being shown in Fig 6.18.

## Results

The raw results (the two memory matrices after training) are not reproduced here, as they require some manipulation to become informative. Similarly, there are no test picture results, as no algorithm for using these matrices in testing has been defined. (The investigation is concerned solely with the training and the machine's reaction to this.)

## Discussion

Sixteen values may be recorded in either of the two counters in each memory matrix cell. To present the information usefully, the total number of cells left in each of the 256 possible combinations are counted. This is shown in Fig 6.23 below, where a table of 16 rows and 16 columns for each memory matrix is shown. In each entry in the table, the number of cells with a '0' total and a '1' total given by the axes is shown.

There are several points to note :

- 1 The left hand side of the table corresponds to few '0' stimuli, the right hand side to many '0' stimuli,
- 2 Similarly, the lower region corresponds to few '1' stimuli, the upper region to many.

This results in :

- 3 Those totals grouped around the lower left hand corner correspond to little training of any kind. (Indeed, those in the 0,0 square correspond to completely untrained cells, '?' when implemented

(a) Trained on Set in Fig 6.1b

↑ '1' Stimuli Rec'd	15+	5	.	.	.	.	.	.	.	.	.	.	.	.	8	.	
	14	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	
	13	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	
	12	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	
	11	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	
	10	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	
	9	.	.	.	.	.	.	.	.	.	.	.	.	.	.	4	
	8	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	
	7	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	
	6	8	.	.	.	.	.	.	.	.	.	.	.	.	.	.	
	5	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	
	4	10	.	.	.	.	.	.	.	.	.	.	.	.	.	.	
	3	24	.	8	.	.	.	.	.	.	.	.	.	.	.	.	
	2	20	8	4	.	.	.	.	.	.	.	.	.	.	.	.	
	1	26	.	.	.	.	.	.	.	.	.	.	.	.	4	8	
	0	293	17	4	.	12	12	.	4	.	.	.	.	4	.	29	
		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15+

'0' Stimuli Rec'd →

(b) Trained on Set in Fig 6.18

↑ '1' Stimuli Rec'd	15+	.	.	8	.	.	.	.	.	.	.	.	.	.	.	.	
	14	.	.	.	.	.	1	.	.	.	.	.	.	.	.	.	
	13	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	
	12	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	
	11	.	.	.	.	.	.	3	.	.	.	.	.	.	.	.	
	10	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	
	9	4	.	.	.	.	.	.	.	.	.	.	.	.	.	.	
	8	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	
	7	4	4	.	8	.	.	.	.	.	.	.	.	.	.	.	
	6	.	1	.	.	.	.	.	.	.	.	.	.	.	.	.	
	5	.	8	.	.	.	.	.	.	.	.	.	.	.	.	8	
	4	.	8	.	.	.	.	.	.	.	.	.	.	.	.	4	
	3	12	4	8	.	.	.	.	.	.	.	.	.	.	.	8	
	2	.	.	.	.	8	.	4	.	.	.	.	.	.	.	4	
	1	37	12	.	4	.	.	.	.	8	.	.	.	.	.	20	
	0	148	48	34	20	8	.	8	8	8	.	2	.	.	4	34	
		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15+

'0' Stimuli Rec'd →

Fig 6.23 Exp 17 : Totals for Two F9 M/c Memory Matrices



before.)

- 4 Those totals grouped in the upper left hand corner correspond to predominantly '1' stimuli (at least more '1's than '0's seen in training) and thus imply consistent training to generate '1' outputs. A similar situation applies for '0' stimuli in the lower right hand corner.
- 5 The upper right region represents cells that have seen considerable amounts of both '0' and '1' stimuli. This corresponds to inconsistent training.

#### Behaviour during Training

A set of stylized tables of this type as they would be expected to develop during training is given in Fig 6.24.

#### Decisions in Testing

Such a table can be used to experiment with different decision boundaries in the testing phase. Examples of possible decision boundaries and their implications are given in Fig 6.25. This gives insight into how a LPP machine may be much more finely 'tuned' in testing to take maximum advantage of a non-ideal training set presented to it.

#### Numerical Analysis

The totals in the rows and columns in these tables may themselves be totalised, yet in one very important sense this loses the very information we have been at pains to gather : the correlation between different '0' and '1' stimuli for the same feature. A more profitable analysis involves the totalling of the entries in the tables along the diagonals. There are two sets of diagonals and they both

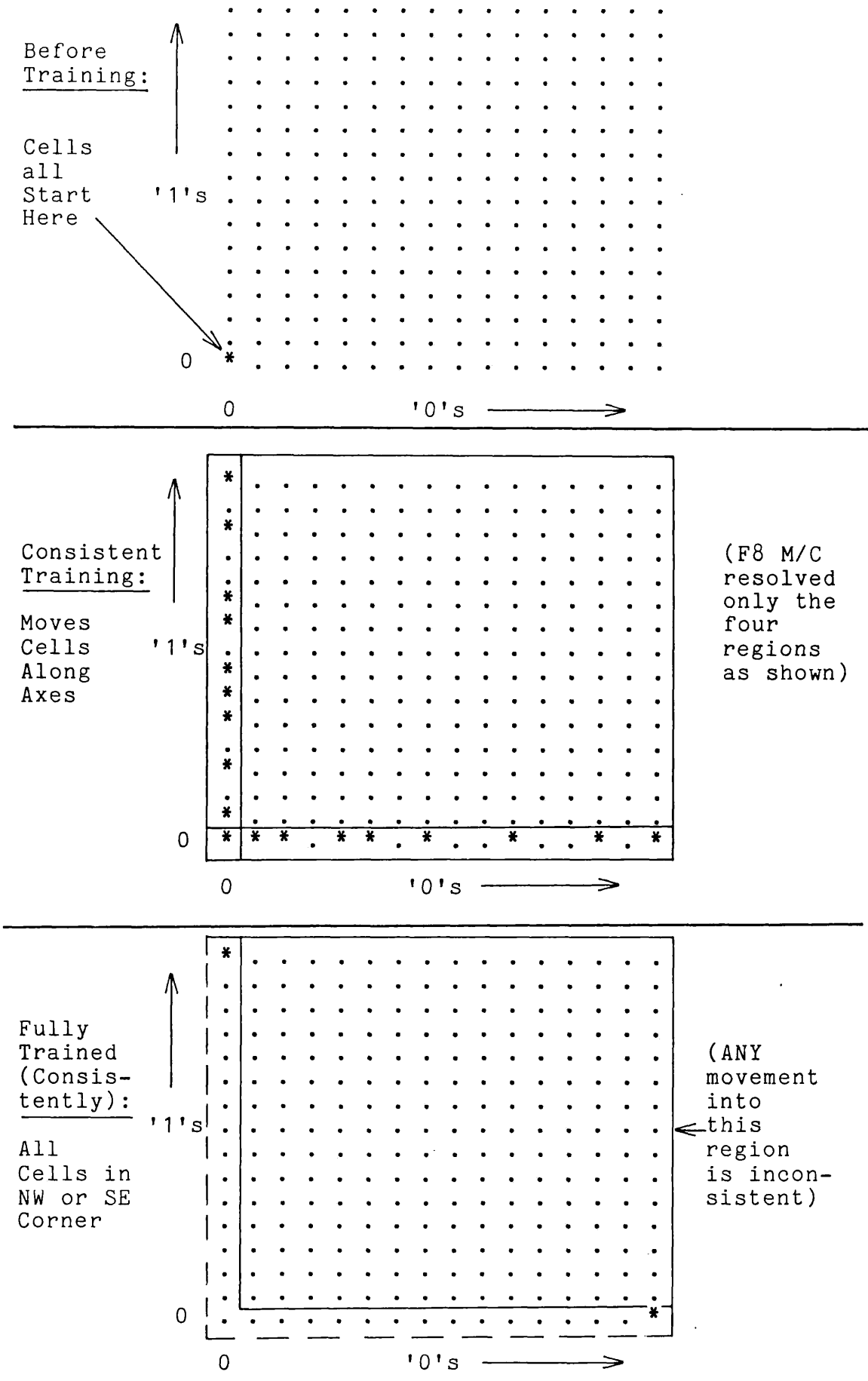
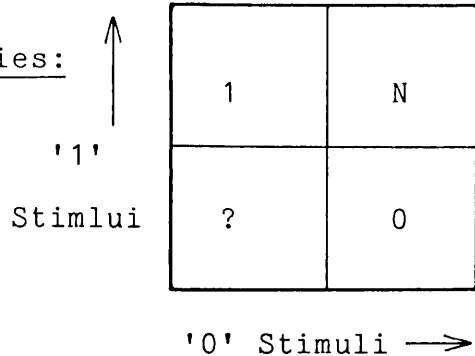


Fig 6.24 F9 M/c Development During Training

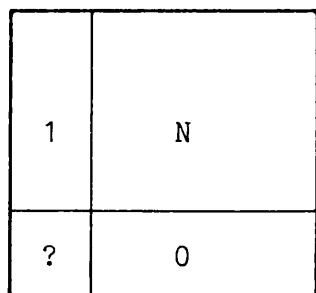
Simple Boundaries:



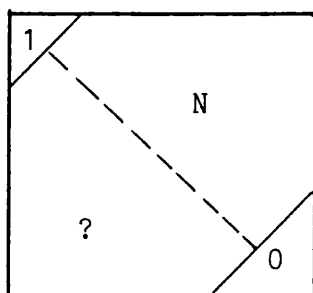
? - Output '?' }  
 0 - Output '0' } { under  
 1 - Output '1' } { test  
 N - Output 'N' } { if  
 } { cell  
 } { lies  
 } { in  
 } { this  
 } { region

Not necessarily equally sized regions :

Eg if risk of mis-processing is high :

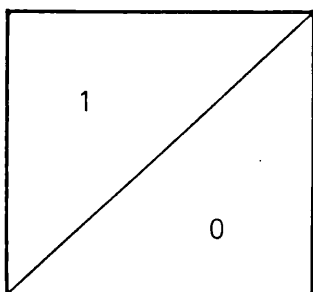


or :



(Possibly unnecessary to distinguish between '?' and 'N')

Alternatively, if a decision must be made, whatever the risk :



This is simply: 'Choose the output whose total is bigger'

Fig 6.25 F9 M/c : Testing Decision Boundaries

generate useful data as indicated in Fig 6.26. An illustration is also shown of the expected development of these tables during training.

This data has been generated and plotted in Fig 6.27, from the data in the tables of Fig 6.23. These give a numerical feel for the two most important considerations here when implementing a LPP machine :

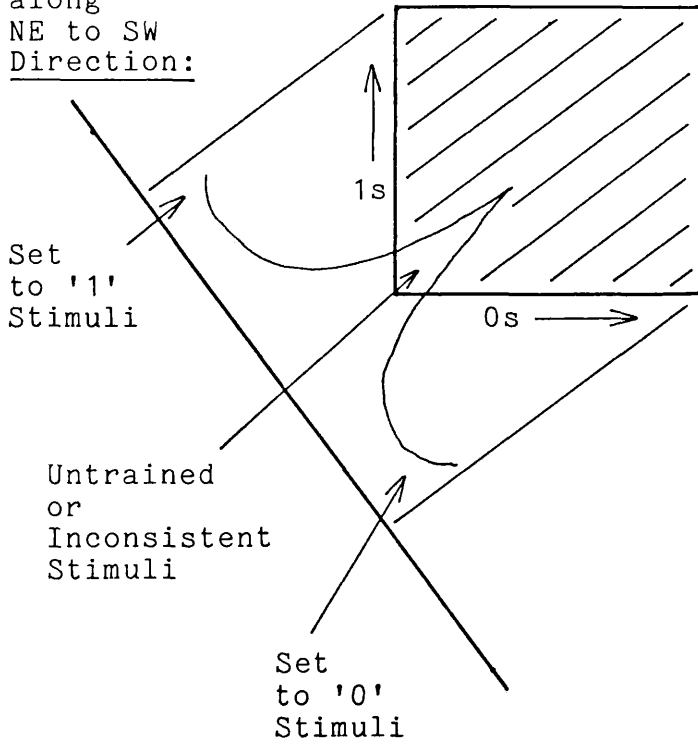
- 1 the extent to which the available training is consistent and unlikely to confuse the machine,
- 2 the minimum size of machine needed to resolve easily between the three peaks of insufficient, accurate and inconsistent training.

The first consideration above would draw information from the second and fourth graphs in Fig 6.27 (ie. 'b' and 'd'), the diagonal totals taken along a NW to SE direction. This shows the three peaks of insufficient, consistent and inconsistent training which could be broadly separated by the suggested boundaries shown dotted on the graphs.

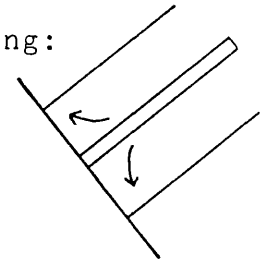
The first training set (used to generate the Fig 6.27b graph) can be seen to contain small, but readily identifiable peaks of inconsistent points, which as such can be guarded against with the F9 machine. Similarly, there is a clear 'ground' between the peaks of insufficient and consistent training in both graphs 'b' and 'd'; where a decision boundary can be confidently drawn.

The second consideration above uses the graphs 'a' and 'c' to measure how the available machine resolution compares with the training data, and to draw the ultimate decision boundaries to be used in testing. These translate to

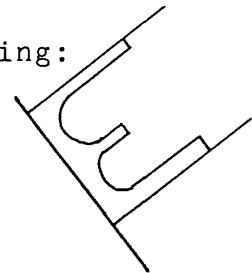
Diagonals' Totals along NE to SW Direction:



Before Training:



After Training:



Diagonals' Totals Along NW to SE Direction:

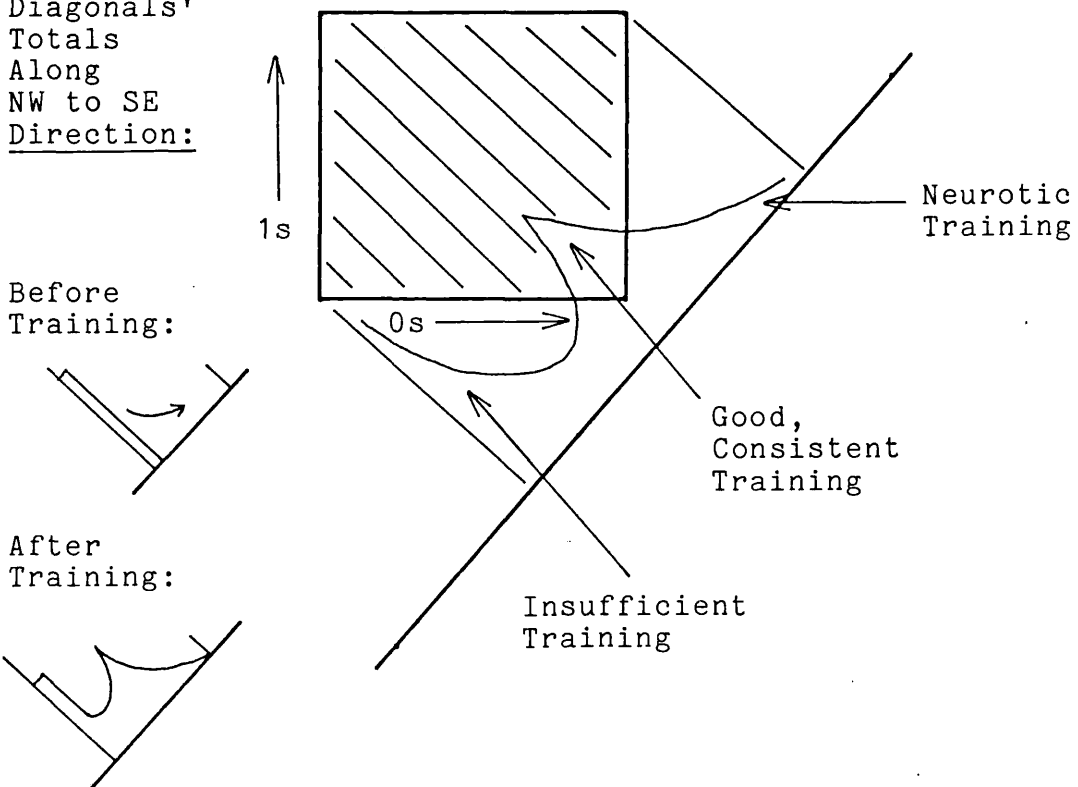
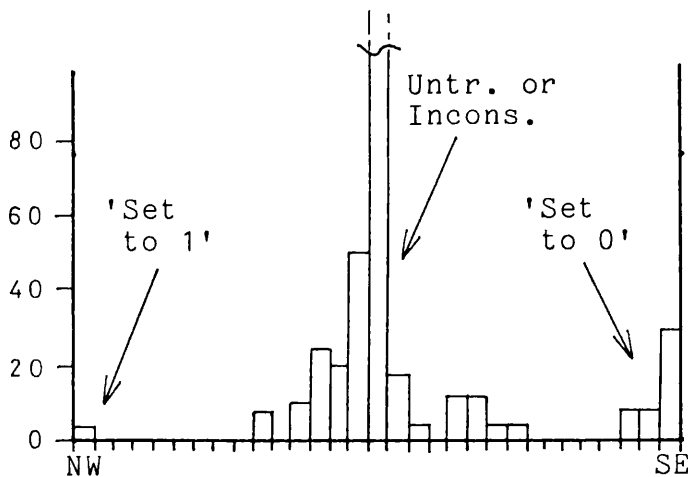


Fig 6.26 F9 M/c : Implications of Diagonals' Totals

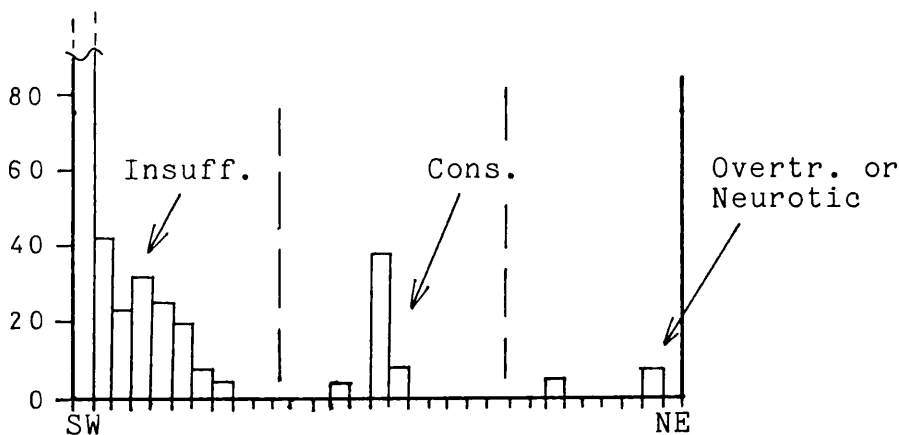
(a)  
Trained  
to  
'Thin'  
as in  
Exp 13

NE/SW  
Totals



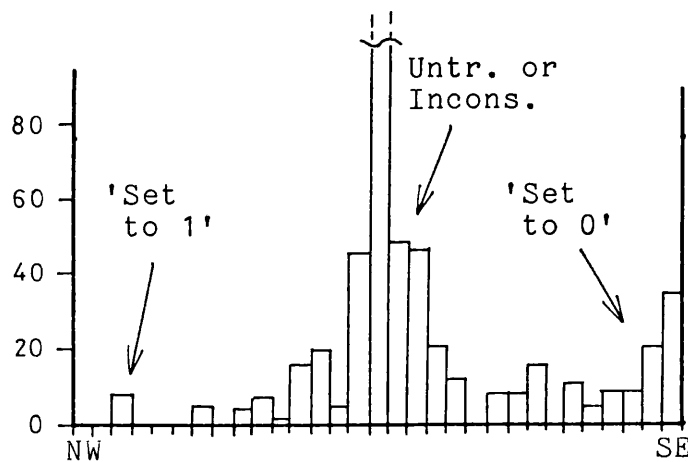
(b)  
Trained  
as  
above

NW/SE  
Totals



(c)  
Trained  
to  
'Remove  
Noise'  
as in  
Exp 15

NE/SW  
Totals



(All  
Data  
from  
Tables  
in  
Fig 6.23)

(d)  
Trained  
as  
above

NW/SE  
Totals

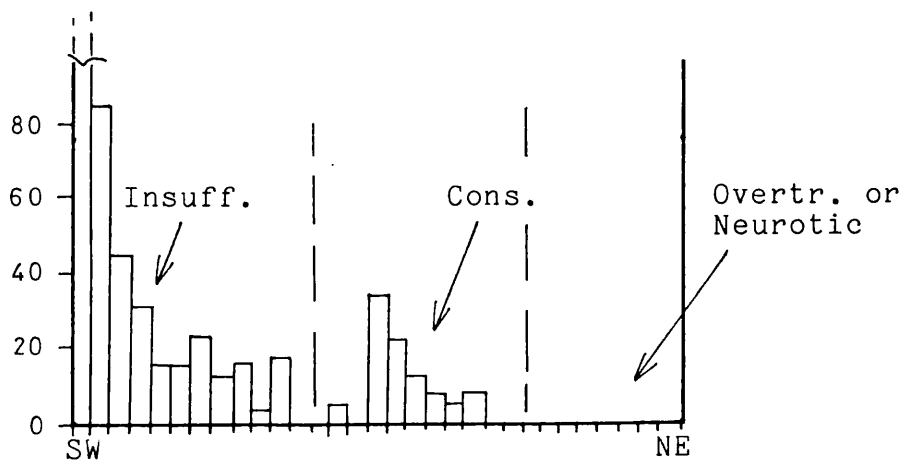


Fig 6.27 Exp 17 : Diagonals' Totals Graphs

diagonal boundaries on the tables in Fig 6.23, in the manner shown in Fig 6.25. In the case of graph 'a', the machine is obviously capable of easily resolving the peaks of '1', 'untrained or inconsistent' and '0' stimuli. It even appears to be too powerful, having wasted a large number of levels that are not necessary.

However, in the case of graph 'c', the peaks are not so readily separable, and while reasonable boundaries can be drawn, these show a possible need for a machine with more potential levels in each cell (or alternatively more training.)

### Summary

It can be seen from the above experiments that several quantitative measures have been developed :

- 1 The suitability of the resolution of a machine for differentiating between the peaks of consistent, inconsistent and insufficient training,
- 2 The quality of the training itself in the two aspects :
  - sufficiency
  - consistency
- 3 The quantity of the training with regards to the possibility of excessive training in two aspects :
  - excessive, but good training (the machine is over powerful, and can easily resolve the training algorithm accurately),
  - excessive, but poor training (confusing the machine, which is incapable of resolving the algorithm).

It is believed that such techniques as those developed here give considerable insight into the potential power of LPP machines.

### 6.5 A Summary of the Experimental Work

This chapter, in conjunction with Chapters 3 and 5, completes the documentation of the experimental work performed on the various LPP machines. The problems of performing such experimental work can be summarized in three major considerations :

- 1 The basic machine has an unlimited number of variations possible in terms of its internal structure, operation and size,
- 2 The range of tasks the machine can perform is potentially large, and also covers many different types of operation,
- 3 The results cannot be easily quantified for interpretive purposes. This is because the inputs and outputs (as in all digital picture processing) are in the form of spatial arrays of pixels, which do not lend themselves readily to assessment by rigorous means.

The first of these two points when combined together give a multitude of combinations to be explored - each new combination requiring evaluation by a method that is frustrated by the third point above. However, in spite of these difficulties, experiments can be performed that do lead to conclusive results, and predictions from



extrapolations have been fulfilled. This has confirmed the validity of the predominantly pragmatic analysis used throughout these experiments.

### The Experiments 1 to 17

(Note that Experiments 1 to 12 were all devoted to parallel testing.)

The initial proving run of Experiment 1 showed that the concept of a trainable picture processing system was possible, and that it could work satisfactorily after training by examples alone.

The immediate realisation that the performance was greatly dependent on the training received led to Experiment 2, where the quantity of training was altered, and the effect on the results noted.

The initial internal state of the machine also had a considerable effect on the final results, as shown in Experiment 3.

A variation in the memory matrix cell structure and operation (the 'heart' of the machine) was attempted in Experiment 4.

Experiment 5 showed how the operation also depends on other internal parameters, such as thresholds for comparison; and also illustrated grey-scale processing.

The range of tasks was extended to illustrate the breadth and generality of picture processing applications that could be attempted with these machines in Experiment 6.

A new system for processing the memory matrix cell contents was adopted in Experiment 7 that appeared to be near optimal in terms of memory space requirements,

processing time and computational effort for this particular machine.

Rotation and reflection of the input window in training were introduced in Experiment 8 as a further enhancement to extract more information from the training set.

The effect of the window scan direction and the particular task attempted - where relevant - was illustrated in Experiment 9.

Experiment 10 used a smaller (5-bit) window as a method of introducing the technique of examining the memory matrix directly. This was used as an aid to interpretation of the machine's behaviour thereafter.

Once a more rigorous method of evaluating the training quality became available, Experiment 11 investigated the correspondence between the training set size, performance and the 'figures of merit' derived from this technique.

The use of 'down-loaded' memory matrices as a means of inserting the required algorithms into the machine was attempted in Experiment 12. However, this did not constitute any form of machine self-training or learning.

Experiment 13 was the first to involve sequential testing. In this sub-divided experiment, the training was specially created to be nearer 'optimal', in that it contained examples of a great number of features processed, and thus defined the required task closely. This experiment also made detailed comparisons of the different modes of operation available : viz. parallel and sequential processing, and the case of feedback.

A different type of memory matrix addressing format was used in Experiment 14, which was computationally more

costly, but more efficient in memory requirements.

Tasks that do not involve shape analysis were attempted in Experiment 15. These indicated the small window size used becoming restrictive, and that further work would benefit from a greater finesse in digitisation.

Experiments 16 and 17 concentrated on the behaviour of the LPP machine when 'asked to do the impossible'. The machine could detect and measure inconsistent training, and these experiments quantified this effect and its implications.

#### Experiment and Format Lists

This set of Experiments 1 to 17 is summarized in a list in Fig 6.28, which may be useful in following the development of the practical work contained herein. There is also a list of the major variations in the LPP machine formats that have been used (F1 to F9) in Fig 6.29.

This concludes the practical experimental work.

Preliminary Experiments

Exp.No.	Section	
1	3.4	Proving Run (Initial experiment)
2	3.5	Training Set Size (1 and 8 pairs)
3	3.6	Initialisation ('0' or '1' in M.M)
4	3.8	Two and Many Valued M.M Cells (One threshold)
5	3.9	Variable O/P Threshold and Grey Level Outputs

Main Set of Experiments

6	5.2	A Range of Separate Picture Processing Tasks (Clean, Invert, Thin, Thicken)
7	5.3	Tri-state/Bi-state M.M Cells
8	5.5	Augmenting Training by Window Symmetry Operations
9	5.6	The Effect of Scan Direction on an Anisotropic Picture Processing Task (with and without r+r)
10	5.7	5-bit Window and the Direct Examination of the Memory Matrix (5-bit/9-bit)
11	5.9	The Variation of TP with Training Set Size
12	5.10	Down-Loaded Memory Matrix ('Edge')

Exps. mainly on Training Methods

13	6.1	Training by specially prepared Examples (Parallel/Sequential Processing with Feedback)
14	6.2	Variations in the Addressing Function (k,t,P0)
15	6.3	Locating and Tracking of Objects
16	6.4	LPP Machine 'Neurosis'
17	6.4	Measuring of Training Quality

Fig 6.28 The Experiments 1 to 17

Format No.	Description	Experiments
F1	16 <sup>2</sup> , 9-bit Window, Bi-state M.M, Set or Clear	1,2,3,4
F2	16 <sup>2</sup> , 9-bit Window, Multi-levelled M.M, Increment or Decrement	4,5
F3	32 <sup>2</sup> , 9-bit Window, Bi-state M.M	6,7
F4	32 <sup>2</sup> , 9-bit Window, Tri-state M.M, No (r+r)	7,8,9,10
F5	32 <sup>2</sup> , 9-bit Window, Tri-state M.M, With (r+r)	8,9,11,12,13,15
F6	32 <sup>2</sup> , 5-bit Window, Tri-state M.M, No (r+r)	10
F7	32 <sup>2</sup> , 9-bit Window, Bi-state M.M, (k,t,P0) Addressing Function	14
F8	32 <sup>2</sup> , 9-bit Window, 4-state M.M, 0,?,N,1 to show Inconsistent Training	16
F9	32 <sup>2</sup> , 9-bit Window, 2x16 state counters in each M.M cell, to show Training Consistency in Detail	17

Fig 6.29 The LPP Machine Formats F1 to F9

## CHAPTER 7

THE SIMULATION OF LEARNING PICTURE PROCESSORS  
ON A MICROCOMPUTER7.1 The Need for Software Simulation of the LPP Machine

It is clear from the experiments described in the preceding chapters that it has proved possible to construct successfully working LPP machines. There are several alternative methods by which such working machines could have been created. These fall broadly into two categories :

- 1 the actual construction of the hardware, as specified in the layout and operation definitions of the machine,
- 2 the simulation of these machines on a general purpose emulator, such that it performs as the equivalent hardware.

In research work at this early stage of a complex system's life, it is generally accepted that the latter alternative offers more benefits as will be briefly discussed below.

The Advantages of Simulation

The predominant factor in judging the cost of the software or hardware approaches to generating a complex machine lies in the flexibility of either system. Where modifications are to be made to the basic machine, and where

in addition the number of such modifications will be large, the solution that facilitates these changes will be preferred. The software simulation approach provides this facility and also enables the 'virtual machine' (the machine being simulated) to be placed at the centre of an existing computing system, with the resultant access to facilities already available. There are several examples of this type of facility :

- 1 the means to feed picture information into the virtual machine,
- 2 the storage capability : it will be of great use to be able to store picture (and other) bulk data permanently,
- 3 the display of visual data in a recognisable form before, during and after the processor has acted upon it.

The speed with which an initial design and subsequent modifications can be made is another factor. The software approach allows generality with only reprogramming. The only apparent disadvantage in simulation at this early stage is the processing speed of the resultant machine. A simulated machine necessarily runs significantly slower than a purpose built hardware device. However, there is usually the opportunity for estimating relatively accurately the speed of an equivalent hardware device, once the simulation is running. Consequently, this need not be a problem in the research laboratory which is not running in a 'real time'

environment.

It should be mentioned that a compromise between hardware and software is possible in simulation, and is often an optimal solution. That is, within a framework of a simulated machine, some sub-sections can be composed of hardware that is interconnected to the simulating computer. An example in this case would be the use of a shift register type processor (61) for the extraction of windows of pixels at high speed. This could be built to the specification of the machine being simulated, and accessed by the rest of the simulating program. This approach is often superior to either a totally hardware or software based machine in terms of overall efficiency.

However, this early work on the LPP machine uses the predominantly software based approach to simulation as described below. The underlying hardware equivalents are only referenced for the purpose of performance analysis or for suggesting new versions of LPP machines.

## 7.2 The Specification of a Suitable Simulator

The Simulation System is organised as one main section and a number of auxiliary sections to facilitate operations. The main section includes the means for setting up, training and testing of a virtual LPP machine, such that it behaves as an actual machine. The auxiliary sections permit the handling of picture data on the various devices available, examination of the internal state of the machine, and the cascading and feedback of pictures around such machines. These sections are expanded upon below.



### 7.2.1. Train/Test Section

This constitutes the main core of the simulator, and enables the operator to define and exercise a LPP machine in either of its two basic modes of operation : training or testing.

In the case of training, the operator supplies the simulator with the relevant information regarding the source devices for the input and example pictures and the number of such pairs. In testing, the source of the test input pictures and the destination of the resultant output is required.

The exact format of the LPP machine depends predominantly on the version of the simulator currently in operation and, to a lesser extent, on some operator selectable options specified in response to prompts from the simulator. (It will be appreciated that many versions of the simulator were created, as a result of many LPP machine variants being created for experiment. These vary in details of operation, yet the major principles remain the same.)

### 7.2.2. Data Handler Section

This section handles picture data, to facilitate the setting up and movement of picture files to be used by the above Train/Test section. There are several requirements within this section, namely to move, edit, display or print pictures under operator control.

The movement of pictures occurs from a source device (video camera, disk storage, paper tape reader) to a destination device (disk or paper tape) and is usually used to create or modify files or sequences of pictures in the required place and device. The operator can specify the

source, destination, number and other picture parameters before the transfer occurs.

The editing facility allows pictures to be moved in a manner similar to the above, but pauses with each picture displayed on a VDU for editing by the operator under cursor control. The cursor can be moved over any pixels, which can be altered as desired, the new picture then continuing on to its destination.

The display of pictures involves the movement of pictures from a source to a VDU for visual inspection by the operator. This would generally be the inspection of a picture file before or after processing by the LPP machine. A number of pictures can be displayed simultaneously, dependent on the picture size used.

The printing of hard copy versions of these low resolution ( $16^2, 32^2$ ) pictures can be effected by moving pictures from a source device to a print buffer, and then to a character printer to form a permanent record.

### 7.2.3. Memory Matrix Handler

This section allows the operator to examine, change, load, store or print the simulated contents of the memory matrix of the virtual LPP machine. This facilitates interpretation of the machine's operation, by examination of the resultant memory matrices after training, and to make selective changes to it to see how this affects performance.

Complete memory matrices can be generated by the operator and tested, hence by-passing the normal 'train-then-test' cycle. This can be a valuable aid to understanding the machine's characteristics.

These memory matrices can be stored on disk and subsequently re-loaded, to enable re-runs of tests without repeating the same training phase on each occasion. Training can also be halted at stages throughout the training period, and the memory matrix at each stage stored, to investigate how the information in the memory matrix develops.

#### 7.2.4. Cascading and Feedback of Data

The use of picture storage media as an intermediate store allows the cascading of several (possibly different) LPP machines, and allows the use of feedback. This may be effected by one of two methods. Each pass through each machine stage may be treated as a separate test run, by temporarily storing the intermediate results, and then running the next LPP stages on this data. Alternatively, the later versions of the simulator have the facility for feedback within the internal working store of the simulator, thus avoiding the use of intermediate storage and the corresponding processing time penalty. In either case the result is the same and illustrates the operation of these multiple pass LPP machines.

This concludes a description of the facilities included in the simulator. The hierarchical structure of these sections and the functions of the sub-sections is shown in Fig 7.1. The exact construction of such a software tool depends on the hardware available, as much of the processing is related to hardware generated (visual) data. Consequently, there now follows a description of the hardware upon which this simulator will run.

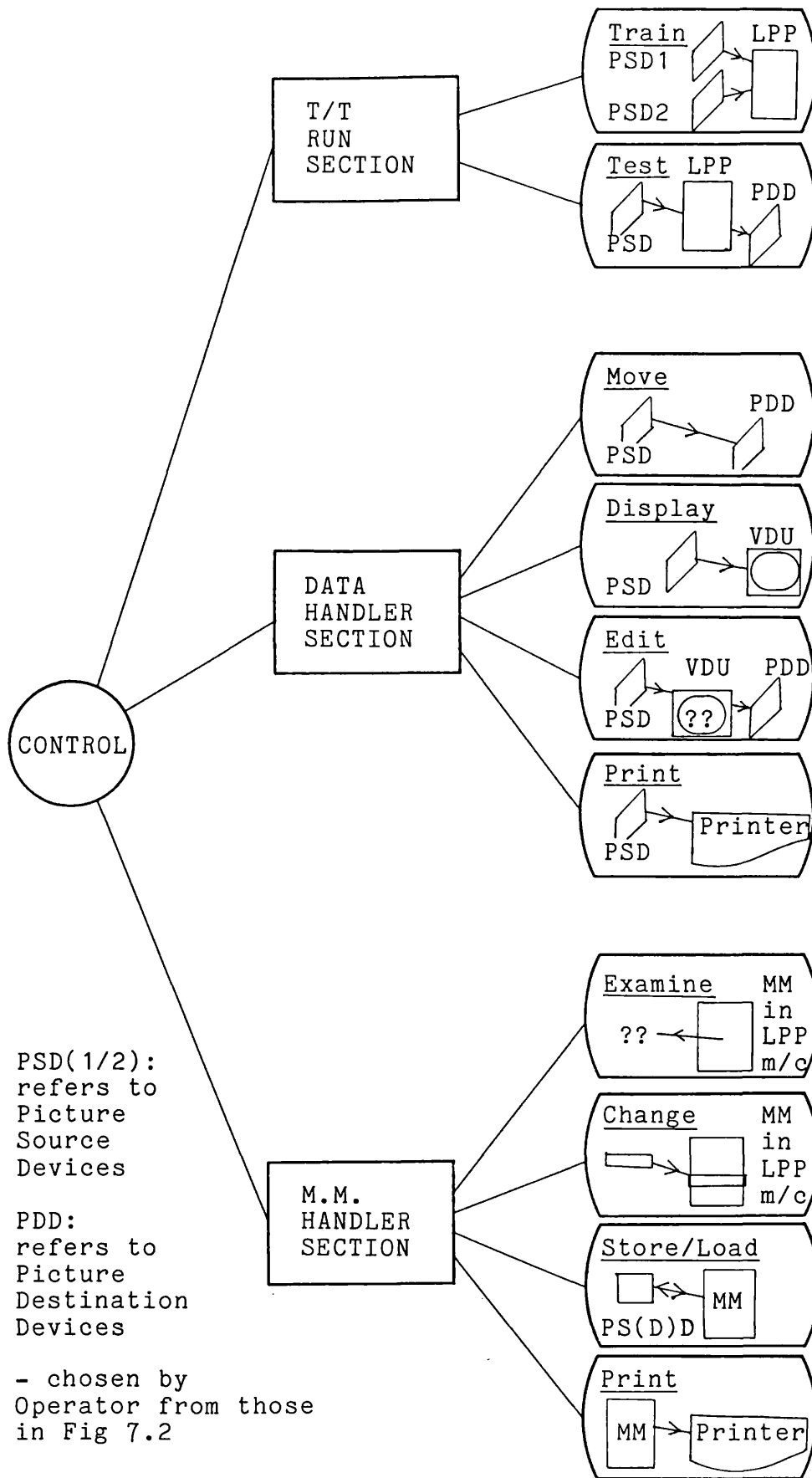


Fig 7.1 Sections of the Computer LPP Simulator

### 7.3 The Hardware Available for Picture Processing

In order to implement a simulator as described above, there is an obvious need for a suitable hardware environment. The choice of computers was restricted to one of two general categories :

- 1 large, remote mainframes, accessed via modem links,
- 2 small local machines, accessed by any local devices.

The former have the advantages of great processing speed and power, the availability of large quantities of backup storage and high system integrity and reliability. While these features are all highly desirable, they are offset by the single major disadvantage of such systems - the speed and methods available for transmitting large quantities of data to and from the system. In the field of visual picture processing, it will be appreciated that vast quantities of data are processed, necessitating high speed data transfer if experiments are to be performed in a realistic time.

Consequently, the availability of high speed video input and output devices connected to a small local machine resulted in the choice of such a machine for these experiments. These high speed devices were of the form of special purpose interfaces to digitize pictures from a conventional video camera, and to display digitized pictures. Similar systems have been described already in the literature (14).

The computer system used was a conventionally structured machine, organised around a single Motorola M6800 microprocessor (52), incorporated into a MSI-6800 micro-

computer (49,48). The main elements of the relevant hardware are described below :

- 1 CPU with 1 MHz clock
- 2 48K bytes RAM, 1K byte ROM
- 3 2K memory mapped RAM, displayed as 64x32  
video alphanumeric characters
- 4 Video input interface from camera
- 5 Floppy disk storage system
- 6 Paper tape punch
- 7 Paper tape reader
- 8 Control terminal
- 9 Printer

These devices are interconnected in a conventional bus structure as shown in Fig 7.2. This hardware forms the system on which the simulator described is implemented.

#### 7.4 The Structure and Operation of the Simulator

A simulator with the properties described in Section 7.2 was set up to run on the hardware described in Section 7.3. In addition to these facilities, the additional software tool required was a self-assembler package. This takes the form of a program, resident in the computer which enables the creation of an assembly code file (the source listing of the simulator) and the conversion of this file to a machine code file executable by the computer. The use of assembly code (and hence machine code) as opposed to a high level language interpreter or compiler on this machine was to maximize the available size, power and speed of

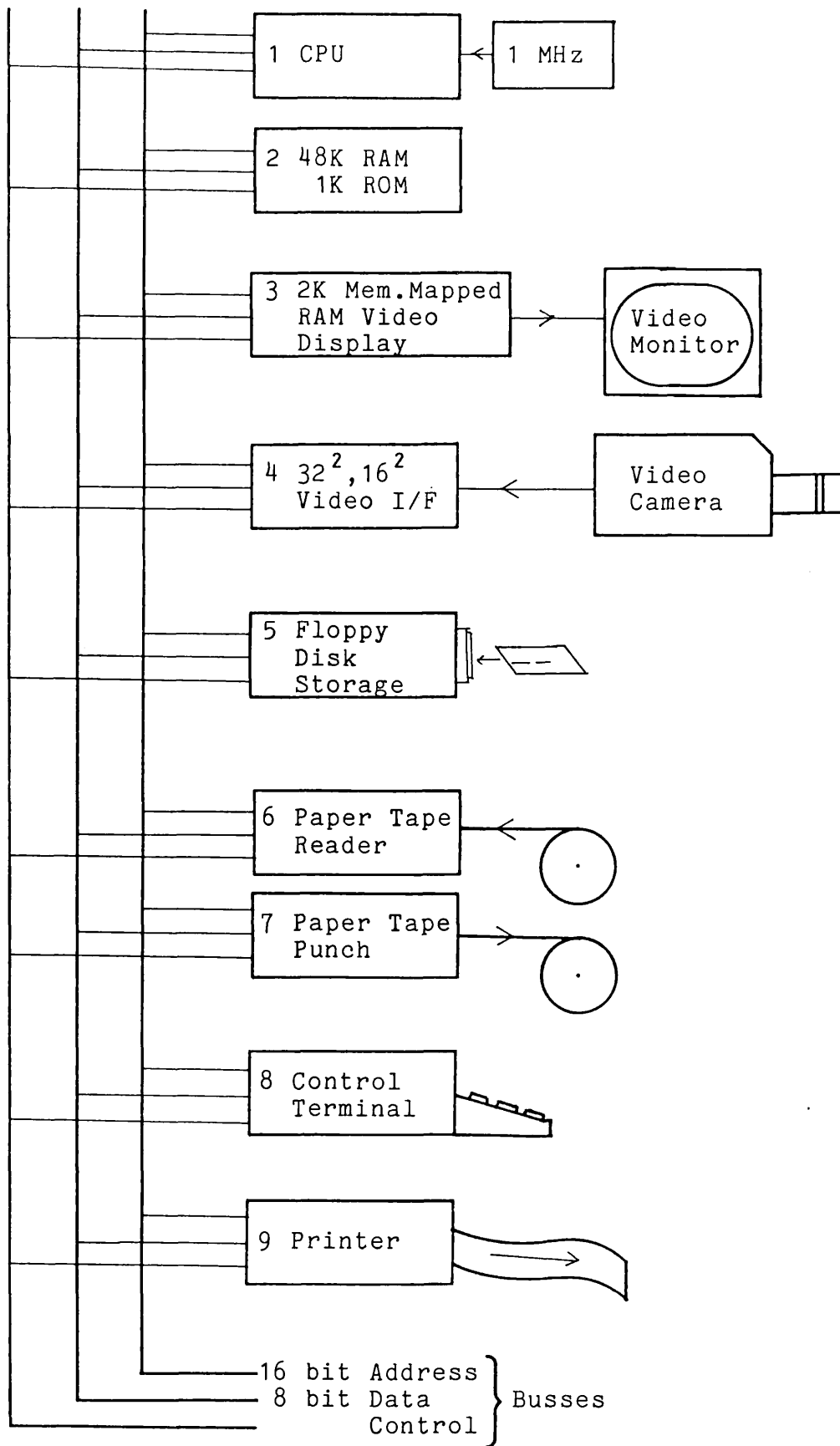


Fig 7.2 Hardware Used for Picture Processing

processing. Using this assembler, the source code for the LPP simulator was created, debugged, modified and tested.

### General Simulator Layout

The simulator is divided into three main parts, predominantly to facilitate the handling of a large program such as this, which comprises some 2000 lines of assembly code. These parts may be defined in terms of the modules in Fig 7.1 :

<u>Part 1</u>	<u>'LPPF5'*</u>	Control Section
		Train/Test Run Section
		Data Handler

( \* That is, this version simulates the F5 LPP m/c)

<u>Part 2</u>	<u>'LPPMM1'</u>	Memory Matrix Handler
<u>Part 3</u>	<u>'LPPSR21'</u>	A set of Sub-routines for :
		I/O Routines
		Calculations
		Display Routines
		Internal LPP Functions

A complete annotated assembly listing of these three parts of the simulator appears in Appendices 1a-c. Assembled code from each part is loaded into the machine at run time and these divisions become transparent. The remaining structure that is visible from the operator's viewpoint is described below. (In what follows, the labelling of each module follows the mnemonic name given in the listing in



Appendix 1. These names are usually self explanatory.)

### Operation

The program takes the form of an interrogating interpreter. Once entered, actions are carried out in accordance with the operator's responses to the simulator's queries. The sequence of events that causes the simulator to enter the various modules generally takes the following form :

- 1 The simulator announces the module in which it is currently waiting (the 'current' module)
- 2 The simulator provides a list of the modules that can be entered from the current module and requests that a choice is made ('menu-driven')
- 3 the operator responds with a valid reply, defining which new module is to be entered. (Invalid responses are ignored and control returns to '1' above.)
- 4 The desired module is entered
- 5 Dependent on the module, the simulator requests all the relevant parameters for the operation to proceed  
(For example, if in the Data Mover Section which transfers pictures between storage devices, the simulator would request the source and number of pictures to be moved and their destination)
- 6 Once all the relevant parameters have been satisfactorily supplied, the simulator executes the

function, and returns to the control level '1' above.

The actual modules, their functions and options available are listed below. This should be studied in conjunction with Fig 7.1 above.

Control and Three Main Modules

- N.B. 1. The names used for these Sections in the listings in Appendix 1 are shown thus : 'NAME',
2. 'Data' below refers to Picture Data, unless 'Cell Data' is specified, referring to Memory Matrix Cell contents.

---

<u>'LOOP'</u> can enter : (Control Section)	Train/Test Run Module Data Handler Module Memory Matrix Handler Module
<hr/>	
<u>'TTRUN'</u> can enter :	Train Section Test Section Control Section
<u>'DHAND'</u> can enter :	Move Data Section Display Data Section Edit Data Section Print Data Section Control Section
<u>'MMHAND'</u> can enter :	Print Addresses Section Print Cell Data Section Keyin Cell Data Section Totalize Cell Data Section Control Section

---

Train/Test Run Module


---

<u>'TRAIN'</u> requests :	Source and number of IPP Training Patterns  Source of EXP Training Patterns  Value of Picture Field Edge Point to use  Preset Value of M.M (if applicable)
then :	Trains Virtual Machine with Data as Specified  Requests if and where resultant M.M is to be stored on disk  Returns to 'TTRUN' Module

---

<u>'TEST'</u> requests :	Source and Number of IPP Test Patterns  Destination of OPP Patterns  Serial or Parallel Operation  Pause or not after each Test Pattern (for visual Inspection)  Value of Picture Field Edge Point to use  If and from where M.M on disk is to be loaded into Virtual machine  Number of Feedback passes to be made for each pattern
then :	Tests Virtual Machine with Data as specified  Returns to 'TTRUN' Module

---

Data Handler Module

---

<u>'MOVED'</u> requests :	Source and number of patterns to be moved  Destination of Patterns  then : Moves Data as specified  Returns to 'DHAND' Module
<u>'DISP'</u> requests :	Source and number of Patterns to be Displayed on L.H. Side of VDU  Source of Patterns to be Displayed on R.H. Side of VDU  then : Displays Data as Specified Pausing between each Pair  Returns to 'DHAND' Module
<u>'EDIT'</u> requests :	Source and Number of Patterns to be Edited  Destination of Resultant Patterns  then : Edits Patterns singly on VDU and Moves Results to Specified Destination  Returns to 'DHAND' Module
<u>'PRINTD'</u> requests :	Source and Number of Patterns to be Printed on L.H. Side of Paper  Source of Patterns to be Printed on R.H. Side of Paper  then : Prints Patterns as specified  Returns to 'DHAND' Module

---

## 7.5 The Introduction of LPP Machine Variants into the Basic Simulator

The simulator described above has been structured as a set of nested subroutines, called as required. A specific, fixed set of subroutines constitutes a particular LPP simulator. In changing the LPP machine being simulated, the change necessary in the simulator is facilitated by this nested structure. An example of this is described below, although it will be appreciated that many more versions of the simulator were created than are fully documented here.

At the lowest level of subroutine calls, the functions used in the Train and Test Sections follow the internal functions described in general terms in Section 4.2. For example, the subroutine labelled 'CADDR' (line 5000 in the listing of 'LPPF5' in Appendix 1a) is exactly equivalent to the function 'f<sub>2</sub>' in Section 4.2, where the window contents (the variables 'P0' to 'P8' in 'LPPSR21' lines 3050 to 3130) are re-arranged to form the memory matrix address ('ADDR' in 'LPPSR21' line 3180). Generally, each of these functions that describes the internal working of a particular variant of the LPP machine constitutes a single subroutine.

Consequently, it only requires a change in a particular well-defined subroutine (or sometimes a new subroutine to completely replace the old one) to effect a change in the LPP machine specification. In the example above, a change is made to the routine 'CADDR', which is then called as and when required in the train and test cycles of the simulator. Assuming it still takes the correct input variables (P0-P8) and produces the output variable (ADDR) in the correct format and position, no further changes need be made to the

remainder of the simulator to emulate the new machine. An example of such a change by the insertion of a new subroutine was described in Section 6.2 Experiment 14, where the LPP machine format was changed from F5 to F7 by this method.

(The generation of a wide variety of machines becomes simple using this method, and further confirms the greater efficiency of simulation as a solution to this problem.)

### 7.6 An Example of the Simulator in Operation

To facilitate an understanding of how the simulator works in practice, an annotated example of the interactive exchange that occurs between the simulator and the operator is presented. An actual experiment from this thesis will be performed : Experiment 11 (Part 2) - the training with four pairs of patterns and subsequent testing with one pattern (see Section 5.9). An examination of the resultant memory matrix is then made, using the 'Totalize' facility. (This counts the number of cells set to each of the three - in this case - possible values.)

The printout below takes the following form :

- 1 the outputs generated by the simulator are in upper case letters, not underlined,
- 2 the operator's responses and commands are in upper case letters, and underlined,
- 3 the annotations explaining the actions are in lower case letters in parentheses and indented,

4 the current memory mapped display (showing the patterns being processed) is shown where relevant to the current operation. The pattern format used here is  $32^2$ , two such patterns can be displayed simultaneously on the VDU.

Sample Printout - Experiment 11 (Part 2)

(All numbers are in hexadecimal)

\*

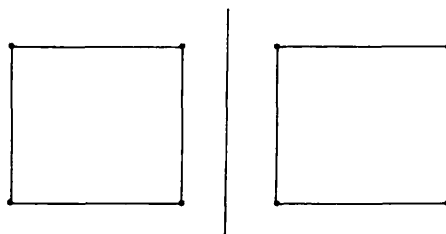
\*G 0100

LPP SYSTEM 10 - MEMORY MATRIX FORMAT F5

(system entered, version of simulator  
and format announced)

VDU TO BE CLEARED ("Y" OR "N") ? Y

(request to clear memory mapped VDU,  
response : Y(es), hence appears as -)



CONTROL LOOP - DATA HANDLER , T/T RUN , M.M. HANDLER ? T

(control loop prompt, command to enter  
t/trun section)

T/T RUN SECTION -

TRAIN OR TEST RUN ("N" OR "T") ? N

(comand to enter train section)

INPUT PATTERN (IPP) - SOURCE OF DATA -

TAPE , DISK , CAMERA , X(DUMMY) ? D

STARTING TRACK AND SECTOR (TTOS) ? 0000

NO. OF SOURCE CHARACTERS (HH) ? 04

INCREMENTAL STEP IN SOURCE FILE (HH) ? 01

(relevant parameters requested for ipp source file :  
response is that characters will come from disk,  
track/sector address 0000, four patterns separated  
by a step of '1' i.e consecutively placed on disk)



EXAMPLE PATTERN (EXP) - SOURCE OF DATA -  
 TAPE , DISK , CAMERA , X(DUMMY) ? D  
 STARTING TRACK AND SECTOR (TTOS) ? 0604

INCREMENTAL STEP IN SOURCE FILE (HH) ? 01

(as above for exp source file :  
 however it is assumed that there is the same  
 number of patterns as ipp as they come in pairs)

EDGE POINTS ("1" OR "0") ? 0

(request for picture field edge point value)

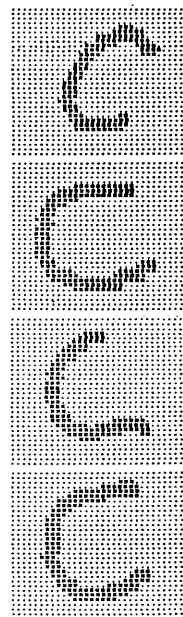
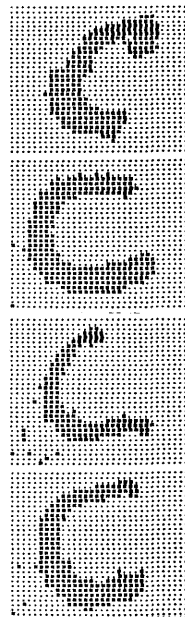
PRESET MEMORY MATRIX ("Y" OR "N") ? Y

(preset m.m cells to 'bit x' value)

READY (X) ? Y

(pause prompt, to ensure all relevant devices have  
 been correctly initialised eg. disks inserted.  
 It is here, now all the relevant information has  
 been supplied, that the actual training of the  
 virtual machine occurs. VDU displays ipp+exp pairs  
 as they are processed - )

IPPs  
  
 (four pairs  
 of 'raw'  
 and 'clean'  
 letters  
 'C')



EXPs

STORE MEMORY MATRIX ("Y" OR "N") ? Y  
 STARTING TRACK AND SECTOR (TTOS) ? 4000  
 READY (X) ? Y

(after training, option is given to store m.m  
 contents on disk for later examination or  
 reloading. This is done at t/s 4000 - a scratch  
 area on the disk)

CONTROL LOOP - DATA HANDLER , T/T RUN , M.M. HANDLER ? T  
 (return to control loop - re-enter t/trun section)

T/T RUN SECTION -  
 TRAIN OR TEST RUN ("N" OR "T") ? T  
 (enter test section)

INPUT PATTERN (IPP) - SOURCE OF DATA -  
 TAPE , DISK , CAMERA , X(DUMMY) ? D  
 STARTING TRACK AND SECTOR (TTOS) ? 0703  
 NO. OF SOURCE CHARACTERS (HH) ? 01

(ipp source file details - one pattern from disk  
 at t/s 0703)

OUTPUT PATTERN (OPP) - DESTINATION OF DATA -  
 DISK , X(DUMMY) ? D  
 STARTING TRACK AND SECTOR (TTOS) ? 4100

(opp destination details - results will be placed  
 on disk at t/s 4100 - scratch area - for later  
 examination, comparison, printing or use as input  
 to further machines)

SERIAL OR PARALLEL ("S" OR "P") ? P  
 (testing mode option)

PAUSE AFTER EACH PATTERN ("Y" OR "N") ? N  
 (facility to pause if desired between test patterns  
 to facilitate visual inspection while a test set  
 runs through machine)

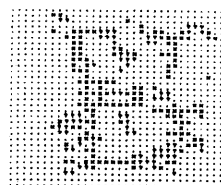
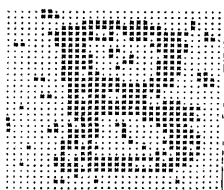
EDGE POINTS ("1" OR "0") ? 0

LOAD MEMORY MATRIX ("Y" OR "N") ? N  
 (facility to load m.m from disk, used if machine  
 had not just been trained above)

NO. OF PASSES (HH) ? 01  
 (number of feedback passes to be made by each  
 test pattern)

READY (X) ? Y  
 (here, the virtual machine is tested now all the  
 required information has been gathered. The VDU  
 displays the test patterns (ipp+opp together) as  
 the machine proceeds through the test set,  
 originally shown in Fig 5.28)

IPP



OPP

CONTROL LOOP - DATA HANDLER , T/T RUN , M.M. HANDLER ? M

(return to control loop, and enter  
m.m handler section)

MEMORY MATRIX HANDLER -  
PRINT ADDRESSES , DATA SETS , KEYIN M.M. , TOTALIZE  
OR CONTROL ? T

(function required ? - 'totalize')

LOAD MEMORY MATRIX ("Y" OR "N") ? N

(option to load m.m from disk, but is still  
in core due to above training, hence no need  
to re-load)

NO. OF M.M. LOCS SET TO BIT 0 - 09A  
NO. OF M.M. LOCS SET TO BIT X - 14A  
NO. OF M.M. LOCS SET TO BIT 1 - 01C

(simulator examines m.m in core, counts  
number of cells set to 0, X and 1, and outputs  
results on terminal in hexadecimal)

MEMORY MATRIX HANDLER -  
PRINT ADDRESSES , DATA SETS , KEYIN M.M. , TOTALIZE  
OR CONTROL ? C

(return to control loop)

CONTROL LOOP - DATA HANDLER , T/T RUN , M.M. HANDLER ? \_

(simulator awaiting further commands)

This concludes this example of the simulator listed in Appendix 1 in operation. As stated above, many versions of the simulator were created to simulate the many different versions of the LPP machine used. However, all of these simulators operated in a manner similar to that shown above.

## CHAPTER 8

## CONCLUSION

8.1 Introduction

This chapter is divided into several parts. The first will detail further experiments that would have been attempted immediately following the experiments already contained herein. A broader range of experiments and variations will also be suggested, if these investigations were to be developed to any greater extent.

The work contained in this thesis and the results which spring from it are then summarised. The implications of these results are considered in relation to the future of trainable systems in this and other applications in particular and artificial intelligence in general.

8.2 Detailed Further Work

Throughout these experiments, there have been references to LPP machine developments that might be usefully investigated. Chapter 4 represents an attempt at formalizing a range of possible alternatives regarding the detailed structure and operation of these machines. There, the suggestion was made for cascaded machines, possibly with feedback around multiple stages - the 'compound' machine (Section 4.6). This promises to exhibit interesting behaviour, even if extremely complex to interpret. However, this would form a valuable attempt at synthesizing a

learning machine composed of so many layers that its behaviour could not be easily deduced before it operated. Such a machine represents a 'deep' machine, with many learning layers between input and output, as opposed to 'broad' machines (with fewer layers, yet wide data paths between inputs and outputs) which have been shown to exhibit coherent 'intelligent' behaviour. These successes may lend inspiration to attempt these deep, compound LPP machines.

Other alternatives that would have been attempted involve the use of different (predominantly larger) window sizes, following from the fact that the final experiments illustrated the small window size to be a limitation. Variations in the pixel tessellation (eg. a hexagonal lattice) could also have been attempted, yet no immediate benefit or loss was envisaged from this alternative.

Changes in the experimentation were suggested by the arrival of a new video interface, unfortunately too late for inclusion in this experimental work. This is a new system for digitizing video signals to a higher resolution of  $128^2$  8-bit pixels. These 8-bit pixels are displayable as one of 256 grey levels, and an example of an image produced on this system is used in the frontispiece of this thesis. Grey scale processing should be possible with the LPP system. This assumes that the address generated from the window of grey scale pixels is kept to a manageable size, to avoid the need for an enormous (and thus untrainable) memory matrix. Careful choice of the size of window, number of grey levels and the transformation from window to address, should enable

a practical trainable grey-scale picture processor. (The new system also has pseudo-colour outputs, which could be usefully employed in displaying processing by examples.)

The tasks that could be attempted include grey scale stretching, colour falsification or modification. These would be trivially simple to implement as a window of one pixel could be used - generating a memory matrix address directly from each pixel. More complex processing, taking a window of multi-valued pixels could implement correspondingly more complex tasks. Any task that has a local spatial dependence could be processed by such a window oriented machine. Examples of this in fields other than picture processing are audio frequency spectrograms (possibly of speech) which are essentially two dimensional images, and consequently potential sources of suitable data. The problem here may be the provision of suitable examples of processed speech.

This may now be stated as a sufficient condition for such machines : if any well-defined task of this type (albeit by an unknown method) is capable of being illustrated by examples, then this task may be implemented using these trainable systems.

An alternative development for further work is the construction of working hardware, rather than a simulation. The realisation of near instantaneous processing speeds (for small pictures), pipelined (cascaded) processors and possibly larger frame storage are exciting possibilities here.

### 8.3 Broader Experimental Work

In Chapter 4 it was stated that modifications to the 'General LPP Machine' could be envisaged that were beyond the realms of the 'generalized' description given therein. The example was given of a window which scanned in a non-orderly fashion, but rather followed some feature of the picture content. This example is worthy of investigation, as it represents a potentially very powerful processing system which concentrates its action in specific local areas. It is often the case in picture processing, that if a local function is to be executed, local examination of the picture is not only necessary but more efficient. However, this will reduce the machine's generality, and so this cost must be examined closely.

It must be remembered that radical changes in the machine, whilst improving the performance in a particular application, may make it 'specialized'. The attraction of the general LPP machine as described in Chapter 4 lies in its task independence, by virtue of its internal arrangement. Consequently, many of the behavioural results gained by experimentation on a particular task are truly general, and thus applicable to the machine when acting on any task.

Many new techniques of image description by machine are emerging, often to increase efficiency in data storage. An example of this is the 'quadtree' or 'pyramidal' representation (76) where the resolution of samples is variable over the image, dependent on the image content. This method of data reduction could possibly serve as an alternative to the use of a scanning window in the

overriding requirement of such systems : the need to greatly reduce the quantity of data coming in. However, a careful choice of organisation of the data rearrangement must be made to ensure that the resultant machine remains :

- trainable by example,
- able to generalize, and
- capable of actually producing coherent outputs.

In fact, these requirements which have so far been applied to a spatial window could be extended to a system acting on data extracted from a temporal window. This may have possible applications in stochastic systems, or communications, where a stream of data in time is to be processed. Again, the problem will lie in providing suitable examples to train the machine.

#### 8.4 A Summary of the Experimental Work

The first chapter introduced computers applied to various tasks requiring intelligence. An example of this is the field of picture processing, where much research work has already been done in the last twenty-five years. The many alternative approaches and methods were discussed, two of which are synthesized here into a new type of machine - the trainable picture processor. These techniques are :

- 1 picture processing by look-up tables
- 2 RAMs used as learning machines



The second chapter suggested the layouts needed to implement LPP (Learning Picture Processor) machines as a practical reality. Some initial experimental investigations showed this to be a practicable method of using such machines. Variations in the internal and external conditions of operation resulted in different performances being observed and discussed.

A general system for developing and specifying a broad range of variations on this theme was proposed. This system was then used to attempt more ambitious investigations in the fifth and sixth chapters. These gave insight into the more subtle behavioural aspects of the machine. Techniques were also developed (other than merely 'observing output') to investigate the internal states and resultant behaviour of these machines. Some general conclusions and results were drawn from this investigation, summarized separately in the section below.

A description was given of the hardware and software system used to simulate the LPP machines throughout these experiments. The advantages and reasons for simulation were also discussed, and an example of the operation of this simulator was given.

Finally, this chapter suggests further work that might be attempted on these systems. Some of the wider applications are mentioned, in which such learning processors could also be applied.

## 8.5 A Summary of the Main Results

The main results gathered from these investigations are summarized below :

- 1 It is feasible to create a learning machine that will process pictures, having been trained only by experience,
- 2 The process performed will reflect the process illustrated by the examples provided,
- 3 A single machine can perform a range of tasks by re-training for each task alone,
- 4 Different complexities of machines can be envisaged. To a certain extent, the more sophisticated the machine the better the test performance, although diminishing returns may eventually become evident,
- 5 Such machines are capable of generalisation - the ability to process previously unseen pictures,
- 6 The internal size of a sequentially scanning machine is independent of the picture size processed, but the processing time is dependent on this size,
- 7 The performance depends to some extent on the internal arrangements and operation of the machine,
- 8 The performance depends to a much larger extent on the quality and quantity of examples presented to the machine in representing the desired process,

- 9 Several measurements can be taken from a given training set : quantity, consistency, etc.,
- 10 Symmetry operations can considerably increase the effective information extracted from the training set,
- 11 Sequential scanning of inputs will bias the algorithm generation towards the end of the scan period,
- 12 Much useful information can be gained from direct observation of the machine's memory matrix after training: both with regard to the particular training set and the machine's reaction to it,
- 13 If severe, but justifiable restrictions are placed on the processing possible, it is feasible to attempt a subset of all possible algorithms by their automatic generation,
- 14 Special training can be created artificially that is near optimal in expressing a required algorithm,
- 15 These machines exhibit the usual traits in the sequential as opposed to parallel mode of testing,
- 16 Feedback can be of great use in certain applications eg. thinning to a unit width skeleton,
- 17 Totally different types of internal transforms can give comparable test results, yet possibly with improved storage efficiency,
- 18 The machine can detect size comparable with the window size used,

- 19 The machine can determine the resolution needed to extract most of the information available in a given training set,
- 20 A workable machine capable of performing useful picture processing could be ultimately very small and thus cheap,
- 21 Such a machine, if purpose-built in hardware, has a potentially high processing rate, in both training and testing.

#### 8.6 Implications of These Results

It is possible to forecast some implications from the above results. As the need grows for machine generated pictures in a larger range of applications, there will be an equivalent need for machines to process these images. The possibility of small, cheap, fast processors of the type described here must surely be one candidate to help fill this need. Allied to the fact that these machines are adaptable and furthermore re-trainable without re-programming, this makes them a flexible, as well as cost-effective alternative.

By judicious choice of the internal size and organisation, a particular performance capability can also be specified, in a compromise between price and performance. Thus machines can be envisaged that have sufficient powers to execute their task without being over expensive. This must represent an ideal potential solution.

However, the problems of training such machines must not be underestimated. Since the performance of the machine depends largely on this, careful consideration must be given here. For example, can the machine be trained 'locally', and thus re-trained on site? Could 'factory-training' be used, with the corresponding economy yet loss of flexibility? Can training examples be provided in sufficient numbers and quality by an external means? These are the questions that must be answered before the use of such trainable machines in practical picture processing applications becomes effective.

#### 8.7 Wider Applications of Trainable Systems

It has been shown how the Learning Picture Processing system is in principle capable of tackling any task. It is proposed to leave the realm of the experimental work done here, and suggest that any signal processing - whatever the media, or whatever the signal represents - can be implemented on such a machine.

Any signals transducible to an electrical media - and thus able to be processed by an electronic device - should also be candidates for such intelligent processing. Sonar, microwave, radio, infra-red and X-rays are all examples of media capable of carrying such signals with high complexity and redundancy, which are already regarded as 'imaging' processes - usually representing two or three dimensional spatial images. Sound, temperature, pressure and other 'non-imaging' signals should also be capable of enhancement by this method.

Consideration of these alternative media for processing by trainable systems highlights the basic minimum requirements for such a machine. These are necessary environmental conditions for the subsequent development of the internal operations to make such a machine a practical reality.

These conditions have been stated before, and are summarized here :

- 1 A system exists where an orderly transformation in some signal is required,
- 2 External to the machine, there exists the facility for providing 'examples' of the transformation that is to occur (possibly by provision of 'before and after' examples of signals that have been processed),
- 3 A training period is allowed prior to processing, wherein the machine is given access to these examples.

(In addition, these signals must all be in a form that can be presented to and produced by the machine.)

If all these conditions are met, then a machine should be able to 'learn by example' to process correctly. It will thereafter be limited by internal consideration, such as - memory size, processing power available (and hence throughput) and the ability to react to the training correctly.

It is interesting to note that not only do these conditions apply to human learning, but also to 'unintelligent' learning. The robot paint sprayer, for example, which has its hand guided by a trained operator is

acting under the above conditions. However, it cannot 'generalize' - deal with later inputs substantially different from those used in training. The above conditions are necessary, but not sufficient for a learning machine. The intelligent machine must derive from its training some higher concept of what is required of it; to enable it to handle gross deviations in testing. The ability to generalize is a well known requirement of intelligent systems.

The experimental work has examined such learning machines in a very limited range of applications. However, it has shed some light on how such a class of machines may be constructed so as to act in an environment defined by the conditions above.

The internal actions that are necessary may be summarized in general terms as :

- 1 The machine must extract from its training stimuli a representation of what is required of it ('learn'),
- 2 This must be stored internally in such a manner as to be retrievable in a coherent form for later use ('remember'),
- 3 The description stored earlier of this operation must be capable of transforming later stimuli in a manner similar to that originally presented to the machine ('perform').

The limitations on the machine in isolation are readily predictable, often dependent on the internal arrangements used. The limitations on the performance of the entire

system (ie. the machine and its environment supplying the signals and examples) depends closely on this ability to provide suitable and accurate examples.

This thesis does not suggest where or how these examples can be produced in general. This is ultimately where the problem in developing this kind of system will lie. The band of applications where such examples can be provided is possibly narrower than might be hoped. However, it is a result of this thesis that if examples can be provided, by whatever means, learning machines can be built to respond coherently and take correct advantage of these stimuli.

#### 8.8 Future Trends in Artificial Intelligence

The machines described herein illustrate some of the possible trends developing in electronic data processing. That is, large numbers of small machines are being used, rather than the reverse. The low cost, great numbers and wide availability of such machines is bound to lead to a situation where cheap, local processing prevails.

The problem will lie not in the hardware, but in the software effort required to drive it all. This is where the techniques of artificial intelligence may be able to help. Much of the burden can be lifted from software engineering if adaptive software and systems can be produced that can 'program themselves'.

This is the goal, not only at the grand levels of artificial intelligence, but also at the lower, yet equally important and useful level of data processing of the type



described here. In fact, it is suspected that there will be many more applications using these small, relatively simple systems with adaptive processing capabilities, than the large all-powerful intelligent machine.

It is also likely that such machines may become ever more divorced from classical 'Von Neumann' computer architectures. The processors described here, for example, whilst using conventional sub-systems as components (RAMs, registers, gates, etc.) are not organised in the conventional 'stored program' manner. This has already been discussed in the literature (3) as a trend developing in existing learning machines. Undoubtedly, this will develop to a stage where radically different architectures of data processing devices will co-exist, as more knowledge is gained regarding intelligent processes.

The ultimate processor at present - the human brain - still represents this challenge. It is organised totally unlike conventional computers of today, which is a portent of their ultimate and inevitable obsolescence. The present results from scratching the surface at the workings of intelligent machines are however encouraging. Totally different types of computer are on the way. This provides inspiration in the path forward for such work in the future.

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## APPENDICES

Appendix 1      Assembly Listing of LPP Software Simulator

App. 1a	Part 1	'LPPF5'	(8 sheets)
App. 1b	Part 2	'LPPMM1'	(5 sheets)
App. 1c	Part 3	'LPPSR21'	(7 sheets)

Appendix 2      Memory Matrix Listings

App. 2a	M.M Cell Addresses and Features for F5 Machine	(4 sheets)
App. 2b	M.M Cell Contents Trained to 'THIN' in Experiment 8	(2 sheets)
App. 2c	M.M Cell Contents Trained to 'CLEAN UP' in Experiment 11	(2 sheets)
App. 2d	M.M Cell Contents Trained to 'EDGE FIND' in Experiment 12	(2 sheets)



Assembly Listing of LPP Software Simulator  
 Part 1 - Control, Train/Test, Data Handler Sections

Address	Op Code	Op Name	Comments
01090	011D	26 05	
01100	011F	BD 06AB	
01110	0122	20 E8	
01120	0124	C1 4D	
01130	0126	26 05	
01140	0128	BD 3200	
01150	0128	20 DF	
01160	012D	20 DD	
01170			
01180	012F	CE 03F0	DHAND
01190	0132	BD 1700	
01200	0135	C1 43	
01210	0137	26 01	
01220	0139	39	
01230	013A	C1 4D	
01240	013C	26 05	
01250	013E	BD 0160	
01260	0141	20 EC	
01270	0143	C1 44	
01280	0145	26 05	
01290	0147	BD 0600	
01300	014A	20 E3	
01310	014C	C1 45	
01320	014E	26 05	
01330	0150	BD 0981	
01340	0153	20 DA	
01350	0155	C1 50	
01360	0157	26 05	
01370	0159	BD 0960	
01380	015C	20 D1	
01390	015E	20 CF	
01400			
01410	0160	CE 03E5	MOVED
01420	0163	BD 1731	
01430	0166	BD 1772	
01440	0169	BD 177F	
01450	016C	7F 1300	
01460	016F	BD 1843	
01470	0172	CE 021A	
01480	0175	FF 134E	
01490	0178	7F 1353	
01500	017B	7C 1353	
01510	017E	CE 03E5	
01520	0181	BD 1797	
01530	0184	BD 1875	
01540	0187	CE 021A	
01550	018A	FF 0301	
01560	018D	7F 0300	
01570	0190	7F 030D	
01580	0193	7C 030D	
01590	0196	7E 0199	
01600			
01610	0199	CE 04E0	IOLOOP
01620	019C	BD 1700	
01630	01A2	B7 030E	
01640	01A5	BD 1800	
01650	01A8	BD 0225	
01660	01AB	BD 1819	
01670	01AE	BD 0225	
01680	01B1	FE 0301	IO4
01690	01B4	AD 00	
01700	01B6	7A 030E	
01710	01B9	26 60	
01720	01BB	BD 1830	
01730	01BE	BD 022F	
01740	01C1	BD 08BF	
01750	01C4	7A 134A	
01760	01C7	27 51	
01770	01C9	FE 1358	
01780	01CC	BD 171C	
01790	01CF	FF 1358	
01800	01D2	B6 134B	
01810	01D5	B7 135C	
01820	01D8	FE 1348	IO3
01830	01DB	BD 171C	
01840	01DE	FF 1348	
01850	01E1	7A 135C	
01860	01E4	27 10	
01870	01E6	FE 1346	
01880	01E9	8C 14B5	
01890	01EC	27 EA	
01900	01EE	BD 1800	
01910	01F1	BD 0225	
01920	01F4	20 E2	
01930	01F6	B6 1353	IO2
01940	01F9	B7 135C	
01950	01FC	FE 1350	
01960	01FF	BD 171C	
01970	0202	FF 1350	
01980	0205	7A 135C	
01990	0208	27 95	
02000	020A	FE 134E	
02010	020D	8C 14B5	
02020	0210	27 EA	
02030	0212	BD 1819	
02040	0215	BD 0225	
02050	0218	20 E2	
02060	021A	39	DUMMY
02070	021B	7D 1354	IO5
02080	021E	27 91	
02090	0220	BD 09F6	
02100	0223	20 8C	
02110	0225	FE 1340	ITRAN
02120	0228	DF 00	
02130	022A	FE 133A	
02140	022D	6E 00	
02150	022F	FE 133A	
02160	022D	6E 00	

Is it T ?  
 Yes, T/Trun...  
 Is it M ?  
 Yes, M/handler...  
 Illegal - ignore  
 - DATA HANDLER LOOP  
 "Data Handler ?"  
 Is it C ?  
 Return to Control  
 Is it M ?  
 Yes, Move data...  
 Is it D ?  
 Yes, Display data...  
 Is it E ?  
 Yes, Edit data...  
 Is it P ?  
 Yes, Print data...  
 Illegal - ignore  
 - MOVE DATA BETWEEN  
 - BULK STORAGE MEDIA  
 Initialize Source  
 (as IPP)  
 Specify L.H. VDU  
 Dummy Source of  
 for EXP  
 Initialize Desti-  
 nation (as OPP)  
 Dummy function  
 Specify NO pauses  
 Specify ONE pass...  
 Perform Transfer  
 - TO PERFORM IP/OP  
 - TRANSFERS AND

- 'JSR IOFUNC'  
 Get IPP Parameters  
 Do I/P transfer  
 Get EXP Parameters  
 Do I/P transfer  
 Get Function  
 Perform Function  
 Passes finished ?  
 Get OPP Parameters  
 Do O/P transfer  
 Pause, if told to  
 End of Source  
 file ?  
 Increment Disk T+S  
 for OPP File by 1  
 Store IPP File  
 increment  
 Increment Disk T+S  
 for IPP File by  
 'INCR1'  
 Is IPP Source a  
 disk file ?  
 No, so do an I/P  
 transfer to skip  
 unwanted patterns  
 Store EXP File  
 increment  
 Increment Disk T+S  
 for EXP File by  
 'INCR1'  
 Is EXP Source a  
 disk file ?  
 No, so do an I/P  
 transfer to skip  
 unwanted patterns  
 (Dummy Function)  
 If Y1 pass, copy  
 pattern if in  
 'Parallel mode'  
 from R>L.H. VDU  
 - DO I/P TRANSFER  
 - 'JSR SOURCE'

LDA A  
 STA A  
 JSR  
 GIPPP  
 ITRAN  
 JSR  
 GEXPP  
 ITRAN  
 JSR  
 IOFUNC  
 O, X  
 PASSNO  
 DEC  
 BNE  
 JSR  
 GOPPP  
 ITRAN  
 JSR  
 DPAUSE  
 DEC  
 SRCNOI  
 DUMMY  
 BEG  
 DTSO  
 JSR  
 INXTS  
 STX  
 DTSO  
 LDA A  
 INCR1  
 STA A  
 INCR1  
 LDX  
 STSI  
 JSR  
 INXTS  
 STX  
 STSI  
 DEC  
 INCR1  
 BEG  
 IO2  
 LDX  
 SRCI  
 &D2B2V  
 BEG  
 IO3  
 JSR  
 GIPPP  
 JSR  
 ITRAN  
 BRA  
 IO3  
 LDA A  
 INCR1  
 LDX  
 STSE  
 JSR  
 INXTS  
 STX  
 STSE  
 DEC  
 INCR1  
 BEG  
 IOLOOP+6  
 LDX  
 SRCI  
 &D2B2V  
 BEG  
 IO2+6  
 JSR  
 GEXPP  
 ITRAN  
 BRA  
 IO2+6  
 RTS  
 VDU000  
 IO4  
 BEG  
 JSR  
 COPY10  
 BRA  
 IO4  
 LDX  
 STS  
 TRACK  
 STX  
 SOURCE  
 LDX  
 SOURCE  
 JMP  
 O, X











Assembly Listing of LPP Software Simulator

Part 1 - Control, Train/Test, Data Handler Sections

06350	0A2D	BD	112E	JSR	XYLOC	Get pixel at x,y	06890	0AB4	7C	1300	INC	VDUND	Get pixel at x,y
06360	0A30	A6	00	LDA	O,X	from LH VDU	06900	0AB7	BD	112E	JSR	XYLOC	
06370	0A32	B7	0307	STA	PERMO	Store in 'PERMO'	06910	0ABA	A6	00	LDA	O,X	Is pixel '0' ?
06380	0A35	7C	1300	INC	VDUND		06920	0ABC	B1	132E	CMP	A	No, load '0' in acc.
06390	0A38	BD	112E	JSR	XYLOC	Get pixel at x,y	06930	0ABF	27	05	REQ	**7	Yes, load '1' in acc.
06400	0A3B	A6	00	LDA	O,X	from RH VDU	06940	0AC1	B6	132E	LDA	A	Store acc. at x,y
06410	0A3D	B7	0308	STA	PERM1	Store in 'PERM1'	06950	0AC4	20	03	BRA	**5	Is it < 3 ?
06420	0A40	86	20	LDA	A	'TEMP0-1'	06960	0AC6	B6	132F	LDA	A	No, increment x
06430	0A42	B7	0309	STA	TEMPO	Put 'space' in	06970	0AC9	A7	00	STA	O,X	Is it 1 ?
06440	0A45	B7	030A	STA	TEMPI	'TEMPO-1'	06980	0ACB	20	0E	BRA	O,X	Yes, decrement y
06450	0A48	7F	030B	CLR	COUNT1	Initialize	06990	0ACD	81	33	EDF7		Back to edit loop
06460	0A4E	7F	030C	CLR	COUNT2	software counters	07000	0ACF	2E	16	CMP	A	Is it 3 ?
06470	0A4E	7F	1300	EDF2			07010	0AD1	BD	0B27	BGT	EDF8	
06480	0A51	BD	112E	CLR	VDUND	On LH VDU :0'	07020	0AD4	81	31	JSR	INXCXO	No, increment x
06490	0A54	A6	00	JSR	XYLOC	swap 'TEMPO'	07030	0AD6	26	06	CMP	A	Is it 1 ?
06500	0A56	F6	0309	LDA	B	and pixel at x,y	07040	0AD8	BD	0B1E	BNE	**8	
06510	0A59	E7	00	LDA	O,X		07050	0ADB	7E	0A2A	JSR	DECYCO	Yes, decrement y
06520	0A5B	B7	0309	STA	TEMPO		07060	0ADE	81	33	JMP	EDF1	Back to edit loop
06530	0A5E	7C	1300	INC	VDUND		07070	0AEO	26	F9	CMP	A	Is it 3 ?
06540	0A61	BD	112E	JSR	XYLOC	On RH VDU :	07080	0AE2	BD	0B32	JSR	INCYCO	Yes, increment y
06550	0A64	A6	00	LDA	O,X	swap 'TEMPI'	07090	0AE5	20	F4	BRA	EDF7	
06560	0A66	F6	030A	LDA	B	and pixel at x,y	07100	0AE7	81	37	CMP	A	Is it < 7 ?
06570	0A69	E7	00	STA	O,X		07110	0AE9	2D	15	BLT	EDF9	
06580	0A6B	B7	030A	LDA	A		07120	0AEB	BD	0B15	JSR	DECXCO	No, decrement x
06590	0A6E	B6	F502	EDF3			07130	0AEE	81	37	CMP	A	Is it 7 ?
06600	0A71	47	11	BSR	A	Get control	07140	0AFO	26	05	BNE	**7	Yes, decrement y
06610	0A72	25	11	INC	EDF4	terminal flag	07150	0AF2	BD	0B1E	JSR	DECYCO	
06620	0A74	7C	030B	INC	COUNT1	Key pressed ?	07160	0AF5	20	E4	BRA	EDF7	
06630	0A77	26	F5	BNE	EDF3	No, increment	07170	0AF7	81	39	CMP	A	Is it 9 ?
06640	0A79	7C	030C	INC	COUNT2	count 1, try again	07180	0AF9	26	E0	BNE	EDF7	
06650	0A7C	B6	030C	LDA	A	Increment count2,	07190	0AFB	BD	0B32	JSR	INCYCO	Yes, increment y
06660	0A7F	84	3F	AND	A	Test count2=\$40 ?	07200	0AFE	20	DB	BRA	EDF7	
06670	0A81	26	EB	BNE	EDF3	No, try flag again	07210	0B00	81	34	CMP	A	Is it 4 ?
06680	0A83	20	C9	BRA	EDF2	Yes, flash pixels	07220	0B02	26	05	BNE	**7	
06690	0A85	7F	1300	EDF4		Flag set, so :	07230	0B04	BD	0B1E	JSR	DECYCO	Yes, decrement y
06700	0A88	BD	112E	CLR	VDUND	On LH VDU,	07240	0B07	20	D2	BRA	EDF7	
06710	0A8B	B6	0307	JSR	XYLOC	restore 'PERMO'	07250	0B09	BD	0B32	JSR	INCYCO	No, increment y
06720	0A8E	A7	00	LDA	A	to x,y	07260	0B0C	20	CD	BRA	EDF7	
06730	0A90	7C	1300	STA	O,X		07270	0B0E	81	52	CMP	A	Is it R ?
06740	0A93	BD	112E	INC	VDUND	On RH VDU,	07280	0B10	26	C9	BNE	EDF7	No, illegal-ignore
06750	0A96	B6	0308	JSR	XYLOC	restore 'PERM1'	07290	0B12	7E	0A1F	JMP	EDFUNC	Yes, restart edit..
06760	0A99	A7	00	LDA	O,X	to x,y	07300			*			
06770	0A9B	B6	F503	LDA	A	Get character	07310	0B15	7D	1318	DECXCO	TST	XCO
06780	0A9E	84	7F	AND	A	'E'	07320	0B18	27	03	BEG	**5	- DEC XCO WITHOUT
06790	0AA0	81	45	CMP	A	Is it E ?	07330	0B1A	7A	1318	DEC	XCO	- ALLOWING XCO < 00
06800	0AA2	26	01	BNE	**3		07340	0B1D	39		RTS		
06810	0AA4	39		RTS		Yes, End edit	07350		*				
06820	0AA5	81	30	CMP	A	Is it < 0 ?	07360	0B1E	7D	1319	DECYCO	TST	XCO
06830	0AA7	2D	65	BLT	EDF10		07370	0B21	27	03	BEG	**5	- DEC XCO WITHOUT
06840	0AA9	81	39	CMP	A	No, is it > 9 ?	07380	0B23	7A	1319	DEC	XCO	- ALLOWING XCO < 00
06850	0AAB	2E	61	BGT	EDF10		07390	0B26	39		RTS		
06860	0AAD	81	35	CMP	A	No, is it \$ ?	07400		*				
06870	0AAF	25	1C	BNE	EDF6	Yes, on RH VDU :	07410	0B27	F6	1318	INXCXO	LDA	B
06880	0AB1	7F	1300	CLR	VDUND		07420	0B2A	C1	1F	CMP	B	\$*1F

## Assembly Listing of LPP Software Simulator

## Part 1 - Control, Train/Test, Data Handler Sections

```

07430 0B2C 27 03      BEG      **5
07440 0E2E 7C 1318   INC      XCO
07450 0B31 39      RTS
07460
07470 0B32 F6 1319   * INCYCD LDA B   YCO      - INC YCO WITHOUT
07480 0B35 C1 1F     CMP B   $#1F  - ALLOWING YCO ) 1F
07490 0B37 27 03   BEG      **5
07500 0B39 7C 1319   INC      YCO
07510 0B3C 39      RTS
07520
07530 0B3D BD E0B1   * NPASS   JSR      WAIT2  - GET NO. OF PASSES
07540 0B40 CE 04ED   LDX     $XNPASS - FROM TERMINAL
07550 0B43 BD E07E   JSR     PDATA1  "No. passes ? "
07560 0B46 BD E055   JSR     BYTE    Get 2 hex digits
07570 0B49 B7 030D   STA A  PASSES  into 'PASSES'
07580 0B4C 7E E0B1   JMP     WAIT2   Do CRLF
07590
07600      END
TOTAL ERRORS 00000
ENTER PASS : 1P,2P,2L,2T

```







Assembly Listing of LPP Software Simulator

Part 2 - Memory Matrix Handler Section

03220	34E1 B6	1337	LDA A	PRTON	Turn printer ON	03760	355C FF	3581	* PMMADD	STX A	SAVEX	- PRINT M.M. ADDR
03230	34E4 BD	E1D1	JSR B	OUTEEE	Clear column count	03770	355F B6	3581	LDA A	LDA A	SAVEX	- IN 3 DIGIT HEX
03240	34E7 5F	AD3	CLR B	CRLFSX	Do 2x CRLFs	03780	3562 BD	E06B	JSR	JSR	OUTHR	- AND 2 SPACES
03250	34E8 BD	3577	JSR	CRLFSX	Print MM address	03800	3565 B6	3582	LDA A	LDA A	SAVEX+1	Print:
03260	34EB BD	3577	JSR	CRLFSX	Incr.MM address	03810	3568 BD	E067	JSR	JSR	OUTHL	RH digit(SAVEX)
03270	34EE BD	355C	JSR	PMMADD	Incr.col.count	03820	356B B6	3582	LDA A	LDA A	SAVEX+1	RH digit(SAVEX+1)
03280	34F1 08		INX		Col.count = 16 ?	03830	356E BD	E06B	JSR	JSR	OUTHR	RH digit(SAVEX+1)
03290	34F2 5C		CMP B	£*10	No, loop back,...	03840	3571 BD	E0CC	JSR	JSR	OUTS	Do 2 spaces
03300	34F3 C1	10	BNE	*-7	Decrement MM addr.	03860	3574 7E	E0CC	JMP	JMP	OUTS	
03310	34F5 26	F7	JSR	DEX16	Do 2x CRLFs	03870	3577 FF	3581	* CRLFSX	STX	SAVEX	- 'CRLF' WHILST
03320	34F7 BD	3464	JSR	CRLFSX	Clear column count	03880	357A BD	E0B1	JSR	JSR	WAIT2	- SAVING 'X'
03330	34FA BD	3577	JSR	CRLFSX	Print top line	03890	357D FE	3581	LDX	LDX	SAVEX	
03340	34FD BD	3577	CLR B	P234	Incr.MM addr.	03900	3580 39		RTS	RTS		
03350	3500 5F		JSR		Incr.col.count	03910						
03360	3501 BD	3475	INC B	£*10	Col.count = 16 ?	03920	3581 0002		* SAVEX	RMB	2	Temporary
03370	3504 08		INC B	*-7	No, loop back,...	03930	3583 0002		SAVEX1	RMB	2	Variable stores
03380	3505 5C	10	BNE	DEX16	Do CRLF	03940			* TOTAL	JSR	LMM+14	- TOTALIZE BITS SET
03400	3508 26	F7	JSR	CRLFSX	Clear column count	03950	3585 BD	088E	TOTAL	LDA A	BITO	- TO BIT 0,X+1
03410	350A BD	3464	JSR	CRLFSX	Print centre line	03960	3588 B6	132E	JSR	JSR	CNT	"Load MM ?"
03420	350D BD	3577	CLR B	P105	Incr.MM addr.	03970	358B BD	35A0	JSR	LDA A	BITX	Count 'BIT0's,
03430	3510 5F	348F	INX		Incr.col.count	03980	358E B6	135F	JSR	LDA A	CNT	Count 'BIT's,
03440	3511 BD	348F	INC B	£*10	Col.count = 16 ?	03990	3591 BD	35A0	JSR	LDA A	BIT1	Count 'BIT1's,
03450	3514 08		CMP B	*-7	Decrement MM addr.	04000	3594 B6	132F	JSR	JSR	CNT	Do CRLF
03460	3515 5C		JSR	DEX16	Do CRLF	04010	3597 BD	35A0	JSR	JSR	WAIT2	
03470	3516 C1	10	INC B	CRLFSX	Clear column count	04020	359A BD	E0B1	JSR	JSR	MMHAND	
03480	3518 26	F7	BNE	P876	Print bottom line	04030	359D 7E	3200	JMP	JMP		
03490	351A BD	3464	JSR		Incr.MM addr.	04040			* CNT	PSH A		- PRINT LABEL AND
03500	351D BD	3577	CLR B		Incr.col.count	04050	35A0 36		CNT	PSH A		- TOTAL
03510	3520 5F		JSR		Col.count = 16 ?	04060	35A1 36			LDX	£XNLOC	"No. of MM locs="
03520	3521 BD	34AD	JSR		No, loop back,...	04070	35A2 CE	35F1		LDX	PDATAI	
03530	3524 08		INC B		Do 2x CRLFs	04080	35A5 BD	E07E	JSR	JSR		Counting 'BIT0's ?
03540	3525 5C		CMP B	£*10	1st quarter	04090	35A8 32		PUL A	PUL A		Yes, print "0"
03550	3526 C1	10	BNE	*-7	done ?	04100	35A9 B1	132E	CMP A	BITO		Counting 'BITX's ?
03560	3528 26	F7	JSR	CRLFSX	2nd quarter	04110	35AC 26	04	BNE	CNT1		Yes, print "X"
03570	352A BD	3577	JSR	CRLFSX	done	04120	35AE 86	30	LDA A	£'0		No, print "I"
03580	352D BD	3577	JSR	CRLFSX	Do 2x CRLFs	04130	35B0 20	0B	BRA	CNT3		Print dash " - "
03590	3530 8C	4080	CPX	£MMST+£80	1st quarter	04140	35B2 B1	135F	CMP A	BITX		Clear 16-bit count
03600	3533 27	1F	BEG	AD2	done ?	04150	35B5 26	04	BNE	CNT2		Get 1st MM addr.
03610	3535 8C	4100	CPX	£MMST+£100	2nd quarter	04160	35B7 86	58	LDA A	£'X		C(CELL)=A ?
03620	3538 27	1A	BEG	AD2	done	04170	35B9 20	02	BRA	CNT3		Yes, incr. count
03630	353A 8C	4180	CPX	£MMST+£180	3rd quarter	04180	35BB 86	31	LDA A	£'1		Incr. MM addr.
03640	353D 27	15	BEG	AD2	done ?	04190	35BD BD	E1D1	JSR	OUTEEE		
03650	353F 8C	4200	CPX	£MMST+£200	4th quarter	04200	35C0 CE	360F	LDX	£XDASH		
03660	3542 26	A3	BNE	AD3	done ?	04210	35C3 BD	E07E	JSR	PDATAI		
03670	3544 B6	0306	LDA A	FFEEED	Do formfeed	04220	35C5 7F	3581	CLR	SAVEX	SAVEX+1	
03680	3547 BD	E1D1	JSR	OUTEEE	Turn printer OFF	04230	35C9 7F	3582	CLR	SAVEX	£MMST	
03690	354A B6	1938	LDA A	PRTOFF	Return	04240	35CC CE	4000	LDX	£MMST		
03700	354D BD	E1D1	JSR	OUTEEE	Do formfeed	04250	35CF 32		PUL A			
03710	3550 7E	3200	JMP	MMHAND		04260	35D0 A1	00	CMP A	0'X		
03720	3553 39		RTS			04270	35D2 26	03	BNE	£+5		
03730	3554 B6	0306	LDA A	FFEEED		04280	35D4 BD	35E3	JSR	INCSX		
03740	3557 BD	E1D1	JSR	OUTEEE		04290	35D7 08		INX			
03750	355A 20	8B	BRA	AD3								







Assembly Listing of LPP Software Simulator

Part 3 - Sub-routine Facilities Section  
(Used by Parts 1 and 2)

Address	Instruction	Comments	Address	Instruction	Comments
01090	LSR A	acc. at position	01630	LDX A	VDULOC
01100	DEC B	given by Z	01640	STA A	O,X
01110	BRA	**4	RTS		
01120	LDX B	VDULOC			
01130	LDA B	Get byte (pixel)			
01140	PSH B	from VDU			
01150	PSH A	Stack pixel			
01160	CMP B	Is pixel = "1" ?			
01170	BNE	**9			
01180	LDX	Yes, OR buffer			
01190	ORA A	byte with bit			
01200	BRA	mask			
01210	COM A	No, invert mask			
01220	LDX	and AND buffer			
01230	AND A	byte with mask			
01240	STA A				
01250	LDX	Upper half of			
01260	JSR	buffer to store			
01270	JSR	tri-state pixels			
01280	PUL A				
01290	PUL B				
01300	CMP B	Is pixel = "0" ?			
01310	BEG	**6			
01320	ORA A	No, OR buf. byte			
01330	BRA	with mask			
01340	COM A	Invert mask, AND			
01350	AND A	with buf. byte			
01360	STA A				
01370	RTS				
01380	LDX				
01390	LDA A	- TRANSFER BIT			
01400	LDA B	- BUF ) BYTE VDU			
01410	REG	Get buffer byte			
01420	ROL A				
01430	DEC B	Rotate byte so			
01440	BRA	carry contains			
01450	ROL A	bit, pointed to			
01460	BRA	by 'ZCO'			
01470	BEG	Is bit = "1" ?			
01480	JSR	No, so test upper			
01490	JSR	half of buffer			
01500	LDA A	Get upper buf. byte			
01510	LDA B				
01520	BEG				
01530	ROL A	Rotate byte so			
01540	DEC B	carry has bit			
01550	BRA	pointed to by			
01560	ROL A	'ZCO'			
01570	BEG	Is bit = "1" ?			
01580	LDA A	No, set 'BITO',			
01590	BRA	BITO			
01600	LDA A	BITX			
01610	BRA	Yes, set 'BITX',			
01620	LDA A	Get 'BITI',			
01630	FE	130E	BTDV1		
01640	A7	00			
01650	112B	39			
01660	112E	BD	1032	XYLOC	
01670	1131	7F	1314		
01680	1134	FF	1312		
01690	1137	B6	1319		
01700	113A	01			
01710	113B	B7	1315		
01720	113E	BD	1018		
01730	1141	FE	1316		
01740	1144	FF	1312		
01750	1147	B6	1318		
01770	114A	44			
01780	114B	44			
01790	114C	B7	1314		
01800	114F	B6	1318		
01810	1152	46			
01820	1153	46			
01830	1154	46			
01840	1155	84	CO		
01850	1157	B7	1315		
01860	115A	BD	1018		
01870	115D	FE	1316		
01880	1160	FF	130E		
01890	1163	39			
01900	1164	CE	0000	EDGET	
01920	1167	FF	1327		
01930	116A	FF	1329		
01940	116D	B6	1319		
01950	1170	26	05		
01960	1172	73	1327		
01970	1175	20	07		
01980	1177	81	1F	ET1	
01990	1179	26	03		
02000	117B	73	1329		
02010	117E	B6	1318	ET2	
02020	1181	26	05		
02030	1183	73	1328		
02040	1186	20	07		
02050	1188	81	1F	ET3	
02060	118A	26	03		
02070	118C	73	132A	ET4	
02080	118F	39			
02090	1190	BD	112E	GETPO	
02110	1193	A6	00		
02120	1195	B7	131E		
02130	1198	39			
02140	1199	BD	112E	PUTPO	
02150	119C	B6	131E		

Assembly Listing of LPP Software Simulator

Part 3 - Sub-routine Facilities Section  
(Used by Parts 1 and 2)

Address	Instruction	Comments	Address	Instruction	Comments	Address	Instruction	Comments
02170	119F A7 00	STA A 0,X	02710	1220 A6 81	LDA A \$B1,X	02850	1300	ORG
02180	11A1 39	RTS	02720	1222 20 03	BRA GWP7+3	02860	1300 0001	VDUIND RMB 1
02190		* GETWIN	02730	1224 B6 131D	LDA A EDGE	02870	1301 0001	RUFND RMB 1
02200	11A2 BD 1164	JSR	02740	1227 B7 1325	LDA A P7	02880	1302 B000	VDUOST FDB
02210	11A5 BD 112E	JSR	02750	122A 7D 1327	TST LHE	02890	1304 B020	VDUJST FDB
02220	11A8 BD 1010	JSR	02760	122D 26 09	BNE GWP8	02900	1306 B400	VDU2ST FDB
02230	11AB 09	DEX	02770	122F 7D 132A	TST BHE	02910	1308 B420	VDU3ST FDB
02240	11AC 01	NOP	02780	1232 26 04	BNE GWP8	02920	130A 3E00	BUFOST FDB
02250	11AD A6 41	LDA A \$41,X	02790	1234 A6 80	LDA A \$80,X	02930	130C 3F00	BUF1ST FDB
02260	11AF B7 131E	STA A PO	02800	1236 20 03	BRA GWP8+3	02940	130E 0002	VDULOC RMB 2
02270	11B2 7D 1327	TST LHE	02810	1238 B6 131D	LDA A EDGE	02950	1310 0002	BUFLUC RMB 2
02280	11B5 26 04	BNE GWP1	02820	123B B7 1326	LDA A P8	02960	1312 0002	DSUM1 RMB 2
02290	11B7 A6 40	LDA A \$40,X	02830	123E 39	RTS	02970	1314 0002	DSUM2 RMB 2
02300	11B9 20 03	BRA GWP1+3	02840		* Main Variable Table :	02980	1316 0002	DSUM3 RMB 2
02310	11BB B6 131D	GWP1				02990	1318 0001	XCO RMB 1
02320	11BE B7 131F	STA A P1				03000	1319 0001	YCO RMB 1
02330	11C1 7D 1327	TST LHE				03010	131A 0001	ZCO RMB 1
02340	11C4 26 09	BNE GWP2				03020	131B 0001	B2VDIR RMB 1
02350	11C6 7D 1328	TST THE				03030	131C 0001	B2DDIR RMB 1
02360	11C9 26 04	BNE GWP2				03040	131D 0001	EDGE RMB 1
02370	11CB A6 00	LDA A \$0,X				03050	131E 0001	P0 RMB 1
02380	11CD 20 03	BRA GWP2+3				03060	131F 0001	P1 RMB 1
02390	11CF B6 131D	GWP2				03070	1320 0001	P2 RMB 1
02400	11D2 87 1320	STA A P2				03080	1321 0001	P3 RMB 1
02410	11D5 7D 1328	TST THE				03090	1322 0001	P4 RMB 1
02420	11D8 26 04	BNE GWP3				03100	1323 0001	P5 RMB 1
02430	11DA A6 01	LDA A \$1,X				03110	1324 0001	P6 RMB 1
02440	11DC 20 03	BRA GWP3+3				03120	1325 0001	P7 RMB 1
02450	11DE B6 131D	GWP3				03130	1326 0001	P8 RMB 1
02460	11E1 B7 1321	STA A P3				03140	1327 0001	LHE RMB 1
02470	11E4 7D 1328	TST THE				03150	1328 0001	THE RMB 1
02480	11E7 26 09	BNE GWP4				03160	1329 0001	RHE RMB 1
02490	11E9 7D 1329	TST RHE				03170	132A 0001	BHE RMB 1
02500	11EC 26 04	BNE GWP4				03180	132B 0003	ADDR RMB 3
02510	11EE A6 02	LDA A \$2,X				03190	132E 60	BIT0 FCB \$60
02520	11F0 20 03	BRA GWP4+3				03200	132F FF	BIT1 FCB \$FF
02530	11F2 B6 131D	GWP4				03210	1380 0001	TNTK RMB 1
02540	11F5 B7 1322	STA A P4				03220	1331 0001	ORP RMB 1
02550	11F8 7D 1329	TST RHE				03230	1332 2E	PITO FCB \$2E
02560	11FB 26 04	BNE GWP5						
02570	11FD A6 42	LDA A \$42,X						
02580	11FF 20 03	BRA GWP5+3						
02590	1201 B6 131D	GWP5						
02600	1204 B7 1323	STA A P5						
02610	1207 7D 1329	TST RHE						
02620	120A 26 09	BNE GWP6						
02630	120C 7D 132A	TST BHE						
02640	120F 26 04	BNE GWP6						
02650	1211 A6 82	LDA A \$82,X						
02660	1213 20 03	BRA GWP6+3						
02670	1215 B6 131D	GWP6						
02680	1218 B7 1324	STA A P6						
02690	121B 7D 132A	TST BHE						
02700	121E 26 04	BNE GWP7						





Assembly Listing of LPP Software Simulator

Part 3 - Sub-routine Facilities Section  
(Used by Parts 1 and 2)

Address	Instruction	Comments	Register	Label	Address	Instruction	Comments	Register	Label
05400	LDA A	Y finished ?	Y	YCD	05870	FCC	DESTINATION OF DATA -	FCC	
05410	CMF A				05880	FCC	\$OD,\$OA	FCC	
05420	BEG				05890	FCC	'DISK', X(DUMMY) ?	FCC	
05430	JMP	Yes....			05900	FCC		FCC	
05440	LDA A	Increment x			05910	FCC		FCC	
05450	LDA B	by 'DX'			05920	ORG	\$1700	ORG	
05460	ADD B				05930	STX	SAVEX	STX	
05470	ADC A				05940	JSR	WAIT2	JSR	
05480	STA A				05950	LDX	PDATAL	LDX	
05490	STA B				05960	LDX	INEEE	LDX	
05500	INC XCD				05970	JSR	WAIT2	JSR	
05510	LDA A	x finished ?			05980	TAB		TAB	
05520	CMF A				05990	JMP		JMP	
05530	BEG	Yes.....			06000	LDX	AXSTAS	LDX	
05540	JMP	Get response to			06010	JSR	PDATAL	JSR	
05550	JSR	"O.K. ?"			06020	JMP	BADDR	JMP	
05560	CMF A	Is it Y ?			06030	INX	SAVEX	INX	
05570	BEG	No, do again....			06040	STX	SAVEX+1	STX	
05580	JMP	Yes, return....			06050	LDA A	\$%FO	LDA A	
05590	JMP				06060	BEG	INXTS1	BEG	
05600	JMP				06070	CLR	SAVEX+1	CLR	
05610	TVXMIN EQU	Machine addresses			06080	INC	SAVEX	INC	
05620	TVXMAX EQU	of Low Resolution			06090	INC	SAVEX	INC	
05630	TVYMIN EQU	interface			06100	LDX	INXTS1	LDX	
05640	TVYMAX EQU	registers			06110	LDX	INXTS1	LDX	
05650	TVXP EQU				06120	LDX	INXTS1	LDX	
05660	TVYP EQU				06130	LDX	INXTS1	LDX	
05670	TVCW EQU				06140	LDX	INXTS1	LDX	
05680	TVCR EQU				06150	LDX	INXTS1	LDX	
05690	XMIN	Variables used			06160	STX	SINIT1	STX	
05700	YMIN	in above routine			06170	JSR	WAIT2	JSR	
05710	DX				06180	LDX	SAVEX	LDX	
05720	DY				06190	JSR	PDATAL	JSR	
05730	XP				06200	LDX	AXSINIT	LDX	
05740	YP				06210	JSR	PREP+9	JSR	
05750					06220	CMP B	\$%T	CMP B	
					06230	BNE	\$%T	BNE	
					06240	LDX	\$%T2B2V	LDX	
					06250	STX	SOURCE	STX	
05760	XTVR1 FCC	Text strings :			06260	RTS		RTS	
05770	FCC	'SATISFACTORY CAMERA IMAGE			06270	CMP B	\$%D	CMP B	
05780	FCC	("Y" OR X) ?			06280	BNE	S4	BNE	
05790	FCC	'STARTING TRACK AND SECTOR			06290	JSR	GETTS	JSR	
05800	FCC	(TTOS) ?			06300	STX	WAIT2	STX	
05810	FCC	'ND. OF SOURCE CHARACTERS			06310	JSR	WAIT2	JSR	
05820	FCC	(HH) ?			06320	LDX	\$%D2B2V	LDX	
05830	FCC	'INCREMENTAL STEP IN SOURCE			06330	BRA	S3	BRA	
05840	FCC	FILE (HH) ?			06340	CMP B	\$%C	CMP B	
05850	FCC	'SOURCE OF DATA -			06350	BNE	\$%C	BNE	
05860	FCC	\$OD,\$OA			06360	LDX	\$%VREAD	LDX	
05870	FCC	'TAPE, DISK, CAMERA,			06370	BRA	S3	BRA	
05880	FCC	X(DUMMY) ?			06380	CMP B	\$%X	CMP B	
					06390	BNE	SINIT1+12	BNE	
					06400	LDX	\$%DUMMY	LDX	

Assembly Listing of LPP Software Simulator

Part 3 - Sub-routine Facilities Section  
(Used by Parts 1 and 2)

Address	Op Code	Op Name	Comments	Op Name	Comments	Address	Op Code	Op Name	Comments
06410	1770 20 D8	BRA S3		STX		06950	181C FF 1300		- from EXP stores,
06420	1772 CE 161D	SINIT2 LDX		LDX		06960	181F FE 134E		to general stores
06430	1775 BD E0/E	JSR PDATA1	- GET NO.OF SOURCE	LDX		06970	1822 FF 133A		
06440	1778 BD E055	JSR BYTE	- CHARS.	LDX		06980	1825 FE 1350		
06450	177B 8D 133E	STA A SRCNO	"No.?", I/P byte	LDX		06990	1828 FF 1340		
06470	177E 39	RTS	from terminal	LDX		07000	182B FE 1352		
06480			to 'SRCNO'	BRA		07010	182E 20 E5		
06490	177F B6 133E	SINIT3 LDA A SRCNO	GET INCREMENTAL			07020			
06500	1782 4A	DEC A	- IF NECESSARY			07030	1830 FE 1354	GOPPP	GET OPP PARAMETERS
06520	1783 2F OF	BLE S11	Is No.= 1 ?			07040	1833 FF 1300		
06530	1785 BD E081	JSR WAIT2	No.			07050	1836 FE 1356		
06530	1788 CE 163E	LDX &XINCR	"Increment ?"			07060	1839 FF 133C		
06540	178B BD E07E	JSR PDATA1				07070	183C FE 1358		
06550	178E BD E055	JSR BYTE	I/P byte			07080	183F FF 1342		
06560	1791 B7 133F	STA A INCR	to 'INCR'			07090	1842 39		
06570	1794 7E E081	JMP S11				07100			
06580						07110	1843 FE 1300	SIPPP	STORE IPP
06590	1797 FF 135A	DINIT STX	INIT DEST AND			07120	1846 FF 1344		PARAMETERS
06600	179A BD E081	JSR WAIT2	- AND RELEVANT			07130	1849 FE 133A		
06610	179D FE 135A	LDX	PARAMTERS			07140	184C FF 1346		
06620	17A0 BD E07E	JSR PDATA1	"(Section)?"			07150	184F FE 1340		
06630	17A3 CE 169F	LDX &XDINIT	"Destination ?"			07160	1852 FF 1348		
06640	17A6 BD 1709	JBR PREP+9				07170	1855 FE 133E		
06650	17A9 20 05	BRA D2				07180	1858 FF 134A		
06660	17AB FF 133C	STX DEST				07190	185B 39		
06670	17AE 20 20	BRA D10				07200			
06680	17B0 C1 44	CMP B &'D	Is it D ?			07210	185C FE 1300	SEXPP	STORE EXP
06690	17B2 26 11	BNE D3	Yes, 'disk',...			07220	185F FF 134C		PARAMETERS
06700	17B4 CE 1400	LDX &V2B2D				07230	1862 FE 133A		
06710	17B7 FF 133C	STX DEST				07240	1865 FF 134E		
06720	17BA BD 1713	JSR GETTS	Get T+S			07250	1868 FF 1340		
06730	17BD FF 1342	STX DTS				07260	186B FF 1350		
06740	17C0 BD E081	JSR WAIT2				07270	186E FE 133E		
06750	17C3 20 08	BRA D10				07280	1871 FF 1352		
06760	17C5 C1 58	CMP B &'X	Is it X ?			07290	1874 39		
06770	17C7 26 05	BNE D4	Illegal - ignore			07300			
06780	17C9 CE 100F	LDX &DUMMY	Yes, 'dummy',...			07310	1875 FE 1300	SOPPP	STORE OPP
06790	17CC 20 DD	BRA D5				07320	1878 FF 1354		PARAMETERS
06800	17CE 20 C7	BRA D4				07330	187B FE 133C		
06810	17D0 39	RTS				07340	187E FF 1356		
06820						07350	1881 FE 1342		
06830	1800	ORG \$1800				07360	1884 FF 1358		
06840	1800 FE 1344	GIPPP LDX	GET IPP PARAMETERS			07370	1887 39		
06850	1803 FF 1300	STX VDUNO				07380			
06860	1806 FE 1346	LDX SRCI	- from IPP stores,			07400			
06870	1809 FF 133A	LDX SOURCE	to general stores						
06880	180C FE 1348	LDX STSI							
06890	180F FF 1340	STX STS							
06900	1812 FE 134A	LDX SRCNO							
06910	1815 FF 133E	GIPPP1 STX							
06920	1818 39	RTS							
06930									
06940	1819 FE 134C	GEXPP LDX	GET EXP PARAMETERS						

TOTAL ERRORS 00000  
ENTER PASS + IP,2P,2L,2T

END











## Memory Matrix Cell Contents from F5 Machine

Trained to 'THIN' using Rot.+Ref. in Experiment 8

512 Cells with Addresses in Range 000-1FF (Hex)

'Preferred Subset' of Cells are boxed

000	001	002	003	004	005	006	007	008	009	00A	00B	00C	00D	00E	00F
.	?	?	?	.	?	.	?	?	?	?	?	.	?	.	?
010	011	012	013	014	015	016	017	018	019	01A	01B	01C	01D	01E	01F
.	?	?	?	?	?	.	?	.	?	?	?	.	?	.	.
020	021	022	023	024	025	026	027	028	029	02A	02B	02C	02D	02E	02F
?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?
030	031	032	033	034	035	036	037	038	039	03A	03B	03C	03D	03E	03F
.	?	?	?	.	?	?	?	.	?	?	?	.	.	?	.
040	041	042	043	044	045	046	047	048	049	04A	04B	04C	04D	04E	04F
.	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?
050	051	052	053	054	055	056	057	058	059	05A	05B	05C	05D	05E	05F
?	?	?	?	?	?	?	?	.	?	?	?	?	?	?	?
060	061	062	063	064	065	066	067	068	069	06A	06B	06C	06D	06E	06F
.	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?
070	071	072	073	074	075	076	077	078	079	07A	07B	07C	07D	07E	07F
.	?	?	?	?	?	?	?	.	.	?	?	.	.	.	.

080	081	082	083	084	085	086	087	088	089	08A	08B	08C	08D	08E	08F
?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?
090	091	092	093	094	095	096	097	098	099	09A	09B	09C	09D	09E	09F
?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?
0A0	0A1	0A2	0A3	0A4	0A5	0A6	0A7	0A8	0A9	0AA	0AB	0AC	0AD	0AE	0AF
?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?
0B0	0B1	0B2	0B3	0B4	0B5	0B6	0B7	0B8	0B9	0BA	0BB	0BC	0BD	0BE	0BF
?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?
0C0	0C1	0C2	0C3	0C4	0C5	0C6	0C7	0C8	0C9	0CA	0CB	0CC	0CD	0CE	0CF
.	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?
0D0	0D1	0D2	0D3	0D4	0D5	0D6	0D7	0D8	0D9	0DA	0DB	0DC	0DD	0DE	0DF
.	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?
0E0	0E1	0E2	0E3	0E4	0E5	0E6	0E7	0E8	0E9	0EA	0EB	0EC	0ED	0EE	0EF
.	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?
0F0	0F1	0F2	0F3	0F4	0F5	0F6	0F7	0F8	0F9	0FA	0FB	0FC	0FD	0FE	0FF
.	.	?	?	?	?	?	?	?	.	?	?	.	.	?	.

## Memory Matrix Cell Contents from F5 Machine

Trained to 'THIN' using Rot.+Ref. in Experiment 8

512 Cells with Addresses in Range 000-1FF (Hex)

'Preferred Subset' of Cells are boxed

100	101	102	103	104	105	106	107	108	109	10A	10B	10C	10D	10E	10F
.	?	.	?	?	?	.	?	?	?	?	?	.	?	.	.
110	111	112	113	114	115	116	117	118	119	11A	11B	11C	11D	11E	11F
?	?	?	?	?	?	?	?	?	?	?	?	?	?	.	.
120	121	122	123	124	125	126	127	128	129	12A	12B	12C	12D	12E	12F
?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?
130	131	132	133	134	135	136	137	138	139	13A	13B	13C	13D	13E	13F
?	?	?	?	?	?	?	?	?	?	?	?	?	?	.	.
140	141	142	143	144	145	146	147	148	149	14A	14B	14C	14D	14E	14F
?	?	.	?	?	?	?	?	?	?	?	?	?	?	?	?
150	151	152	153	154	155	156	157	158	159	15A	15B	15C	15D	15E	15F
?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?
160	161	162	163	164	165	166	167	168	169	16A	16B	16C	16D	16E	16F
.	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?
170	171	172	173	174	175	176	177	178	179	17A	17B	17C	17D	17E	17F
?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	.

---

180	181	182	183	184	185	186	187	188	189	18A	18B	18C	18D	18E	18F
.	?	.	?	.	?	.	.	?	?	?	?	?	?	?	.
190	191	192	193	194	195	196	197	198	199	19A	19B	19C	19D	19E	19F
?	?	?	?	?	?	?	?	?	?	?	?	?	?	.	.
1A0	1A1	1A2	1A3	1A4	1A5	1A6	1A7	1A8	1A9	1AA	1AB	1AC	1AD	1AE	1AF
?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	?
1B0	1B1	1B2	1B3	1B4	1B5	1B6	1B7	1B8	1B9	1BA	1BB	1BC	1BD	1BE	1BF
?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	.
1C0	1C1	1C2	1C3	1C4	1C5	1C6	1C7	1C8	1C9	1CA	1CB	1CC	1CD	1CE	1CF
.	?	.	.	?	?	.	.	?	?	?	?	?	?	.	.
1D0	1D1	1D2	1D3	1D4	1D5	1D6	1D7	1D8	1D9	1DA	1DB	1DC	1DD	1DE	1DF
?	?	?	?	?	?	?	?	?	?	?	?	?	?	?	.
1E0	1E1	1E2	1E3	1E4	1E5	1E6	1E7	1E8	1E9	1EA	1EB	1EC	1ED	1EE	1EF
.	.	?	.	?	?	.	.	?	?	?	?	?	?	?	?
1F0	1F1	1F2	1F3	1F4	1F5	1F6	1F7	1F8	1F9	1FA	1FB	1FC	1FD	1FE	1FF
.	.	.	.	?	?	?	.	.	.	?	.	?	.	?	X

## Memory Matrix Cell Contents from F5 Machine

Trained to 'CLEAN UP' using Rot.+Ref. in Experiment 11

100 Pairs of Characters used in Training Set

512 Cells with Addresses in Range 000-1FF (Hex)

Cells set to '?' (Initialisation State) are boxed

000	001	002	003	004	005	006	007	008	009	00A	00B	00C	00D	00E	00F
.	.	.	.	.	.	.	X	.	.	.	X	.	X	.	.
010	011	012	013	014	015	016	017	018	019	01A	01B	01C	01D	01E	01F
.	.	.	.	.	.	.	.	.	X	.	X	.	.	.	X
020	021	022	023	024	025	026	027	028	029	02A	02B	02C	02D	02E	02F
.	.	.	.	.	.	.	X	.	X	?	.	.	X	.	.
030	031	032	033	034	035	036	037	038	039	03A	03B	03C	03D	03E	03F
.	X	.	X	.	.	.	X	.	.	.	.	.	X	.	.
040	041	042	043	044	045	046	047	048	049	04A	04B	04C	04D	04E	04F
.	.	.	.	.	.	.	?	.	.	?	?	.	?	?	?
050	051	052	053	054	055	056	057	058	059	05A	05B	05C	05D	05E	05F
.	.	?	?	.	.	.	?	.	.	?	?	.	X	?	X
060	061	062	063	064	065	066	067	068	069	06A	06B	06C	06D	06E	06F
.	X	.	X	.	?	?	?	.	X	?	X	?	X	?	X
070	071	072	073	074	075	076	077	078	079	07A	07B	07C	07D	07E	07F
.	.	.	?	.	X	X	X	.	X	?	X	.	X	.	X

080	081	082	083	084	085	086	087	088	089	08A	08B	08C	08D	08E	08F
.	.	.	X	.	.	.	X	.	.	?	.	.	X	.	.
090	091	092	093	094	095	096	097	098	099	09A	09B	09C	09D	09E	09F
.	.	?	?	?	?	?	?	.	X	?	X	.	?	?	X
0A0	0A1	0A2	0A3	0A4	0A5	0A6	0A7	0A8	0A9	0AA	0AB	0AC	0AD	0AE	0AF
.	X	?	.	?	?	?	X	?	.	?	?	?	X	.	X
0B0	0B1	0B2	0B3	0B4	0B5	0B6	0B7	0B8	0B9	0BA	0BB	0BC	0BD	0BE	0BF
.	X	?	X	?	?	?	?	.	.	.	X	?	X	.	X
0C0	0C1	0C2	0C3	0C4	0C5	0C6	0C7	0C8	0C9	0CA	0CB	0CC	0CD	0CE	0CF
.	X	.	X	.	?	?	X	.	X	?	X	?	?	?	X
0D0	0D1	0D2	0D3	0D4	0D5	0D6	0D7	0D8	0D9	0DA	0DB	0DC	0DD	0DE	0DF
.	.	?	?	.	?	?	?	.	X	?	?	X	X	?	X
0E0	0E1	0E2	0E3	0E4	0E5	0E6	0E7	0E8	0E9	0EA	0EB	0EC	0ED	0EE	0EF
.	.	.	.	?	?	?	X	.	.	.	X	?	X	X	X
0F0	0F1	0F2	0F3	0F4	0F5	0F6	0F7	0F8	0F9	0FA	0FB	0FC	0FD	0FE	0FF
.	X	?	X	?	X	?	X	.	.	.	X	.	X	X	X

Memory Matrix Cell Contents from F5 Machine

Trained to 'CLEAN UP' using Rot.+Ref. in Experiment 11

100 Pairs of Characters used in Training Set

512 Cells with Addresses in Range 000-1FF (Hex)

Cells set to '?' (Initialisation State) are boxed

100	.	.	.	X	.	.	.	.	.	.	X	.	.	.	X
110	.	.	.	<span style="border: 1px solid black;">?</span>	.	.	.	X	.	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	X	.	X	.
120	.	.	.	X	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	.	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	X	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	X
130	.	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	.	<span style="border: 1px solid black;">?</span>	X	X	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	X	<span style="border: 1px solid black;">?</span>	X	X
140	.	.	.	.	.	.	.	X	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	.	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>
150	.	.	.	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	.	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	X
160	.	.	.	X	.	<span style="border: 1px solid black;">?</span>	X	X	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	X
170	.	X	X	X	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	X	<span style="border: 1px solid black;">?</span>	X	<span style="border: 1px solid black;">?</span>	X	<span style="border: 1px solid black;">?</span>	X	X
<hr/>															
180	.	X	.	.	.	.	.	X	.	X	.	.	X	.	.
190	.	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	.	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	X	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	X	X	X	X
1A0	.	X	.	.	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	X	<span style="border: 1px solid black;">?</span>	X	.	X	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	X
1B0	<span style="border: 1px solid black;">?</span>	X	<span style="border: 1px solid black;">?</span>	X	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	X	<span style="border: 1px solid black;">?</span>	X	X	X	<span style="border: 1px solid black;">?</span>	X	X
1C0	.	.	.	X	.	X	.	X	.	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	X	X	X	X
1D0	.	X	<span style="border: 1px solid black;">?</span>	X	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	<span style="border: 1px solid black;">?</span>	X	X	X	<span style="border: 1px solid black;">?</span>	X	<span style="border: 1px solid black;">?</span>	X	X
1E0	.	X	.	.	<span style="border: 1px solid black;">?</span>	X	.	X	<span style="border: 1px solid black;">?</span>	X	.	X	<span style="border: 1px solid black;">?</span>	X	X
1F0	.	X	.	X	<span style="border: 1px solid black;">?</span>	X	.	X	.	X	X	X	.	X	X

## Memory Matrix Cell Contents from F5 Machine

Trained to 'EDGE FIND' using Rot.+Ref. in Experiment 12

This M.M. was 'keyed in' by operator and is consequently

NOT the result of training by example

512 Cells with Addresses in Range 000-1FF (Hex)

'Preferred Subset' of Cells are boxed

000	001	002	003	004	005	006	007	008	009	00A	00B	00C	00D	00E	00F
.	X	.	X	.	X	.	X	.	X	.	X	.	X	.	X
010	011	012	013	014	015	016	017	018	019	01A	01B	01C	01D	01E	01F
.	X	.	X	.	X	.	X	.	X	.	X	.	X	.	X
020	021	022	023	024	025	026	027	028	029	02A	02B	02C	02D	02E	02F
.	X	.	X	.	X	.	X	.	X	.	X	.	X	.	X
030	031	032	033	034	035	036	037	038	039	03A	03B	03C	03D	03E	03F
.	X	.	X	.	X	.	X	.	X	.	X	.	X	.	X
040	041	042	043	044	045	046	047	048	049	04A	04B	04C	04D	04E	04F
.	X	.	X	.	X	.	X	.	X	.	X	.	X	.	X
050	051	052	053	054	055	056	057	058	059	05A	05B	05C	05D	05E	05F
.	X	.	X	.	X	.	X	.	X	.	X	.	X	.	X
060	061	062	063	064	065	066	067	068	069	06A	06B	06C	06D	06E	06F
.	X	.	X	.	X	.	X	.	X	.	X	.	X	.	X
070	071	072	073	074	075	076	077	078	079	07A	07B	07C	07D	07E	07F
.	X	.	X	.	X	.	X	.	X	.	X	.	X	.	X

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080	081	082	083	084	085	086	087	088	089	08A	08B	08C	08D	08E	08F
.	X	.	X	.	X	.	X	.	X	.	X	.	X	.	X
090	091	092	093	094	095	096	097	098	099	09A	09B	09C	09D	09E	09F
.	X	.	X	.	X	.	X	.	X	.	X	.	X	.	X
0A0	0A1	0A2	0A3	0A4	0A5	0A6	0A7	0A8	0A9	0AA	0AB	0AC	0AD	0AE	0AF
.	X	.	.	.	X	.	.	.	.	.	.	.	.	.	.
0B0	0B1	0B2	0B3	0B4	0B5	0B6	0B7	0B8	0B9	0BA	0BB	0BC	0BD	0BE	0BF
.	X	.	.	.	X	.	.	.	X	.	.	.	.	.	.
0C0	0C1	0C2	0C3	0C4	0C5	0C6	0C7	0C8	0C9	0CA	0CB	0CC	0CD	0CE	0CF
.	X	.	X	.	X	.	.	.	X	.	.	.	X	.	.
0D0	0D1	0D2	0D3	0D4	0D5	0D6	0D7	0D8	0D9	0DA	0DB	0DC	0DD	0DE	0DF
.	X	.	X	.	X	.	X	.	X	.	.	.	X	.	X
0E0	0E1	0E2	0E3	0E4	0E5	0E6	0E7	0E8	0E9	0EA	0EB	0EC	0ED	0EE	0EF
.	X	.	X	.	X	.	.	.	X	.	.	.	.	.	.
0F0	0F1	0F2	0F3	0F4	0F5	0F6	0F7	0F8	0F9	0FA	0FB	0FC	0FD	0FE	0FF
.	X	.	.	.	X	.	X	.	X	.	.	.	X	.	.

Memory Matrix Cell Contents from F5 Machine

Trained to 'EDGE FIND' using Rot.+Ref. in Experiment 12

This M.M. was 'keyed in' by operator and is consequently

NOT the result of training by example

512 Cells with Addresses in Range 000-1FF (Hex)

'Preferred Subset' of Cells are boxed

100	101	102	103	104	105	106	107	108	109	10A	10B	10C	10D	10E	10F
.	X	.	X	.	X	.	X	.	X	.	X	.	X	.	X
110	111	112	113	114	115	116	117	118	119	11A	11B	11C	11D	11E	11F
.	X	.	X	.	X	.	X	.	X	.	.	.	X	.	X
120	121	122	123	124	125	126	127	128	129	12A	12B	12C	12D	12E	12F
.	X	.	X	.	X	.	X	.	X	.	.	.	X	.	.
130	131	132	133	134	135	136	137	138	139	13A	13B	13C	13D	13E	13F
.	X	.	X	.	X	.	X	.	X	.	.	.	X	.	X
140	141	142	143	144	145	146	147	148	149	14A	14B	14C	14D	14E	14F
.	X	.	X	.	X	.	X	.	X	.	X	.	X	.	X
150	151	152	153	154	155	156	157	158	159	15A	15B	15C	15D	15E	15F
.	X	.	X	X	X	X	X	.	X	.	X	.	X	X	X
160	161	162	163	164	165	166	167	168	169	16A	16B	16C	16D	16E	16F
.	X	.	X	.	X	.	X	.	X	.	.	.	X	.	X
170	171	172	173	174	175	176	177	178	179	17A	17B	17C	17D	17E	17F
.	X	.	X	.	X	X	X	.	X	.	X	.	X	X	X

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180	181	182	183	184	185	186	187	188	189	18A	18B	18C	18D	18E	18F
.	X	.	X	.	X	.	X	.	X	.	X	.	X	.	X
190	191	192	193	194	195	196	197	198	199	19A	19B	19C	19D	19E	19F
.	X	.	X	.	X	.	X	.	X	.	.	.	X	.	X
1A0	1A1	1A2	1A3	1A4	1A5	1A6	1A7	1A8	1A9	1AA	1AB	1AC	1AD	1AE	1AF
.	X	.	X	.	X	.	.	.	.	.	.	.	.	.	.
1B0	1B1	1B2	1B3	1B4	1B5	1B6	1B7	1B8	1B9	1BA	1BB	1BC	1BD	1BE	1BF
.	.	.	.	.	X	.	X	.	.	.	.	.	X	.	.
1C0	1C1	1C2	1C3	1C4	1C5	1C6	1C7	1C8	1C9	1CA	1CB	1CC	1CD	1CE	1CF
.	X	.	X	.	X	.	X	.	X	.	.	.	X	.	X
1D0	1D1	1D2	1D3	1D4	1D5	1D6	1D7	1D8	1D9	1DA	1DB	1DC	1DD	1DE	1DF
.	X	.	X	.	X	.	X	.	X	.	X	.	X	.	X
1E0	1E1	1E2	1E3	1E4	1E5	1E6	1E7	1E8	1E9	1EA	1EB	1EC	1ED	1EE	1EF
.	X	.	X	.	X	.	X	.	.	.	.	.	X	.	.
1F0	1F1	1F2	1F3	1F4	1F5	1F6	1F7	1F8	1F9	1FA	1FB	1FC	1FD	1FE	1FF
.	X	.	X	.	X	.	X	.	X	.	.	.	X	X	X