An Implementation of OCR System Based on Skeleton Matching

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Abstract

This report gives a general review of the development of Optical Character Recognition (OCR), about its key problems and various of the techniques used. An implementation based on skeleton matching is introduced in detail, which is used mainly for printed character recognition and is insensitive to font style and size. This report emphasises on the implementation principles for text sectioning, preclassifier design, thinning algorithm, template database and matching strategy. An experiment is described to observe the system performance. Compared with conventional methods used, this implementation has included some new techniques, such as character dimension dependent broad classification method, AVP value used in fine classification and spelling check based post-processing method, in order to obtain a good performance.

Chapter 1

Introduction

Optical Character Recognition (OCR) is the process by which the printed characters in a document are converted automatically into computer internal codes that can be processed by computers as a textual data file.

1.1 The use of OCR systems

At the present time, keyboarding remains the the most common way of inputting data into computers. This is probably the most time consuming and labour intensive operation [Moore 1990]. OCR is the machine replication of human reading and has been the subject of intensive research for more than three decades [Stevens 1970, Rabinnow 1969, Andersson 1969]. The origin of the character recognition can be found as early as 1870 when Carey invented the retina scanner, that is an image transmission system using a mosaic of photocells. It first appeared as an aid to the visually handicapped and the first successful attempt was made by the Russian scientist Tyurin in 1900. The modern version of OCR appeared in 1940s with the development of the digital computers. It is the first time OCR was realised as a data processing approach, with a particular application to the business world [Mantas 1986]. The principle motivation for the development of OCR systems is the increased demand for capturing printed documents or text as well as pictures. The application areas include:

- Use by blind and deaf people

- Use of the photosensor as a reading aid and transfer of the recognition result into sound output or tactile symbols through stimulators.
- Use in postal department
- Reading the address and post code to classify the different district mail.
- Use in machine vision
- Use in publishing industry and in library systems
- Combined with computer word processing and desk-top publishing techniques which have been highly developed in recent years, OCR provides a revolutionary approach for computer storing, editing, accessing, indexing and republishing documents.
- Use in direct processing of documents
- As a multi-purpose document reader for large scale data processing. A attempt made by an UKC student to reproduce historical documents for teaching and researching history by the the approach of OCR together with hypertext can be found in [McGuinness 1990].
- Use in bank and security service
- For reading bank cheques, credit card imprints, and personal signatures on identification cards, etc.
- Use in business applications
- For reading product identification codes, goods declare forms and digital bar codes, etc.

1.2 The development of OCR systems

As long as the technical developments include the tremendous increase in computing power such as the capacity and the speed, and falling costs, as well as the progress in scanning technology stimulated by working out standards of Group Three digital facsimile, it is likely to result in a large market in the near future for improved OCR systems [Moore 1990].

In the past decades, a large number of research works have been reported on this topic and many commercial establishments have manufactured systems of varying capabilities. Portable, desk-top, medium size and large size systems costing as high as half a million dollars are available, and are in use for various applications [Govindan 1990].

Almost all the OCR systems have a number of difficult problems where recent advances in these aspects have been made. Recognition rate is obviously of prime importance. This is an area where systems have often fallen down. Recognition rate levels of 95% may sound high, but it still means that there can be five mistakes in every hundred characters which is unacceptable for full text retrieval applications. (One page of normal printed document may contain 5000 characters and therefore 250 wrong characters may occur) The latest systems are claiming recognition rate levels of over 99%. However the recognition rate is highly affected by many factors, such as the fonts, type size, the quality of printing, the thickness of paper, the background of text, the resolution of scanner and even the slight skewing of the text image to be scanned. The recognition rate may vary from 100% to 50% or even lower. So, perhaps it is meaningless to measure the performance of OCR systems only by the recognition rate.

The capability of processing characters in various fonts, typefaces, sizes and sets is also very important. The very first systems could only process one or two sets of characters in fixed type and size. This was the intention for issuing the OCR-A and OCR-B as two international standards in 1968. However, they never became widely used as most application required using characters which were not defined in these standards. Today the methodologies in character recognition which use sophisticated techniques have enabled the recognition of a wide variety of both complex typewritten and handwritten characters, symbols and word/script including Chinese and Japanese characters. Because that the Chinese characters are ideographs composed by strokes which in average are five times as many as in western characters, and the amount of daily used characters is over 6000 which is roughly equivalent to entire western words, the computer recognition of Chinese characters is considered to be a very hard problem and regarded as one of the ultimate goals of character recognition research. Nowadays, many OCR systems developed in China and Japan have reached fairly good performance. The information about this research can be found in [Zhang 1987, Yin+ 1986, CIRC 1988, Shu 1982, Mori+ 1980]. Besides these, so far we have seen systems that can recognise English(Latin), Cyrillic(Russian), Arabic, Indian, Greek characters and so on, in omnifont[1].

Since western character recognition has its special difficulties compared with Chinese character recognition, for example, the variable width and height, the overlapping and upper-lower cases,

[1]Characters with various fonts and sizes.

western character recognition is by no means easier. Other problems in handwritten character recognition and script recognition as well as on-line recognition probably are more difficult, and few systems are available in use today. For a review of this area please see [Davis+ 1986, Tappert+ 1990, Nouboud+ 1990].

Speed of operation is also a factor. This is decided by the type of recognition logic employed and usually is contrary to the recognition capability. The more characters can be recognised the slower the speed is. As computer processing power has grown, so also has speed of processing led by certain modern technologies such as concurrent processing and database technique, the time taken in character recognition is now much less than in the past. Scanning time and the time used in verification processing have to be taken account for as well. Modern systems can be expected to take up to 60 seconds to scan and convert a page of text.

Finally, the question is price. Like most computer related technologies, this has been falling steadily since the first working OCR systems were introduced. OCR can now be handled by a micro computer, (an example can be referred to [CIRC 1988]) scanners are available for about the same cost as a personal computer, and software to run the system can be purchased for hundreds rather than thousands of pounds. Running costs including staff time, will have to be included on top. Of course, larger scale systems offering a wider range of functions consequently cost higher price. Some practical OCRs can be found in [Govindan 1990, Mantas 1986, Moore 1990] and their prices vary from $1000 to half a million dollars.

Until recently however for most application efficient optical character recognition remained a potential rather than a practical technology: recognition rate left much to be desired and the price of OCR systems restricted its use to big organisations with continuing large scale text conversion problems. Furthermore, the range of written material suited to OCR treatment was very limited [Moore 1990].

1.3 Construction of OCR systems

In generally, a typical OCR system is composed by several parts as shown in Figure 1.1.

The system can be divided into four major parts, according to the dashed boxes in Figure 1.1. They are:

1. Preprocessing part

   The function of this part is using a page scanner to transfer the original text image into a

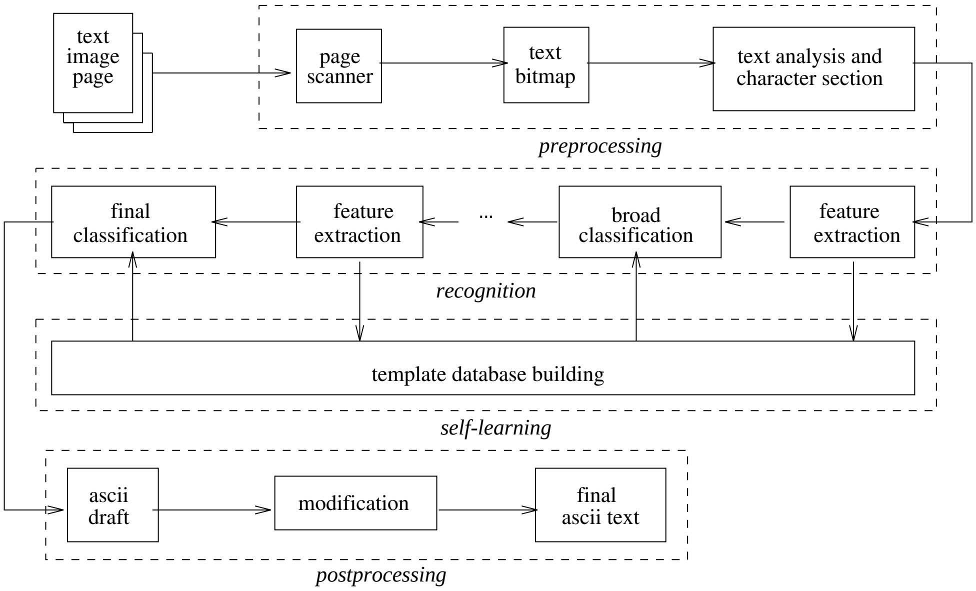


Figure 1.1: Construction of an OCR system

bitmap file or binary matrix. Text analysis techniques are applied thereafter to section the text image into lines and characters. The position of each character is recorded in order to rebuild the ASCII text file.

2. Self-learning part
   Most modern OCR systems have this function to enrich the knowledge when an unknown character is met. Character recognition is based on the database previously built in, which contains the important features related to the characters which are known already. It is necessary that this database is able to self expand as more and more new characters are met in order to increase the recognition ability. It is realised through adding new characters features and their human-given meanings into the database.

3. Recognition part
   This is the main part above all. It extracts input character features and compares these features with those recorded in the database used by the recognition. If the features are matched or closely matched, the input character is classified into a class within which all the characters

have these common features. The classification usually falls into several stages. The last stage is called final classification while the others are called broad classification. After the final classification, an individual character (result) is sorted out.

4. Postprocessing part
   The ASCII text consisting of both the recognised and rejected characters normally needs editing and modification. The purpose of this stage is to correct the mistakes, as they usually appear after the recognition stage, and supply their due meanings (ASCII characters) to the rejected characters.

For the preprocessing stage, the most important task is on the text section. A great many documents comprise not only text lines, but also pictures, maps, forms, titles or headers, etc., while the recognition stage can only process individual characters. Therefore, the superfluous information other than character text should be removed.

The methodologies applied in the recognition stage are not different to that applied in any general image pattern recognition problem, with respect to image analysis and pattern recognition. However, because of the particularity of the character recognition problem, the main methodologies used in OCR have formed their own family and can be summarised as follows [Gaillat and Berthod 1979].

1.4 Global analysis method

The key to the recognition is feature abstraction whose intention is to eliminate the redundant information which is irrelevant to the attributes of the character, while its steadable information which distinguishes this character from others should be extracted out for comparison use. Much research has concentrated effort on this topic and they can be classified into two major categories labeled as global analysis and structure analysis respectively. Global analysis directly makes use of the shape matrix to find the features of characters. Some of the most important methods are listed below.

1. Point by point global comparison
   This is the traditional method implemented by pattern matching (also called matrix or template matching) in which each digitised character is compared to a set of characters stored in

memory. When a character is matched (or closely matched), it is assigned the ASCII code linked with the corresponding character template, see Figure 1.2.

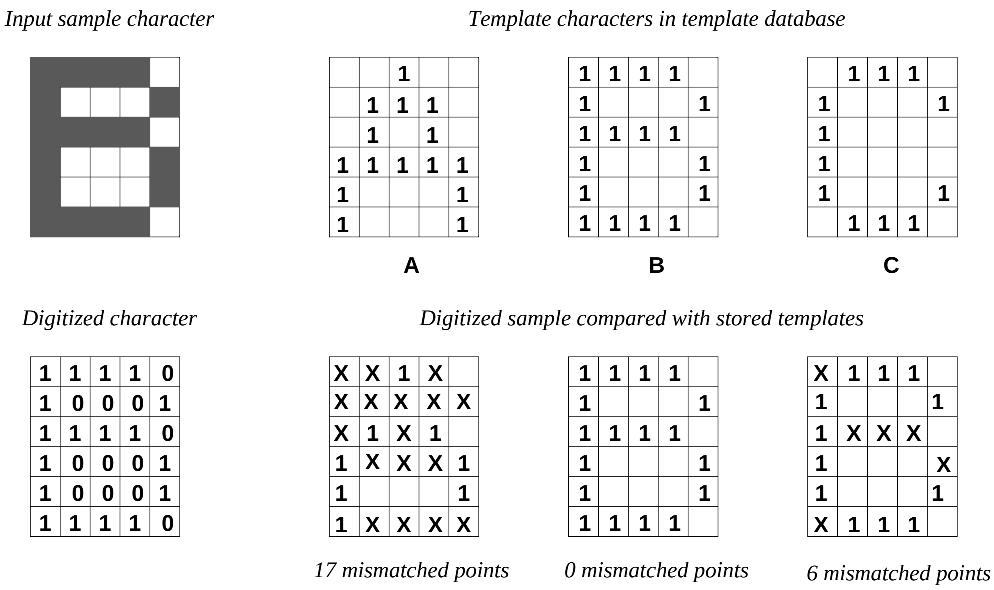


Figure 1.2: Template matching of digitised characters

The process is repeated for each character in turn. The comparison methods can be as simple as one-to-one comparison, or as complex as decision tree analysis in which only selected pixels are tested. This type of technique suffers from sensitivity to noise and is not adaptive to differences in writing style. As it is matching against existing pattern, the systems of this kind only suit those fonts whose templates have already been stored, usually only one font or typeface. However, this is a basic and effective approach.

2. Transformations
   Global transformation and series expansion technique help to reduce dimensionality of the feature vector and provides features invariant to some global deformations like translation and rotation, since the properties of characters are described in different feature space, for instance, frequency field. The possible transformations include Fourier, Hadamard, Rapid, Karhunen-Loeve, Walsh, moment calculations, and finally rotations according to the principal axis of inertia. An example of moment feature extraction is given below:

For a point in the matrix $I(i,j)$, the summary of distances from every point in the matrix is:

$$M(x,y) = \sum_{i=1}^{m}\sum_{j=1}^{n} G(i,j) i^x j^y$$

where $m \times n$ is the matrix size,

$$G(i,j) = \begin{cases} 1 & \text{if } (i,j) \text{ is a plack pixel} \\ 0 & \text{if } (i,j) \text{ is a white pixel} \end{cases}$$

$x + y$ is called the order of the moment.
A class of moment features can be selected as

$$\{M(0,0), M(0,1), M(1,0), M(1,1), \cdots, M(u,v)\}$$

(u,v) is a pair of arbitrary integer.

Such feature extraction techniques demand high computational requirements. The topological feature is not used sufficiently.

3. Cellular features
   This method divides a character into $n \times n$ components (Cellulars). Each cellular is checked in turn in eight directions to see if it has a horizontal or vertical stroke passing through. If it has, the cellular with its position is marked as a cellular feature. The input character can be sorted out by comparing these features with those stored in the template database. See Figure 1.3. It is useful in recognition of printed characters.

4. X- Y- projection
   Projecting the character shape in X and Y directions, two projection values can be obtained, each of which represents the stroke distributions on these two directions. These values are good feature properties after Fourier transformation and can be used in broad classification (refer to the recognition stage described above). This method is shown in Figure 1.4.

5. Mesh features
   Firstly the character matrix is divided into $m \times n$ components. Then for each component, the proportion between the areas of strokes and of the whole element is calculated. The $m \times n$ proportions form a mesh feature space, see Figure 1.5. It is often used in printed character recognition.

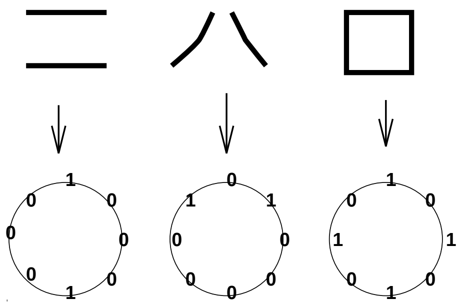


Figure 1.3: Cellular features

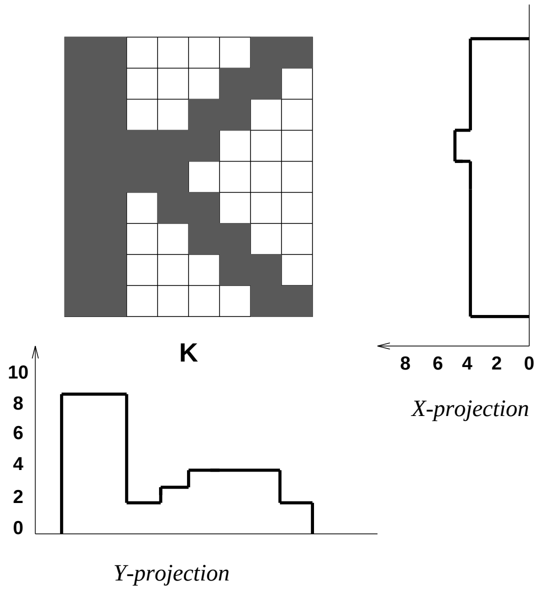


Figure 1.4: X- Y- projection features

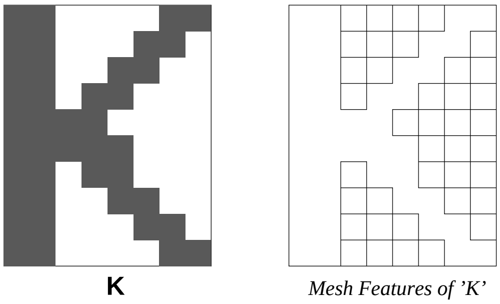


Figure 1.5: Mesh features

Besides these, there are many features obtained from other global analysis manners, such as peripheral features, surrounding coding features, Loci features, etc. Useful reading matter can be found in [Lin+ 1987, Sakai+ 1976, Glucksman 1971].

1.5 Structure analysis method

Geometrical and topological feature analysis methods are the most popular technique investigated by researchers. The features may represent global and local properties of the characters. These include strokes, bays in various directions, end points, intersections of line segments, loops, stroke relations, angular properties and sharp protrusions. These features have high tolerance to distortions and style variations, and also tolerate a certain degree of translation and rotation. They help to process characters at high speeds. However, the extraction processes are normally very complex, and it is difficult to generate masks for these type of features. Furthermore, these methods work well in recognition of characters which are mainly composed by vertical and horizontal strokes, like Chinese. While for western characters, they are probably less suitable. Some important methods are illustrated below.

1. Outline features
   The outline shape of a character usually contains very distinct and stable information to distinguish it from others. The contour can be achieved by contour tracing as proposed in [Bakis+ 1968]. The outline features like end points, intersections of line segments, bays, loops, length, directions, bumps and holes can easily be derived from the contour information.

2. Skeleton features of strokes
   The skeleton of a character embodys the basic shape information which is, in a sense, font independent. Extracting high quality skeleton for skeleton matching and topological analysis is therefore an ideal method for characters recognition, whereas in practice it remains a dream of many technicians, because of its subjective character and hard to avoid deformations. Plenty of reports about this research in past years can be found. For some examples, see [O'Gorman 1990, Y.S.Chen+ 1990, Sossa 1990, C.S.Chen+ 1990, Bourbakis 1989, Xia 1989, Arcelli 1985 1981]. Most of the skeletonisation algorithms can be classified into two essential types. The first one is medial-axis transform (MAT), which searches for the set of centers and radii of the maximal blocks contained in the objects. This kind of algorithm can preserve all the details of the objects. However, it cannot make sure that all the initial object's topology can be preserved due to the property of discrete space. Moreover, it manifests noise-sensitivity. The second type is referred to as thinning algorithms. The essence of this approach is to delete iteratively the border points if their removal does not effect the connectivity of the objects. This kind of algorithm usually has to use template matching and contour tracing because of the the disconnection of the original pattern into a number of components. The time required in these algorithms is linearly proportional to the pattern area, i.e, the size of images and the maximal thickness of the pattern. For this reason, parallel approaches appeared to make the process faster. In parallel thinning, all the pixels of the pattern are examined and, if necessary, removed simultaneously. Skeleton features can be used together with topological analysis to get end points, intersections of line segments, bays, loops, directions, bumps and holes, that might be used in the final classification.

3. Complex index features
   Complex index is the value which represents the degree of complexity in both vertical and horizontal directions. It can be described as a ratio between the total stroke length in one direction and the stroke's density in that direction. It is usually used in broad classification.

4. Edges and line segments
   Using a sub window moving across the shape matrix, a series of segments of lines is generated, by which the slope and curvature of the line can be evaluated. These features can be used to establish the graph representation of the characters. Having this representation, end points, intersection points, nodes or loops of the stroke can easily be found. They may be used in

recognition of hand written characters.

Besides these, some other solutions such as root resolving, stroke transform and coding etc., are also used. Reading matter can be found in [Stallings 1972, Jeng and Chang 1988] .

Self-learning is a fundamental procedure in the intelligent OCR systems. In some systems such as Kurtzweil K-5100 which is used in University of London Computer Center, when unknown characters are encountered, they are shown on the screen and the operator can key in their meanings. After that, the computer can "remember" these characters and it never interrogates the operator when meets them again. It can be thought of as "learning from experience". Since it goes along as it learns, more and more characters can be recognised. However, the methodology used here is rather of database techniques than OCR itself. It demands that the feature abstraction should be processed automatically and template databases have to be expandable.

Another important aspect in recognition is the clustering and comparing algorithm. For the character sets of large quantities, it is useful to use clustering method to put the characters which have similar features into a cluster, according to a certain criteria. Through this classification, the number of characters to be compared with is reduced significantly, so some sort of real time processing can be achieved. The recognition rate can be increased as well, since the final classification algorithm can be applied within a smaller cluster and performed thoroughly. Assume that the whole feature space is $S_w, C_1, C_2, \ldots, C_n$ are clusters in S_w, i.e., $C_1, C_2, \ldots, C_n \subset S_w$, Let V be feature variance in the feature space. $V(S_w)$ is the total variance in the whole space, while $V(C_i, C_j)$ $(i, j \leq n)$ and $V(C_k)$ represent the between cluster and within cluster invariance respectively. We have

$$V(S_w) = V_b + V_w$$

$$V(b) = \sum_{i=1}^{n} \sum_{j=1}^{n} V(C_i, C_j)$$

$$V(w) = \sum_{k=1}^{n} V(C_k)$$

The purpose of classification is to maximise $V(b)$ and minimise $V(w)$ based on the similarity of certain character features. The similarity can be measured by Euclidean Distance, Minkowsky Distance, Correlation Coefficient, etc., while the classification methods can be chosen from Batchelor and Wilkin's, H-means, K-means, Neighbourhood Function and Hidden Markov Model(HMM), etc. For detailed discussion please see [Jeng+ 90].

After feature abstraction, the features must be compared with those stored in the template database. The entry of the best matched character in the database is the recognition result. An example of an employed method is the Template Matching method.

We assume that the input character feature is $(X_1, X_2, \ldots, X_n)$ and template feature is $(Y_{i1}, Y_{i2}, \ldots, Y_{in})$, $i = 1, \ldots, k$, i.e., it has k clusters. Sample distance is represented as:

$$S(X_i, Y_{ik}) = \frac{(X_i, Y_{ik})}{\|X_i\| \, \|Y_{ik}\|}$$

where $\|X_i\|$, $\|Y_{ik}\|$ are the vector distances, (X_i, Y_{ik}) is inner product of vectors, its value is between 0 and 1 after normalisation.

The more similar the two vectors are, the larger the value of S. When S gets its maximum value, the corresponding template character is the recognition result.

Some other methods used include Relaxation Matching, Differential Pattern Matching, Dynamic Programming, Vector Quantisation, Neural Networks and Branch and Bound Search. For more informations please see [Jeng 1990].

Not only a good recognition strategy can achieve a high recognition rate, but also additional methods can significantly improve its performance. Postprocessing is another important stage in the whole procedure, whose aim is to reduce the mistakes in the result. Up to now, none of the recognition algorithms can avoid making errors, i.e., have 100% recognition rate in all circumstances. For this reason, means for finding and correcting such errors are indispensable. Several approaches have been developed to detect misspelled words and offer suggestions for the correct word. (see [Peterson 1980]) With the progress in database systems, various question-and-answer systems have also appeared. Usually these systems search for a word that corresponds exactly to the input in a built in dictionary. If they fail in searching for the input word, however, they merely display a warning message. For more flexible human-machine communication, it is desirable to use a spelling correction programme to search for the most likely word. Research work in this area can be found in [Takahashi+ 1989, Sinha 1989, Wells 1989]). Beside this semantic analysis, context based syntactic analysis is desirable. However it is still a unsolved problem in artificial intelligent and natural language understanding, and the technique rarely appears in the commercial systems.

This report describes a current system that recognises printed characters of certain fonts and various sizes for the Roman alphabets. The system combines several techniques in order to improve the overall recognition rate. The result has achieved a fairly good recognition rate and processing time is comparatively short. Anyhow, the research so far is not complete. Some additional techniques such as separating merged and joined characters could be applied to get better result. Nevertheless, some characteristics of this system can be summarised as below:

1. A friendly user interface was developed using X11 programming environment. Users can easily chose functions such as building up template databases, clipping a text image, setting preknowledge, previewing text file and monitoring the performance, etc.

2. Scaling is used directly on the text image at first. All the characters fall into four classes corresponding to the four template databases. This can significantly reduce the effects of noise and distortion from the thinning algorithm. From a user's point of view, it can deal with various sizes of characters.

3. An efficient thinning algorithm is applied to abstract the skeleton of the character image. Because the skeleton contains most of the structural information which are font independent or nearly independent, using skeleton matching combined with the scaling technique can suit the need of "omnifont" recognition.

4. An approximative comparing algorithm is used. Clustering and classification is based on the dimensions of characters. The comparison method incorporates the features of Dynamic Programming [Fu+ 1986] and Neural Networks [Rokert 1988], to get a closest matching result. Therefore, this system allows certain distortion to exist between sample and template characters so as to suit the wide applications.

As we described above, the global statistic analysis is more suited for processing a large quantity of characters as it is less time consuming, and for building up template database for the reason of easy feature abstraction; while the structure analysis is more ideal for processing various fonts and sizes because of owning better feature space. For printed character recognition, as well as the main aim of this system, it is desirable to combine the advantages of each of them. In this implementation, the skeleton analysis is a structural method whereas the matching is by a point-to-point global comparison. The benefit is that a good feature space can be established, however the processing is rather simple. Furthermore, the skeleton-based template database is not as large as that used in normal point-to-point matching, since it needs less templates in the database. A compression technique is also applied to make the database as small as possible.

Chapter 2

System outline

Xocr (X-environment Optical Character Recognition) is a real implementation of the character recognition system. So far, it contains nearly 10,000 C source lines and was developed in about one years time. At the first beginning, we have following design goals in mind:

1. Combine as much as possible of efficient feature analysis with global analysis techniques to achieve good overall recognition rate.

2. Aim at printed character recognition and to achieve the flexibility for the case of omnifont processing as much as possible.

3. Avoid making any change in system software and hardware, make full use of the existing facilities with ordinary system configuration.

4. Realise the system as succinctly as possible and make it easy to put into practical use.

2.1 System support

This system is developed on Sun workstations with SunOS[1] and X11[2] Window System. The system is written in C language and X interface. A page scanner was used to generate the bitmap images which normally have 300dpi resolution. The computer used was Sun4 workstation linked by NFS

[1]Sun, SunOS and Sun workstations are trademarks of Sun Microsystems, Inc.

[2]X Window is trademark of the Massachusetts Institute of Technology.

network with at least 8 Mbyte direct memory space and virtual memory. The real image was captured by a HP ScanJet Plus[3] image scanner which had 300 dpi resolution. It allows the pictures up to A4 size to be digitally sampled and turned into bitmap files that can be edited or stored on disk. The *xscan* interface has been used which allows images to be easily scanned and saved in various formats and size [Hesketh 1990].

“When run, *xscan* displays a window containing two main areas: the preview area and control area, see Figure 2.1.

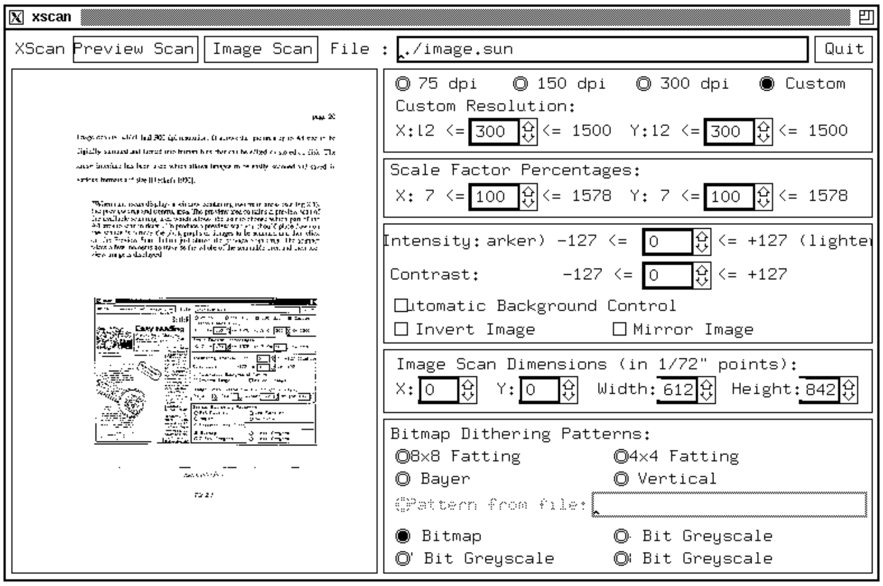


Figure 2.1: *Xscan* user interface

The preview area contains a preview scan of the available scanning area which allows the user to choose which part of the A4 area to scan in detail. To produce a preview scan you should place down on the scanner’s surface the photographs or images to be scanned and then click on the Preview Scan button just above the preview scan area. The scanner takes a few moments to traverse the whole of the scannable area and then preview image is displayed.

[3]HP ScanJet Plus is trademark of Hewlett Packard Company.

When the preview scan completed you can now choose to perform an Image Scan on a particular part of the scannerable area. To choose this area drag out a rubber box using the left mouse button. This defines the area that the scanner will scan in detail. The control area has various controls that allow you to change the dots-per-inch scanning resolution or to set the type of output.

The scanned image is saved to a file whose name is given in the box in the top right hand corner. This should be a unix file name and relative to the directory that *xscan* was start from.

Xscan uses the Sun rasterfile format to save the image it scans. the image can be saved as one of two distinct types:

- Bitmap image – A bitmap image is one which has two colours, a foreground and background colour. (This is the only image type that can be used in the *xocr* system)
- Greyscale image – A greyscale image is made up of different shades of gray ranging from black to white. These images can only be viewed directly on a colour screen and produce results similar to black and white photographs.

  ... Greyscale images can be rendered as bitmaps using two normal methods, they can be either dithered using any one of the four dither patterns built in to the scanner or they can be thresholded. ... Thresholding by hand can use the *gip* command." (More information about *gip* can be found in [Hesketh 1990]).

The user uses the four parameter boxes on the right of the *xscan* screen to obtain the optimum settings. The resolution and intensity control are heavily used in prepare scanning documents for *xocr* . Various values might be tried by various values before an optimised setting has been found. The quality of scanned image can be examined through file viewer tools like *vf* [Russell+ 1985].

For bitmap images, contrast has no effect on the result. Automatic background control which can filter background noise but might bring some losses on the pattern edges and make some strokes broken, thus we should take care in using it.

In fact, *xocr* can accept two kinds of image input format, one is X11 bitmap file, the other Sun raster file. However, only X11 bitmap file is used internally. Sun raster file will be transformed into X11 bitmap file automaticly using the *suntox11* facility provided by the X11 system. The definitions of the header structure of rasterfile and bitmap can be found in the manual page RASTERFILE(5) and BITMAP(1).

2.2 *Xocr* user interface

Xocr command usage is:

```
xocr [-bm bitmap-file] [-rf raster-file]
     [-tdir tdb-dir]
     [-tdb1 first-tdb-name] [-tdb2 second-tdb-name]
     [-tdb3 third-tdb-name] [-tdb4 fourth-tdb-name]
     [-out ascii-output-file]
     [X options . . . ]
```

where, *-bm* and *-rf* options indicate whether a bitmap or Sun raster file is used as input text image. *-tdir* followed by *tdb-dir* indicates which directory the template databases are accommodated in. Different set of template databases scatted in different directory can be chosen by this option. *first-tdb-name, second-tdb-name, third-tdb-name* and *fourth-tdb-name* are the names of four template database files used by *xocr* (described later). *Ascii-output-file* is the file name where the recognition result – ascii coded characters are written. By default, the *tdb-dir* is the current working directory; the template databases used are *tdb1.Z, tdb2.Z, tdb3.Z* and *tdb4.Z* , whereas they might not exist at the beginning. (*.Z* is the suffix of compressed file names, see COMPRESS(1)). The default *ascii-output-file* is *ascii.out* .

After a proper command has been keyed in, an typical *xocr* user interface is shown as Figure 2.2. *Xocr* provides a window consisting of the following five areas:

1. Operation section
   This area contains all the buttons to activate operations, such as to clip a region, i.e., choose a part of whole image for processing; set preknowledge (described later), build up template database, start recognition, preview ascii output file, monitor the performance, change related file name and inquire system parameters and so on.

2. Message window
   This area displays the system messages to feed back to the user.

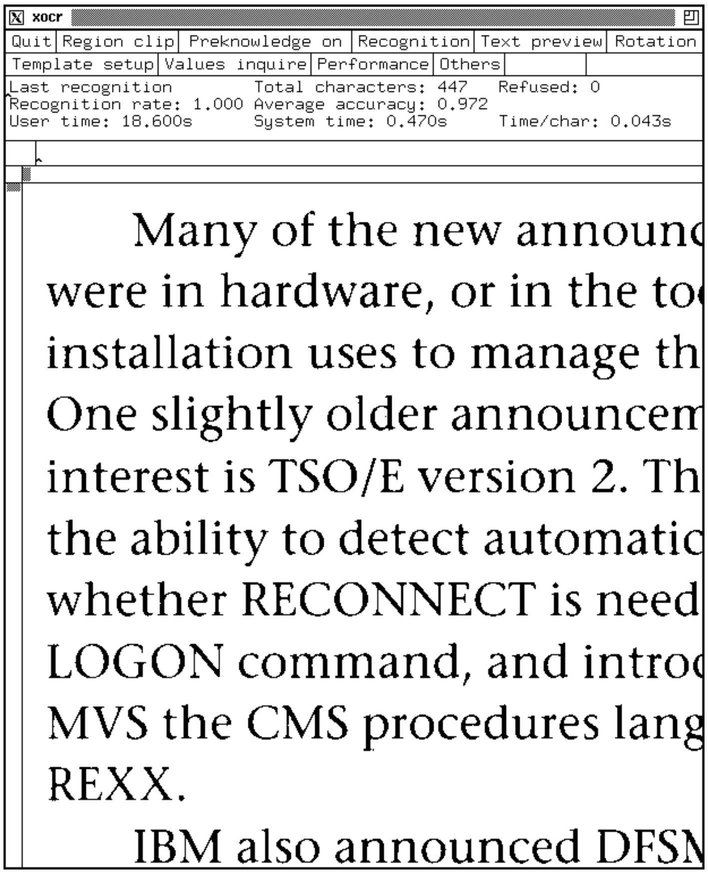


Figure 2.2: *Xocr* user interface

3. Input window
   This area is headed by an input flag which is set when an input is needed. The input information is edited and accepted within this area.

4. Text image display window
   When a text image file whether in raster file or bitmap file format has been properly indicated, the text image is loaded here after a short delay. When the clipping region operation is selected in the operation selection area, a rubber-band-rectangle can be dragged out from this window to choose the working area. The window can scroll in both vertical and horizontal directions. The mouse pointer position in this window can be reflected from the position display window above when any mouse button has been pressed.

   The ascii text (recognition result) is also displayed and edited here when text preview is selected.

Relevant operations

1. Clip a region
   Firstly, select the 'Region clip' button. Then move the mouse to the image window, press the left button, a rubber- band-rectangle will appear. The dragging can be continued after the image scrolling (in case of dealing with the image part outside the display window) by pressing the middle button while moving the mouse. After the rectangle has covered the proper area, pressing the right button will save the clipping. Once the left button has been pressed, the previous region will be lost.

2. Pre-knowledge set
   There are two pre-knowledge, which are the size of character 'O' and the offset between two words. They can significantly benefit the section procedure. The input image will be sectioned into lines and characters, these two pre-knowledge can help to make good justification between upper case and lower case characters, and also help to separate the words correctly. Therefore, the user would be better give these two values. The former can be obtained by clipping a capital letter 'O' in the image wherever possible, if not, other capital letters can be instead. The latter is input through the input window.

3. Template setup
   The template can be setup whether at the beginning or in the middle of *xocr* execution

(except that it has to be done at the beginning when none of the templates is available). When 'Template setup' has been selected, a section process starts, then a box will be around each character, and it waits for the user to input the name of the character. After the input has been given, a check procedure will be exerted to avoid building redundant template in the database. The input of the character name should be paid a great attention, since the input will directly write to the database file and there is no easy way to correct the mistakes. The template comes from a region if a region has been selected or from the whole image if no region has been found.

4. Recognition
   There are two options to the recognition. When 'Interactive' has been selected, *xocr* will stop at each unknown character which has not been met before, in other words, no template in the database can match the input character. After the user has input the character name, the recognition will continue, and the unknown character is remembered. This is called self-learning. For non-interactive recognition, *xocr* never stops at any character, and marks any unknown characters as '[]' which means that the characters are rejected. The number of recognised characters is displayed on the output window while the recognition is working.

5. Inquire values
   Some important parameters used by *xocr* can be inquired and will be displayed on the output window when the user selects the name concerned in 'Value inquire'.

6. Performance display
   When the user selects the 'Performance' button, the statistic result of the last recognition will be displayed on the output window, which includes: the total characters, rejected ones, recognition rate, time used and so on.

7. Ascii text preview
   The recognition result is ascii text, and can be displayed and edited at this stage. There are two options to view the text, one is with spelling check and another is without spelling check. Because some similar characters like '1' and 'l' may be confused when being recognised, sometimes we need a spelling check to pick out these mistakes.

   When the user previews the text with spelling check, the ascii text is displayed on the text display window (or the image window), two subwindows will popuped as well and can be placed anywhere convenient. One of the subwindows is named 'Misspelled' which contains all the mis-spelled words, another is 'Suggestion' which contains possible correct options for each mis-spelled word. When the user types <ctr-R>, the third subwindow which is the replace window will be popup. This is part of the operations of Athena asciiText widget, further information about this can be found in the relevant document. To get the suggestions, the user can move the mouse to one of the mis-spelled words in 'Misspelled' window and press the left button twice. Soon afterwards, the corresponding suggestion will appear in the 'Suggestion' window. The current mis-spelled word will automatically become the search text of the replace window. When the user chooses the preferred suggestion by pressing the left button twice in 'Suggestion' window, the right word will become the replace text of replace window. Then the user can press the 'Search' and 'Replace' button to replace the text. All the text windows are fully editable.

When the user chooses the preview function without spelling check, only the ascii text is displayed on the text display window.

Selecting any button will save the text file.

8. Rotate the image
   A scanned image usually appears inclined, it can be corrected by this command. When the user has chosen this button, there will be five new windows and two new button placed in the input area, which are listed below:

   (1) X0 and Y0: Coordinates of the first pixel in a inclined line;

   (2) X1 and Y1: Coordinates of the second pixel in the same inclined line;

   (3) Ok: This is the button to start image rotation;

   (4) Cancel: This button will end the image rotation, and restore the input area as before.

   (X0, Y0) and (X1, Y1) could be any pixels in the same inclined line. *Xocr* determines the rotating angle by these two coordinates. After the image has been rotated, the inclined line will become a horizontal one. This function sometimes might cause some loss of image quality.

9. Others
   File names can be changed and bitmap or raster image file can be reloaded through the popup

menus of this selection. It is the normal way to quit the text preview and go on to process next document image.

For further details please refer to the manual page XOCR(1).

The next part will explain how the functions are realised according to each of the stage described above.

Chapter 3

System Implementation

3.1 Preprocessing

3.1.1 Inclined image correction

A scanned image usually appears inclined. This is because that there is no mechanism available in ordinary scanner to easily correct this inclination. However, the image inclination has a serious effect on the section stage. The text image might not be sectioned into lines to lines correctly because the detection of lines is based on the horizontal projection, and no evident zero projections could be found in heavily inclined images.

Image rotation is realised by the trigonometric transformation to of each pixel in the bitmap. The rotation is around the up-left corner of the original image. The user inputs coordinates of two pixels in the same inclined line. The angle formed by the line passing through the two pixels and the horizontal line is the rotation angle. Rotating the image by this angle in the opposite direction results in the corrected image.

Let $F(i, j)$ be the pixel in (x, y) position of the text image:

$$F(i,j) = \begin{cases} 0 & \text{for white pixels} \\ 1 & \text{for black pixels} \end{cases} \tag{3.1}$$

The image is like in Figure 3.1, where (X_s, Y_s) is the up-left corner of the image while (X_e, Y_e) is the bottom-right corner.

Let (x_0, y_0) and (X_1, Y_1) be the two coordinates input by the user, the rotation angle θ is:

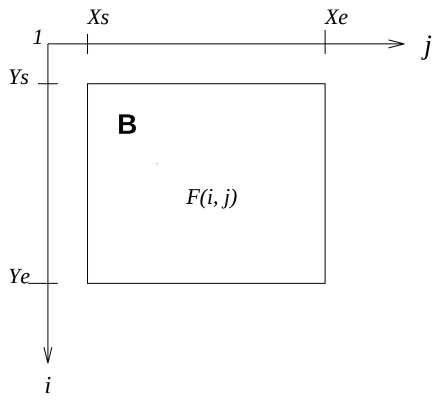


Figure 3.1: The image

$$\theta = -arc\,tan\frac{y_1 - y_0}{x_1 - x_0} \tag{3.2}$$

$(x_1 - x_0 > 0)$

Let $P(x, y)$ be a black pixel in the original image B. The new pixel position in the transformed image B' is $P'(x', y')$:

$$P'(x', y') = \begin{cases} x' = rcos(\theta_0 + \theta) \\ y' = rsin(\theta_0 + \theta) \end{cases} \tag{3.3}$$

where:

$r = ((x_1 - x_0)^2 + (y_1 - y_0)^2)^{1/2}$

$\theta_0 = arc\,tan(y/x)$ where x $\neq 0$

See Figure 3.2.

3.1.2 Line section and character section

The text image scanned by a image scanner may contain text, titles, pictures, graphics, tables and so on. Some noise may also be involved. Text section is processed manually instead of auto analysis. This is because that on the one hand, to separate text image from titles, pictures or graphics is no longer a difficult task for the operator using mouse dragging in a window system, and the amount

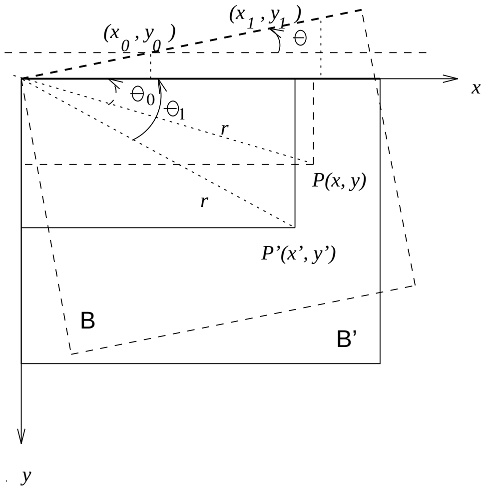


Figure 3.2: Image rotation

of separation work is usually not too much; on the other hand, choosing the text image by hand can increase the system flexibility since not all the text image is always needed for recognition in practice.

The section algorithms must be performed upon the pure text image in order to get the information for each characters. The later stage can use this information to find each character in the whole text image and reorganise the ascii text in the same sequence as the original characters appeared. The information from text analysis is recorded in the following data structure named `info_type`.

```
typedef struct {
int             up_position;        /* Position of top edge of the current line */
int             low_position;       /* position of bottom edge of the current line *
char_info_type  char_info[MAX_CHAR]; /* Information of each character
                                       in current line */
info_type       *next;              /* Pointer to next line */
}info_type;
```

`char_info_type` is defined as:

```
typedef struct {
int     up_position;    /* Top edge of the current character */
```

```
int      low_position;   /* Bottom edge of the current character */
int      left_position;  /* Left edge of the current character */
int      right_position; /* Right edge of the current character */
int      ccase;          /* The value is as below if it discovered that
                            current character is of:
                                0 -- Upper case
                                1 -- lower case
                                2 -- special character like `.',`'',`:',... */
char name[CHARNAME_MAX]; /* The ascii name of this current character */
char_info_type * next;   /* Pointer to next char */
}char_info_type;
```

The information is stored in a global array of structures with above type. The information is grabbed by two steps:

Line section

Line section finds the top and bottom edges of each text line in the text image. The principle used here is horizontal projection analysis.

Let $F(i, j)$ be the same image shown above. The projection of all pixels in the horizontal direction is:

$$P_h(j) = \sum_{j=X_s}^{X_e} F(i, j) \tag{3.4}$$

$F(i, j) \in B(X_s, X_e, Y_s, Y_e)$

The top edge of the line can be judged by formula 3.5. i is the top edge of the line, if it satisfies:

$$(\sum_{j=1}^{L} F(i, j) \geq P_1) \wedge (\sum_{j=1}^{L} F(i+1, j) \geq P_2) \wedge \cdots \wedge (\sum_{j=1}^{L} F(i+k, j) \geq P_{k+1}) \tag{3.5}$$

where L is the length of current line, $k, P_1, \ldots, P_{k+1}$ are constants greater than 0. In the case when noise exists, assume that maximum width and height of noise are N_w and N_h, a supplement condition is:

$$(N_w \leq min(P_1, P_2, P_3, \cdots, P_{k+1})) \wedge (k > N_h) \tag{3.6}$$

Similar with top edge decision, i is the bottom edge of the line if i satisfies:

$$(\sum_{j=1}^{L} F(i,j) \leq Q_1) \wedge (\sum_{j=1}^{L} F(i+1,j) \leq Q_2) \wedge \cdots \wedge (\sum_{j=1}^{L} F(i+m,j) \leq Q_{m+1}) \wedge (\sum_{j=1}^{L} F(i+m+1,j) = 0) \tag{3.7}$$

where $m, Q_1, \ldots, Q_{m+1}$ are constants not less than 0. In the case when noise exists, the supplementary condition is:

$$N_w \geq max(Q_1, Q_2, Q_3, \cdots, Q_{m+1}) \tag{3.8}$$

The decision of N_w, N_h can be set as a portion of the width and height of standard character – W_{pk} and H_{pk} in the preknowledge. (Normally they are the width and height of 'O'), for instance,

$$N_w = a_0 W_{pk}$$

$$N_w = a_1 H_{pk}$$

In this system a_0 and a_1 are all equal to 1/20 which are experimental results.

If the preknowledge has not been given, they are set to the default values obtained from experiment.

Character section

Character section searches for the left and right edges of each character in the current line. The principle used here is projection analysis in vertical direction. For the image of Figure 3.1, the projection of all pixels in vertical direction is:

$$P_v(j) = \sum_{i=Y_s}^{Y_e} F(i,j) \tag{3.9}$$

$F(i,j) \in B(X_s, X_e, Y_s, Y_e)$

j is the left edge of a character if it satisfies:

$$(\sum_{i=1}^{H} F(i,j) \geq P_1) \wedge (\sum_{i=1}^{H} F(i,j+1) \geq P_2) \wedge \cdots \wedge (\sum_{i=1}^{H} F(i,j+k) \geq P_{k+1}) \tag{3.10}$$

where H is the height of current line, $k, P_1, \ldots, P_{k+1}$ are constants greater than 0. In the case when noise exists, another condition have to be added:

$$(N_h \leq min(P_1, P_2, P_3, \cdots, P_{k+1})) \wedge (k > N_w) \tag{3.11}$$

Similar with top edge decision, j is the right edge of the line if it satisfies:

$$(\sum_{i=1}^{H} F(i,j) \leq Q_1) \wedge (\sum_{i=1}^{H} F(i,j+1) \leq Q_2) \wedge \cdots \wedge (\sum_{i=1}^{H} F(i,j+m) \leq Q_{m+1}) \wedge (\sum_{i=1}^{H} F(i,j+m+1) = 0) \tag{3.12}$$

where $m, Q_1, \ldots, Q_{m+1}$ are constants not less than 0. In the case when noise exists, another condition have to be added:

$$N_h \geq max(Q_1, Q_2, \cdots, Q_{m+1}) \tag{3.13}$$

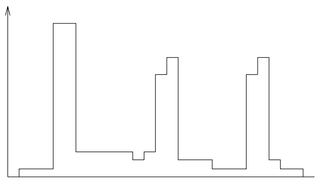
However, character section is much more complex than line section. This is because in many sample documents, lots of characters are either overlapped (merged) or joined. See Figure 3.3.

Figure 3.3: (a) Overlapped (merged) characters ‘tu’ : (b) Joined characters ‘mn’

In the situation listed above, it is almost impossible to use the projection method to get fair results. Let us see the vertical projection of ‘tu’ as in Figure 3.4, where there is no evident trough which can be used as a criterion to separate these characters.

It might be argued that in case of Figure 3.3 (b) that threshold could be used in this case. Unfortunately, it is not always true. Also see Figure 3.4. We notice that the projection of ‘u’

tu



Y-projection

Figure 3.4: Y-projection of overlapped 'tu'

sometimes has a very similar trough inside the character so that it is hard to tell which trough can be considered as threshold to separate characters or as the property of a character to be preserved, i.e., if we want to separate 't','u', 'u' must be broken too.

For the situation of Figure 3.3 (a), an alternative approach in our early research was proposed based on contour filling by connectivity (see [Pavlidis 1982]).

We firstly select a point which is the leftmost dark pixel in the current line as a seed and propagate its colour (values other than 0, 1 which indicate white or white pixels) to adjacent pixels until the contour of a character is reached. (For discrete characters, contour is of one of its components) The algorithm can be described recursively in simple terms: Let C be the colour of the seed, S and F be the filled region at some step. We set $F = S$ initially, and then at each step we add to F all pixels whose colour is C if who have a direct neighbour in F. Thus the contour filling is performed on the basis of connectivity. After the contour of the first character has been found the algorithm is repeated from the second seed in right direction whose colour is set different from the previous one, until all the characters in the current line are achieved.

Recursive filling algorithm can be described below.

Definition 1 *Two pixels are said to be* **direct neighbours** *(abbreviated as* **d-neighbours***) if the respective cells share a side, and indirect neighbours (abbreviated as i-neighbours) if those cells* *touch only at a corner. The name neighbour denotes either type. The term N-neighbour where $0 \leq N \leq 7$ will be used to denote that pixel whose position is marked N in Figure 3.5.*

3	2	1
4	P	0
5	6	7

Figure 3.5: N-neighbours

Algorithm 1 RecursiveFilling

```
BEGIN
    Set seed to mostleft pixel of current text line
    WHILE seed not meet the mostright pixel of the current line
        C = COLOUR(seed)
        CALL FILL(seed)
        seed = SECOND_SEED(seed)
    ENDWHILE
END
```

Procedure 1 Fill(P)

```
BEGIN
    Set the colour of p to C
    FOR n = 1, 2, 3, 4, 5, 6
        IF the colour of P_N is not C
            CALL FILL( P_N )
            { P_N denotes the N-neighbour of P, 0 ≤ N ≤ 7 }
        ENDIF
    ENDFOR
END
```

Function 1 COLOUR(P)

```
BEGIN
    IF P is the first seed
        RETURN 1
    ELSE
        RETURN last seed's colour + 1
    ENDIF
End
```

Function 2 SECOND_SEED(P)

```
BEGIN
    RETURN nearest pixel to the previous seed in right
    direction whose value is not the colour of previous seed
END
```

However, this solution is difficult to use in practice. This is because the poor quality scanned images contain many broken strokes thus a character has no connectivity expected. Moreover, it brings some side affects. For instance, a discrete character will divide into several parts, these must be recognised separately and we have to use a additional algorithm to combine them. Another problem is that this algorithm is extraordinary time consuming.

For the time being, no special effort has been made for this case. The merged characters are left alone. They will be rejected or recognised by the operator in the recognition stage. It is hoped that a better solution can be found and applied to the system in the future.

As for the case of Figure 3.3(b), we consider the connected characters as a single character. At first look, one may think that the possible combinations of connected characters would be of huge amount. However, the only possible combinations in a real document should be existed in a dictionary. Therefore, a solution can be made to pick out all the possible combinations from a dictionary and store their templates in the database. The number of combinations might not be too large. Also because this situation does not happen frequently, it is believed that the four template databases idea (described later) can support this implementation since the combinations are usually stored in the 32$\times$24 database which is rarely used in normal sample comparison. Furthermore, some unseparated characters can also be processed in the postprocessing stage.

3.1.3 Preclassification and normalising

In this system, all the characters are classified into four classes according to their dimensions. The reason for doing so is:

- This method can process various sizes of characters.
- The global point-to-point comparison of skeletons needs the sample characters to have same dimensions of the templates.
- This is one kind of broad classification which can speed up the recognition procedure and improve the recognition rate.
- The most important point is that it can overcome the deforms caused by most thinning algorithms to a great extent, as we know that thinning deforms increase with the thickness of the patterns. Many characters or symbols have very simple strokes such as ‘I’, ‘l’, ‘.’ and ‘-’, in conventional processing, they will be scaled into only one dimension. A stop mark ‘.’ printed on a paper often becomes a blob after scanning and normalisation. See left side of Figure 3.6 (a).

  It can be said that there is no thinning algorithm can get correct result from these patterns. The deforms also occur when thinning the characters or symbols like ‘I’, ‘l’ and ‘-’, etc. However if the scaled size is not too big, say 4×4 instead of 16×16 in Figure 3.6 (b), the thinning result may be very close to the correct result.

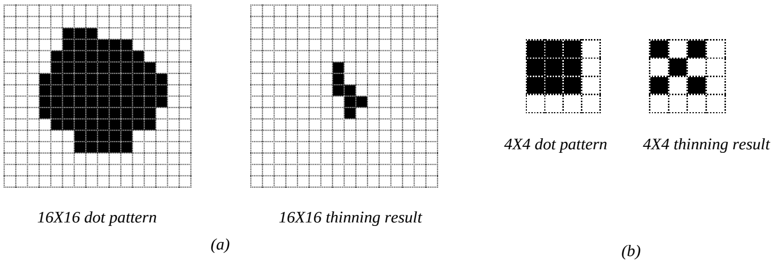


Figure 3.6: Thinning result of a dot pattern

In order to get a better result, some characters like ‘.’,‘-’ and ‘|’ are firstly detected to assign their meanings instead of being recognised later. The detection is according to the standard character dimension given by the preknowledge or according to the average dimension.

- Another important use is that it can reduce or eliminate noise. The noise usually has very small dimensions. If it is scaled down, which is the normal case in the system (described later), a blob of noize in the printed paper may become only a single point in the scaled image. It may not have serious effects on the recognition stage if we use the later described matching algorithm.

The scaled dimension should neither be too big nor too small. If it is too large, the comparison time will be increased and recognition speed will slow down. If it is too small, some details of strokes may be lost after scaling. We chose the dimensions of 32×24, 24×24, 12×24 and 12×12 just because that they are suitable for this purpose. The normally used font size is about 12 point (1/6 inch) on ordinary printed documents. If it is scanned by 300 dpi, which is the ordinary resolution, a character pattern contains 50×50 pixels will be generated. For an English character set, a most complicated character may contain no more than 4 strokes in one side. Thus a reasonable dimension should be able to distinguish 8-9 (4×2) lines in each side. See Figure 3.7.

In other words, the dimension chosen for an ordinary character should not be smaller than 9×9. On the other hand, an original stroke with normal width 6 (50/9) pixels, will have 4 pixels width in 32×32 dimension it might be about 4 pixels; in 24×24 dimension about 2.8 pixels and in 12×12 about 1.4 pixels. They are enough to preserve most details of the strokes. The scaled pattern of Figure 3.7 (a) in 32×32, 24×24 and 12×12 are shown in Figure 3.7 (b), (c) and (d) respectively.

Therefore, four default template databases are used, they are:

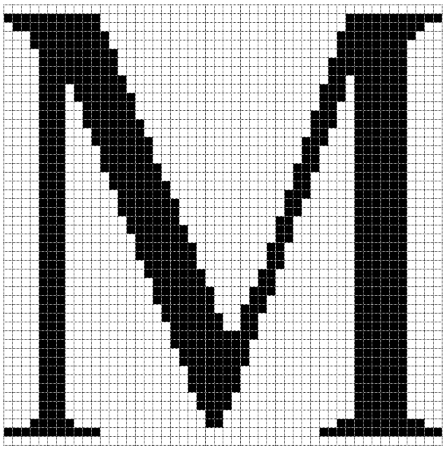
tdb_32×24 This database usually stores template skeletons of very wide characters. Most of connected characters are stored here as well.

tdb_24×24 This database usually stores characters with normal dimensions, like ‘A’, ‘e’, ‘2’, ‘&’, etc.

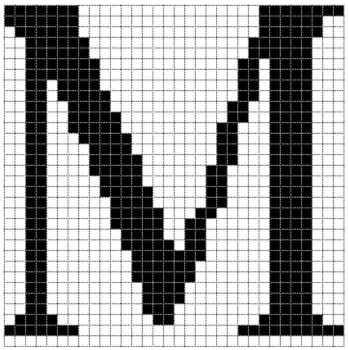
tdb_12×24 This database usually stores “thin’ characters like ‘1’, ‘l’, ‘i’, etc.

tdb_12×12 This database usually stores very small characters like ‘,’, ‘*’, ‘’’, etc.

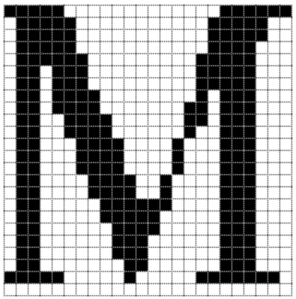
The classification is processed automatically. A set of approximate criteria to classify a character into one of the four classes is described below. Some characters with border dimensions exist in more than one database in order to increase the “hit percentage”.



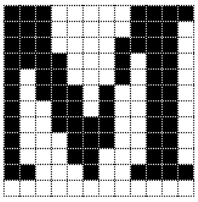
(a) "M" in 50X50



(b) "M" in 32X32



(c) "M" in 24X24



(d) "M" in 12X12

Figure 3.7: ‘M’ in different sizes

Let C_w and C_h be the width and height (in pixels) of character C, W_j and H_j be the yardsticks used to judge which class C falls into.

C belongs to *tdb_32×24* if C_w and C_h satisfy the following conditions:

$$(C_w > a_0 W_j) \vee ((W_j < C_w \leq a_0 W_j) < (C_w + a_0 C_w + 1))$$

C belongs to *tdb_24×24* if C_w and C_h satisfy the following conditions:

$$\begin{aligned}
&(W_j < C_w \leq a_0 W_j) \vee \\
&(C_w > a_0 W_j \geq (C_w - a_1 C_w - 1)) \vee \\
&(C_w < W_j \leq (C_w + a_1 C_w + 1))
\end{aligned}$$

C belongs to *tdb_12×24* if C_w and C_h satisfy the following conditions:

$$\begin{aligned}
&(((C_w - a_1 C_w - 1) \leq W_j) \wedge (C_h > H_j)) \vee \\
&(((C_w - a_1 C_w - 1) \leq W_j) \wedge ((C_h - a_1 C_h - 1) \leq H_j < C_h) \wedge ((C_h + a_1 C_h + 1) > H_j)) \vee \\
&((C_w \leq W_j) \wedge (C_h \leq H_j \leq (C_h + a_1 C_h + 1)))
\end{aligned}$$

C belongs to *tdb_12×12* if C_w and C_h satisfy the following conditions:

$$\begin{aligned}
&(((C_w - a_1 C_w - 1) \leq W_j) \wedge (C_h \leq H_j)) \vee \\
&(((C_w - a_1 C_w - 1) \leq W_j) \wedge ((C_h - a_1 C_h - 1) \leq H_j < C_h)) \vee \\
&((C_w \leq W_j) \wedge (C_h > H_j))
\end{aligned}$$

If preknowledge is available, W_j and H_j are set to half of the width and height of the standard character respectively. Otherwise, W_j is set to the minimum of 15/16 average width of characters and 15/42 average height of lines; H_j is set to 15/42 average height of lines. There are two factors to determine W_j because the width of a character is an unsteady value and it needs average height of lines to make auxiliary decision. 15/16 and 15/42 are the statistics counted from normal English printing. That means in ordinary English printing, 15/16 average width of characters closely equal to 1/2 width of character ‘O’; 15/42 of average height of characters closely equal to 1/2 height of

'O'. ('O' is usually used as standard character in preknowledge) Average values are counted from the section stage.

a_0 is the border width to incorporate a character into the 32×24 database instead of 24×24. It is set to 2.5 in this system. a_1 is a coefficient greater than 0. it makes the classification deviation link up with the sizes of characters. In this system a_0 is set to 1/20.

3.1.4 Scaling

Scaling is a simple process which can be described as below:

Let $(u_0, v_1), (u_0, v_1)$ be the coordinates of upper-left corner and lower-right corner of a character in the original plane. After normalisation, they become $(1, 1)$ and (k_0, k_1). $k_0 \in \{24, 12\}, k_1 \in \{32, 24, 12\}$, we have

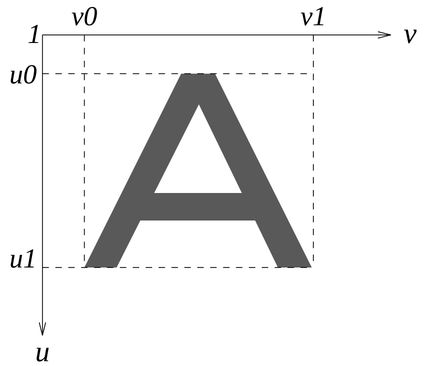
$$\begin{cases} i = 1 + k_0 \frac{u-1}{L(u_1 u_0)} \\ j = 1 + k_1 \frac{v-1}{L(v_1 v_0)} \end{cases} \tag{3.14}$$

where

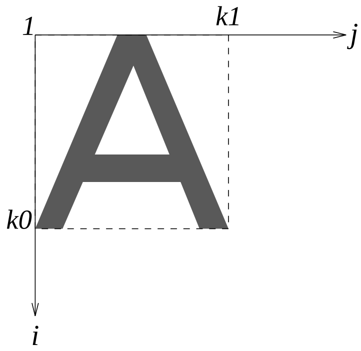
$L(u_1 u_0) = u_1 - u_0$

$L(v_1 v_0) = v_1 - v_0$

See Figure 3.8.



(a) Unscaled



(b) Scaled

Figure 3.8: Scaling (normalisation)

We use LAG (Line Adjacency Graph) (see [Pavlidis 1982]) to represent a character image. The algorithm is:

Algorithm 2 Scaling

```
BEGIN
    FOR each old run line in the original image
        CALL ChangeSize(k_0, k_1)
    ENDFOR
END
```

Procedure 2 ChangeSize

```
BEGIN
    Calculate the start position of new run line using formula 3.14
    Calculate the length of new run line using formula 3.14
    Record new run line
END
```

3.1.5 Thinning

A complete discussion of the thinning algorithm used in this system can be found in [Li 1990]. It is summarised below.

Theo Pavlidis gave the definition of skeleton in [Pavlidis 1982].

Definition 2 *"Let R be a plane set, B its boundary, and P a point in R. A nearest neighbour of P on B is a point M in B such that there is no other points in B whose distance from P is less than the distance PM. If P has more than one nearest neighbour, then P is said to be a skeletal point of R. The union of all skeletal points is called the* **skeleton** *or* **medial axis** *of R."*

He indicated that:

"A line drawing or text must be digitised at a high enough resolution to assure that no lines will be broken and that the ends of the serifs will be preserved. Such a resolution will cause a width of more than two pixels in other locations. Thinning is required in order to recapture the lineal structure of the input without destroying its connectivity.

The skeleton of a set of pixels R is a set found as follows. First, the skeletal pixels and the contour pixels of R are determined. Then, all the contour pixels that are not skeletal are removed and the set thus found replaces R. The process is repeated until a set consisting of only skeletal pixels is left.

Most of the algorithms in the literature define skeleton pixels as only those that fit either of the patterns of Figure 3.9."

A	A	A
0	P	0
B	B	B

A	A	A
A	P	0
A	0	2

At least one of each group of pixels marked with A or B must be none zero

Figure 3.9: Neighbourhood patterns of multiple pixels

Algorithm 3 Thinning

Note:

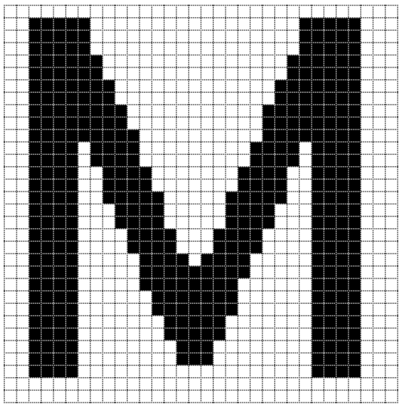
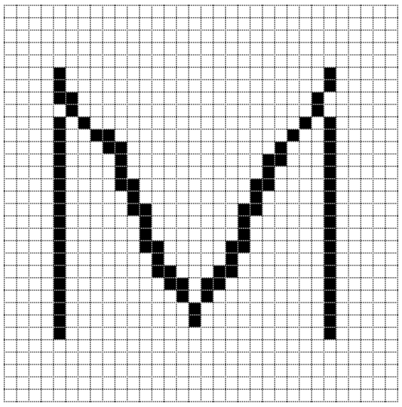
I is the input image. P is the set of patterns of neighbourhoods of skeletal pixels shown in Figure 3.9, including also a 90° rotation of the first pattern and three 90° rotations of the second pattern. Flag remain, when set to true, is used to denote that nonskeletal pixels may remain. Flag skel is set to true when the neighbourhood of a pixel matches one of the pattern in P. A "one" in the pattern matches any nonzero element of the neighbourhood.

```
BEGIN
    Set the flag remain to true
    WHILE remain is true
        Set remain to false No change has been made
        FOR all pixels p of the image I
            IF p is 0
                FOR i=0,1,2,3,4,5,6 and 7
                    IF i-neighbour of p is 1
```

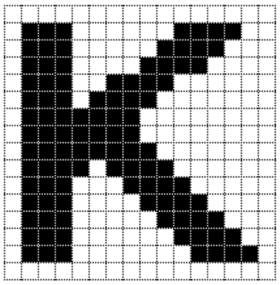
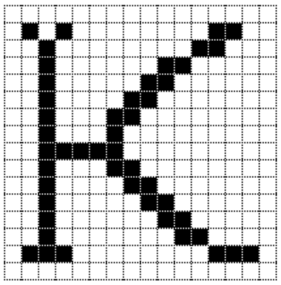
```
                        Set flag skel to false
                        FOR all patterns P
                            IF the neighbourhood of p's i-neighbour matches
                            the pattern P
                                Set skel to true and exit from the loop
                            ENDIF
                        ENDFOR
                        IF the flag skel is true
                            Set i-neighbour of p to 2 skeletal pixel
                        ELSE
                            Set i-neighbour of p to 3 deletable pixel
                            Set remain to true
                        ENDIF
                    ENDIF
                ENDFOR
            ENDIF
            FOR all pixels p of I
                IF p is 3
                    IF neighbourhood of p matches the pattern P
                        Set p to 1
                    ELSE
                        Set p to 0 and also set remain to true
                    ENDIF
                ENDIF
            ENDFOR
        ENDFOR
    ENDWHILE
END
```

Some examples of the application of the algorithm are shown in Figure 3.10.

After preprocessing, a text image is resolved into a set of subimages, each of which contains the skeleton of a single character. The subimages are sorted into four classes, which are 32×24, 24×24, 12×24, 12×12, according to their dimensions. They may be used either as templates to be

"M" in 32X32 and its thinning result

"K" in 16X16 and its thinning result

Figure 3.10: Some thinning result

merged into the database or as samples to be recognised in the later stage.

3.2 Template database and implementation of self-learning

A record in the template database has following data structure:

```
typedef struct {
unsigned long   tdb_bitmap[];   /* Skeleton pattern */
float           projection;     /* Average vertical projection */
int             ccase;          /* Upper case or lower case indicator */
char            name[];         /* character name */
tdb_type        *next;          /* Pointer to next template */
} tdb_type;
```

where `tdb_bitmap` stores the characters' skeleton bitmap. The four databases mentioned above have similar structures except that each `tdb_bitmap` has different dimensions. Even though we have a preclassifier used which sorts all the characters images into four classes, some databases still have too many templates. For example, tdb_24×24 usually stores normal characters and is large. Because that large template database brings slow recognition speed, it would be better to build some other broad classifiers. Average vertical projection AVP is another criterion of classification. Average vertical projection of Figure 3.1 is defined as:

$$AVP = \frac{\sum_{i=Y_s}^{Y_e} F(i,j)}{\sum_{j=X_s}^{X_e} C(j)} \tag{3.15}$$

where

$$C(j) = \begin{cases} 1 & \text{if } \sum_{i=Y_s}^{X_e} F(i,j) > 0 \\ 0 & \text{if } \sum_{i=Y_s}^{X_e} F(i,j) = 0 \end{cases}$$

The reason why to chose AVP as a classifier is that it has light relation with various fonts and typefaces. For example, 'H' in Times-Roman font has four evident hairline serifs while in Helvetica has sanserives. See Figure 3.11.

It is known that AVP of (a) is 3.50, AVP of (b) is 3.33. We can see that AVP classifier is able to sort characters with different fonts correctly. An argument may be made that some characters like 'E' have "vertical serives" which probably have a strong effect on AVP. However, in general, the number of characters which have "vertical serives" is much fewer than the number of characters

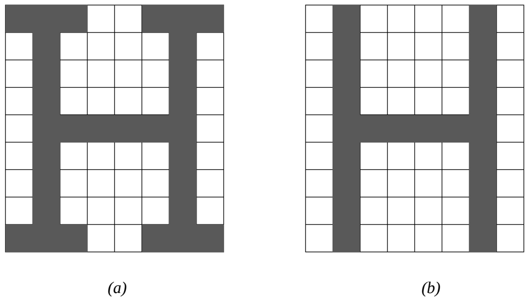


Figure 3.11: Two fonts of 'H'

which have "horizontal serives" and it does not interfere the use of AVP as a broad classifier. The calculation of AVP is performed in the preprocessing stage.

Another element of above structure is `ccase`. The terms upper case and lower case have lost their ordinary meanings here. Here they are specially used to tell the difference of characters which have similar shapes but different cases like 'O' and 'o', 'C' and 'c', 'P' and 'p', etc. They almost have the same shape after normalising. It is extremely difficult to distinguish them if there is no auxiliary method assistance. `ccase` was introduced to solve this problem.

Let C_h and C_w be the height and width of current character, H_{pk} and W_{pk} be the height and width of standard character in the preknowledge, L_h be the height of current line, D_{lc} be the difference between top positions of current line and current character, b_0, b_1, b_2, b_3, b_4 and b_5 be constants greater than 0. We have:
character C is in upper case if

$$(C_h > b_0 H_{pk}) \wedge (D_{lc} < b_1 H_{pk})$$

with preknowledge available, or

$$(C_h > b_2 L_h) \wedge (D_{lc} \geq b_3 L_h)$$

without preknowledge available;
character C is in lower case if

$$(C_h \leq b_0 H_{pk}) \vee ((C_h > b_2 L_h) \wedge (D_{lc} < b_3 L_h))$$

with preknowledge available, or

$$(C_h \leq b_2 L_h) \vee ((C_h > b_0 H_{pk}) \wedge (D_{lc} \geq b_1 H_{pk}))$$

without preknowledge available;
character C is in special case, i.e., '.', '-', '|', 'I', 'l', etc., if

$$(C_h \leq b_4 H_{pk}) \wedge (C_w \leq b_5 W_{pk})$$

with preknowledge available, or

$$(C_h \leq b_6 L_h) \wedge (C_w \leq b_7 L_h)$$

without preknowledge available.

In this system b_0 is set to 0.85, b_1 0.2, b_2 0.5, b_3 0.15, b_4 0.1, b_5 0.15, b_6 0.08 and b_7 0.1. These are statistical results based on the normal English printing.

As for the $name$ in the above data structure, it is the name of current template character given by the operator when the template database was established or expanded. When the template database is being built, the system automatically sets up the input flag in the input area of the *xocr* interface and produces a frame around the current character until the name of the character has been input by the operator. The name is recorded in *tdb_name* . See Figure 3.12.

A similar way to add in templates is through the interactive recognition. The recognition process stops at any sample character whose recognition is below a gate value, which is a little higher than that in non-interactive case. The recognition process continues after the user has input the character name. The character is remembered in the database as a new template.

After the template database has been built, an input sample can be recognised by comparing the sample skeleton with the skeletons of the templates stored in the template database. The template database is loaded into the memory when the system starts at the very beginning, except that it does not exist at all, in this case, the template database can be built while interactive recognition is running. The number of templates can be expanded at any time and the databases both inside

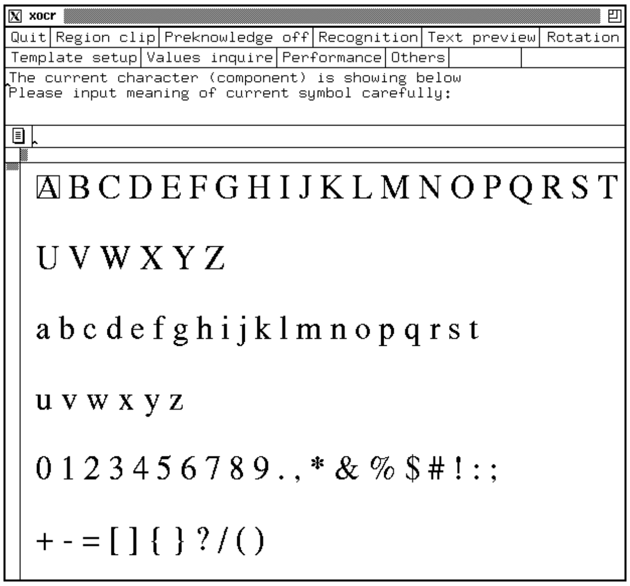


Figure 3.12: Template character input

memory and outside memory will be updated synchronously. A redundancy check is performed when a new template is added into the database so as to keep the database as small as possible. The templates in the database are stored in ascii code and can be modified by users. When stored on disk, the database is compressed by adaptive Lempel-Ziv coding method, which can reduce 50-60% of textual space (see [Welch 1984]). Recognition implementation will be explained in the next section.

3.3 Character recognition

In this stage, the features of an input character will be compared with certain templates stored in the database. The closest match is considered the recognition result. If none of the matches is close enough (or the difference is too big), the input character is said to be rejected.

So far, three broad classifiers are established. They are based on:

1. dimensions of characters – 32×24, 24×24, 12×24 and 12×12

2. character cases – upper case, lower case and special case
3. AVP

Using the three classifiers, firstly an input sample can find a set of templates to be compared with in the database which have the same dimension and same case as the sample, and an AVP which is in a certain range around the AVP of the templates. Secondly, a final classifier which is based on the skeleton matching will be used on this set of templates to find out which of them is the final result. The matching algorithm is explained below.

Let T be the set of templates in the database, it can be expressed as: $T = \{t_k\}$ where $k = 1, 2, 3, \ldots, K$, K is the total number of templates.

Each t_k in turn can be expressed as: $t_k = \{s_l\}$ where $l = 1, 2, 3, \ldots, Lk$, Lk is the the total skeletal pixels number of template t_k.

$F(i, j)$ is defined as same as equation 3.1.

Let p_1 and p_2 be two pixels in the two matching planes, we define:

$$f(p_1, p_2) = \begin{cases} W_1 & \text{if } p_1 \text{ is in the same position of } p_2 \\ W_2 & \text{if } p_1 \text{ is 0- 2- 4- 6-neighbour of } p_2 \\ W_3 & \text{if } p_1 \text{ is 1- 3- 5- 7-neighbour of } p_2 \\ W_4 & \text{if } p_1 \text{ is not N-neighbour of } p_2\text{, N = 0, 1, 2, } \ldots\text{, 7} \end{cases} \tag{3.16}$$

$W1 > W2 > W3 > W4$

This is a simplified distance function to measure the distance between p_1 and p_2.

Let

$$D_{k1} = \frac{\sum_{l=1}^{L_k} f(s_l, (i, j))}{\sum_{l=1}^{L_k} W_1} \tag{3.17}$$

and

$$D_{k2} = \frac{\sum_{l=1}^{L_k} f((i, j), s_l)}{\sum_{l=1}^{L_k} W_1} \tag{3.18}$$

for $F(i, j) = 1$.

Let

$$D_k = min(D_{k1}, D_{k2}) \tag{3.19}$$

and

$$D_r = min(D_1, D_2, \cdots, D_k) \tag{3.20}$$

where $r \in \{1, 2, \ldots, K\}$

If $D \geq e, 0 \geq e \leq 1$, we say that t_r is the recognition result, otherwise $F(i, j)$ is rejected.

The rejected characters are simply labeled with '[]', the operator can easily find the places and do necessary modification.

Algorithm 4 Recognition

Note:

Constant W1, W2, W3 and W4 have tremendous influences on the recognition result, they thus have to be carefully chosen. The higher the difference between W1, W2, W3 and W4 is, the more the accurate matching will be examined. If it is too high, many input characters will be rejected. If it is too low, many characters will be recognised incorrectly. In this system they are set to 14, 10, 5 and 0 respectively. e is the rejection threshold and is set to 0.7. e1 is rejection threshold in first pass and is set to 0.98. If the first pass of comparison cannot achieve the accuracy of e1, then second pass is performed. avp_range indicates that in which area of AVP the first pass is compared. For example, if avp_range is 0.5, then all the template whose AVP is between sample AVP $\pm$ 0.5 will be compared with. avp_range is set 0.5 here. For the sake of conciseness, the attributes related to sample precede with s_ ; while to template with t_ .

BEGIN
- *Set $D_{k1}, D_{k2}, D_k, r, D_r$ to 0*
- *Set pass to 0*
- *Select a proper template database according to the s_dimension*
- FOR *all templates in the database*
  - IF *input sample and template have different case*
    - SKIP *to next template*
  - ENDIF
  - IF *pass is 0 and the difference of s_AVP and t_AVP is greater than avp_range*
    - SKIP *to next template*
  - ENDIF
  - IF *pass is 1 and the difference of s_AVP and t_AVP is less than avp_range*
    - SKIP *to next template*
  - ENDIF
  - *Calculate D_{k1} using equation 3.17*

```
    ENDFOR
    FOR all templates in the database
        IF t_D_k1 is greater than e_1
            Calculate D_k2 using equation 3.18
        ENDIF
    ENDFOR
    Get D_k from D_k1 and D_k2 use equation 3.19
    Get D_r from D_k use equation 3.20
    IF D_r is greater than e
        Record r and D_r as recognition result
    ELSE
        Record “rejected” in the sample data structure
    ENDIF
END
```

3.4 Postprocessing

An interactive misspelling correcting function based on spelling check is applied in this stage in order to increase the system performance. There are two things that may make the final recognition result unacceptable. One comes from the rejected characters which are marked by ‘[]’. Another is caused by the mis-recognised characters. For example, ‘l’ is recognised as ‘1’, ‘Z’ as ‘2’, etc. Both these two case will generate misspelled words. Therefore if we can find a way to correct the wrong words, the recognition result might be improved a lot.

Xocr provides a convenient way to do this work. It can list all the misspelled words, give the correct suggestions and do replacement, as described in section 2.2. Figure 3.13 shows the correction interface.

A spelling-correcting system requires the following functions:

1. A check as to whether the input word is correctly spelled or not (spelling check).

2. A search to provide likely alternative words (spelling correction) (See [Takahashi+ 1990].

Two approaches to providing these functions have been proposed. In one, the exact-match method, candidates for the correctly spelled word are generated from an input word by using certain

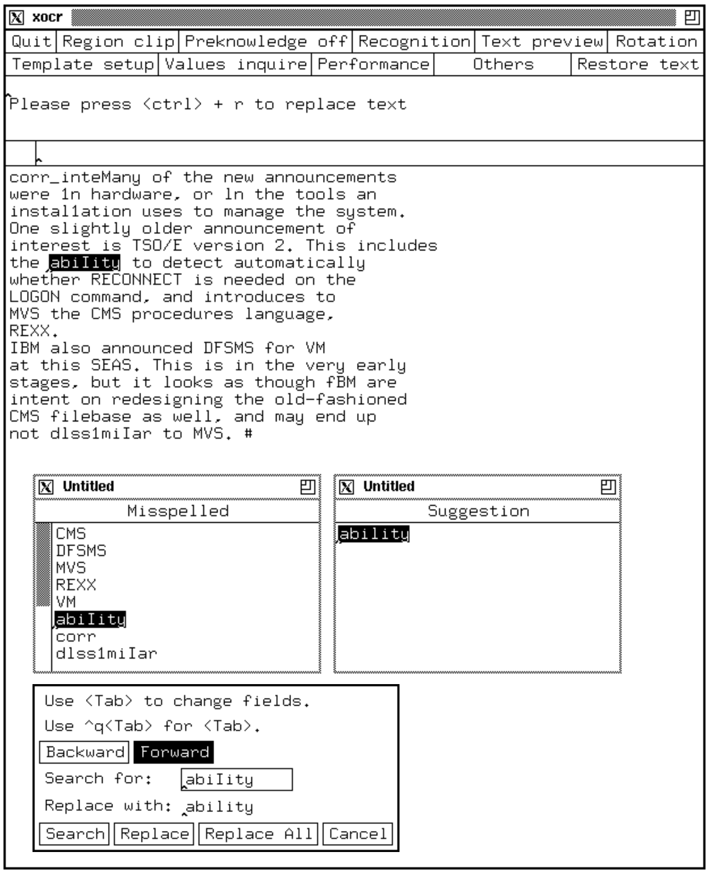


Figure 3.13: *Xocr* correction interface

applied rules which define patterns of misspelling; these candidates are then checked to determine whether they are in the dictionary. This method is widely used because of its simple dictionary structure. Another method, the best match method, searches for words that are spelled similarly to the input word. The former has a lower capability than the second method because that it is very difficult to discover the errors not defined in the rules. A large amount of statistical data is also needed to construct rules specific to each input method. The second approach is hardly practical because it takes a long time to calculate the similarities between an input word and each word in the dictionary. Also some complicated dictionary structures have to be used as well.

In the *xocr* system, a solution based on the best match method was developed. However, because of the use of a hash index, the searching time is fairly short and the structure of the dictionary is quite simple.

Xocr calls *spell* (See SPELL(1)) for spelling check. Since *spell* is a mature text preparing tool, there is no need to redesign such a system to pick up misspelled words.

Xocr uses a dictionary which contains more than 36,000 words, ordered by their length sequence. A hash table consisted of first positions of words with different lengths was built in order to speed up the searching.

In order to get an effective system, we have to make it clear which kind of misspelling we are dealing with.

A misspelled word generated by *xocr* usually has following appearance:

$$XX \ldots X[] \ldots X[] \ldots X$$

where X represents any one in the characters set; '[]' indicates that a character in this position is unknown or there are several overlapped characters missed here. Therefore, a '[]' might match at least one characters in a candidate. The word can be represented as:

$$s_1[]s_2, \cdots, []s_n$$

where $s_1, s_2, \ldots, s_n$ are segments delimited by '[]'s. n is the total number of segments.

Except this case, there are few chances for misspelling by missing a character in a sample word. Thus the problem becomes how to find candidates which have the best match of segments $s_1, s_2, \ldots, s_n$ in the same order as they occurred in the sample.

Assume that the length of sample is L_s; let $L_{c1}, L_{c2}, \ldots, L_{cm}$ be the lengths of candidates, where m is the total number of candidates. We have:

$$0 \leq L_{ci} - L_s \leq L_0 \tag{3.21}$$

$i \in \{1, 2, \ldots, m\}$

L_0 is a constant, in this system L_0 = 3.

Let $M_1, M_2, \ldots, M_n$ be the matched rate of the segments. The matched rate compared by candidates c_i is marked as $M_{ji}, j \in \{1, 2, \ldots, n\}$. A candidate c_k is chosen to be a correcting suggestion if it satisfies:

$$a_k \sum_{j=1}^{n} M_{jk} = max(a_1 \sum_{j=1}^{n} M_{j1}, a_2 \sum_{j=1}^{n} M_{j2}, \cdots, a_m \sum_{j=1}^{n} M_{jm}) \tag{3.22}$$

where a_i are weights determined by difference between the two lengths:

$$a_i = 1 - a_0 \frac{|L_{ci} - L_s|}{L_{ci}} \tag{3.23}$$

$i \in \{1, 2, \ldots, m\}$

a_0 is a constant whose value is 0.5 in the system.

As for M_{ji}, it is the ratio between the number of matched characters in a certain range of a candidate, and the number of all the characters in the segment. See Figure 3.14.

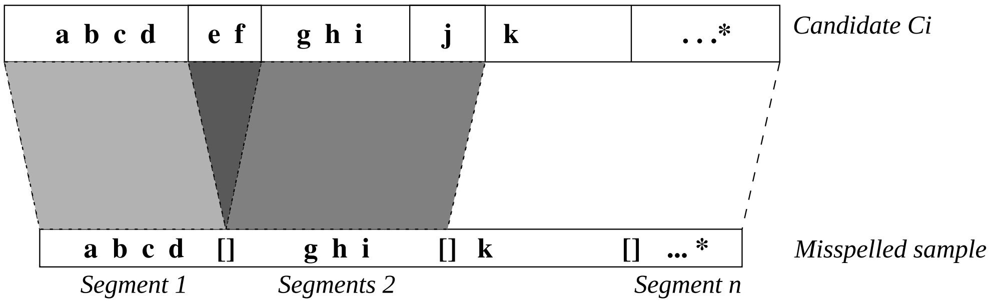


Figure 3.14: Matching candidates

In Figure 3.14, the darkest shadow is the overlapped area of two succeed segments in the candidate, which is to be matched by both corresponding segments in the sample. In this system it at most matches two characters. It means that a '[]' may represent no more than two missed characters.

The algorithm can be described as follow.

Algorithm 5 SpellingCorrection

Note: c_i, a_i and M_j have the same meaning as listed above.

```
BEGIN
    Call spell to pick up all the misspelling words
    FOR each misspelling word (sample)
        Dissemble the sample into segments separated by '[]'
        Adjudge the searching area (start and end position) in the dictionary
        according to the sample length by condition 3.21
        FOR each candidate ci in the searching area
            Calculate a_i using equation 3.23
            Calculate M_ji as described above
        ENDFOR
        FOR each candidate
            Chose the candidate with maximum M_j as correction suggestion
            using equation 3.22
        ENDFOR
    ENDFOR
END
```

This programme runs in the background while the interactive correcting runs in the foreground to avoid the inconvenience brought about by the execution time.

So far the *xocr* realisation has been described. Some results obtained from experiments are given in the next section to show the system profile.

Chapter 4

Performance and experiment

The complete performance testing has not been done yet. An application experiment is shown below.

Figure 4.1 is a text image (from ULCC News November 1989) to be recognised.

Many of the new announcements were in hardware, or in the tools an installation uses to manage the system. One slightly older announcement of interest is TSO/E version 2. This includes the ability to detect automatically whether RECONNECT is needed on the LOGON command, and introduces to MVS the CMS procedures language, REXX.

IBM also announced DFSMS for VM at this SEAS. This is in the very early stages, but it looks as though IBM are intent on redesigning the old-fashioned CMS filebase as well, and may end up not dissimilar to MVS. ■

Figure 4.1: A sample text image

After scanning, the image can be seen in Figure 2.2, see Page 19. The scanner was set to:

Bitmap dithering patterns:	bitmap
Resolution:	300 dpi
Scale factor percentage:	100
Intensity:	0
Contrast:	0
Automatic background control:	no

The *xocr* setting is:

Preknowledge	standard width:	30
	standard height:	30
	offset between words:	9

Template

The fonts was adopted from X11 built in fonts library, which is named:
-adobe-times-medium-r-normal–34-240-100-100-p-170-iso8859-1
These characters were included:

A,B,C,D,E,F,G,H,I,J,K,L,M,N,O,P,Q,R,S,T,U,V,W,X,Y,Z
a,b,c,d,e,f,g,h,i,j,k,l,m,n,o,p,q,r,s,t,u,v,w,x,y,z
1,2,3,4,5,6,7,8,9,0,.,,,*,&,%,$,#,!,:,;,+,=,[,],{,},?,/,(,)

templates number and space in the databases are shown in Table 4.1- 4.2.

Table 4.1: Templates number

Databases dimension	Without self-learning	With self-learning
32×24	2	2
24×24	61	76
12×24	23	26
12×12	2	4

Recognition result without self-learning is as follows:

Table 4.2: Templates space

Databases	Without self-learning		With self-learning	
	Uncompressed	Compressed	Uncompressed	Compressed
32×24	454	298	454	298
24×24	13568	5284	16994	6489
12×24	5259	1767	5855	1883
12×12	174	129	383	240

```
Man[] of lhe new announcemen{s
were 1n hardware[] or ln {he lools an
ins{al1a{ion uses lo manage lhe s[]slem.
One sligh{l[] older announcemenl cf
inler[]sl is TSO/E version Z. This includes
lhe abiIil[] lo []el[]cl aulomalicall[]
whelher RECONNECT is neede[] cn lhe
LOGON ccmm[]n[][] []nd 1nlrcduces lo
MVS {he CMS procedures language[]
REXX.
IBM also announced DFSMS for VM
al lhls SEAS. This is in lhe ver[] earl[]
s{ages[] bu{ 1l looks as {hough fBM ar[]
inlenl on re[]esigning lhe ol[][]fashioned
CMS filebase as well[] an[] mav []n[] up
pcl []lss1miIar lo MVS. []
```

Recognition result with self-learning is as follows:

```
Many of the new announcements
were in hardware, or ln the tools an
instal1ation uses to manage the system.
```

```
One slightly older announcement of
interest is TSO/E version 2. This includes
the abiIity to detect automatically
whether RECONNECT is needed on the
LOGON command, and introduces to
MVS the CMS procedures language,
REXX.
IBM also announced DFSMS for VM
at this SEAS. This is in the very early
stages, but it looks as though fBM are
intent on redesigning the old-fashioned
CMS filebase as well, and may end up
not dissimiIar to MVS. #
```

Recognition result with spelling correction is as follows:

```
Many of the new announcements
were in hardware, or ln the tools an
installation uses to manage the system.
One slightly older announcement of
interest is TSO/E version 2. This includes
the ability to detect automatically
whether RECONNECT is needed on the
LOGON command, and introduces to
MVS the CMS procedures language,
REXX.
IBM also announced DFSMS for VM
at this SEAS. This is in the very early
stages, but it looks as though IBM are
intent on redesigning the old-fashioned
CMS filebase as well, and may end up
not dissimilar to MVS. #
```

System performance is listed in Table 4.3 (the speed of the Sun Sparcstation1 which was the machine being used is 12.5 mips).

Table 4.3: System performance

	No self-learning	Self-learning	Spelling correction
Total number of characters	447	447	447
Rejected number	28	0	0
Recognition rate (%)	93.7	100	100
Recognised number	319	447	447
Correct number	364	442	446
Correct rate (%)	81.43	98.88	99.78
Average matching accuracy (%)	89.9	87.5	87.5
User time (matching only) (s)	46.11	46.02	46.02
System time (s)	0.47	1.15	1.15
Time/per character (s)	0.104	0.106	0.106

Chapter 5

Conclusion

The development of a character recognition method using skeleton matching has been presented. This research involved the text section method, preclassifier selection, thinning algorithm design, template database implementation, matching strategy and spelling correction technique. An experiment was made to observe the system performance. A survey of general methodology in OCR by recent year's research was also summarised in the beginning of this report.

Various improvement aspects might be worthwhile:

Many OCR algorithms could be processed concurrently. For example, the thinning procedure can be applied to all the characters concurrently and the matching procedure can also be performed on all the characters at the same time. It is probably more desirable to modify the programme in concurrent processing environment, such as to use OCCAM language and run the system on transputers. A limitation is that many X11 facilities will not be available if this is done

The skeleton of a character could be further processed to abstract more crucial informations, such as start points, end points, pronounced angles or corners, the T junctions, and crossing of strokes. These can be used as features instead of the whole skeleton in order to reduce the memory space and accelerate the speed. However, this idea cannot be realised until a better thinning algorithm is developed. Many thinning algorithms used today bring about lots of distortions and the crucial points would not be very reliable.

Some other approaches like contour analysis could be combined together to increase the recognition rate. Joined and overlapped characters should be treated more earnestly and further development is expected to separate them. Also an automatic general text analyser seems very attractive. But they are expected not to conflict with the original intention that to make the system as ingenious as possible.

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