

COMPUTER RECOGNITION OF TOTALLY UNCONSTRAINED HANDWRITTEN ZIP CODES

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This paper deals with the application of automatic sorting of envelopes with totally unconstrained handwritten numeric postal ZIP codes and presents a complete model (including preprocessing, feature extraction and classification modules) of a ZIP code reader/sorter.

Different recognition methods, including statistical, structural and combined were developed and their performance on real-life ZIP code samples (8540 numerals) were measured.

The statistical recognition method was used as a front-end recognizer and predictor of an unknown character. Based on edge classification, a new technique was implemented to define and extract the structural features.

In the combined recognition method, unknown characters were identified either by the statistical or structural method. Its recognition reliability was found to be in the interval (96.29%, 95.94%) with substitution and rejection rates between (3.45%, 3.96%) and (2.36%, 7.01%) respectively.

1. INTRODUCTION

This paper deals with the application of automatic sorting of envelopes with totally unconstrained handwritten numeric postal ZIP codes. The basic components of such a ZIP code reader/sorter are shown in Fig. 1.

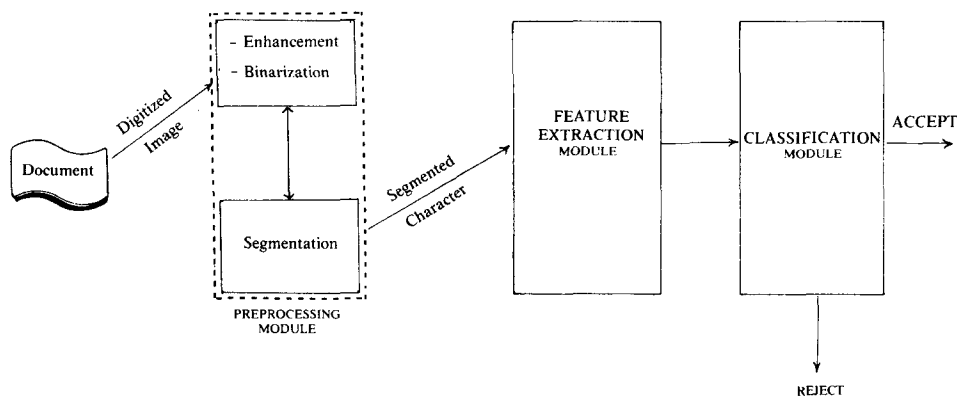


Fig. 1. Basic components of ZIP code reader/sorter.

A ZIP code reader/sorter consists of an optical scanner, a preprocessing module, a feature extraction module and a classification module⁴. In this study both numerical (statistical) and structural (topological) features were extracted. The classification module consists of two sub-modules, namely, prediction module (a front-end recognizer and predictor of an unknown character) and structural module (a back-end recognizer). Numerical features are used in the prediction module and structural features in the structural module. The classification procedures for these two modules are discussed in Sect. 4.

The recognition performance was tested on totally unconstrained handwritten ZIP code data collected from the dead letter envelopes by the U.S. postal services at different locations. ZIP codes were digitized on a grid of 64×224 , 0.153 mm square elements which corresponds to a resolution of 166 dots per inch. The encoding of the grey level ranges from 0 to 15. This data pose a variety of problems like: (1) the paper quality (rough, coarse matte, linen, smooth, glossy, ribbed, ridges and others), paper colors ranging from white to black, paper patterns (none, straight, figured, shaded and others); (2) ink colors (blue, black, green, red, brown and others); (3) pen types (quill, ballpoint, felt tip, pencil and others) and (4) writing style and random distortions such as field intrusions, skipping, right and left tappers, variations, skewness, open loops, nesting, write-overs, overlap and touching, etc., (Fig. 2).

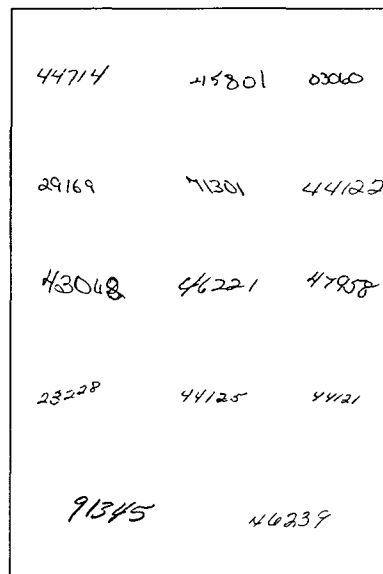


Fig. 2. Some samples of original ZIP codes.

2. PREPROCESSING

Preprocessing is an important part of a pattern recognition system. The reliability of the whole recognition system heavily depends on the quality of the preprocessed image. The preprocessing steps required to represent the constituents of each ZIP code image

in a form suitable to the recognition stage are: binarization; enhancement and segmentation.

2.1. Binarization

The purpose of binarization is to transform a multi-gray level image into a two level image. An iterative scheme has been implemented to determine a binarization threshold by converting a unimodal histogram into a bimodal histogram of a ZIP code image.

2.2. Enhancement

A region growing approach is adopted to improve the quality of an image. The quality of an image is judged during the segmentation process. An image is considered of poor quality, if the number of objects are not equal to five (number of digits in a ZIP code). The basic idea behind this approach is based on the region growing process.¹⁰

2.3. Segmentation

Segmentation is a process to determine the constituents of an image. Segmentation methods can be roughly categorized as “projection-based”, “pitch-based”, “recognition-based” and “region-based” techniques. The first two techniques are suitable for typewritten texts where characters are equally spaced and there is a significant gap between adjacent characters. In the “recognition-based” methods segmentation is performed by recognizing a character in a sequential scan. For handwritten or handprinted texts where variations in handwritings are unpredictable, the performance of these methods is dubious. The “region-based” method is the only alternative for the segmentation of totally unconstrained handwritten characters. In this method different regions belonging to the character images are identified and recorded. There are several possible approaches (contour tracing, sequential scanning etc.) for object identification. In this research, a region-based segmentation method has been developed. The objective of this segmentation method is not merely to get the isolated images of the constituents of a ZIP code, but also to reveal some characteristics (touching, broken, overlapping, part of a character nested under one another but not touching, etc.), useful in assessing the possibility of processing a ZIP code.

2.3.1. Object labelling and segmentation

The object labelling method proposed here is similar to the method discussed in Ref. 11. Starting from the bottom left corner, every image is scanned column-by-column from bottom to top. Information regarding the starting and ending coordinates of every component and object label encountered at the i^{th} scan is recorded in a tuple $(T_i^k(j), j=1, 2, 3, 4)$ where k denotes the component number and the last field is used to store the object labels. Two lists L_i and L_{i-1} of tuples, formed at the i^{th} and $(i-1)^{\text{th}}$ scans are used for the object labelling. Labels are assigned by examining the component connectivity of lists L_i and L_{i-1} . To establish the connectivity among objects, after each scan a C-matrix (component connectivity matrix) is created.

The C-matrix together with the two vectors $\mathbf{A}_{m, 1}$, where $a_k = \sum_{k'=1}^n c_{k, k'}$ and $\mathbf{B}_{1, n'}$, where $b_{k'} = \sum_{k=1}^m c_{k, k'}$ are used to detect the starting, termination, continuation, split and merging states of regions.

The component coordinates belonging to the different objects are recorded in separate lists. These lists are used for the computation of the area, span of an object etc. The final outcome of the entire process is the number of object lists which corresponds to the total number of objects in a ZIP code image. This segmentation method is described in Ref. 2.

3. FEATURE DEFINITION AND EXTRACTION

During the past several decades considerable research has been done to define and extract the good quality features¹². Generally speaking, features used to solve a pattern recognition problem can be grouped into two wide groups: numerical features and structural features. Numerical features are generally used to deduce the global information while the structural features are used to derive the global structure of a pattern.

Algorithms to extract the numerical features are easy to implement but these features are highly sensitive to style variations, translation and rotation, and do not provide the structural description of a pattern. The use of structural features reflecting the geometrical and topological properties of a pattern has been suggested to account for the variation in pattern¹³. Commonly used structural features are strokes, bays (cavities), end points, intersections of line segments, and loops (see Refs. 3, 5, 9 and 15).

Unlike the numerical features, extraction of the structural features is difficult. Design of algorithms to extract the structural features is still a topic of research. A new scheme capable of extracting the structural properties from a pattern is developed and implemented. Details of this scheme are presented in Sect. 3.3.

One of the aims of this research was to study the performance of a combination of the structural and the numerical features on the totally unconstrained handwritten numeric patterns. An extension of the multi-directional characteristic loci features are used as the numerical feature.

3.1. Numerical (Statistical) Features

A method to extract the numerical features used in this study is described below.

Starting from the top left corner, every input pattern is scanned row-by-row. At each boundary point a list consisting of the following information is generated.

- Boundary point co-ordinates (row number and column number).
- Black region counts in the north, east, south and west directions (C_N , C_E , C_S , and C_W). In each direction the counts are coded—no region as “0”, one region is “1”, two regions as “2”, three regions as “3” and four regions as “4”. Counts more than four which seldom occur are set to four for our application.

- Adjacent black run length (B_N, B_E, B_S, B_W) in the north, east, south and west directions.
- Adjacent white run length (W_N, W_E, W_S, W_W) in the north, east, south and west directions.

White and black run lengths are quantized on the scale of four—no black or white run length as “0”, short as “1”, medium as “2”, large as “3” and extra large as “4”. In the cases of north and south directions, if a run length is less than one-fourth of the height of the character pattern then it is coded as short; if it lies between one-fourth and half of the height, it is coded as medium; if it lies between half and three-fourths of the height, it is coded as large; otherwise it is coded as extra large. Using the width of a character pattern, similar codes are assigned to the black and white run lengths for the east and west directions.

Finally, using the boundary coordinates, height and width of the pattern, the zone numbers for boundary points are calculated. Each character image is divided into 20 rows and 15 columns, this partitioning was done by incorporating the average height to width ratio.

All feature values are stored in a table of size $M \times n$, where M is the number of zones and n denotes the number of features. This table is used to decode the features as $u_{ijk} = 1$ if the j^{th} feature takes value $k \in \{0, 1, 2, 3, 4\}$ in the i^{th} zone; otherwise it is assigned a value 0.

3.2. Shapes and Structural Features

The objective of the feature definition is to find the characteristic(s) of the patterns which can be used to distinguish one pattern from another, and shape is such a characteristic. The importance of shape features has long been recognized in solving many practical pattern recognition problems. The study of shapes is an active topic of research in pattern recognition. In the survey on character recognition application, Suen et al. [1980] recommended the syntactic approach¹⁷ as a possible solution to achieve the optimal recognition result. In fact, the success of such an approach (syntactic/structural) highly depends on the precise definition of shape primitives.¹⁶

Most shape extraction algorithms operate in stages. In the first stage local shape features (primitives) are extracted. In subsequent stages, using these primitives or higher level shapes, and shape derivation rules, even higher level shapes are extracted. There are several approaches to implement these algorithms. Among the best approaches is the implementation based on the theory of formal languages. Nadler⁸ described a method to construct a one stage automation to extract the cavities while Mori and Doh⁷ described a two stage automation.

For practical applications a shape extraction algorithm must be simple, deterministic and dynamic in nature. To meet these requirements a method based on edge type classification and the inherent relationship between the different types of edges has been investigated and implemented. Our approach does not depend on *a priori* intuitive shape definition. Depending upon the scanning method, it gives the inherent shapes

which constitute the fundamental shape. Edge type classification and inherent concatenation relationships among different types of edges are described below.

In a horizontal (raster) scan, new edges are detected either by the appearance or a split in a body region. Considering these situations as “context” we can only get any one of the four basic types of edges. These are outer left (e^1), outer right (e^2), inner left (e^3) and inner right (e^4) (Fig. 3). The starting or splitting point of a body region is considered as the “head” and the termination or merger point as the “tail” of an edge. In a sequential scan, a body region can be in one of the five states i.e. start, split, merge, termination or continuation state. These states can be easily detected by the conditions given in Ref. 2. Using concatenation relations “X” (head-to-head) and “—” (tail-to-tail) and edge types e^1 , e^2 , e^3 and e^4 , all the possible edge-to-edge relationships and corresponding shape formations (R_1, R_2, \dots, R_{12}) are shown in Fig. 4 where “X” and “—” denote the head-to-head and tail-to-tail concatenations. The relationship $e_i^k \times e_j^l$, $i \neq j$, $k \neq l$ represents the head-to-head concatenation of the i^{th} (k^{th} type) edge with the j^{th} (l^{th} type) edge. Similarly, $e_i^k - e_j^l$ means the concatenation of the tail of the i^{th} edge with the tail of the j^{th} edge.

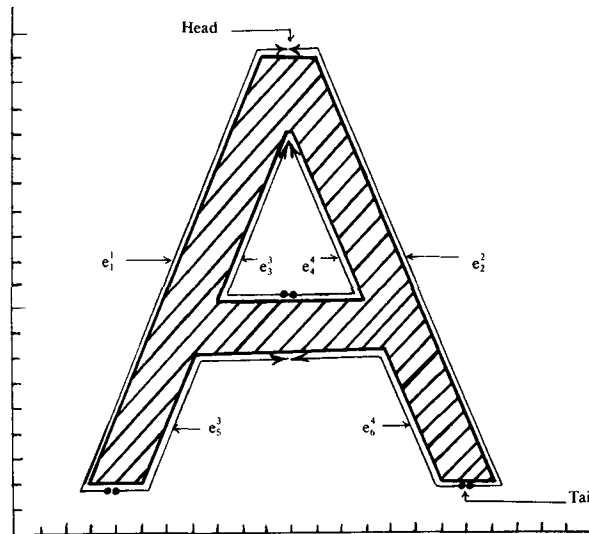


Fig. 3. Basic edge definition.

In this study, cavities and end points facing different directions (up, down, left or right etc.) and hole are used as shape (Fig. 5). Simple forms of these features can be easily deduced from the edge type classification and edge-to-edge concatenation relationships while scanning a pattern in a desired direction. Extraction of these shapes for the horizontal scan is described below and higher order shapes is discussed in Ref. 1.

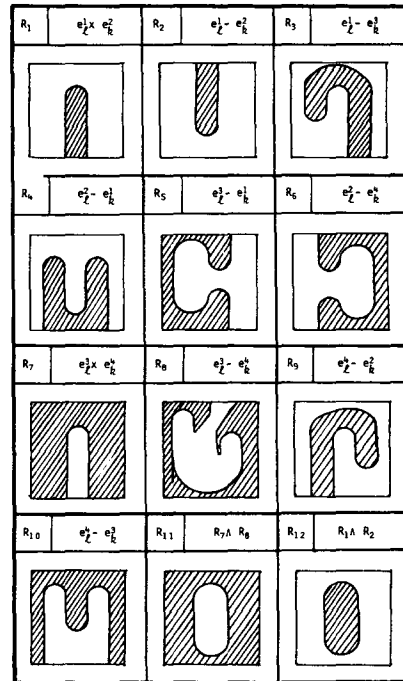


Fig. 4. Twelve possible shapes (R_1, R_2, \dots, R_{12}).

		Shapes			End Points		Hole
		Fundamental Cavities			Direction		Mp
Opening direction	Equal arm length	Unequal arm length		Direction	End Points		Hole
		c_1	c_2		c_3	E_1	
North	Equal arm length	c_1	c_2	c_3	North	E_1	
		c_4	c_5	c_6		E_2	
South	Equal arm length	c_4	c_5	c_6	South	E_2	
		c_7	c_8	c_9		E_3	
East	Equal arm length	c_7	c_8	c_9	East	E_3	
		c_{10}	c_{11}	c_{12}		E_4	
West	Equal arm length	c_{10}	c_{11}	c_{12}	West	E_4	
		c_{13}	c_{14}	c_{15}			
North-West	Equal arm length	c_{13}	c_{14}	c_{15}			
		c_{16}	c_{17}	c_{18}			
South-East	Equal arm length	c_{16}	c_{17}	c_{18}			
		c_{19}	c_{20}	c_{21}			
North-East	Equal arm length	c_{19}	c_{20}	c_{21}			
		c_{22}	c_{23}	c_{24}			
South-West	Equal arm length	c_{22}	c_{23}	c_{24}			

Fig. 5. Some shapes used as structural features.

Let e_i^k and e_j^l be the i^{th} and j^{th} edges of k^{th} and l^{th} types respectively involved in the formation of a shape. Conditions to detect different fundamental shapes are:

(a) The beginning of a blob

The relationship $e_i^1 \times e_j^2$ where $i \neq j$ implies the beginning of a blob formed by the i^{th} and j^{th} edges.

(b) The end of a blob

The relationships $e_i^1 - e_j^2$, $e_i^1 - e_j^3$, $e_i^4 - e_j^2$ or $e_i^4 - e_j^3$ imply the end of a blob involving the i^{th} and j^{th} edges.

(c) Fundamental cavity type¹

The relationships $e_i^2 - e_j^1$, $e_i^2 - e_j^4$, $e_i^3 - e_j^1$ or $e_i^3 - e_j^4$ imply the formation of a cavity opened at the top by the i^{th} and j^{th} edges.

(d) Fundamental cavity type²

The relationship $e_i^3 \times e_j^4$ implies the formation of a cavity opened at the bottom by the i^{th} and j^{th} edges.

The end points are detected by locating the beginning or end of a blob. If the limb width is less than one-fifth of the width of a character matrix and limb length greater than one-third of the height of a character matrix then a blob is considered as an end point.

Fundamental cavities are further characterized on the basis of their ranks. The rank of an edge is a unique positive integer. Every edge is assigned a rank in increasing order according to the order of their appearance. Suppose that two edges e_i^2 and e_j^1 with respective ranks $r(e_i^2)$ and $r(e_j^1)$ are involved in the formation of the cavity of type, then the three different cavities formed are: $r(e_i^2) < r(e_j^1)$, (left branch is bigger, or both the branches are equal) and $r(e_i^2) > r(e_j^1)$ (right branch is bigger).

Using the edge-to-edge concatenation relationship, two kinds of holes can be extracted: a simple hole which can be detected directly from the relationship R_{11} . Another type of hole, a complex hole which can be detected by analyzing the chains of edges. It should be noted that a chain encircling a blob and the one forming a hole differs in only one respect. A chain which forms a hole must contain at least one edge pair with the relationship R_7 , whose rank is smaller than all other pairs with R_2 relationships. Clearly, this simple test can detect holes in a binary pattern.

The occurrence of these shapes together with their spatial distribution are used as the structural features. The positions of end-points were captured by dividing the character matrix into 4×4 (4 rows and 4 columns) zones. And the span of other shapes were captured by dividing the character matrix into 32×32 zones.

4. A STAGewise CLASSIFICATION SCHEME

In this research the recognition process is divided into two stages: using the numerical features in the prediction module, and the structural features in the structural module.

4.1. Prediction Module

The primary objective of this module is to predict the expected class of an unknown character. But, if the prediction towards a particular class is found to be very strong then the unknown character is recognized within this module; otherwise it is passed to the structural module along with the prediction information.

The identity of an unknown character is predicted using the class weights. The prediction procedure is based on the assumption that numerical features assuming values $\{0, 1, 2, 3, \text{ or } 4\}$ independently classify an unknown pattern into a unique class. The prediction procedure is as follows:

Let u_{ijk} be the j^{th} feature extracted from an unknown pattern. $u_{ijk} = 1$ if the j^{th} feature takes the value k in the i^{th} zone; otherwise $u_{ijk} = 0$. Euclidean distances D_k^r and angles θ_k^r between the feature $U = (u_{ijk})$ and the r^{th} class weight $W^r = (W_{ijk}^r)$ vectors for a given k in all M zones is computed according to:

$$D_k^r = \sqrt{\sum_{i=1}^m \sum_{j=1}^n (W_{ijk}^r - u_{ijk})^2}$$

$$\theta_k^r = \cos^{-1} \frac{\sum_{i=1}^m \sum_{j=1}^n W_{ijk}^r u_{ijk}}{\sqrt{\sum_{i=1}^m \sum_{j=1}^n (W_{ijk}^r)^2} \sqrt{\sum_{i=1}^m \sum_{j=1}^n (u_{ijk})^2}}$$

For each value of $k \in \{0, 1, 2, 3, 4\}$ using the distance, five predictions about an unknown were made by taking that value for which D_k^r is minimum. Similarly, other five predictions were made by considering the five minimum values of θ_k^r over all the classes. In case of a tie or whenever no feature assumes a particular value of k , the prediction for that value of k was ignored.

Weight vectors for each class were obtained using the notion of fuzzy entropy⁶. Feature weighting procedure is described below.

Suppose that there are m classes and let $X^r = (x_1^r, x_2^r, \dots, x_n^r)$ be the numerical features obtained from the training sample of the r^{th} class, where x_j^r takes its discrete values in the range 0 to L ($L=4$). Suppose that η_{ijk}^r is the frequency of occurrence of the j^{th} feature in the i^{th} zone taking a value k in the r^{th} class. The proportion η_{ijk}^r/N_r , where N_r is the number of training samples in the r^{th} class, can be used as the membership grade for the r^{th} class if the j^{th} feature assumes the value k in the i^{th} zone. The fuzzy entropy due to the j^{th} feature can be computed according to the following:

$$H_{ijk} = \frac{\sum_{r=1}^m r_{ijk}^r \ln r_{ijk}^r}{\ln m}$$

where

$$r_{ijk}^r = \frac{\xi_{ijk}^r}{\sum_{r=1}^m \xi_{ijk}^r}$$

and

$$\xi_{ijk}^r = \frac{\eta_{ijk}^r}{N_r}.$$

H_{ijk} takes a value 1 when the j^{th} feature in the i^{th} zone with value k contributes no discriminatory information when all the classes are equally likely. The confidence factor due to the j^{th} feature assuming value k in the i^{th} zone is computed by

$$\lambda_{ijk} = 1 - \frac{K_{ijk}}{m} H_{ijk}$$

where K_{ijk} is the count of classes for which $\eta_{ijk}^r = 0$.

The confidence factor λ_{ijk} and the proportion ξ_{ijk}^r are used to compute the weight of a feature element taking a value k in the i^{th} zone. The weight is computed as $w_{ijk}^r = \xi_{ijk}^r \lambda_{ijk}$.

4.2. Structural Module

This module is used as the second stage recognizer. In this module decision regarding an unknown character is made by incorporating the prediction information and computing the fuzzy membership characteristic values. The recognition procedure and the computation of membership characteristic values are described below.

Let $C = \{c_1, c_2, \dots, c_m\}$ and $X = \{x_1, x_2, \dots, x_n\}$ denote the sets of m pattern classes and n structural features extracted from an unknown pattern respectively. Assume that the presence of a feature element divides the pattern set C into two subsets: (a) the subset p^i in which the i^{th} structural feature is present and (b) the subset in which it is absent. Considering each subset p as a fuzzy subset ($c/\mu_p^i(c)$) where $c \in C$ and $(\mu_p^i(c))$ is the degree of membership characteristic and can be interpreted as a measure of confidence by which an unknown pattern is identified as one of the members of the set C whenever structural feature element x_i is present in a character pattern. Thus, given a set of structural feature X , it is expected that an unknown character may belong to the set $\mathcal{P} = \bigcup_{i=1}^n p^i$ whose membership characteristic is computed by

$$\mu_p(p) = \frac{\psi_p^-}{\psi_p^- + \psi_p^+}, \quad \text{for all } p \in \mathcal{P},$$

where ψ_p^+ and ψ_p^- are the Euclidean distances of a pattern p of \mathcal{P} from ideal and non-ideal prototypes p^+ and p^- respectively. These distances are computed using the membership characteristic $\mu_R(p, x)$ of the fuzzy relation R in $P \times X$ and the membership characteristic $\mu_R^+(x) = \max_{p \in \mathcal{P}} (\mu_R(p, x))$ and $\mu_R^-(x) = \min_{p \in \mathcal{P}} (\mu_R(p, x))$ of the ideal and non-ideal prototypes respectively. $\mu_R(p, x)$ is obtained from the frequency of occurrence of the structural feature x in a pattern class p .

The membership characteristic function $\mu_p(p)$ takes the values in the interval $[0,1]$. Its value approaches to one whenever ψ_p^+ approaches zero, that is, the pattern $p \in \mathcal{P}$ is very similar to the ideal prototype p^+ . On the other hand $\mu_p(p)$ approaches zero whenever ψ_p^- is close to 0, that is, p is very similar to the non-ideal prototype p^- . The value of $\mu_p(p) = 1/2$, if $\psi_p^+ = \psi_p^-$ leads to an indeterminate situation. Thus, a simple procedure can recognize an unknown pattern as $p^* \in \mathcal{P}$, if $\mu_p(p^*)$ is maximum and greater than 0.5, and p is predicted with the maximum frequency; otherwise it is rejected.

5. EXPERIMENTAL RESULTS

The experimental data set consists of 8540 digit images taken from the ZIP code database. During the training session of the prediction module the classifier was trained in steps of 200 samples (20 samples/class). One of the reasons to train the classifier in steps is to study its prediction behaviour for both the seen and unseen patterns. After each training step two tests were performed, one to test the prediction ability of this module on the data already included in the training set and the other to test the same on the data not included in the training set. For both tests, a set of 200 samples were randomly selected from the training set and outside the training set. The prediction capability (at least one correct prediction out of 10) is illustrated in Figs. 6(a-b) which show that after training on the 2000 samples, the prediction for both the training and testing data fluctuates in the range of 94% to 98%. The training was stopped after 5000 samples (500 samples per class) because no significant change in the prediction behaviour was observed.

The recognition performance of the system on both training and testing sets is summarized in Table 1 which shows the individual recognition results of: (a) statistical method—within the prediction module; (b) structural method—within the structural module and (c) combined method—combining the results of the prediction and structural modules. The recognition reliabilities, substitution and rejection rates, for these methods, were computed using the following expressions:

$$\text{Reliability} = (N1/(N-N3))*100$$

$$\text{Substitution rate} = (N2/N)*100$$

$$\text{Rejection rate} = (N3/N)*100$$

where,

N = Sample size

$N1$ = Number of correctly classified samples

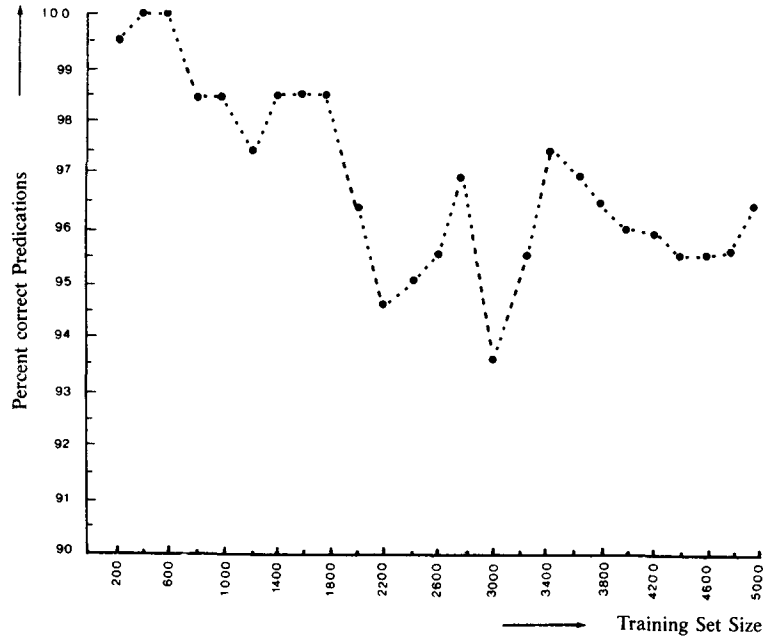


Fig. 6(a). Prediction performance on the training set.

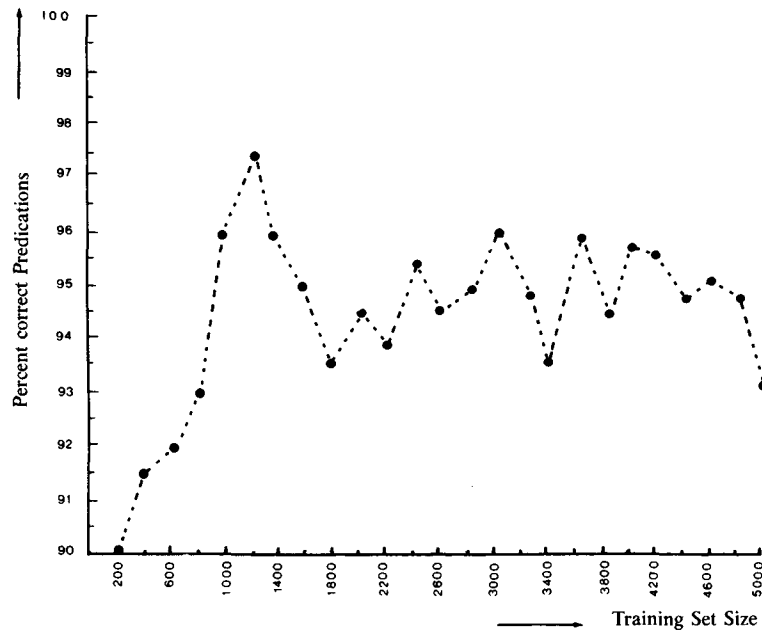


Fig. 6(b). Prediction performance on the test set.

N2 = Number of misclassified samples

N3 = Number of rejected samples.

An unknown character was recognized within the prediction module if all the active decisions from the ten predictions place an unknown character either into a unique pattern class or two different pattern classes with one class having higher prediction than the other class. In case of a tie or when all the active decisions place an unknown character into more than two classes, the unknown character was processed by the structural module.

Table 1. Performance summary.

Recognition Schemes	Training set				Testing set			
	Reliability	Substitution	Rejection	Sample size	Reliability	Substitution	Rejection	Sample size
Statistical	94.17%	3.90%	33.12%	5000	95.32%	3.22%	31.22%	3540
Structural	99.08%	0.18%	7.13%	1656	99.06%	0.73%	22.48%	1103
Combined	95.94%	3.96%	2.36%	5000	96.29%	3.45%	7.01%	3540

For the structural module, the classifier was trained on the same 5000 samples (500 samples/class) as used in the prediction module. The performance of this approach was tested on the data rejected by the prediction module.

In the combined method, unknown characters were recognized by either the statistical or structural method. Results of this method were obtained by considering the recognition results of the within the prediction and structural modules.

6. CONCLUDING REMARKS

The practical applicability of a character recognition model cannot be judged unless it is tested with field data. Through extensive experiments, it has been shown that our model can perform with high accuracy while operating in the real-life environment to meet industrial standards. It should be noted, in this experiment the substitution errors (3.45%, 3.96%) for the combined recognition result is higher than the substitution errors (0.18%, 0.73%) of the recognition result of the structural module. This is due to the flexible recognition criterion used in the prediction module which allows approximately 31% to 33% data to be processed by the structural module. The substitution error for the combined method can be minimized by applying some rigid recognition criterion in the prediction module. One such criterion—recognize a character if it is uniquely predicted instead of split decisions, has been applied. This criterion substantially reduced the substitution errors (0.45% to 0.56%) within the prediction module. However, in this case approximately 61% to 65% data will have to be processed by the structural module. Under this criterion the substitution error for the combined recognition result is expected to be below one percent.

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