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NEURAL NETWORK BASED HANDWRITTEN CHARACTER RECOGNITION FOR CONFLICT RESOLUTION

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Abstract

A Handwritten character recognition system has been developed by using the Kohonen Neural Network. Resolving the conflicts in the recognition of handwritten numerals and thus eliminating the substitution error is the main thrust of the work. The developed system architecture consists of two stages. The first stage is feature extraction and the second is classification. Feature extraction involves collection of useful data from the sample. Classification is the categorization of the sample by a discrimination function in a feature space consisting of feature vectors. The data base used in our work is based on the U S Zip code database. The samples were originally collected from the dead letter envelops by the U S postal services at different locations in U S. The database consists of 250 distinct samples each of size 15 × 15. The results obtained from the developed system show that the system is hundred percent reliable. Substitution is completely eliminated while at the same time maintaining a fairly high recognition rate.

KEYWORDS : Neural Network, Substitution Error, Learning, Feature Vector, Encoder, SOM Classifier.

1 Introduction

A Handwritten character recognition system has been developed by using the Kohonen Neural Network. Resolving the conflicts in the recognition of handwritten numerals and thus eliminating the substitution error is the main thrust of the work. We have eliminated the substitution error completely while maintaining a fairly high recognition rate.

Recognition characters by computers is a topic of intense research for many years[1, 2]. Driven by the challenge of matching human performance and by the numerous applications in data processing, hundreds of researchers have made contributions to this field. Many systems have been developed but more work is still required before human performance is matched[3]. While these systems have no difficulty with well formed samples, their challenge is to maintain a high performance level with samples which are distorted or written in more 'personal' styles. Further more since errors are costly and delay service, maximum reliability is required[4].

One way to improve reliability is to focus on the problem of confusion. If the confusion is between numerals or in a broader sense classes can be resolved then most of the substitution error can be eliminated. When a pattern is incorrectly recognized or for a pattern of the system assign the same confidence values for two different classes a substitution error is said to occur. As the substitution error increases, reliability of the system decreases.

Neural network can be used for improving the recognition of isolated numerals, because, rather than programming them, we train the neural nets by examples. They have appeared in an alternative to the structural or statistical methods in pattern recognition[7]. Programs neednot give neural nets quantitative description of objects being recognized and sets of logical criterion to distinguish such objects from similar objects. Instead, we give examples of objects with their identification. The network memorizes this information by modifying the values in its weight matrix and will produce the correct response when the object is seen again[8, 9]. The learning ability of the neural network has made it very appropriate for the present problem[10]. Furthermore, we propose Kohonen self-organizing map for conflict resolution of unconstrained handwritten characters with good classification performance.

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2 Modified Feature Extraction

Feature extraction is an integral part of any recognition system. Feature extraction method is used to reduce the bitmap image of a sample into a vector of real numbers and thus reduce the complexity of the classifier. A barmask encoder, which is similar to the seven segment alpha-numeric is used. Two additional vertical bars (V3, V4) are used to take care of the vertical strokes as in 'I' and 'T' and four additional diagonal bars(D1,D2,D3,D4) are used to take care of the cross strokes as in 'X' and 'N'. The final design of the encoder consists of thirteen bars - three horizontal, six vertical and four diagonal bars, using which features are extracted[5]. The bit map of a sample can be divided into thirteen regions as shown in the bar mask encoder. The number of pixels in each region is counted. A feature value is given by the number of marked bits(pixels) in the corresponding region divided by the total number of bits in that region.

This method is suitable for only the upper case letters of the English alphabet. This cannot be used for the recognition of unconstrained hand-written characters. One of the drawbacks of the method is that if the horizontal features are displaced (which is usual in case of unconstrained handwritten numerals) they are not properly taken care of. This drawback can be eliminated by making the vertical regions unsymmetrical and enabling them to extract the horizontal features as well along with the vertical features. Thus, in the modified method, the displaced horizontal features are taken care of by the vertical regions.

The modified encoding method makes use of a 15×15 bitmap as shown in Fig. 1. The bitmap is divided into (i) three horizontal regions(H1,H2,H3), (ii) six vertical regions (V1,V2,V3,V4,V5,V6) (iii) four diagonal regions (D1,D2,D3,D4). Using these thirteen regions, thirteen features of each pattern are extracted. For example, the horizontal feature H1 is defined as the number of marked bits in the region H1 divided by the total number of bits in that region. Similarly all other features are extracted. The extracted features are used for training the SOM.

3 Self-Organizing Map

Kohonen's self-organizing map uses unsupervised learning to modify the internal state of the network and to model the features found in the training data set. The map is autonomously organized by a cyclic process of comparing the input patterns to the vectors at each node. The node vector with which inputs match is selectively optimized to represent an average of the training data. Then, all the training data are represented by the node vectors of the map. Thus, starting with a randomly organized set of nodes, the proposed method proceeds to the creation of the feature map representing the prototypes of the input pattern.

By means of SOM algorithm described above the numerical data are self-organized into a feature map. The SOM classifier is then used to perform the classification.

The performance of the handwritten character recognition system is evaluated by the following criterion:

1. Recognition Rate: Percentage of samples recognized correctly,
2. Substitution Rate: Percentage of samples recognized incorrectly,
3. Rejection Rate: Percentage of samples that cannot be assigned to any particular class.

The confidence levels returned by the developed character recognition system are used to estimate the above values.
Recognition(REC)=rec DIV total no. of samples;
Substitution(SUB)=sub DIV total no. of samples;
Rejection(REJ)=rej DIV total no. of samples;
Reliability(Rel)=rec DIV (rec+sub).

4 Experiments and Results

The results are summarized in Table. 1. All the entries are in percentages. The first column represents the threshold value. The second column represents the portion of currently recognized patterns. The third column reports the portion of patterns which are recognized incorrectly. The fourth column shown the portion of patterns rejected. The last column of the table is reliability, which is computed as shown in the following equation. The reliability rate refers to the portion of the recognized patterns that are correctly identified[2].
Reliability=Recognition/(Recognition+Substitution)

Experiments have been conducted using different sets of the sample database, each of size 15×15. The sample

Table 1: Performance of Neural Network based recognition system when 250 samples are trained and same 100 samples are tested

Lambda	Recognition(%)	Substitution(%)	Rejection(%)	Reliability(%)
0.10	97.0	0	3.0	100.0
0.20	97.0	0	3.0	100.0
0.30	97.0	0	3.0	100.0
0.40	97.0	0	3.0	100.0
0.50	97.0	0	3.0	100.0

database has been formed by making use of the samples selected from various research papers of Concordia university, which are originally selected from the 17,000 sample database of U.S. Postal services collected from various parts of USA.

From the result shown it can be inferred that the developed system is robust and 100% reliable since the substitution error is maintained at zero in all the experiments.

5 Conclusions

In this paper, a handwritten character recognition system using Kohonen's self-organization map for conflict resolution on ambiguous patterns has been developed. The developed system resolves the confusion completely and the substitution error is nil. The system is robust and accurate in the recognition of unconstrained handwritten characters. This architecture is very useful is resolving conflicts of unconstrained hand-written characters in PIN and ZIP codes of mailing addresses. The results obtained from the developed system show that the system is hundred percent reliable. The main application of the developed system is in proper identification of ZIP or PIN code of a postal address, which in turn resolves the dead-letter problem of the postal department. Other application include processing of cheques in a banking environment and auditor billing systems.

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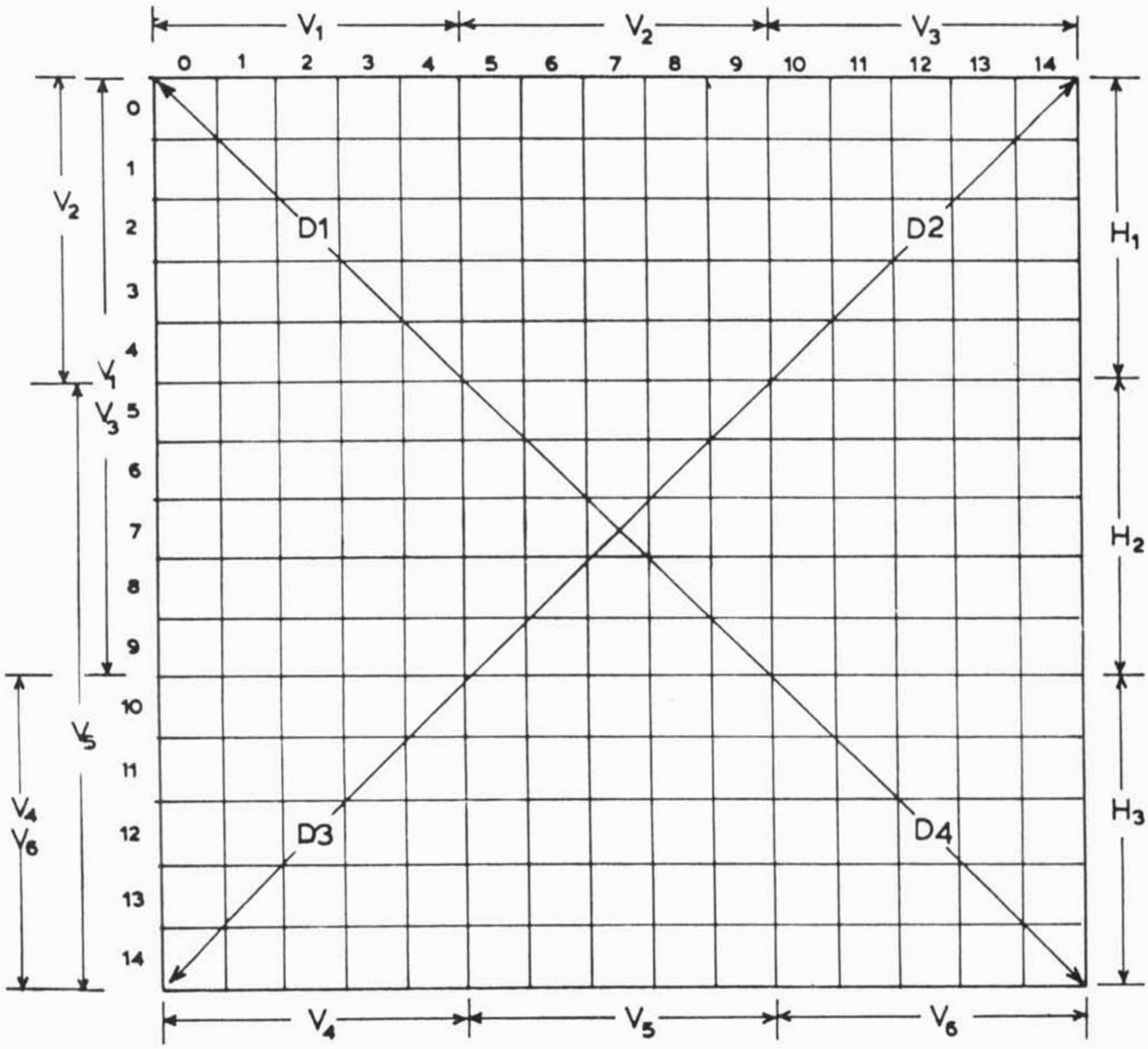

Fig.1 Thirteen Segment Encoder