A neuro-expert system model for conflict resolution

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We describe here a neural network and expert system model for conflict resolution of unconstrained handwritten numerals. The neural network classifier is a combination of modified self-organizing map and learning vector quantization. The basic recognizer is the neural network. It solves most of the cases, but fails in certain confusing cases. The expert system, the second recognizer, resolves the confusions generated by the neural network. The results obtained from this two-tier architecture are compared with those of a combination of four algorithms. This work shows that it is possible to eliminate the substitution while maintaining a fairly high recognition.

NOTWITHSTANDING the progress accomplished in the last few years in the field of pattern recognition, the problem of matching human performance in handwritten character recognition remains a challenge even today[1]. Most of the recognition accuracy rates reported so far are over 95% (ref. 2). 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. Furthermore, since errors are costly and delay service, maximum reliability is required.

Based on the consensus of individual opinions observed in human interaction, the Concorde University research team has developed a multiple expert system (4 algorithms approach)[3]. The performance of this system was compared with the opinions given by a group of human experts. Ideally it is required that the system must be able to differentiate the unrecognizable and confusion categories and to give the same counts as those given by human experts. Also, in case of confusions the machine should produce the same confusing pair as human experts do. The multiple expert system does not fulfill these expectations. It is suggested that a statistical and/or neural network model would be a good complement for the multiple expert system[3]. Here we present a neuro-expert system for unconstrained handwritten numeral recognition. Interest in neural networks is rapidly growing and several neural network models have been proposed for various difficult problems, especially classification problems[4]. Traditional classifiers test the competing hypothesis sequentially, whereas neural network classifiers test the competing hypothesis in parallel, thus providing high computational rates[5,6].

Expert system is a validation module which makes a more informed decision about the classification than the neural network. We have proposed a generalized artificial neural network-based expert system tool for character recognition, especially in case of confusions. The confidence levels obtained from the neural network are stored in the knowledge base using frame model of knowledge representation[5].

The issue taken up here is to resolve the confusion between the conflicting numerals by eliminating the substitution error, and to compare the results of the developed system with the results of the combination of four algorithms method.

The conventional feature extractor converts input handwritten characters into a highly compressed form[6]. This method is suitable only for the uppercase letters of the English alphabet. However, the feature extraction of all the unconstrained handwritten characters which are written in different styles is not possible. For example the horizontal features extracted for the samples using this method are not recognized properly. This disadvantage is taken care of in the modified feature extractor by making the vertical regions unsymmetrical.

The modified encoding method makes use of a 15×15 bit map as shown in Figure 1. The figure shows (i) three horizontal regions (H_1, H_2, H_3), (ii) six vertical regions (V_1, V_2, V_3, V_4, V_5, V_6) and (iii) four diagonal regions (D_1, D_2, D_3, D_4). Using these thirteen regions, thirteen features of the pattern are extracted. These features are used during the training process of the neural network. The training process is carried out using Kohonen's modified self-organizing map (MSOM) and learning vector quantization method (LVQ).

Kohonen's self-organizing map uses unsupervised learning to modify the internal state of the network and

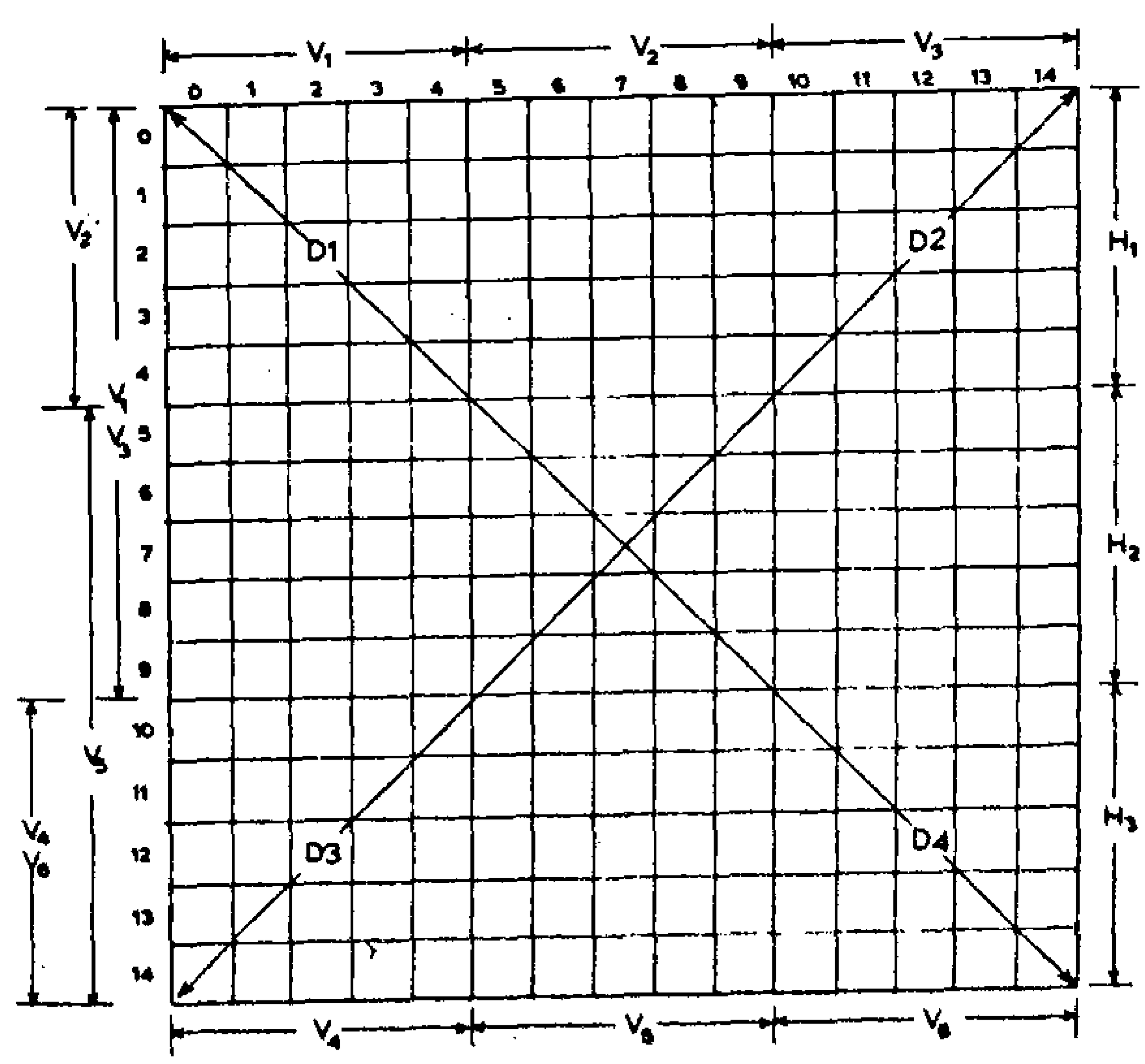

Figure 1. Thirteen-segment encoder.

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 the inputs match is selectively optimized to present 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 a feature map representing the prototypes of the input patterns.

In the conventional SOM the misclassification is more[4,9] because the minimum distance formula is applied for both the standard (machine printed numerals) and the distorted sets of samples. This is overcome in MSOM by applying the minimum distance formula for only the standard set of samples. A sample is compared only with the nodes represented by the standard set of samples (which form the centroids for each class). Using the minimum distance formula and the winner node (that is the node which matches the sample most), the weights in the neighbourhood of this winner node are updated. The MSOM is organized by a cyclic process of comparing the input patterns to vectors at each node twice. The so obtained MSOM is further fine-tuned using the LVQ technique[9,10].

Kohonen has suggested that if the nodes of the SOM are used for pattern recognition, their classification accuracy can be multiplied if nodes are fine-tuned using supervised learning principle[9].

The LVQ uses supervised learning to modify the internal state of the network provided by MSOM and to remodel the features found in the training data. A fine-tuned map is autonomously organized by a cyclic process of comparing input patterns to the vectors at each node. Fine-tuning is achieved by selecting training vectors **X** with known classification, and presenting them to the network to examine the cases of misclassification. The best match comparison is performed at each node and the winner node is noted. By means of the LVQ algorithm, patterns are self-organized into a fine-tuned feature map.

We have introduced a two-tier architecture-character recognition system (Figure 2). The basic recognizer is the neural network, which recognizes most of the cases correctly but fails in certain confusing cases and expert system is the second recognizer, which resolves tl confusion generated by the neural network.

The confidence levels obtained from the neural netwo are stored in the knowledge base using the frame mod of knowledge representation[5]. This knowledge is captur and applied to the validation module (expert syster for conflict resolution. The output from the neural ne work is double checked by the validation module who inference engine decides if the sample could be potential confusion. If there is no confusion, the outp from the validation module is the same as the neu network output with a higher confidence level. If the is a high probability of confusion, the inference engi calls the appropriate specialized module which will gi

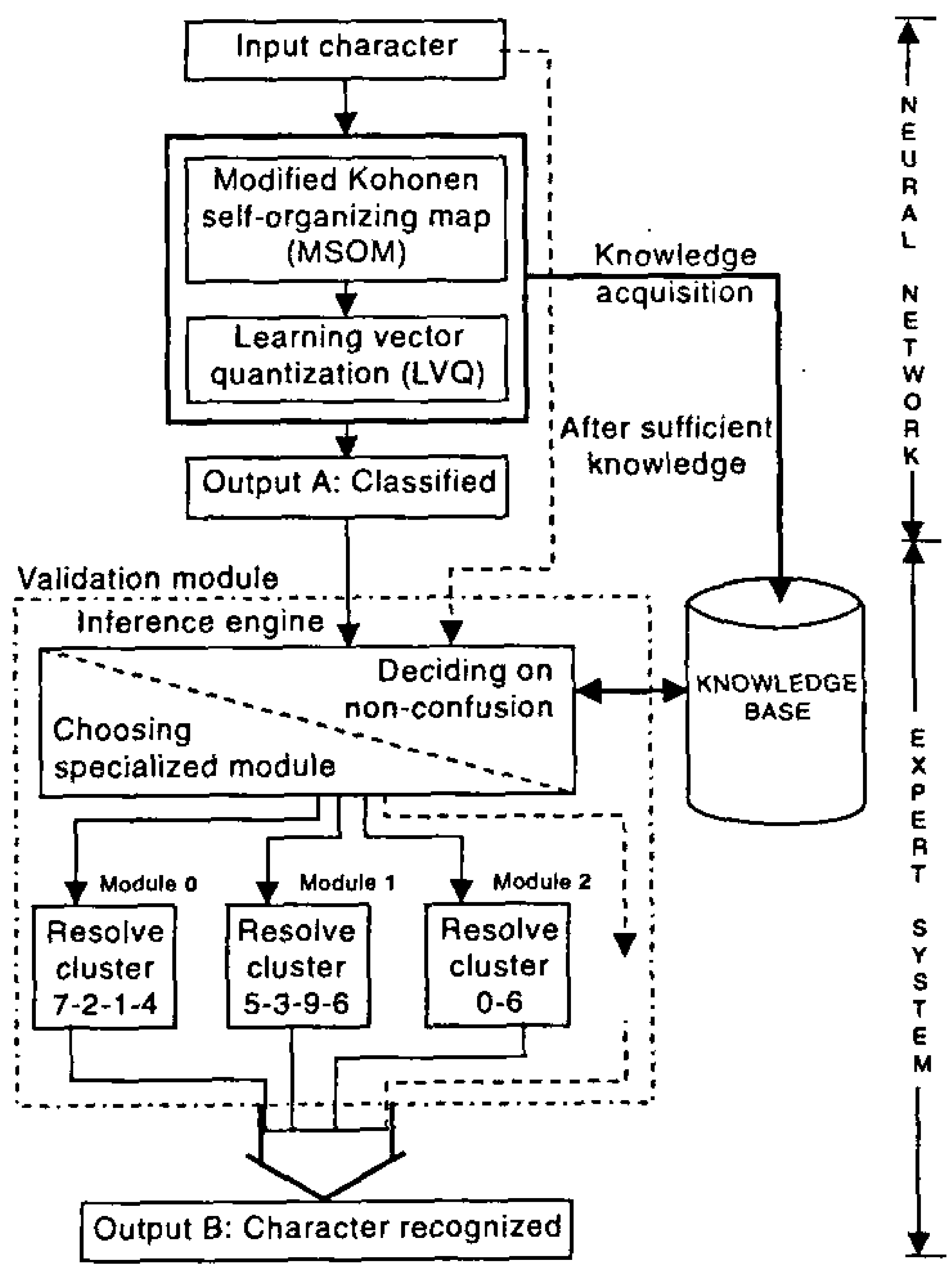

Figure 2. Two-tier architecture of the neural network expert syst

Table 1. Performance comparison of 4 algorithms approach and neuro-expert system

		Samples rejected by human experts			Confusion in case of human experts						
						Conf.				Unambiguo	
Type of system	No. of samples	Rec. (%)	Conf. (%)	Rej. (%)	Rec. (%)	Same pair (%)	One member same (%)	Different pair (%)	Rej. (%)	Sub. (%)	Re (%
4 Alg. method	360	33.33	33.33	33.33	50	35	55	10	0	11	8
Neuro-expert system	360	87.5	0	12.50	69	44.4	44.4	11.11	0	0	10

the final output that is different from the neural network output. In the above process the average experts' opinion is computed. The pattern with maximum average opinion (maximum confidence level) is recognized. The knowledge modelling stage needs to be executed only once for a training set of patterns. But the decision-making stage will be executed for every test pattern.

The operations carried out by the expert system are as follows: (i) Mapping of conflicting character onto the classifier and collecting the confidence levels. (ii) Searching for the maximum confidence level. (iii) Searching for the next maximum confidence level. (iv) Comparing the maximum and the next maximum confidence levels for checking the presence of confusion. (v) In case of a confusion, define the clusters which contain one or more interrelated classes. (vi) Processing of the current confidence levels of a set of samples into their equivalent knowledge representation form. (vii) Growth of the knowledge base on the basis of current history. (viii) Finding the cluster that contains maximum confidence value class. (ix) Collecting the opinions of experts about the classes of a cluster. (x) Finally, computing the average experts' opinion for each class. The class with maximum experts' opinion contains the recognized character.

The sample database for the experiment has been generated by taking samples selected from various papers of Concorde University (which were originally selected from 17,000 sample database of US Postal service collected from various parts of USA) as seed values.

We have chosen the net size as 15×15 in which the initial neighbourhood size is 9, i.e $N_j(0) = 9$ and the number of input nodes (features) is 13. The value of alpha at various stages during the training process is as follows.

No. of iterations	Alpha
0 to i	0.923971
i to $2i$	0.4120
$2i$ to $3i$	0.23420
$3i$ to $4i$	0.051246
$4i$ to $5i$	0.0018231

where $i = (2 * \text{no of samples} * N_j(0))$ DIV 5, i.e. the total number of iterations.

Table 1 shows a comparative performance of the 4 algorithms approach[2] and the neuro-expert system. The set of 360 samples (most difficult to recognize) which were classified by a group of human experts[2] was presented to the neuro-expert system and the results obtained were compared with those of the 4 algorithms approach. The following observations were made.

(i) The samples rejected by human experts were presented to the two systems, the neuro-expert system uniquely recognized (Rec.) 87.5% of the samples as compared to 33.33% of the 4 algorithms approach.

(ii) The samples that were considered to be confusing by human experts were presented to the two systems, the neuro-expert system recognized 69% as compared to 50% of the 4 algorithms approach. Out of the remaining the 4 algorithm approach gives confusion pairs of which 35% of the samples correspond to the

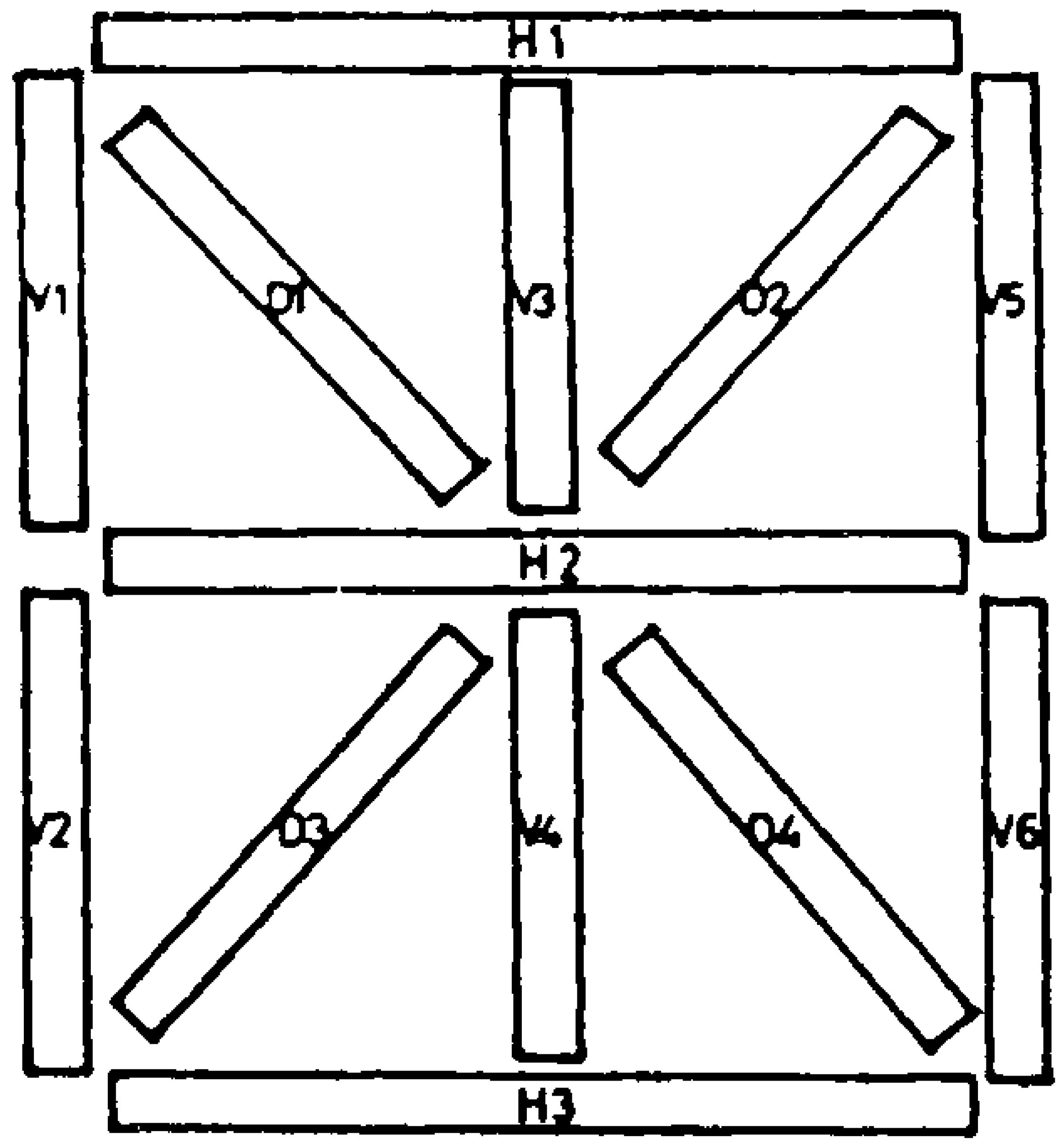

Figure 3. Conventional bar mask encoder.

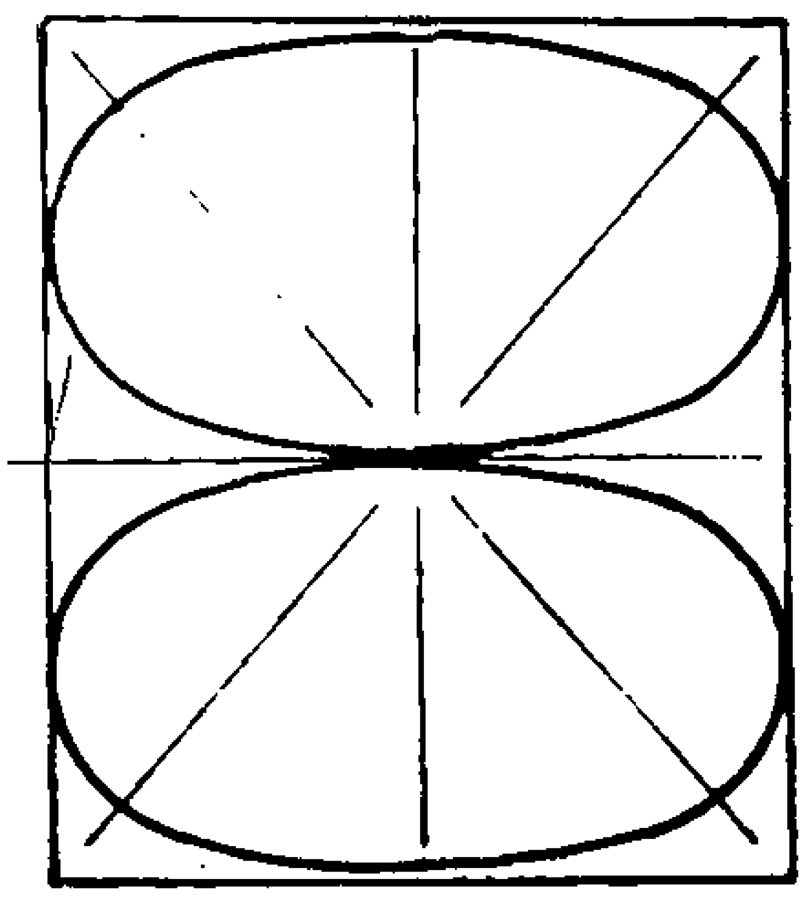

Figure 4. Machine-printed numeral 8.

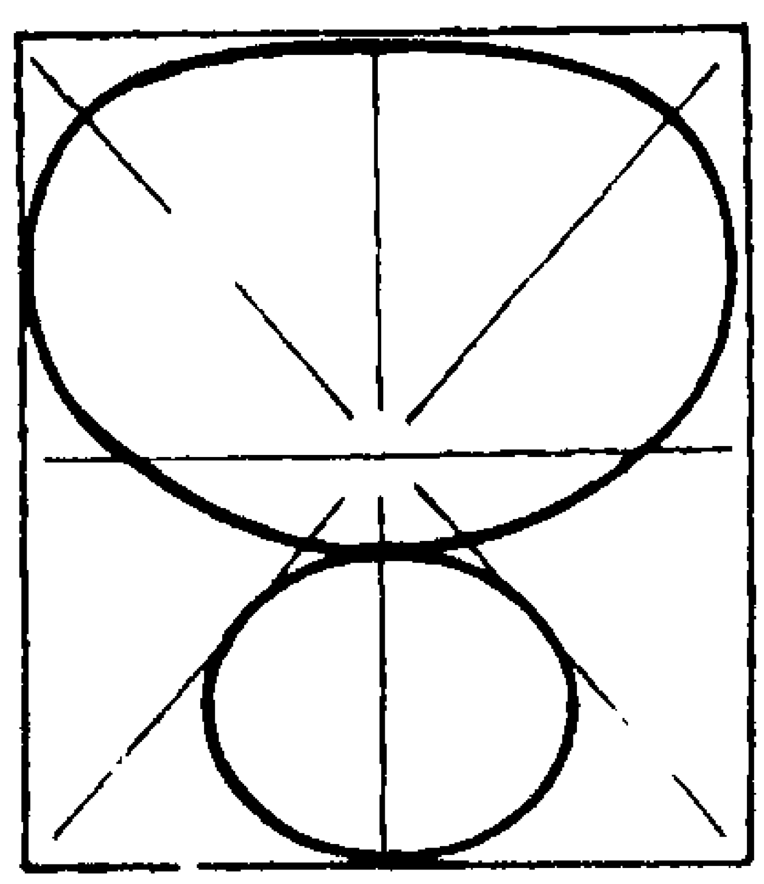

Figure 5. Unconstrained handwritten numeral 8 with horizontal feature displaced downwards.

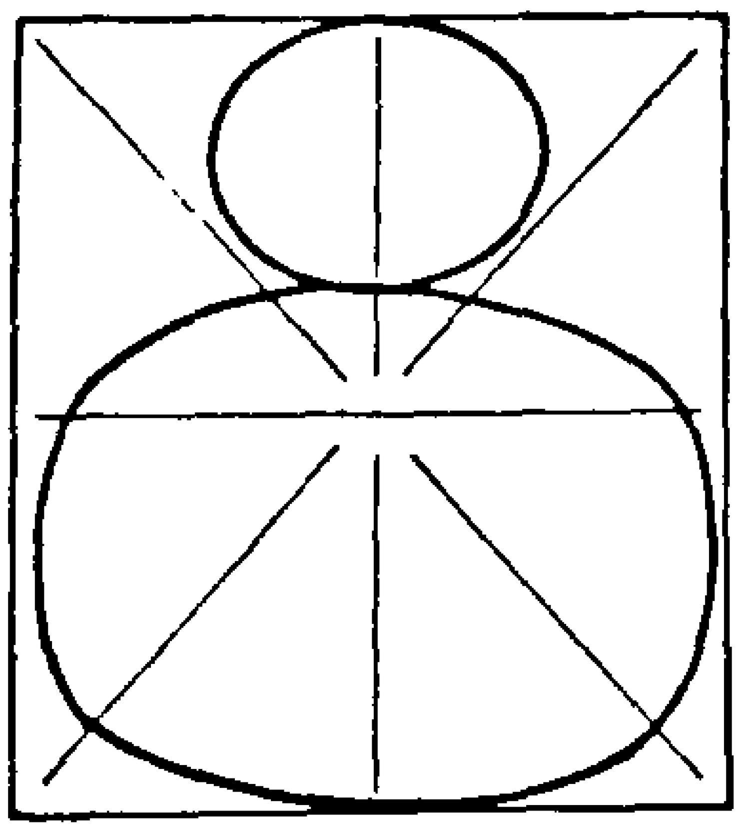

Figure 6. Unconstrained handwritten numeral 8 with horizontal feature displaced upwards.

same pairs as those given by the human experts. For 55% of samples it gives a pair in which one digit member of the confusion pair is common in both and it gives a totally different pair for the remaining 10% of samples. The neuro-expert system gives confusion pairs of which 44.4% of the samples correspond to the same pairs as those given by the human experts. For 44.4% of samples it gives a pair in which one digit member is the same as that in the human pair and it gives totally different pair for the remaining 11.11% of samples.

(iii) Of the samples which were uniquely classified by human experts, 89% were recognized by 4 algorithms approach and there was substitution in case of 11% of the samples. The neuro-expert system recognized all the samples and the substitution (Sub.) rate is nil.

From the above observations we can infer that the performance of the neuro-expert system is comparable with that of the 4 algorithms approach.

The better performance of the neuro-expert system can be attributed to the following:

1. *Choice of features.* The feature extraction method (Figure 3) has been modified to suit the recognition of unconstrained handwritten numerals. The vertical regions have been made unsymmetrical to cope with the displaced horizontal features. The above point is illustrated in Figures 4–6. Figure 4 shows a machine-printed numeral 8, the horizontal feature exactly lies on horizontal region H_2, but in Figures 5 and 6 the horizontal feature is displaced and lies in H_1 and H_3 respectively. Thus the horizontal feature which is most important in this case (since it distinguishes 8 from 0) is not extracted consistently. This problem occurs with many other numerals also. This drawback can be eliminated by making the vertical regions unsymmetrical and enabling them to extract the horizontal features as well along with the horizontal regions. In the modified method the displaced horizontal features will be taken care of by the vertical regions. Thus a number of conflicts will be resolved, eliminating the substitution error and increasing the recognition rate.

2. *Use of expert system.* By using the expert system as a validation module, the reliability of the system increases. The neural network classifier acts as a basic recognizer, which recognizes most of the samples correctly. Difficult or distorted samples which cannot be recognized by the neural network are passed on to the expert system, which is capable of taking a more informed decision. The neural network identifies the pair among which confusion occurs and the expert system is then used to resolve the confusion. Even the samples recognized correctly by the neural network are passed onto the expert system which checks the decision and returns a higher confidence level. This increases the reliability of the system.

In this paper a neural network using the modified Kohonen self-organizing map and learning vector quantization techniques, and expert system model for conflict resolution on ambiguous patterns has been accomplished. The results lead to infer some interesting properties of the human behaviour in the classification process. The developed system resolves the confusion completely. The paper also shows that the results obtained from the neuro-expert system using MSOM and LVQ are comparable with the 4 algorithms approach developed by the research team of Concorde University. The system is robust and accurate in the recognition of unconstrained handwritten characters. This two-tier architecture has been very useful in resolving conflicts of unconstrained handwritten characters in PIN or ZIP codes of mailing addresses. In particular, this work should be very useful in overcoming the dead letter problem of postal department.

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