SOME APPROACHES TO THE RECOGNITION OF HANDWRITTEN NUMERALS

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ABSTRACT

The present work deals with the recognition of handwritten isolated numerals by utilizing a recent approach, which aims at tackling the variability in the writing styles. A two pronged approach involving pre-classification and the recognition has been followed in this paper. For the pre-classification of numerals, two approaches have been presented. The first is heuristic based and the second is stroke based. A recent feature extraction method, namely sector data method, which takes care of variability in the handwritten numerals, has been incorporated into the system thus the variability involved in the writing styles of different individuals is taken care of by extracting features from the sector based approach. The back propagation neural networks have been used in the recognition process using the features extracted from the sector-based approach. On the basis of recognition rates obtained with samples written by different individuals, it is concluded that the sector based approach is better suited for the recognition of numerals when pre-classification is made on the basis of strokes.

1. Introduction

The recognition of handwritten numerals has many applications such as automatic Postal sorting, automatic bank cheque processing etc. The earlier systems known as Optical Character Recognition (OCR) systems that had been developed were confined to recognize only the printed or handwritten numerals of fixed size and fonts. But, the present study aims at producing a system, which could recognize numerals of any arbitrary size, shape and fonts. There are numerous approaches that address the problem and they vary in the features extracted from the graphical representation of the numerals. The system of Sridhar[8] recognizes both the hand printed and machine printed text for postal address interpretation. Fairhurst and Rahman[9] have used a new hybrid approach to recognize handwritten numerals. Ahmadi etal. [10] and Cho[11] have employed a multistage classifier for recognizing totally unconstrained handwritten numerals. Abuhaibiba and Ahmed [13] have generated a set of fuzzy constrained numerals graph

models. These can tolerate a large degree of flexibility by which the structures consisting of straight-line segments and loops (two stroke sequence) are constructed. Rocha and Pavlidis [14] have used shape analysis model for the recognition of numerals using the variation in numeral shapes from the prototypes. Classification of numeral shapes is defined as a minimization problem among the possible transformations that map an input shape to prototypical shapes. In this paper, we have experimented sector based approach [19] for the recognition of numerals. The motivation behind this work is to judge the potential of this approach for feature extraction and then use the neural networks for the recognition after they are trained with the features extracted.

The organization of the paper is as follows: Section 2 briefly discusses the preprocessing steps used. The pre classification schemes are presented in section 3. Section 4 deals with the feature extraction and conclusions are in section 5.

2.Pre-processing of characters

We have applied normalization and thinning in the pre-processing stage. Other steps such as slant correction, slope correction and pruning are not crucial for the present work though they can be experimented with.
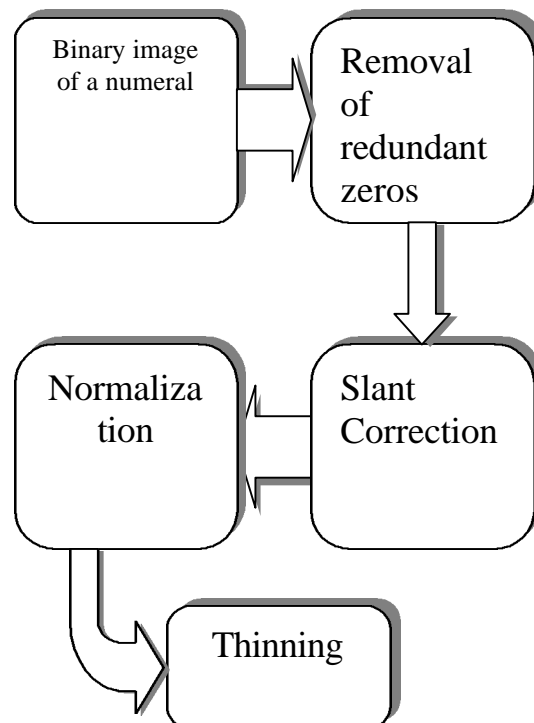
Fig 1: Preprocessing of numerals

2.1 Normalization and Thinning

Normalization is required as the size of a numeral varies from person to person and even with the same person from time to time. Before thinning, the broken parts of numerals if any are joined. Usually the numeral '5' has broken parts. The broken part is joined to the rest of the body by extending it backwards until it meets the body. This backward direction is the direction opposite to the writing style. This is done in the following way. For this, a boundary scan of the broken part is done until we reach the point where we started. The binary file is scanned again to find any other boundary other than the marked boundary.

If there exists some other boundary then it is joined with the marked boundary by finding the angle of the stroke associated with the marked boundary and extending the stroke till it meets the other boundary. Thinning is the process to extract and apply additional constraints on the pixel elements that need to be preserved such that a linear structure of the input image will be recaptured without destroying its connectivity. In the context of image processing, thinning is considered as an iterative procedure which removes points or layers of outline from a pattern until all the lines or curves are of unit width or of single pixel wide. Thus, the reduced pattern is known as the *skeleton.* A comprehensive survey of thinning methods is given in Lee and Suen [9]. Naccache and Singhal [5] made a study of fourteen thinning algorithms based on iterative erosion of boundary. A standard four-pass thinning procedure proposed by Rosenfield and Kak[12] has been used in this work. This algorithm is a specialized shrinking process which deletes points, whose removal does not locally disconnect their neighborhoods from the numeral matrix at each iteration and this guarantees connectivity property of the numeral.

3. Pre-classification

The central issue in numeral recognition is the selection of proper features. In order to decide the identity of the numeral, features, which will exhibit the distinct characteristics of the numerals, are extracted. Ideally, the features should enable the system to discriminate correctly from one class of numerals from other classes.

3.1 Using a heuristic approach

The structural features like end points, junction points and number of branches are found to vary from numeral to numeral. So, in this work, two methods are used for pre-classification of numerals. In the first method, a preference level, say, zero, is set on the basis of distances extracted from the numerals. The numerals satisfying the preference levels are grouped under one category and the rest the grouped into another category. The proposed method partitions the normalized file into 16 parts with each part forming a matrix of size [5x4.]. From this matrix, for each pixel '1' encountered in the binary file, distance is calculated from the position of this pixel to the left-hand top corner of the matrix. The distances for all such pixels in the matrix are summed up. So, in all a normalized numeral yields 16 features which ma be zero and nonzero. The location of zero values in the positions designated in Table. 1 is used to categorize the numerals as per Table 1(a). For example, if position 7 and 10 contains zeros then the numeral is pre-classified as 0. Then the features of numeral 0 extracted using the sector based approach are loaded into the neural network for verification. This pre-classification leads to the first category consisting of numerals 0,1,4,5 and 7. The remaining numerals belong to the second category. The scheme is also rotationally invariant. For other numerals pre-classification is not possible and their features are directly used in the neural network for recognition. A few samples of handwritten numerals are shown in Fig.2.

3.2 Using stroke approach

Here, numerals are grouped into four categories based on strokes. A stroke is the traversal of numeral from a junction having a odd number of branches or from an end point or from any pixel having '1'[16]. The staring point is chosen in the order of priority., i.e. first junction point, if not, the end point else any pixel containing '1'. The traversal is made by finding the neighbor of each pixel and then marking the present pixel, so that, it is not traversed twice. Likewise the procedure of traversing and marking pixel is repeated.

4. The Proposed Sector based approach for Feature Extraction

The approach of Hanmandlu et al.[15] for the recognition of handwritten capital letters of English text is adapted to the present numeral recognition. In this, the centroid of black pixels in the numeral array is calculated. On experimentation, the division of numeral into twelve sectors is found to be optimal. Then the total number of 1's in the normalized numeral is calculated. In each sector, the sum of vector distances of all pixels '1' from the centroid is computed and normalized by dividing with the total number of pixels '1's present in the numeral. Similarly, the normalized angles are computed for all the sectors. The centroid data is also normalized and is taken as additional two features. In total we have 26 features. This feature database is created for all input numeral sets.

4.1 Configuration of ANN's for different methods of preclassification

Once the feature vector is chosen, the number of neurons in the input layer is fixed. The number of neurons in the output is also fixed based on the categorization of numerals. The preclassification using the preference levels suggests the number of output neurons to be employed. For example, if any one of 0,2,4,5,7 is the outcome of preclassification we need only one-output neurons. The number of numerals present in each category guides the structure of the network in the case of stroke sequence. For example, category-1 requires three output nodes, as there are seven numerals in this category. The configurations of ANN's for different preclassification methods are given in Table 3.

4.2 Results

As different people write in different ways, we have used handwritten samples of numerals both for the training and testing purposes. Tables 4 & 5 give the number of samples used in the training and testing phases of recognition process and Tables 6 & 7 depict the recognition rates obtained for the two methods of preclassification respectively. The results demonstrate that the preclassification based on stroke method is better than that based on preference level method. It is found that recognition rate is drastically reduced without preclassification of numerals.
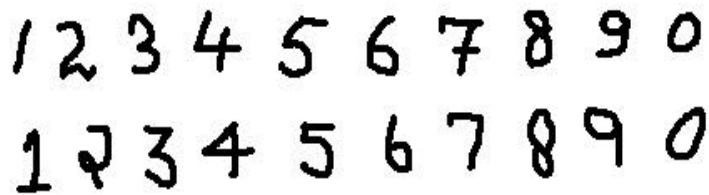
Fig. 2 : Samples of Handwritten Numerals

5. Conclusions

This work presents a handwritten numeral recognition system. Two approaches are presented for the pre-classification of numerals. A recent feature extraction method, namely sector data method, which takes care of variability in the handwritten numerals, has been incorporated into the system. On the basis of recognition rates obtained with samples written by different individuals, we can conclude that the sector based approach is better suited for the recognition of numerals when preclassification is made on the basis of strokes. In this paper, nature of the stroke is not considered which may result in the improvement in the preclassification of the numerals. The two preclassification techniques can be combined resulting in better recognition rate and better utilization of memory. Then other methods proposed earlier [1,15] like Ring method and Fusion method that is a combination of both ring and sector methods can be used for feature extraction to ascertain further improvement in recognition rates.

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APPENDIX

Table 1: The position number of mark in the normalized file.

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

Table 1.1(a): Preference level for specific numerals

Numeral	Σ dist $= 0$ In positions
0	**7&10**
2	**5&6**
4	**4&13**
5&7	**9**

Table 2 : Preference classification of Numerals

Category	Numeral	Number of strokes
1	**0,1,2,5,6,7,9**	**1**
2	**1,2,7,9**	**2**
3	**3,4,8**	**3**
4	**8**	**4**

Table 3 : Configuration of ANN`s for Sector data method

Preclassification Technique	No.of input nodes	No. of hidden notes	No. of output Nodes
Preclassification Technique	No.of input nodes	No. of hidden notes	No. of output Nodes
Preference level method	26	15	1 or 4
Stroke sequence Method	26	15	3 for cat. 1,2 for cat.2 2 for cat. 3,1 for cat.4

Table 4 : handwritten samples used in training and

testing for Numerals using stroke sequence method

Category	training Sample	Testing Samples
Without preference Level	1240	300
Withpreference level		
`0'	120	40
`2'	110	35
`4'	140	40
`5' & `7'	220	69
Other	750	150

Table 5: Handwritten samples used in training and

Testing for Numerals using stroke sequence method

Category	training Sample	Testing Samples
1	755	200
2	460	145
3	210	80
4	100	25

Table 6 : Recognition rates for numerals with/ without

Preference levels

Numerals	Sector data Method
Without preference Level	84%
With preference level	
`0'	90%
`2'	88%
`4'	91%
`5' & `7'	88%
Others	86%

Table 7: Recognition rates for numerals using stroke

Sequence method for preclassification

Numerals	Sector data Method
1	87%
2	90%
3	94%
4	99%