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Selective Subset of Relative Density Feature Extraction Algorithm for Unconstrained Single Connected Handwritten Numeral Recognition

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ABSTRACT

The recognition of handwritten characters and numerals has been a challenging problem among the researchers for few decades. This paper proposes a selective relative density feature extraction algorithm for recognizing unconstrained handwritten numerals independent of the languages. The proposed method consists of image enhancement, representation, selected relative density and recognition phase. The handwritten numerals must be enhanced with dilation, in order to connect the broken digits. After enhancement, the dilated binary images can be represented as a mid-point aspect ratio class interval values. There can be M * N zones and subsequently there would be 2^{M*N} relational density exist using mid-point aspect ratio class interval values. In order to minimize the number of features, a subset of selected W relative densities has been extracted from the binary image since the relative density is too large to be handled efficiently. The minimum distance classifier technique has been used to recognize the given numerals. The proposed algorithm would be an alternative to recognize the handwritten numerals for recognizing unconstrained handwritten numerals. The method sounds promising with a recognition rate of 93.02304%.

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INTRODUCTION

A numeral recognition system has a variety of commercial and practical applications in postal automation, bank cheque processing, automatic data entry, reading aid for the blinds, vehicle number plate recognition etc. The challenge of building a numeral recognition system which can match the human competence provides a strong motivation for research in this field. The recognition of handwritten numerals, characters, symbols and multifont numerals by computer has been a topic of intense research for almost five decades. A variety of algorithms, combination of features and feature sets have been adopted to try to capture essential information from handwritten numerals. Using different feature sets, and recognition algorithms researchers have obtained accuracy rate up to 99.10% ±0.40 for numerals of their respective languages, but the feature sets and recognition algorithms may not work for other languages because of variant in shapes, orientation etc. The strategy used for numeral recognition can be broadly classified into two major categories, namely, decision theoretical and structural. In the decision theoretic approach, an unknown pattern vector $\boldsymbol{x}$ is said to belong to the i^{th} pattern class if, upon substitution of $\boldsymbol{x}$ into all decision functions, the decision functions yields the largest numerical value. Example includes minimum distance classifier, correlations, optimum statistical classifier and neural networks. In the second category, efforts are aimed at capturing the structural relationships among characters, generally from their skeletons or contours. Examples include, matching by shape numbers. Kazua Kamata *et al*, (1988) used structural approach and proposed fourteen pattern primitives as a feature set and primitive tree for classification and has achieved 96% recognition accuracy using 300 handwritten numerals. Keiji Yamada, Hiroyuki Kami, Jun Tsukumo (1989), used decision theoretical approach, they used three neural networks, first, globally connected neural network into which a grey level character image is input, second, locally connected neural network into which a grey level character image is input and third, network into which contour features for a character are input and obtained 99.12%, 99.14% for 40 and 100 hidden units respectively. Christine Nadal, Raymond Legault and Ching Y. Suel (1990) presented two methods, one classifies samples based on structural features extracted from their skeletons and the other makes use of their contours, and has achieved recognition rate 84.85%. J. T Lin and R.M. Inigo (1991) used Back Propagation Neural Network with different structures and images are normalized to size 19 * 19. A lucid scope has been given in the paper as, increasing

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training numerals the recognition rate would proportionally increase. Jun Cao, M. Shridhar, F. Kimura, M. Ahmadi (1992), each image is divided into rows and columns, called zones. In each zone, a local histogram of the chain code is calculated. The feature vector is composed of these local histograms. They concluded that the neural net classifier outperforms the statistical classifier when the feature vector size is small. Both classifiers are effective in recognizing handwritten numerals with very low error rates and low rejection rates. Takahiko Kawatani (1993), used four feature extraction families, first, concavity measurements, second, horizontal and vertical projections, third, polygonization of both the internal and the external numeral boundaries and fourth feature includes top, bottom, left and right extrema of the numeral. The recognition rate has been 98.05%. Feng Pan, Mike Keane (1994), proposed a new set of aspect invariant moments, which are suitable for neural networks. Their experimental results have proved high recognition rate of 98.73% and low substitution rate of 1.06%. M.H. Shirali-Shahreza *et al* (1995), designed 32 segment bar mask for shadow coding Arabic Numerals irrespective of size and translation and obtained recognition accuracy of 97.8%. Jianming Hu and Hong Yan (1996) proposed structural method for describing both printed and handwritten characters. The additional features considered are direction points (D) to characterize the curve changes in horizontal and vertical directions and the bend points (B) are used to detect the curvature changes of a curve in one direction. They have used 102 prototypes for characters and recognition rate of 97.08% was achieved, using thinning algorithms as the pre-processing method. Thien M. Ha and Horst Bunke (1997) proposed perturbation approach, reversing an input image to one of its standard forms, CEDAR and NIST database was used which gave a result of 99.09%, 99.54% recognition rate respectively. Xuefang Zhu (1998) grouped three different categories of primary features namely, boundary distances in a segment, pixel densities in a segment and line distances from centroid in a segment. To reduce the percentage of the error rate, voting system was used to obtain the final result. Alceu de S. Britto Jr *et al* (2003) proposed 10 column and 10 row based zoning scheme without making the features size invariant. Their experiments have shown that HMMs can provide high recognition performance 98% close to those provided by the use of Neural Networks (99%). B.V. Dhandra *et al* (2006) proposed multifont numeral recognition without thinning, using four directional density of pixels. 99.78% of accuracy was achieved and average time required for execution per numeral was found to be 0.0160 seconds using Minimum Distance Classifier. Binu P. Chacko, Babu Anto P (2007) used both structural and statistical features and the recognition rate obtained was 93.3% and 95.7% respectively. They have applied thinning algorithm to extract features and represented the image in a 4 * 4 grid. Ying Wen, Pengfei Shi (2008) proposed improved LDA and Bhattacharyya distance based classifier for numeral recognition. S.V. Rajashekararadhya, P. Vanaja Ranjan (2009) proposed zone and distance metric based feature extraction techniques and computed the distance between the image centroid to each pixel present in the zone. They have obtained 50 features and used support vector machine for classification. They used normalization and thinning during pre-processing stage, the recognition rate 97.25% for Kannada numerals was obtained. S. Impedovo, *et al* (2010) addresses the problem of selecting the feature membership function for zoning based classification. Several membership functions have been considered, based on abstract level, ranked level and measurement level weighting models and they have found, on average, the exponential membership functions seems to provide the best results, the recognition rate being 85.26%. Mahesh Jangid *et al* () used two types of features, namely, zoning density and background directional distribution with various zones 4 *4, 5 * 5 and 6 * 6 and obtained 98.76%, 98.91% and 98.54% recognition rate respectively. D. Impedovo, G. Pirlo (2012) proposed a multi-objective genetic algorithm with optimal number of zones along with the optimal zones, defined through Voronoi diagrams and obtained a minimum error rate of 6%. From the literature it reveals that there are methods which are efficient in the recognition of numerals but they suffer from thinning requirements and also they fail to meet the accuracy when worked with different language numerals. The challenge is to develop a method that removes size restrictions and language independent. The present study aims at producing a numeral recognition system, which could have numerals of any size, shape and language with reasonable amount of space and time. The organization of the paper is as follows. In section 3 database collections and pre-processing of data has been described. In section 4 representations of the numerals and in section 5 and 6 feature identification followed by feature selection has been described respectively. The proposed methodology has been described in section 7. The experimental results are reported in section 8 and the conclusion of the work is given in section 9.

3. Database collection and pre-processing of data:

In this paper, the standard database comprising of English numerals, the MNIST handwritten database has been used for both training and testing. It has a training set of 60000 numerals and testing set of 10000 numerals. To validate the numerals available in the database, pre-processing and tolerance limits have been applied. In the pre-processing procedure, small gaps of a numeral image have been bridged using dilation process. Statistical tolerance limits has also been applied to obtain the numerals with a standard height, width, and minimum and maximum aspect ratio. The lower tolerance limit can be obtained by applying the formula, $Mean - K * S$ and the upper tolerance limit = $Mean + K * S$, where Mean refers to average height of a particular numeral, K=3.291(sample size > 1000 and confidence limit =99.9%) and S is the standard deviation. From the experiment conducted, the tolerance values obtained for validation of the numerals is tabulated in Table 1. Figure 1 shows the sample data set for training which have been obtained after dilation and tolerance limits procedures.

Table 1: Shows the tolerance limit height and width, lower and upper tolerance limit of aspect ratio of the numeral from the training data.

Numerals	Lower tolerance limit (Height)	Lower tolerance limit (Width)	Lower tolerance limit (Aspect ratio)	Upper tolerance Limit (Aspect ratio)
0	14	9	0.425835	1.820406
1	16	2	0.320	5.399727
2	13	9	0.364921	1.827389
3	15	6	0.40325	2.144832
4	16	7	0.427453	2.136789
5	8	6	0.186222	2.025031
6	13	5	0.468586	2.311148
7	14	6	0.453196	2.166947
8	16	6	0.436202	2.232329
9	16	5	0.565917	2.394791

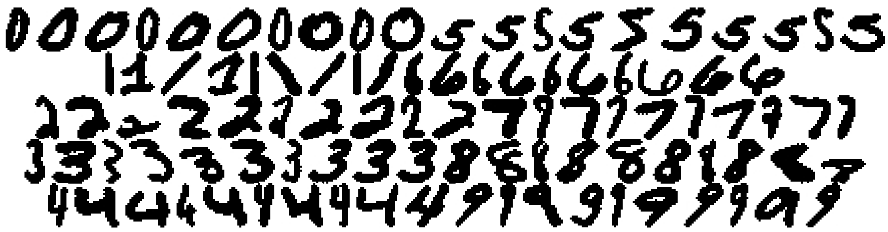

Fig. 1: Shows sample data set for training which was obtained after dilation and tolerance limits procedure.

4. Representation of the numerals:

One of the important components of handwriting recognition scheme is the selection of good representation without affecting the shape of the numerals. Aspect ratio value (height / width) varies from 0.33 to 5.40 for handwritten numerals due to intra class variance of the numerals of the same class. Based on the aspect ratio midpoint value of a numeral, the number of zones can be obtained along x and y axis. Table 2 shows the class interval, midpoint value and number of zones along x axis and y axis.

Table 2: Shows the number of zones required along x axis and y axis based on Midpoint values.

Serial No	Class Interval (based on aspect ratio)	Mid Point Value	Number of Zones (along y axis)	Number of Zones (along x axis)
1	0.55 – 0.64	0.60	3	5
2	0.65 – 0.74	0.70	7	10
3	0.75 – 0.84	0.80	4	5
4	0.85 – 0.94	0.90	9	10
5	0.95 – 1.04	1.0	4	4
6	1.05 – 1.14	1.10	11	10
7	1.15 – 1.24	1.20	6	5
8	1.25-1.34	1.30	13	10
9	1.35-1.44	1.40	7	5
10	1.45-1.54	1.5	6	4
11	1.55-1.64	1.6	8	5
12	1.65-1.74	1.70	17	10
13	1.75-184	1.80	9	5
14	1.85-1.94	1.90	19	10
15	1.95-2.04	2.0	6	3
16	2.05-2.14	2.10	21	10

5. Feature identification:

The methodology followed for extraction of features based on the above representation scheme plays a vital role in the recognition rate of a numeral. Theoretically, there are ‘M’ zones in the set A and ‘N’ zones in the set B. Then the set of all ordered pairs (a, b) where a ϵ A and b ϵ B, is called the Cartesian product and is denoted by A × B. Since a relation from A to B is precisely a subset of A × B, the set of all relations from A to B is precisely the set of all subsets of A × B. Therefore, the number of relations from A to B is equal to the number of subsets of A × B. Since, number of elements in A is M zones and number of elements in B is N zones, we have A × B = M × N zones. Therefore, A × B has 2^{M*N} number of subsets [20]. Let A = {1, 2, 3…M} and B = {1, 2, 3…N} and let the relation R from A to B be defined as relational density of the zone (feature), i.e., Relational density of the zone = total number of white (black) pixels in the given area / (total number of white pixels + total number of black pixels). Therefore, 2^{M*N}, relational density zone can be obtained from the given M * N zones.

For example, Let A = {1, 2, 3} and B= {1, 2, 3, 4, 5}, we have, $2^{3*5} = 2^{15}$ = 32768 relational density zone can be obtained.

Table 3: Depiction of three row zones long y axis and five column zones along x axis.

Z1	Z2	Z3	Z4	Z5
Z6	Z7	Z8	Z9	Z10
Z11	Z12	Z13	Z14	Z15

6. Feature selection:

From feature identification procedure, the number of features we could extract is exponential, so, we have narrowed down the number of features based on four primitive descriptors, namely, relational density along x axis (from left to right), along y axis (top to bottom), along the major diagonal (left to right) and along the minor diagonal (from right to left). Hence, the numbers of features become polynomial W.

7. Proposed methodology:

The proposed method uses relative density of the pixels as the main feature in the classification process. Initially, pre-processing is carried out for connecting broken numerals using dilation method, the number of zones selection has been done using midpoint class interval values. After selecting the number of zones along x and y axis, standard block size (16 *16) of the zone has been assigned and the image is re-sized for feature extraction. This procedure will be done for all similar images of same zone size along both axes. The relative densities of the zone are computed for 1*2, 2*1 and 2*2. The mean relative density of the pixels for each group (cluster) are found using hierarchical clustering algorithm and finally stored in the feature vector library. To classify the numeral, we have used minimum distance classifier and the nearest feature vector is estimated. The Euclidean distance between the feature vector and the mean feature vector is determined and assigned the numeral class to the nearest mean vector. Figure 2(a) shows the original image and Figure 2(b) shows the corresponding image divided into 4 * 4 zones based on mid class interval procedure. Relative density of the zones 1*2 are obtained and shown in Table 4.

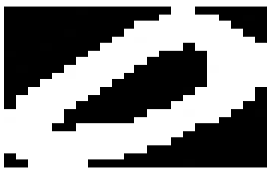

Fig. 2(a): Shows the original image.

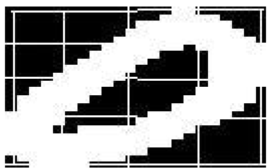

Fig. 2(b): Shows the image is divided into 4 * 4 zones based on mid class interval procedure.

Table 4: The zone relative density 1*2 (1 row * 2 columns as the parameter).

0.0097	0.3516	0.6445
0.2246	0.6055	0.8281
0.7460	0.6640	0.7617
0.7422	0.5078	0.2441

Algorithm for Training Numerals:

Input: Binary Numeral Image from the database
Output: Store Feature Vector in the Library
Step 1: Pre-process the image to connect the broken digits (dilation)
Step2: Perform labelling connected component algorithm to crop the image.
Step3: Obtain the number of zones along x and y axis based on the midpoint aspect ratio interval.
Step 4: Resize the image
Step 5: Compute the relative density of the pixels for 1*2, 2*1, 2*2
Step 6: Repeat the steps 1 to 5 to group the images using Hierarchical Clustering Algorithm and store the mean relative density feature vector in the library.
End of the Training Numerals Algorithm.

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Algorithm for Testing a Numeral:
Input: Isolated Binary Numeral Image
Output: Recognition of the numeral
Step 1: Pre-process the image to connect the broken digits.
Step2: Perform labelling connected component algorithm to crop the image.
Step3: Obtain number of zones along x and y axis based the midpoint aspect ratio interval.
Step 4: Resize the image
Step 5: Compute the relative density of the pixels for 1*2, 2*1, 2*2
Step 6: Calculate the Euclidean distance between the input feature vector and the mean feature vectors and assign the class to the nearest mean vector
End of the Testing a Numeral Algorithm.
On the basis of the proposed algorithm, the flow of the system is provided in the following figures and tables.

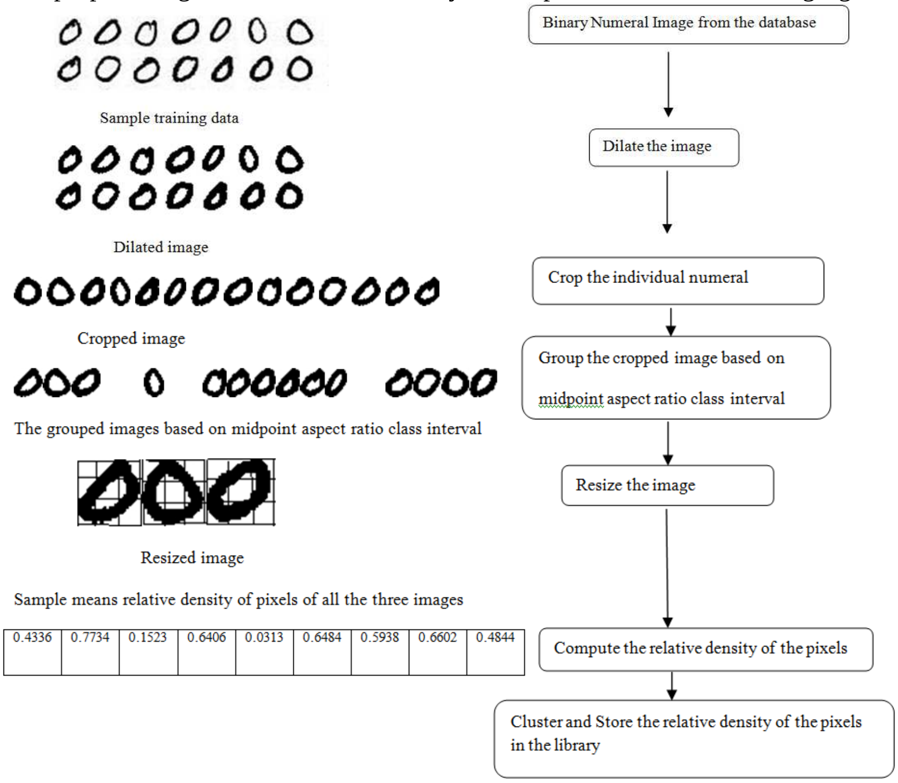

Fig. 3: Flow of the system.

8. Experimental results:

For the purpose of experimentation, handwritten numerals from MNIST database have been used. .A total of 58631 samples were used for training purpose and 9621separate samples were used for testing. In the Experiment, we have achieved 93.02304% as recognition rate.

Table 5: Confusion matrix for given test data (Experiment).

	0	1	2	3	4	5	6	7	8	9	Accuracy %	#recognized Data	#Test data
0	950	1	1	3	0	0	4	1	1	0	98.85536	950	961
1	2	1105	4	2	2	0	3	0	6	1	98.22222	1105	1125
2	10	1	916	22	0	9	3	10	10	0	93.37411	916	981
3	0	2	10	888	0	31	0	6	36	6	91.01124	891	979
4	4	2	6	1	867	0	10	2	6	42	91.17021	857	940
5	5	1	5	48	5	707	13	1	18	3	87.71712	707	806
6	1	3	0	0	1	12	890	0	2	0	97.90979	890	909
7	1	4	7	3	12	1	0	935	4	36	93.22034	935	1003
8	20	12	9	31	8	37	8	7	801	19	84.13866	801	952
9	2	1	2	16	9	1	1	16	4	913	94.6114	913	965
										Mean	93.02304		

To prove the eminence of the proposed algorithm a comparative analysis with the popular and best algorithms has been attempted. The table 6 shows the comparison of proposed with existing algorithms.

Table 6: Comparison of proposed method with the existing methods.

Authors	No. of samples in Data set	Feature Extraction Method	Classifier	Accuracy %
Kazua KAMATA *et al* (1988)	300	Structural features	Decision tree	96%
Keiji YAMADA *et al* (1989)	Not available	Contour based on the direction and curvature for a character contour	Basic Multi-layered neural network with three kinds of inputs	98.3%, 98.8%, 99.1%
Christine Nadal (1990)	2000	Structural features from their skeletons, other makes use of their contours	A tree classifier	84.85%
J.T. Lin and R.M. Inigo (1991)	500	Not available	Back Propogation Neural network	70%
Jun Cao, M.Sridhar *et al* (1992)	11000	Local histogram of the chain codes	Statistical and neural network	96.02%
Takahiko KAWATANI (1993)	10000	cconcavity measurements, horizontal and vertical projections, polygonization of both the internal and the external numeral boundaries and top, bottom, left and right extrema of the numeral		98.05%
Feng Pan, Mike (1994) Keane	8000	Aspect invariant, moment order	Neural networks	98.73%
M.H. Shirali-Shahreza *et al* (1995)	2600	Shadow coding	Probabilistic Neural Network	97.8%
Jianming Hu and Hong Yan (1996)	10000	Primitive coding and global description	Structural method	99.7%
Thien M. Ha and Horst Bunke (1997)	17000	Projections and contour histograms	Knn	99.54%
Alceu de S. Britto Jr (2003)	195000	Foreground features namely, transitions from background and foreground, Background features based on concavity information	HMM	97.9%
Binu P. Chacko *et al* (2007)	Not available	Statistical and structural features	Neural network	95.7%
Ying Wen, Pengfei Shi (2008)	100	Linear discriminant analysis	Improved LDA and Bhattacharyya Distance	96.93%
S. Impedovo, R. Modugno, G. Pirlo (2010)	18467	Holes, vertical up and down cavities and endpoints, horizontal left, right cavities, horizontal left and right end points	Knn	85.26%
K. N. Saravanan & Dr. R. Anitha	9621	Relative density of pixels	Minimum Distance Classifier	93.02304%

9. Conclusion:

In this paper we have proposed a relative density feature extraction algorithm for the recognition of single connected component numerals. Minimum distance classifier has been used for classification. The recognition rate of 93.02304% has been achieved for English numerals. The table shows the previous work cited has better performance than the proposed method. The reason could be the dataset used and the size of the database. Our future work aims to decrease the number of features and combine other feature set to improve the recognition rate and apply the proposed algorithm to other language numerals and check the robust nature of the algorithm.

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