MOMENT AND DENSITY BASED HADWRITTEN MARATHI NUMERAL RECOGNITION

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Abstract

In this paper, we present an OCR for handwritten Marathi Numerals recognition using two sets of features, namely, density and central moments. Central moments of order 3 and 4 are computed globally for the numeral image while density features are computed by dividing the numeral image into different zones. The combined features are fed to the classifiers namely, minimum distance, k-nearest neighbor (k-NN) and Support Vector Machines (SVM) to classify the unknown numeral patterns. The proposed method provided encouraging results.

Keywords

Handwritten numerals, moment, density, NN, K-NN, SVM classifier.

1. Introduction

The task of assigning handwritten character/numeral to one of predefined classes is hard problem, since the variation of the numerals in each class is high. To solve this problem various moments have been used for feature extraction in the past few years. Some published works in the literature based on moment features is discussed here.

Central moments, invariant moments and Zernike moments used for recognition of characters of different languages are reported in [1, 2, 4, 5, 9]. In [3], pre-segmented letters were first partitioned into main body and secondary components. Then moment features were extracted from the whole letter as well as from the main body and the secondary components. Using multi-objective genetic algorithm, efficient feature subsets were selected. Finally, various feature subsets were evaluated according to their classification error using an SVM classifier. In [5], extended moment invariants have been utilized as Persian characters image descriptor. In classification stage, four different classifiers namely minimum mean distance, nearest neighbor rule, multi layer perceptron, and fuzzy min-max neural network has been used. Higher order Zernike moments are used as shape descriptors for classifying Devnagari numerals in [6]. In [9], handwritten Devnagari character is preprocessed and chain code histogram and moment invariant features are extracted and fed to Multilayer Perceptrons as a preliminary recognition step. Finally, the results of both MLP's are combined using weighted majority scheme. Due to rotation invariance and orthogonal properties of Zernike moments, they are found to perform better in terms of computational complexity and classification performance. Ramtake et. al. [8] proposed moment invariants for recognition of Marathi handwritten numerals. The Hu's moment invariants are well known to be invariant under translation, rotation, scaling and reflection. They are measures of the pixel distribution around the center of gravity of the character and allow capturing the global character shape information. An OCR system for basic Kannada characters employing moment features is reported in [7]. Hu's invariant moments and Zernike moments are used to extract the features of printed Kannada characters. The system is capable of handling different font sets and sizes. Neural classifiers have been effectively used for the classification of characters. S.N. Nawaz et. al [10] have proposed an approach for Arabic off line character recognition. A set of seven invariant descriptors have been used to represent the Arabic character. Further Neural network is applied for classification. In [1], feature extraction method based on moment invariants is applied to handwritten digits recognition. The features are computed using 15 special Summed-area Tables (SATs), which allows for fast computation at different positions and angles. The feature extraction method uses moments up to the 4th order. Persian optical character recognition using geometrical central moments as character image descriptor is described in [4]. With regard to reversal shape of "seven" and "eight" Persian numerals where central moments cannot discriminate them , the feature vector is enriched by an extra statistical feature, that is, count of upper half of image pixels divided by count of lower half of image pixels. From the above explanation it is evident that moments can be considered as potential features for recognition of character and numerals. This motivated us to enrich density features with central moments and test the efficacy of the system for handwritten Marathi numerals. A brief description about the central moments is given in the following section.

2. Marathi Numerals and Preprocessing

Marathi is spoken by about 71 million people in Indian state of Maharashtra and neighboring states. Percentage wise it is the fourth widely spoken Indian language. Marathi script is written with Devanagari alphabet. Since the standard database for Marathi handwritten numerals is not available, to our knowledge, the database is created with respect to variety in handwriting style. Data collection is done on a sheet specially designed for data collection. Data is collected from persons of different professions. A sample data sheet is shown in figure-1. Since, data is collected in a predefined format slant correction is assumed to be performed. The collected documents are scanned using HP Scanjet scanner at 300 dpi to obtain gray scale images. The images are then binarized using Otsu's method. The speckles in the binarized images are removed using morphological erode and dilate operations. The numerals are cropped by fitting a minimum bounding box on the numeral. To bring uniformity among the numerals the cropped numeral is normalized to a size of 40x40 pixels. A total of 2500 binary digital images representing Marathi handwritten numerals are obtained. Each image represents a numeral (binary 1) that is unconstrained, isolated and clearly discriminated from the background (binary 0).

Figure1: Sample handwritten datasheet

3. Feature Extraction

3.1 Density

In the proposed method, the binary image representing the handwritten numeral is preprocessed as described in the Section 2 and is normalized to a size of 48 x 48 pixels. The size-normalized image is divided into n equal number of zones in sequence for n= 4,9,16 and 36 respectively.
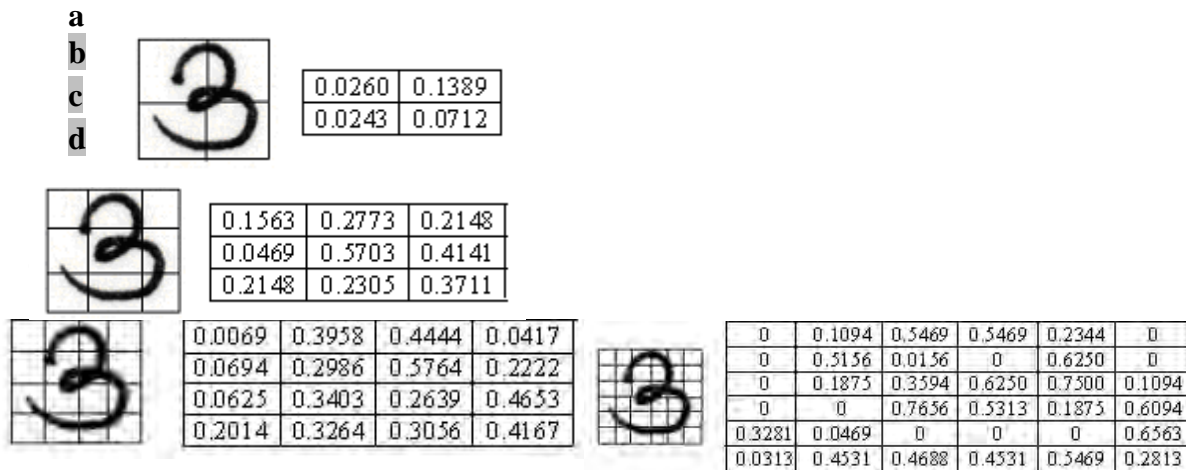

Figure 2 Zoning. Image divided into (a) 4 zones (b) 9 zones (c) 16 zones and (d) 36 zones An entry in a cell represents the density for that zone

The density of the zone is computed by taking the ratio of total number of object pixels (i.e. pixels representing the numeral viz. binary 1) to total number of pixels in the zone (Equation 1). This is carried out for all the zones in the image. Totally 65 features are extracted from the image (Refer algorithm for details). An example is shown in Figure 2.

$$den(Z) = \frac{No.\,of\,object\,pixels\,in\,the\,zone, Z}{Total\,number\,of\,pixels\,in\,this\,zone} \qquad (1)$$

3.2 Moments

A lot of useful information about a binary object can be gained from the moments of the object. Most often moments are computed for connected components of binary images for the analysis of shape. For an arbitrary function f(x,y), one may compute moments as

$$m_{pq} = \int\limits_{-\infty}^{+\infty} \int\limits_{-\infty}^{+\infty} x^p \, y^q \, f(x,y) \, dx \, dy \quad for \ p,q=0,1,2, \ldots \quad (1)$$

For digitized data (including images) we must replace the integral with a summation over the domain covered by the data.

$$m_{pq} = \sum_{i=-\infty}^{+\infty} \sum_{j=-\infty}^{+\infty} i^p \, j^q \, f(i,j) \qquad (2)$$

where x, y, i, j are region point co-ordinates, i.e. pixel co-ordinates in digitized images. It is common to normalize the moments by dividing by m_0 (or m_{00}). This allows one to compute moments which depend only on the shape and not the magnitude of f(x,y). The result of normalizing moments gives measures which contain information about the shape or distribution (not probability dist.) of f(x,y).

A uniqueness theorem states that if *f(x, y)* is piecewise continuous and has non zero values only in a finite part of the xy plane, moments of all orders exist and the moment sequence m_{pq} uniquely determines *f(x,y)*.

In many applications such as shape recognition, it is useful to generate shape features which are independent of parameters which cannot be controlled in an image. Such features are called invariant features. There are several types of invariance. For example, if an object may occur in an arbitrary location in an image, then one needs the moments to be invariant to location. For binary connected components, this can be achieved simply by using the central moments, μ_{pq}.

The central moments can be expressed as

$$\mu_{pq} = \int\limits_{-\infty}^{+\infty} \int\limits_{-\infty}^{+\infty} (x-\bar{x})^p \, (y-\bar{y})^q \, f(x,y) \, dx \, dy \qquad (3)$$

where $\bar{x}$ and $\bar{y}$ are the co-ordinates of the region's center of gravity (centroid). These can be obtained using the following equations:

$$\bar{x} = \frac{m_{10}}{m_{00}} \ and \ \bar{y} = \frac{m_{01}}{m_{00}} \qquad (4)$$

For a digital image, equation (2) becomes

$$\mu_{pq} = \sum_x \sum_y (x-\bar{x})^p \, (y-\bar{y})^q \, f(x,y) \qquad (5)$$

Moments may be computed for several orders. The central moments of third order can be obtained using the following equation.

$$\mu_{pq} = \sum_x \sum_y (x-\bar{x})^p \, (y-\bar{y})^q \, f(x,y) \quad for \quad p,q = 0,1,2,3 \qquad (6)$$

such that $p+q \leq 3$

If an object is not at a fixed distance from a fixed focal length camera, then the sizes of objects will not be fixed. In this case size invariance is needed. This can be achieved by normalizing the moments,

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\gamma}}, \ where \ \gamma = \tfrac{1}{2}(p+q)+1. \qquad (7)$$

Rotation invariance can be achieved if the coordinate system is chosen as μ_{11}. This is not always needed, for example if objects always have a known direction.

The moments computed are usually used as features for shape recognition. The major disadvantage of moments in general is that they are global features rather than local. This makes them not suited for recognizing numerals which are partially obstructed

4. Classification

4.1 Minimum distance classifier

The Euclidean distance of the test pattern to all the vectors in the training pattern is computed and the test pattern is assigned to the class of the sample that has the minimum Euclidean distance.

4.2 k-Nearest Neighbor (k-NN) classifier

The key idea, similar to minimum distance, behind k-NN classification is that similar observations belong to similar classes. The test numeral feature vector is classified to a class, to which its nearest neighbor belongs to. The nearest factor is based on minimum Euclidean Distance. Feature vectors stored priori are used to decide the k-nearest neighbor of the given feature vector.

4.3 Support Vector Machines

The SVM classifier is basically a two class classifier based on the discriminant functions. A discriminant function represents a surface, which separates the patterns as two classes. For OCR applications a number of two class classifiers are trained with each one distinguishing one class from the other. Each class label has an associated SVM and a test example is assigned to the label of the class whose SVM gives the largest positive output.

Algorithm

Input: Isolated Marathi numeral image in gray scale.

Output: Recognized numeral display.

Method:

1)Apply median filer three times to gray scale image to eliminate noise.

2)Binarize the image, using Otsu's thresholding technique, to obtain numeral as 1 and background 0.

3)Perform region labeling, fit a minimum rectangle bounding box and crop the numeral.

4)Size normalize the cropped image to a window of size 48x48 without disturbing aspect ratio.

5)Perform the following to compute density features of size 65

a.	Divide the image in to equal zones of size 4, 9, 16, 36, respectively in sequence.

b.	In each sequence and for each zone, compute density of the object pixels (on pixels representing the numeral) and store as feature vector.

6)Compute central moments of order 3 and 4 and store as feature vector of size 96 for the image obtained in step 4.

7)Combine features obtained in step 5 and step 6 to obtain feature vector of size 161.

8)Input the feature vector to the classifier that assign the test image to a class based on the criteria defined by the classifier.

5. Experimental Results

The experiments were carried out on the data set of 12692 digital images representing the isolated Marathi handwritten numerals. The data set is partitioned into training set and test set applying the k-fold crossing validation technique. The performance using minimum distance classifier in terms of the recognition rate is presented in table 1. An average recognition rate of 96.31 % is achieved. Recognition accuracy using k-NN classifier is presented in Table 2. An overall recognition of 96.55% is obtained, which is approximately equal to the result of minimum distance classifier. Table 3 presents five-fold result using SVM classifier. The results are encouraging and average recognition accuracy of 97.89 % is obtained. Results obtained clearly indicate that enriching the density features with central moment features yielded better recognition results. The details of the recognition of numerals in the form of confusion matrix for SVM classifier is presented in Table 4.

Table 1 Recognition results (in %) using K-Nearest Neighborhood (K=3) classifier

Marathi Numerals	Fivefold cross validation					Average Recognition
	Fold-1	Fold-2	Fold-3	Fold-4	Fold-5	
Zero	100.00	100.00	100.00	100.00	100.00	100.00
One	96.60	95.76	94.42	95.02	93.12	94.98
Two	93.56	93.50	92.44	91.36	94.82	93.14
Three	92.32	95.38	95.20	97.28	96.60	95.36
Four	99.24	94.44	95.32	98.48	96.34	96.76
Five	97.20	98.86	92.20	90.87	96.00	95.03
Six	94.30	91.24	97.14	98.48	98.21	95.87
Seven	97.66	98.52	99.10	97.42	96.41	97.82
Eight	99.24	98.40	95.36	97.38	98.48	97.77
Nine	94.92	98.78	93.66	98.46	96.20	96.40
Av. Rec.	96.50	96.49	95.48	96.48	96.62	96.31

Table 2 Recognition results (in %) using K-Nearest Neighborhood (K=3) classifier

Marathi Numerals	Fivefold cross validation					Average Recognition
	Fold-1	Fold-2	Fold-3	Fold-4	Fold-5	
Zero	100	100	100	100	100	100
One	96.60	95.76	94.42	95.02	94.42	95.24
Two	93.56	95.60	94.68	91.36	95.20	94.08
Three	92.32	95.38	95.20	96.38	96.60	95.18
Four	99.24	95.14	95.32	98.48	96.34	96.90
Five	97.20	98.86	92.20	90.87	96.00	95.03
Six	94.30	91.24	97.14	98.48	98.21	95.87
Seven	97.66	98.52	99.10	99.24	96.41	98.19
Eight	99.24	98.40	95.36	99.24	99.60	98.37
Nine	94.92	98.78	93.66	99.62	96.20	96.64
Av. Rec.	96.50	96.77	95.71	96.87	96.90	96.55

Table 3 Recognition results (in %) using SVM classifier

Marathi Numerals	Fivefold cross validation					Average Recognition
	Fold-1	Fold-2	Fold-3	Fold-4	Fold-5	
Zero	100.00	100.00	100.00	100.00	100.00	100.00
One	99.61	97.64	97.25	96.85	94.44	97.16
Two	96.85	98.03	94.49	93.31	98.41	96.22
Three	98.03	96.85	96.07	98.82	98.81	97.72
Four	99.21	98.82	96.85	98.43	97.62	98.19
Five	98.03	98.82	94.10	90.56	98.81	96.07
Six	94.10	98.03	99.61	98.43	98.41	97.72
Seven	99.61	100.00	99.61	99.21	96.43	98.97
Eight	99.21	100.00	98.82	99.21	99.60	99.37
Nine	94.89	99.21	97.25	99.61	96.43	97.48
Av. Rec.	97.96	98.74	97.40	97.44	97.90	97.89

Table 4 Confusion matrix for SVM classifier

Numerals	0	1	2	3	4	5	6	7	8	9	Avg. Rec.
0		0	0	0	0	0	0	0	0	0	100.00
1	0		6	7	1	4	0	0	1	17	97.16
2	0	10		13	1	2	4	0	3	15	96.22
3	0	1	16		3	1	5	0	0	3	97.72
4	0	0	1	1		9	10	0	2	0	98.19
5	0	10	3	2	13		16	2	0	4	96.07
6	0	1	5	5	4	3		0	2	9	97.72
7	5	0	0	0	0	1	3		3	1	98.97
8	0	0	2	0	1	0	2	0		3	99.37
9	0	9	4	2	2	3	10	0	2		97.48

Few observations from the confusion matrix are discussed below.

1. Recognition accuracy for numeral zero is 100%. Also, for numerals eight, seven and four the recognition rates are higher.
2. Most of the time one is misclassified with nine and vice-versa due to varied writing style of user. Figure 3.1(a) shows an example where the numerals 1 and 9 look similar.
3. Confusion occurs between numeral1 1 and 2, numerals 3 and 2, numerals 5 and 6, between numerals 5 and 1, and between numerals 7 and 0. The main reason for such confusion is due the style of handwriting by the writers. Example Figures are shown in Figure 3(b) through Figure 3(e).
4. Some numerals in database cannot be recognized by human also Figure 3.1 (g). Such numerals reduce the overall recognition rate of system.

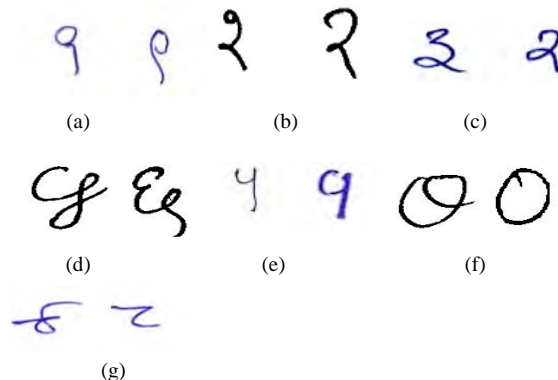(a)   (b)   (c)

(d)   (e)   (f)

(g)

Figure 3 Confusing images of few handwritten numerals from the data set
(a) Numerals One and Nine (b) Numerals One and Two (c) Numerals Three and Two (d) Numerals five and Six (e) Numerals five and One
(f) Numerals Seven and Zero (g) Unknown numerals (may be representing numeral8)

Summary

An efficient method for recognition of isolated Marathi numerals has been presented with emphasis on feature extraction method. Density based on zoning approach, and central moments are used as features to facilitate recognition process. Experiments are carried out on a database size of 12690 numeral images using fivefold cross validation method. The proposed system is independent of variability involved in the writing style of different individuals and is thinning free. Recognition rate obtained with Support Vector Machine (SVM) classifier (97.89%) is better compared with minimum distance classifier (96.31 %) and k-Nearest Neighbor (k-NN) classifier (96.55%).

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