Marathi Handwritten Numeral Recognition using Zernike Moments and Fourier Descriptors

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ABSTRACT
In this paper, we present a method for automatic recognition of isolated Marathi handwritten numerals in which Zernike moments and Fourier Descriptors are used as features. After preprocessing the numeral image, Zernike moment and the Fourier Descriptor features of the numeral are extracted. These features are then fed in the k-NN classifier for classification. The proposed method is experimented on a database of 12690 samples of Marathi handwritten numeral. We have obtained recognition accuracy of 96.58% using k-NN classifier.

Keywords
Numeral recognition, Zernike moment, Fourier Descriptors.

1. INTRODUCTION
The aim of handwritten numeral recognition (HNR) system is to classify input numeral as one of K classes. In Feature analysis, information relevant for pattern classification is extracted from the input numeral. The pattern classification step labels the numeral as one of K classes using the class models. Over the years, considerable amount of work has been carried out in the area of HNR. Various methods have been proposed in the literature for classification of handwritten numerals. These include Hough transformations, histogram methods, principal component analysis, and support vector machines, nearest neighbor techniques, neural computing and fuzzy based approaches [1, 2]. A study on different pattern recognition methods are given in [3, 4]. An extensive survey of recognition performance for large handwritten database through many kinds of features and classifiers is reported in [5]. In comparison with HNR systems of various non Indian scripts [e.g. Roman, Arabic, and Chinese] we find that the recognition of handwritten numerals for Indian scripts is still a challenging task and there is spurt for work to be done in this area. Few works related to recognition of handwritten numerals of Indic scripts can be found in the literature [6,7,8,9]. A brief review of work done in recognition of handwritten numerals written in Devanagari script is given below.

Hanmandlu et.al [10] presented a technique for recognition of handwritten Hindi (Devanagari script) numerals based on the modified exponential membership function fitted to the fuzzy sets. The features used are the normalized distances computed using the box approach. The exponential membership function is modified by two structural parameters that are estimated by optimizing the entropy subject to the attainment of membership function to unity. N. Sharma, U. Pal et.al. [11] have proposed a quadratic classifier based scheme for the recognition of offline Marathi handwritten numerals and characters. The bounding box of a numeral is segmented into blocks and the Fourier Descriptorshistogram is computed for each of the blocks. These Fourier Descriptors features are fed to the quadratic classifier for recognition. Reena Bajaj et.al [12] has proposed a recognition scheme for handwritten Marathi numerals. Three different types of features, namely, density features, moment features and descriptive component features are used. Three different neural classifiers have been used for classification of the numerals. Finally, the outputs of the three classifiers are combined using a connectionist scheme. A method based on invariant moments and the division of numeral image for the recognition of handwritten Devanagari numerals is proposed by Ramteke et.al. [13]. Seven central invariant moments are used as features. The Gaussian Distribution Function has been adopted for classification.

A general fuzzy hyper line segment neural network which combines supervised and unsupervised learning in a single algorithm, used for handwritten Devanagari numeral character recognition, is reported by P.M. Patil et.al. [10].

The rest of the paper is organized as follows. In Section 2 a brief overview of data collection and pre-processing is presented. Section 3 deals with the feature extraction and section 4 describe classification. The experimental results obtained are presented in Section 5. Conclusion is given in Section 6.

2. DATA SET AND PREPROCESSING
Devanagari script, originally developed to write Sanskrit, has descended from the Brahmi script sometime around the 11th century AD. It is adapted to write many Indic languages like Marathi, Mundari, Nepali, Konkani, Hindi and Sanskrit itself. Marathi is an Indo-Aryan language spoken by about 71 million people mainly in the Indian state of Maharashtra and neighboring states. Marathi is also spoken in Israel and Mauritius. Marathi is thought to be a descendent of Maharashtri, one of the Prakrit languages, which developed from Sanskrit. Since 1950 Marathi has been written with the Devanagari alphabet.

Standard dataset for Marathi numeral is not available till today. Therefore, dataset of Marathi handwritten numerals 0 to 9 is created by collecting the handwritten documents from writers. Data collection is done on a sheet specially designed for data collection. Writers from different professions were chosen including students, clerks, teachers, and vendors and were asked to write the numerals. No constraints were imposed on the use of ink or pen except that they have to write the numerals in the boxes of the sheets provided to them. A sample sheet of handwritten numerals is shown in figure 1.

Figure1. Sample sheet of handwritten numerals

The collected data sheets were scanned using a flat bed scanner at a resolution of 300 dpi and stored as grayscale images. The raw input of the digitizer typically contains noise due to erratic hand movements and inaccuracies in digitization of the actual input. The noise present in the image is removed by applying median filter three times. Since, data is collected in a predefined format slant correction is assumed to be performed. Binarization of image is performed using Otsu's global thresholding method [15]. The noise as isolated locations and spikes around the end of the numerals are removed using morphological open and close operations. A minimum bounding box is then fitted to the numeral and the numeral is cropped. To bring uniformity among the numerals the cropped numeral image is size normalized to fit into a size of 40x40 pixels. A total of 12690 binary images representing Marathi handwritten numerals are obtained. Each image represents a handwritten numeral (binary 1) that is unconstrained, isolated and clearly discriminated from the background (binary 0).

3. FEATURE EXTRACTION

Two well-defined methods of feature extraction used in our method are Zernike moments and Fourier Descriptors. A brief description about Zernike moment and Fourier Descriptors is given below.

3.1 Zernike moment

The Zernike moments introduce a set of complex polynomials which form a complete orthogonal set over the interior of a unit circle, i.e., x2 + y2 ≤ 1. In fact Zernike moments are the projection of the image function on some orthogonal basis functions. Let the set of these basis functions be denoted by

Vn,m(x, y). These polynomials are defined by

$$V_{n,m}(x, y) = V_{n,m}(\rho, \theta) = R_{n,m}(\rho) e^{jm\rho} \quad (1)$$

where n is a non-negative integer, m is a non-zero integer subject to the following constrain: n − |m| is even and |m| < n. Also, ρ is the length of the vector from origin to the (x, y) pixel, θ is the angle between vector ρ and xaxis in a counter-clockwise direction, and Rn,m(ρ) is the Zernike radial polynomial. The Zernike radial polynomials, Rn,m(ρ), are defined as :

$$R_{n,m}(\rho) = \sum_{s=0}^{n-|m|} \frac{(-1)^s (n-s)!}{s!\left(\frac{n+|m|}{2}-s\right)!\left(\frac{n-|m|}{2}-s\right)!} \rho^{n-2s}$$

Note that Rn,m(ρ) = Rn,−m(ρ). The Zernike moment of order n with repetition m for a digital image is

$$Z_{n,m} = \frac{n+1}{\pi} \sum\sum_{x^2+y^2 \le 1} f(x,y) V^*_{n,m}(x,y) \Delta x \, \Delta y$$

Where V*n,m(x, y) is the complex conjugate of Vn,m(x, y).

To compute the Zernike moments of a given image, the image center of mass is taken as the origin. We first have computed Zernike moment of input image in which we obtained two

3.2 Fourier Descriptors

The Fourier transform of a boundary representation (chain code, signature, complex boundary function) is used to represent the region's shape. One can low pass filter the boundary function spectrum without destroying the characteristic shape of the region. This means that only the amplitudes and phases of the low frequency components in the spectrum (i.e. the low-order Fourier coefficients) are required to characterize the basic shape of the object and they can be used as shape descriptors. Before calculating the Fourier descriptors input image must be segmented and boundary of the object must be determined. The boundary will be presented as an array of complex numbers which correspond to the pixels of the object boundary if the image is placed in the complex plane. Fourier descriptors are now calculated by combining Fourier transform coefficients of the complex array.

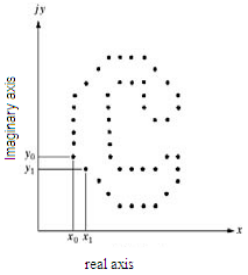

Figure 2 A digital boundaries and its representation as a complex sequence

The points (xo, yo) and (x1, y1) are the first two points in the sequence. As shown in Figure 2, the K-point digital boundary in the xy-plane starting at an arbitrary point (x0, y0) co-ordinate pairs (x0, y0), (x1, y1), (x2, y2),……..(xk-1, yk-1) are encountered in traversing the boundary say, in the counterclockwise direction. These co-ordinates can be expressed in the form of x(k)= xk and y(k) = yk. With this notation, the boundary itself can be represented as sequence of co-ordinates

4. CLASSIFICATION

4.1 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.

5. RESULT

Experiments were carried out on a database of 12690 isolated Marathi handwritten images obtained as described in section 2. The numeral images were grouped into two subsets to carry out experiments. One subset was chosen as test set and other subset form training set. Table 1 and Table 2 presents the results obtained testing our HNR system on Marathi handwritten numerals database. Overall recognition rate using k-NN classifier is 96.58 % as shown in Table 1.

Table1. Recognition rate of Marathi Handwritten Numerals

Input Marathi Numerals	Number of Test Samples	Number of samples correctly recognized	Recognition accuracy in percentage
०	275	271	98.55
९	224	206	91.96
२	250	245	98.00
३	270	248	91.85
४	272	264	97.06
५	259	254	98.07
६	284	271	95.42
७	365	358	98.08
८	275	274	99.64
९	245	238	97.14
Average Recognition			**96.58**

6. CONCLUSION

In this paper we have presented an efficient method for recognition of Marathi handwritten numerals using Fourier descriptors and Zernike moments. The average recognition of 96.58 % is achieved using k-NN classifier. The proposed method is found to be very good and can be extended for Marathi character recognition.

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