Marathi Handwritten Numeral Recognition using Fourier Descriptors and Normalized Chain Code

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ABSTRACT
In this paper, we present a novel method for automatic recognition of isolated Marathi handwritten numerals. Chain code and Fourier Descriptors that capture the information about the shape of the numeral are used as features. After preprocessing the numeral image, the normalized chain code and the Fourier descriptors of the contour of the numeral are extracted. These features are then fed in the Support Vector Machine (SVM) for classification. The proposed method is experimented on a database of 12690 samples of Marathi handwritten numeral using fivefold cross validation technique. We have obtained recognition accuracy of 98.15%.

General Terms
Handwritten numeral recognition, pattern recognition, image analysis.

Keywords
Marathi handwritten numerals, feature extraction, Fourier descriptors, chain code, Support Vector Machines.

1. INTRODUCTION
The aim of handwritten numeral recognition (HNR) system is to classify input numeral as one of K classes. Conventional HNR systems have two components: feature analysis and pattern classification, as shown in Fig. 1. In Feature analysis step, 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.

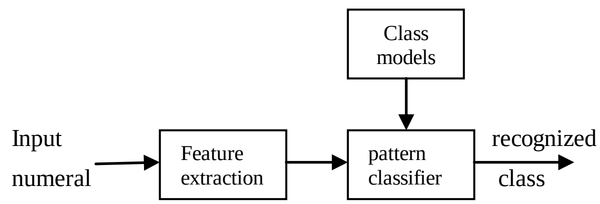


Figure1. Conventional HNR system

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 chain code histogram is computed for each of the blocks. These chain code features are fed to the quadratic classifier for recognition.

Reena Bajaj et.al [12] have 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].

It is clear from the literature survey that, still there is lot of scope to design a robust system for recognition of handwritten numerals written in Devanagri script. Further, features of numerals extracted combining both Fourier descriptors and chain code is not found in the publications. These features accommodate the variability of samples of handwritten numeral images in different domains (frequency domain and spatial domain). This has motivated us to propose a method for recognition of handwritten numerals using Fourier descriptors and chain code.

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. Figure 2 below presents a listing of the symbols used in Marathi for the numbers from zero to nine.

०	१	२	३	४	५	६	७	८	९
0	1	2	3	4	5	6	7	8	9

Figure 2. Numerals 0 to 9 in Devanagari script

To the best of our knowledge 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 3.

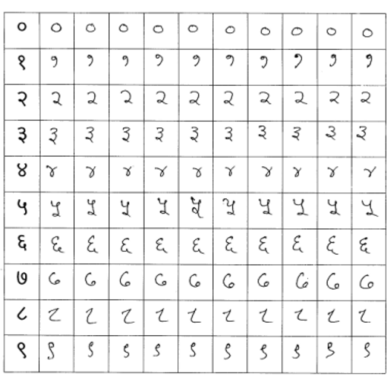


Figure 3. Sample sheet of handwritten numerals

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). Sample binary images of handwritten Marathi numerals are shown in figure 4.

Figure 4: Preprocessed binary images

3. FEATURE EXTRACTION

A well-defined feature extraction algorithm makes the classification process more effective and efficient. Two well-defined methods of feature extraction used in our method are Fourier descriptors and normalized chain codes. A brief description about Fourier descriptors and chain code is given below.

3.1 Fourier descriptors

Fourier transformation is widely used for shape analysis [16,17] The Fourier transformed coefficients form the Fourier descriptors of the shape. These descriptors represent the shape in a frequency domain. The lower frequency descriptors contain information about the general features of the shape, and the higher frequency descriptors contain information about finer details of the shape. Although the number of coefficients generated from the transform is usually large, a subset of the coefficients is enough to capture the overall features of the shape. The high frequency information that describes the small details of the shape is not so helpful in shape discrimination, and therefore, they can be ignored. As the result, the dimensions of the Fourier descriptors used for capturing shapes are significantly reduced. The method of computing the transform is explained below.

Suppose that the boundary of a particular shape has K pixels numbered from 0 to $K-1$. The k-th pixel along the contour has position (x_k, y_k). Therefore, we can describe the contour as two parametric equations:

$$x(k) = x_k$$

$$y(k) = y_k$$

We consider the (x, y) coordinates of the point not as Cartesian coordinates but as those in the complex plane by writing

$$s(k) = x(k) + I\, y(k)$$

We take the discrete Fourier Transform of this function to end up with frequency spectra.

The discrete Fourier transform of s(k) is

$$a(u) = \frac{1}{k}\sum_{k=0}^{K-1} s(k)e^{-j2\pi uk/K}, \quad u = 0, 1, \ldots, K\text{-}1$$

The complex coefficients a(u) are called the *Fourier descriptors* of the boundary. The inverse Fourier transform of these coefficients restores s(k). That is,

$$s(k) = \sum_{u=0}^{K-1} a(u)e^{j2\pi uk/K}, \quad k = 0, 1, \ldots, K\text{-}1$$

The algorithm for computing Fourier descriptors is given below.

Input: Gray scale handwritten numeral image

Output: 32 dimensional Fourier descriptors

Method 1:

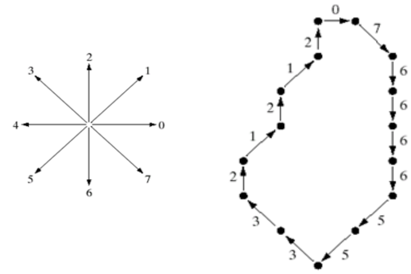
1. Remove noise by applying median filter three times.
2. Binarize the image by applying Otsu's algorithm to obtain the binary image with numeral representing binary 1 and background 0
3. Remove noise (eg. Spikes) by applying erode and dilate morphological operations respectively.
4. To bring uniformity among the numerals, fit a bounding box to the numeral image, crop, and resize it to a size of 40 x 40 pixels.
5. Extract the boundary of the numeral image and resample the boundary in order to obtain a uniform resampling along the running arc length of the boundary(Figure 5).
6. Represent the boundary in the complex plane where the column-coordinate is the real part and the row-coordinate the imaginary part.
7. Compute Fourier transform and obtain the invariant 32 dimensional Fourier descriptors

The invariance is obtained by -nullifying the 0-th Fourier descriptor (position invariance), dividing all Fourier descriptors by the magnitude of the 1-st Fourier descriptor (size invariance) and only considering the magnitude of the Fourier descriptors (orientation and starting point invariance). By applying this normalization, the 0-th and 1-th Fourier descriptors do not provide any information. Hence these are eliminated. Experimentally we have chosen number of coefficients of Fourier descriptors to be 32. These descriptors, invariant to scale, translation and rotation, form the feature vector.

Figure 5. Contour of handwritten numerals

3.2 Chain Code

Freeman chain codes[18] are generated by locating a boundary pixel, also called as starting pixel, and then moving along the boundary either clockwise or anticlockwise, finding next boundary pixel and assign this new pixel a code depending upon its location from the previous pixel. The process of finding the next pixel is terminated when starting pixel is encountered. The codes may be 4-directional or 8-directional depending upon 4-connectivity or 8-connectivity of a pixel to its neighboring contour pixel. An 8-directional chain coded image is given in figure 6.



Chain code: 076666553321212

Figure 6: 8- connectivity chain code

It is observed that the chain code for different numerals has different length code and length of each chain code depends on the size of the handwritten numeral. More ever length of chain code is very high in case of certain handwritten numeral. We have solved this problem by normalizing the chain code values as explained below.

Assume that the following chain code is generated for a numeral contour by traversing it in anticlockwise (clockwise) direction.

V1= [1 2 2 2 1 2 1 2 1 1 2 0 1 0 1 0 0 0 0 0 0 7
7 0 0 0 1 0 0 0 0 0 0 0 0 0 7 0 0 7 0 7 6 6
6 7 6 6 7 6 6 6 6 6 7 6 6 6 6 5 6 6 6
5 6 6 5 5 6 5 4 4 5 4 5 4 5 4 4 4 5 4 4
4 4 4 3 4 4 4 3 4 4 3 4 3 4 4 3 2 3 3 2 3
2 3 2 3 2 2 2 2 2 2 2 2 2 2]

Compute the frequency of the codes 0,1,2…..7. For vector *V1* we have the frequency vector V2 as below.

V2= [23 8 19 10 20 9 20 8]

The normalized frequency, represented by vector *V3*, is computed using the formula

$$V3 = \frac{V2}{|V1|} \quad \text{where } |V1| = \sum V2$$

For the example considered above, we have

V3= [0.1966 0.0684 0.1624 0.0855 0.0015
0.0769 0.1709 0.0684]

Finally, concatenating the vectors V2 and V3 we get the required feature vector of size 16. The algorithm for computing normalized chain codes is given below.

Input: Gray scale handwritten numeral image

Output: Normalized chain code of length 16.

Method 2:

1. Perform steps 1 to 5 of method1.

2. Trace the boundary in counterclockwise direction and generate 8 dimensional chain codes 0 to 7 (Fig. 6).
3. Compute the frequency of the codes 0 to 7.
4. Divide frequency of each code by sum of the frequencies.
5. Combine values obtained in step 3 and 4 to obtain feature vector of length 16.

4. CLASSIFICATION

Support Vector Machines (SVM) has been considered as one of the powerful classifiers for character and numeral recognition. SVM is defined for two-class problem and it finds the optimal hyper-plane which maximizes the distance, the margin, between the nearest examples of both classes, named support vectors [19]. Given a training database of M data: $\{x_m | m=1,...,M\}$, the linear SVM classifier is then defined as:

$$F(x) = \sum \alpha_j x_j \, . \, x + b$$

where $\{x_j\}$ are the set of support vectors and the parameters α_j and b have been determined by solving a quadratic problem.

The linear SVM can be extended to a non-linear classifier by replacing the inner product between the input vector x and the support vectors x_j, through a kernel function K defined as:

$$K(x, y) = \phi(x) \, . \, \phi(y)$$

This kernel function should satisfy the Mercer's Condition. The performance of SVM depends on the kernel. We have used RBF (Gaussian) kernel, which outperformed the other commonly used kernels in the preliminary experiments. An excellent tutorial on SVM is given in [20].

The SVM (binary classifier) is applied to our multiclass character recognition problem by using one-versus-rest type method. The problem now is a 10-class problem with 10 equal to the number of segments in total. The SVM is trained with the training samples using Gaussian kernel. The feature vector of test image is obtained as described in section 3 and input to the SVM for classification.

5. EXPERIMENTAL RESULTS

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 five subsets to carry out five-fold cross validation. During each iteration, one subset was chosen as test set and rest of the subsets were combined to form training set. Fourier Descriptors and normalized chain codes are computed for all the images in the training set by performing method1 and method 2 described in section 3. The result of the training step consists of the (Model) set of support vectors determined by the SVM based method (Fig. 7).

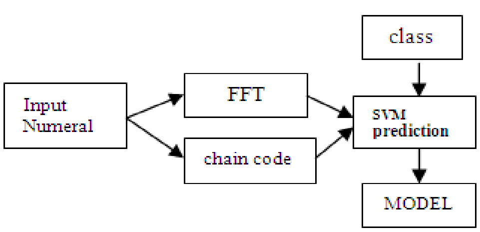


Figure 7. Training process

During the recognition step, the Fourier Descriptors and normalized chain codes are computed in the same way, and the model determined during the training step is used to perform the SVM decision. The output is the image class (Fig. 8).

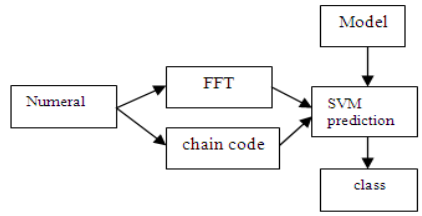


Figure 8. Recognition process

The proposed method is implemented using Matlab 6.1 software and Statistical Pattern Recognition Tool Box for Matlab (ftp://cmp.felk.cvut.cz/pub/cmp/articles/Franc-TR-2004-08.pdf). Table 1 presents the results obtained testing our HNR system on Marathi handwritten numerals database. Overall recognition rate of 98.15% is achieved. We noted that numeral zero has the highest recognition rate of 99.92%. The second highest recognition rate was for numeral eight (98.90%). This is because of their distinct shape from other numerals. Table 2 shows confusion matrix for Marathi numerals. The misclassification rate was higher for numerals six, two and seven. This is because due to certain handwriting styles of different individuals, it is difficult to distinguish between numerals. As a result some misrecognition occurs. An example is shown in Figure 6.

Table1. Recognition rate of Marathi Handwritten Numerals

Marathi Numerals	Fivefold cross validation					Overall Recognition
	Fold-1	Fold-2	Fold-3	Fold-4	Fold-5	
०	100.00	100.00	100.00	100.00	99.60	99.92
१	100.00	97.25	99.61	97.25	99.60	98.74
२	92.92	98.03	97.64	98.03	98.41	97.01
३	98.82	98.03	95.28	99.61	98.41	98.03
४	98.03	97.64	97.64	98.82	96.83	97.79
५	98.03	100.00	93.31	99.21	99.60	98.03
६	96.07	97.64	95.28	98.82	95.63	96.69
७	99.61	97.64	98.43	98.43	94.44	97.71
८	100.00	95.67	99.61	100.00	99.21	98.90
९	99.61	99.21	99.61	98.43	96.43	98.66
Overall recognition	98.31	98.11	97.64	98.86	97.82	98.15

Table2. Confusion Matrix

Numerals	०	१	२	३	४	५	६	७	८	९
०	1268							1		
१		1253	2	2	1	2		3	6	
२		1	1231		13			11	11	2
३	1	1	7	1244	1		14		1	
४	2		6	2	1241	11		1		6
५	1		1		12	1244	4	4		3
६		3	1	10	2	14	1227	4	3	5
७	4	7				8	2	1240	7	1
८	5		1					3	1255	5
९	1		2		4	4	3	2	1	1252

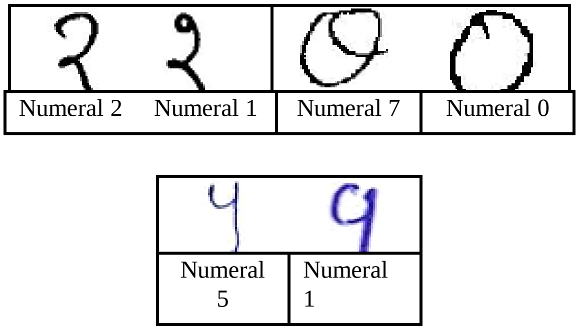


Figure 6. Confusing handwritten numerals

The performance of the proposed method in terms of the recognition rate is compared with the contemporary work and is given in Table 3. The proposed method performs well and appears promising compared to other methods in the literature.

Table 3: Comparison of results of proposed method with other methods in literature

Author	Data set	Features used	Feature size	Classifier	Recognition rate (%)
Ref. [10]	2460	Density, Moment, etc.	48	MLP	89.68
Ref. [11]	3500	vector distance	48	Fuzzy	96.00
Ref. [12]	--	directional chain code information	64	quadratic	98.86
Ref. [13]	2000	Ring data	--	Fuzzy	99.5
Ref. [14]	2000	Invariant moments	78	Gaussian	92.28
Proposed method	12690	FD and chain codes	48	SVM	98.15

6. CONCLUSION

In this paper we have presented an efficient method for recognition of Marathi handwritten numerals using Fourier descriptors and normalized chain codes. SVM is used for classification. The average recognition of 98.15 % is achieved using 5-fold cross validation method. The proposed method is compared with other methods in terms of size of feature vector and recognition rate and is found to be very good. The proposed method can be extended to recognition of numerals of other Indic scripts.

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