# Printed and Handwritten Kannada Numeral Recognition Using Crack Codes and Fourier Descriptors Plate

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# ABSTRACT

Selection of feature extraction method is most important factor in achieving high recognition performance in automatic numeral recognition systems. This paper presents an efficient and novel method for recognition of machine printed and handwritten Kannada numerals using Crack codes and Fourier Descriptors. Printed and handwritten Kannada numerals are scan converted to binary images and normalized to a size of 40 x 40 pixels. Crack code that represents the line between the object pixels and the background (the 'crack') is computed. The code obtained is then represented in complex plane and 10 dimensional Fourier descriptors are computed and are used as features. SVM classifier is used in the recognition phase. The proposed combination of feature extraction method and SVM classifier is applied with success to a database of 2500 printed multi-font printed Kannada numerals and 3150 handwritten Kannada numerals. The experiment is carried out using five-fold cross validation method. The average recognition accuracy of 99.76% and 95.22 % are obtained for printed and handwritten numerals, respectively.

## **General Terms**

Pattern recognition, feature extraction, pattern classifier, numeral recognition.

# **Keywords**

Crack code, Fourier descriptors, SVM, handwritten Kannada numerals, printed Kannada numerals, five-fold cross validation

# **1. INTRODUCTION**

The recognition of machine printed and handwritten numerals has been the subject of much attention in pattern recognition because of its number of applications such as bank check processing, interpretation of ID numbers, vehicle registration numbers and pin codes for mail sorting. Promising feature extraction methods have been identified in the literature for recognition of characters and numerals of many different scripts. These include template matching, projection histograms, geometric moments, Zernike moments, contour profile, Fourier descriptors, and unitary transforms. A brief review of these feature extraction methods is found in [1]. Various methods have been proposed, and high recognition rates are reported, for the recognition of English handwritten digits [3 - 5]. In Indian context, some studies on Devanagari, Bangla Kannada, Oriya and Tamil numerals recognition are reported [6-9]. Compared to the work attributed in the area of Devanagari and Bangla numerals,

only few works related Kannda numeral recognition can be identified [10-12].

Selection of a feature extraction method is most important factor in achieving high recognition performance in character/numeral recognition systems. Different feature extraction methods have been proposed for numerals belonging to different Indian scripts. We briefly review them below. U. Pal and B. B. Chaudhuri [6] have reported a complete printed Bangla OCR system for recognition of Bangla numerals and characters. In [7] recognition of handwritten Devanagari numerals is described. Three different types of features, namely, density features, moment features and descriptive component features are used. Hanmandlu et.al [8] have proposed a fuzzy based approach to recognition of multifont numerals. The preprocessed numeral image is partitioned in to fixed number of sub images called boxes and normalized vector distance of foreground pixels are computed and used as features. Multi-font numeral recognition without thinning based on directional density of pixels is reported in [9]. The outer densities of pixels for each of the direction are computed in four directions viz. bottom, top, left and right. The ratios of these densities are taken with the total area of the cropped numeral image and are stored in a feature vector. In [10] a 10-segment string concept, water reservoir principle, horizontal and vertical strokes, and end points are used as features for Kannada handwritten numerals. Using Image fusion method and basic nearest neighbor classifier recognition of Kannada Handwritten numerals is reported by G, G. Rajput et.al. in [11]. In this method, 64 dimensional features represented as 8x8 pattern matrices are used to classify the handwritten Kannada numerals using nearest neighbor classifier. In [12], a modified quadratic classifier based scheme towards the recognition of off-line offline handwritten numerals of six popular Indian scripts, namely, Kannada, Telugu, Tamil and Malayalam numerals is reported. The features used for classification are obtained from the directional information of contour points of the numerals. Rajashekararadhya [13] presented zone centroid and image centroid based distance metric feature extraction system for Indian script numeral recognition. The numerals centroid is computed and the numeral image is divided in to n equal zones. Average distance from centroid to the each pixel in the zone is computed.

From the literature survey it is clear that most of the work done for numeral recognition includes feature extraction methods in spatial domain and relatively less work has been reported for feature extraction in frequency domain. Images in the spatial domain can be transformed into the frequency domain by using Fourier transform method. Fourier descriptors can be used to describe boundary (chain code, crack code, signature, and complex boundary function) of an object and can used as features for object classification [14, 15]. This motivated us to work towards recognition of Kannada numerals using Fourier descriptors obtained from the crack code of the numeral images. To the best of our knowledge, features extracted in this sequence are not reported in publications related to automatic digit recognition. The rest of the paper is described as follows.

Section 2 describes data collection and preprocessing. Feature extraction is explained in section 3. Recognition method is described in section 4. Experimental results are discussed in section 5 and conclusion is given in section 6.

# 2. DATASET AND PREPROCESSING

#### 2.1 Data Collection

Kannada, the official language of the southern Indian state of Karnataka, is a Dravidian language. The Kannada alphabet was developed from the Kadamba and Cālukya scripts used between the 5th and 7th centuries AD. Under the influence of Christian missionary organizations, Kannada script was standardized at the beginning of the 19th century. The writing style is from left to right. Kannada like Devanagari script is built up from a base character set of 49 characters: 15 vowels and 34 consonants. Further, there are about as many stress marks as there are base characters. Stress marks (vothus) modify the base characters and are appendages.

Most of the positional base 10 numeral systems in the world have originated from India, where the concept of positional numerology was first developed. The Indian numeral system is commonly referred to in the West as the Hindu-Arabic numeral system or even Arabic numerals, since it reached Europe through the Arabs. Figure 1 below presents a listing of the symbols used in Kannada scripts for the numbers from zero to nine.

0	1	2	3	4	5	6	7	8	9
0	0	9	a	¥	ж	ø	٤	U	£

Figure 1. Kannada numerals 0 to 9

To the best of our knowledge standard dataset for handwritten and printed Kannada numerals is not available till today. Therefore, dataset of printed and handwritten Kannada numerals (isolated) 0 to 9 is created. The procedure followed is explained below.

Printed numerals come in multi-font styles and sizes. To create the database of printed numerals, multi-font style and multi size numerals were chosen from Nudi 3.0 and Baraha 8.0 Kannada software packages. Numerals of 10 different font-styles namely BRH kasturi, BRH vijaya, Nudi Akshara-01, Nudi Akshara-02, Nudi Akshara-04, Nudi Akshara-05, Nudi Akshara-07, Nudi Akshara-09, Nudi B Akshara and BRH Amerikannada of 10 different font sizes 14, 16, 18, 20, 22, 24, 26, 28, 36, 48, and 72 were collected. Apart from these, samples of machine printed numerals were also scanned from printed Kannada text books. A total of 2500 images representing machine printed Kannada numerals were obtained and stored as data set. Few images of printed numerals are shown in Figure 2.

BEH Kanun	0 U D T A A V F T Q E
BEH Vijkys	3 3 3 3 8 8 8 6 0 0
Nudi Alabam-01	00096886586
Neth Alebum-02	୦୦୭୬୫୫୧୭೮୮
No.di Abiham 04	၀ဂ ၁ ၃ မ ೫ ေ ေ ေ ေ ေ
Nuti Alaham-09	၀ဂ ၅ & ೪ % ೯ ೭ ೮ ೯
Nucli Aksham-07	၀ဂ ၁ ೩ ೪ ೫ ೯ ೭ ೮ ೯
Nudi Abdum 09	೦೧೨೩೪೫೬೭೮೯
Nucl B Actions	00 9 9 8 8 8 6 6 6 6
BBH Amerikannada	೧೧೨೩೪೫೬೭೮೯

Fig. 2: Samples of printed Kannada numerals 0 to 9

Dataset of totally unconstrained handwritten Kannada numerals 0 to 9 is created by collecting the handwritten documents from writers belonging to different professions. Writers were asked to write the numerals on plain A4 size papers. No constraints were imposed on the use of ink or pen. Writers were chosen from schools, colleges and professionals and the purpose of collection was not disclosed to them. The collected documents were scanned using HP flatbed scanner at 300 dpi which yield low noise good quality gray scale images. It is ensured that the skew introduced during the document scanning is negligible and hence ignored. A sample image of scanned document is shown in Fig 3. The individual numerals were extracted manually from the scanned documents and labeled.

0	0 -	02	8	23	٤	2 0	<del>,</del> 8		
0	0		a.	8	28	2	2	e	E-
${}^{\circ}$	Λ		2	8	28	ē_	2	5	5
0	$\sim$		2	ę,	æ	٤	2	0	8
0	0	_0	æ	8	æ	٤	2	cr.	e -
0	0	2	2	8	25	٤	2	e-	_
ö	ຄ	_0	2	*	æ	٤	2	e-	E .

Fig. 3: A sample sheet of Kannada Handwritten numerals 0 to 9

# 2.2 Preprocessing method

The first step in preprocessing is to binarize the numeral image (printed and hand written) so that the numeral image has pixel values 0 and 1. A thresholding application has to be performed on scanned gray scale images. We used Otsu's method [13] for the purpose of selecting the threshold and binarizing the gray scale images, so that resulting image has 0 as background pixels and 1 as foreground pixels. The noise in the image is removed using morphological open and close operations. Further, the spike effect along the boundary of the numerals, due to thrersholding operation, is eliminated using spurring operation [13]. A bounding box is then fitted over the numeral and the numeral is cropped. To bring about uniformity among all the numerals, they are normalized to a window size of 40x40 pixels. The 40x40 size of the window is selected due to the fact that the handwritten numerals collected from writers fall around this size. A total of 2500 and 3150 numeral images representing Kannada machine printed and handwritten numerals, 0 to 9, respectively, are obtained and stored as data set. Each numeral image represents a numeral (binary 1) that is unconstrained, isolated and clearly discriminated from the background (binary 0). A portion of dataset of both Printed and Handwritten images is shown in the Figure 4. The block diagram of preprocessing step is shown in the Figure 5.

#### (a) Printed numerals

٥	<i>a</i> -	n 2	8	25	А.	2 4	= R	-	
0	2	_*	R.	8	25	2	2	cr	c-
Ó	Λ	_0	2	皆	"X	_ع	2	65	5-
Ġ	Λ	~~	э.	¢,	94			e	
o	Ο	_	÷R	8	81	٤	2	v	۳
۰	Ω	_°	R.	8	23	٤,	2,	¢7	۲
ö	ត	_₽	â	¥	ы			e	
0	n	-	-2	¥	<b>3</b> 4	٤	ع	U	£-

(a) Handwritten numerals

Fig. 4: Preprocessed binary images

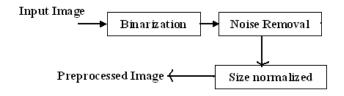


Figure 5. Preprocessing method

## **3. FEATURE EXTRACTION**

The traditional goal of the feature extractor is to characterize an object by making numerical measurements. Good features are those whose values are similar for objects belonging to the same category and distinct for objects in different categories. For extracting the features we have used crack code and Fourier Descriptors. A brief overview of Crack code and Fourier descriptors is given below.

## 3.1 Crack Code

One of the ways to encode the contour or boundary by a connected sequence of straight line segments of specified length and direction is Chain code [16, 17]. Another view is the crack code, the crack belongs to the boundary lies between a foreground and background pixel. Encoding this line (a sequence of horizontal and vertical pixel edges) yields the crack code of the digitized object boundary [17] (identified as the bold line in Figure 6). Codes are represented with 4 possible directions as shown in Fig. 6. Crack codes are efficient in representing the region borders.

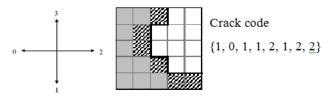


Fig. 6: a) Direction b) The "crack" is shown with the thick black line

The algorithm for generating the crack code is given below.

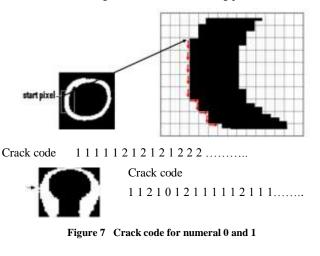
- Identify a pixel P that belongs to the class "objects" and a neighboring pixel (4 neighbor connectivity) Q that belongs to the class "background".
- Depending on the relative position of Q relative to P, identify pixels U and V as follows:

COE	)E 0	 COE	)E 1	 COE	)E 2	_	COE	)E 3
٧	Q	Q	Ρ	Ρ	U		U	۷
U	Ρ	V	U	Q	٧		Ρ	Q

- A pixel has a value of "1" if it belongs to the class "object" and "0" if it belongs to the class "background".
- Pixels U and V are used to determine the next "move" (i.e., the next element of crack code) as summarized in the following truth table:

U	v	P'	Q'	TURN	CODE
х	1	۷	Q	RIGHT	CODE-1
1	0	U	V	NONE	CODE
0	0	Ρ	U	LEFT	CO DE+1

Crack code for Kannada numerals 0 and 1 is shown infigure 7. Arrow mark in the figure indicates the starting pixel.



To compute the Fourier transform, the code computed from the numeral boundary are represented as points in the complex plane using look-up table 1.

Table 1:	Lookup	table	(j i	is i	maginary	number)
----------	--------	-------	------	------	----------	---------

Current CC	Next CC	Zn
Any Code	Same Code	0+0j
North	East	-1+j1
West	South	-1+j1
North	West	1+j1
East	South	1+j1
South	East	-1-j1
West	North	-1-j1
South	West	1-j1
East	North	1-j1

#### **3.2 Fourier Descriptors**

The Fourier descriptors are used to describe the boundary of a shape using the Fourier methods. The Fourier transformed coefficient form the Fourier descriptors of the shape. These descriptors represent the shape of the object in frequency domain. 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. We assume that  $z_0, z_1, \ldots, z_{N-1}$  is a sequence of complex numbers representing the boundary coordinates in a counter-clockwise order. We define the Fourier descriptor  $C_k$  as the k'th discrete Fourier transform coefficient of the sequence.

$$C = \sum_{n=0}^{N-1} z_n \ e^{-2 \pi \ ik \ n/N} \tag{1}$$

We can achieve rotational invariance and invariance with respect to the starting point by using only the absolute values of the descriptors  $C_k$ . We can also achieve translational invariance by discarding the Fourier descriptor  $C_0$ . Scale invariance is achieved by dividing the Fourier descriptors by  $|C_1|$ .

The block diagram representing the feature extraction method is shown in figure 8. Algorithm for extracting the features of the numeral is presented below.

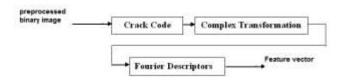


Figure 8: Feature vector extraction

Algorithm: Feature extraction

Input: Gray scale image representing Kannada numeral Output: Feature vector of length 12

#### Method:

1) Remove the noise using median filter

- Convert the gray scale image to binary with 1 representing object pixel and 0 representing background pixel
- 3) Apply morphological erode and dilate operations to remove noise and fill the holes
- 4) Compute crack code of the outer boundary of the image using algorithm 3.1
- 5) Represent the code in the complex coordinate plane and compute the Fourier transform using equation (1) for n = 0...11.

#### 4. CLASSIFICATION

Classification methods based on learning from examples have been widely applied to character recognition. This class of methods includes statistical methods, artificial neural networks, support vector machines, multiple classifier combination, etc. SVM classifier has brought forth significant improvements of recognition accuracies in recent years. In this paper we have adopted SVM for classification purpose. An SVM is a binary classifier with discriminant function being the weighted combination of kernel functions over all training samples [18-19]. A number of simple kernels include polynomial SVM, Radial Basis Function (RBF) SVM, and Two-layer neural network SVM. Since, we have chosen RBF (Gaussian) kernel,

 $\exp\left(\frac{\|\mathbf{x}_t - \mathbf{x}_f\|^2}{2\sigma^2}\right)$ , we have to tune the kernel size, i.e. the value of

 $\sigma$ . This has been done empirically for each database, choosing the kernel  $\sigma$  value providing minimum error rate. After learning by quadratic programming (QP), the samples of non-zero weights are called support vectors (SVs). SVM learning often results in a large number of SVs, which should be stored and computed in classification. For multi-class classification, binary SVMs are combined in either one-against-others or one- against-one (pairwise) scheme [20].

#### 5. EXPERIMENTAL RESULTS

Experiments were conducted to test the efficiency of our novel feature extraction method using SVM classifier. The proposed method was experimented on both machine printed and handwritten numerals images obtained as described in section 2. K-fold cross validation was used to study the recognition accuracy of the proposed system. When using the k-fold method, the training dataset is randomly partitioned into k groups. The learning algorithm is then trained k times, using all of the training set data points except those in the kth group.

The data set is divided into five subsets of equal sizes. Testing is carried out on each subset using rest of the subsets for training purpose. The recognition rates obtained by using SVM classifier, for all the five test subsets are obtained and average is computed. The recognition results for the five subsets of Machine printed and Hand Printed is presented in table 2 and 3. An overall recognition accuracy of 99.76 % is achieved for printed numerals and 95.22 % for hand written numerals. The recognition accuracy for printed numerals is impressive compared to handwritten numerals. This is due to the fact that handwritten numerals vary largely in shape and style making the task of recognition more complex. The error in classification can be minimized by correcting the slant of the numerals in preprocessing stage.

Printed	K-fold cross validation									
Kannada Numerals	First fold	Second fold	Third fold	Fourth fold	Fifth Fold	Average recognition				
•	100	100	100	100	100	100				
0	100	100	100	100	100	100				
2	100	100	99	100	99	99.60				
2	99	100	98.55	100	100	99.51				
8	98.55	100	99	100	98.55	99.22				
33	100	100	100	100	100	100				
ک	100	98.55	99	100	100	99.51				
2	100	99	100	100	100	99.80				
US	100	100	100	100	100	100				
8	100	100	100	100	100	100				
	Avera	ige Recog	nition r	ate		99.76				

 Table 2: Recognitions results of Machine Printed numerals

**Table 3: Recognitions results of Hand Printed Numerals** 

Handwritten	K-fold cross validation									
Kannada Numerals	First fold	Second fold	Third fold	Fourth fold	Fifth Fold	Average recognition				
0	95.00	98.33	98.33	100	100	98.33				
0	100	96.66	100	100	99.38	99.20				
_9	93.33	93.33	93.33	90.00	96.66	93.33				
Q.	90.00	93.33	93.33	93.33	90.00	91,99				
8	93.33	93.33	95.00	95.00	96.66	94.66				
224	93.33	95.00	93.33	96.00	93.33	94.19				
2	93.33	98.00	95.00	96.66	95.00	95.59				
2	98.00	93.33	96.00	95.00	90.00	94.46				
5	95.00	93.33	96.00	93.33	98.33	95.19				
8	95.00	95.00	95.00	96.66	.95.00	95.33				
	Averag	e Recogn	ition rat	le		95.22				

## 6. CONCLUSIONS

We have described an efficient method for recognition of hand written and machine printed Kannada numerals using crack code and Fourier Descriptors. Promising recognition results are obtained by combining these features and using SVM Classifier. The experiments have been carried out on 2500 printed images and 5000 handwritten images using k-fold cross validation method. The average recognition of 99.76 % is achieved for Printed and 95.22% for Handwritten Numerals. The incorrect classification is largely attributed to the style of handwriting where certain numerals look similar and exhibit similar features. The novelty of the proposed method is that it is thinning free. The results obtained encourage us to continue the research with the following aims: To test the robustness of the method in case of noisy images by introducing Gaussian noise in the images. Improved recognition is always desired. We can improve the recognition accuracy of our system by tuning the features. One way to achieve this is to normalize the codes and use this as weight for the codes before computing the Fourier transform. Finally, it is desirable to reject the decision for those patterns with low confidence.

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#### 8. REFERENCES

- Øivind Due Trier, Anil K. Jain and Torfinn Taxt, Feature Extraction Methods for Character Recognition- A survey, Pattern Recognition, Volume 29, Issue 4, April 1996, pp 641-662.
- P. Berkes, "Handwritten Digit Recognition with Nonlinear Fisher Discriminant Analysis", Artificial Neural Networks: Formal Models and Their Applications - ICANN 2005, 2005, pp. 285–287.
- [3] Cheng-Lin, Kazuki, Hiroshi, and Hiromichi, Handwritten Digit Recognition: Investigation of Normalization and Feature Extraction Techniques", Pattern Recognition, 37(2004), pp. 265–279.
- [4] E. Kussul and T. Baidyk, "Improved Method of Handwritten Digit Recognition Tested on MNIST Database", Image and Vision Computing, 22(2004), pp. 971–981.
- [5] C.L. Liu, K. Nakashima, H. Sako, H. Fujisawa, Handwritten digit recognition: benchmarking of state-of the-art technique. Pattern Recogn. vol 36, pp 2271–2285(2003)
- [6] B. B. Chaudhuri and U. Pal, A complete printed Bangla OCR system, Pattern Recognition, vol. 31, pp. 531-549, (1998).
- [7] Reena Bajaj, Lipika Dey and Santanu Chaudhur, "Devnagari numeral recognition by combining decision of multiple connectionist classifiers", Vol. 27, Part 1, pp. 59– 72, February 2002.
- [8] Hanmandlu M, M.Hafizuddin, M Yusuf and V K Madasu, Fuzzy based Approach to recognition of multifont Numerals , Proc. Of 2<sup>nd</sup> National Conf. on Document Analysis and Recognition (NCDAR), Mandya, vol., pp 118-126, (2003)
- [9] Dhandra. B.V, Benne. R.G, Hangarge M, Handwritten Kannada Numeral Recognition Based on Structural Features. Proceedings of International Conference on Computational Intelligence and Multimedia Applications, vol 2, pp-224-228, (2007)
- [10] Dinesh Acharya U, N V Subbareddy and Krishnamoorthy, Isolated Kannada Numeral Recognition Using Structural Features and K-Means Cluster, Proc. of IISN-2007, (2007) 125-129.
- [11] G.G.Rajput and Mallikarjun Hangarge, "Recognition of Isolated Kannada Numeral Based on Image Fusion Method", PReMI 2007, LNCS 4815, pp. 153–160, 2007.
- [12] U. Pal, T. Wakabayashi, N. Sharma and F. Kimura, "Handwritten Numeral Recognition of Six Popular Indian Scripts", In Proc. 9th International Conference on Document Analysis and Recognition. pp. 749-753, Curitiba, Brazil, September 24-26, 2007.
- [13] S.V. Rajashekararadhya et.al "Efficient Zone Feature Extraction Algorithm for Handwritten Numerals Recognition of Four South Indian Scripts", Journal of Theoretical and Applied Information Technology 2008

- [14] Eric Persoon and King-sun Fu 1977. Shape Discrimination Using Fourier Descriptors. IEEE Trans. On Systems, Man and Cybernetics, Vol. SMC- 7(3):170-179.
- [15] Fethi Smach, Cedric Lemaître, Jean-Paul Gauthier Johel Miteran, Mohamed Atri 2008. Generalized Fourier Descriptors with Applications to Objects Recognition in SVM Context, J Math Imaging Vis, Springer Science+Business Media 30: 43–71.
- [16] Rafael C. Gonzalez, Richard E. Woods, Digital Image Processing. Pearson Education Asia, 2nd Edition, 2002.

- [17] www.sampl.ece.ohiostate.edu/EE863/2003/ee863-11.ppt
- [18] V. Vapnik, The Nature of Statistical Learning Theory, Springer-Verlag, New Work, 1995.
- [19] C.J.C. Burges. A tutorial on support vector machines for pattern recognition, Knowledge Discovery and Data Mining, 2(2): 1-43, 1998.
- [20] U. Kressel, Pairwise classification and support vector machines, Advances in Kernel Methods: Support Vector Learning, B. SchÄolkopf, C.J.C. Burges, A.J. Smola(eds.), MIT Press, 1999, pp.255-268.