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COMBINED CLASSIFIERS IN RECOGNITION OF HANDWRITTEN KANNADA NUMERALS: A HYBRID APPROACH

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The recognition of handwritten numeral is an important area of research for its applications in post office, banks and other organizations. This paper presents automatic recognition of handwritten Kannada numerals using both unsupervised and supervised classifiers. Four different types of structural features, namely, direction frequency code, water reservoir, end points and average boundary length from the minimal bounding box are used in the recognition of numeral. The effect of each feature and their combination in the numeral classification is analyzed. Combining classifiers has proved to be an effective solution to several classification problems in pattern recognition. In the image classification, it is often beneficial to consider each feature type separately, and to integrate the initial classification results by a final classifier. In this paper, we developed a robust hybrid approach where fuzzy *k*-Nearest Neighbor (fuzzy *k-NN*) and fuzzy *c*-means (FCM) as base classifiers for individual feature sets, the results of which together forms the feature vector for the final *k*-Nearest Neighbor (*k-NN*) classifier. Testing is done, using different feature sets, individually and in combination, on a database containing 1600 samples of different numerals and the results are compared with the different existing methods.

Keywords: Structural Features, Numeral Recognition, Fuzzy *k* Nearest Neighbor, Fuzzy *c*-means, Multiple Classifiers, Classification Result Vector.

1. Introduction

Character and Numeral recognition has a great potential in data and word processing for instance, automated postal address and PIN code reading, data acquisition in bank checks, processing of archived institutional records etc. Extensive studies have been carried out on recognition of characters in the languages like English, Chinese, Japanese and Arabic. They mostly differ in feature extraction schemes and classification strategies [5]. Considerable amount of work has been carried out in numeral recognition through regional decomposition, histogram methods, Hough transformations, PCA, support vector machines, nearest neighbor, neural computing based approaches and fuzzy theory based approaches. An extensive survey of recognition performance for large handwritten database through many kinds of features and classifiers is reported in [2]. A comprehensive survey on online and offline handwritten recognition is given in [6].

Among studies on Indian scripts, most of the pieces of existing work are concerned about Devanagari and Bangla script characters. Some studies are reported on the recognition of other languages like Tamil, Telugu, Oriya, Kannada, Panjabi, Gujarathi, etc. Structural and topological feature based tree classifier and neural network classifiers are mainly used for the recognition of Indian scripts [1]. Neural Networks and Fuzzy based numeral recognition are reported for Hindi and Bangla Tamil Numerals [24-26]. Among studies on Kannada Numeral Recognition, most of the work uses Nearest Neighbor classifier [12-15]. Quadratic classifier and *K*-Means Cluster are also used [16,11]. The features extraction techniques include structural features [11, 14], image reduction [15], randon transform [13], image fusion [12] and directional chain code [16].

Considering real life classification problems it is usual that the features are spread in many different ways. A survey of feature extraction methods for character recognition is reported in [3]. A common approach is to select the features of different category which are complementary and combine them into a single feature vector. However, when different types of features are combined into the same feature vector, some large-scaled features may dominate the distance, while the other features do not have the same impact on the classification [10]. Instead, separate classifiers can be used to classify based on each visual feature individually [17]. The final classification can be obtained based on the combination of separate base classification results. Hence the non-homogenous properties of individual features do not necessarily affect directly on the final classification. In this way, each feature has its own affect on the classification result.

It has been found that a consensus decision of several classifiers can give better accuracy than any single classifier [18]. Therefore, combining classifiers has become a popular research area during recent years. The goal of combining classifiers is to form a consensus decision based on opinions provided by different base classifiers. Combined classifiers have been applied to several classification tasks, for example

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to the recognition of faces, handwritten characters identification, and fingerprint verification [19, 20].

In this paper, four different category of features are combined to obtain high degree of accuracy in handwritten Kannada numeral recognition. The features include direction frequency code, water reservoir, end points and average boundary length. The direction code frequency includes the frequency of 8-direction codes in direction chain code of the numeral in six different blocks. The second type of feature set specifies the presence of water reservoirs in the numeral along with their proportionate size, position and direction. The third type of feature set includes the number of end points in the numeral along with their position in the grid. The fourth set, average boundary length, includes the average length of numeral boundary from the minimal bounding box in four different directions. Effect of each feature set in the numeral recognition is measured, individually and in combination with single and multiple classifiers.

We present a method to the classification of numerals using combined classifiers. In this method, four different features sets are fed to separate fuzzy *k*-NN and fuzzy *c*-means base classifiers. The outputs of these base classifiers are combined into a feature vector [8] that is used in the final classification using *k*-nearest neighbor.

2. Kannada Numeral Set

The Kannada language is one of the four major south Indian languages. It is spoken by about 50 million people in the Indian states of Karnataka, Tamilnadu, Andhra Pradesh and Maharashtra. The Kannada alphabet consists of 16 vowels and 36 consonants. It also include 10 different symbols representing the ten numerals of the decimal number system (Table 1).

Table 1
Kannada Numerals

English Numerals	1	2	3	4	5	6	7	8	9	0
Kannada Numerals	೧	೨	೩	೪	೫	೬	೭	೮	೯	೦

3. Preprocessing and Feature Selection

The page containing multiple lines of isolated handwritten Kannada Numerals is scanned through a flat bed scanner at 300 DPI and is binarized using global threshold. Noise removal is done using median filter. The binary image is thinned, in the case of direction code frequency and end points feature extraction. The image is then processed to lines and numerals using appropriate horizontal and vertical projections.

To separate the lines, horizontal projection profile method is applied to the image. A horizontal projection profile is the histogram of the number of ON pixels along each row of the image. The OFF pixels (blank space) between the text lines specify the boundary of each line to be segmented. The projection profile gives valleys of zero height for these OFF pixels between the text lines. Segmentation of the image into separate lines is done at these valley points.

A vertical projection is applied to the image for numeral segmentation. The space between isolated characters is used to determine the character boundaries. With the vertical projection profile approach OFF pixels between each character give valleys with zero value, which indicate the numeral boundary. This information is used to separate the isolated numerals from the lines.

The bounded box approach is used to get the exact boundary of the numeral. While extracting direction frequency code, the numeral images are normalized to 10×10 grid sizes. The normalization is done using run length code approach with necessary error correction. The different features are extracted and stored as vectors which are used as input for four different fuzzy *k* Nearest Neighbors and fuzzy *c*-means clusters for classification.

3.1 Direction Code Frequency (DCF)

Each numeral image is first thinned and then the minimal bounding box containing the numeral is divided into three equal horizontal and vertical blocks (Figure 2). In each of these blocks, the direction chain code [16] for each contour point is noted and the frequency of the direction codes is computed. Here we use chain code of eight directions (Figure 1). Thus, in each block we get an array of eight integer values representing the frequencies and these frequency values together form a feature set. Thus, for 3 + 3 blocks we get $(3 + 3) \times 8 = 48$ features. To normalize features, we divide each of the frequency values by the maximum frequency.

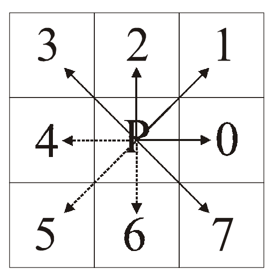

Figure 1: For a Point *P* the Direction Codes for its Eight Neighboring Points are Shown.

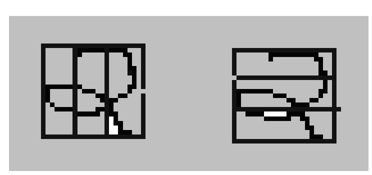

Figure 2: Horizontal and Vertical Blocks for Calculating Direction Code Frequency.

3.2 Average Boundary Length (ABL)

Average Boundary Length feature vector, of dimension four, include average length of the numeral boundary with respect to minimal bounding box in all the four directions (left, top, bottom and right). In each direction, the distance between the bounding box and the first numeral boundary pixels in that direction is calculated (Figure 3.) whose average value gives the average boundary length in that direction.

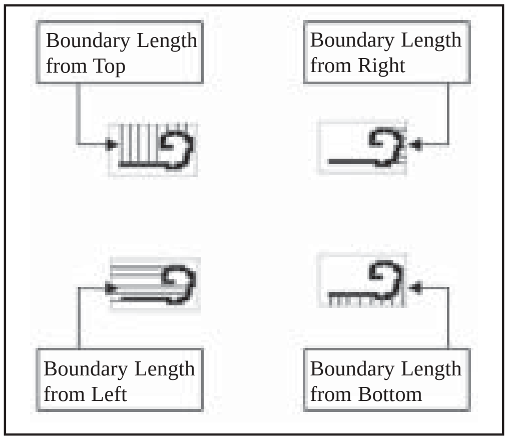

Figure 3: Boundary Length from Bounding Box

3.3 Water Reservoir (WR)

The water reservoir principle is as follows. If water is poured from one side of a component, the cavity regions of the component where water will be stored are considered as reservoirs [7]. The direction of reservoir, start and end positions, height and width (all with respect to bounding box of the numeral image), together form water reservoir vector of the numeral. The vector includes possible water reservoirs from bottom, left, top and right of the numeral, as shown in Figure 4.

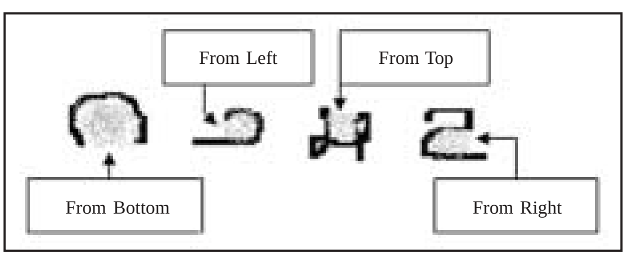

Figure 4: Water Reservoirs in Numerals

3.4 End Points (EP)

Number of end points and their position (which quadrant of the numeral grid) is used to form a separate feature set. For example, numeral zero don't include any end points, while, numeral 1 has two end points and normally they fall in 1st and 4th quadrants (Figure 5).

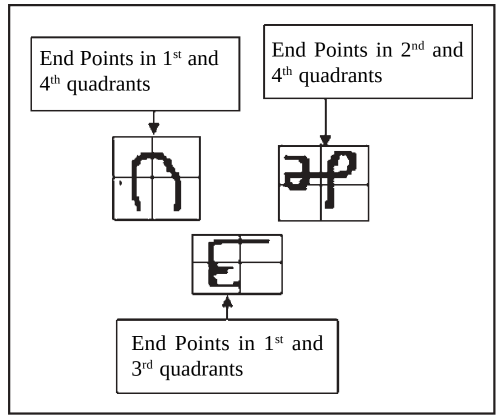

Figure 5: Numeral End Points and their Positions

4. CLASSIFICATION

The use of classifier combinations has been a subject of an intensive research work during last ten years. Popular solutions on this field are bagging, boosting, probability-based classifier combination. If the probability distributions of the base classifiers are not available, a simple combination strategy is voting. In the voting-based classifier combinations, the majority of the base classifier outputs decide the final class of an unknown sample. Voting-based classifier combinations have been used in pattern recognition in [19], [21]. A modified method, Classification result vector (CRV) based method, where the results of base classifiers are combined into a feature vector for the final classifier, used in the non-homogenous rock images outperforms other classifier combinations methods [8].

In the proposed method (Figure 7), CRV-based method is extended. Instead of using only one result class label from each of the base classifiers, membership values for each of the class labels is generated. Moreover, to achieve robust and better classification rate, a hybrid technique [27] is used where both supervised (fuzzy *k*-NN and unsupervised classifiers (FCM) are used as the base classifiers for each of the four feature sets.

The fuzzy *c*-means algorithm [27] generalizes the hard *c*-means algorithm to allow a point to partially belong to multiple clusters and is given below:

FCM (X, c, m, ε)

X : an unlabeled data set

c : the number of clusters to form

m : the parameter in the objective function

ε : a threshold for the convergence criteria

Initialize ptototype $V = \{v_1, v_2, \ldots, v_c\}$

Repeat

$$V^{\text{Previous}} \leftarrow V$$

Compute the membership functions using Equation (1).

$$v_i = \frac{\sum_{x \in X} (\mu C_i(x))^m \times x}{\sum_{x \in X}^{n} (\mu C_i(x))^m} \quad 1 \le i \le k \tag{1}$$

Update the prototype, v_i in V using Equation (2).

$$\mu C_i(x) = \frac{1}{\sum_{j=1}^{k} \left(\frac{\|x - v_i\|^2}{\|x - v_j\|^2} \right)^{\frac{1}{m-1}}} \quad 1 \le i \le k, x \in X \tag{2}$$

Until $\sum_{i=1}^{C} \| v_i^{\text{Previous}} - v_i \| \le \epsilon$

Given a set of classified data, the *k-NN* algorithm determines the classification of an input based on the class labels of *k* closest neighbors in the classified dataset. The fuzzy *k*-nearest neighbor algorithm is a fuzzy classification technique that generalizes the *k*-nearest neighbor algorithm. It assigns to an input *x* a membership vector ($\mu_{c1}(x)$, $\mu_{c2}(x)$, $\mu_{c1}(x)$, ... $\mu_{cl}(x)$) where *l* is the total number of classes. The class memberships are calculated based on the following formula [27] :

$$\mu_{Ci}(x) = \frac{\sum_{j=1}^{k} \mu_{Ci}(x_j) \frac{1}{\|x - x_j\|^{2/(m-1)}}}{\sum_{j=1}^{k} \frac{1}{\|x - x_j\|^{2/(m-1)}}} \tag{3}$$

where x_1, x_2, …, x_k denotes the *k* nearest neighbors of *x*. The fuzzy *k-NN* algorithm [27] simply contains two major steps:

1. Find the *K*-nearest neighbors of the input *x*.
2. Calculate the class membership of *x* using Equation (3).

The parameter m in equation (3) serves as a function similar to the parameter m in FCM.

Both supervised and unsupervised base classifiers give the fuzzy membership values of each numeral class. These fuzzy membership values provide better information in resolving conflicts between the results of different base classifiers. The final classification based on combined classification result vector is done by *k*-nearest neighbor classifier.

The classification procedure (Figure 7) consists of four steps:

1. **Feature extraction:** Four different complementary feature sets are extracted from the numeral image.
2. **Base (I) Level classification:** The numeral image is classified using hybrid technique (fuzzy *c*-means and fuzzy *k*-NN) based on each feature set separately.
3. **Feature Vector generation for Final Classifier:** The output of each base classifier is the fuzzy membership values for each of the ten numerals. These classifier results are combined to form a feature vector, CRV.
4. **Final Classification:** The final classifier *k*-NN decides the class of the numeral image based on CRV.

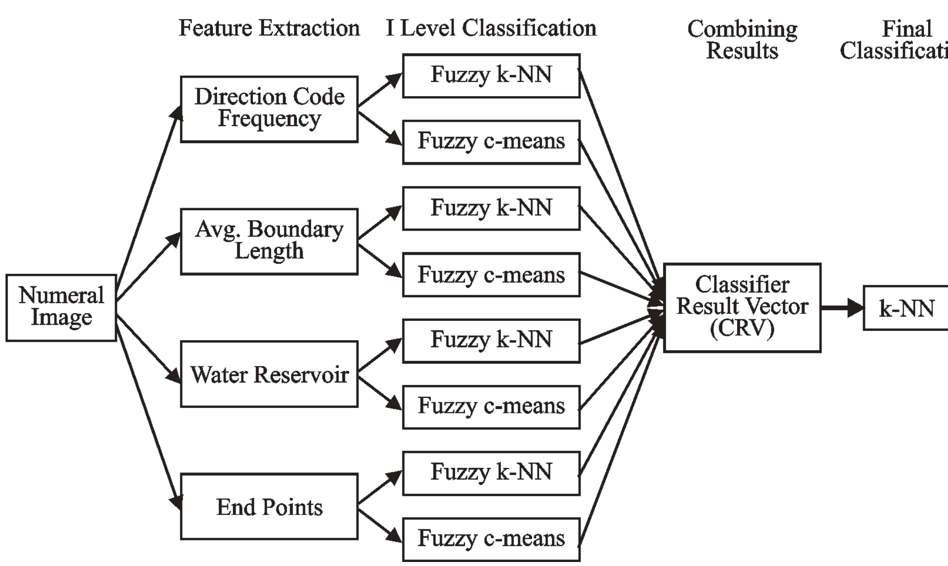

Figure 7: Classification Process

In this approach, the features extracted from the image are used in the classification only in step two. The fuzzy membership values of different unsupervised and supervised classifiers based on different category of features will provide a better feature set in the final classification and make the final classification insensitive to variations and non-homogeneities of input images.

5. RESULTS AND DISCUSSION

In order to evaluate the proposed approach, the system is tested with 1600 samples of different numerals, with different size and style collected from different individual writers. Five-fold cross validation technique. with 80% of the data for testing and rest 20% data for testing is used. A sample set of numerals used to test the system is given in Figure 6.

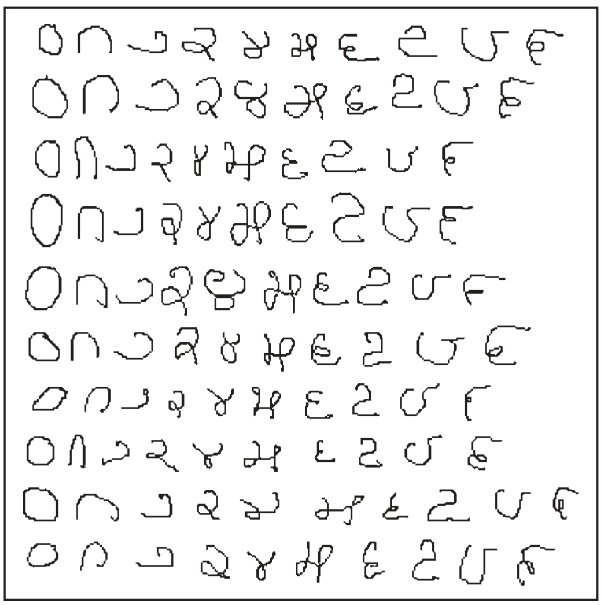

Figure 6: Sample Dataset

The recognition results for different features, individually and in combination are presented in Table 2. Features individually exhibit a recognition rate of 46% to 94.5%. On combining them, a maximum of 82% recognition rate is achieved. With multiple classifiers, the recognition rate varies from 89.5% to 99.5% with different *k* values and zero percent rejection. As evident in the results (Table 2), fuzzy *k*-NN (98.5%) and FCM (89.5% to 91%) are far better candidates to *k*-NN (66.5% to 79%) for base classifier. It gives the fuzzy membership values for each of the class labels and provides better information in resolving the conflicts between the results of different base classifiers at the final classification. Combining the membership values of fuzzy *k*-NN and FCM makes the system more robust and provides a better classification rate (99% to 99.5%). A value of *3 to k* (fuzzy *k*-NN) and and *2 to m* (fuzzy *k*-NN and FCM) is selected. Recognition rate of different feature sets when combined with different base classifiers (fuzzy *k*-NNs, fuzzy *c*-means and hybrid) are shown in Figure 8. The result of voting [19] when applied on *k*-NN base classifiers (90.5% to 92.0%) is also shown in Table 2. From

Table 2
Classification Results

Features	*k-NN (Final Classifier) Classification Rate (in %)*			
	k=3	*k=5*	*k=7*	*k=9*
Direction Frequency Code	94.5	94	92.5	91.5
Avg. Boundary Length	88	86.5	88.5	87
Water Reservoir	71	70.5	68.5	68
End Points	47	46	47	46
All the four feature sets	82	78.5	78.5	76.5
Result of k-NN Base Classifier for each feature set	92	91	91.5	90.5
Classifier (k-NN) Result Vector	77	79	76.5	66.5
Classifier (fuzzy c-NN) Result Vector	89.5	90.5	90.5	91
Classifier (fuzzy k-NN) Result Vector	98.5	98.5	98.5	98.5
Classifier (Hybrid: fuzzy k-NN and fcm) Result Vector	99	99	99	99.5

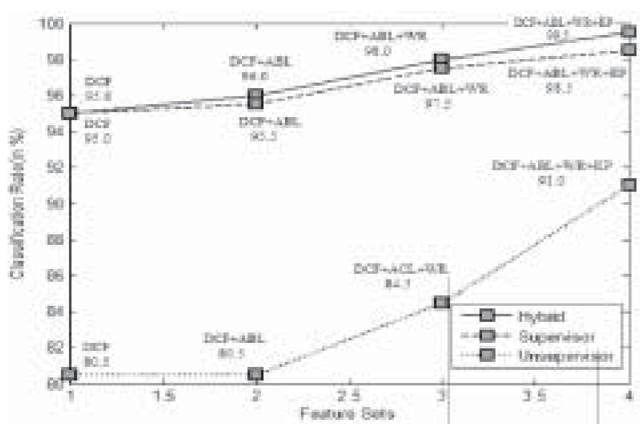

Figure 8: Numeral Classification Rate based on Combination of Different Feature Sets with Combined Classifiers

these results, it is clear that there is significant increase in the recognition rate when the features of different category, which are complementary, are combined with multiple fuzzy *k*-NN and FCM classifiers. The classification results are compared with the different contemporary methods (Table 3).

Table 3
Comparative Results of Proposed Method with Contemporary Methods

Method	*Feature Extraction Method*	*Feature Size*	*Sample Size*	*Classifier (in %)*	*Classification Rate*
Dinesh Acharya *et. al.* [11]	Structural Features	40	500	K-Means	90.5
Rajaput *et. al.* [12]	Image Fusion	NA	1000	NN	91.2
V. N. Manjunath Aradhya *et. al.* [13]	Randon Transform	NA	1000	NN	91.2
Rajashekararadhya *et. al.* [14]	Structural Features	50	800	NN	92
Ganpatsingh G [15]	Image Reduction	64	2250	k-NN	95.72
N Sharma *et. al.* [16]	Chain Code	64	2300	Quadratic Classifier	97.87
Proposed Method	Structural Features	74	1600	Hybrid Classifier	99.5

6. CONCLUSION

In this paper, four different types of structural feature sets are used in the recognition of Kannada numerals. It is often beneficial to combine different visual features to obtain the best possible classification result. Instead of combining them into a single feature vector, each feature set is given to separate base classifier. A hybrid technique with both supervised and unsupervised classifiers is used at the base level. The final classification is done based on the classification result vector by combing the fuzzy membership values of the base classifiers. Comparison of results with the contemporary methods justifies the usefulness of multilevel hybrid classifiers in the recognition of handwritten Kannada numeral images.

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