Multilevel Classifiers in Recognition of Handwritten Kannada Numerals

Dinesh Acharya U., N. V. Subba Reddy, and Krishnamoorthi Makkithaya

***Abstract*—**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 based on structural features. Five different types of features, namely, profile based 10-segment string, water reservoir; vertical and horizontal strokes, 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 using nearest neighbor classifiers. It is common to combine multiple categories of features into a single feature vector for the classification. Instead, separate classifiers can be used to classify based on each visual feature individually and the final classification can be obtained based on the combination of separate base classification results. One popular approach is to combine the classifier results into a feature vector and leaving the decision to next level classifier. This method is extended to extract a better information, possibility distribution, from the base classifiers in resolving the conflicts among the classification results. Here, we use fuzzy k Nearest Neighbor (fuzzy k-NN) as base classifier 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 features, individually and in combination, on a database containing 1600 samples of different numerals and the results are compared with the results of different existing methods.

***Keywords*—**Fuzzy k Nearest Neighbor, Multiple Classifiers, Numeral Recognition, Structural features.

I. 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, principal component analysis, 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 to the recognition of faces or handwritten characters face identification, and fingerprint verification [19],[20] .

In this paper, the five different category of features are combined to obtain high degree of accuracy in handwritten

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Kannada numeral recognition.. The features include profile based 10-segment string, water reservoir, vertical and horizontal strokes, end points and average boundary length. The 10-segment string is projection profile string based on 7-segment display concept [22]. The 7-Segment concept is extended to 10-segments in order to capture the unique characteristics of Kannada numerals. 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 vertical and horizontal strokes present in different portions of the numeral. Fourth one represents the number of end points in the numeral along with their position in the grid. The fifth 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, five different features sets are fed to separate fuzzy k-nearest neighbor(fuzzy k-NN) base classifiers[9]. The outputs of these base classifiers are combined into a feature vector[8] that is used in the final classification using k-NN.

II. 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 includes 10 different symbols representing the ten numerals of the decimal number system.

TABLE I
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

III. 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 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 ten segment features, the segmented numeral images are normalized to
10 X 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 five different fuzzy k Nearest Neighbors for classification.

A. 10-Segment Features (TS)

The 7-segment display concept is extended to approximate the Kannada numerals. Instead of seven, ten segments [11] are used to capture the unique features of Kannada numerals as shown in Fig. 2. The normalized image (10 X 10) of the numeral is used to extract the ten segments. A logical box enclosing the number is divided into 10 overlapping regions and each of the 10 regions is mapped to a separate segment (Fig. 1). Regions A to H are of size 5 X 5, while I and J are of size 4 X 5. The pixels in each region are projected to get the corresponding segment. Horizontal projection is applied to the regions A,B,E,and F and vertical projection is applied to the regions C,D,G,H,I and J. A threshold is used to check the availability of sufficient number of pixels in each of the regions. The regions, which pass the threshold test, will set the corresponding segments and provide the segment string for numeral recognition.

B. 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 Fig. 3.

C. Horizontal and Vertical Strokes (VH Strokes)

Horizontal-like and Vertical-like strokes in different window sizes (30% and 60%) of the numeral is used to form the V/H stroke feature vector. The presence of these strokes is determined from all the four sides of the numeral using projection profile method. The V/H strokes at the contour are captured by 30% window size and V/H strokes in the middle of the numeral are captured by 60% window size (Fig. 4).

D. 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 doesn't include any end points, while,

numeral 1 has two end points and normally they fall in 1st and 4th quadrants (Fig. 5).

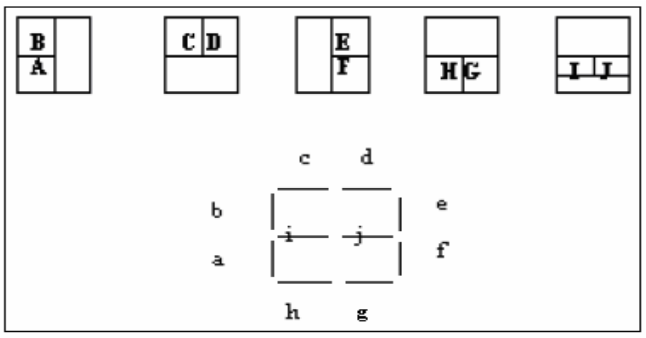

Fig. 1 Ten overlapping regions and corresponding segments

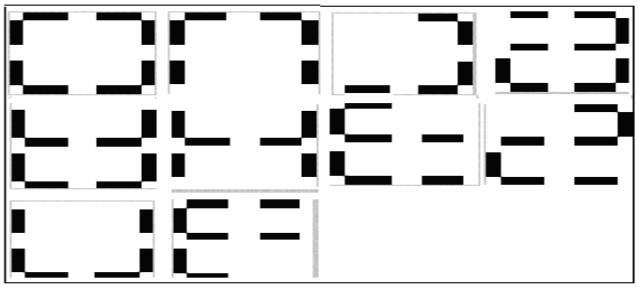

Fig. 2 10-Segment representation of numerals 0 to 9

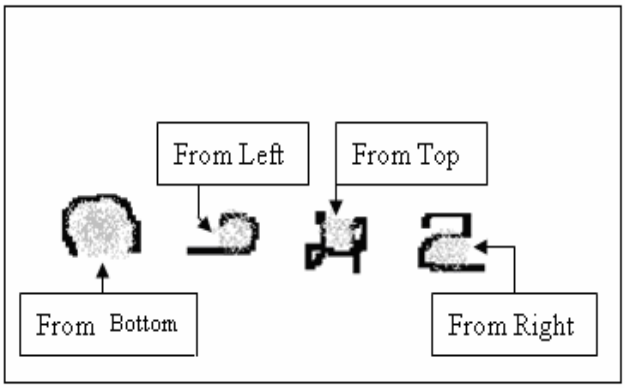

Fig. 3 Water Reservoirs in Numerals

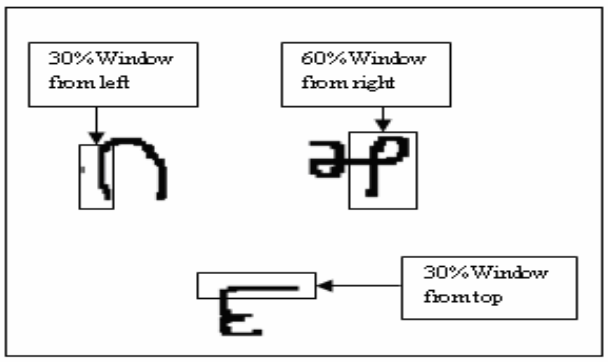

Fig. 4 Different Window Sizes to capture V/H Strokes

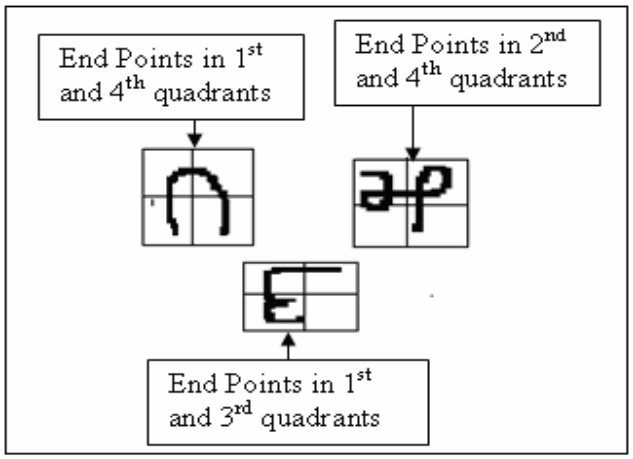

Fig. 5 Numeral End Points and their Positions

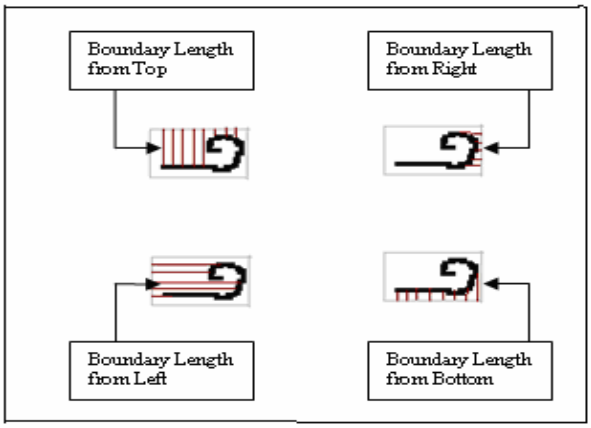

Fig. 6 Boundary Length from bounding box

E. 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 (Fig. 6) whose average value gives the average boundary length in that direction.

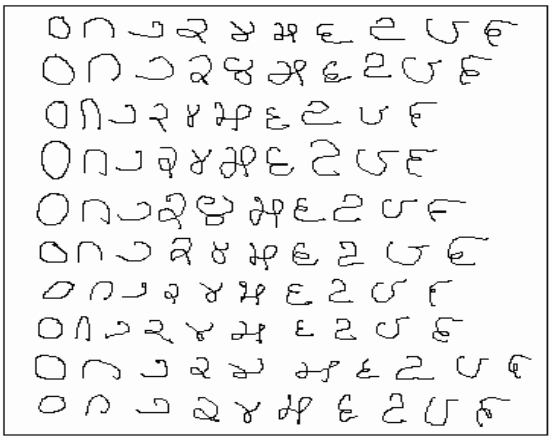

Fig. 7 Sample Dataset

IV. 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 (Fig.8), 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. Fuzzy k-NN[9], used as the base classifier for each of the feature sets, gives the membership values of each numeral class. 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 $(\mu_{c1}(x), \mu_{c2}(x), \ldots \mu_{cl}(x))$ where l is the total number of classes. The class memberships are calculated based on the following formula [27]:

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

where m is the parameter in the objective function and 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).

These class 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-NN classifier.

The classification procedure (Fig. 8) consists of four steps:

1. **Feature extraction:** Five different complementary feature sets are extracted from the numeral image.
2. **Base (I) Level classification:** The numeral image is classified using 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.
4. **Final Classification:** The final classifier k-NN decides the class of the numeral mage based on combined result vector.

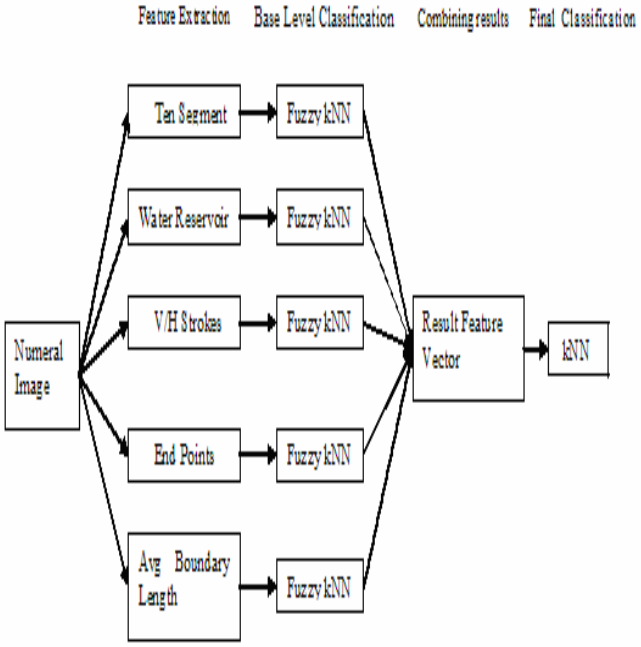

Fig. 8 Classification process

In this approach, the features extracted from the image are used only in base level classification. The class membership values of different base 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.

V. 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, using five-fold cross-validation technique. A sample set of numerals used to test the system is given in Fig. 7.

The recognition results for different features, individually and in combination are presented in Table II. Features individually exhibit a recognition rate of 45.5% to 88.5%. On combining them, a maximum of 91.5% recognition rate is achieved. With multiple classifiers, the recognition rate varies from 97% to 98% with different k values and zero percent rejection. As evident in the results (Table II), fuzzy k-NN is a far better candidate to k-NN(69% 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. A value of *3 to k* and *2 to m* is selected for fuzzy k-NNs. Recognition rate of different features when combined with a single classifier(k-NN) and in combination with different base classifiers(fuzzy k-NNs) are also shown in Figs. 9 and 10. Even though, the feature set average boundary length don't improve the classification rate with

single classifier (Fig. 9), its impact is significant in multilevel classifiers (Fig. 10). The results of voting [19] based classifier(k-NN) combinations (85.5% to 89.5%) is also shown in Table II. From 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 classifiers. The classification results are compared with different existing methods (Table III).

TABLE II
CLASSIFICATION RESULTS

Features	Final Classification Rate(in %)				
	k=1	k=3	k=5	k=7	k=9
Ten Segment	52.5	56.5	51.5	54	56.5
Water Reservoir	74	71	70.5	68.5	68
V/H Strokes	72.5	75.5	78	77	78.5
End Points	45.5	47	46	47	46
Avg. Boundary Length	88.5	88	86.5	88.5	87
All the above	90	91.5	90.5	90	90.5
Voting (k-NN Base Classifiers)	87.5	89.5	85.5	87.5	89
Classifier(k-NN) Result Vector	79	74	74	71.5	69
Proposed Method	***97.5***	***97***	***98***	***98***	***97.5***

TABLE III
COMPARATIVE RESULTS OF PROPOSED METHOD WITH OTHER EXISTING METHODS

Method	Feature Extraction Method	Feature Size	Sample Size	Classifier	Classification Rate(in %)
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	44	1600	Multiple classifiers	98

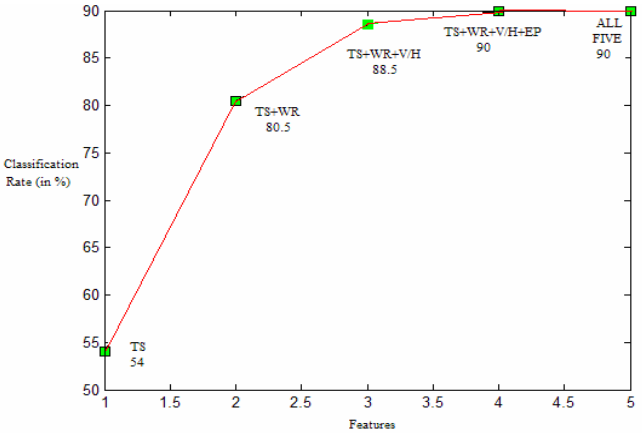

Fig. 9 Numeral Classification Rate based on combination of different features with a single classifier

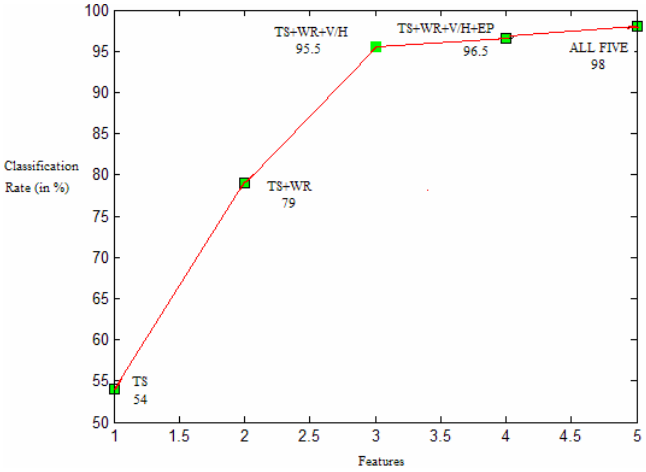

Fig. 10 Numeral Classification Rate based on combination of different features with multiple classifiers

VI. CONCLUSION

In this paper, five different types of structural features 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. 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 existing methods justifies the use of multilevel classifiers in the recognition of handwritten Kannada numeral images. However, exhaustive testing of the system is required over a benchmark dataset.

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