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Kannada Numerical Handwritten Word Recognition System

Dr. K M Rajesh[1]

Assistant Professor and HOD, Department of Computer Science, JSS College for women, Chamarajanagara District-571313, Karnataka, India

Nandeesh P[2]

Assistant Professor, Department of Computer Science, JSS College for women, Chamarajanagara District-571313, Karnataka, India

ABSTRACT

This paper presents an automation of Kannada numerical handwritten word recognition system in that main challenge is recognition of handwritten words. The identification of Kannada handwritten words plays an important role because in Kannada script many words have a same size and same shape. The recognition of Kannada handwritten words is an important application in number plates, banks and other organizations. In this work we consider dataset contains 50 documents for each documents contains the 0-9 Kannada handwritten words 10 classes. Here we extracting the two different types of feature namely Gabor and LPBV (local binary pattern variance). The effect of each feature and their Combination in the words and signature classification is analysed using the K-nearest neighbour classifiers. It is common to combine multiple categories of features into a single feature vector for the classification and also we apply the dimensionality reduction technique. Calculated Classification results based on feature extraction methods, varying the K values and randomly splitting the testing and training samples.

Keywords

Gabor, local binary pattern, Local binary pattern variance, K-nearest neighbour, Dimensionality.

I. INTRODUCTION

Kannada script is the visual form of Kannada language. It originated from southern Bramhi lipi of Ashoka period. It underwent modifications periodically in the reign of Sathavahanas, Kadambas, Gangas, Rastrakutas, and Hoysalas. Even before seventh-Century, the Telugu-Kannada script was used in the inscriptions of the Kadambas of Banavasi and the early Chalukya of Badamiin the west. From the middle of the seventh century the archaic variety of the Telugu-Kannada script developed a middle variety. The modern Kannada and Telugu scripts emerged in the thirteenth Century. Kannada script is also used to write Tulu, Konkani and Kodava languages [3]. Here we review of identification on Kannada handwritten numerical words. In this work we consider the legal amount written in the words, amount written in the numerical, account number. In that main challenge is recognition of hand written words, recognizing the numeral, Since identification of hand written words plays an important role in analyzing the Kannada handwritten words. The recognition of handwritten legal number in words of Kannada language is challenging because of similar size and shape of many words. Moreover many words have same suffixes or prefix.

II. RELATED WORK

Jayadevan R, et al. [1] they proposed recognition technique is combination of two approaches. The first approach is based on gradient structural and cavity (GSC) features along with a binary vector matching (BVM) technique. The second approach is based on vertical projection profile (VPP) feature and dynamic time warping (DTW). A number of highly matched words in both the approaches are considered for the recognition step in the combined approach based on a ranking scheme. The dataset has been grouped into three sub-datasets namely DB1, DB2 and DB3. DB1 contains data collected from 90 individuals in Marathi language where each individual contributed 114 word templates and a hand written cheque. The DB1 has 10,260(114×90) handwritten words and 90 handwritten cheques in Marathi language. DB2 also has data in Marathi language, collected from 70 individuals with comparatively poor handwriting. DB2 has 7,980(114×70) handwritten words and 70 handwritten cheques. DB3 contains data in Hindi language collected from 80 individuals. Each individual contributed 106 word templates and a handwritten cheque. The DB3 has 8,480(106×80) handwritten words and 80 handwritten cheques in Hindi language. The three sub-datasets collectively have 26,720 handwritten Devanagari words and 240 handwritten cheques. The result is 55.2% to 80.23% dependent upon the 3 datasets.

Shreedharamurthy S K, et al. [12] they developed the Neural Network based Kannada Numerals Recognition System in this paper a novel approach for feature extraction in spatial domain to recognize segmented Kannada numerals using artificial neural networks. They develop the handwritten Kannada numeral recognition system using spatial features and neural networks. Handwritten numerals are scan converted to binary images and normalized. The features are extracted using spatial coordinates and are classified using the feed forward neural network classifier.They used spatial features and artificial neural network as classifier. To recognizes the hand written Kannada numerals. They have used 100 samples of numerals from the created data base, sample patterns. The accuracy based Out of which 80 patterns used for training phase and 20 samples for testing phase.

Mehta M, et al. [2] they develop the Automatic Cheque Processing System (English) they consider the forgery detection. An account holder gives cheques to another person as account payee or self-cheque. It is been observed that a number of forgery cases have been registered as cheque forgery, where some person has forged the signature of another person and provided a self-cheque to himself. In this paper we propose a mechanism for recognition of cheque fields, like name, amount and also verify the signature and its authenticity. We propose a unique two stage model of Automatic Cheque processing with detecting skilled forgery in the signature by combining two feature types namely Sum graph and HMM and classify them with knowledge based classifier and probability neural network. We proposed a unique technique of using HMM as feature rather than a classifier as being widely proposed by most of the authors in signature recognition. The accuracy based on good correct classification rate for any number of classes. The lowest rate of correct classification is 86% and the highest is 92%.

Dhandra B.V et al. [17] they develop Zone Based Features for handwritten and printed Mixed Kannada Digits Recognition they consider the field of Optical Character Recognition (OCR), zoning is used to extract topological information from patterns. They propose Zone based features for recognition of the mixer of Handwritten and Printed Kannada Digits. A digit image is divided into 64 zones and pixel density is computed for each zone. This procedure is sequentially repeated for entire zone. Finally 64 features are extracted for classification and recognition. There could be some zone column/row having empty foreground pixels. Hence the feature value of such particular zone column/row in the feature vector is zero. The KNN classifiers are used to classify the mixed handwritten and printed Kannada digits. They have obtained 97.32% & 98.30% recognition rate for mixed handwritten and printed Kannada digits by using KNN classifiers respectively.

Dinesh Acharya U. [11] they proposed the Multilevel Classifiers in Recognition of Handwritten Kannada Numerals The recognition of handwritten numeral is an important area of research for its applications in post office, banks and other organizations. In that 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.

Dhandra B.V. et al. [18] they develop a script independent approach for handwritten bilingual Kannada and telugu digits recognition, handwritten Kannada and Telugu digits recognition system is proposed based on zone features. The digit image is divided into 64 zones. For each zone, pixel density is computed. Feature extraction is a problem of extracting the relevant information from the preprocessed data for classification of underlying objects/characters. The preprocessed digit image is used as an input for feature extraction. For extracting the potential feature from the handwritten digit image, the frame containing the preprocessed/normalized image is divided into non overlapping zones of size 8 x 8 and obtained 64 zones. For each zone, the pixel density is computed and there pixel densities are used as a feature for recognition. Hence, 64 features vector is used for recognition of a digit. The KNN and classifiers are employed to classify the Kannada and Telugu handwritten digits independently and achieved average recognition accuracy of 95.50%, 96.22% and 99.83%, 99.80% respectively. For bilingual digit recognition the KNN classifiers are used and achieved average recognition accuracy of 96.18%, 97.81% respectively.

José Eduardo Bastos dos Santos. [7] they develop the Text Extraction in Bank Cheque Images features are used to shape features, Mean, Standard deviation, Skewness, Range, Solidity, Extend, and Area feature, the subtraction approach means by subtracting empty cheque from filled cheque. In subtraction approach the extracting information is losing. It means geometrical distortions, alignment of cheque, graphical security elements, accuracy is based on data sample the result is 93%.

III. DATASET

The dataset containing the 50 member's handwritten documents. Here the datasets are we have 50 documents, in this we used a black ink ball pen. When we are collecting dataset 25 members know a Kannada language, 25 members don't know the Kannada language for that members we gave example copy and asked to write Kannada handwritten words. We scanned the 50 documents and converted in to PNG image format next cropping the each characters. In this work we consider the 10 class such as written in the special symbol as shown in the figure.

IV. PROPOSED METHODOLOGY

We propose Kannada handwritten words recognition system. Here we manually segment each block such as Payee Field, Courtesy Field. After the Separation of the Field word segmentation is performed only for courtesy digit. We use K- K-nearest for recognition of for courtesy digit.

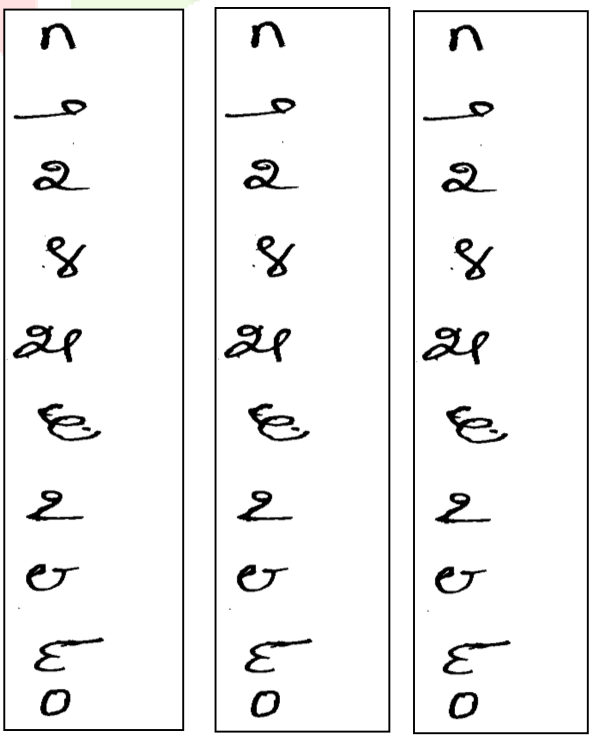

Figure 1. Kannada words belonging to an individual from the database

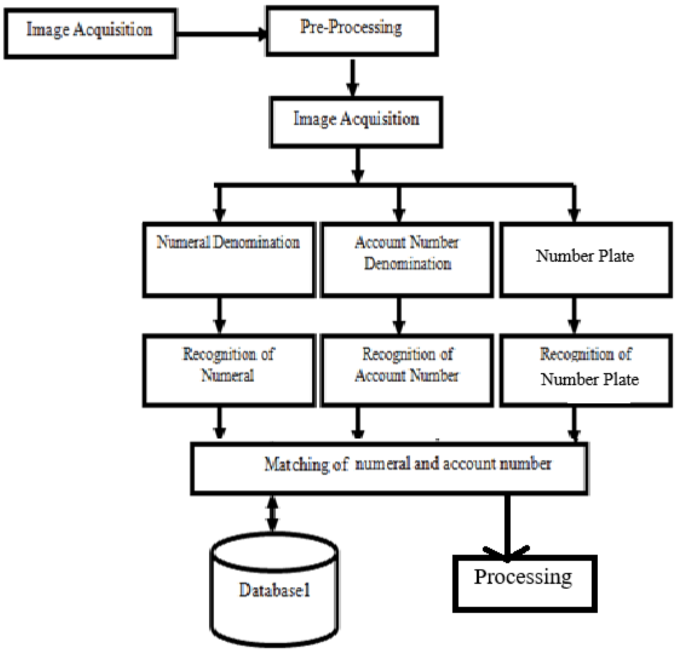

Figure 2. Block diagram

3.1 Pre-Processing

After extraction of cheque and number plate images, segment the blocks such as written in numerical and account number blocks are used. In this step we also remove the noise in image, also segment each word in the numerical. Next step is extracting features based on the segmented blocks. in this work we consider the three types of feature extracting methods namely Gabor, Shape and LBP(local binary pattern).

Shape features

In this work we extracting the shape features Shape is an important visual feature and it is one of the basic features used to describe image content. Here we extracted shape features based on the maximum boundary [11], maximum boundary farther divided into 14 types there are.

Area: the actual number of pixels in the region.

Euler Number: specifies the number of objects in the region minus the number of holes in those objects. This property is supported only for 2-Dimenstional input label matrices.

Orientation: the angle between the *x*-axis and the major axis of the ellipse that has the same second-moments as the region.

Extent: specifies the ratio of pixels in the region to pixels in the total bounding box. Computed the area divided by the area of the bounding box.

Perimeter: The distance around the boundary of the region. Pixel value measurements compute the perimeter by calculating the distance between each adjoining pair of pixels around the border of the region. If the image contains discontinuous regions, pixel value measurements returns unexpected results

Extrema: 8-by-2 matrix that specifies the Extrema points in the region. Each row of the matrix contains the X- and Y-coordinates of one of the points. The format of the vector is (top-left, top-right, right-top).

Convex Area: specifies the number of pixels in binary image that specifies the convex hull, with all pixels within the hull filled in the image is the size of the bounding box of the region.

Filled Area: The number of pixels in filled image.

Convex Hull: P (value)-by-2 matrixes that specifies the smallest convex polygon that can contain the region. Each row of the matrix contains the X- and Y-coordinates of one vertex of the polygon.

Solidity: the proportion of the pixels in the convex hull that are also in the region. Computed Area / Convex Area.

Eccentricity: specifies the eccentricity of the ellipse that has the same second-moments as the region. The eccentricity is the ratio of the distance between the foci of the ellipse and its major axis length. The value is between 0 and 1. (0 and 1 are degenerate cases; an ellipse whose eccentricity is 0 is actually a circle, while an ellipse whose eccentricity is 1 is a line segment).

Major Axis Length: specifying the length (in pixels) of the major axis of the ellipse that has the same normalized second central moments as the region.
Equiv Diameter: specifies the diameter of a circle with the same area as the region. Computed as square root (4*Area/pi).
Minor Axis Length: the length (in pixels) of the minor axis of the ellipse that has the same normalized second central moments as the region.

1) Gabor

Gabor method is based on the filters, taking the input image varying scale and angles extracting the features. Scale means varying height and angles means rotating the input image [9]. Gabor features are widely used in many computer vision applications such as image segmentation and pattern recognition. To extract Gabor features, a set of Gabor filters tuned to several different frequencies and orientations is utilized. Gabor filters by decomposing into 1-Dimenstional Gaussian filter. Gabor features are based on Gabor filter responses over the most straightforward technique to conduct the filtering operation is by performing the convolution in the spatial domain. The complexity of convolution depends directly on the size of the convolution mask. The mask in this case is the Gabor filter [14], [13].

It is a linear filter used for edge detection. Frequency and orientation representations of Gabor filters are similar to those of the human visual system. Gabor wavelet is widely adopted to extract texture from the images for retrieval and has been shown to be very efficient. Basically Gabor filters are a group of wavelets, with each wavelet capturing energy at a specific frequency and specific orientation. The scale and orientation tuneable property of Gabor filter makes it especially useful for texture analysis[16].

After applying Gabor filters on the image with different orientation at different scale, we obtain an array of magnitudes:

$$\sum(m,n) = \sum_x \sum_y |g_{mn}(x,y)|$$

Where, m=0,1…….. $M-1$; n=0,1…..... $N-1$.

These magnitudes represent the energy content at different scale and orientation of the image. The main purpose of texture-based retrieval is to find images or regions with similar texture. It is assumed that we are interested in images or regions that have homogenous texture.

2) LBP(Local binary pattern)

The LBP is a gray-scale and rotational invariant texture operator which characterizes the spatial structure of the local image texture. The Gray-scale invariance is achieved by assigning a unique pattern label to every pixel in an image depending on binary pattern generated by comparing its value with those of its neighbourhoods [15]. A pattern label is computed by

$$LBP_{P,V} = \sum_{P=0}^{P-1} S(g_P - g_C)2^P$$

Where $S(g_P - g_C) = \begin{cases} 1, & (g_P - g_C) \geq 0 \\ 0, & (g_P - g_C) < 0 \end{cases}$ (1)

Here, $g_C$is the gray value of the central pixel of circularly symmetric neighborhood g_P(P=0,1.......$P-1$), $g_P$is the gray value of its neighbors, Pis the number of neighbors and R is the radius of the neighborhood.

The $LBP_{P,V}$ operator produces 2^Pdifferent output values, corresponding to the 2^Pdifferent binary patterns that can be formed by the P pixels in the neighbour set. When the image is rotated, the gray values g_P will correspondingly move along the perimeter of the circle around. Since g_0 is always assigned to be the gray value of element $(0,R)$ to the right of cg rotating a particular binary pattern naturally results in a different,$LBP_{P,V}$value. Therefore, rotation invariance is achieved by assigning a unique label to each rotation invariant local binary pattern. That is,

$$LBP_{P,R}^{ri} = min\{ROR(LBP_{P,R}, i) | i = 0,1 \ldots \ldots P-1\} \quad (2)$$

Where, $ROR(LBP_{P,R}, i)$performs a circular bit-wise right shift on the Pbit number$LBP_{P,R}$ i times. The uniform value (U) of an$LBP_{P,R}^{ri}$pattern is defined as the number of spatial transitions (bitwise 0/1 changes) in that pattern and is given by,

$$U(LBP_{P,R}^{ri}) = |S(g_{P-1} - g_c) - S(g_0 - g_c)| + \sum_{P=1}^{P-1} \left| S\left(g_P - g_C\right) - S(g_{P-1} - g_c) \right| \quad (3)$$

As recommended in [4] if the uniformity measure (U) of a pattern is less than or equal to 2, then the pattern is referred as uniform pattern and it is assigned with a label in the range 0 to P corresponding to the spatial transition. All other non-uniform patterns $(U > 2)$are assigned to a label $P + 1$.Therefore we have,

$$LBP_{P,R}^{riu2} = \begin{cases} \sum_{P=0}^{P-1} S(g_P - g_c) & if\ U(LBP_{P,R}^{ri}) \leq 2 \\ P + 1 & otherwise \end{cases} \quad (4)$$

The LBP with radius (R) and pixels (P) calculated over the entire image of size $N \times M$is resulted in a labeled image. This labeled image is represented by a histogram as follows.

$$\underset{k \in [0,k]}{\mathrm{H}}[k] = \sum_{i=1}^{N} \sum_{j=1}^{M} f\left(LBP_{P,R}^{riu2}(i,j), k\right) \quad (5)$$

Where, $\left(LBP_{P,R}^{riu2}(i,j), k\right) = \begin{cases} 1 & LBP_{P,R}^{riu2}(i,j) = k \\ 0 & otherwise \end{cases}$

Where, k is the maximal LBP pattern label.

3.2 Recognition

Recognition is the partitioning of the features space into decision regions which correspond to classes, a recognition algorithm provides the parameter estimates for the features identified in the feature extraction step. The distinction between feature extraction and recognition steps is blurring, as computing enhancements allow for automation of entire process. In this work we have used the K-NN classification algorithm [8]. it is non parametric classifier, the K-NN classifier is the simplest of all machine learning algorithms, objects are classified by majority vote of its neighbor, with assigned to the class most common amongst its K-nearest neighbors, if K=1(varying the values K) then the object is simply assigned to the class labels of its nearest neighbors. The distance measures are used to calculate the distance of the objects. The different distance measures are, Euclidean distance, City block distance (Sum of absolute differences) and Cosine distance (one minus the cosine of the included angle between points). After extracting the feature matrix we have divide into two parts. One is training which means train the system along with class labels another is testing which means testing the samples, the output of this classifier is class label(nearest neighbor class labels) of the testing samples.

We consider the one example of 3 class problem such as Red, Blue and Green. Applying the K-NN classifier of this problem and Labeled training instances in instance space (class labels: red, green, blue), as shown figure 4.

In this figure to testing sample $\boldsymbol{a}$ classifier considers K value as 3. KNN classifier takes 3 nearest neighbors of $\boldsymbol{a}$ in this example there are two green samples and one is red. So the classifier calculate the distance of objects and vote the near objects in that which one is maximum votes then that class label of object is the output of the testing sample $\boldsymbol{a}$ .the green is a class label of testing sample.

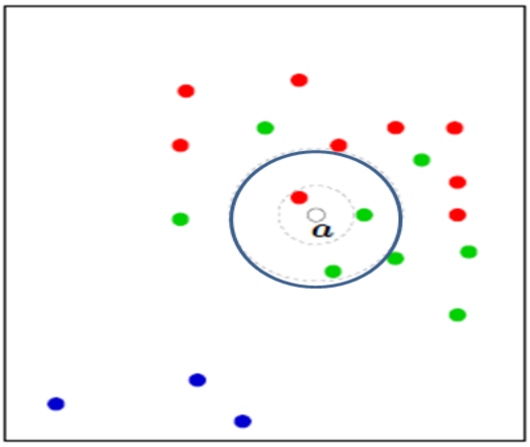

Figure 3. Examples for K-NN

In this case we use the K-NN classifier along with city block distance formula in all blocks such as numerical written in the words, amount written numerals.

4 Experiment results

The experimental results are based on the datasets. In this work the dataset is Kannada handwritten words. We have conduct an experiment on two datasets separately extracting the features such as shape features, Gabor features and LPB consideration each feature and calculated the accuracy The results of these experiments are describes in the following.

4.1 Experimental Results On Kannada Numerical Handwritten Words

Here we have 10 classes such as 10 numerals written in the word.

4.1.1 Results on Features

The experiment has been conducted on Gabor and Shape features with varying of K values. The K value is varied with 1 to 17 in steps of 2. In all experiments are conducted with selecting a specified number of training and testing samples randomly. Experimentation is conducted using 1distance measures: city-block distance measures. The results of Gabor and Shape feature experiments are given in table 6.1.1.

Table 6.1.1 Classification Results on Gabor and Shape features with City Block Distance Measure.

Distance Measure	K	Dividing the Training/Testing		
		30/70	50/50	70/30
City block	1	13.16	13.19	20.00
	5	12.81	12.84	16.69
	9	11.13	11.94	14.76
	13	11.94	11.84	13.31
	17	16.69	11.97	12.98

4.1.2 Results on LBP (Local Binary Pattern)

The experiment has been conducted on local binary pattern features with varying of K values. The K value is varied with 1 to 17 in steps of 4. In all experiments are conducted with selecting a specified number of training and testing samples randomly. Experimentation is conducted using distance measures: city-block distance measures. The results of local binary pattern feature experiments are given in table 6.1.2.

Table 6.1.2 Classification Results on local binary pattern features with City Block Distance Measure.

Distance Measure	K	Dividing the Training/Testing		
		30/70	50/50	70/30
City block	1	13.58	13.45	20.16
	5	13.71	13.65	19.03
	9	13.16	13.26	17.26
	13	12.81	12.65	15.57
	17	12.13	11.90	14.36

4.2 Summary of result

We obtained the maximum classification results of handwritten words using Gabor and LBP features along with City Block distance measure. Results are as show in the table .

V. CONCLUSION

In this paper we worked recognitions of Kannada numerical handwritten words. The recognition of Kannada handwritten words is very difficult task because handwriting is different for different person. We obtained the best result on Kannada handwritten words is 55% of accuracy when concatenation of 2 features as Gabor, LBP features. And the best result is 89.32% accuracy when concatenation of 2 features as Gabor, and LBP features.

VI. FUTURE WORK

Future we plane handwriting identification which means account holder written the cheque or not. Person identification based on account number and processing the cheque. Apply the different feature extraction methods and different classifiers.

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