Offline Kannada Handwritten Numeral Recognition:
Holistic Approach

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Abstract. Offline kannada handwritten numeral recognition is difficult problem in pattern recognition. Many researchers have expressed their ideas to recognise it with different aspects. This paper introduces a holistic approach based system to recognize the offline handwritten kannada numerals. Our holistic approach system is tested on a database of $147 \times 10$ kannada digits contributed by 147 writers. Some writers have not written numerals in straight line due to that we lost some of the digits while segmentation, though we achieved overall recognition accuracy of 95.98%.

Keywords: OKHNR, OCR architecture, Gradient vector, Quadratic classifiers.

1. Introduction

The conversion of handwritten kannada Numerals on a paper into digital (electronic) form facing more problems with great electronic importance. There are some solutions for clearly printed documents in many language scripts. Solutions to hand writing still face many challenges in almost all the languages. That is due to styles differs from person to person, due to sizes, shapes, etc. Here for kannada handwritten numeral recognition, the ideas were taken from various papers of different language handwritten recognition [1,2].

1.1 Kannada numeral overview

From the view point of recognition, kannada numerals consist of exactly ten digits of which only a digit (0) is commonly used in Kannada and English (figure 1). The numbers (group of digits) are written horizontally from left to right as in English called sample (figure 2).

Offline recognition of handwritten kannada digit is particularly challenging task due to more curves in shapes. Furthermore the digits are usually not written in print fashion. Segmentation of digits from numbers is often easier than in kannada text or English text as they are not connected. Furthermore the high individual variation in writing kannada digits (figure 3) contributes to the problem. Many techniques have been developed for identifying individual digits.

1.2 Overview of the recognition process

While various algorithms vary in their implementation but most follow a typical path from document to UNICODE text. Figure 4 shows a general process of kannada hand written numeral recognition.

The recognition process works recursively as shown in figure 5. The output of early stage of classification can be used in input for the later stage to improve the accuracy rate of early process.

<table>
<thead>
<tr>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
</table>
| Kannada digits & their equivalent english digits.

Figure 1. Kannada digits & their equivalent english digits.

FFULFUSION, HULOOD, HULSON, NOU

Figure 2. Sample kannada numbers.
1.3 Databases

Large database have been built along with the development of recognition technology. Dataset of kannada handwritten numerals 0 to 9 is created by collecting the handwritten documents from writers. As we know hand written numeral styles, shapes and sizes varies from person to person we have collected approximately 500 samples from persons of different professions (students, lecturers, clerks, business man) and age groups.

2. Document Preprocessing

Scanned image is converted into a form suitable for later steps pre-processing stage. Pre-processing step involves noise removal, smoothing, binarization, segmentation, normalization of characters, slant adjustments, etc. Individual writing styles are disruptive to kannada handwritten numeral recognition due to the complexity in the digits. To overcome from
these problems normalization algorithms can be used. Here digits are usually not connected as in script languages, hence segmentation can be done easily. Each digit should cover approximate same area but usually this will not be found in handwriting. We concentrate on two pre-processing steps normalization and segmentation.

2.1 Segmentation

The accuracy of segmenting Numerals is essential for the performance of kannada numeral recognition system. Firstly, document image segmented into lines then into digits [3]. A typical segmentation process of handwriting kannada numeral is shown in figure 6. In kannada, the numerals are always written in disconnected fashion like print fashion. Somehow segmentation is bit easier than in script languages such as English. There are two widely used techniques in segmentation process, connected component analysis and vertical projection. The adaptive thresholding is used to segregate dark foreground from the light background. After the thresholding, horizontal projection of the document image is calculated. Horizontal boundaries between segmented digits are determined using this projection. And then vertical projections are used to find the gaps between the digits.

2.2 Digit normalization

Normalization is the most important preprocessing operation for digit recognition. Usually, the image of the digit is compared with predefined size to give representation of fixed dimensionality for classification. The aim for digit normalization is to minimize variation of the shapes of the digits in order to provide feature extraction process[4] and also to improve accuracy of classification. In this binarization step, image will be having only two colours either black or white. White is used for foreground color and rest is background color. Binarization is based on the filtering with structuring element. Structuring element is binary image, which is passed over the grayscale image. Since the pixels can have only two values the morphological operations like erosion, dilation, morphological opening and morphological closing can be performed using the structuring element. Opening manages to enlarge small holes, remove small objects & separate objects. After binarization of an original image filtering is done. In the process of filtering, median filter is applied in normalization process. In this method, input pixel is replaced by the median of the pixels contained in a filter window.

\[ v(m, n) = \text{median}\{y(m - k, n - l), (k - l) \in w\} \]

Here \( w \) is 3*3 window. In this median filter, arranging the pixel values in the 3*3 window in increasing order and picking a middle value. This median filter is used for removing isolated lines. After the filtering process binary image is converted back to gray-scale image and then smoothing operations are used for blurring and also noise reduction. Blurring is used for removal of small details from an image. Smoothing can be done by filtering which is neighbourhood operation. Here 3*3 masks are passed over the complete image to smooth it, and this process can be repeated until there is no change in the image. These masks can fill or remove single pixel indentation in all the edges. After removing the noises from the gray-scale image of size 128*128 is resized to 64*64.

3. Recognition

Numerical recognition problem is examined carefully. The techniques are wide ranging. In this paper holistic approach is considered with the idea that recognize the digit. While recognition, a common classifier is mostly used to search candidates of fine classifier. Clustering based common classifier define candidate cluster number for each character for each digit that point out within class diversity in the feature space and they use a candidate refining module to minimize the size of the candidate set [5–7].
3.1 Holistic approaches

Since kannada numerals are highly complex, there is a high number of potential feature sets. Due to the shape of a kannada digits, several features presents themselves. After choosing such a set of features, initial digits recognition vary. Gradient features are extracted from gray scale image (value ranges from 0 to 255). 3*3 sobel operators are used to get the vertical and horizontal gradient at each image pixel. Then L directions with an equal internal $2\pi/L$ are defined and decompose the gradient vector into its two nearest directions in the manner of parallelogram, which is illustrated in figure 8.

At the stage of classification, the performance of the classifier “modified quadratic discriminien function (MQDF)” is enhanced by multiple discrimination schemes, including minimum classification error training on the classifier parameter. Modified distance representation for similar digits discrimination. The QDF distance for a $d$-dimentional feature vector $x$ can be represented as follows:

$$g_i(x) = (x - \mu_i)^T \sum_i^{-1} (x - \mu_i) + \log | \sum_i |$$

$i = 1, 2, \ldots, C$. Where $C$ represents number of classes, $\mu_i$ and $\sum_i$ represents the mean vector and covariance matrix. Orthogonal decomposition on $\sum_i$ is used on $\sum_j$, and replacing the minor eigen values with constant $\sum^2$ to adjust for the estimation error caused by the small training set, the MQDF distance is derived as follows:

$$g_i(x) = \frac{1}{\sigma^2} \left\{ \|x - \mu_i\| - \sum_{j=1}^{k} \left( 1 - \frac{\sigma}{\lambda_{ij}} \right) [\Phi_{ij}^T (x - \mu_i)]^2 \right\} + \sum_{j=1}^{k} \log \lambda_{ij} + (d - k) \log \sigma^2$$

$I = 1, 2, \ldots, c$. Where $\lambda_{ij}$ and $\Phi_{ij}$ represents the $j^{th}$ eigen values and the corresponding eigen vector of $\sum_i$. $K$ represents the number of principle axis.

4. Experimental Results

In this research work experiments were carried out with database containing 1470 handwritten kannada digits. There were 147 people of different age groups and from various fields such as business, education, industry, service, etc and also from the students of English & kannada medium. Each of 147 people wrote digits from 0 to 9. As we discussed...
Table 1. Accuracy of individual kannada digit.

<table>
<thead>
<tr>
<th>Numerals</th>
<th>Kannada Numeral</th>
<th>Total number of Samples</th>
<th>Number of samples recognised</th>
<th>% of accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>ः</td>
<td>147</td>
<td>147</td>
<td>100%</td>
</tr>
<tr>
<td>1</td>
<td>अ</td>
<td>147</td>
<td>147</td>
<td>100%</td>
</tr>
<tr>
<td>2</td>
<td>च</td>
<td>147</td>
<td>143</td>
<td>97.24%</td>
</tr>
<tr>
<td>3</td>
<td>छ</td>
<td>147</td>
<td>134</td>
<td>91.11%</td>
</tr>
<tr>
<td>4</td>
<td>ज</td>
<td>147</td>
<td>140</td>
<td>95.23%</td>
</tr>
<tr>
<td>5</td>
<td>झ</td>
<td>147</td>
<td>131</td>
<td>89.11%</td>
</tr>
<tr>
<td>6</td>
<td>ञ</td>
<td>147</td>
<td>145</td>
<td>98.63%</td>
</tr>
<tr>
<td>7</td>
<td>ट</td>
<td>147</td>
<td>146</td>
<td>99.31%</td>
</tr>
<tr>
<td>8</td>
<td>ठ</td>
<td>147</td>
<td>133</td>
<td>90.47%</td>
</tr>
<tr>
<td>9</td>
<td>ड</td>
<td>147</td>
<td>145</td>
<td>98.63%</td>
</tr>
<tr>
<td>Overall</td>
<td></td>
<td>1470</td>
<td>1411</td>
<td>95.98%</td>
</tr>
</tbody>
</table>

Figure 9. Graph showing accuracy of recognition.

Table 2. Performance comparison with existing work.

<table>
<thead>
<tr>
<th>Authors</th>
<th>Number of Samples</th>
<th>Classifier</th>
<th>Percentage of Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>M. Hanmandl u et al. [8]</td>
<td>3500</td>
<td>Bacterial Forgoing and Fuzzy set</td>
<td>96%</td>
</tr>
<tr>
<td>G. S. Lehal et al. [9]</td>
<td>1000</td>
<td>MQDF</td>
<td>89%</td>
</tr>
<tr>
<td>Ujjwal Bhattachan [10]</td>
<td>18794</td>
<td>Wavelet-based multire solution, MLP &amp; KNN</td>
<td>99.04%</td>
</tr>
<tr>
<td>R. J. Ramteke et al. [14]</td>
<td>2000</td>
<td>Gaussian Distribution</td>
<td>92.28%</td>
</tr>
<tr>
<td>U. Pal et al. [12]</td>
<td>22546</td>
<td>Quadratic</td>
<td>98.86%</td>
</tr>
<tr>
<td>Reena bajaj et al. [13]</td>
<td>2460</td>
<td>MLP</td>
<td>89.68%</td>
</tr>
<tr>
<td>C. Vasantha Lakshmi et al. [11]</td>
<td>9800</td>
<td>Spline, PCA</td>
<td>94.25%</td>
</tr>
<tr>
<td>Proposed system</td>
<td>1470</td>
<td>Quadratic classifiers</td>
<td>95.98%</td>
</tr>
</tbody>
</table>

in this paper due to style of writing, size of the digit were very different from person to person, hence it is challenging to get 100% accuracy. For the handwritten kannada digit 8 we reached 90.47%, for digit 5 we got 89.11%, and for the digit 3 we got 91.11% accuracies and for the rest of the digits we have achieved more than 95% of accuracy and even 100% of accuracy for 0 and 1 which is shown in table 1. And also we have plotted a graph for accuracy of various numerals which is shown in figure 9.

5. Conclusion

In this paper, gradient features and quadratic classifier with multiple discrimination schemes are used for offline handwritten kannada numeral recognition. The features are invariant with respect to rotation, size and shape. From
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this approach we achieved a good percentage of accuracy. Future work focuses on connected numerals, different sizes of numerals, different styles of numerals with more number of samples.

References


