Probabilistic Neural Network based Approach for Handwritten Character Recognition

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Abstract—In this paper, recognition system for totally unconstrained handwritten characters for south Indian language of Kannada is proposed. The proposed feature extraction technique is based on Fourier Transform and well known Principal Component Analysis (PCA). The system trains the appropriate frequency band images followed by PCA feature extraction scheme. For subsequent classification technique, Probabilistic Neural Network (PNN) is used. The proposed system is tested on large database containing Kannada characters and also tested on standard COIL-20 object database and the results were found to be better compared to standard techniques.

Keywords: Handwritten Character Recognition, Subspace Methods, PCA, Neural Networks, PNN.

I. INTRODUCTION

Recognition of unconstrained handwritten characters is one of the most interesting and challenging topics in automatic document analysis and processing. In recent years, Optical Character Recognition (OCR) has been greatly developed because of the prevalence of Internet and multimedia techniques. In OCR applications, handwritten character recognition, especially digit recognition, is dealt with in postal mail sorting, bank check processing, data entry, etc. In recent decades many researchers worked on this topic. Most of the works related to handwritten character recognition are done in English, Chinese, Japanese and Arabic. However, some preliminary work has also been done on Indian scripts. A multistage scheme for the recognition of handwritten Bengali characters is reported in [13]. An analysis of the Bengali character set has been carried out to isolate specific high-level features that can help in forming smaller sub-groups within the characters. A two-stage classification system for recognition of handwritten Devnagari numerals is described in [11]. The paper describes the concept of supervised and unsupervised learning and it can be used for pure classification, clustering and for hybrid classification. The features extracted remained robust to rotation, scaling and translation invariant. An offline handprinted Bangla numeral recognition scheme using multistage classifier system comprising of Multilayer Perceptron (MLP) neural network is described in [2]. Method based on multiresolution analysis for Telugu character recognition are discussed in [12]. Online handwritten character recognition of Devnagari and Telugu characters using Support Vector Machines is reported in [16]. The input to the recognition system consists of features of the strokes in each written character. An Support Vector Machines (SVM) based stroke recognition module has been considered for generalization capability. Work on online Tamil handwritten character recognition on elastic matching schemes is reported in [9]. A quadratic classifier based scheme for the recognition of off-line handwritten numerals of Kannada is discussed in [14]. The features used in the classifier are obtained from the directional chain code information of the contour points of the characters.

Handwritten character recognition for any Indian writing system is rendered complex because of the presence of composite characters; enormous variability of handwriting styles and about 250 different character shapes is present in each script. With this background, a well known Fourier Transform combined with PCA used for extracting features from the character image is proposed [1]. In order to work with well classification scheme, Probabilistic Neural Network (PNN) architecture for efficient representation of images is used.

The organization of the paper is as follows: In section 2, proposed feature extraction and classification technique are presented. In section 3, experimental results and comparative study are discussed. Finally, conclusion is reached at the end.

II. PROPOSED METHOD

In the following section, an overview of Fourier transform and PCA with brief description regarding PNN is discussed.

A. Fourier Transform
Fourier transform is a widely used image processing technique, which is often applied to the enhancement of image description information and visual effect [7]. In this work, we combine it with popular image recognition technique like PCA to enhance the classification information and improve the recognition effect. We first obtain filtered images (pre-processed) by the selection of appropriate Fourier frequency bands of character images. We then propose to carry out image classification/recognition by using PCA method.

Suppose that the original image sample set is $A$, each image matrix is of size $m$-by-$n$ and expressed by $f(x,y)$, where $1 \leq x \leq m, 1 \leq y \leq n$ and $m \geq n$. Assuming there are $c$ known pattern classes ($w_1, w_2, ..., w_c$) in $A$, perform a two-dimensional discrete Fourier transform on each image by

$$F(u,v) = \frac{1}{mn} \sum_{x=1}^{m} \sum_{y=1}^{n} f(x,y) \exp\left(-j2\pi\left(\frac{ux}{m} + \frac{vy}{n}\right)\right)$$

(1)

Where $j = \sqrt{-1}$, $\exp()$ denotes the exponential function, and the size of $F(u,v)$ is also $mn \times mn$. Let $F(u_0, v_0)$ indicates zero frequency band. Shift $F(u_0, v_0)$ to the centre of image matrix, i.e., to the point $(\frac{m}{2}, \frac{n}{2})$. Since the frequency domain is represented by the matrix form, we use a square box $Box(l)$ to represent the $l^{th}$ frequency band, where $0 \leq l \leq \frac{m}{2}$. The four vertices of the Box($l$) are $(u_0-l, v_0-l)$, $(u_0+l, v_0-l)$, $(u_0-l, v_0+l)$ and $(u_0+l, v_0+l)$, respectively. So, the $l^{th}$ frequency band denotes:

$$F(u,v) \in Box(l)$$

(2)

Retain Original Values if $F(u,v) \in Box(l)$

$$0 \text{ if } F(u,v) \notin Box(l)$$

(3)

and perform an inverse Fourier transform on the current $F(u,v)$ values as follows:

$$f(x,y) = \frac{1}{mn} \sum_{x=1}^{m} \sum_{y=1}^{n} F(u,v) \exp\left[j2\pi\left(\frac{ux}{m} + \frac{vy}{n}\right)\right]$$

(4)

Hence, for all the images in $A$, we obtain the corresponding filtered images, which construct new samples set $Y_l$. After deriving these band-passes filtered (i.e. preprocessed) images, we apply PCA for subsequent recognition process. Here we call, the method applying PCA as Fourier-PCA (F-PCA).

B. Principal Component Analysis

The PCA technique regards each character image as a feature vector in a high dimensional space by concatenating the rows of the image and using the intensity of each pixel as a single feature vector [17]. Let there be $N$ characters ($A_1,A_2,..,A_N$) constituting the training set denoted by $m \times n$ matrices. Now the average matrix $\overline{A}$ of all training samples has to be calculated then subtracted from the original characters $A_i$ and the result is stored in $\Phi_i$:

$$\overline{A} = \frac{1}{N} \sum_{i=1}^{N} A_i$$

(5)

$$\Phi_i = A_i - \overline{A}$$

(6)

In the next step, the covariance matrix $C$ is calculated as follows:

$$C = \frac{1}{N} \sum_{i=1}^{N} \Phi_i \Phi_i^T$$

Now the eigenvectors $U_i$ ($i = 1, ..., N$) and the corresponding eigenvalues $\lambda_i$ ($i = 1, ..., N$) are calculated. From the above $N$ eigenvectors, only $k$ should be chosen corresponding to largest eigenvalues. The highest the eigenvalues, the more characteristic features of a character does the particular eigenvector describe. Using the $k$ eigenvectors $U_k$, feature extraction done by PCA is as follows:

$$F_i = U_k^T (A_i - \overline{A})$$

(7)

C. Probabilistic Neural Network (PNN)

Over the last two decades, Artificial Neural Networks have been widely used to solve complex classification problems [4].
On the other hand, there is a consensus in machine learning community that SVM is most promising classifiers due to their excellent generalization performance [5]. However, SVMs for multiclass classification problems are relatively slow and their training on a large data set is still a bottle-neck. The PNN was introduced by Donald Specht [15]. This network is based on concepts used in classical pattern recognition problems. In particular, the PNN models the popular Bayesian classifier [8], a technique which minimizes the expected risk of classifying patterns in the wrong category. One of the main criticisms of Bayes’ classification techniques is the lack of information about the class probability distributions. They are usually unknown and must be estimated in some way. The apriori probabilities \( p_i \) may be known or can easily estimated directly from a sample of the pattern vectors, but the probability density functions \( f_i(x) \) are generally more difficult to estimate. Without any real knowledge of the distributional form it is more appropriate to use nonparametric estimation methods. One powerful nonparametric technique is based on the use of parzen windows [10], which are used to construct a family of estimates from kernels. The general form of the estimator is given by the following equation

\[
f(x) = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{\sigma} \exp \left( -\frac{(x-x_i)^T(x-x_i)}{2\sigma^2} \right)
\]

where the \( x_i \) are independent, identically distributed random variables. The weighting function \( l \) must be bounded.

Parzen’s results have also been extended to the multivariate distribution case by [6]. One use of the weighting kernel function \( l \) is the multivariate exponential (Gaussian) function. For this case, equation 61 takes the form:

\[
f(x) = \frac{1}{2\pi^{n/2}\sigma^n} \sum_{i=1}^{k} \exp \left( -\frac{(x-x_i)^T(x-x_i)}{2\sigma^2} \right)
\]

The inherent advantage of the PNN architecture is the speed with which it can be trained and can handle data that has points outside the norm thus performing better than other neural architectures.

Brief algorithm of the proposed method is shown below:

**Algorithm: Fourier-PCA Training**

Input: A set of training sample images
Output: A knowledge Base (KB):
Method:
1. Acquire the training samples \( A_s \)
2. Apply Fourier-PCA technique for feature extraction on set of training samples.
3. Store the feature matrix in KB

**Algorithm Fourier-PCA Training Ends**

The corresponding testing algorithm is as follows:

**Algorithm: Fourier-PCA Testing**

Input:
(i) The Knowledge Base:
(ii) Test Image, I.

Output: Class label / Identity of I.
Method
1. Obtain the feature matrix \( F \) of the pattern I
2. Apply PNN method for subsequent classification
3. Label the class/Identity using step 2.

**Algorithm Fourier-PCA Testing Ends**

## III. EXPERIMENT RESULTS

Each experiment is repeated 26 times by varying number of projection vectors \( t \) (where \( t = 1...20, 25, 30, 35, 40, 45, \) and 50). Since \( t \), has a considerable impact on recognition accuracy, we chose the value that corresponds to best classification result on the image set. All of our experiments are carried out on a PC machine with P4 2.4GHz CPU and 512 MB RAM memory under Matlab 7.0 platform.

### A. Experiment on Handwritten Characters

Handwritten recognition is an active topic in OCR application and pattern classification/learning research. In OCR applications, Kannada alphabets recognition is dealt with postal mail sorting, bank cheque processing, form data entry, etc. For these applications, the performance of handwritten Kannada alphabets recognition is crucial to the overall performance. For experimentation, we considered samples from 100 individual writers and total of 5000 character with total number of classes 50 (vowels and consonants) is considered. Some of the sample images of handwritten Kannada vowels and consonants are shown in Figure 2(a) and (b). For a total of 100 samples, the system is trained for 65 samples and remaining 35 samples are used during testing. Table 1 shows the recognition accuracy of proposed method for handwritten characters. The proposed method is also compared with the method discussed in [1] and standard PCA method discussed in [17]. Table 1 gives the comparison of PCA, F-PCA and Proposed method on recognition accuracy and running time costs. It can be seen from Table 1 that proposed method based on PNN performs better compared to other existing methods. Running time costs for training of PCA method is less compared to other two methods, because of the extra preprocessing step involved in that methods.

<table>
<thead>
<tr>
<th>Methods</th>
<th>Accuracy in (%)</th>
<th>Time (Seconds)</th>
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<tbody>
<tr>
<td>PCA</td>
<td></td>
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<tr>
<td>F-PCA</td>
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<tr>
<td>Proposed method</td>
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![Figure 2. Sample image of Kannada script](image-url)
B. Experimentation on English Handwritten Characters

We also extended our experiment on handwritten characters of English alphabets. We considered samples from 200 individual writers and total of 12400 character set are considered (26+26+10). Some of the sample images of handwritten characters are shown in Fig. 3. We train the system by varying the number of training samples by 50, 75, 125, 175 and remaining samples of each character class are used during testing. Figure 4 shows the best recognition accuracy obtained from the methods for varying number of samples. From the figure it is clear that PNN based method results better accuracy compared to other F-PCA, PCA based techniques.

C. Results on the COIL-20 Object Database

In this section, we experimentally evaluate the performance of proposed method with PCA and FLD based methods on COIL-20 database, a standard object database commonly used by most researchers. The database contains 1440 gray scale images of 20 objects. The objects were placed on a motorized turntable against a black background. The turntable was rotated through 360 degrees to vary object pose with respect to fixed camera. Images of the objects were taken at pose intervals of 5 degrees, which corresponds to 72 images per object. Figure 5 shows the sample objects considered from COIL-20 database. We have conducted a series of experiments by varying the number of training views (p) of objects. For comparative analysis of various approaches, we consider first 36 views of each object for training and remaining 36 views for testing. So, size of both the training and the testing database in this experiment is 720. The superiority in terms of accuracy of proposed method over other methods is quite evident from Table 2.

IV. CONCLUSION

In this paper Fourier Transform combined with PCA for feature extraction and PNN architecture for Image recognition is presented. The performance of the system is tested on totally unconstrained handwritten Kannada characters and also on COIL-20 object database. The main advantage of selecting PNN architecture is that it can enhance the recognition accuracy and can perform better compared to other neural nets. The database containing handwritten characters have very complex structure and shape due to individuals. The recognition performance and for COIL-20 object database are found to be encouraging. The computation time taken by proposed method is quite more compared to other two methods. The proposed system is tested only for vowels and consonants. There are about 250 different characters to be tested and need for improvement in recognition accuracy.

REFERENCES

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