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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 [3]. The paper extracts horizontal and vertical strokes from handwritten numeral images and computed a shape feature vector for each such stroke. Hidden Markov Models (HMM) and Multi Layer Perceptron (MLP) classifiers were used for classification purpose.

A recognition system for handwritten Bangla numerals and its application to automatic letter sorting machine for Bangladesh post is reported in [18]. Rotation, Scale and Translation handwritten Devnagari numeral character recognition using general fuzzy neural network 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 ($w_1, w_2, \dots, w_c$) in A , perform a two-dimensional discrete Fourier transform on each image by

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

Where $j = \sqrt{-1}$, $\exp()$ denotes the exponential function, and the size of $F(u,v)$ is also $m \times n$. 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 $\text{Box}(l)$ to represent the l^{th} frequency band, where $0 \leq l \leq \frac{m}{2}$. The four vertices of the $\text{Box}(l)$ 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: $F(u, v) \in \text{Box}(l)$

Figure 1. Illustration of Fourier frequency spectrum with different frequency bands

The Fourier spectrum with different frequency bands are shown in Fig. 1. If we select the l^{th} frequency band, retain the values of $F(u,v)$, otherwise set the values of $F(u,v)$ to zero. But, which principle should we follow to select the appropriate bands? Here, we propose a simple Two-dimensional discriminatory criterion to evaluate the discriminatory power of the frequency band and to select the appropriate bands:

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

$$0 \text{ if } F(u, v) \notin \text{Box}(l) \quad (2)$$

$$F(u, v) = \{\text{Box}(i)\}$$

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

$$f(x, y) = \frac{1}{mn} \sum_{u=1}^m \sum_{v=1}^n F(u, v) \exp \left[j2\pi \left(\frac{ux}{m} + \frac{vy}{n} \right) \right] \quad (3)$$

Hence, for all the images in A , we obtain the corresponding filtered images, which construct new samples set Y_i . 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 ($A_1, A_2, \dots, A_N$) constituting the training set denoted by m by n matrices. Now the average matrix $\bar{A}$ of all training samples has to be calculated then subtracted from the original characters A_i and the result is stored in Φ_i :

$$\bar{A} = \frac{1}{N} \sum_{i=1}^N A_i \quad (4 \& 5)$$

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

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

$$C = \frac{1}{N} \sum_{i=1}^N \Phi_i \Phi_i^T \quad (6)$$

Now the eigenvectors $U_i (i = 1 \dots N)$ and the corresponding eigenvalues $\lambda_i (i = 1 \dots N)$ 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:

$$F_i = U_k^T (A_i - \bar{A}) \quad i = 1 \dots N \quad (7)$$

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 be 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

$$f_h(x) = \frac{1}{n_h} \sum_{i=1}^{n_h} l\left(\frac{x - x_i}{\sigma}\right) \quad (8)$$

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:

$$f_h(x) = \frac{1}{2\pi^{n/2} \sigma^n} \sum_{i=1}^{n_h} \exp\left[-\frac{(x - x_i)^T (x - x_i)}{2\sigma^2}\right] \quad (9)$$

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_i 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 $t = 1, \dots, 20, 25, 30, 35, 40, 45$, 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.

Figure 2. Sample image of Kannada script

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 1. Recognition Accuracy for Kannada Handwritten Characters

Methods	Accuracy in (%)	Time (Seconds)
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