Face Recognition using a Newly Developed Linear Subspace Learning Method

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Abstract—Face recognition is considered a specific physiological biometric in order to identify an individual according to the physical features of the human face. Much research has been conducted in such areas, but still more accurate processes are required for biometric facial recognition. This article presents a novel linear subspace learning method for face recognition which not only can take advantage of principle components analysis (PCA) as a successful feature extraction, but also can apply nearest local centroid mean vector (LMKNCN) as an effective classifier to improve the classification performance. The main goal of this particular scheme is to handle two common existing issues in recognition techniques: named sensitivity to the training sample size and negative effects of outliers. Moreover, to illustrate the performance of proposed developed PCA, we compare it with the latest dimensionality reduction techniques such as traditional PCA and KPCA on publicly available face dataset. Experimental results illustrate that our newly developed method has significantly achieved better performance over the same face database compared with the former KNN-based algorithms.

Index Terms—Face Recognition; Biometrics; Learning Method; KNN.

I. INTRODUCTION

Nowadays, access to reliable personal authentication systems has become increasingly important to the modern lifestyle [1, 2]. Authentication system is considered compulsory for security reasons, such as door access control for secure access area, intensive care unit, financial security and robot face recognition which is captivating and an astonishing technology[3, 4].Therefore, many researches and manufactures have decided to develop a reliable personal authentication system[5].So, biometrics[6]has become their major interest as the subject of identifying people for authentication[7, 8].Recently, besides traditional biometric characteristics such as iris, signature, fingerprint and voice, a lot of new biometric traits have become available for authentication such as hand / finger geometry, retina, gait, and face information[9, 10]. Although biometrics provides security and safety, every biometric trait may have its own robustness and weakness; hence, scientists and researchers have to specify the appropriateness of a biometric trait which will be able to apply in various applications. This work is focused on a face recognition[11],which is one of the more successful ways to reach the goal of figuring out who somebody really is. Facial recognition technology has recently absorbed various research attempts due to the surge in demands of real-world application where a high level of safety and security is required[12, 13].

As the proposed method works on analyzing face image data, the approach of using dimensional reduction technique in order to extract and then classify data has been brought up. Principal Component Analysis (PCA) [14, 15]is an effective and fundamental way to obtain the most important features from the images. However, the aforementioned traditional PCA applies the K-nearest neighbor technique to classify data in which the final classification accuracy severely declines particularly with existing outliers or in cases where the size of the training sample is too small[16, 17]. This is one of the disadvantages of a KNN classifier which has negative effect on the recognition performance. Kernel Principal Component Analysis (KPCA)[18] was suggested as an extension of PCA to improve its performance while it still suffers from the negative effects of KNN which is applied in KPCA as a classifier. Furthermore, Local mean-based k-nearest Centroid neighbor (LMKNCN) classifier[16]was proposed aiming to fix existing problems in the KNN classifier.

Throughout this article, we present a new linear subspace learning technique which employs PCA as a dimensional reduction technique while the LMKNCN technique is applied to classify data, instead of traditional KNN rule, aiming to enhance the recognition rate. In point of fact, the proposed recognition method is a successful extension of PCA which mainly handles the existing problems in the traditional PCA with a KNN-based algorithm[19].

A Yale (A) face database consisting of 165 grayscale images is used in this research which is taken from 15 individuals. Figure 1 demonstrates a set of cropped face images with the information about the whole head and as seen below each subject has various expressions.

This research is arranged in the following order: In the next section, our proposed algorithm is briefly explained. Section III summaries the identification process. In Section IV, the recognition results of the experimental comparisons between traditional PCA, KPCA and our newly developed

Figure 1: An individual's sample from YALE database

PCA technique on aforementioned real face data set are reported in detail. In the final section, we conclude the article with future work.

II. OVERVIEW OF PROPOSAL FRAMEWORK

The main framework of face recognition has been illustrated in Figure 2 which consists of three general steps: Enrolment, Image Processing and the process of Identification. As it can be seen, for better comparison, PCA and KPCA have been employed as a feature extraction. In addition, a LMKNCN classifier is employed, instead of using traditional KNN, to improve the performance of classification procedure. Following this section, Identification process part is explained, which is the main purpose of this paper.

III. IDENTIFICATION

A. The Extraction of Features

Principle component analysis is an effective dimensional reduction technique used to condense data analysis with the main goal of reducing dimensionality and extracting the features within the image. Kernel Principal Component Analysis was introduced as a non-linear version of PCA in which a kernel function is applied first to map the data set, and then the mapped data goes to PCA for the following procedure.

B. Classification
i. The KNN Classifier

The KNN classifier is applied in former PCA which is the fundamental algorithm in pattern classification and just considers the neighbors proximity around the query pattern(X)[8].

The nearest neighbor formulation first presented by Hodge [21][22].In spite of the fact that the KNN classifier is an effective and fast technique, it has some classification issues such as dramatic accuracy reduction where the size of training sample is small and especially when exposed to the outliers.

The basic logic of this rule is outlined as:

- Discover the KNN for given query pattern (X)
- Set the most used class to X

Here is a brief explanation of KNN's main mathematics: First, let's assume $T_k^{NN}(X) = \{(X_i^{NN}, Y_i^{NN})\}_{i=1}^{N}$ for x which computes by the simple following formulausing the Euclidean distance metric:

$$d(X, X_i^{NN}) = \sqrt{(X - X_i^{NN})^T(X - X_i^{NN})} \tag{1}$$

Then,$d(X, X_i^{NN})$indicates the distance between X_i^{NN} and X. Final step is determining the class label of query X by the majority voting of those identified neighbors as follows:

$$c = \arg\max_{cj} \sum_{(X_i^{NN}, Y_i^{NN}) \in T_k^{NN}(X)} \delta(c_{j=}Y_i^{NN}) \tag{2}$$

where $\delta(c_{j=}Y_i^{NN})$ is equal one if $c_{j=}Y_i^{NN}$,and it is equal zero otherwise. It means that X belongs to the class c with the greatest voted class among k-nearest neighbors.

ii. The LMKNCN Classifier

A brief review of the LMKNCN classifier is provided in this section. This classifier not only deals with the neighbor's proximity but also takes in to the holographical distribution of extracted data all around the given query pattern. Following is the concise mathematical explanation behind the LMKNCN classifier striving to forecast query pattern's class label:

There are five main steps for the LMKNCN algorithm as follows:

First some definitions: Let's X be the query pattern while k is the Size of the neighborhood and $T = \{X_{ij} \in R^m\}_{n=1}^{N}$:A training set, $Ti = \{X_{ij} \in R^m\}_{j=1}^{N_i}$:A training set for each class, $C_1, ..., C_M$: M is a class number in T, $N_1, ..., N_M$: as training samples number located in T_i.

Step 1: First the distances between given query pattern and training samples compute for each class:

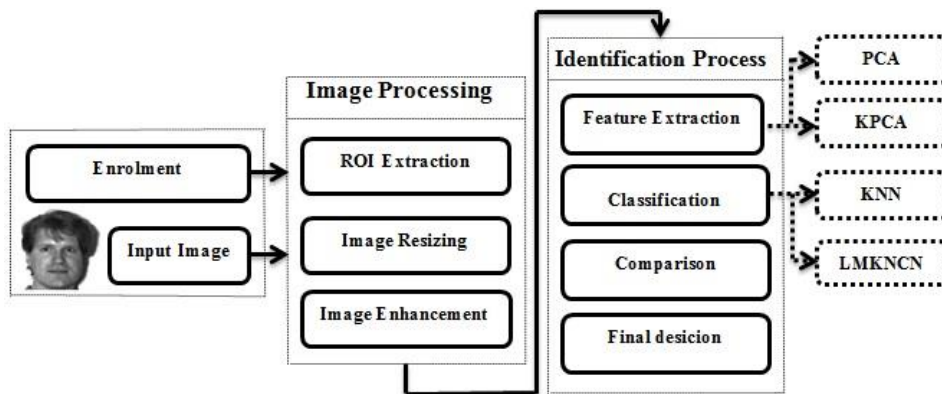$$d(X, X_{ij}) = \sqrt{(X - X_{ij})^T(X - X_{ij})} \tag{3}$$

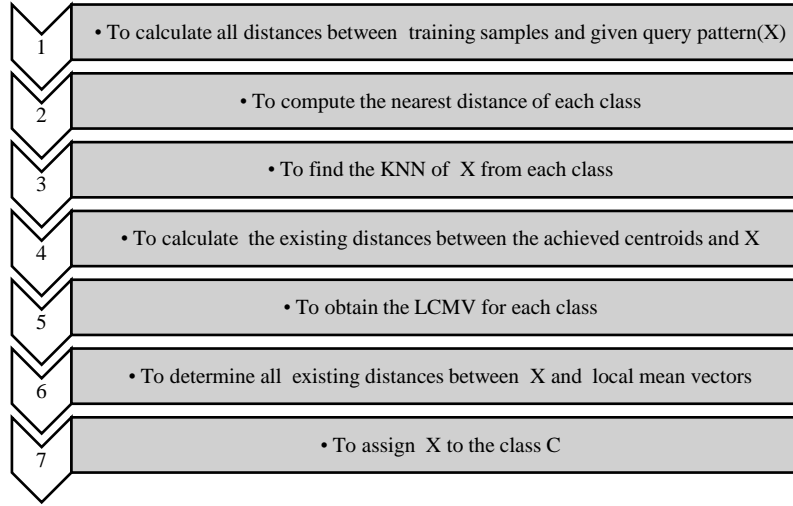Figure 2: The main framework of Face recognition algorithm

Figure 3: LMKNCN algorithm implementation flow

Step 2: In each class, c_i devotes to the first nearest centroid neighbor of x:

$$c_i[min\_index, min\_dist] = min\,(d(X, Xij)) \quad (4)$$

$$X_{i1}^{NCN} = X_{min-index} \quad (5)$$

Step 3: K nearest centroid neighbors of x finds as following:

$$\text{Set } S_{i(X)} = T_i - R_i^{NCN}(X)$$
$$S_i(X) = \{X_{il}^{NCN} \in \mathrm{R}^m\}_{l=1}^{L_i(X)} \quad (6)$$

$$sum_i^{NCN} = \sum_{r=1}^{j-1} X_{ir}^{NCN} \quad (7)$$
$$\text{For } l = 1 \text{ to } L_i(X)$$

$$X_{il}^c = 1/j(X_{il} + sum_i^{NCN}(X)) \quad (8)$$

Then $d_{il}^c(X, X_{il}^c)$ calculates as distances between acquired centroids X_{il}^c and given X:

$$d_{il}^c(X, X_{il}^c) = \sqrt{(X - X_{il}^c)^T(X - X_{il}^c)} \quad (9)$$

Step 4: Assign u_{ik}^{NCN} to the local centroid means vector for each class:

$$u_{ik}^{NCN} = 1/k \sum_{j=1}^{k} X_{ij}^{NCN} \quad (10)$$

Step 5: Final is finding the closest local centroid mean vector (LCMV) for each class and designating X to the class c as follows:

$$c = \arg min_{ci}\, d(X, u_{ik}^{NCN}) \quad (11)$$

IV. EXPERIMENTAL RESULTS

To ensure fair and reliable comparison between the former PCA and the newly proposed version using LMKNCN, the implementation of all possible number of training images from 5 to 9 have been conducted on Yale face database. As it is known from the theory of former PCA, after extracting the features from both training and test data, a comparison between them is made using Euclidian distance, while in our proposed PCA, after feature extracting, the distances between the test and training features are achieved using the powerful LMKNCN classifier which can very well explain the significant of our proposed PCA.

To further verify the recognition performance of the proposed PCA, the performance of classification is desperately degraded by the existing outliers around query pattern and particularly in a case where the size of training sample is too small, while our new extended PCA successfully over comes the aforementioned issues. To describe this considerable performance, it should be mentioned that our proposed algorithm not only considers the neighbors proximity but also considers the geometrical dissemination around the given query pattern. From Figure 4, implementation results obviously indicate that our newly developed PCA's performance is much better than the other two KNN-based algorithms in all possible training numbers.

V. CONCLUSION

We have proposed a new linear subspace learning method using a combination of principle components analysis as an effective dimensionally reduction and LMKNCN classifier aiming to improve some existing problems in the KNN-based algorithms. To conclude, all conducted implementation on the publicly available Yale face data base clearly prove that the proposed recognition technique has a significant improvement in classification performance by taking advantage of the mentioned merits of the PCA and LMKNCN techniques, compared with two other traditional KNN-based algorithms. This implies that the combination of the PCA as a dimensional reduction and LMKNCN classifier has a considerable effect on classification performance, particularly when the size of the training

image is too small. As a future project, we aim to enhance the proposed method with some kernel tricks and develop some alternative schemes to discover the nonlinear data structures.
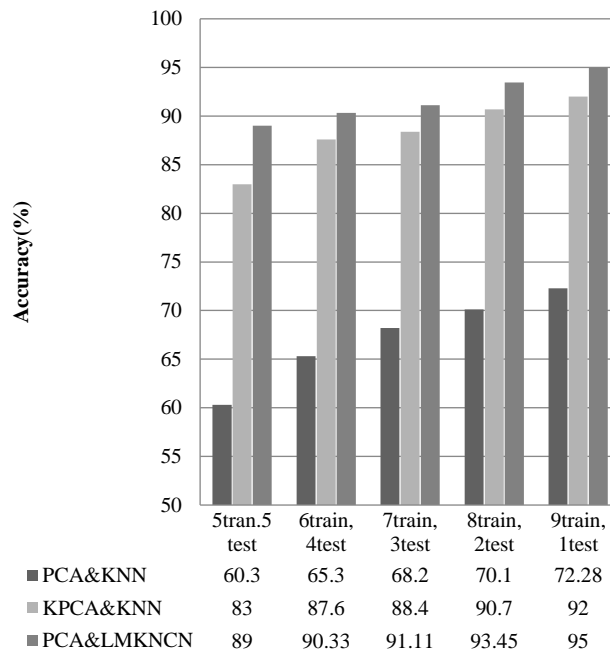

	5tran.5 test	6train, 4test	7train, 3test	8train, 2test	9train, 1test
■ PCA&KNN	60.3	65.3	68.2	70.1	72.28
■ KPCA&KNN	83	87.6	88.4	90.7	92
■ PCA&LMKNCN	89	90.33	91.11	93.45	95

Figure 4: The comparison results for traditional PCA, KPCA and newly developed PCA using LMKNCN

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