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Face Recognition System Based on Kernel Principle Component Analysis and Fuzzy-Support Vector Machine

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Abstract

In recent year, Face recognition system has taken much attention and used for different types of purposes for instance web application authentication, online investment and banking, mobile authentication, smart home security, virtual reality, database management and retrival etc.. In this paper, we are going to proposed a Face Recognition System by using Kernel Principal Component Analysis method and Fuzzy Support Vector Machines. Kernel Principal Component Analysis is used to play the main role in features extractor and Fuzzy Support Vector Machines are used to treat the face classification problem. Many studies were done on the Cambridge ORL Face database to assess the achievements and performance of the Face Recognition System. As well as comparisons between Kernel Principal Component Analysis and other component abstraction methods such as Principle Component Analysis and Linear discriminated Analysis and also compressions between Fuzzy Support Vector Machines and other classification methods such as Artificial Neural Networks are done. The experimental results show that the proposed methods give better results than other methods.

1. Introduction

The technology of Face Recognition System (FRS) includes computer recognition of individual identity based on the genmetric or statistical features retrevied from face images[1]. This innovation can be applied in various applications, for example, individuality validation and reconnaissance. FRS must have the ability to manage the diverse changes in face featchers. Anyhow, "the variations between the images of the same face due to illumination and the viewing pose are near always larger than the image variations due to change in face identity" [2].

A traditional Principal Component Analysis (PCA) is a awesom technique for retriveing structure from possibly high-dimensional data sets, which corresponds to extracting the eigenvectors that are associated with the largest eigenvalues from the input distribution.This eigenvector examination has just been generally utilized as a part of face handling [3,4]. A kernel PCA, as of late proposed as a nonlinear augmentation of a PCA [5,6] registers the main segments in a high-dimensional component space, which is nonlinearly identified with the information space in [7].

Statistical Learning Theory (SLT) was presented by Vapnik in 1995 which concentrated on machine learning advancement in small data set [8,9,10] and Fuzzy Support Vector Machines (FSVMs). Support Vector Machines (SVM) was a new classification and regression tool based on this theory, "SVM has been very successful in pattern recognition, function estimation problems, and modeling of nonlinear dynamic systems "[9].

In building up a SVM classifier, "the main imperative advance is feature choice and extraction. In the demonstrating, every single accessible component can be utilized as the contributions of SVM, yet superfluous features or corresponded features could break down the speculation execution of SVM" [11].

Fuzzy SVM (FSVM) is a variation of the SVM calculation that has been projected to deal with the issue of anomalies and clamor [12,13]. In FSVM, training illustrations are relegated diverse fuzzy membership esteems in light of their significance, and

these participation values are consolidated into the SVM learning calculation to make it less delicate to exceptions and commotion.

The purpose of this paper is to introduce the face recognition system based on KPCA, FSVMs. Firstly, the features are extracted using KPCA and then these features are used as the inputs of Fuzzy-FSVMs to select imported features from them and solve classification problem.

This paper is organized as the following sections. In Section 2, we introduce the proposed system structure with some basic theories are introduce briefly. In Section 3, gives the experimental results. Section 4 gives the results of experiment one and experiment two, and followed by the conclusions in the last section, section 5.

2. The Proposed System Structure

The structure of this system is described as shown in the next Figure (1);the system is divided into three main stages: preprocessing, feature extraction and classification. The preprocessing stage is used to reduce the effect of the light condition as well as normaliz the face image in respect to size and rotation and ultimately performs a photometric normalization procedure on the facial region.

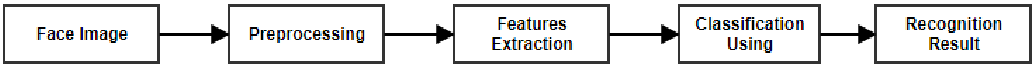

Figure1: shows the basic system structure of a propose system

The second stage is the features extraction .In this stage, The KPCA method is used to extracted features for both training data and testing data. The result of this stage is a set of representative features that extract from the normalized facial region.

The final stage in this system is classification stage which classifies the features set that extracted from the given face image according to the information that system obtained from training stage. The stages of the system are elaborated as follow:

2.1 Preprocessing:

The aim of this stage is to minimized the effect of lighting on the image and also normalizes the size of the image in respect to size, before features extraction it is essential and necessary to accomplish some pre-processing. In this paper, a two by two median filter is used to remove noises in the image. The following processing is conducted:

i. Illumination gradient correction:

This process is to utilized to figure the best-fit estimation of shine and subtracts this incentive from all pixels in the sub-picture. It is known that" for face patterns, illumination correction can be used to minimize the heavy shadows caused by extreme lighting angles" [13].

ii. Histogram equalization:

The face featchers may be not that clear because of changes in illumination brightness and differences in camera response curves. Histogram equalization, "is consider as type of image transformation that can be use to flatten the histogram of the image, and compensate the above mentioned changes and differences" [13]

2.2 Features Extraction:

The conventional PCA permits only straight dimensionality. If the information has more difficult structures, conventional PCA won't be extremely useful to tackle this issue. Fortunately, kernel PCA enables us to sum up customary PCA to nonlinear dimensionality and it has been first presented by (Schäolkopfet al., 1999).The kernel principal component analysis (KPCA) is a non-linear extension of the conventional PCA calculation.

i. Kernel Principle Component Analysis

First, Assume that we have a nonlinear transformation $\emptyset(x)$from the original D-dimensional feature space to an M-dimensional feature space, where usually M $\gg$ D.Then each data point x_i is projected to a point $\emptyset(x)$ .Now, traditional PCA method can be performed and kernel methods can be used to simplify this computation.

First, let assume that the projected new features have zero mean [14]:

$$\frac{1}{N}\sum_{i=1}^{N}\emptyset(x_i) = 0 \qquad (1)$$

The matrix of features M x M, calculated by [14]

$$C = \frac{1}{N}\sum_{i=1}^{N}\emptyset(x_i)\,.\,\emptyset(x_i)^T \qquad (2)$$

$$C\, v_k = \lambda_k v_k \text{....}(3)$$

where k = 1, 2,……, M. From Eq. (2) and Eq. (3),we have [13]

$$C = \frac{1}{N}\sum_{i=1}^{N}\emptyset(x_i)\,.\,\{\emptyset(x_i)v_k\}^T = \lambda_k v_k \qquad \text{…(4)}$$

The Eq. (4) can be rewritten to obtain the Eq. (5) [14]:

$$v_k = \sum_{i=1}^{N} a_{ki}\ \emptyset(x_i) \text{ …..(5)}$$

After substituting v_k Eq. (4) with Eq. (5), we can obtain the following [14]:

$$\frac{1}{N}\sum_{i=1}^{N}\emptyset(x_i)\ \emptyset(x_i)^T\sum_{j=1}^{N}a_{kj}\ \emptyset(x_j) = \lambda_k\sum_{i=1}^{N}a_{ki}\ \emptyset(x_i) \qquad \text{…(6)}$$

If the kernel function can be defined as the following [14]:

$$k(x_i, x_j) = \emptyset(x_i)\ \emptyset(x_j)^T \text{ …..(7)}$$

And after multiply both sides of Eq. (6) by $\emptyset(x_l)^T$, the following was obtained [14]:

$$\frac{1}{N}\sum_{i=1}^{N} k(x_l, x_j) \sum_{j=1}^{N} a_{kj}\ k(x_i, x_j) = \gamma_k \sum_{i=1}^{N} a_{ki}\ k(x_l, x_j) \quad \text{….(8)}$$

$$K^2 a_k = \lambda_k N\ a_k \ldots\ldots (9)$$

and

$$K_{i,j} = k(x_i, x_j) \quad \text{…..(10)}$$

And a_k is the N-dimensional column vector of a_{ki} [14]:

$$a_k = [\, a_{k1}, a_{k2}, a_{k2}, \ldots\ldots, a_{kN}]^T \quad \text{….(11)}$$

a_k can be solved by the following [14]:

$$K_{ak} = \lambda_k N_{ak} \ldots (12)$$

And the resulting KPCA can be calculated using [14]:

$$\lambda_k(x) = \emptyset(x)^T v_k = \sum_{i=1}^{N} a_{ki}\ k(x, x_i) \ldots\ldots (13)$$

The Gram matrix is given by [14]

$$\widetilde{K} = K - l_N - K\ l_N + l_N K\ l_N \ldots . (14)$$

In kernel methods, no need compute $\emptyset(x_i)$ absolutely. The kernel matrix can be directly constructed from the training data set {xi}. The Gaussian kernel that describes in the Eq. (15) is used in this experiments:

$$k(x,y) = \exp(-\,||x-y||^2/2\sigma^2 \ldots (15)$$

2.3 Classification:

Classification is the final stage in the system. It is aimed to classify the features that related to each class according to its class. In this paper, FSVMs classifier is applied to classify the data. FSVM is one of successfully classifier method that widely used for object detection, human face detection and recognition in particular.FSVM can be used for both linear and non-linear classifier. In this section, the two types of classification will be explained.

ii. Fuzzy Support Vector Machine:

FSVM is created by presenting the idea of fuzzy association capacity to FSVM. In established FSVM, each example point is dealt with similarly i.e. each info is completely relegated to 1 of the 2 classes. Be that as it may, in numerous applications some information focuses are distinguished as exceptions and may not be precisely relegated to one of the two c1asses.To take care of this issue, fuzzy membership to each information purpose of FSVM is presented to such an extent that diverse information focuses can influence one of a kind addition to the development of choice to the surface .FSVM additionally regards each contribution as a contribution of inverse class with higher participation. Suppose the training sample pointsare considered as [12-13]:

$$SP = \{(A_i, z_i, \mu_i); i = 1,2,\ldots\ldots M\} \quad \text{…(16)}$$

Here, each $A_i \in R^N$ is a training sample and z; E {-l, +l} represents its class label;,μ_i; is fuzzy membership. Selecting the right fuzzy memberships for a given problem is very important for FFSVM [12,13].

3. Experiments and Results:

Two types of experiments are implemented using two types of databases are used to evaluate the performance of the proposed method. The first experiments focus on compare the performance of KPCA with other methods such as traditional PCA and LDA using FSVM as classifier in this experiments, while the second experiment The Yale [17] and ORL [18] database are used in both experiments. Yale database includes 15 particular subjects with 11 unique pictures for each subject while ORL database consists of 40 particular subjects with 10 unique pictures for each subject. For a few subjects, the pictures were caught in different circumstances, under various lighting conditions, facial points of interest and outward appearances. Every one of the pictures was brought with a white homogeneous foundation. The Yale database had images that had resolution of (243 x 320) pixels having per pixel of 265 gray levels while ORL database Had images that had resolution of (92x112) pixels and with 256 gray levels per pixel. The comparison is leading to the conclusion that the best results is obtained based on KPCA+FSVM comparing to (PCA-LDA)+FSVM. The second experiment is between two types of classifiers (SVMs and feed forward neural network) to show who of them is better for classification and the results prove that SVMs is gaiven results better than feed forward neural network . Finally, K-nearest neighborhood is used to identify the person. Eleven sample images of one person from the Yale database are shown in Figure 2 and number of sample of orl database are shown in figure 3.

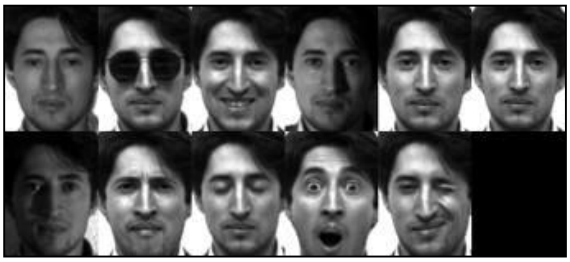

Figure 2: Some samples chosen from Yale datasets

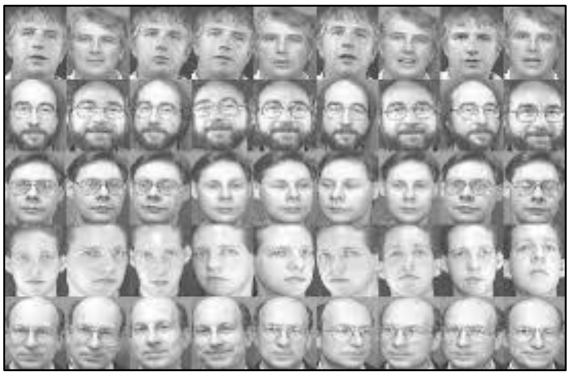

Figure 3: Number of samples chosen from the ORL datasets

4. the results of Experiment one and Experiment two

i. Experiment One:

In this experiment, the performance of KPCA based FSVM classifieragainst combination of PCA and LDA (Fisher face) basedFSVM classifier are calculated. The experimental results show that the proposed method gives better accuracy rate compare

than the combination of PCA and LDA. Table 1 describes the result of this experiment on Yale database and Table 2 describes the result of this experiment on ORL database.

Table 1: ACCURACY RATE OF COMBINATION OF (PCA+LDA) AND PROPOSED METHOD based Yale databse

Method	*Number of training sample*	*Number of testing sample*	*Accuracy Rate (%)*
KPCA+FSVM	60	105	97.14
(PCA-LDA)+FSVM	60	105	96.190

Table 2: ACCURACY RATE OF COMBINATION OF (PCA+LDA) AND PROPOSED METHOD baased ORL databse

Method	*Number of training sample*	*Number of testing sample*	*Accuracy Rat (%)*
KPCA+FSVM	200	200	95
(PCA-LDA)+FSVM	200	200	93.5

ii. Experiment two:

The second experiment is implemented to evaluated the KPCA based FSVM classifier against KPCA based ANNs classifier. The experimental results provide that KPCA based FSVM give high accuracy rate against KPCA based ANNs and, Table 2 gives the result of the classification rate corresponding to KPCA based FSVM classifier and KPCA based ANNs classifier.

TABLE 3: ACCURACY RATE OF COMBINATION OF (PCA+LDA) AND PROPOSED METHOD based Yale database

Method	*Number of training sample*	*Number of testing sample*	*Accuracy Rate (%)*
KPCA+ANNs	60	105	93.33
KPCA+FSVM	60	105	97.14

TABLE 4: ACCURACY RATE OF COMBINATION OF (PCA+LDA) AND PROPOSED METHOD based ORL database

Method	*Number of training sample*	*Number of testing sample*	*Accuracy Rate (%)*
KPCA+ANNs	200	200	94
KPCA+FSVM	200	200	95

5. Conclusion

A method of FRS based on the KPCA features extraction method has been proposed in this paper. The proposed KPCA method to select the most discriminative features from face images. Optimal strong classifier called FSVMs is used to classify these features according to its class. Two types of experiments are implemented to evaluate the performance of the proposed method, we carried it out on the widely used face databases called Yale and ORL databases. These experiments have shown that KPCA method can give more information about face image than both PCA and LDA, and so are more distinctive, where the accuracy rate reaches 97.15% and that the proposed classifier method FSVMs more discrimination power compare than another classifier such as ANNS.

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نظام تمييز الوجة بالاعتماد على نواة المكون الرئيسي و الة المتجة الداعم–الضبابي

حارث عبدالله حسين

قسم الرياضيات ، كلية علوم الحاسوب والرياضيات ، جامعة تكريت ، تكريت ، العراق

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الملخص

في السنوات الاخيرة،استحوذ نظام التعرف على الوجه الكثيرمن الاهتمام واستخدم في أنواع مختلفة من التطبيقات مثلا للتحكم في الوصول إلى شبكة الإنترنت والخدمات المصرفية عبرالإنترنت، وأمن المعلومات و تفاعل الكمبيوترالبشري والواقع الافتراضي واسترجاع قاعدة البيانات و غير ذلك الكثير .. في هذا البحث،استخدام طريقة تحليل المكونات الرئيسية (KPCA) و (FSVM). حيث لعبKPCA دور رئيسي في استخرج الميزات واستخدمتFSVM لعلاج مشكلة تصنيف الوجه. تم إجراء عدد من التجارب على قاعدة بيانات(ORL) لتقييم أداء نظام التعرف على الوجوه. وكذلك المقارنات بين KPCAوغيرها من أساليب استخراج ميزة مثل (PCA) و (LDA) وأيضا مقارنة بينFSVM و طرق التصنيف الأخرى مثل الشبكات العصبية الاصطناعية (ANN). أظهرت النتائج أن الطرق المقترحة تعطي نتائج أفضل من الطرق الأخرى.