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Optimized Method for Real-Time Face Recognition System Based on PCA and Multiclass Support Vector Machine

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Abstract

Automatic face recognition system is one of the core technologies in computer vision, machine learning, and biometrics. The present study presents a novel and improved way for face recognition. In the suggested approach, first, the place of face is extracted from the original image and then is sent to feature extraction stage, which is based on Principal Component Analysis (PCA) technique. In the previous procedures which were established on PCA technique, the whole picture was taken as a vector feature, then among these features, key features were extracted with use of PCA algorithm, revealing finally some poor efficiency. Thus, in the recommended approach underlying the current investigation, first the areas of face features are extracted; then, the areas are combined and are regarded as vector features. Ultimately, its key features are extracted with use of PCA algorithm. Taken together, after extracting the features, for face recognition and classification, Multiclass Support Vector Machine (SVMs) classifiers, which are typical of high efficiency, have been employed. In the result part, the proposed approach is applied on FEI database and the accuracy rate achieved 98.45%.

Keywords: *Face Detection, Feature Extraction, PCA, SVM Classifier, Face Recognition.*

1. Introduction

Automatic face recognition system (AFRS) is one of the core technologies in computer vision, machine learning, and biometrics [1] due to its wide range of applications such as forensics, vigilance, law enforcement, user access, human computer interaction and for various other security purposes. It is superior over fingerprints and other biometrics since it works without the involvement and knowledge of the individual concerned [2]. After many years of investigation, AFRS is still very challenging due to the low quality of face images [3], and the rich variations of facial images from the same or different subjects, e.g., lighting, expression, occlusion, misalignment, and so on [1]. For different communities to benchmark and verify their AFRS methods, many large-scale face databases, such as facial recognition technology (FERET) [4], [5], face recognition grand challenge (FRGC) [6], labeled faces in the wild (LFW) [7], [8], and PubFig [9], have been established and used as evaluation platforms. The process of Face Recognition comprises of Face Detection, feature extraction and verification or identification [1], [10]. This paper highlights the extraction and identification stages in the AFRS process. For feature extraction in this paper; instead of using whole pixel of face as feature, first we extract the facial feature position such as eyes, nose, mouth, ears and eyebrow and then we combined this position value to making hybrid vector. After extracting hybrid vector we used PCA algorithm for dimension reduction and finally we fed extracted feature vector to the multiclass support vector machine for precise recognition. Section two briefly reviews some related work. In section three proposed methods is presented. In section four the practical result of the paper and in section five, conclusion is presented.

2. Related Work

Several approaches have been proposed in the literature for handling one or more of the factors, like pose, illumination, and resolution, which affect AFRS performance. We provide pointers to a few of the recent approaches in this section.

Blanz and Vetter [11] propose a 3D morphable model based approach in which a face is represented using a linear combination of basis exemplars. The shape and albedo parameters of the model are computed by fitting the morphable model to the input image. Romdhani et al. [12] provide an efficient and robust algorithm for fitting a 3D morphable model using shape and texture error functions. Zhang and Samaras [13] combine spherical harmonics illumination representation with 3D morphable models [11]. An iterative approach is used to compute albedo and illumination coefficients using the estimated shape. For AFRS across pose, local patches are considered more robust than the whole face, and several patch-based approaches have been proposed [14]. In a recent paper, Prince et al. [15] proposed a generative model for generating the observation space from the identity space using an affine mapping and pose information. It is only recently that researchers have started looking at the problem of matching face images. Most of these efforts follow a super-resolution (SR) approach. Baker and Kanade [16], [17] propose an algorithm to learn a prior on the spatial distribution of the image gradients for frontal facial images. Chakrabarti et al. [18] propose a learning-based method using kernel principal component analysis (PCA) for deriving prior knowledge about the face class for performing SR.

Liu et al. [19] propose a two-step statistical modeling approach for hallucinating a high-resolution (HR) face image from a low-resolution (LR) input. The relationship between the HR images and their corresponding LR images is learned using a global linear model and the residual high-frequency content is modeled by a patch-based nonparametric Markov network. Xiong et al. [20] use manifold learning approaches for recovering the HR image from a single LR input. Yang et al. [21] address the problem of generating an SR image from a LR input image from the perspective of compressed sensing.

A novel patch-based face hallucination framework is proposed by Tang et al. [22]. Since many AFRS systems use an initial dimensionality reduction method, Gunturk et al. [23] proposed eigenface-domain AFRS in the lower dimensional face space. The main aim of most SR algorithms is to generate a good HR reconstruction, and they are usually not designed from a matching perspective. Recently, Hennings-Yeomans et al. [24] proposed an approach to perform SR and recognition simultaneously. Using features from the face and SR priors, they extract an HR template that simultaneously fits the SR as well as the face-feature constraints. Arandjelovic and Cipolla [25] propose a generative model for separating the illumination and down-sampling effects for the problem of matching a face in a LR query video sequence against a set of HR gallery sequences.

Recently, an MDS-based approach [26] was used for improving the matching performance of LR images assuming that the probe images are in the same pose and resolution as the gallery images. Given an LR face image, Jia and Gong [27] propose directly computing a maximum likelihood identity parameter vector in the HR tensor space, which can be used for recognition and reconstruction of HR face images. There also has been some research on AFRS across blur [28].

3. Proposed Method

The process of face recognition comprises of face detection, feature extraction and classification. In our proposed method we highlight the extraction and identification stages and for detection stage we used of our method that we mentioned earlier in [29].

3.1 Face Detection

For face detection we proposed a method in [29] based on color probabilistic estimation technique. First, for estimation of skin distribution we used statistical feature such as mean and standard deviation by Equation (1) and (2) respectively, then we applied Gaussian model for skin detection that determined by the Equation (3). Finally by using a tunable threshold (Equation 4) and mathematical morphology such as opening and closing we extracted facial feature for face detection.

$$Mean(R) = {}^{1}/_{n \times m} \sum_{\substack{0 \le i \le m \\ 0 < j < n}} P(i,j,1) \tag{1}$$

$$STD(R) = \sqrt{{}^{1}/_{n \times m} \sum_{\substack{0 \le i \le m \\ 0 < j < n}} (P(i,j,1) - mean(R))^2} \tag{2}$$

$$F(x, mean, STD) = exp\left\{-0.5 \times {(x - mean)^2}/_{STD}\right\} \tag{3}$$

Threshold = Min {P (Train | Skin) For Each Train pixels}
= Min {N (R_{Train}, Red -$mean_{Train}$, Red-std_{Train}) ×
N (G_{Train}, Green_ $mean_{Train}$, Green-std_{Train}) ×
N (B_{Train}, Blue_ $mean_{Train}$, Blue-std_{Train})
For Each RGB_{Train} pixels} (4)

Where, P(i, j, 1) means the intensity of pixel in i_{th} row and j_{th} column in red channel. Also, m and n are the size of train image. Figure 1 shows these operating gradually.

Fig. 1 Face detection stage gradually a: input image b: extracted skin region and morphology operation c: extracted facial feature region

3.2 Feature Extraction

In this part we used facial feature location, such as eyes, nose, eyebrow, mouth, brow and ears as our feature set. For extraction these feature location we used Equation (4) and mathematical morphology that we denoted in [29]. Figure 2 shows these extracted locations. By using of these region boundaries we extracted facial feature pixel from main image in gray scale mode (Figure 2(b)). Then we used these values as our feature set. Although, the extracted feature vector of the facial feature can be used directly in face classification, many studies, in the field of data analysis and feature selection, suggest that not all the features are useful for classification accuracy. In this research we have used the Principal Components Analysis (PCA) technique for feature reduction.

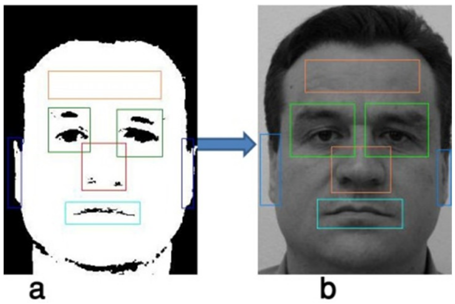

Fig. 2 (a): Extracted facial feature location in black white mode (b): Extracted facial feature location in corresponding grayscale image

3.2.1 Reducing Features by PCA

The Principal Component Analysis (PCA) was independently proposed by Karl Pearson and Harold Hotelling to turn a set of possibly correlated variables into a smaller set of uncorrelated variables. The idea is that a high-dimensional dataset is often described by correlated variables and therefore only a few meaningful dimensions account for most of the information. The PCA methods find the directions with the greatest variance in the data, called principal components. The PCA algorithm descript as follow: Let $X = \{x_1, x_2, \dots, x_n\}$be a random vector with observations $x_i \in R^2$

A. Compute the mean μ by Equation (5):

$$\mu = {}^{1}/_{n} \sum_{i=1}^{n} x_i \quad (5)$$

B. Compute the Covariance Matrix S by Equation (6):

$$S = {}^{1}/_{n} \sum_{i=1}^{n} (x_i - \mu)(x_i - \mu)^T \quad (6)$$

Compute the eigenvalues ϑ_i and eigenvectors v_i of S by Equation (7). Then order the eigenvectors descending by their eigenvalue. The k principal components are the eigenvectors corresponding to the k largest eigenvalues. The k principal components of the observed vector x are then given by Equation (8).

$$Sv_i = \vartheta_i v_i, i = 1,2, \dots, n \quad (7)$$

$$y = W^T(X - \mu) \quad (8)$$

Where $W = \{v_1, v_2, \dots, v_n\}$. The reconstruction from the PCA basis is given by Equation (9):

$$X = Wy + \mu \quad (9)$$

The experimental results show that the PCA classifier performs well for our data set.

3.3 Classification by SVMs

Support vector machines (SVMs) [30] are very popular and powerful in pattern learning because of supporting high dimensional data and at the same time, providing good generalization properties. Moreover, SVMs have many usages in pattern recognition and data mining applications such as text categorization [31] and [32] phoneme recognition [32], 3D object detection [34], image classification [35], bioinformatics [36] etc. At the beginning, SVM was formulated for two-class (binary) classification problems. The extension of this method to multi-class problem is neither straightforward nor unique. DAG SVM [37] is one of the methods that have been proposed to extend SVM classifier to support multi-class classification.

3.3.1 Binary support vector machine formulation:

$X = \{(x_i, y_i)\}^n i = 1$ be a set of n training samples, where $x_i \in R^m$ is an m-dimensional sample in the input space, and $y_i \in \{-1,1\}$ is the class label of sample xi. SVM finds the optimal separating hyper plane (OSH) with the minimal classification errors. The linear separation hyper plane is in the form of Equation (10).

$$f(x) = W^T x + b \quad (10)$$

Where w and b are the weight vector and bias, respectively. The optimal hyper plane can be obtained by solving the optimization problem (13), where $\zeta_i$is slack variable for obtaining a soft margin while variable C controls the effect of the slack variables. Separation margin increases by decreasing the value of C. In a support vector machine, the optimal hyper plane is obtained by maximizing the generalization ability of the SVM. However if the training data are not linearly separable, the obtained classifier may not have high generalization ability, even though the hyper planes are determined optimally. To enhance linear severability, the original input space is mapped into a high-dimensional do product space called the feature space. Now using the nonlinear vector function $\varphi(x) = (\varphi_1(x), \dots, \varphi_l(x))^{\Psi}$ that maps the m-dimensional input vector x into the l-dimensional feature space, the OSH in the feature space is given by Equation (11):

$$f(x) = W^T \varphi(x) + b \quad (11)$$

The decision function for a test data is Equation (12):

$$D(x) = Sign(W^T \varphi(x) + b) \quad (12)$$

The optimal hyper plane can be found by solving the following quadratic optimization problem:

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$$Minimize\ \frac{1}{2}||W||^2 + C\sum_{i=1}^{n}\zeta_i$$
$$Subject\ to\ y_i(W^T\varphi(x)+b) \geq 1-\zeta_i$$
$$\zeta_i \quad \geq 0, i=1,\dots,n \qquad (13)$$

3.3.2 Multiclass support vector machine:

As described before, SVMs are intrinsically binary classifiers, but, the classification of faces involves more than two classes. In order to face this issue, a number of multiclass classification strategies can be adopted [38] and [39]. The most popular ones are the one-against-all (OAA) and the one-against-one (OAO) strategies. The one-against-one constructs $(n(n-1))\ /\ 2$ decision functions for all the combinations of class pairs. Experimental results indicate that the one-against-all is more suitable for practical use. We use OAA for face classification.

4. Result and Discussion

Our suggestive method have been done on Intel Core i3-2330M CPU, 2.20 GHz with 2 GB RAM under Matlab environment. Figure 3 shows the face of worked systems.

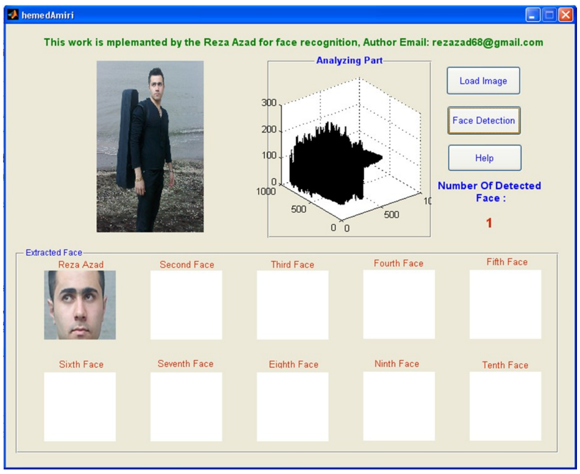

Fig. 3 Face recognition system by Matlab

In this study, for experimental analysis, we considered a FEI database. The FEI face database is a Brazilian face database that contains a set of face images taken between June 2005 and March 2006 at the artificial intelligence laboratory of FEI in São Bernardo do Campo, São Paulo, Brazil. There are 14 images for each of 200 individuals, a total of 2800 images. All images are colorful and taken against a white homogenous background in an upright frontal position with profile rotation of up to about 180 degrees. Scale might vary about 10% and the original size of each image is 640x480 pixels. All faces are mainly represented by students and staff at FEI, between 19 and 40 years old with distinct appearance, hairstyle, and adorns. The number of male and female subjects is exactly the same and equal to 100. Figure 4 shows the sample of FEI databases.

Fig. 4 Sample of FEI database images

For evaluation of proposed method we have divided the data set using three partitioning strategies. In the first strategy (strategy A), we have taken 60% data in training set and other 40% data in the testing set. In the second strategy (strategy B), we have considered 70% data in training set and remaining 30% data in the testing set. Strategy C has 100% data in training set and 100% data in testing set. Table 1 shows the success rate for each strategy.

Table 1: Success rate of proposed method on each strategy via SVM

Data Set	Classier	Strategy	Success Rate
FEI	SVM	A	97%
		B	98.45%
		C	100%

Further we used some classifier based on Euclidean distances for recognition stage.

4.1 Other Classifier for recognition stage

For further experience we used some classifier such as Euclidean distance(ED), standardized Euclidean distance(SED), Mahalanobis distance(MD), City block metric(CBM), Minkowski metric(MM), Chebychev distance(CD), Cosine distance(CoD), Correlation distance(CorD), Hamming distance(HD), Jaccard distance(JD) and Spearman distance(SD) that denoted by the Equation (14) to (24). Table 2 shows the result of these classifiers on FEI databases. Figure 5 shows the success rate of classifiers on frontal and side images.

$$ED = d_{st}^2 = (x_s - x_t)(x_s - x_t)' \qquad (14)$$

Where x_s is a train data vector and x_t is the test data vector.

$$SED = d_{st}^2 = (x_s - x_t)V^{-1}(x_s - x_t)' \qquad (15)$$

Where V is the n-by-n diagonal matrix whose j_{th} diagonal element is $(s_j)^2$, where S is the vector of standard deviations.

$$MD = d_{st}^2 = (x_s - x_t)C^{-1}(x_s - x_t)' \qquad (16)$$

Where C is the covariance matrix.

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$$CBM = d_{st} = \sum_{j=1}^{n} |(x_{sj} - x_{tj})| \qquad (17)$$

$$MM = d_{st} = \sqrt[p]{\sum_{j=1}^{n} |(x_{sj} - x_{tj})|^{p}} \qquad (18)$$

$$CD = d_{st} = Max_j\{|x_{sj} - x_{tj}|\} \qquad (19)$$

$$CoD = d_{st} = 1 - \frac{x_s x_t'}{\sqrt{(x_s x_s')(x_t x_t')}} \qquad (20)$$

$$CorD = d_{st} = 1 - \frac{(x_s x_s')(x_t x_t')'}{\sqrt{(x_s - x_s')(x_s - x_s')'}\sqrt{(x_t - x_t')(x_t - x_t')'}} \qquad (21)$$

Where $x_s' = \frac{1}{n}\sum_j x_{sj}$ and $x_t' = \frac{1}{n}\sum_j x_{tj}$.

$$HD = d_{st} = (\# \frac{x_{sj} \neq x_{tj}}{n}) \qquad (22)$$

$$JD = d_{st} = \frac{\#[(x_{sj} \neq x_{tj}) \cap (x_{sj} \neq 0) \cup (x_{tj} \neq 0)]}{\#[(x_{sj} \neq 0) \cup (x_{tj} \neq 0)]} \qquad (23)$$

$$SD = d_{st} = 1 - \frac{(r_s - r_s')(r_t - r_t')'}{\sqrt{(r_s - r_s')(r_s - r_s')'}\sqrt{(r_t - r_t')(r_t - r_t')'}} \qquad (24)$$

Where r_{sj} is the rank of X_{sj}, r_s and r_t are the coordinate-wise rank vectors of X_s and X_t and $r_s' = \frac{1}{n}\sum_j r_{sj} = \frac{(n+1)}{2}$, $r_t' = \frac{1}{n}\sum_j r_{tj} = \frac{(n+1)}{2}$.

Table 2: Success rate of classifiers on FEI database

Data Set	Classifier	Success Rate
FEI	ED	88.10
	SED	88.20
	MD	87.30
	CBM	85.00
	MM	84.22
	CD	88.60
	CoD	89.30
	CorD	91.50
	HD	92.59
	JD	94.21
	SD	90.73

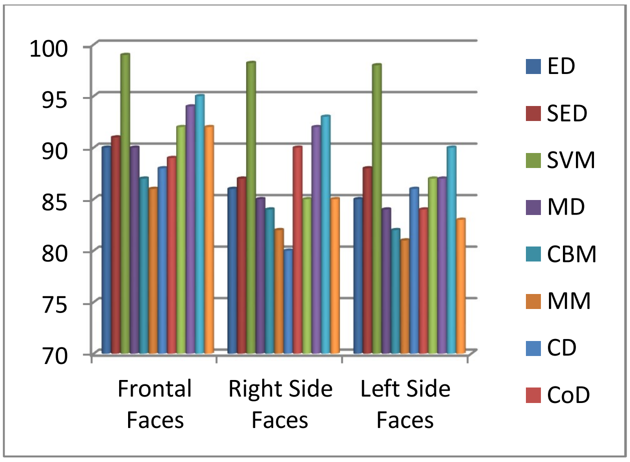

Fig. 5 Success rate between classifiers

Further we evaluated our method on complex background images and we obtained high accuracy rate. Figure 6 shows the sample of these images. High detection rate shows the quality of proposed approach to use in every applications, which are needed a face recognition stage. Low complexity in computation and time are some of other advantages of the proposed approach.

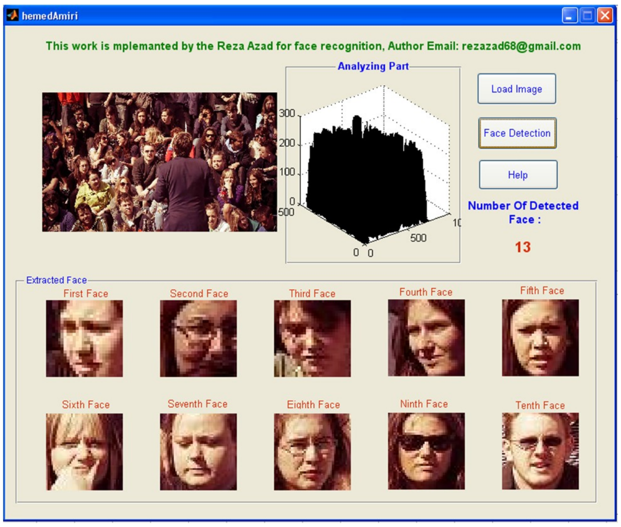

Fig. 6 Sample of images with complex background that system detects and recognized it correctly

5. Conclusion

In this paper we proposed a novel and improved way for face recognition. In the mentioned approach, first, the place of face is extracted from the original image and then is sent to feature extraction stage, which is based on Principal Component Analysis (PCA) technique. Then, the facial feature areas are combined and are regarded as vector features. Ultimately, its key features are extracted with use of PCA algorithm. Taken together, after extracting the features, for face recognition and classification, Multiclass Support Vector Machine (SVMs) classifiers, which are typical of high efficiency, have been employed. We evaluated our approach on FEI database and the accuracy rate achieved 98.45%. Further in the result part by comparison classifiers we detected SVM as best classifier for our databases.

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