Smart Dual Stage Identity Authentication for Attendance Monitoring

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Summary
The field of computer vision and pattern recognition is making great developments every day. It has already become clear that autonomous authentication is a sensible and innovative tool that can be applied in several applications. Image analytics technology such as facial recognition is crucial for authenticating autonomous identities. Automating the process of recognizing faces is challenging because faces move constantly, and they often wear accessories. This paper proposes a novel Bayesian approach to low resolution surveillance video attendance monitoring based on PCA-LDA processing with face biometrics. A publicly available database was used for the experimental evaluation process of the PCA-LDA combined scheme. It was found out that this method is highly effective at capturing the inherent features of human faces as well as discriminating identities from low resolution surveillance video. It is intended to implement it at the hardware level and monitoring classes' attendance in the future studies.

Keywords:
Biometric; Attendance; PCA; LDA; Bayesian

1. Introduction

Smart Human identification using facial recognition is one of the most perspective technologies in confirming an individual's identity. It is a way of identifying a human face with the help of modern technology[1]. It works based on biometric approach which utilizes automation to validate the identity of an individual. To do that initially it relies on individuals' physiological characteristics. Generally, for identification, the biometric identification method uses (a) one or combination of physiological attributes which includes fingerprints, iris patterns, face feature or (b) one or more behavioral patterns that consisting of hand-writing, voice, or key-stroke sample [2]. Sometimes individuals are very much reluctant to use the iris for the identification for inherent protectiveness of human[3]. In contrast, the identification system based on face has the benefit of being passive. This is a non-intrusive system which can validate an individual identity in an easy and natural manner. The face recognition normally begins with the pattern of the face on an individual. In this process, the image is normalized, and the illusion and geometric changes are extracted from the image. The image also examines the specific landmarks of an individual's face appearance as well as location [4]. In most face recognition method normally comprises of two major parts (a) the detection of the face and normalization (b) identification of the face [5]. Fig. 1 shows the basic face recognition method.

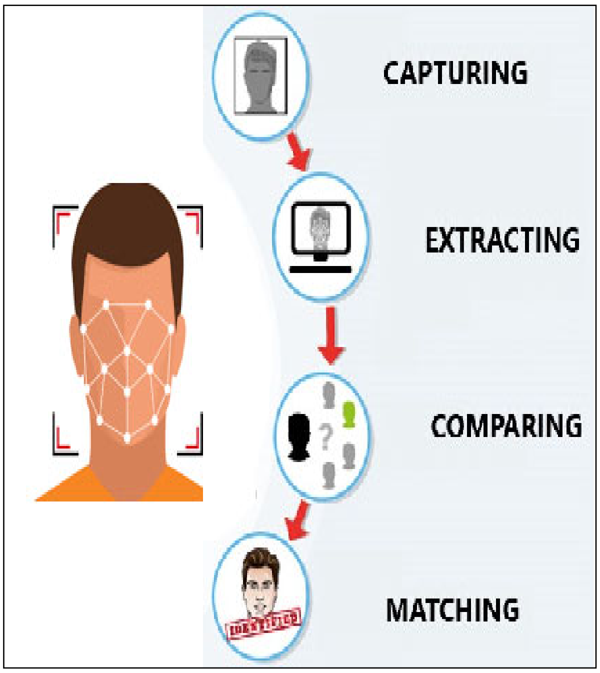

Fig. 1. Basic face recognition method

In the practical application, it uses biometrics to map facial features from a photograph or video and it is a difficult and challenging task, in particular whilst someone is walking or moving [6]. Recently, spotting identification utilizing the pattern from face has become a famous in field of biometrics as well as in computer vision. Research on identity authentication for attendance systems from video has been gaining attention by the public and commercial

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sectors in recent years. It has been observed that videos possess distinctive properties which make available both human being and autonimc computer system to acknowledge and identify the faces correctly even though sometime it has difficult viewing conditions [7]. There are, however, important challenges in research due to the fact that most video-based applications do not allow for controlled recordings.

In this research paper, we have worked on the video-based application while an individual is walking or moving. To identify an individual, we have used Bayesian method established on PCA-LDA processing for attendance monitoring from the low resolution surveillance video with cues obtained from the face biometrics.

2. Background

Recently, several research works were conducted by the researchers for the face recognition to identify individuals. The work previously done can be categorized as (a) Neural networks approach (b) Hidden Markov Model approach (c) 3D morphable model approach (d) Geometrical Feature Matching approach (e) Template Matching approach (f) Graph Matching approach and (g) Eigenfaces approach.

In neural network approach, the properties of non-linearity make the feature extraction efficient. Different neural networks approach has been applied for face recognition by the researchers. In the neural network approach, the training and testing is necessary. In [8]–[12] the researchers have worked for face recognition based on the neural networks. It has been observed that in this type of approach, the training need to be done efficiently and this create the problem when the number of classes increased.

Hidden Markov model is a stochastic based modeling for non-stationary vector of time series. It requires a one-dimensional sequence of the observation. Several researchers has implemented this method for the recognition of face in [13]–[15], in this type of approach, the images are normally two dimensional. Hence to implement this method, the images should be converted to one dimensional.

The vector space representation of the faces is necessary in the 3D morphable model, where the vector shape and texture represent the human real face. Researchers have worked on this type of approach in [16]–[18]. The models seem to have high computational cost.

Geometric feature point is extracted from the face and compute them in the Geometrical Feature Matching approach. The advantage of the method is that it can work with the low-resolution image. The authors in [19]–[21] studied and implemented Geometrical Feature Matching approach. In this type of method, it is dependent on the location of the feature element location.

The templet matching approach uses the Euclidian distance based on a templet to represent the image. The method was investigated by the authors in [22]–[24]. The implemented approached has observed that most of the applied techniques have limitations and need improvements.

In graph matching approach, it looks for the closest stored graph and match with that. With this, the objects are memorized as sparse graph. In [25]–[27] the authors of the research papers have investigated the graph matching approach. The studies have worked on small sample as this type of method is good for small sample.

One of the most studied approaches is the eigenface approach. Several researches have worked on this method in [28]–[30]. The method is effective, and this uses basically the principal component analysis to effectively represent the images an individual face. This can work with the minimum number of features.

This paper proposes a set of physiological characteristics that establish identity. Our analysis was based on the combination of principal component analysis and linear discriminant analysis. The methodology is explained in the following sections.

3. Method of Identification Scheme

Security In our proposed scheme the experimental evaluation used the public video database for human activities, this contains total six human actions. We have used this database because whatever action the individual is we should be able to recognize the face of the individuals. In the video we have six actions al together which includes clapping and waving of hands, running, boxing as well as walking. So that human can nor forge the systems. the database currently consists of about 2400 sequences. In order to take the sequence a static camera with the frame rate of 25fps and the background for the sequence was homogenous. Down-sampled to 160 * 120 pixels, the sequences average four seconds in length in average. Figure 2 shows some of the sample images from the video sequences.

Fig. 2. Sample images from human action database for walking sequences.

The trials of experiment conducted; we have utilized hundred video sequences for 25 humans. Out of the 25 human There have been 19 boys and 6 girls in the complete dataset of walking. Moreover, we have accomplished some picture pre-processing stages corelated to cropping, filtering and histogram equalization. After that we have separated the capabilities based on both principal component analysis (PCA) and linear discriminant analysis (LDA). In this stage for the training and testing the separate set is applied. A classification of the features of low dimensional PCA as well as LDA was performed afterwards using classifiers. In our process three different classifiers was examined that are k-NN – the linear and quadratic from Bayesian classifiers. Two prominent approach PCA and LDA combination with stated classifiers allows to accomplish substantial enhancement in the accuracy of recognition, in comparison to the traditional Euclidean distance approach suggested the previous research works predominantly. This is due to the fact that the Bayesian classifiers have the ability to include previous recorded information, and it is capable of predicting how a systems performance will alternate whilst going from one environment to another [31]. Alternatively, k-NN is very powerful easy classifier which has the ability to reduce the noise [32]. The block diagram of the proposed multimodal identification approach is shown in Fig. 3.

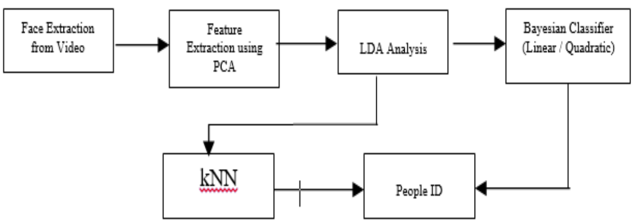

Fig. 3. Proposed identification scheme from video.
below:

4. PCA Features

The Principal Component Analysis (PCA) is a projecting computational method for analyzing and summarizing large data tables. PCA is applied if different applications that includes face recognition, image compression even to detect the anomaly in the data. Most importantly it is a popular method to find patterns in the high dimension data [33].

Considering, $\{x_1, x_2, \ldots, x_n\}$, $x_n \in R_N$, the random vector is n, and N is the vector dimensionality that can be obtained row-by-row sequences of a specific image.

The calculation ground is characterized as $\sum x = E([x - E(x)][x - E(x)]T)$, in which the expectation operator is $E(\cdot)$. The transpose operation is denoted by T. The factorized covariance matrix $\sum x$ as in Equation (1):

$$\sum x = \Phi \wedge \Phi \ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

In Equation (1), The orthogonal eigenvector matrix of $\sum x$; $\wedge = \{\wedge 1 \ \ \wedge 2 \ldots \wedge N\} \in R_N \times N$ is $\Phi = [\Phi 1, \Phi 2 \ldots \Phi N] \in R_N \times N$ that is the diagonal Eigen value matrix of $\sum x$, where the diagonal features element are in descending order . One of the key features of PCA is the reconstruction of the optimal signal. The reconstruction using a subset of principal components based on the minimum mean square error (MSE). Dimensionality reduction is an immediate application of this property:[34]

$$y_k = PT_{pca}[x_k - E(x)], k = 1, 2, \ldots, n \ldots (2)$$

In which $P_{pca} = [\Phi_1, \Phi_2, \ldots, \Phi_m], m \leq N$. The lower dimensional vector $y_k \in R_m$ encapsulates the most sensitive feature elements of the original data x_k [35].

If $f \in R_{N_1}$ and $g \in R_{N_2}$ represents the PCA vectors relating to an individual's data extracted from video, N_1 and N_2 represents the dimensionality of the facial features specifications.

In the experiment we have obtained the low dimensional element feature vectors, $f' = Mf\boldsymbol{f}$ and $g' = Mg\boldsymbol{g}$, by applying the PCA approach as shown in the Eq. (2). Where the PCA conversion matrices for face are Mf and Mg. We have chosen a subcategory of principal components to create the lower dimensional face element features, $f' \in R_{m_1}$ and $g' \in R_{m_2}$, the dimensionality of the reduced face element feature specifications is m_1 and m_2. In contrast, we might lose some distinctive feature elements of the real information data during transformation process from the high dimensional space to the low dimensional space. Conversely, we exclude the eigenvectors corresponding to the small Eigenvalues from the reduced space, in order to achieve a more robust PCA & LDA projection as well as reduce the curse of dimension. The Eigen value spectrum of a covariance matrix contains useful information about the dimensionality of the feature space[36]. Face features must be normalized so that their values are within similar ranges. In or research we have used a linear method, that provide the normalization [37]. To do that it utilizes the corresponding estimates of the mean and the variance. Considering, the jth feature value in the ith feature vector w_{ij}, we can draw the following equation (3)

$$\widehat{w}_{ij} = \frac{(w_{ij} - w'_j)}{\delta_j}, i = 1, 2, \ldots, I,\ j = 1, 2, \ldots, L \text{ ..(3)}$$

In which, $(\frac{1}{I}) \sum_{i=1}^{I} w_{ij}$ and $S_B.I$ is considered to be the number of existing feature vectors and each feature vector represents by the number of features, L. Thus, the normalized feature elements have a zero mean and unit variance. In order to have the effective information data we have used the walking individual in video. Moreover, out of the video we have extracted most of the possible potential combinations of each and every image, in order to create the maximum number of vectors, h the side of the face feature elements is used. In particular, we obtain two separate feature vectors of walking individuals side face of an individual from a single video. Hence, the cohort of ever potential low dimension vectors h obtained by analyzed the PCA for side face supports to decrease the challenge of torment of dimensionality for the following consequent LDA transformation.

5. Transformation of LDA

In order to do the LDA transformation we consider, w1,w2, . . . ,wc and n1, n2, . . . , nc which represent the classes and the number of sequence of feature vectors h within each class. With $\boldsymbol{w} = \boldsymbol{w_1} \cup \boldsymbol{w_2} \cup \ldots \cup \boldsymbol{w_c}$ and $\hat{n} = n_1 + n_2 + \cdots + n_c$.

The value of $\hat{n}$ is two times of n. The number of classes is c. LDA pursues a transformation matrix W which increases the ratio of the between-class scatter matrix S_B to the within-class scatter matrix [38].

$$\sum_{i=1}^{c} n_i (M_i - M)(M_i - M)^T \text{ ....(4)}$$

$$S_w = \frac{J(W)|WTS_BW|}{|WTS_WW|}$$

The within-class scatter matrix is $S_w = \sum_{i=1}^{c} \sum_{h \varepsilon w_i} (h - M_i)(h - M_i)^T$ and the between-class scatter matrix is $S_B = \sum_{i=1}^{c} n_i (M_i - M)(M_i - M)^T$, where

$$M_i = \left(1/n_i\right) \sum_{h \varepsilon w_i} and\ M = \left(1/\hat{n}\right) \sum_{h \varepsilon w} h \text{.........(5)}$$

are the means of the class i and the grand mean, respectively. Based on the characteristics of the face, we generate an unlimited number of concatenated feature vectors by combining side face features. Each video contains two features that can identify a person's face. Four concatenated features are constructed out of these two features. Considering, V_i , i = 1, 2, . . . , c, the mean of the training synthetic features of class i, be the prototype of class i. The unknown individual is classier to class K to whom the synthetic feature p is the nearest neighbor:

$$||p - V_K|| = min||p - V_i|| \text{ ....(6)}$$

For a single individual with multiple synthetic features, Equaton. (6) meaning that the unidentified of unidentified individual is classified to a specific class which considered to have the lowest possible distance out of all the distances corresponding to all the classes.

The Bayesian linear and quadratic classifiers are an alternative to Euclidean distance-based classification (Bayesian linear classifiers)[39]. Using Bayesian decision rules, Bayesian linear and quadratic discriminant classifiers classify learned feature vectors [7]. Linear classifiers fit multivariate normal (MVN) densities based on pooled covariance estimates, but quadratic discriminant classifiers fit MVN densities stratified by group. Observations are assigned to groups using likelihood ratios in both methods. For instance, the class representing the highest probability in a set of classes M described by a set of known parameters in a model Ω is the class represented by the extracted feature vector X. This is shown in Eq.(7)) and is known as Bayes decision rule.

$$X \in M_k \qquad P(M_k | X, \Omega) \geq P(M_l | X, \Omega) \qquad \forall l \neq k \text{ ...(7)}$$

In order to do probability calculation of a-posteriori as presented, we have utilized Bayes law. By assuming that features are distributed normally, Bayes Quadratic classifiers progress to a quadratic classifier format known as Bayes Quadratic classifier. The Ω model contains the covariance of our exercise vectors along with the mean, and probabilities are identified as explained before. The particulars on the experiments are stated in next section.

6. Experimental Results and Discussion

Two different comprehend-set of experiments are conducted. The approaches of both set of experiments almost similar except the algorithms and their combinations.

6.1 Recognition Performance with PCA-Features

Using PCA transformations, we conducted Bayesian and k-nearest neighbor classifiers. Based on PCA only features, Table 1 shows recognition accuracy. Based on this experimental scenario, Bayesian-linear classifiers were 85% accurate, Bayesian quadratic classifiers were 90% accurate, and 1-NN classifiers were 95% accurate. It is still not possible to recognize some bad quality faces despite using a 100% accurate transformation technique and a poor-quality image. Even though the side faces were low resolution, PCA still managed to model them efficiently. It is anticipated that it is not possible for PCA to capture the vigorous and dynamic variations of face accurately, regardless of how effective its classifier is.

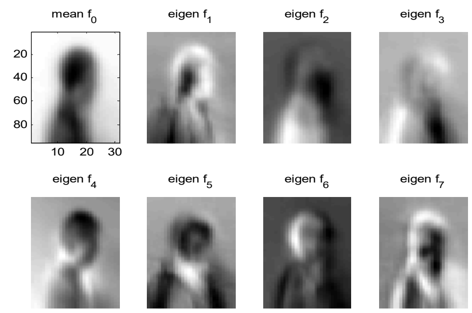

Fig. 3: Extracted Eigen Faces

Table 1: The result of PCA with Bayesian Classifiers and 1-Nearest Neighbour Classifier

Name	**Face-Only**
Bayesian-linear	85 %
Bayesian-quadratic	90 %
1-NN classify	95 %

6.2 Identification Precisions With PCA-LDA Features

The PCA vectors were transformed into LDA space for this set of experiments, and we achieved 100% accuracy. In table 2 it is clearly visible that the given data set for all three classifiers are providing accurate variance of individuals by PCA features along with subspace of LDA. Combination of the elements of face feature in PCA as well as LDA subspace we have achieved 100 % of the recognition accuracy for the three different types of classifiers. Thus, it was a synergistic fusion, with the help of PCA to reduce the dimensionality and LDA is for capturing the inter-person and intra-person correlated variants correctly.

Table 2: PCA - LDA with Bayesian Classifiers and 1-Nearest Neighbour Classifier

Name	**Face-Only**
Bayesian-linear	100%
Bayesian-quadratic	100%
1-NN classify	100%

7. Conclusions and Further Plan

Face recognition is considered to be the first biometric identifier. The use of biometric technology, such as facial recognition, allows individuals to be identified without their knowledge. Humans can recognize one another by sight but implementing this on computers for automated systems is difficult. Numerous methods have been developed by several researchers across the globe but still the shortcomings are there to achieve the good result for identification. Based on low resolution surveillance video, our research has used PCA-LDA to identify people using cues extracted from their face biometrics for monitoring the attendance. The method was implemented on a publicly available database. Considering the experimental evaluation of the implemented method it possesses a good result in identifying the individuals. These algorithms form a powerful combination that captures the inherent modality of human faces and discriminates between identities in poor quality video with blur backgrounds. Our future experiments will be concentrating on number of unattended method laterally with the data from real time or uncontrolled environment.

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