

THE BIOMETRIC-BASED MODULE OF SMART GRID SYSTEM*

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Abstract. Within Smart Grid concept the flexible biometric-based module base on Principal Component Analysis (PCA) and selective Neural Network is developed. The formation of the selective Neural Network the biometric-based module uses the method which includes three main stages: preliminary processing of the image, face localization and face recognition. Experiments on the Yale face database show that (i) selective Neural Network exhibits promising classification capability for face detection, recognition problems; and (ii) the proposed biometric-based module achieves near real-time face detection, recognition speed and the competitive performance, as compared to some existing subspaces-based methods.

1. Introduction

The Smart Grid vision embraces the idea of a society of connected smart devices and systems that self-assemble and seek operational efficiencies and reliable performance [1]. Smart grid will aid in the integration “micro-generation” facilities into the intelligent system. How successful the Smart Grid project can be largely depends on how well it defends against remote network-based attacks. User authentication for accessing the Smart Grid is the first and strongest line of defense against these types of attacks. Modern password based authentication mechanism has been proven inadequate. It is believed that biometric authentication will significantly improve the security of the Smart Grid network. In this paper we propose face recognition technology base on selective Neural Network to authenticate users accessing the Smart Grid. Considering Smart Grid technology we are focused on biometric-based module. This module is an important subsystem of Smart grid. Such subsystem are of particular importance at module range on any abstraction level for application-specific data analysis and processing, thus allowing to leverage the underlying communication infrastructure and use and combine information generated by various devices, to produce added value across multiple environments. In a biometric-based module, there are different modalities that can be used (fingerprints, face, iris, retina, voice etc.). Among those modalities, face is considered one of the top choices because, face recognition is one of the most common human experiences: it is easy to capture at a distance and in a non-cooperative manner and, finally, face recognition technology base on selective Neural Network is fairly

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accurate. Automatic face recognition by computer can be divided into two approaches [2], namely, content-based and face-based. In content-based approach, recognition is based on the relationship between human facial features such as eyes, mouth, nose, profile silhouettes and face boundary [3, 4, 5, 6]. The success of this approach relies highly on the accurately is difficult. Face-based approach [7, 8, 5, 9] attempts to capture and define the face as a whole. Principal Component Analysis (PCA) [7, 8, 10, 11, 12] has been proven to be an effective face-based approach. Sirovich and Kirby [10] first proposed using Karhunen-Loeve transform to represent human faces. In their method, faces are represented by a linear combination of weighted eigenvector, known as eigenfaces. Turk and Pentland [8] developed a face recognition system using PCA. However basic PCA-based methods suffer from two limitations, namely, poor discriminatory power and large computational load. Another disadvantage of PCA-based method is the high computational load in finding the eigenvectors. The computational complexity of this is $O(d^2)$ where d is the number of pixels in

the training images which has a typical value of 128×128 . The computational cost is beyond the power of most existing computers.

In view of the limitations in existing PCA-based approach, we proposed a new approach – applying PCA on Viola–Jones method for feature extraction. In the proposed method an image is decomposed into a number of subbands with different frequency components using the Viola–Jones method.

2. Analytical review of recognition methods

The Viola–Jones method is the first object detection framework to provide competitive object detection rates in real-time [2]. The main disadvantages of Viola–Jones method are robustness (very high detection rate and very low false-positive rate always); real time (for practical applications at least 2 frames per second must be processed); face detection (not recognition – the goal is to distinguish faces from non-faces).

The Viola–Jones method consists of 4 steps:

- Haar Features Selection;
- Creating Integral Image;
- Adaboost Training algorithm;
- Cascaded Classifiers.

The Viola–Jones method illustrated in Figure 1.

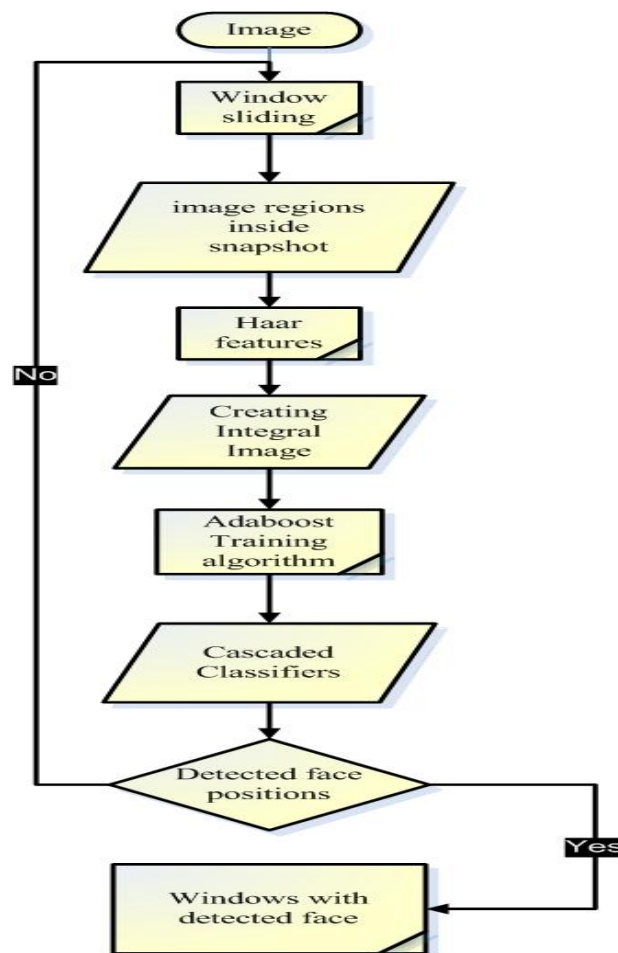


Figure 1. The Viola-Jones method.

The features employed by the detection framework universally involve the sums of image pixels within rectangular areas. As such, they bear some resemblance to Haar basis functions, which have been used previously in the realm of image-based object detection [3]. However, since the features used by Viola-Jones method all rely on more than one rectangular area, they are generally more complex. The value of any given feature is always simply the sum of the pixels within clear rectangles subtracted from the sum of the pixels within shaded rectangles.

The rectangular features of this sort are rather primitive when compared to alternatives such as steerable filters. Although they are sensitive to vertical and horizontal features, their feedback is considerably coarser.

PCA is used to find a low dimensional representation of data. Some important details of PCA are highlighted at [14].

Let $X = \{X_n, n = 1, \dots, N\} \in R^{d \times d}$ be an ensemble of vectors. In imaging applications, they are formed by row concatenation of the image data, with $d \times d$ being the product of the width and the height of an image. The average vector in the ensemble is defined as

$$E(X) = 1/N \sum_{n=1}^N X_n. \quad (1)$$

After subtracting the average from each element of X , we get a modified ensemble of

vectors,

$$\bar{X} = \{\bar{X}_n, n = 1, \dots, N\}, \quad (2)$$

where $\bar{X}_n = X_n - E(X)$.

The auto-covariance matrix M for the ensemble X is defined as

$$M = \text{cov}(\bar{X}) = E(\bar{X} \otimes \bar{X}) \quad (3)$$

where M is $d^2 \times d^2$ matrix, with elements $M(i, j) = 1/N \sum \bar{X}_n(i) \bar{X}_n(j)$, $1 \leq i, j \leq d^2$.

It is well known from matrix theory that the matrix M is positively definite (or semi-definite) and has only real nonnegative eigenvalues [13]. The eigenvectors of the matrix M form an orthonormal basis for R^{d^2} . This basis is called the K - L basis. Since the auto-covariance matrix for the K - L eigenvectors are diagonal, it follows that the coordinates of the vectors in the sample space X with respect to the K - L basis are un-correlated random variables. Let $\{Y_n, n = 1, \dots, N\}$ denote the eigenvectors and let K be the $d^2 \times d^2$ matrix which columns are the vectors $Y_1, \dots, Y_N$. The adjoint matrix of the matrix K , which maps the standard coordinates into K - L coordinates, is called the K - L transform. In many applications, the eigenvectors in K are sorted according to the eigenvalues in a descending order. In determining the $d \times d$ eigenvalues from M , we have to solve a $d^2 \times d^2$ matrix. Usually, $d=128$ and therefore, we have to solve a 16×16 matrix to calculate the eigenvalues and eigenvectors. The computational and memory requirement of the computer systems are extremely high.

Basically, eigenface is the eigenvector obtained from PCA. This idea is first proposed by Sirovich and Kirby [10]. After that, Turk and Pentland [8] developed a face recognition system using PCA. PCA illustrated in Figure 2.

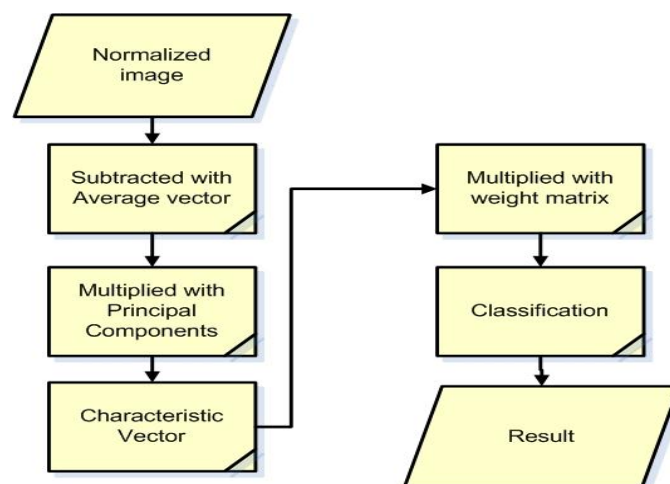


Figure 2. PCA block-diagram.

Multilayer Perceptron Neural Network is a good tool for classification purpose [15, 16]. In this paper, the function approximation capabilities of selective neural net [17] are exploited to recognize faces.

3. The proposed method

A Viola–Jones method-based PCA method is developed so as to overcome the limitation of the original PCA method; furthermore, we have utilized a selective neural net in order to carry out the classification of faces. We adopted a selective neural net [17] which is fed by the reduced input units, feature vectors generated by combination of Viola–Jones method and PCA. The combination of new Viola–Jones method-based PCA and selective neural net is illustrated in Figure 3.

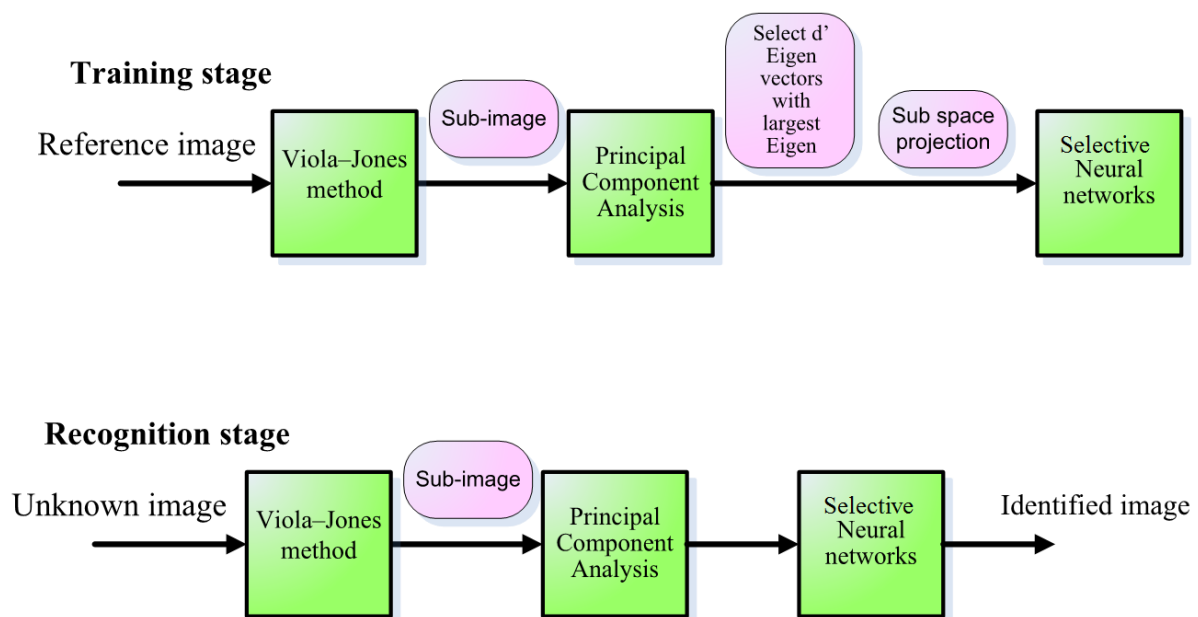


Figure 3. Block diagram of the proposed face recognition system.

Proposed system consists of two stages, namely training step in which the feature extraction, dimension reduction, also training of selective neural net have been performed and the recognition step identifies the unknown face image. The training stage includes the feature extraction of reference images and the adjustment of selective neural net parameters. The extracting feature identifies the representational basis for images in the domain of interest. Subsequently, the recognition stage translates the input unknown image according to the representational basis, identified in the training stage.

There are three significant steps in the training stage. In the first step, Viola–Jones method is applied to detection of faces in an image. In the next step, Principal Component Analysis (PCA) is performed on the sub-images to obtain a set of representational basis by the selection of d' eigenvectors corresponding with the largest eigenvalues and sub-space projection. Finally, the feature vectors of reference images obtained by previous steps are used so as to train selective neural network using algorithm of level-by-level generating [17]. Processing in the recognition stage is similar to the training stage, except that recognition stage also incorporates steps to match the input unknown images with those reference images in the database by selective neural net. When an unknown face-image is presented to the recognition stage, Viola–Jones method and PCA are applied to transform the unknown face-image into the representational basis identified in the recognition stage, and the classification is achieved by trained selective neural net [17].

The biometric-based module carries out function of identification of the user of system. The biometric-based module's architecture consists of three components: the face detection on image, the image normalization and the face recognition. Face recognition module works on the basis of Viola-Jones method, PCA and trained selective neural net. The biometric-based module's architecture illustrated in Figure 6.

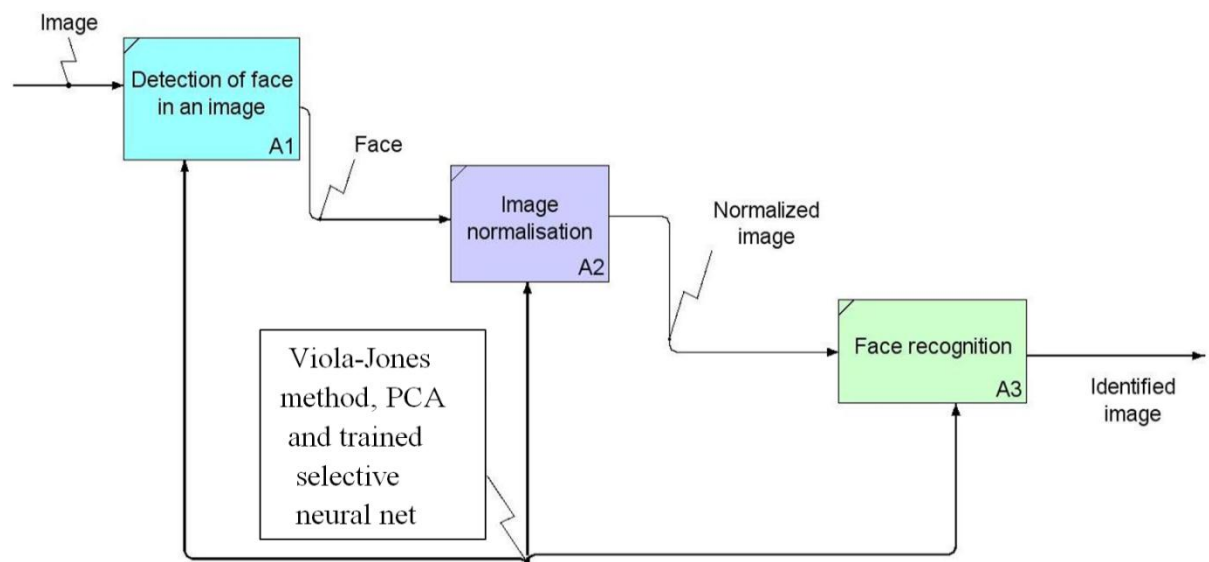


Figure 4. The biometric-based module's architecture.

The selective Neural Net (S NN) implemented by usage OpenCV NN.

4. Experimental result

To evaluate the performance of the proposed method, we used the face-images database of Yale University [18]. This database consists of 165 images (15 persons (males and females), with 11 images for each person). There are 11 images per subject, one per different facial expression or configuration. We used selective Neural Net architecture which is fed by the reduced input units, feature vectors generated by combination of Viola-Jones method and PCA. The selective neural net was trained on 22 samples (train set has 15 persons (males and females), with 2 images for each person). The experiment results are illustrated in the Table 1 and Table 2. Recognition rate on the Yale face-images database of the proposed methods is compared with recognition rate other methods [30].

Table 1. Performance comparison of recognition rate.

Methods	Recognition rate (%)
IPCA (Incremental PCA)	78,47
PCA	80,80
I(2D)PCA	81,19
PCA + MLP NN	81,27
I(2D) ² PCA	81,39
2DPCA	82,05
(2D) ² PCA	82,13

PCA	85,71
SPCA	88,57
Viola–Jones + S NN	89,45
WPCA	89,52
Viola–Jones method + PCA + S NN (proposed method)	90,35
SWPCA (Symmetrical Weighted Principal Component Analysis)	93,33

Table 1 shows the good performance of the proposed method. The correct recognition accuracy with Viola–Jones method + PCA + S NN improved almost by 4,64% compared with PCA and 0,9% compared with Viola–Jones + S NN.

The proposed method provides good Recognition rate (90,35 %).

Table 2. The biometric-based module's result

Characteristics	Result
The database Maximum size for a face recognition	to 500 persons
Recognition and identification time (at the capacity of base up to 100 records)	no more than 4 sec.
The maximum speed of recognition and identification	to 3 faces/sec.

The GUI biometric-based module's result presented in Figure 5.

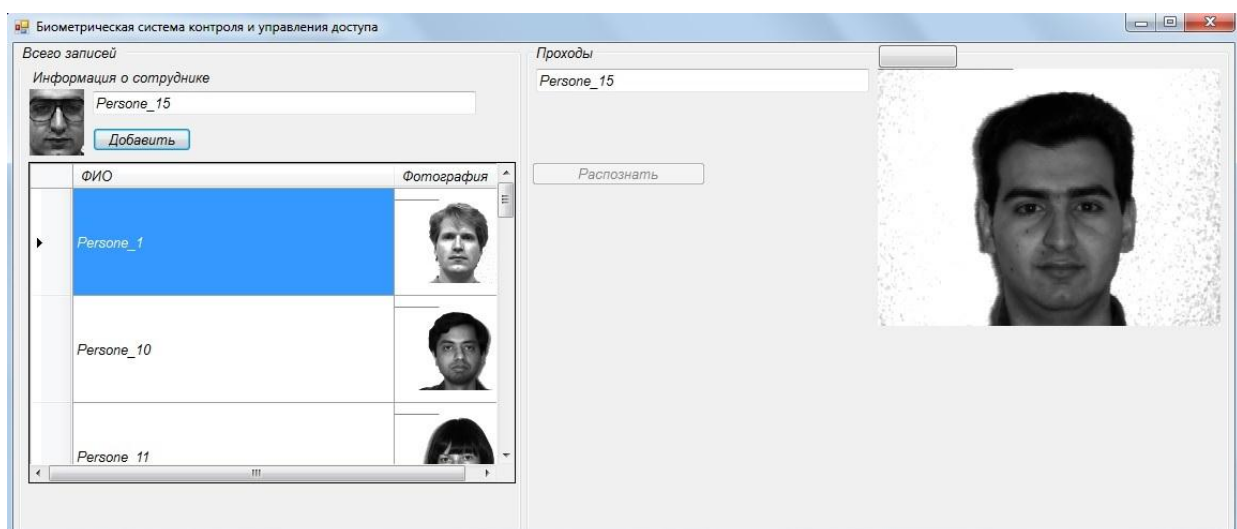


Figure 5. The biometric-based module's result.

The GUI biometric-based module displays image with normalized histogram (at the left), identified data (name person), input image and face-images database users of the module.

5. Conclusions

Within Smart Grid concept the flexible biometric-based module base on Viola–Jones method, Principal Component Analysis and selective Neural Network is developed. The formed as the selective Neural Network the biometric-based module uses the proposed method which includes three main stages: preliminary processing of the image, face localization and face recognition. Experiments on the Yale face database show that (i) selective Neural Network exhibit promising classification capability for face detection, recognition problems; and (ii) the proposed biometric-based module achieves near real-time face detection, recognition speed and the competitive performance, as compared to some existing subspaces-based methods.

The biometric-based module has flexible architecture and easily implements in Smart Grid technology. Experiments show that the biometric-based module provides good effectiveness and secure for Smart Grid technology.

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