A New Approach for Face Image Enhancement and Recognition

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Abstract

A new approach is presented to improve the face recognition accuracy. This approach is based on the contrast enhancement using high-frequency emphasize filtering and histogram equalization. In the presented method, image contrast and the global (or local) visualization are enhanced using digital filtering and equalizing the histogram of the pixel values over entire image. For this, first the face images are transformed into a high-frequency domain and then the global thresholding technique, by Otsu method, is applied to the image. Then, the values lower than threshold has only been considered. For dimension reduction and also feature extraction purpose the linear method such as two dimensional principle component analysis (2DPCA) and two *dimensional linear discriminant analysis* (*2DLDA) are adopted. In the last stage of the algorithm, the simple minimum distance method is exploited for the classification. Experimental trials demonstrate that the presented method is leading to the promising recognition rates and noticeable improvement in the face recognition system.*

Keywords: *face recognition, face image enhancement, high-frequency emphasis filtering, 2DPCA, 2DLDA*

1. Introduction

Face recognition is one of the most outstanding abilities of human vision, and is probably the biometric method easier to understand. This is the reason that the features of individual face are considered in security and access control systems, law enforcement, surveillance. Many of scientists and research groups are involved in face recognition methods and systems. With the expectation to make the computer like the humans, having the ability to recognize people, and perceive in close contact [1-4]. Building an automated system that accomplishes such objective is very challenging. The challenges mainly come from the large variations in the visual stimulus due to illumination conditions, facial expressions, aging, and disguises such as facial hair, glasses [4-13].

During the past two decades, many face recognition systems have been proposed as reviewed in [13-23]. An important part of these systems is feature extraction. In this stage, a proper face representation is needed. This would be computationally feasible and also robust to possible intrinsic and extrinsic facial variations [13]. Several feature extraction methods have been exploited in face recognition systems including Eigenfaces [8], Fisherfaces [6], Laplacian faces, nearest feature line-based subspace analysis, neural networks, elastic bunch graph matching, wavelets, and kernel methods [1, 2, 4], Principal Component Analysis (PCA) [13, 15] and Linear Discriminant Analysis (LDA) have successfully been exploited.

In face recognition literature, there are various face representation methods based on global features, including a large number of subspace-based methods and some spatial-frequency techniques [13]. In face recognition, persons are identified by use of a stored set of face images. In traditional appearance-based models, the intensity of each pixel in a face image is used as an input feature. Since there are more than tens of thousands of pixels in a face image [18], so facial image data are always high-dimensional and considerable computational time is required for the classification purpose. Thus the subspace methods, by projecting patterns to a lower dimensional space, are widely exploited. In practical situations, when the image dimension is prohibitively large, one is often forced to use linear techniques. Two important linear techniques for extracting discriminative feature and also dimension reduction are PCA and LDA. The focuses of some researchers are based on projective maps. The main aspect of these methods is generating feature vector for each face image, then classify the input face image in the database. Generating feature vector also has the advantages of reducing dimension of the input images [21]. The PCA method performs dimension reduction by projecting the original data onto lower dimensional subspace spanned by the leading eigenvectors of the covariance matrix. The LDA method searches for the projective axes on which the data points of different classes are far from each other (maximizing between class scatter), while constraining the data points of the same class to be as close to each other as possible (minimizing within class scatter) [5]. Many researchers propose methods based on spatial-frequency techniques, such as Fourier transform [1, 24] and Discrete Cosine Transform (DCT) [2, 3]. In these methods, face images are transformed to a lower frequency domain bands contain most facial discriminating features and ignoring high bands containing noise [1, 13, 19].

An important issue to improve the performance of face recognition system is enhancing face image. The aim of image enhancement is that the images have better visual quality. By enhancing the brightness, contrast and resolution of image can be improved. This is a part of pre-processing stage that can influence the feature extraction and therefore the final recognition performance. For instance in [22, 23], the image enhancement has been considered in face recognition system. Song et al. [23], calculates, before feature extraction stage, the illumination difference between right and left part of face. If there is a large amount of difference than take the mirror of average illuminated part.

In this paper the impact of image enhancement procedure on the face recognition are also considered. For feature extraction stage, we used the combination of 2DPCA and 2DLDA. The simulation results show that our image enhancement procedure noticeably increases the face recognition accuracy.

In what follows general background information and also pre-processing stages are given in the next section. Then the proposed arrangement and finally experimental results are presented in the Sections 4 and 5, respectively.

2. Background

A brief conceptual block diagram of face recognition and verification system is illustrated in the Figure 1. This diagram illustrates the training stage at top and the test stage at the top of the figure. The pre-processing includes image size conversions, image histogram equalization and some other enhancement process. Then the weight vector constructed in the feature extraction stage is compared with the of every face database member. If there is at least one face in database similar to the acquired image, then the input face is classified as "known", otherwise “unknown".

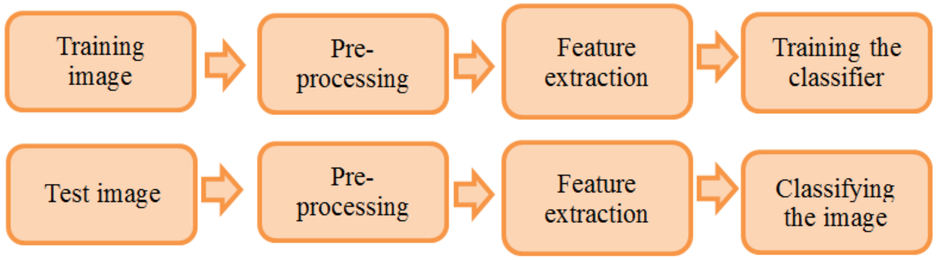

Figure 1. Block Diagram of Recognition/Verification System

2.1 Pre-processing

In this section, various processing including high-frequency emphasis filtering, histogram equalization, adaptive thresholding and intensity-level slicing are described.

2.1.1 High-Frequency Emphasis Filtering

High-frequency emphasis [25, 26], has a filter transfer function given by eq. (1)

$$H_{he}(u, v) = a + bH_{hp}(u, v) \tag{1}$$

Where $a \geq 0$ and $b > a$, typical values of a are in the range of 0.25 to 0.5 and typical values of b are in the range 1.5 to 2.0. $H_{hp}(u, v)$ is the transfer function of the corresponding high-pass filter in this paper. The transfer function of the Butterworth High-Pass Filter (BHPF) of order n is adopted, and the transfer function is given by eq. (2)

$$H_{hp}(u, v) = 1/\{1 + [D_0/D(u,v)]^{2n}\} \tag{2}$$

Where D_0 is the specified nonnegative quantity, and $D(u,v)$ is the distance from point (u,v) to the center of the frequency rectangle.

Let f and g denote two discrete functions in the two dimensional discrete space, and let $f(x, y)$ denote the gray level of point (x, y) in image, $g(x, y)$ denote the gray level of point (x, y) in enhanced image, F and G denote Fourier transform of corresponding image. The expression of high-frequency emphasis follows directly from (1) and (2)

$$G(u, v) = H_{he}(u, v)\, F(u, v) = (a + b/\{1 + [D_0/D(u,v)]^{2n}\})F(u,v) \tag{3}$$

The convolution theorem tells us that the corresponding process in the spatial domain is

$$g(x,y) = h_{he}(x,y) * f(x,y) \tag{4}$$

Where $h(x,y)$ is the inverse Fourier transform of the filter transform function $H(u, v)$.

2.1.2 Histogram Equalization

Histogram equalization based on the probability theory is a common method for enhancing the low contrast and the appearance of a digital image by effectively spreading out the most frequently occurred intensity values through a nonlinear transformation function and is commonly histogram modification approach [15]. The main propose of histogram equalization is to allow pixels in areas of lower contrast to gain a higher contrast [26-31].

2.1.3 Thresholding

Thresholding is a non-linear operation converting gray-level images into binary images by selecting an appropriate decision. By this operation pixels are assigned to two levels below or above the specified threshold value [32, 33]. If the pixel lies above the threshold, it will be marked as foreground, and if it is below or equal to the threshold as background. The threshold value may adaptively be determined according to image content, intensity or color value.

2.1.4 Intensity-Level Slicing

Intensity-level slicing or gray level slicing methods belong to the category of point operations and function by changing the pixel value, or gray level, by a mapping process. The mapping equation can be typically linear or nonlinear. Typical applications of intensity-level slicing include contrast enhancement and feature enhancement [25, 34].

3. Proposed Method

This paper is focused on the second and third stages of the Figure 1 which are two key parts of a successful face recognition system. The pre-processing stage includes image resizing, high-frequency emphasis filtering, histogram equalization, adaptive thresholding and intensity-level slicing, as shown in Figure 2.

In the feature extraction block the 2DPCA is performed first and then 2DLDA is used for the second feature extraction in the 2DPCA transformed space. This has three important advantages easier and accurate evaluation of the covariance matrices, reduction the time required for the determination of the corresponding eigenvectors and finally significant increase in the face recognition accuracy [35]. In the classification, we used the Nearest Neighbor (NN) classifier due to its simplicity and performance in our experiments. Its training is very fast, robustness to noisy training data and effectiveness for the large training data set [36].

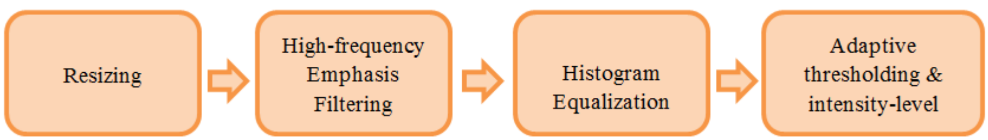

Figure 2. Block-diagram of pre-processing stage

In the following, each part of the system is examined.

High-Frequency Emphasis Filtering:

In an image, edges and other abrupt changes in gray levels are associated with high-frequency components. Image sharpening can be achieved in the frequency domain by a high-pass filtering process in the Fourier Transform. In this case, we multiply a high-pass filter function by a constant value and add offset so that high-frequency components of image are enhanced and the gray-level tonality due to the low frequency components are retained.

As it is discussed above, the texture of face image is enhanced by the algorithm of high-frequency emphasis filtering, in our simulation $a=0.5$ and $b=1.5$. In order to further improvement in contrast of face and background, histogram equalization is used [26]. Choosing the high-pass filter for pre-processing envolves a lot of trial and error. Experiments were conducted with Butterworth and Gaussian filters and improvement in performance was observed with Butterworth filter. To study the impact of the High-frequency emphasis with Butterworth filter, in Figure 3, their maximum recognition rates were compared with the Gaussian filter. The figure shows the impact of Butterworth and Gaussian filter in recognition rate in the left and right, respectively.

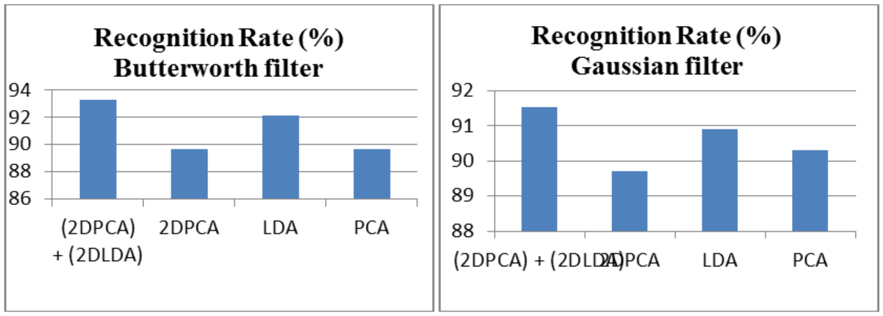

Figure 3. Comparison of Butterworth Filter and Gaussian Filter

The result of simulation is shown in Figure 4. The left picture is a faces in the utilized database after resizing and the right picture is the result of high-frequency emphasis filtering.

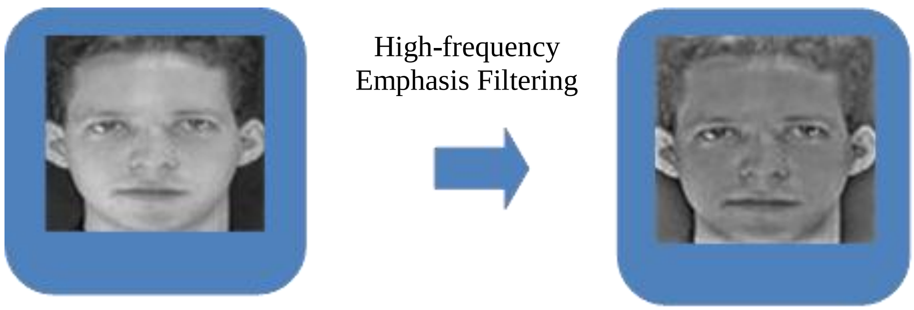

Figure 4. Original Image and the Result of High-frequency Emphasis

Histogram Equalization:

Automatic face recognition performance is also affected by illumination [37, 38]. The problem is that the variation between images of different faces can be smaller than the variations between images of the same face under different illumination. It can even be shown that illumination causes larger variation in face images than pose [39]. At the very beginning of modern machine face recognition, it became quite clear that different illumination in various images will be a problem [15, 40]. Image pre-processing and normalization is significant part of face recognition systems. Changes in lighting conditions lead to dramatic decrease in the recognition performance [41]. Histogram equalization is an effective method in stretching the range of gray levels and enlarging the contrast of image. It also makes the change of the order of gray levels of the original image completely controllable. Therefore, it can enhance images effectively [26].

Figure 5 is the result of applying histogram equalization on the Figure 4. Between these two figures, it can be seen that the contrast of face image and background become more, and the outline of the face image is clearer.

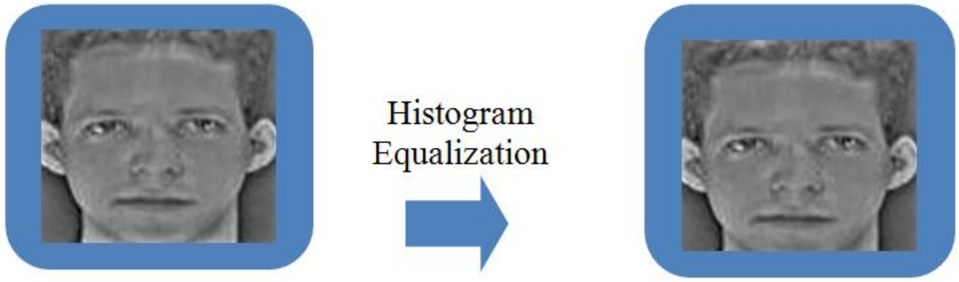

Figure 5. Face image after high-frequency emphasis filtering and the result of histogram equalization

Thresholding:

Thresholding is an essential task in the image processing and pattern recognition. In general, automatic thresholding techniques are classified into two basic groups: global and local methods. Global thresholding uses only one threshold value estimated based on statistics or heuristics on global image attributes while local methods exploit threshold values that change dynamically in the image. Many techniques for global image thresholding have been proposed in the literature [32, 42]. In this work Otsu's method is exploited for the global thresholding [43]. The threshold is individually calculated for each image so we called it adaptive thresholding.

Intensity-Level Slicing:

Image enhancement techniques are used to emphasize and sharpen image features for the purpose of display and analysis. Highlighting a specific range of gray levels in certain ranges is often desired. In this paper we use a type of intensity-level slicing shown in Figure 6. This transformation preserves intensities less than threshold and reduces all other intensities to a lower level.

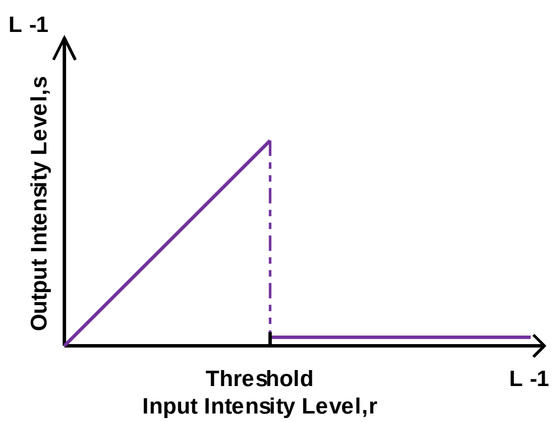

Figure 6. Intensity-level slicing that used in this paper

In the face recognition whole face plays an essential role. This overall appearance is determined based on the darker areas. For instance, the overall border of a face can be characterized by hair, and the dark areas of the face such as the eyes, nose, mouth *etc.* give us useful information about the face. It is obvious that the fine or pale lines on the face play unimportant role in this type of recognition. In human face there are areas with lower intensity level (darker), showing important features of the face, and operate efficiently in face recognition. By emphasizing on this regions and ignoring the greater intensity level (brighter areas), we can continue the recognition process. This kind of procedure allows us keeping the essential features, less memory requirements and smaller processing time. Our criterion to distinguish between the light from dark areas is Otsu's thresholding method. This method calculates the threshold for each image individually. Since this kind of thresholding is binary and has value between 0 and 1. It can therefore be used in gray scale by its multiplying by 255. Finally, we keep the regions with equal or higher than threshold times 255 and those with lower than threshold with their original values. Figure 7 shows the result of face image after intensity level slicing. The threshold calculated by Otsu method was 0.4941. Multiplying the threshold by 255, the threshold for gray scale image will be 126, approximately.

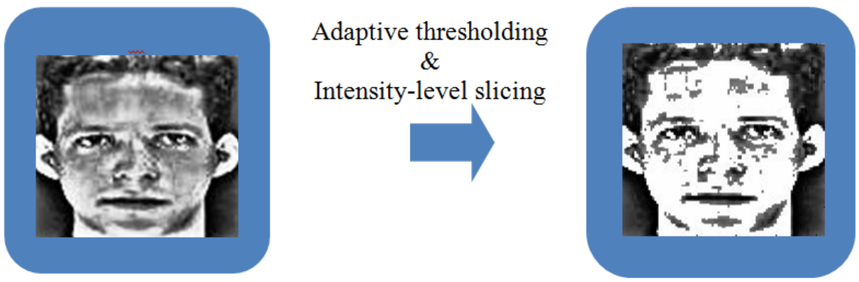

Figure 7. Face image after histogram equalization and the result of face image after pre-processing

Feature Extraction: 2DPCA + 2DLDA:

The 2DPCA method is an appropriate technique for 2D data set such as images [44, 45]. There is another method called two Dimensional Linear Discriminant Analysis (2DLDA) which is also a well-known method for feature extraction and dimension reduction. These methods have been used in many applications such as [46, 47] and [48]. In contrast to the covariance matrix of PCA, the size of the image covariance matrix of 2DPCA is much smaller [45]. In both PCA and 2DPCA the eigenvectors (Eigenfaces) can be calculated by using the Singular Value Decomposition (SVD) techniques [49, 50]. The process of generating the covariance matrix is actually avoided [44]. This technique is effective for reducing computation when the training sample size is much smaller than the dimensionality of the images [15, 49].

In this paper, we combine 2DPCA and 2DLDA to reduce the dimension, which is also called two Dimensional Fisher Principal Component Analysis (2DFPCA) [35].

In this paper, we used *20* feature vectors for 2DPCA. Our results show that the number of 2DLDA's Eigen vectors required to optimize this algorithm is only *10*. The number of Eigen vectors of 2DPCA and 2DLDA are selected in such a way that the performance of 2DPCA + 2DLDA is optimized.

4. Experimental Results

Two databases were used to validate the effectiveness of our method. We conduct experiments on the AT&T (Olivetti) database and Yale face database. AT&T database consists of *400* images (*112×92* Pixels), *10* different images from *40* individuals. The Yale database contains *165* images of *15* individuals (*11* images per individual) (*100×100* pixels), the images were taken at different times, varying the lighting, facial expressions (open / closed eyes, smiling / not smiling) and facial details (glasses / no glasses). All the images were taken against a dark homogeneous background with the subjects in an upright, frontal position (with tolerance for some side movement). The images were resized to 95×105 pixels in this experiment.

In Figure 8, maximum recognition rate achieved by 2DLDA plus 2DPCA were compared with 2DPCA, LDA and PCA. The recognition rate on the testing set for this case is *95.7565%*.

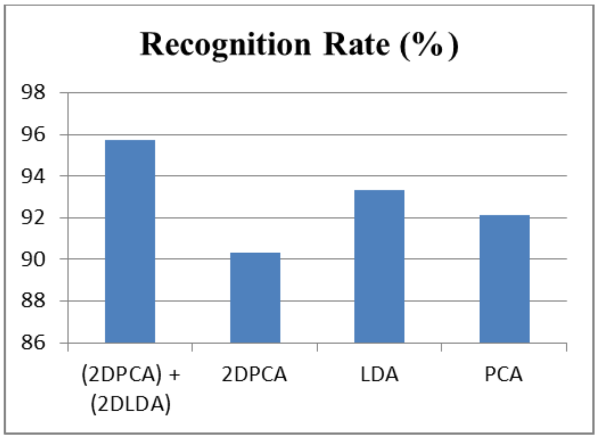

Figure 8. Comparison of proposed method with 2DPCA, LDA and PCA

We designed a series of experiments for different 2DLDA selected eigenvectors. Table 1 show that the performance of 2DPCA + 2DLDA is optimized at $d = 10$. The Maximum recognition rate was *95.7576%* obtained using twenty 2DPCA eigenvectors.

The results of performing the presented method on the two database show that the proposed method has low computational time. It can be used as a real time face recognition process in places that the time of recognition is important. The average recognition time is *0.5*s, approximately. All experiments were performed on a PC (Intel processor, Core i*7*, *1.73* GHz, *4* GB RAM) and the algorithms was coded in Matlab *2009b*, *64* bits [17].

Table 1. Comparison of the top recognition accuracy (%) 2DPCA + 2DLDA for varying 2DLDA's eigenvectors and 20 2DPCA's eigenvectors

Number of 2DLDA's selected eigenvectors	5	7	9	10	12
Top recognition %	93.9394	93.3333	93.9394	95.7576	93.9394

5. Conclusion

We have presented a new approach to improve the face recognition accuracy. This method uses linear phase high-frequency and emphasizes for digital filtering and histogram equalization for contrast enhancement to achieve improvements. The results obtained using this method indicate sharper edges and give more details. The novelty of this paper is that the face recognition is based on the high-frequency emphasis filtering, global thresholding and the combine of 2DPCA and 2DLDA. At the first step, the face images are transformed into high-frequency emphasis domain. After that, the global thresholding apply to the images, after we choose the threshold by Otsu's method, for each image and then we multiply it with 255 to find the suitable threshold for our gray scale image. The 2DPCA + 2DLDA are used to reduce the dimension of face images, which can speed up the recognition algorithm and minimum distance is used for classifying them. Experiments are conducted on the Yale face database and AT&T (Olivetti) database (ORL) results demonstrate that the maximum recognition rate of 95.7576 is achieved.

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