ISSN: 0067-2904

Design of an Efficient Face Recognition Algorithm based on Hybrid Method of Eigen Faces and Gabor Filter

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Abstract

Face recognition is one of the most applications interesting in computer vision and pattern recognition fields. This is for many reasons; the most important of them are the availability and easy access by sensors. Face recognition system can be a sub-system of many applications. In this paper, an efficient face recognition algorithm is proposed based on the accuracy of Gabor filter for feature extraction and computing the Eigen faces. In this work, efficient compressed feature vector approach is proposed. This compression for feature vector gives a good recognition rate reaches to 100% and reduced the complexity of computing Eigen faces. Faces94 data base was used to test method.

Keywords: Face Recognition, PCA, Eigen faces, Gabor filter, Complex number.

تصميم خوارزمية تتسم بالكفاءة للتعرف على الوجوه بالاعتماد على طريقة هجينة للوجوه المميزة و مرشح غابور

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الخلاصة:

تمييز الوجوه هو أحد أكثر التطبيقات أهمية في مجال رؤية الكمبيوتر و مجال تمييز الانماط و ذلك لعدة اسباب أهمها هو تواجد الوجوه و سهولة استحصالها من قبل المتحسسات. نظام تمييز الوجوه ممكن ان يكون كنظام جزئي من عدد من التطبيقات. في هذا البحث أقترحت خوارزمية تمييز وجوه تعتمد على دقة مرشح غابور في استخلاص الصفات المميزة و طريقة حساب الوجوه المميزة. اقترحت و نوقشت في هذا البحث طريقة لضغط متجه المميزات. هذا الضغط انتج تميز جيد وصل الى 100% و أيضا قلل من تعقيد حساب الوجوه المميزه. أستعملت قاعدة البيانات Faces94 لاختبار هذه الطريقة.

1. Introduction

Biometric is referring to the autonomous identification of individuals based on his/her biological or social appearances. This approach of identification is favored over traditional approaches containing passwords and Personal Identification Numbers (PIN) for many substantial reasons like stolen and forgetting these traditional identifications [1]. Face recognition is a challenging problematic task in the area of pattern recognition and image processing; it is a challenging mission in terms of hardware that is generating physical implementation and software that is emerging algorithmic solutions [2].

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The trails in planning automatic face recognition algorithms are several and various. There are charged with the duty of resulting a measure of similarity between a particular pair of facial images, such tasks obvious in the following basic stages are accomplished by furthermost face recognition algorithms; they are feature extraction and classification with preprocessing to the facial image [3].

Feature extraction is defined as the procedure that commences with feature selection; it is implemented to generate effective and functional information that is beneficial for distinguishing between faces of different individuals and constant with respect to the variations in the images of the same individual. The nominated features selection is established upon the application requirements; they play as a major factor to conclude the involvedness and accomplishment of the analysis and pattern classification. The objective of face analysis is to extract valuable information from facial images [4-5]. Turk and Pentland [6] in 1991 technologically, had incubated a near real time face recognition system by computing the Eigen face of the trained dataset images depending on the Principle Component Analysis (PCA). They achieved a good recognition rate but their system still sensitive to lighting and orientation changes. Many researchers adopted this approach behind them to develop the face recognition systems and have tried to develop this method either by preprocessing or on a part of its flow. Alex al et [7] were combined the results of PCA with the components of Discrete Cosine Transform (DCT). Poon al et [8] were cropped the faces from images then preprocessed the facial images by Gradient faces algorithm then applied the result to PCA. They eliminate the illumination invariant features effect. Haghighat et al [9] had used as part of their biometric identification Gabor filter with PCA. As Gabor filter outputs a huge number of features, they assumed to down sampling these hugged features produced a smaller feature vector then applied it as a dimensionality reduction approach (PCA).

2. Gabor Filter and the proposed approach

Gabor filters are commonly used in feature extraction methods. Gabor filter is a sinusoidal wave modulated by Gaussian function. Gabor filter is based on the frequency, orientation and Gaussian kernel [10]. With varying of these factors a set of Gabor filter banks are generating to be convoluted with the image to generate the corresponding features in a complex numbers form.

The suggested method is depending on reducing the spectrum array by extracting the high energy DC component from each Gabor filter applied. Then the amplitude (absolute) value has been computed. They were assembled as the feature vector of the given face. Two scales and four orientations have been considered. This can produce a small in size efficient in energy feature vector components. These feature vectors are then applied to Feature Eigen Face (FEF) algorithm that depends on PCA approach to produce the Eigen faces that used in recognition.

To generate the Gabor filter bank the following equations were followed.

$$g(x,y) = \left(\frac{f^2}{\pi \times \text{gama} \times \text{eta}}\right) exp(bete^2 \times yprime^2 - alpha^2 \times xptime^2)\, exp(i\, 2\pi \times f \times xprime) \quad \textbf{(1)}$$

$$xptime = x\cos(theta) + y\sin(theta) \quad \textbf{(2)}$$

$$yprime = y\cos(theta) - x\sin(theta) \quad \textbf{(3)}$$

Where f represents the frequency of the sinusoid function, theta is the orientation of the Gabor function. Alpha and bete values specify the sharpness of the Gaussian along x and y axis. And eta is the spatial ratio specifying the ellipticity of the Gabor function.

Then these filter banks are convoluted with the facial images and only the first components of convoluted each filter is used. The absolute value of the complex generated numbers is used and it is computed by:

$$abs(x) = \sqrt{real(x)^2 + imag(x)^2} \quad \textbf{(4)}$$

The details of extracting the features utilized Gabor filter are shown in algorithm 1.

Algorithm (1): Feature extraction by Gabor Filter algorithm

Input: *in* 2D array of data. Gs set of gabor filters.

Output: Fv feature vector.

Begin

Step1: Get s and v values; //the scale and orientation of the Gabor filter from Gs set.

Step2: initialize r set of s by v groups as a result set.

Step3: for all filters convolute with the original data.

$$r(s_i, v_j) = in \otimes Gs(s_i, v_j) \qquad where\ i = 1..s,\ j = 1..v.$$

Step4: initialize Fv vector as a feature vector

Step5: from all r sets get the DC values and compute its magnitude value by:

Step5.1: compute f by:

$$f = abs\left(r(s_i, v_j)(1{,}1)\right) \qquad where\ i = 1..s\ , j = 1..v.$$

Step5.2: insert f value in the feature vector.

End.

Gabor filters bank generation is affected by factors of size, scale and orientation. Size of the filters has been reduced as much as possible to keep extracting discriminative. Scale of filters has been described by:

$$\boldsymbol{s_i = \frac{f_{max}}{(\sqrt{2})^{i-1}} \qquad where \qquad \begin{matrix} i = 1, 2, \dots, S \\ f_{max}\ is\ the\ central\ maximun\ fraguency \end{matrix}} \tag{5}$$

Orientation has been described by:

$$\boldsymbol{\theta_j = \frac{j-1}{V}\pi \qquad where \qquad j = 1, 2, \dots, V} \tag{6}$$

An example to illustrate the behavior of Gabor filter has been presented in the following. Let the size of filter be 5×5 , S number of scales is 3 and V the number of orientation is 5.

$\boldsymbol{f_{max} = 0.25}$.

$\boldsymbol{s_i = 0.25,\ 0.1768,\ 0.1250}$.

$\boldsymbol{\theta_j = 0, \frac{\pi}{5}, \frac{2\pi}{5}, \frac{3\pi}{5}, \frac{4\pi}{5}}$.

The generated filters bank has been shown in Figure-1 for real part and Figure-2 for magnitude part. Convoluted these filters with the image in Figure-3 reducing the set of convoluted images is shown in Figure-4 for the magnitude part of the features while Figure-5 shows the real part of the results.

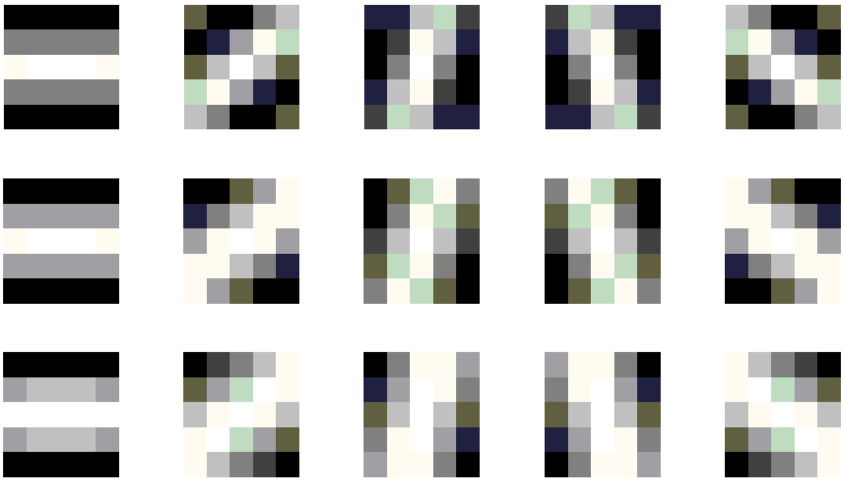

Figure 1- Real part of Gabor filter with three scales and five orientations

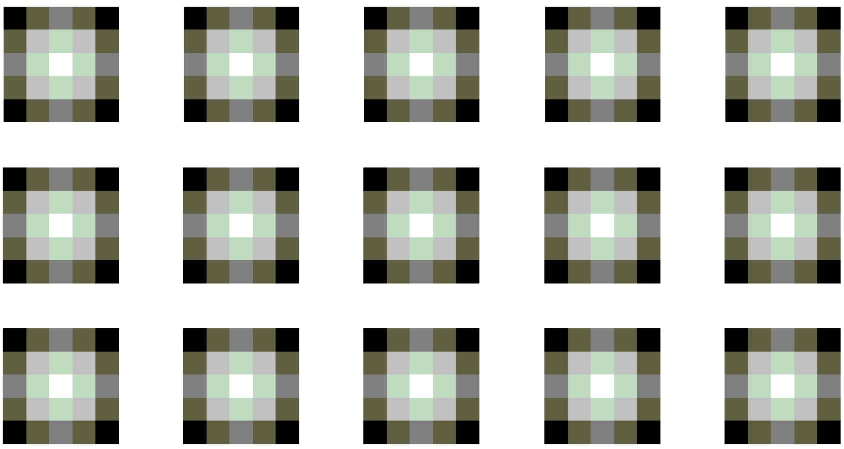

Figure 2- Magnitude part of Gabor filter with three scales and five orientations.

Figure 3- Facial image from Faces94 database.

Figure 4- Magnitude part of convoluted set of Gabor filters with facial image in Figure-3.

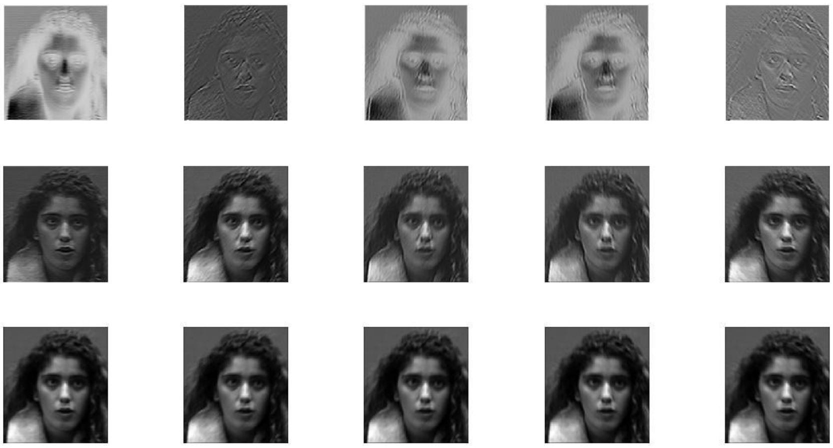

Figure 5- Real part of convoluted set of Gabor filters with facial image in Figure-3.

3. Implementations and test results.

The software to implement and test the proposed method is Matlab® 2010a. The database FACES94 is used in testing. The database has images of 153 individuals grouped to male, female and male_staff each has 20 image taken while he/she is spoken with a little variation to positon. The image is colored with resolution of 180×200. In the work the images are converted to grayscale images as a first step.

Several points have been considered to reduce the computational complexity. The computational complexity of Gabor filter is $O(N^2 \times M^2)$ where N is the dimensions of image and M is the dimensions of mask filters.

The filters are stored separately that enable the convolution to be done separately for each filter. By this separation the convolution time and complexity has been reduced significantly.

The representation of Gabor filters with the variation of scale and orientation means the relation between pixels masked by the filter (i.e. the pixels that effected by the mask filter). The distribution of the effectiveness of mask filters is shown in Figure-6 where columns represent scale value and rows represent orientation value.

The complete Gabor filter effectiveness on the image can be indicating by the distribution of magnitudes shown in Figure-7. Convolution with filter in this shape with complicated merging of the energy of the filters is expensive in both time and space. The choice to deal with each filter separately for convolution has been the choice in this work.

Depending on the application, researchers have freedom to use the real value or the magnitude value of the convoluted images by filters. For feature extraction the magnitude value (absolute) of the convoluted image by filters is used. Since this value has the whole energy of each component. That served to represent compressed (packed) energy of each component.

From the above example, when the image is of resolution 128×128 and there are 15 Gabor filter then there are $128 \times 128 \times 15 = 245{,}760$ components of features in the feature vector. This is extremely large numbers. Some researchers depend on down sampling the features by some factors depending on the idea that correlated features of images effect on the convoluted features. By this reduction if the down sampling is by factor 4 means 4 by rows and 4 by columns, the down sampling feature vector would have the size of $245{,}760/(4 \times 4) = 15{,}360$.

Depending on the basic definition of Gabor filter that it is Gaussian function modulated by Fourier transform, what means that the component arranged as DC and AC components. DC components have the most energy of the filter. The proposed method has been depending on this idea to reserve the DC component of each filter to represent the discriminative feature in the feature vector. That means the down sampling has been done in the factor of the size of the convoluted image. The feature vector size has been in the size of the number of filters. For this experiment it would be 15 components in feature vector.

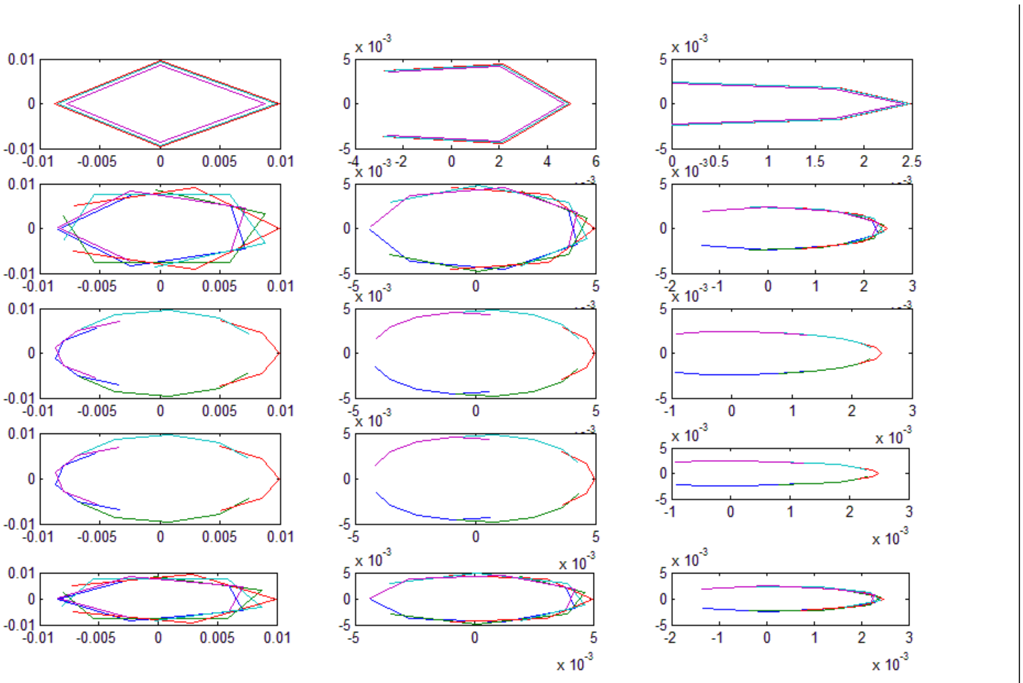

Figure 6- set of Gabor filters with 3 scales and 5 orientations (for each filter x axis is represented the x values and y axis is represented the y values).

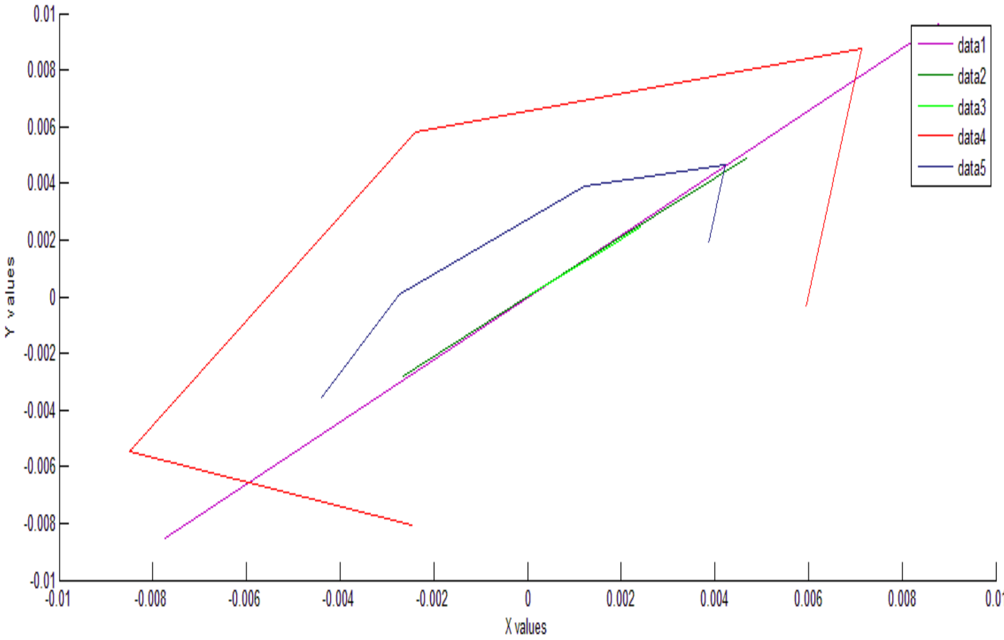

Figure 7- Effectiveness of the whole set of Gabor filters

Then this partially feature vector is applied to FEF algorithm to compute the Eigen faces. Experiments with training set of 100 images (10 images per individual) and testing set of 216 images (12 images per individual) are shown in Table-1. These experiments showed the effects of the scale, orientation and filter size on recognition rate and number of selected FEFs in FEF algorithm.

Table 1-Varying in scales, orientation, filter size on recognition rate, and number of selected FEVs of GB method

Trail	*Scale ranges*	*Orientation ranges*	*Filter size*	*Transmitted data size without the header*	*Number of selected FEVs*	*Recognition rate (%)*
1	2	2	3X3	4	4	98.6
2	2	3	3X3	6	6	99
3	2	4	3X3	8	8	96
4	2	5	3X3	10	2	98.1
5	3	2	3X3	6	1	96.4
6	3	3	3X3	9	2	96.8
7	3	4	3X3	12	2	98
8	3	5	3X3	15	2	98.6
9	3	5	5X5	15	5	100
10	3	5	7X7	15	8	97
11	3	5	9X9	15	9	94.6
12	3	5	39X39	15	15	63.33
13	4	5	5X5	20	5	97.6

The experiments have indicated that in trail 9 where the filter size is 5X5 with 3 scales and 5 orientations is the best choice since the recognition rate reaches to 100% with traveling feature vector of size 15 and the selected FEVs would be 5. As noticed from Table-1 that small changes in recognition rate occurs but the effect of increasing the orientations effects well on both recognition and selected number of FEVs Which means that the elements of traveling feature vector have significant valuable values that served the FEF algorithm to select valuable Eigen values that work well in recognition.

As seen that enlargement the filter size has not helping. Trails 8, 9, 10, 11 and 12 shows that large number has not served FEF algorithm to select completely meaningful FEFs to represent the feature space well and the recognition rate has been decreased.

In short, sufficient filter size was required which it is 5X5 and the effect of increasing the orientations is more than increasing scales.

The performance of this method has been appeared in two ways: recognition rate and the selected FEVs which mean that the features selected have a high energy that the selected FEVs is contented in size and energy.

The method has been tested over several sets of training and testing dataset. Each training dataset has different numbers of images per individual. Experiments have shown that there is no effect of increasing the number of training images per individual for more than two images in recognition criteria. And no effect at all in the number of selected FEFs. Table-2 describes the results in details.

Table 2- Recognition rate with FEFs number per different number of trained images in GB method

Number of Images used in Training (per individual)	*Number of Images used in Testing (per individual)*	*Number of FEFs*	*Recognition Rate (%)*
1	12	4	98
2	12	4	100
5	12	4	100
10	10	4	100

Testing with the trail of training over 2 images per individual is illustrated by the testing of two examples. Testing for an authenticated individual shown in Figure-8a and the distance errors with the FEFs is shown in Figure-8b. It is clear that recognizing the faces is obviously discriminatory to the classes. And testing for unauthenticated individual shown in Figure-9a and the distance errors with the FEFs is shown in Figure-9b. It is clear that all the values are high (i.e exceed the threshold value).

The experiments over only PCA give a resolution of 95% and recorder a longer time in computing FEFs. This is due to size of input to the FEF algorithm.

Figure 8- a: input tested facial image of authorized individual.

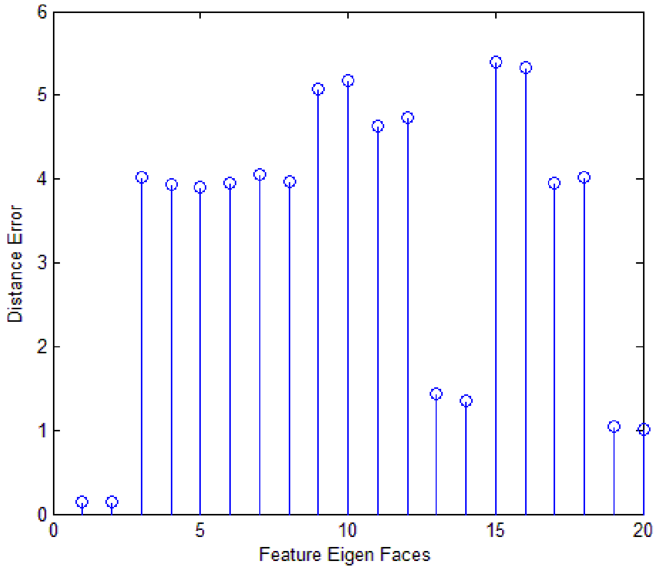

Figure 8- b: **b** Euclidean distance of the testing image in a with FEF manipulated by Gabor filter.

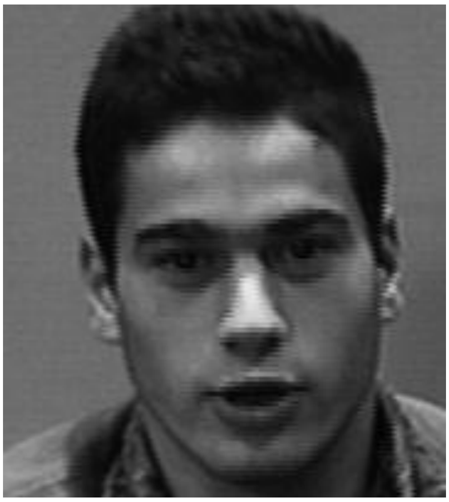

Figure 8- a: input tested facial image of unauthorized individual.

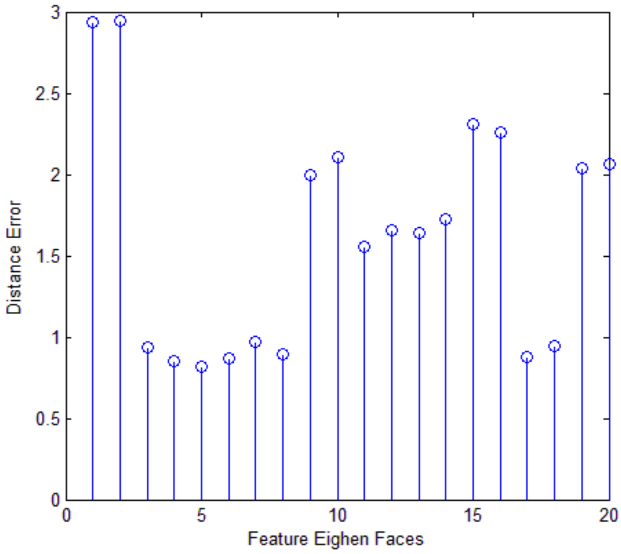

Figure 8-b: Euclidean distance of the testing image in a with FEF manipulated by Gabor filter.

4. Conclusion.

This paper has presented a face recognition technique based of hybrid method of Gabor filter and computing Eigen faces. The experiments show that the number of training images per individual is playing an important role in the accuracy of recognition. Also, the parameters of Gabor filter of scale, orientation and filter size are effecting clearly on the recognition rate and the number of selected Eigen faces.

The suggested system is fast and has less computation than using PCA approach only to compute Eigen faces. Reducing the computational complexity of Gabor filter is depended in the suggested method by selection the minimum filter size that can produce a good recognition rate reaches to 100%. The aspects of speed and simplicity give the approach the tendency to be suitable in real time system and multimedia network communication as well as to implement it on low cost hardware implementations. As a future work other feature extraction method can be combined with it to produce faster and more accurate recognition.

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