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Face recognition approach using Gabor Wavelets, PCA and SVM

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Abstract

Face recognition is an important research field of pattern recognition. Up to now, it caused researchers great concern from these fields, such as pattern recognition and computer vision. In general, we can make sure that the performance of face recognition system is determined by how to extract feature vector exactly and to classify them into a class correctly. Therefore, it is necessary for us to pay close attention to feature extractor and classifier. In this paper, we propose a methodological improvement to raise face recognition rate by fusing the phase and magnitude of Gabor's representations of the face as a new representation, in the place of the raster image, although the Gabor representations were largely used, particularly in the algorithms based on global approaches, the Gabor phase was never exploited, followed by a face recognition algorithm, based on the principal component Analysis approach and Support Vector Machine (SVM) is used as a new classifier for pattern recognition. The performance of the proposed algorithm is tested on the public and largely used databases of FRGCv2 face and ORL databases. Experimental results on databases show that the combination of the magnitude with the phase of Gabor features can achieve promising results.

Keywords: *Biometrics, Principal components Analysis, Eigen face, Identification of the face, Gabor,SVM.*

1.INTRODUCTION

The safety of persons, goods or information is one of the major preoccupations our societies today. Also, the great weakness of the current means of identity verification is clear here: the identity of a person is directly related to what it owns (a passport, magnetic badge, etc…). However, a badge can be stolen, guessed password or broken by brute strength algorithms: this leads to identity theft.

Face recognition is considered to be an important part of the biometrics technique, and meaningful in scientific research [15]. It is the ability to establish a subject's identity based on his facial characteristics. Automatic face recognition has been extensively studied over the past two decades due to its important role in a number of application domains, such as access control, visual surveillance [1].

Many achievements have been made since the problem was proposed. Matthew Turk et al. [16] presented a near-real-time face recognition system by introducing Eigen faces in facial image feature extraction. Chengliang Wang, Libin Lan, Yuwei Zhang and Minjie Gu [17] proposed an effective recognition technique using Principle Component Analysis and Support Vector Machine. Face recognition using Gabor filters was firstly introduced by Martin Lades et al. [18], and soon proved to be a very effective means in human facial features extraction. Xiao-ming [13] proposed a face recognition algorithm combined a vector features consisting of the magnitude of Gabor, PCA and for classification SVM.

In general, a lot of methods are proposed to overcome the difficulty of face recognition. A good face recognition methodology should consider representation as well as classification issues, and a good representation method should require minimum manual annotations.

In this paper, we proposed a face recognition system that combines magnitude and the phase of Gabor filter, PCA and SVM as a classifier.

This paper is organized as follows. In Section 2 we explain the detection face. The section 3 we describe the Gabor wavelet. Section 4 presents the Eigen face approach. Section5 introduce Support Vector Machine (SVM). Section 6 gives the experimental results of the proposed method tested on the public and largely used databases of FRGCv2 face and ORL. Conclusions and perspective works are given in Section 7. This process of training and recognition is shown in Figure 1:

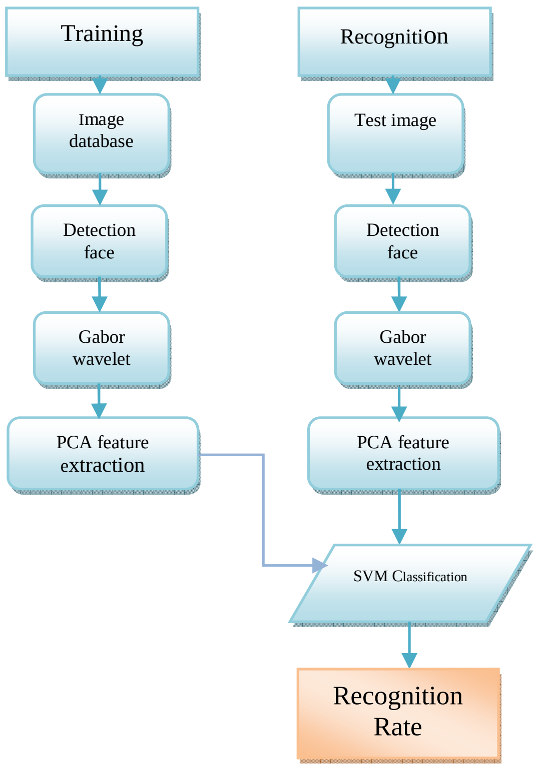

Figure 1. Recognition Process

2. Detection Face

Detecting human faces from an image is a key problem in various face-related applications such as face tracking, face recognition, facial expression recognition, etc. The purpose of face detection is to determine whether or not there are any faces in an image and, if any, the location of each face is shown. We have used Open CV to detect faces in our database FRGCv2 and ORL.

Open CV is an open source computer vision library which is written in C and C++ and runs under Linux, Windows and Mac OS X[12]. The object detector of Open CV has been initially proposed by Paul Viola and improved by Rainer Lienhart [8].

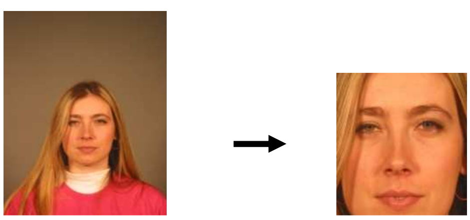

Figure 2. Detection face with open cv

3.GABOR WAVELET

The Gabor wavelet, which captures the properties of orientation selectivity, spatial localization and optimally localized in the space and frequency domains, has been extensively and successfully used in face recognition [3]. Daugman pioneered the using of the 2D Gabor wavelet representation in computer vision in 1980's [2].

Gabor wavelets (filters) characteristics for frequency and orientation representations are quite similar to those of human visual system. These have been found appropriate for texture representation and discrimination. This Gabor-wavelet based extraction of features directly from the gray-level images is successful and widely been applied to texture segmentation, and fingerprint recognition. The commonly used Gabor filters in face recognition area [3],[4] are defined as follows Eq. (1)

$$\Psi_{\mu,v}(\boldsymbol{z}) = \frac{||\mathbf{k}_{\mu,v}||^2}{\sigma^2} e^{(-||\mathbf{k}_{\mu,v}||^2 ||\mathbf{z}||^2/2\sigma^2)} \left[e^{i\mathbf{k}_{\mu,v}\mathbf{z}} - e^{-\frac{\sigma^2}{2}}\right] \quad (1)$$

Where:

μ and v define the orientation and the scale of the Gabor filters, z = (x, y) and $k_{\mu,v}$ is defined as following form Eq. (2):

$$k_{\mu,v} = k_v e^{i\varphi u} \quad (2)$$

k_v = kmax/f^v and $\varphi u = \pi\mu/8$. kmax is the maximum frequency, and f is the spacing factor between kernels in the frequency domain. Usually, σ = 2π, kmax = π/2 and f = √2. In this paper, μ ∈ {0, 1... ,7} and v ∈ {1, 2, 3, 4}.

The Gabor wavelet representation of a face image is obtained by doing a convolution between the image and a family of Gabor filters as described by Eq. (3). The convolution of image I(z) and a Gabor filter $\Psi_{\mu,v}(z)$ can be defined as follows:

$$F_{\mu,v}(z) = I(z) \times \Psi_{\mu,v}(z) \quad (3)$$

Where z = (x, y), * denotes the convolution operator, and $F_{u,v}(z)$ is the Gabor filter response of the image with orientation u and scale v.

The solutions suggested on each level of this chain resulted in a significant improvement of the performances compared to the traditional approaches. For the recognition algorithms, we proposed to fuse the phase and the magnitude of Gabor's representations of the face as a new representation, in the place of the raster image. Although the Gabor representations were largely used, particularly in the algorithms based on global approaches, the Gabor phase was never exploited.

Convolving the image with these 40 Gabor kernels can then generate the Gabor features. The magnitudes and the phases are used to form the final face representation. The input image is a facial image that is geometrically normalized and whose size is 64*64 pixels. So, the size of our vector is (64*64*40*2) too large to solve this problem we are going to sample it.

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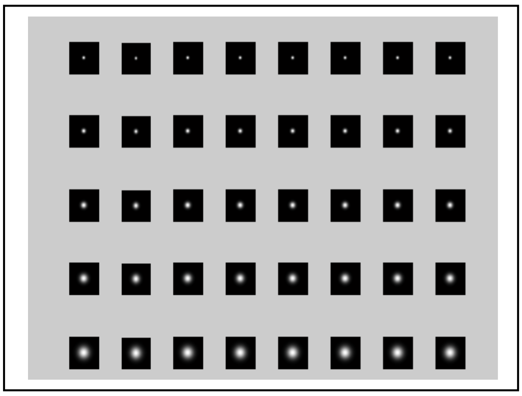
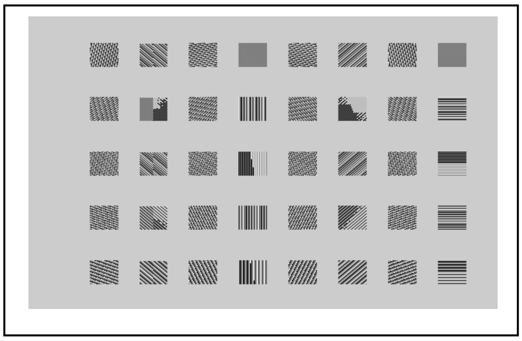


(a)



(b)

Figure 3. The magnitude part of the representation. (b) The phase part of the representation.

4. PRINCIPAL COMPONENT ANALYSIS"PCA"

Which is also known as Karhunen-Loeve expansion, is a classical feature extraction and data representation technique, and this technology is widely used in the areas of pattern recognition and computer vision [3]. Principal component analysis is proposed by Turk and Pentland in 1991, which is often used for extracting features and dimension reduction. In this paper, the PCA face recognition algorithm is used to extract the eigenvectors of the face images.

In mathematical terms, we wish to find the principal components of the distribution of faces, or the eigenvectors of the covariance matrix of the set of face images, treating an image as a vector in a very high dimensional space [5].

During this phase, we load the database. In general, we apply many transformations before loading. Indeed, the signal contains information useful to the recognition and only the relevant parameters are extracts. The model is compact representations of the signal which make ease the phase of recognition, but also reduce the quantity of data to be stored Eq. (4):

$$\begin{pmatrix} a_{1,1} & \cdots & a_{1,m} \\ \vdots & \ddots & \vdots \\ a_{n,1} & \cdots & a_{n,m} \end{pmatrix} \longrightarrow \begin{pmatrix} a_{1,1} \\ \vdots \\ a_{n,1} \\ \vdots \\ a_{1,m} \\ \vdots \\ a_{n,m} \end{pmatrix} \qquad (4)$$

Then, let the training set of face images be $\Gamma_1, \Gamma_2, \Gamma_3\ldots, \Gamma_M$. The average face of the set is defined by Eq. (5)[6]:

$$\Psi = \frac{1}{M}\sum_{i=1}^{M} \Gamma_i \qquad (5)$$

Each face differs from the average by the vector Eq. (6):

$$\Phi_i = \Gamma_i - \Psi,\ i = 1\ldots M \qquad (6)$$

In the next step the covariance matrix C is calculated according to Eq. (7):

$$C = \sum_{i=1}^{N} \Phi_i \Phi_i^T = A\,A^T \qquad (7)$$

The matrix C is N^2 by N^2, and determining the N^2 eigenvectors and Eigen values is an intractable task foe typical image sizes. We need a computationally feasible method to find these eigenvectors Eq. (8):

$$\begin{pmatrix} e_i = & Av_i \\ \lambda_i = & \mu_i \end{pmatrix} \qquad (8)$$

From M eigenvectors (Eigen faces) e_i, only M_1 should be chosen, which have the highest Eigen values. The higher the Eigen value, the more characteristic features of a face does the particular eigenvector describe. Eigen faces with low Eigen values can be omitted, as they explain only a small part of characteristic features of the faces. After M_1 Eigen faces e_i are determined, the 'training' phase of the algorithm is finished.

The process of classification of a new (unknown) face Γ_{new} to one of the classes (known faces) proceeds in two steps.

First, the new image is transformed into its Eigen face components. The resulting weights form the weight vector Ω_T Eq. (9) [6]:

$$W_k = e_k^T (\Gamma_{new} - \Psi),\ k = 1\ldots\ldots\ldots.M',\ \Omega_T = [w_1, w_2, ..., w_{M'}] \qquad (9)$$

The weights form a vector $\Omega_T = [w_1, w_2... w_{M'}]$ that describes the contribution of each Eigen face in representing the input face image, treating the Eigen faces as a basis set for face images. The vector may then be used in a standard pattern recognition algorithm to find which of a number of predefined face classes, if any, best describes the face. The used method for determining which face class provides the best description of an input face image is the support vector machines: SVM.

5.SUPPORT VECTOR MACHINES

Support vector machines are learning machines that classify data by shaping a set of support vectors [10]. SVMs provide a generic mechanism to robust the surface of the hyper plane to the data through. Another benefit of SVMs is the low expected probability of generalization errors [11]. Moreover, once the data is classified into two classes, an appropriate optimizing algorithm can be used if needed for feature identification, depending on the application [12]. SVM creates a hyper-plane between two sets of data for classification; in our work, we separate the data into two classes: face belongs to the train database and face doesn't belong to the train database. Input data X that fall one region of the hyper-plane, (XT•W– b) > 0, are labeled as +1 and those that fall on the other area, (XT•W– b) < 0, are labeled as -1.

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We seek the linear classifier that separates the data with the lowest generalization error. Intuitively, this classifier is a hyper plane that maximizes the margin error, which is the sum of the distances between the hyper plane and positive and negative examples closest to this hyper plane.

We consider the example in (a) where there are many possible linear classifiers that can separate the data, but there is only one that maximizes the margin shown in (b). This classifier is termed the optimal separating hyper-plane (OSH).

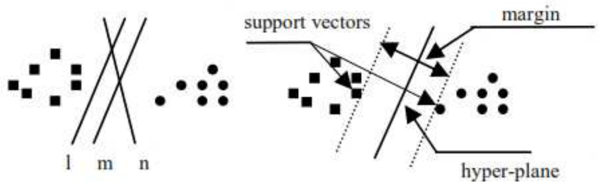

Figure 4. (a) Arbitrary hyper-planes: l, m, n; (b) Optimal hyper-plane

6. EXPERIMENT AND RESULTS

Our system is a system of identification, so the system must guess the identity of the person. The system compares the vector characteristic of the test image with the different models contained in the database (type of problem 1: n) using the Euclidean distance or the SVM classifier.

In identification mode, we talk about open problem since it is assumed that an individual has no model in the database (impostor) may seek to be recognized. So, you're doing a study on the database of learning for the appropriate threshold θ which allows us to identify whether that person is in our database or not he is an imposter.

The execution of the biometric system is estimated by measuring the rate of false acceptance (FAR) Eq. (10), the rate of false rejection (FRR) Eq. (11) and the equal error rate (ERR) Eq. (12).

$$FAR = \frac{\text{false acceptance numbers}}{number\ of\ impostors} \quad (10)$$

$$\text{FRR} = \frac{\text{false rejection numbers}}{\text{number of customers}} \quad (11)$$

$$EER = \frac{\text{false acceptance numbers+ false rejection numbers}}{Total\ number} \quad (12)$$

To illustrate the efficiency of the system, we use two database a color database FRGC face and grayscale database ORL face.

The FRGC consisted of progressively difficult challenge problems. Each challenge problem consisted of a data set of facial images and a defined set of experiments. One of the impediments to developing improved face recognition is the lack of data. The FRGC challenge problems include sufficient data to overcome this impediment. The set of defined experiments assists researchers and developers in making progress on meeting the new performance goals [7].

The ORL have ten different images of each of 40 distinct subjects. For some subjects, the images were taken at different times, varying the lighting, facial expressions (open / closed eyes, smiling / not smiling) and facial details (glasses / no glasses) [9].

Figure 5. FRGC Face

Figure 6. ORL Face

The design of a system of pattern recognition requires a basis of learning and a validation to assess the performance of the method.

The FRGC distribution consists of six experiments. In our work, we use two experiments 1 and 4.

In experiment 1, the gallery consists of a single controlled still image of a person and each probe consists of a single controlled still image. Experiment 1 is the control experiment [7].

In experiment 4, the gallery consists of a single controlled still image, and the probe set consists of a single uncontrolled still image [7].

ROC graphs are two-dimensional graphs in which FRR and FAR rate is plotted on the Y axis and Threshold is plotted on the X axis. The figure 7 below shows the ROC curve applied in the FRGC database:

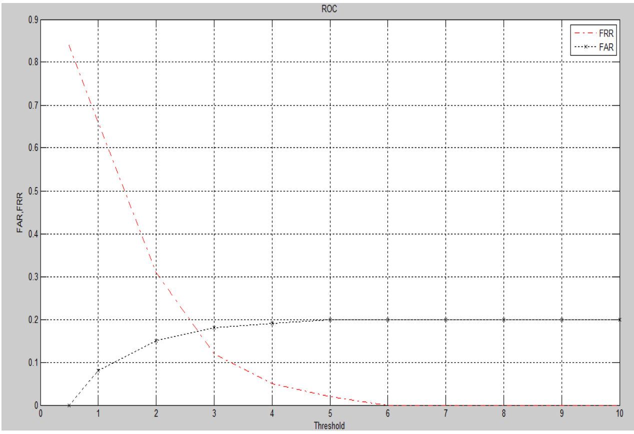

Figure 7. Curve ROC of the ORL database.

We note that both error rate FRR and FAR are inversely proportional increases if FRR increases FAR decreases, therefore we must choose a compromise between FAR and FRR. We can conclude from this figure that the threshold is $2.7*10^{13}$

The figure 8 below shows the ROC curve applied in the ORL database:

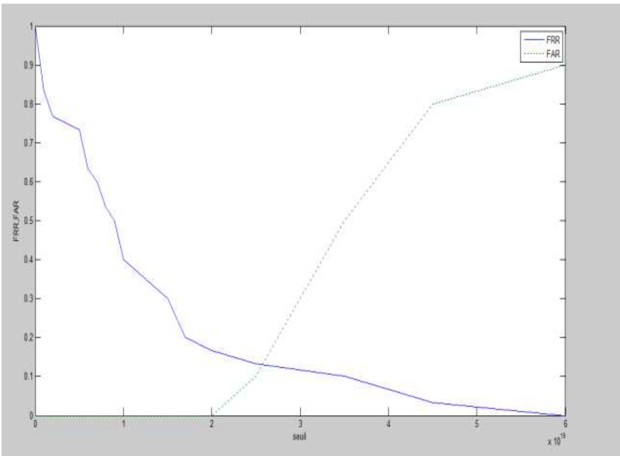

Figure 8. Curve ROC of the ORL database.

we can conclude from this figure that the threshold is $2.5*10^{19}$

In the first part of experiment we have use only the algorithm PCA. The input image is a face image detected with Open CV and normalized geometrically so the size of the face is 64*64 pixels.

Table 1 gives the equal error rate after using PCA with the experience 1 and the experience 4 of the FRGC database.

The first protocol P1 evaluates performance comparison of images (reference and tests) belonging to sessions to acquire the same semester. The second protocol P2 evaluates performance testing sessions belonging to image acquisition two consecutive semesters and one last test P3 performance of image reference and test, separated by a year.

Tables I and II list the equal error rates for the FRGC and ORL databases, respectively.

TABLE I. ERR OF PCA FOR THE FRGC DATABASE

		EER
Exp 1	***P1***	0.26
Exp 1	***P2***	0.53
Exp 1	***P3***	0.41
Exp 2	***P1***	0.81
Exp 2	***P2***	0.8
Exp 2	***P3***	0.9

TABLE II. ERR OF PCA FOR THE ORL DATABASE

	EER
30 features	0.2

According to tables I and II, we have EER very high which makes the application less reliable. This is due to the influence of the change of light and change poses to our database on Eigen face, which leads us to try to reduce its error rate with using Gabor features. For the second table, the error rate has clearly decreased. It notes that use of the magnitude and the phase to represent face has an important influence on the performance of the application and the improvement of error rates.

Tables III and IV give the equal error rate after using the magnitude and phase of Gabor to extract the characteristic vector, the algorithm of recognition PCA and for classification we use Euclidian distance.

TABLE III. ERROR RATE FOR FUSING MAGNITUDE ET PHASE OF GABOR, PCA AND EUCLIDIEN DISTANCE FOR THE FRGC DATABASE

		EER
Exp 1	***P1***	0.17
Exp 1	***P2***	0.33
Exp 1	***P3***	0.20
Exp 2	***P1***	0.26
Exp 2	***P2***	0.3
Exp 2	***P3***	0.4

TABLE IV. ERR FOR FUSING MAGNITUDE ET PHASE OF GABOR, PCA AND EUCLIDIEN DISTANCE FOR THE ORL DATABASE

	EER
30 features	0.005

Tables V and VI give the equal error rate after using the magnitude and phase of Gabor to extract the characteristic vector, the algorithm of recognition PCA and for classification we use SVM.

TABLE V. ERROR RATE FOR FUSING MAGNITUDE ET PHASE OF GABOR, PCA AND SVM FOR THE FRGC DATABASE

		EER
Exp 1	***P1***	0.09
Exp 1	***P2***	0.18
Exp 1	***P3***	0.11
Exp 2	***P1***	0.13
Exp 2	***P2***	0.15
Exp 2	***P3***	0.20

TABLE VI. ERR FOR FUSING MAGNITUDE ET PHASE OF GABOR, PCA AND SVM FOR THE ORL DATABASE

	EER
30 features	0.001

These tables show that the error rate has clearly decreased. It notes that using the SVM to classify faces have an important influence on the performance of the application and the improvement of the error rates.

The protocol used for learning and the test varies from one section to another. It is therefore difficult to compare the error of classification.

In Table 7, we present the comparison of techniques to achieve the same goal as this paper. Thus, in [13], Xiao-ming reported recognition rate of classification 99.5% it means 0.005 error rate on the database ORL, using a vector features consisting of the magnitude of Gabor, PCA and for classification SVM. Also [14], Li Xianwei pointed out recognition rate of classification 85% it means 0.25 error rate on the database ORL, using a vector features consisting of PCA and for classification SVM. As well, Amjath Fareeth Basha shows the percentage of 98 % using 1-D Continuous wavelet transform (CWT) on the facial images and SVM [19] on the database ORL. The classification rate of our technique is superior to the rest up to techniques.

TABLE VII. COMPARISON BETWEEN THE EXISTING METHODS AND THE PROPOSED

Authors	Techniques	Recognition Rate
Xiao-ming	Magnitude of Gabor, PCA and SVM	99.5%
Li Xianwei	PCA and SVM	85%
Amjath Fareeth Basha	CWT SVM	98 %
Our Method	Magnitude and phase of Gabor, PCA and SVM	99.9%

7.CONCLUSION

The algorithm PCA is a global method using primarily the grayscale pixels of an image. The simplicity to implement this algorithm contrasts with a strong sensitivity to changes in lighting, poses and facial expression. That is why we increase the number of poses for each person. Nevertheless, the PCA requires no a priori knowledge on the image.

Our approach consists on combining the magnitude and the phase of Gabor to extract the characteristic vector, the algorithm PCA for recognition and SVM to classify faces.

The principle that you can construct a sub-vector space retaining only the best eigenvectors, while retaining a lot of useful information, makes the PCA an algorithm effective and commonly used in reducing dimensionality where it can then be used to upstream other algorithms to improve the results of our application.

To conclude, we can say that the recognition of individuals remain a complex problem, in spite of current active research. There are many conditions real, difficult to model and envisage, which limit the performances of the current systems in terms of reliability and real time.

As future work, we propose the implementation of such an algorithm on a target technology in order to benefit from the performances provided by this technology.

REFERENCES

[1] Anil K. Jain, Brendan Klare and Unsang Park, "Face Recognition: Some Challenges in Forensics", in IEEE International Conference Automatic Face & Gesture Recognition and Workshops (FG 2011), 2011 , pp. 726-733.

[2] Zhao Lihong, Yang Caikun, Pan Fen, Wang Jiahe, "Face Recognition Based on Gabor with 2DPCA and PCA", in Control and Decision Conference (CCDC), 2012 24th Chinese, pp. 2632-2635.

[3] Jian Wang, Jian Cheng, "FACE RECOGNITION BASED ON FUSION OF GABOR AND 2DPCA FEATURES", IN International Symposium on Intelligent Signal Processing and Communication Systems, December 2010, pp. 1-4.

[4] C.MageshKumar, R.Thiyagarajan, S.P.Natarajan, S.Arulselvi, "Gabor features and LDA based Face Recognition with ANN classifier", In International Conference Emerging Trends in Electrical and Computer Technology (ICETECT), 2011, pp. 831 - 836.

[5] Nicolas Morizet, Thomas EA, Florence Rossant, Frederic Amiel, Amara Amara, Revue des algorithmes PCA, LDA et

EBGM utilises en reconnaissance 2D du visage pour la biometrie Institut Superieur d'electronique de Paris (ISEP), Departement d'electronique, 2007.

[6] Martinez, A.M, "Recognition of Partially Occluded and/ or Imprecisely Localized Faces Using Probabilistic Approach", Proceeding of IEEE Computer Vision and Pattern Recognition, 2000, pp. 712 - 717.

[7] http://www.nist.gov/itl/iad/ig/frgc.cfm

[8] http://docs.opencv.org/modules/objdetect/doc/cascade_classification.htm

[9] http://www.face-rec.org/databases

[10] Feng Jiao, Wen Giao, Lijuan Duan, and Guoqin Cui, "Detecting adult image using multiple features", In IEEE conference Info-tech and Info-net, 2001, pp.378 - 383.

[11] Joachims T, Making Large-Scale SVM Learning Practical. LS8-Report, University of Dortmund, LS 1998

[12] Vladimir VN, The Nature of Statistical Learning Theory. Springer, Berlin Heidelberg New York, 1995.

[13] Xiao-ming Wang, Chang Huang, Guo-yu Ni, Jin-gao Liu, "Face Recognition Based on Face Gabor Image and SVM", in 2nd International Congress Image and Signal Processing, 2009, pp.1 - 4.

[14] Li Xianwei, Chen Guolong, "Face Recognition Based on PCA and SVM", In IEEE conference Photonics and Optoelectronics (SOPO), 2012, pp.1 - 4.

[15] Jiarui Zhou, Zhen Ji, Linlin Shen, Zexuan Zhu and Siping Chen, "PSO Based Memetic Algorithm for Face Recognition Gabor Filters Selection", IEEE Conference Memetic Computing (MC), 2011, pp.1 - 6.

[16] M.A. Turk and A.P. Pentland, "Face recognition using eigenfaces", In IEEE Conference on Computer Vision and Pattern Recognition, Hawaii, 1991, pp.586-591.

[17] Chengliang Wang, Libin Lan, Yuwei Zhang and Minjie Gu, "Face Recognition Based on Principle Component Analysis and Support Vector Machine", In IEEE Conference Intelligent Systems and Applications (ISA), 2011, pp.1-4.

[18] M. Lades, J.C. Vorbruggen, J. Buhmann, et al, "Distortion invariant object recognition in the dynamic link architecture", IEEE Transactions on Computers, 1993, pp. 300-311.

[19] Amjath Fareeth Basha, Gul Shaira Banu Jahangeer, "Face Gender Image Classification Using Various Wavelet Transform and Support Vector Machine with various Kernels", International Journal of Computer Science Issues, Vol. 9, Issue 6, No 2, November 2012, pp; 150-157.