A Face Identification Algorithm using Two Dimensional Principal Component Analysis Based on Wavelet Transform

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Abstract— **Face is the most common biometric used by humans, its applications range from static, mug-shot verification to a dynamic, uncontrolled face identification in a cluttered background. The main objective of this paper is to construct an effective human face identification system. The presented algorithm combines the scaling process, histogram equalization process, wavelet transform process, two dimensional principal component analysis (2DPCA) process, and support vector machine (SVM) methods to construct a human face identification algorithm. In the presented algorithm, the size normalized and histogram equalized human face images are divided into smaller sub-images by the wavelet transformation, the 2DPCA scheme is applied on LL sub-images to extract the features of human face image, and the SVM classifier is used to do the final identification. The experimental results show that the presented algorithm has good efficiency for human face identification.**

Keywords— **face Recognition, 2DPCA(2D Principal Component Analysis), wavelet transform, histogram equalization**

1. INTRODUCTION

The rapidly increasing commercial, law-enforcement applications and accessibility of practical technologies have caused the evolution of computer vision research **[1, 2]**. Face identification is one of the most distinguished achievements in human vision. Although the face accuracy rate of identification is less than the IRIS, fingerprint identification, but due to its non-invasive characteristic, audience characteristics, most intuitive way, so that the face identification is the most likely be accepted way in biometric recognition. Face identification is a popular research area of computer vision research; it has grown into wide range of commercial products from small size research system. Face identification is one of the biometric applications, in which a user's identity is identified automatically based on the face database. The face database contains templates that are used to identify corresponding customers. An unknown customer's identity will be determined by using the templates' similarity matching. On the other hand, the progressive machine visual learning technique has confident police and national defense to set surveillance systems at migration hot spots to automatically identify customers **[3, 4]**.

There are two categories in face identification technologies: global scheme and component-based scheme **[5]**. In the global scheme, a single feature vector of the whole face region is used as the input of the identification system. Global schemes work well for classifying frontal views of faces. But, they are not robust against pose changes since global features are very sensitive to translation and rotation of the human face. To overcome this problem, an alignment stage is always added before classifying the face. The component-based scheme is to classify local facial components **[6, 7]**. It captures and utilizes maximum variance across the training images to find a basis vector which is the most compact representation of the face. The PCAs extracted from the face image can be used as the project training data and the testing data in lower dimensional face templates. The component-based techniques also work well in identifying human faces that have different poses, and allow a flexible geometrical relation between the components in the identification stage **[8, 9]**.

The discrete wavelet transform (DWT) is a fast, linear, invertible and orthogonal operation. DWT is suitable for the analysis of non-stationary

signals since it allows simultaneous localization in time and in scale, it also decomposes the input signal into high and low frequency components in different resolutions **[10, 11]**. And, the PCAs of a human face image can be easily extracted from the DWT coefficients of the human face image.

In 1995, Vapnik first introduced a neural-network algorithm called support vector machine (SVM), which is a novel learning machine based on statistical learning theory **[12-14]**. The SVM possesses outstanding advantages; (a) the strong theoretical basis provides with high generalization capability and avoids over fitting, (b) the global model can deal with high-dimensional input vectors efficiently, (c) the solution is light and only a subset of training samples contributes to this solution, thus reducing the workload **[14]**.During recent years, due to SVM 's high generalization performance and its attractive modeling features , SVMs have received increasing attention in area of pattern identification **[15]**. In this paper, we present the implementation of support vector machine neural network (SVMNN) to identify human faces using features provided by PCA. The BPNN we proposed has been proven to be better than Euclidean distances.

To explore the utility and demonstrate the efficiency of the proposed scheme, simulations under various conditions are conducted. The experiment results show that our proposed scheme is an efficiency scheme for human face identification. The remainder of this paper is organized as follows: In Section 2, human face identification algorithm is presented. Empirical results are presented in Section 3. Finally, Section 4 concludes this paper.

2. HUMAN FACE IDENTIFICATION ALGORITHM

This paper presented a way to construct the human face identification algorithm to identify the customer's identification from an input color image. **Figure 1** is the flow chart of presented human face identification system. At the beginning of the process, the input R G B color block images are respectively normalized with 64*64 pixels square and are transformed into the YIQ domain. The Y component images Y are then equalized to Y' to enhance the image's contrast and are transformed into DWT domain by a wavelet. Figure 2 shows an original color

human face image, the three corresponding YIQ component images, and the equalized Y component image. Figure 3 shows an equalized Y component image and the lower resolution reference image LL and their associated detail images LH, HL, HH. The system takes the PCAs from the images LL, LH, HL, and HH. Finally, these PCAs are divided into training set and testing set, and are fed into the SVM to train the SVM classifier and use the trained SVM classifier to do the identification for the testing set. The detail processions are described in the follows. Figure 4 shows the LL image of a human face and several corresponding PCAs.
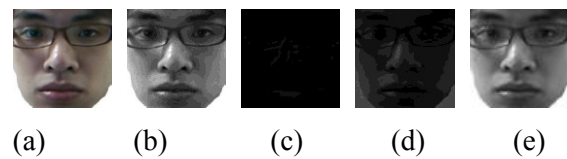

(a)   (b)   (c)   (d)   (e)

Figure 2. Input image, (a) Original color human face image, (b) Y component, (c)I component, (d)Q component, (e)Y component after histogram equalization
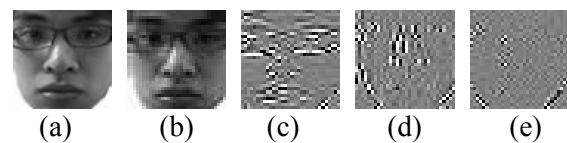

(a)   (b)   (c)   (d)   (e)

Figure 3. DWT image, (a) original Y component after histogram equalization, (b) LL component, (c)LH component, (d)HL component, (e)HH component.
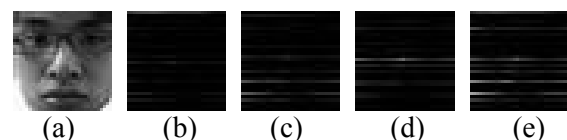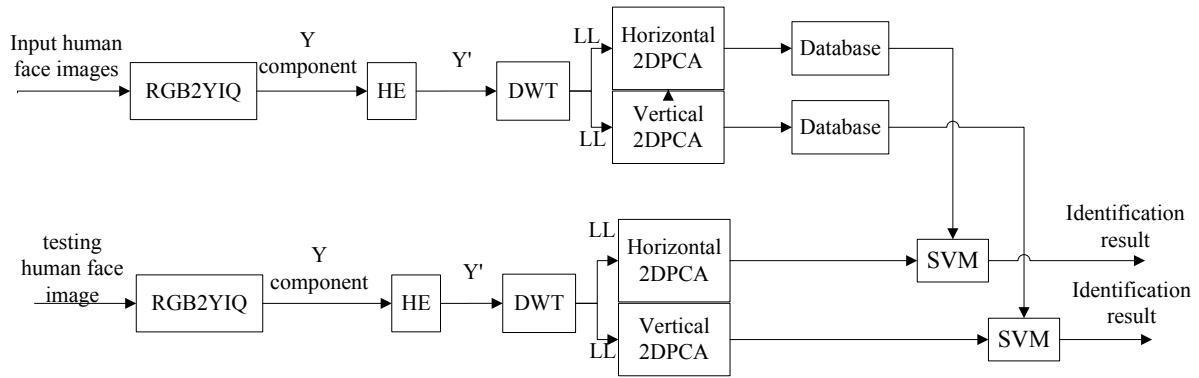

(a)   (b)   (c)   (d)   (e)

Figure 4. The LL image of a human face and its several corresponding PCs. (a)LL image, (b)PCA1 image, (c)PCA2 image, (d)PCA3 image, (e) sum image of PCA1+PCA2+PCA3

RGB2YIQ:The Transformation from RGB domain to YIQ HE : Histogram Equalization
DWT: Discrete Wavelet Transform SVM: Support Vector Machine
Horizontal 2DPCA: Horizontal 2 Dimension Principal Component Analysis
Vertical 2DPCA: Vertical 2 Dimension Principal Component Analysis

Figure 1.The flow chart of presented human face identification system.

2.1. Color Mapping RGB to YIQ

The red, green and blue (RGB) are three dimensions of illumination spectrum. They are enough to compose any color adequately, although the spectrum of illumination is infinite dimensional **[16]**. The image in RGB color space is not suitable for image processing applications, because the image in RGB color space is highly correlated. Other color models like as HIS, L*a*b*, YIQ, YUV, and YCbCr are suitable for image processing applications, they are the reducing redundancy models of the image in RGB color space, obtained by some color transform. A common alternation to the RGB representation of an image is the YIQ representation. The YIQ representation of an image is the standard model in the television transmission. The YIQ representation of an image obtained from the RGB representation of an image is given by equation (1),

$$\begin{bmatrix} Y \\ I \\ Q \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.144 \\ 0.596 & -0.274 & -0.322 \\ 0.212 & -0.523 & 0.311 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (1)$$

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} 1.000 & 0.956 & 0.621 \\ 1.000 & -0.272 & -0.647 \\ 1.000 & -1.106 & 1.703 \end{bmatrix} \begin{bmatrix} Y \\ I \\ Q \end{bmatrix} \quad (2)$$

where Y is the luminance or brightness which refers to color density, I is the hue which is the

dominant such as orange, red or yellow, and Q is the saturation or depth which is the amount of white light mixed with a hue of color. The equation (2) is the inverse transformation of equation (5), to transfer the image in YIQ planes back into the RGB planes.

Most energy of a YIQ image is concentrated in Y plane so that the Y component of an image can represent that image, and we can extract the whole features of that image from its Y component. In this paper, we take the Y component of input human face image and take the wavelet transformation on the taken Y component.

2.2. Histogram Equalization

Histogram equalization is a popular image processing technique that is used to enhance the contrast of an image. Histogram equalization redistributes the gray levels within an image such that every gray level is almost equally to occur. The procedure of histogram equalization is to find a mapping function that maps the probability density function (PDF) of an image's histogram into a uniformly distributed PDF. The input image is then scanned pixel by pixel and the mapping function maps the gray levels of each pixel to produce a histogram equalized image. The brightness and contrast of the histogram equalized images will be increased and standardized such that the features of the image

are observable. In this paper, we take the histogram equalization on the Y component image of the input human face image to standardize Y image's histogram distribution to improve the accuracy of face identification subjected to varying illumination.

2.3. Discrete Wavelet Transform

The discrete wavelet transform (DWT) is a fast, linear, invertible and orthogonal operation, just like the Discrete Fourier transform (DFT). The basic idea lying under the discrete wavelet transform is to define a time-scale representation of a signal (unlike Short Time Fourier Transform (STFT) which defines a time-frequency signal representation) by decomposing it onto a set of basic functions, called wavelet. Wavelets are obtained from a single prototype wavelet, called mother wavelet, by dilations and contractions, that is, scaling, and shifts **[17, 18].** DWT is suitable for the analysis of non-stationary signals since it allows simultaneous localization in time and in scale, unlike STFT which uses fixed time-frequency resolution and thus allows localization only in time or in frequency. Application of DWT results in a multilevel decomposition of the input signal into high and low frequency components in different resolutions according to the number of levels employed, as shown in Figure 5 (a). Let $H(\omega)$ and $G(\omega)$ be a lowpass and highpass filter, respectively,

$$H(\omega) = \sum_k h_k e^{-jk\omega} \qquad (3)$$

$$G(\omega) = \sum_k g_k e^{-jk\omega} \qquad (4)$$

They satisfy the orthogonality condition:

$$|H(\omega)|^2 + |G(\omega)|^2 = 1 \qquad (5)$$

That are necessary for reconstruction capabilities of the transform.

The filters $H(\omega)$ and $G(\omega)$ are also known as quadratic mirror filters. A signal $x[n]$ can be decomposed recursively according to

$$c_{j-1,k} = \sum_n h_{n-2k} c_{j,n} \qquad (6)$$

$$d_{j-1,k} = \sum_n g_{n-2k} c_{j,n} \qquad (7)$$
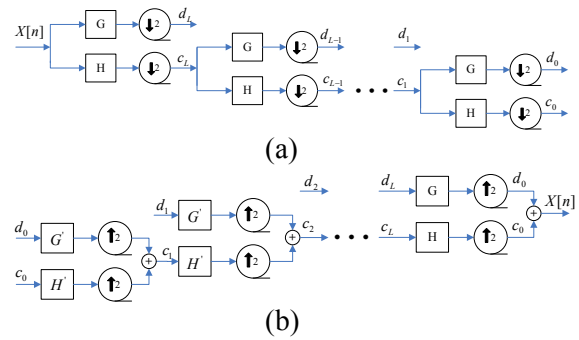

(a)

(b)

Fig. 5 (a) multi-level 1D wavelet decomposition. (b) Multi-level 1D wavelet reconstruction.

which correspond to convolutions followed by down sampling by 2, as can be seen in figure 5 (a). h_k and g_k are the impulse responses of the lowpass and highpass filters, respectively. Index j spans the number if decomposition levels and lies in the range $[0, L+1]$, where $L+1$ represents the index of the high resolution level of the transform and 0 represents the index of the low resolution level. $c_{L+1,K}$ is equal to the input signal $x[k]$. The coefficients $c_{0,k}, d_{0,k}, d_{1,k}, \cdots, d_{L-1,k}, d_{L,k}$ are called the DWT wavelet coefficients of $x[n]$. $c_{0,k}$ is the lowest resolution component of $x[n]$ containing lowpass, 'smooth' information and $d_{j,k}$ are the detail coefficients of $x[n]$ at various bands of frequencies. The signal $x[n]$ can now be reconstructed from its DWT coefficients by considering the recursive formula:

$$c_{j,n} = \sum_n h_{n-2k} c_{j-1,k} + \sum_n g_{n-2k} d_{j-1,k} \qquad \textbf{(8)}$$

The reconstruction process is illustrated in Figure 5.(b) and defines the inverse discrete wavelet transform (IDWT). This time, sampling precedes filtering at each level of the transform. It is obvious that, in the discrete case, DWT and IDWT can be implemented by two-channel tree-structured filter banks (Figure 5). The discrete wavelet transform does not have a single set of basis functions. There are many families of wavelets, the most known of them being the Haar and the Daubechies wavelets. For example, the
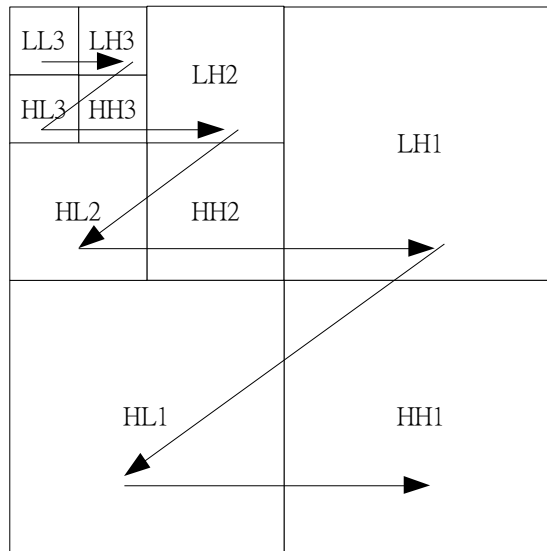
Fig.6 Three level DWT hierarchical decomposition of an image

frequency responses $H(\omega)$ and $G(\omega)$ of the Haar wavelet filters are given by:

$$H(\omega) = \frac{1}{2} + \frac{1}{2} e^{-j\omega} \qquad \textbf{(9)}$$

$$G(\omega) = \frac{1}{2} - \frac{1}{2} e^{-j\omega} \qquad \textbf{(10)}$$

The two-dimensional discrete wavelet transform and its inverse are extensions of the one-dimensional transform. They are simply implemented by using one-dimensional DWTs and IDWTs along each dimension n and m separately:

$$DWT_{n \times m}[x[n,m]] = DWT_n[DWT_m[x[n,m]]] \qquad (11)$$

In this way, separable two-dimensional filters are only considered. Each level is characterized by tree detail coefficient components representing the horizontal, vertical and diagonal edges of the input image. The lowest level consists of the low-resolution lowpass version of the image.

The wavelet transform decomposes a signal into many bands of energy, which are sampled at different rates. Their rates are determined so as to maximally preserve the informational content of the signal while minimizing the sample rate or resolution of each sub-band. Furthermore, Wavelet attempts to maximize the precision of representation in both time and frequency domain. The discrete wavelet transform (DWT) is used to hierarchically decompose an image into a lower resolution reference image LL and their associated detail images LH, HL, HH. At each level, the LL image and the LH, HL, HH images

contain the information needed to reconstruct the reference image at the next higher resolution level. In applications, the host image is usually transformed by DWT to obtain a multi-resolution representation as shown in the Fig. 6.

2.4. Two Dimensional Principal Component Analysis

Principal component analysis (PCA) is a classical technique; it is an optimal linear transformation that transforms the original data space to an orthogonal eigenspace with preserving the global geometric structure of data well in a low-dimensional space.

In the PCA-based face representation and recognition schemes, the two dimensional face image matrices have to be firstly transformed into one dimensional image vectors row by row or column by column [19]. To transform two dimensional matrices into one dimensional vectors frequently leads to a high-dimensional vector space such that it is more difficult to calculate the covariance matrix accurately, because its large size [20]. On the other hand, to find the eigenvectors from a large size covariance matrix is highly time-consuming. A technique called two-dimensional principal component analysis (2DPCA) [20] was recently proposed for overcoming those problems. The 2DPCA directly finds eigenvectors of the covariance matrix without matrix-to-vector conversion. The 2DPCA finds the covariance matrix and the corresponding eigenvectors more accurately more efficiently than PCA, due to the fact that

the size of the image covariance matrix is equal to the size of each element matrix of the data set, which is very small compared to the size of a covariance matrix in PCA. There are two kinds of 2DPCA; the horizontal 2DPCA and the vertical 2DPCA. The detail steps of 2DPCA are described as follows.

2.4.1. Horizontal Two Dimensional Principal component analysis

Step 1: Consider the two dimensional data A with m rows and n columns,

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix}_{m*n} \quad (12)$$

Step 2: Calculate the mean row of matrix A using the following equation,

$$\Psi = \frac{1}{m} \cdot \sum_{i=1}^{m} R_i \quad (13),$$

Where $R_i = [a_{11}, a_{12}, \cdots, a_{1n}]$ is the i- th row vector of matrix A.

Step 3: Calculate the difference matrix,

$$\Phi = \begin{bmatrix} (R_1 - \Psi) \\ (R_2 - \Psi) \\ \vdots \\ (R_m - \Psi) \end{bmatrix} \quad (14)$$

Step 4: Calculate the Covariance Matrix of the difference matrix.

$$C = \Phi^T \cdot \Phi \quad (15)$$

Step 5: Calculate the eigenvalues λ_i, j=1,2,…,n,of the covariance matrix by solving the following characteristic equation,

$$0 = \det(C - \lambda_i) = \begin{bmatrix} C_{11} & C_{12} & \cdots & C_{1n} \\ C_{12} & C_{22} - \lambda & \cdots & C_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ C_{n1} & C_{n2} & \cdots & C_{nn} - \lambda \end{bmatrix} \quad (16)$$

Step 6: Calculate the corresponding eigenvectors $\bar{a}_j = [a_{j1}, a_{j2}, \cdots, a_{jn}]$, j=1,2,…n, of the eigenvalues λ_i, j=1,2,…,n, by solving the following equations system, $0 = (C - \lambda_i I)$.

$$\bar{a}_j = \begin{bmatrix} C_{11} - \lambda_j & C_{12} & \cdots & C_{1M} \\ C_{21} & C_{22} - \lambda_j & \cdots & C_{2M} \\ \vdots & \vdots & \cdots & \vdots \\ C_{n1} & C_{n2} & \cdots & C_{nn} - \lambda_j \end{bmatrix} \begin{bmatrix} a_{j1} \\ a_{j2} \\ \vdots \\ a_{jn} \end{bmatrix} \quad (17)$$

Step 7: Sort eigenvectors in the order of their eigenvalues. Discard useless Eigenvectors (Take the first d eigenvectors as principle components if the input dimensionality is to be reduced to d.).

Step 8: Find the horizontal 2DPCA by multiplying the eigenvectors with matrix A (Project the input data A onto the principle components, which forms the representation of input data.).

$$Y = A \cdot \bar{a}_k, k = 1, \cdots, q \quad (18)$$

2.4.2. Vertical Two Dimensional Principal component analysis

Step 1: Consider the two dimensional data A with m rows and n columns,

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix}_{m*n} \quad (19)$$

Step 2: Calculate the mean column of matrix A using the following equation,

$$\Psi = \frac{1}{n} \cdot \sum_{i=1}^{n} C_i \quad (20),$$

Where $C_i = [a_{12}, a_{22}, \cdots, a_{m2}]^T$ is the i- th column vector of matrix A.

Step 3: Calculate the difference matrix,

$$\Phi = [(C_1 - \Psi), (C_2 - \Psi), \cdots, (C_n - \Psi)] \quad (21)$$

Step 4: Calculate the Covariance Matrix of the difference matrix.

$$C = \Phi \cdot \Phi^T \quad (22)$$

Step 5: Calculate the eigenvalues λ_i, j=1,2,…,n, of the covariance matrix by solving the following characteristic equation,

$$0 = \det(C - \lambda_i) = \begin{bmatrix} C_{11} & C_{12} & \cdots & C_{1n} \\ C_{12} & C_{22} - \lambda & \cdots & C_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ C_{n1} & C_{n2} & \cdots & C_{nn} - \lambda \end{bmatrix} \quad (23)$$

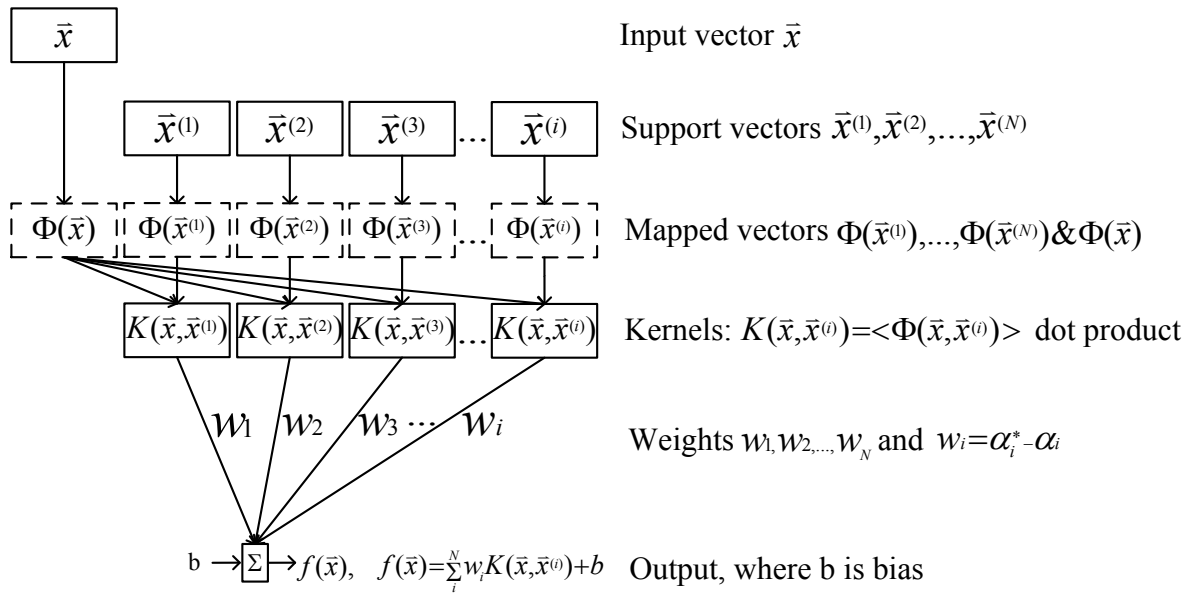Step 6: Calculate the corresponding eigenvectors

Input vector $\vec{x}$

Support vectors $\vec{x}^{(1)},\vec{x}^{(2)},\ldots,\vec{x}^{(N)}$

Mapped vectors $\Phi(\vec{x}^{(1)}),\ldots,\Phi(\vec{x}^{(N)})\&\Phi(\vec{x})$

Kernels: $K(\vec{x},\vec{x}^{(i)})=<\Phi(\vec{x},\vec{x}^{(i)})>$ dot product

Weights $w_1,w_2,\ldots,w_N$ and $w_i=\alpha_i^*-\alpha_i$

Output, where b is bias

Fig. 7 The structure of support vector machine

$\vec{a}_j = \left[a_{j1},a_{j2},\cdots,a_{jn}\right]$, j=1,2,…n, of the eigenvalues λ_i , j=1,2,…,n, by solving the following equations system,0=(C- λ_i I),

$$\vec{a}_j = \begin{bmatrix} C_{11}-\lambda_j & C_{12} & \cdots & C_{1M} \\ C_{21} & C_{22}-\lambda_j & \cdots & C_{2M} \\ \vdots & \vdots & \cdots & \vdots \\ C_{n1} & C_{n2} & \cdots & C_{nn}-\lambda_j \end{bmatrix} \begin{bmatrix} a_{j1} \\ a_{j2} \\ \vdots \\ a_{jn} \end{bmatrix}$$

Step 7: Sort eigenvectors in the order of their eigenvalues. Discard useless Eigenvectors (Take the first *d* eigenvectors as principle components if the input dimensionality is to be reduced to *d*.).
Step 8: Find the horizontal 2DPCA by multiplying the eigenvectors with matrix A (Project the input data A onto the principle components, which forms the representation of input data.).

$$Y = A^T \vec{a}_k, k=1,\cdots,q \qquad (25)$$

The entire face image is considered in the 2DPCA method; hence large variation in illumination will affect the identification rate greatly. So, we divide the original human face image into sub-images by DWT to improve the identification rate. In this paper, all the input human face images were normalized and cropped to a size of 64×60 pixels. The sub-images of an input human face image are the resolution reference image LL and the associated detail images LH, HL, HH obtained from the discrete wavelet transformation of the input human face

image. The size of each sub-image is 32×30 pixels. These sub-image LL was considered for computing 2DPC vector and training the SVM classifiers.

2.5. Support Vector Machine

(24) The SVM possesses outstanding advantages; (a) the strong theoretical basis provides a high generalization capability and avoids over fitting, (b) the global model can deal with high-dimensional input vectors efficiently, (c) the solution is light and only a subset of training samples contributes to this solution, thus reducing the workload .The structure of the SVM is showed in figure 7.

Consider a training data set $T=\{(\vec{x}^{(i)},y_i)\}_{i=1}^{N}$, $\vec{x}^{(i)}\in R^n, y_i\in R$, where $\vec{x}^{(i)}$ is a vector of input variables and y_i is the corresponding scalar output (target) value. The objective over here is to construct a SVM model such that it can accurately predict the outputs, $\{y_i\}_{i=1}^{N}$ corresponding to the input vectors $\{\vec{x}^{(i)}\}_{i=1}^{N}$. With this objective, the linear SVM formula can be given as

$$f(\vec{x}) = w\cdot\Phi(\vec{x})+b \qquad (26),$$

where f is the SVM formula to be built, w the weight vector in feature space, Φ is the transformation function that transfer input vectors

into the high dimension feature space, $w \cdot \Phi(\bar{x})$ is the inner product of w and $\Phi(\bar{x})$, and b is the bias (constant). In this paper, the chosen kernel of the SVM is exponential radial based function (RBF) kernel which is expressed as $\mathrm{K}\left(\bar{\mathrm{x}}^{(i)}, \bar{\mathrm{x}}^{(j)}\right) = -\exp\left(\left\|\bar{\mathrm{x}}^{(i)} - \bar{\mathrm{x}}^{(j)}\right\| / \left(2\sigma^2\right)\right)$, where the kernel width σ is taken to be one, the penalty parameter C is taken as infinity, and the insensitivity value ε is set to 0.01.

3. EXPERIMENT RESULTS

For our experiments, we took a set of color images of human face. The image set consists of 24 people, 6 images of each person, each image of a person is frontal view of human face taken at a different illumination, different facial expressions etc. The normalized image's size is 32*30. These images are divided into two sets; training set and testing set, respectively. Figure 2 shows several sample images taken from the experimental database.
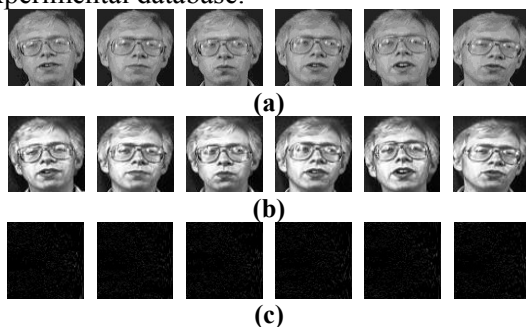

(a)

(b)

(c)

Figure 8. Sample images taken from the experimental database, (a) gray face image of a person in different pose, (b) the corresponding images after scaling and equalization (c) the corresponding eigenface.

The above database of human face images is conducted to test the performance of 2DPCA algorithm for varying number of eigenvectors, for different measure matrices, for horizontal 2DPCA and vertical 2DPCA. Table1 is the table of the performance comparison using the Euclidean distance measure matrix. Table1 shows the performance of the presented 2DPCA identification algorithm for varying number of training images and varying number of 2DPC. Table 1 shows that; (1) more eigenvectors will increase the identification rates, (2) the identification rate using horizontal 2DPCA is higher than that using vertical 2DPCA.

Table2 is the table of the performance comparison that the human face images are processed with normalization and histogram equalization. Table 2 also shows that; (1) more eigenvectors will increase the identification rates, (2) the identification rate using horizontal 2DPCA is higher than that using vertical 2DPCA

Table3 is the table of the performance comparison using the cosine similarity measure matrix. Table 3 shows the performance of the presented 2DPCA identification algorithm for varying number of training images and varying number of 2DPC. Table 1 shows that; (1) more eigenvectors will increase the identification rates, (2) the identification rate using horizontal 2DPCA is higher than that using vertical 2DPCA. (3) The identification rate using Euclidean distance measure matrix is higher than that using cosine similarity measure matrix.

Table 4 is the table of the performance comparison that using the weighted H2DPCA and the human face images are processed with normalization and histogram equalization. Table 4 shows that; (1) more eigenvectors will increase the identification rates, (2) the identification rate using 5 training image for each person is 95.8%, and is independent of the weight of each H2DPC.

Table 5 is the table of the performance comparison that using two weighted V2DPCs and the human face images are processed with normalization and histogram equalization as the preprocessing. Table 5 shows that; (1) more the number of training images will increase the identification rates, (2) the identification rate using 5 training image for each person may increase to 95.8%, while the weight of the first V2DPC is less than 0.6.

The advantage for the human face identification based on 2DPCA and SVM is that it does not require detecting the specific features of human face like as eyes, nose, eyebrows, teeth, and mouth. The 2DPCA based algorithm is not high effective under the various illumination conditions, because it considers the whole information of each face image and represents them with a vector of weights. The weight vectors of the test image will vary largely from the weight vectors of the training images with normal illumination such that it is hard to recognize them correctly.

Table 1

The performance comparison using the Euclidean distance measure matrix

Type and No. of 2D Principal Component	Horizontal 1PC			Vertical 1PC			Horizontal 2PC			Vertical 2PC		
No. of Training images	3	4	5	3	4	5	3	4	5	3	4	5
No. of Testing images	3	2	1	3	2	1	3	2	1	3	2	1
No. of Correct	54	39	22	50	38	16	57	39	21	35	38	20
No. of incorrect	18	9	2	22	10	8	15	9	3	37	10	4
Identification Rate(%)	75	81	92	69	79	67	79	81	88	49	79	83

Table2

The table of the performance comparison that the human face images are processed with normalization and histogram equalization.

Type and No. of 2D Principal Component	Horizontal 1PC			Horizontal 2PC			Vertical 1PC			Vertical 2PC		
No. of Training images	3	4	5	3	4	5	3	4	5	3	4	5
No. of Testing images	3	2	1	3	2	1	3	2	1	3	2	1
No. of Correct	38	27	23	38	27	22	40	35	16	54	35	16
No. of incorrect	34	21	1	34	21	2	32	13	8	18	13	8
Identification Rate(%)	52.7	56	95.8	52.7	56	91.6	55.5	72.9	66.6	75	72.9	66.6

Table3

The table of the performance comparison using the cosine similarity measure matrix

No. of Training images	3				4				5			
Type of 2D Principal Component	Horizontal		Vertical		Horizontal		Vertical		Horizontal		Vertical	
No. of PCs	1	2	1	2	1	2	1	2	1	2	1	2
No. of Correct	7	59	9	44	5	41	26	30	12	21	16	17
No. of incorrect	65	13	63	28	43	7	22	18	12	3	8	7
Identification Rate(%)	9	81.9	12.5	61	10	85	54	62	50	87.5	66	70.8

Table 4

The table of the performance comparison that using the weighted H2DPCA and the human face images are processed with normalization and histogram equalization.

Number of training images	Weight of the1st pc	0.1	0.2	0.3	0.4	0.6	0.7	0.8	0.9
	Weight of the 2nd pc	0.9	0.8	0.7	0.6	0.4	0.3	0.2	0.1
3	No. of Correct	45	45	45	45	32	32	32	32
	No. of incorrect	27	27	27	27	40	40	40	40
	Identification Rate(%)	61	61	61	61	44	44	44	44
4	No. of Correct	33	33	33	33	26	26	26	26
	No. of incorrect	15	15	15	15	22	22	22	22
	Identification rate	68.7	68.7	68.7	68.7	54	54	54	54
5	No. of Correct	23	23	23	23	23	23	23	23
	No. of incorrect	1	1	1	1	1	1	1	1
	Identification Rate(%)	95.8	95.8	95.8	95.8	95.8	95.8	95.8	95.8

Table 5

The table of the performance comparison that using the weighted V2DPCA and the human face images are processed with normalization and histogram equalization.

Number of training images	Weight of the1st pc	0.1	0.2	0.3	0.4	0.6	0.7	0.8	0.9
	Weight of the 2nd pc	0.9	0.8	0.7	0.6	0.4	0.3	0.2	0.1
3	No. of Correct	46	46	46	46	48	48	48	48
	No. of incorrect	26	26	26	26	24	24	24	24
	Identification Rate(%)	63.8	63.8	63.8	63.8	66.6	66.6	66.6	66.6
4	No. of Correct	33	33	33	33	36	36	36	36
	No. of incorrect	15	15	15	15	12	12	12	12
	Identification Rate(%)	68.7	68.7	68.7	68.7	75	75	75	75
5	No. of Correct	23	23	23	23	20	20	20	20
	No. of incorrect	1	1	1	1	4	4	4	4
	ID Rate(%)	95.8	95.8	95.8	95.8	83	83	83	83

4. CONCLUSION

Human face identification system can automatically identify a customer's identification; it has grown into wide range of commercial products and has confident police and national defense to set surveillance systems at migration hot spots to automatically identify customers. This paper combines the histogram equalization, wavelet transform, two dimensional principal component analysis (2DPCA), and support vector machine (SVM) methods to construct a human face identification algorithm. To explore the utility and demonstrate the efficiency of the proposed scheme, simulations under various conditions are conducted. The experiment results show that the presented algorithm is an efficiency scheme for human face identification. The advantage of the present algorithm is that it does not require detecting the specific features of human face like as eyes, eyebrows, nose, and mouth etc. Traditional PCA is not always high effective under the various illumination conditions; the presented algorithm uses the histogram equalization and principal component normalization to improve it.

REFERENCES

[1] O. Deniz , M. Castrillon, M. Hernandez, *Face identification using independent component analysis and support vector machines*, Pattern Identification Letters 24 (2003)2153–2157

[2] Johnny K.C. Ng, Y. Zhong, S. Yang, *A comparative study of Minimax Probability Machine-based approaches for face identification*, Pattern Identification Letters 28 (2007) 1995–200

[3] S. Mitra, M. Savvides, V. Kumar, *Face Identification Using Novel Frequency-Domain Representation of Facial Asymmetry*, IEEE Transactions on Information Forensics and Security, VOL. 1, NO. 3, (2006)350–359

[4] S. Yan, D. Xu, X. Tang, *Face Verification With Balanced Thresholds*, IEEE Transactions on Image Processing, VOL. 16, NO. 1, (2007) 262- 268

[5] B. Heisele, P. Ho, J. Wu, T. Poggio, *Face identification: component-based versus global approaches*, Computer Vision and Image Understanding 91 (2003) 6–21

[6] K. Tan, S. Chen, *Adaptively weighted sub-pattern PCA for face identification*, Neurocomputing 64 (2005) 505–511

[7] R. Gottumukkal, V. K.Asari, *An improved face identification technique based on modular PCA approach*, Pattern Identification Letters 25 (2004) 429–436

[8] H. Wang, Y. Leng, Z. Wang, X. Wu, *Application of image correction and bit-plane fusion in generalized PCA based face identification*, Pattern Identification Letters 28 (2007) 2352–2358

[9] R. Singh, M. Vatsa, A. Noore, *Integrated multilevel image fusion and match score fusion of visible and infrared face images for robust face identification*, Pattern Identification 41 (2008) 880 – 893

[10] Pedro Henrique Cox and Aparecido Augusto de Carvalho,"Discrete Wavelet Transform Signal Analyzer", IEEE Transactions on Instrumentation and Measurement 2007, pp 1640 – 1647.

[11] Christian Tenllado, Member, Javier Setoain, Manuel Prieto, Luis Pin~ uel, and Francisco Tirado, "Parallel Implementation of the 2D Discrete Wavelet Transform on Graphics Processing Units: Filter Bank versus Lifting", Transactions on Parallel and Distributed Systems March 2008 Page(s):299 – 310.

[12] K.Y. Chen, *Forecasting systems reliability based on support vector regression with genetic algorithms*, Reliability Engineering and System Safety 92 (2007) 423–432.

[13] T. Zou, Y. Dou, M. Hong, J. Zou, Y. Ren, *Support vector regression for determination of component of compound oxytetracycline powder on near infrared spectroscopy*, Analytical Biochemistry 355 (2006) 1–7.

[14] Z. Hua, B. Zhang, *A hybrid support vector machines and logistic regression approach for forecasting intermittent demand of spare parts*, Applied Mathematics and Computation 181 (2006) 1035–1048.

[15] U. Stu, W.J. Melssen, L.M.C. Buydens, *Facilitating the application of support vector regression by using a universal Pearson VII function based kernel B*, Chemometrics and Intelligent Laboratory Systems 81 (2006) 29–40.

[16] Arthur R. Weeks, Jr., *Funamentals of Elecroni Image Processng*, SPIE/IEEE Series on Image Science & Engineering, Bellingham, Washington USA, pp. 440-451, 1998.

[17] Caroline Chaux, "Image Analysis Using a Dual-Tree M-Band Wavelet Transform", IEEE Transactions on Image Processing Aug. 2006 Page(s):2397 – 2412.

[18] Ivan W. Selesnick, "A Higher Density Discrete Wavelet Transform", IEEE Transactions on [see also Acoustics, Speech, and Signal Processing, IEEE Transactions on Signal Processing. Aug. 2006 Page(s):3039 – 3048.

[19] Daoqiang Zhang, Zhi-Hua Zhou, e2DT2PCA: *Two-directional two-dimensional PCA for efficient face representation and recognition*, Neurocomputing 69 (2005) 224–231

[20] J. Yang, D. Zhang, A.F. Frangi, J.Y. Yang, *Two-dimensional PCA: a new approach to appearancebased face representation and recognition*, IEEE Trans. Pattern Anal. Mach. Intell. 26 (1) (2004)131–137.