Multi-pose Face Recognition Using Head Pose Estimation and PCA Approach

Li Wei, and *Eung-Joo Lee
*1 *Information Communication Engineering Department, Tongmyong University, Busan, Korean*
*2, **Corresponding author** *Information Communication Engineering Department, Tongmyong University, Busan, Korean*
12li-wei@163.com, ejlee@tu.ac.kr
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Abstract

In this paper, a novel multi-pose face image recognizing method is presented. In this algorithm, the face with multi-pose can be recognized by comparing it with the eigenface which is generated from 3D face model database, view point of the 3D face model is estimated from the face image, the estimation algorithm utilize the facial geometrical feature to estimate head pose parameter which can be applied to the view point of 3D face model. Through the method, the 3D face model can keep the same pose with the real captured face. Finally, a PCA based algorithm is employed to extract the eigenface from the generated exemplar database and input face image. The cosine distance matching method will be used to compare the similarity of face between input one and the generated database. The one which has the maximum similarity can be judged as the positive one of identifying face. In the experiment, we evaluated the efficiency pose estimation algorithm and the recognition approach. We can see the error of the estimation algorithm is near to ±0.05° for frontal face and ±3.9° for near profile face. And the correct recognition rate is close to 96% for frontal face and 72% for near profile face.

Keywords

Face Recognition, PCA, Camera Pose Estimation, 3D Face Model.

1. Introduction

Facial recognition (FR) is a suitable biometric for many applications because of its non-intrusive nature, ease of integration into existing systems, societal acceptance, and potential to identify individuals at a distance without subject cooperation. Most of the current efforts in FR use a 2D representation of the face [1], however, these systems are generally not robust to variations in facial pose, scene lighting, and facial expression, requiring images to be taken in a controlled environment [2]. To address these issues researchers are examining the benefits of 3D data for the FR task [3]. 3D FR systems are believed to be less sensitive to lighting and facial pose variations. In addition, the geometric information available is expected to provide more discriminatory features for FR, including size information which is lacking in most 2D approaches.

Principal component analysis (PCA) has been extensively used for the analysis, compression, modeling, and recognition of objects because of its simplicity and ability for dimensionality reduction. In particular, it has been used for facial recognition [4-5]. The goal of PCA is to derive an optimal basis from a set of training examples (representing signals in class C) such that training examples can be represented as a linear combination of basis vectors. For recognition problems, it is also desirable for the derived basis to have good generalization performance. For instance, the basis should also accurately represent new signals (not in the training set) in signal class **C** as a linear combination. To achieve both data accuracy and efficiency in representing new within class signals, both sufficient variability in the training set and proper correspondence of signal features (in concert with linear combination principals) are needed.

In 2D face analysis this is obtained by a normalization procedure which typically requires certain attributes to be constant across faces. For instance, for a 2D face one often restricts the distance between eyes to be fixed and the nose tip to be placed at a particular pixel in the 2D image. For 3D face recognition, PCA has been applied to range images of faces [6-9]. Range images are often noted as 2.5D representations and two issues may arise when using them for 3D PCA recognition: 1) if normalization is performed using typical 2D methodology, size information which is important for the recognition process is eliminated, 2) if normalization is not performed then proper alignment of facial points necessary for good generalization is not achieved.

Accurate representation of new untrained signals in the signal class will typically require more model parameters and/or training examples.

Also, to recognize an MPIE (multi pose and illumination) face, many researchers suggested the use of a verifier generable 3D face model to generate each possible pose and illumination 2D face image and that these generated 2D face images can be used as a training set to train the classification machine [10] [11]. However, it is an enormous job to generate the training set, and no matter what we do, we still cannot generate enough images for practical pose or illumination purposes.

Therefore, in this paper, we propose an algorithm which can overcome this problem. We assume that each verifier has a 3D face model which can be obtained by any kind of 3D capture equipment. The matching data what we used for recognition is simply the 3D face model of the person in question. The face is captured and input to the system. We firstly detect face features and estimate the head pose by using the head pose estimation algorithm. In the algorithm, geometry relationship between facial features will be utilized. Thus we can estimate the head pose just based on a single 2D face image, the image can be easily acquired from a common camera. The head pose will be applied to the view point of 3D face model in the 3D face database. Like this, image which generated from 3D face model will have the same pose with the real face. What we should do is to select the most similar one with the identifying one. For doing this, we will use PCA method to extract eigenface and use cosine distance matching method to compare them. Framework of the proposed system is shown as Fig 1.

In order to evaluate the efficiency of the proposed system, we have created a 3D face database which includes 200 3D face modes. Each 3D face model is acquired by using the stereo face camera. These 200 exemplars are students in our school. The acquisition method is as described by Naohide Uchida, Takuma Shibahara in their paper [12]. And based on the database, we have carried out the simulation on Windows XP, the simulation result shows that the correction recognition rate for frontal face is 96% and 72% for near profile face.

Rest of this paper is organized as follows: The head pose estimation algorithm is introduced in section 2; Section 3 explains the PCA based eigenface extraction algorithm, and finally the experimental results and conclusions are given in sections 4 and 5, respectively.

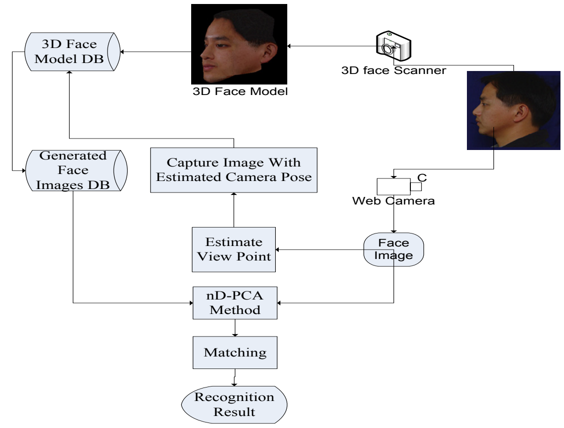


Fig. 1 Framework of the Proposed System

2. HEAD POSE Estimation Based on Face Geometry

In this section, we introduce the view point estimation algorithm which makes use of the facial geometric relationships. It is well known that the 2D images captured by a camera system undergo plane reflection. In the captured image, the depth information of the face is lost through this plane reflection, but fortunately, the plane reflection rule can be represented by the geometric relationship of the face features. For example, it can be seen in Fig 2 that if the camera captures a face from the right side, the distance from the face features (eyes, mouth or nose) to the right face boundary is always longer than that from the left. If we capture the image from the left side, the opposite occurs. Also, the rotation of the head in the reflection direction can be found by observing the vertical deviation of the position of the two eyes.

Firstly, we must detect all of the necessary features. E. J. Lee and K. R. Kwon [13] proposed a robust color based face analysis algorithm for accurate local searches and a robust parameter estimation approach for face alignment. Based on this 2D alignment algorithm, the face feature and face boundary are automatically located and marked with a point. The feature points are accurate enough for estimating the camera pose. Also, as discussed by Martin Bernas and Martin Teisler [14], the most important information of the camera pose is the rotation angle, since any point (A) in 3D space can be rotated to a new point (A') by means of the transformation matrices.

We select the center point of the mouth as the reference point to estimate the camera rotation angle in the X-axis and Y-axis, and finally use the vertical position deviation of the two eyes to estimate the camera rotation angle in the Z-axis. This procedure is discussed in our previous papers [15], [16]. As shown in Fig 2, we can easily see that, when the camera is rotated from one position to another (For example: from the frontal face to the left 45 degree side in the x direction), in the corresponding captured image, the mouth position is also moved linearly from the horizontal center to the corresponding position. Therefore, we can utilize the linear relationship between mouth position and face boundary to calculate the angle (α, β). Then utilize the vertical deviation of the two eyes to calculate the rotation angle in the z-axis (θ). Firstly we need to define the symbols which are used in the algorithm, and for the transfer of the reference frame to the center point of the face region.

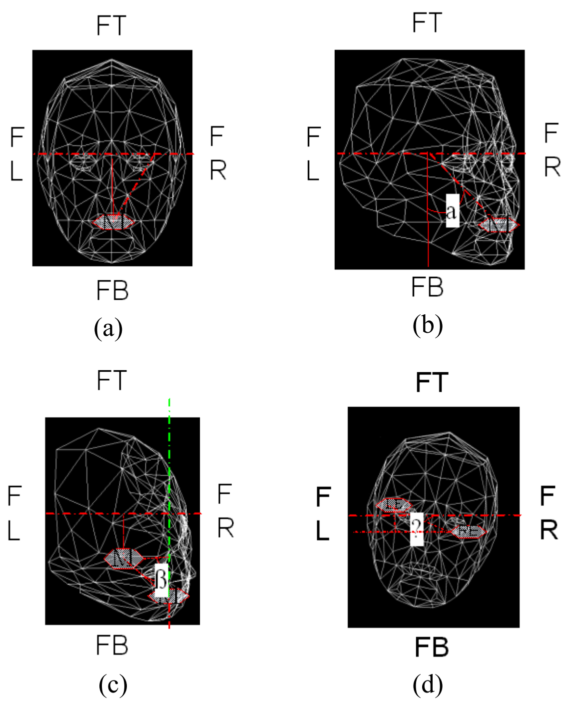


Fig. 2 Face Region Model: (a) Frontal View; (b) Head Rotated at x Position; (c) Head Rotated at y Position and (d) Head Rotated at z Position

In the figure, M is the symbol for the mouth, and FL, FR, FB and FT are the left, right, bottom and top boundaries of the face, respectively. The following subsections describe the decision-making algorithm for the x-axis (α), y-axis (β) and z-axis (θ) in detail.

2.1. View Point Estimation for x Axis (α)

We define that α is 0 in the frontal view and in the range of [-π/2, π/2] when the head is rotated from left to right. As shown in Fig. 2 (b), the distance between the mouth and left boundary of the face can be obtained by the equation

$$D_{ML} = \left| P_M(x) - P_{FL}(x) \right| \tag{1}$$

where PM(x) is the horizontal position of the mouth and PFL(x) is the left boundary of the mouth. The right boundary of the face region can be obtained by the equation

$$D_{MR} = \left| P_M(x) - P_{FR}(x) \right| \tag{2}$$

We can now obtain the horizontal setover between two distances:

$$D_{HS} = D_{ML} - D_{MR} \tag{3}$$

Therefore, a linear equation can be set up to describe the relationship between α and DHS as follows:

$$\frac{D_{HS}}{D_{LR}} = k\frac{\alpha}{\theta} + b \tag{4}$$

where k, θ and b are constant values. We can obtain their values by experiment in two special cases, viz. the frontal view (α=0) right side profile view (α=π/2).

In the case of the frontal view: α=0, PM(x)=0, DML=DLR / 2 and DMR=DLR/2.

In the case of the right side profile view: α=π/2, PM(x)=DLR/2, DML=DLR and DMR = 0.

Then, we can obtain the following group of equations:

$$\begin{cases} \dfrac{\left(\dfrac{D_{LR}/2 - D_{LR}/2}{D_{LR}} - b\right) \times \theta}{k} = 0 \\ \dfrac{\left(\dfrac{D_{LR} - 0}{D_{LR}} - b\right) \times \theta}{k} = \dfrac{\pi}{2} \end{cases} \tag{5}$$

where k, θ and b can be calculated from the group: b=0, θ=k•(π/2). Therefore, the head pose for the x-axis is as follows:

$$\alpha = \frac{\pi}{2} \times \frac{2P_M(x) - D_{LR}}{D_{LR}} \tag{6}$$

2.2. View Point Estimation at y Axis (β)

We also define that β is 0 in the frontal view and in the range of [-π/2, π/2] when the head is rotated vertically. As shown in Fig 2. (c), the distance between the mouth and the top boundary of the face can be calculated by the equation

$$D_{MT} = \left|P_M(y) - P_{FT}(y)\right| \tag{7}$$

where k, θ and b are also constant values.

Usually for the vertical direction, the position of the human mouth is not in the center, so we first transform the coordinates so that the mouth position is at the center point: PM'(y)=PM(y)-DMC. A similar equation can be obtained as follows:

$$\beta = \frac{\pi}{2} \times \frac{D_{VS}}{D_{TB}} \tag{8}$$

where:

$$\begin{aligned} D_{VS} &= D_{MT} - D_{MB} \\ &= 2P_M(y) - D_{TB} - 2D_{MC} \end{aligned} \tag{9}$$

So, the head pose for the y-axis is as follows:

$$\beta = \frac{\pi}{2} \times \frac{2P_M(y) - D_{TB} - 2D_{MC}}{D_{TB}} \tag{10}$$

In equation (6), DLR is the width of the face region, while in equation (10), DTB is the height of the face region and PM(x, y) is the mouth position, and these values can be easily obtained by using the face feature detection algorithm. DMC is a constant value that can be obtained from the frontal view face image by experiment. We made numerous tests based on the FERET face database to determine the value of DTB which was found to be 7/40.

2.3. View Point Estimation at z Axis (Θ)

As shown in Fig 2. (d), it can be seen that when the face rotated about the z-axis, in the captured image there exists a deviation distance between the two eyes in the vertical direction. We can assume that for the standard frontal face view, its value is 0, and when the head rotated about the in z-axis, the rotated angle value can be obtained by equation (11).

$$\theta = \arctan\left(\frac{D_{LR}(x)}{D_{LR}(y)}\right) \tag{11}$$

where DLR(x) and DLR(y) are the horizontal and vertical distances between the two eyes, respectively. They can be defined as follows:

$$D_{LR}(x) = P_{LE}(x) - P_{RE}(x) \tag{12}$$

$$D_{LR}(y) = P_{LE}(y) - P_{RE}(y) \tag{13}$$

where PLE(x, y) is the left eye position and PRE(x, y) is right eye position. Thus, we can get the final equation to estimate the head pose for the z-axis as follows:

$$\theta = \arctan\left(\frac{P_{LE}(x) - P_{RE}(x)}{P_{LE}(y) - P_{RE}(y)}\right) \tag{14}$$

In order to obtain the verification exemplar images from the 3D face model DB, we apply the estimated head pose parameters in the virtual 3D face model. For each face model in the 3D face database, we can apply the head pose to the capture image under the same illumination conditions. Thus a dynamic 2D verification exemplar image database, which includes the same pose as the input one can be created. We also have proposed this method at ICCIT08 [17], and this paper is an update version of the proposed paper.

3. PCA Based eigenFace extraction

As reported above, the images in generated 2D exemplar image database have the same poses as the input ones. In this section, we will associate this database with the PCA method in order to recognize the input face image. Two stages are involved: firstly we use the PCA method to extract the eigenface for each generated exemplar from the 3D face model. Each generated image has the same pose with the input one. Then we calculate the cosine distance between the input one and each exemplar in order to find the most similar one from the generated face database.

3.1. Eigenface Extraction Using PCA

The classical PCA approach can be simply outlined as follows:

1. Construct a covariance matrix of a training sample set;
2. Perform eigenvalue decomposition on it; the first k eigenvectors span an eigen subspace;
3. Project a probe sample onto this subspace to obtain its compact representation or recognition.

4. With higher dimensional datasets such as face images, it is straightforward to use tensors to represent them. In order to recognize a face image, a higher-order tensor based singular value decomposition (HO-SVD) algorithm [18] is exploited in the nD-PCA scheme.

3.1.1. HO-SVD. A higher order tensor is usually defined as $A \in R^{I_1 \times \ldots \times I_N}$, where N is the order of A, and 1≤in≤In, 1≤n≤N. The mode-n vectors of an N-order tensor A are defined as the In-dimensional vectors obtained from A by varying the index in and keeping the other indices fixed. In addition, a tensor can be expressed in matrix form.

Furthermore, the mode-n product, ×n of a tensor $A \in R^{I_1 \times \ldots \times I_n \ldots \times I_N}$ by a matrix $U \in R^{J_n \times I_n}$ along the n-th dimension is defined as,

$$(A \times_n U)_{i_1,\ldots,i_{n-1},j_n,i_{n+1},\ldots,i_N} = \sum_{i_n} a_{i_1,\ldots,i_n,\ldots i_N} u_{j_n,i_n} \tag{15}$$

In practice, mode-n multiplication is implemented first by matrix unfolding the tensor A along the given mode-n to generate its mode-n matrix form A(n), and then performing the matrix multiplication as follows,

$$B_{(n)} = UA_{(n)} \tag{16}$$

Then, the resulting matrix B(n) is folded back to the tensor form, i.e. A×nU=foldn(Unfoldn(A)). In terms of mode-n multiplication, the higher order SVD of a tensor A can be expressed as,

$$A = S \times_1 U^{(1)} \times_2 \ldots \times_N U^{(N)} \tag{17}$$

where, U(n) is a unitary matrix of size In×In, which contains mode-n singular vectors. Instead of being pseudo-diagonal (nonzero elements only occur when the indices i1=…iN), the tensor S (called the core tensor) is all –orthogonal, that is, the two sub-tensors Sin=a and Sin=b are orthogonal for all possible values of n, a and b subject to a≠b. In addition, the Frobenius-norms $\sigma_i^{(n)} \left\| S_{i_n=i} \right\|$ are mode-n singular values of A and are in decreasing order, $\sigma_1^{(n)} \geq \ldots \geq \sigma_{I_n}^{(n)} \geq 0$, which correspond to the mode-n singular vectors $u_i^{(n)} \subset U^{(n)}$, i=1…In respectively. The numerical procedure of HO-SVD can be simply described as, $unfold_n(A) = U^{(n)} \sum^{(n)} V^{(n)^T}$, n=1…N, where, $\sum^{(n)} = diag(\sigma_1^{(n)},\ldots,\sigma_{I_n}^{(n)})$.

3.1.2. nD-PCA. When the PCA technique is applied to image, the first problem encountered is to construct the covariance of the tensor. This will incur complicated tensor computations, such a tensor product, generalized transpose and hermitian symmetrization. In order to avoid this, we firstly reconsider the covariance matrix in the procedure of the PCA. Indeed, the covariance matrix can be rewritten in matrix form as follows.

$$Cov = \frac{1}{M}((X_1 - \overline{X}),\ldots,(X_M - \overline{X})) \begin{pmatrix} (X_1 - \overline{X})^T \\ \ldots \\ (X_M - \overline{X})^T \end{pmatrix} = DD^T \tag{18}$$

where, $\overline{X}$ denotes the mean of the verification exemplar images, and D denotes the difference matrix of the verifier image. Taking the eigenvalue decomposition of Cov is equivalent to the multiplication of the SVD of D as follows, $Cov = U \sum U^T = U \wedge V^T V \wedge U^T$. It is clear that one can construct the difference matrix D rather than the symmetric covariance matrix Cov, and apply the SVD to D to get the principal orthogonal vectors.

In a similar manner, we can also construct a difference tensor instead of the covariance tensor as follows,

$$D = ((X_1 - \overline{X}),\ldots,(X_M - \overline{X})) \tag{19}$$

where, $X_i \in R^{I_1 \times \ldots I_i \times \ldots I_N}$, $D \in R^{I_1 \times \ldots MI_i \times \ldots I_N}$, i.e. N-order tensors $X_n - \overline{X}$, n=1…N are stacked along the ith dimension in the tensor D. Furthermore, applying the HO-SVD of Eq. (19) to D will generate mode-n singular vectors contained in U(n) , n=1…N. According to the mode-n singular values, one can determine the desired principal orthogonal vectors for each mode of the tensor D, except for the mode-I singular vectors in Eq. (20). The projection of the verifier image X on the mode-n principal vectors $U_k^{(n)}$ is expressed as:

$$Y_n = (X - \overline{X}) \times_n U_k^{(n)^T} \tag{20}$$

It can be seen that the projection Yn is still an N-order tensor. This novel compact form of sample X is described as $\tilde{X} = Y_n \times_n U_k^{(n)} + \overline{X}$.

The generated face database which include the same pose images with the input one will be used to training the approach, we will calculate the mean value of the database, and calculate the eigenface for each image by using equation 20. As shown in Fig 3.

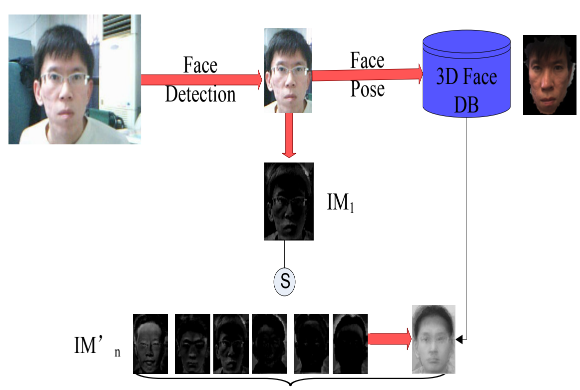


Fig. 3 Flowchart of Eigenface Generation Approach based on PCA

3.2. Cosine Distance Based Face Eigenvector Comparison

For classification and recognition, the cosine distance between two mode-n principal component tensors, Y_n^i and Y_n^j, is adopted as follows:

$$S(Y_n^i, Y_n^j) = \cos\theta = \frac{{Y_n^i}^T Y_n^j}{|Y_n^i||Y_n^j|} \tag{21}$$

The distance from the verifier image to each exemplar image is described in Fig 4.

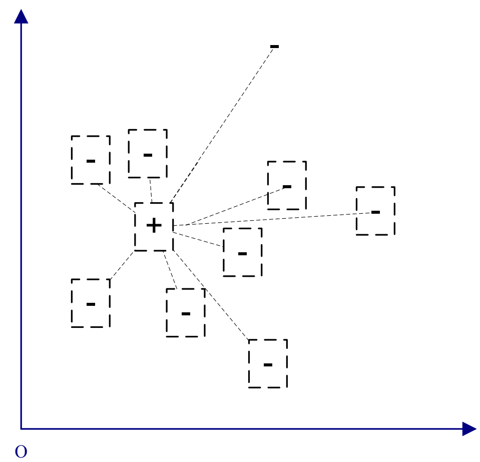


Fig. 4 Diagram of Distance between Verifier Image and Exemplars (+ Symbol for the Verifier and – Symbol for the exemplar)

Firstly, we calculate the distance from the verifier to the exemplar (n) ($1 \le n \le N$), and obtain the integration value for each class as follows:

$$\begin{aligned}\overline{D^2(X, E(n))} &= \frac{1}{M}\sum_{i=1}^{M} S^2(X, E(n)_i) \\ &= \frac{1}{M}\sum_{i=1}^{M} \frac{X_i^T E(n)_i}{|X_i||E(n)_i|}\end{aligned} \tag{22}$$

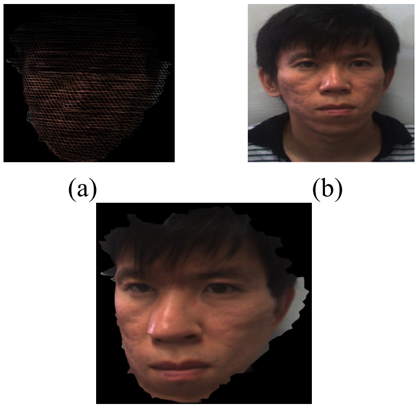
Finally, the minimum distance which can be considered to be similar to the verifier is selected.

4. Experimental Results

Two kinds of experiment were performed for the purpose of testing multi-pose face image generation and PCA based face recognition in order to evaluate the system proposed in this paper.

4.1. Multi-Pose Face Image Generation

We developed a 3D face model DB to generate multi-pose images. Each face model is composed of 46 vertices and the 3D face model texture can be constructed by mapping the frontal face image and profile image to the surface. Face Feature points are used to control the mapping, as shown in Fig 5.



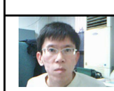
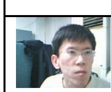
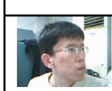
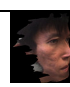
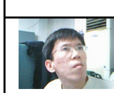
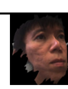
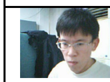
(a) (b) (c)

Fig. 5 3D Face Model: (a). 3D Face Triangle Model; (b). Frontal Face Image; and (c). 3D Face Model

Table 1 shows the results of the camera pose estimation from the 2D face image and the generation result obtained from the 3D face model.

It can be seen from the results that as long as the viewing angle is not too far away from the front view, the proposed pose estimation algorithm makes a satisfactory judgment and the pose of the image captured from the 3D face model is similar to the input one. For each 3D face model in the DB, an image with the same pose can be captured. Thus, the 2D verification exemplar DB can be generated.

Table 1. Camera Pose Estimation and 2D Verification Exemplar Creation Result

Input Image	(α)	(β)	(θ)	Exemplar Image
	0.02	0.10	0.35	
	30.45	0.25	0.45	
	70.68	1.35	2.25	
	21.45	15.64	3.65	
	5.36	20.64	2.68	
	-68.36	3.68	0.95	
	-13.28	-15.36	4.26	

4.2. Face Recognition

In order to verify the validity of the PCA based method for face recognition, we built a 3D model set which contains 200 people. Each person's 3D model is derived from stereo images that captured using the stereo camera. We select 37 feature points as vertexes. Fig 5 shows the position of these feature points. Depth information of each vertex can be calculated based on stereo vision theory. The face 3D structure will be described by these 37 vertexes. Then we attach the texture to the mesh which is composed of the 37 vertexes.

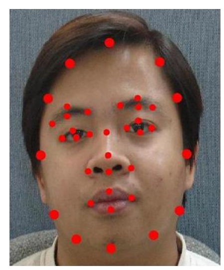
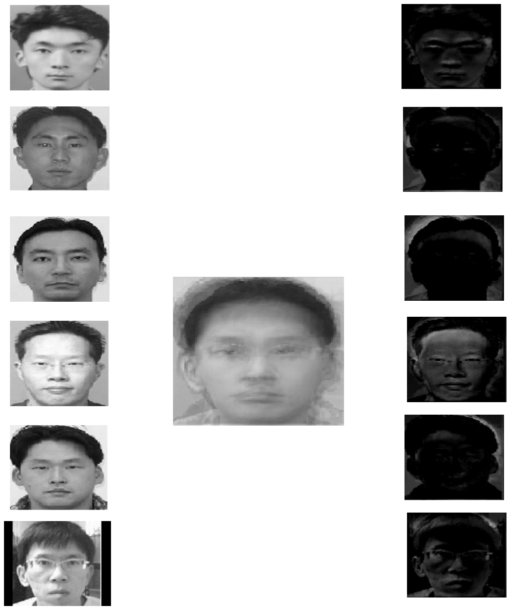


Fig. 6 Position of Selected Face Feature Points

The synthetic images were rendered under conditions of illuminations ranging from -90° to +90° in both the azimuthal and elevation directions where the angle was sampled in intervals of 10°. Then, the PCA based method and cosine distance method are used to classify the input face image. Fig 6 shows the reconstructed images obtained using the PCA on the generated verification exemplar images DB.



(a) (b) (c)

Fig. 7 Reconstructed images obtained by using the PCA on the generated verification exemplar images DB: (a). Resource Images; (b). Mean Image and (c). Reconstructed Result

The PCA algorithm is applied to obtain the eigenface of the input face and the generated sample, following which the cosine distance between the input face and each sample can be computed by using cosine distance equation. The result of the cosine distance equation is shown in Fig 7.

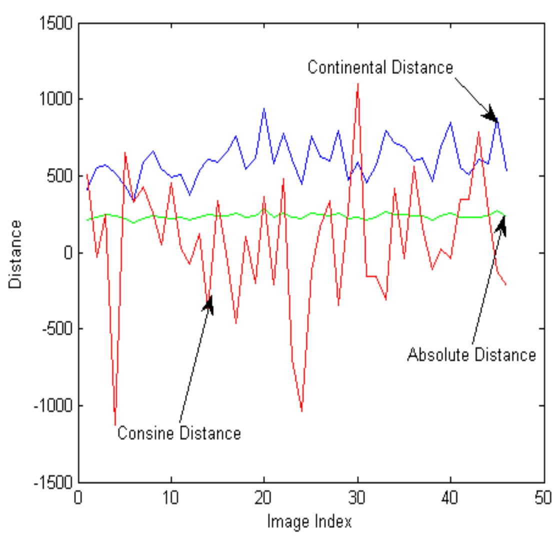


Fig. 8 Distance between Verifier and 46 Verification Exemplar Samples (red line represent the cosine distance result, blue line represent the continental distance result and green line represent absolute distance result)

For comparing with other distance matching algorithm, in the experiment, we calculate 3 kinds of distance which have been used commonly, as shown at Fig 8, we can observe that, for the same testing face DB, the cosine matching algorithm can get a better distance result to separate the most similar image. From the result we can see that the 6th image have the minimum value, so the person whose 3D face model is the 6th can be considered as the certificated person, thus we can gain the information of this verifier. The system simulation is as Fig 9 shows:

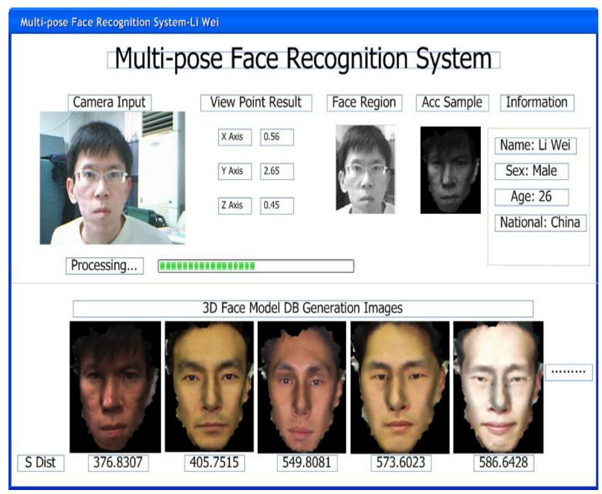


Fig. 9 Multi-pose Face Recognition System Simulation

4.3. Comparison with Other Multi-pose Face Recognition Algorithm

In this experiment, we compared the proposed approach with other approaches with regard to their multi-pose face recognition performance. Until now, there exist many kinds of method to solving the problem of multi-pose face recognition. Such as face recognition based on stereo vision which was proposed by Uchida, N., Shibahara in their paper [12], the Shape from Shading method used for face recognition which was proposed by Y. Hu, Y. Zheng in their paper [20]. By analyzing these methods we can classify them into 2 kinds: one is based on stereo vision which will recognize the 3D face structure information; another is based on 3D face database which created lots of training samples to make sure that each pose is included in the sample database. Our proposed algorithm will use a dynamic database for training the recognition machine. So we will compare the algorithm with the conventional method to evaluate which is more efficiency for multi-pose face recognition.

The CMU-PIE database is selected in the evaluation. CMU-PIE database contains 41,368 face images of 68 subjects, captured using 13 synchronized cameras and 21 flashes under varying PIE [19]. The camera positions are shown in Fig 9. The image which is captured at position (C05, C29) will be used to create the 3D face model.

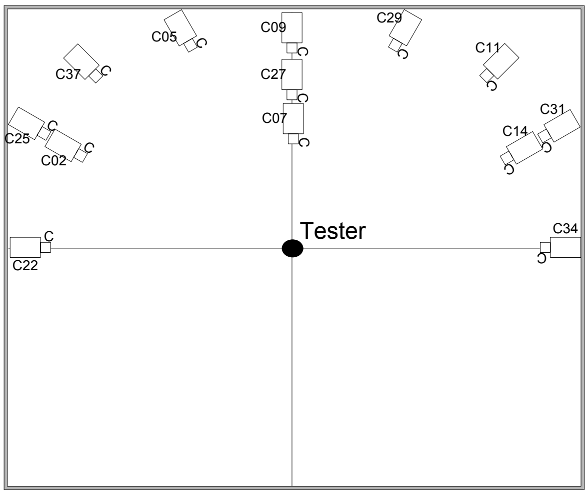


Fig. 10 Camera Positions in Experiment

The recognition rate is computed as the ratio of the number of correct recognitions in the gallery to that the total number of images in the gallery. A summary of the recognition results on the CMU-PIE database are presented in Table 2 and a comparison is shown in Fig. 11.

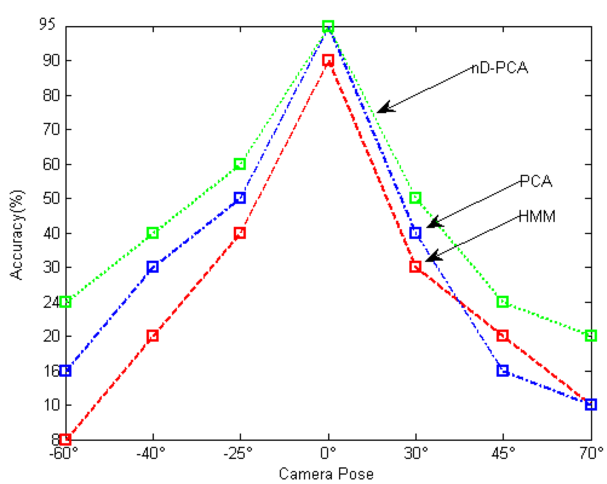


Fig. 11 Comparison of the Recognition Accuracy between the Proposed Face Recognition Algorithm and Conventional Algorithms

Table 2: Recognition Results on the CMU-PIE Image Database on a 2 Quad 2.40GHz CPU

Head Pose	Frontal (C27)	Position (C29)	Position (C31)	Position (C34)
Total No.	884	884	884	884
Stereo Vision Based Method				
CR No.	857	601	371	274
RR(%)	97%	68%	42%	31%
Static 3D Face Model Database Based Method				
CR No.	866	565	477	459
RR (%)	98%	64%	54%	52%
Dynamic Database Based Method (Proposed Method)				
CR No.	848	636	574	353
RR (%)	96%	72%	65%	40%

CR: Correct Positives, RR: Recognition Rate.

The memory content and recognition speed of the above classifiers depend linearly upon the number of classes and the number of poses.

From the chart we can see that all of the algorithms function well for frontal face images, but that for multi PIE images (e.g. camera at position 0°, 45°, -40° and 70°) the proposed algorithm is better than the conventional ones. This is because the still face database contains enough frontal face images to guarantee the accuracy, whereas for any other non-frontal face images, the training face database cannot cover each head pose. Therefore, sometimes when recognizing an input image with an arbitrary pose, it cannot make the correct judgment. And for the stereo vision, when the head turn to an angle at horizontal direction, not all the facial feature can appear in the captured image, sometime one side of face will disappear, so the face features points cannot be detected at all. This can make the result deviate from the truth value. But our proposed algorithm generates the training exemplar images set from the 3D face model dynamically. The pose is also estimated at runtime. Even when user head turn to the profile side, the mouth can also appear in the captured image. So the mouth can be detected and head pose can be estimated exactly. Nevertheless, compare with the result of the frontal view, the proposed algorithm does not produce a better result than the other methods. The reason for this decrease in the recognition rate is that when the face rotates from the frontal view to the profile view, the left or right ear feature in the Y-Cb subspace and Y-Cr subspace, respectively will become more similar to the mouth. However, the mouth feature in these two subspaces will become more inconspicuous. This can cause the mouth detection algorithm to give a bogus result and, consequently, the detection rate decreases to 65% for near-frontal faces and to 40% percent for half-profile faces.

5. Conclusions

In this paper, a new method of multi-pose face recognition was proposed. In the algorithm, we create the training set dynamically according to the estimated head pose. The head pose was estimated by using the mouth position and face boundary relationship. We can apply the head pose to the 3D face model to make it keep the same pose with the verifier image. We will capture image for each 3D model in the database, all these captured images compose the training database which with the same pose. We used PCA method to extract eigenface from the created database, and compare them with the verifier image by using cosine distance matching method to find the most similar one.

Through experiment and comparison with the conventional algorithms, we were able to conclude that the proposed algorithm constitutes a viable method of multi-pose face recognition and that its robustness is much better than that of the conventional ones. Also we propose a method of creating a dynamic training set for multi-pose face recognition. In the experiment, it was found that the dynamic creation training face database is far superior to the static training face database in the multi-pose face recognition field.

Future work will focus on improving the proposed algorithm for the purpose of dealing with face images under multi-illumination conditions. We would also like to evaluate the system on a large set of images and apply to the security field such as the Windows registration system.

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Li Wei received his B. S. at Da lian University of Light Industry in C hina (2002 - 2006), and received his M. S degree at Tongmyong university in Korea. Now he is a Ph.D student of Tongmyong university. His main re search tops are image processing, computer vision, Bi ometrics and face recognition.

Eung-Joo Lee received his B. S. , M. S. and Ph. D. in Electronic Engineering from Kyungpook National University, Korea, in 1990, 1992, and Aug. 1996, respectively. Since 1997 he has been with the Department of Information & Communications Engineering, Tongmyong University, Korea, where he is currently a professor. From 2000 to July 2002, he was a president of DigitalNetBank Inc.. From 2005 to July 2006, he was a visiting professor in the Department of Computer and Information Engineering, Dalian Polytech University, China. His main research interests includes biometrics, image processing, and computer vision.