Pose Invariant Face Recognition under Arbitrary Illumination based on 3D Face Reconstruction

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Abstract. Pose and illumination will be quite difference between probe and gallery images in many face recognition tasks. In this paper, a novel technique for face recognition under varying poses and lightings is proposed by calibrating the pose and light to a reference condition through an illumination invariant 3D face reconstruction. First, from single facial image, the elaborate 3D shape is recovered based on a statistical deformable model regressed through 2D geometry formed by some facial landmarks. Then with the recovered 3D shape, the texture independent on the illumination is generated by spherical harmonics ratio image and finally the illumination invariant 3D face is reconstructed completely. Our method combines the strength of statistical deformable model to describe the shape information and the compact representations of the illumination in spherical frequency space, and handle both the pose and illumination variation simultaneously. This algorithm can be used to synthesize novel views and enhance the performance of general face recognition. Some experimental results on CMU PIE database are presented.

1 Introduction

The face recognition problem has been studied for more than three decades. And so far, the accuracy of face recognition for frontal face with indoor lighting is very high [7]. But in some daily applications, the recognition tasks are difficult for the uncontrolled variations in lighting and pose.

The reason that causes the performance decreasing of face recognition under variations of pose and illumination is the inconsistency of the views and illuminations between the probe and gallery images. The difference in poses and illuminations complexes the recognition based on 2D image. With the development of the face recognition, there appeared many works aiming to tackle pose or illumination problem, even for both pose and illumination blending problem.

In the early stage, no matter to tackle pose or illumination problem, the low dimensional representation is the main cue. Eigenfaces [5] and Fisherfaces [6] apply statistical learning to get the empirical low dimensional pose or illumination space of the faces. These methods have demonstrated their easy implementation and accuracy. But the performance decreases dramatically when the imaging condition is not similar to those of the training images. The Fisher light-fields algorithm [9] proposed by Gross etc tackled the pose and illumination problem by estimating the eigen light-field of the subject’s head from the input gallery or probe images, which was used as the set of features to do recognition finally. Extended this work, Kevin Zhou presented an illuminating light field algorithm, in which a Lambertian reflectance model was used to handle the illumination variation. This leads to a more powerful generalization to novel illuminations than the fisher light field. However, lots of images under multi-poses and multi-lights are needed for the training of this algorithm [4].

Since the pose and illumination variations are all related to the face 3D structure, the pose and illumination invariant face recognition can be easily achieved if the 3D shape is known. Some model-based approaches were proposed to treat the extrinsic parameters as separate variables and model their functional role explicitly. These methods commonly build an explicit generative model of the variations of the face images, to recover the intrinsic features of the face: shape and/or albedo. Georghiades proposed the Illumination Cone [1] to solve face recognition under varying lightings and poses. Sampling for each pose, the corresponding illumination cone is approximated by a low-dimensional linear subspace whose basis vectors are estimated using generative model. This method needs at least seven images of different lighting per person, which is too rigor for the most practical applications. Zhao studied the 2D image transformation under 3D rotation using a Lambertian reflectance model and proposed an algorithm called SSFS (Symmetric Shape From Shading) [14]. This method solved the pose and illumination problem with the aid of a 3D generic model and halved the unknown parameters according to the symmetric information. The most successful face recognition system across pose and lighting is the 3D morphable model [12]. In this method, the shape and the texture of a face are expressed as the barycentric coordinates as a linear combination of the shapes and textures of the exemplar faces respectively. The 3D faces can be generated automatically from one or more photographs by optimizing the shape parameters, the texture parameters and the mapping parameters. This morphable method has been used in FRVT 2002 for its good performance [7]. But the iterative optimal procedure causes the time consuming and the fitting process takes 4.5 minutes on a workstation with a 2Ghz P4 processor.

Inspired by the work of the 3D morphable model [12], we also take the 3D statistical deformable model to represent the 3D shape space of human face. But differ from it, only 2D shape vector of the given facial image is used to recover the whole 3D shape, and the texture is extracted directly from the input image. Based on the recovered 3D shape, we relight the texture image to the standard light condition. Then the illumination invariant 3D face is reconstructed completely. This strategy is based on the assumption that the pose is relevant to the relative locations of some key feature points and independent to the intensity of the image. Then the complicated optimal procedure is avoided by separating the shape and texture. The finally match is performed between the pose and illumination normalized facial images and the gallery images.

The remaining part of the paper is organized as follows: In Section 2, how to realize the pose and illumination invariant face recognition is described in detail, in which two parts are included. In subsection 2.1, the 3D shape reconstruction algorithm based on the statistical deformable model is described. In subsection 2.2 the illumination invariant texture generation with spherical harmonic ratio image is presented. Some synthesized examples based on our algorithm and the experiment results of face recognition across pose and illumination are presented in Section 3, followed by short conclusion and discussion in the last section.

2 Face Recognition Across Pose and Illumination

The whole framework of the face recognition across pose and lighting is as following. First, the irises are located by a region growing searching algorithm [2] and the rude pose class are defined for labeling the sparse feature points in the given facial image. Then 3D shape is reconstructed based on a 2D geometry driven statistical deformable model. Recurring to the recovered 3D shape of the specific person, the illumination invariant texture is obtained by relighting the texture extracted from the given image based on spherical harmonic ratio image. The pose and lighting calibrated image are used as the input of face recognition and get the identity result. Our algorithm can be regarded as a pre-process step of any face recognition system.

In the following subsections, we will explain the two key issues of the proposed framework: the 3D shape reconstruction and the illumination invariant texture generation. Considering that the shape information is enough and effective to 3D shape reconstruction, only the 2D shape vector composed by feature points of the input face is used with the aid of the 3D statistical deformable model. After the 3D face recovered, the 3D face for the given facial image is reconstructed completely with a succeeded texture mapping. Inspired by the low dimension effect of light on Lambertian surface and the compact representation of the canonical illumination in spherical frequency space, face illumination normalization is achieved by relighting with spherical harmonics.

2.1 3D Shape Reconstruction from Single View

It is well known that the most direct solution to do pose normalization for a single facial image is to recover the 3D structure of the specific face. However, without any assumptions, recovering 3D shape from single image is an ill-posed problem. The minimal number of the images necessary to reconstruct the 3D face is three [10]. To overcome this, we use the prior knowledge of the 3D face class as a statistical deformable model. A 3D face data set is used for training to get the statistical deformable model. This example set is formed by 100 laser-scanned 3D faces selected from the USF Human ID 3-D database [11]. All these faces are normalized to a standard orientation and position in space. The geometry of a face is represented by 75,972 vertices and down-sampled to 8,955 vertices in order to predigest computation. In the following paragraph, the whole 3D facial shape reconstruction procedure will be explained explicitly.

We represent the 3D geometry of a face with a shape-vector that is composed by concatenating the X , Y , and Z coordinates of the n vertices as:

$\mathbf{S} = (X_1, Y_1, Z_1, \cdots, X_n, Y_n, Z_n)^T \in \Re^{3n}$. Supposing the number of the 3D face training collection is m , each face vector can then be written as $\mathbf{S_i}$, where $i = 1, \cdots, m$. These shape vectors are aligned in scale and in fully correspondence. Because all face shapes are similar in holistic with some small differences, PCA (Principle Component Analysis) is appropriate for capturing the variance in terms of the principle components and filtering the noise among these shape vectors. Performing an eigen-decomposition to these 3D shapes using PCA and we obtain $d \le (m-1)$ eigen shape vectors, which constitute the projection matrix $\mathbf{P}$. Therefore, the statistical deformable model is formed: $\mathbf{S} = \sum_{i=1}^{m} w_i \mathbf{S_i}$. It denotes that each novel shape vector $\mathbf{S}$ can be written as the linear combination of the shape vectors of the m exemplar faces. It can be rewritten as: $\mathbf{S} = \overline{\mathbf{S}} + \mathbf{P}\boldsymbol{\alpha}$, where $\overline{\mathbf{S}}$ is the mean shape vector and $\boldsymbol{\alpha}$ is the coefficient vector corresponding to the projection matrix $\mathbf{P}$, whose dimension is d .

Expanding this denotation, if the face takes some rotation variation, then the above formulation can be written as:

$$\mathbf{SR} = \overline{\mathbf{S}}\mathbf{R} + \mathbf{PR}\boldsymbol{\alpha} \tag{1}$$

where $\mathbf{R}$ is the rotation matrix, relevant with the three rotation angles around the corresponding three coordinate axes. $\mathbf{SR}$ is the 3D face shape rotated around the original coordinate center. This equation can be proved easily according to the properties of the PCA. We import a denotation $\mathbf{V^R}$, which represents the operator performing a transformation to a 3D vector $\mathbf{V}$ by multiplying a rotation matrix $\mathbf{R}$. So, equation (1) can be rewritten as:

$$\mathbf{S^R} = \overline{\mathbf{S}}^{\mathbf{R}} + \mathbf{P^R}\boldsymbol{\alpha} \tag{2}$$

Similarly, the vector concatenating the X , Y coordinates of k landmarks in 2D image is denoted as $\mathbf{S_I}$. Each 2D landmark corresponds to a fixed point in 3D shape vector with the coincident mapping relation for different faces. The X and Y coordinates of these 3D points concatenated to a shape vector called $\mathbf{S_f}$, that is $\mathbf{S_f} = (X_1, Y_1, \cdots, X_k, Y_k)^T \in \Re^{2k}$. Because the $\mathbf{S_f}$ can be regarded as the partial segment of the 3D shape $\mathbf{S}$, the following equation approximately holds: $\mathbf{S_f} = \overline{\mathbf{S}}_\mathbf{f} + \mathbf{P_f}\boldsymbol{\alpha}$. Here $\mathbf{V_f}$ is imported to denote the 2D shape vector comes from extracting the X and Y coordinates from the 3D vector $\mathbf{V}$. Therefore $\mathbf{S_f^R}$ denotes the result 2D shape vector to extract the X and Y coordinates from the 3D shape vector $\mathbf{S}$ which has been transformed by the rotation matrix $\mathbf{R}$. So, $\overline{\mathbf{S}}_\mathbf{f}$ and $\mathbf{P}_f$ describe the corresponding parts to the 2D landmarks extracted from the 3D mean shape $\mathbf{S}$ and projection matrix $\mathbf{P}$ respectively. The feature landmarks in a facial image on any pose can be represented inferentially by the following formula:

$$\mathbf{S}_f^{\mathbf{R}} = \overline{\mathbf{S}}_f^{\mathbf{R}} + \mathbf{P}_f^{\mathbf{R}}\boldsymbol{\alpha} \tag{3}$$

Our aim is to reconstruct the whole 3D shape information with the coefficient vector $\boldsymbol{\alpha}$, which can be computed from the following equation:

$$\boldsymbol{\alpha} = (\mathbf{P}_f^{\mathbf{R}})^{+}(\mathbf{S}_f^{\mathbf{R}} - \overline{\mathbf{S}}_f^{\mathbf{R}}) \tag{4}$$

where $(\mathbf{P}_f^{\mathbf{R}})^{+}$ is the pseudo-inverse matrix, which can be computed by $(\mathbf{P}_f^{\mathbf{R}})^{+} = \left((\mathbf{P}_f^{\mathbf{R}})^T(\mathbf{P}_f^{\mathbf{R}})\right)^{-1}(\mathbf{P}_f^{\mathbf{R}})^T$. So the crucial element is to compute the accurate $\mathbf{S}_f^{\mathbf{R}}$ of the specific person from the feature landmarks $\mathbf{S}_I$ .The relation between $\mathbf{S}_I$ and $\mathbf{S}_f^{\mathbf{R}}$ can be represented by:

$$\mathbf{S}_I = \left(\mathbf{S}_f^{\mathbf{R}} + \mathbf{T}\right)c \tag{5}$$

For the rotation matrix $\mathbf{R}$, we define it with the three rotation angles α, β, γ. Making use of the 5 key landmarks in a face image and the corresponding 3D facial points of its 3D shape model $\mathbf{S}$, we can refer the three rotation angle parameters by projection computation. The 5 landmarks used to compute the rotation matrix $\mathbf{R}$ are the left and right iris, the nose tip, the left and right mouth corner, which can be gotten from the feature landmarks $\mathbf{S}_f$ labeled manually in face image and the refined 3D shape $\mathbf{S}$ respectively.

In the following, we will describe the iterative algorithm to compute the final shape coefficients vector $\boldsymbol{\alpha}$. In the first iteration, we set the $\overline{\mathbf{S}}_f$ to be the initial value of $\mathbf{S}_f$, and set $\overline{\mathbf{S}}$ to be initial 3D shape $\mathbf{S}$ of a specific person used for pose parameters estimation. The iterative optimization procedure is given below:

(a) Compute the rotation matrix $\mathbf{R}$ by erecting equation group according to 5 points projection computation.

(b) Then the translation $\mathbf{T}$ and scale factor c for the landmarks between $\mathbf{S}_I$ and $\mathbf{S}_f^{\mathbf{R}}$ are calculated based on the computation between these two 2D shape vectors.

(c) Calculate $\mathbf{S}_f^{\mathbf{R}}$ through equation (5) using the $\mathbf{T}$ and c gained above.

(d) Having the new $\mathbf{S}_f^{\mathbf{R}}$, we can get the coefficient vector $\boldsymbol{\alpha}$ easily by equation (4).

(e) Reconstruct the 3D face shape $\mathbf{S}$ for the specific person by equation $\mathbf{S} = \overline{\mathbf{S}} + \mathbf{P}\boldsymbol{\alpha}$

(f) Repeat the step (a) to (e) until the coefficient vector converges or the iteration times reaches the max number.

Finally, We get the optimal 3D shape for the given face. Then we transform the result 3D shape by multiplying the pose matrix $\mathbf{R}$ to get the rotated 3D shape, which has the same pose to the input face. To get more elaborate 3D shape solution, we regulate the X and Y coordinates of the vertices in 3D face according to the corresponding landmarks in 2D image.

2.2 Illumination Invariant Texture Generation with Spherical Harmonic Ratio Image

With the recovered 3D shape and the pose parameters in subsection 2.1, the texture information is extracted from the given 2D facial image. However, the texture varies with the variation of lighting. To get the intrinsic texture, we take the relighting strategy to calibrate the illumination of the extracted texture to the standard condition. Finally, the intrinsic texture can be mapped to the 3D shape and the 3D face is reconstructed completely.

Since the reflection equation can be viewed as a convolution, it is natural to analyze it in frequency-space domain. With spherical harmonics, Basri et al [8] proved that most energy of the irradiance was constrained in the three low order frequency components and got its frequency formula as

$$\begin{aligned} E(\alpha,\beta) &= \sum_{l=0}^{\infty}\sum_{m=-l}^{l} E_{lm} Y_{lm}(\alpha,\beta), \\ &= \sum_{l=0}^{\infty}\sum_{m=-l}^{l} A_l L_{lm} Y_{lm}(\alpha,\beta), \\ &\approx \sum_{l=0}^{2}\sum_{m=-l}^{l} A_l L_{lm} Y_{lm}(\alpha,\beta), \end{aligned} \tag{6}$$

where $A_l\,(A_0 = \pi, A_1 = 2\pi/3, A_2 = \pi/4)$ [8] are the spherical harmonic coefficients of Lambertian reflectance, L_{lm} are the coefficients of the incident light, and Y_{lm} are the spherical harmonic functions.

Given a texture image I, for each pixel (x,y), this equation always holds up: $I(x,y) = \rho(x,y)E\big(\alpha(x,y),\beta(x,y)\big)$. Here, the $\alpha(x,y)$ and $\beta(x,y)$ can be gotten from the normal vector of the 3D face shape. We also assume the albedo ρ is a constant, which can be verified by vision that most regions of the face are skin with almost the same albedo. Let $\mathbf{E_{lm}} = A_l \mathbf{Y}_{lm}$ denote the harmonic irradiance image and $\mathbf{E}$ is a $n\times 9$ matrix of $\mathbf{E_{lm}}$, where n is the pixel number of the texture image. Then the coefficients of the illumination $\mathbf{L}$ can be gotten by solving the least squares problem:

$$\hat{\mathbf{L}} = \arg\min_{\mathbf{L}} \left\| \mathbf{E}(\rho\mathbf{L}) - \mathbf{I} \right\|, \tag{7}$$

Once we have estimated the lighting condition of the given image, relighting it to the standard illumination is straightforward.

For any given point P at position (x,y) on the image, whose normal is (α,β), and albedo is $\rho(x,y)$, then the intensities at P in the original image and the canonical image are respectively:

$$\begin{aligned} I_{org}(x,y) &= \rho(x,y)\sum_{l=0}^{2}\sum_{m=-l}^{l} A_l \hat{L}_{lm} Y_{lm}(\alpha,\beta), \\ I_{can}(x,y) &= \rho(x,y)\sum_{l=0}^{2}\sum_{m=-l}^{l} A_l L_{lm}^{can} Y_{lm}(\alpha,\beta), \end{aligned} \tag{8}$$

where (x,y) ranges over the whole image.

The ratio image of the two different illuminations is defined as

$$R(x,y) = \frac{I_{can}(x,y)}{I_{org}(x,y)} = \frac{\rho(x,y)\sum_{l=0}^{2}\sum_{m=-l}^{l} A_l L_{lm}^{can} Y_{lm}(\alpha,\beta)}{\rho(x,y)\sum_{l=0}^{2}\sum_{m=-l}^{l} A_l \hat{L}_{lm} Y_{lm}(\alpha,\beta)} = \frac{\sum_{l=0}^{2}\sum_{m=-l}^{l} A_l L_{lm}^{can} Y_{lm}(\alpha,\beta)}{\sum_{l=0}^{2}\sum_{m=-l}^{l} A_l \hat{L}_{lm} Y_{lm}(\alpha,\beta)}. \tag{9}$$

Therefore, with the original image and the ratio image, the illumination canonical image is:

$$I_{can}(x,y) = R(x,y) \times I_{org}(x,y) \,. \tag{10}$$

After the elaborated 3D shape and intrinsic texture are gotten, we can reconstruct the whole 3D face of the specific person. For the invisible points in the texture, the interpolation strategy is exploited.

3 Experiments and Results

In this section, we evaluate the performance of the proposed algorithm through pose and illumination invariant face recognition. For a given non-frontal image under arbitrary illumination, we reconstruct its 3D face and the 3D face is illumination invariant. Pose normalization is achieved by rotating the 3D face to a predefined pose. Then the normalized image is used as the input of the general face recognition system to perform recognition.

3.1 Experiment Results for Face Recognition across Pose only

First, the experiment on face recognition across pose only is carried out on 4 pose subsets of CMU PIE database [12], which are pose set 05 (turn right 22.5 degree), pose set 29 (turn left 22.5 degree), pose set 37 (turn right 45 degree) and 11 (turn left 45 degree) respectively. And the gallery images are come from the pose set 27, which are all frontal images. Our face recognition strategy for identity recognition is the method called Gabor PCA add LDA. The similar idea of this algorithm can refer the GFC (Gabor Fisher Classifiers) algorithm proposed in [3]. The training images are selected from the CAS-PEAL Database [13], totally 300 persons, and each person has 6 pose images, 10 frontal images averagely [13]. In our experiment the feature points are labeled manually. Some pose normalization results based on the 3D face reconstruction are presented in Fig. 1 to give a visualize evaluation. The recognition results are listed in Fig. 2, which has intensively proved the good quality of the pose normalization based on our 3D face reconstruction. The recognition match score for the 4 pose sets are improved largely compared with the original recognition, and the recognition rate reaches to 94.85% averagely after pose normalization.

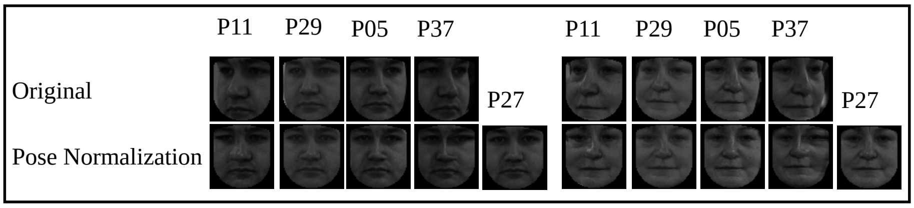
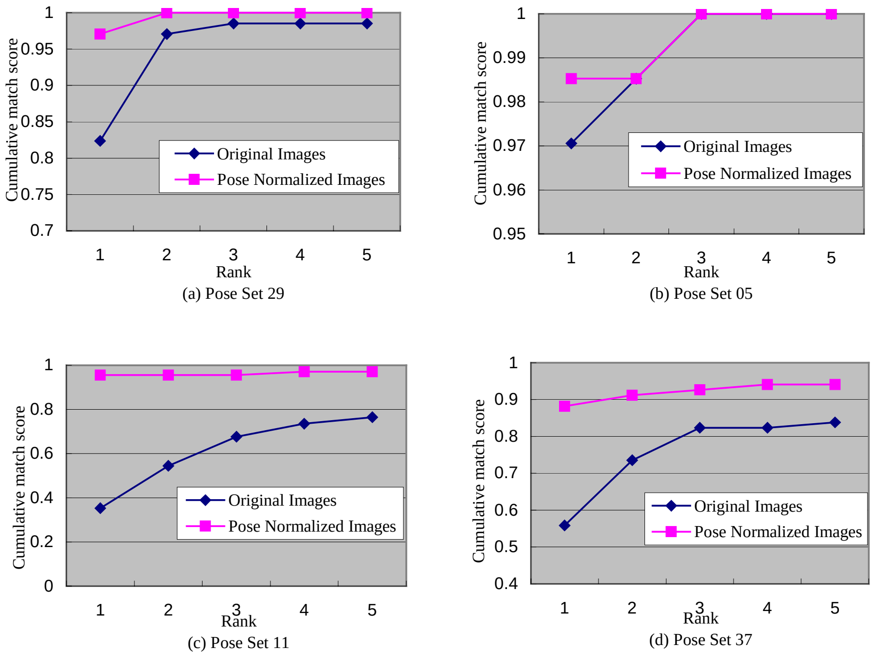


Fig. 1. **The pose normalized images. The first row is the original masked images. The second row is the corresponding pose normalized images, and right to which are the gallery images in 27 to be references.**



(a) Pose Set 29
(b) Pose Set 05
(c) Pose Set 11
(d) Pose Set 37

Fig. 2. **The recognition results on the original images and the pose normalized images in the 4 different pose sets of CMU-PIE database with Gabor PCA add LDA recognition strategy.**

3.2 Experiment Results for Face Recognition across Pose and Illumination

We verify the simultaneous effect of the pose and illumination normalization in this section. In our experiments, we used the “illum” subsets of the CMU PIE database, which provides the facial images under well-controlled poses and lightings. We take the experiment on 2856 images from the 2 pose subsets, 05 and 29, each subset including 21 different kinds of illuminations and the flash numbers are 02-21. The front pose set 27 under flash “11” is taken as the gallery, and the other probe images are all aligned to the frontal pose and the standard light as flash number “11”. Some pose and illumination normalized images are given in Fig. 3 The normalized images in (b) are more similar to the gallery image example as (c) in vision than the original images shown in (a). This pose and illumination normalization is a pre-process step of any face recognition system, so the simplest correlation match strategy is selected to perform our face recognition experiment. The experimental results of face recognition are listed in Table 1.

(a) (b) (c)

Fig. 3. **The pose and illumination calibrated results. (a) shows us the orignal image under 21 kinds of illumination of pose 05 one by one. (b) gives us the pose normalized and the face relighting results. (c) is the correspondence gallery image which comes from flash 11 of pose 27.**

Table 1. Recognition results on 2 pose subsets under 21 different lightings in CMU PIE Database with the correlation match strategy.

F\C	Pose 05 (original)	Pose 05 (calibrated)	Increase	Pose 29 (original)	Pose 29 (calibrated)	Increase
02	0.044	0.206	0.162	0.015	0.235	0.230
03	0.059	0.412	0.353	0.029	0.324	0.295
04	0.103	0.735	0.632	0.059	0.612	0.553
05	0.397	0.897	0.500	0.103	0.882	0.779
06	0.735	0.882	0.147	0.162	0.926	0.764
07	0.676	0.912	0.236	0.118	0.912	0.794
08	0.544	0.897	0.353	0.588	0.956	0.368
09	0.235	0.897	0.662	0.676	0.985	0.309
10	0.324	0.912	0.588	0.088	0.838	0.750
11	0.676	0.912	0.236	0.838	0.971	0.133
12	0.309	0.926	0.617	0.765	0.941	0.176
13	0.074	0.868	0.794	0.221	0.882	0.661
14	0.088	0.897	0.809	0.235	0.912	0.677
15	0.029	0.750	0.721	0.059	0.750	0.691
16	0.029	0.368	0.339	0.044	0.471	0.427
17	0.015	0.221	0.206	0.029	0.279	0.250
18	0.250	0.838	0.588	0.074	0.750	0.676
19	0.647	0.912	0.265	0.118	0.926	0.808
20	0.662	0.912	0.250	0.838	0.971	0.133
21	0.265	0.926	0.661	0.706	0.941	0.235
22	0.074	0.838	0.764	0.118	0.824	0.706
Average	0.296	0.768	0.472	0.280	0.776	0.496

4 Conclusion

In this paper a novel illumination invariant 3D face reconstruction is proposed to recognize facial images across pose and illumination. The 3D shape is recovered from single non-frontal facial image based on a statistical deformable model regressed through 2D geometry formed by some facial landmarks. Recurring to the reconstructed 3D shape, the illumination invariant facial texture is achieved with spherical harmonic ratio image. The experiments results show that the pose and illumination calibrating strategy largely improves the performance of the general face recognition for the probe images under uncontrolled pose and lighting.

Accurate alignment would facilitate the 3D shape recovery and the subsequent recognition. Therefore, one of our future efforts will be the accurate alignment, especially under the non-ideal lighting environment.

References

[1] 1. A.S. Georghiades, P.N. Belhumeur and D.J. Keiegman, “From Few to Many: Illuminition Cone Models for Face Recognition under Variable Lighting and Poses”, IEEE Transactions on PAMI, 2001, vol. 23, pp.643-660.

[2] B.Cao, S.Shan and W.Gao, “Localizing the Iris Center by Region Growing Search”, Proceeding of the ICME2002. 2002, vol. 2, pp. 129-132.

[3] C. Liu and H. Wechsler, "Gabor Feature Based Classification Using the Enhanced Fisher Linear Discriminant Model for Face Recognition", IEEE Trans. Image Processing, 2002, vol. 11, no. 4, pp. 467-476.

[4] K. Zhou and R. Chellappa, “Illuminating Light Field: Image-based Face Recognition Across Illuminations and Poses”, Proc. FG’04, 2004.

[5] M. Turk and A. Pentland, “Eigenfaces for Recognition” Journal of cognitive neuroscience, 1991, vol. 3, no. 1, pp. 71-86.

[6] P.N. Belhumeur, J.P. Hespanha and D.J. Kriegman, “Eigenfaces vs Fisherfaces: recognition using class specific linear projection”. IEEE Trans. on PAMI, 1997.7, vol.20, No.7.

[7] P. Phillips, P. Grother, R. Micheals, D. Blackburn, E. Tabassi and M. Bone, “Face Recognition Vendor Test 2002: Evaluation Report”, FRVT, 2002.

[8] R. Basria and D. Jacobs, "Lambertian Reflectance and Linear Subspaces", Proc. ICCV’2001, pp. 383-390.

[9] R. Gross, I. Matthews and S. Baker, “Eigen Light-Fields and Face Recognition Across Pose”, Proc. FG’02, 2002.

[10] T.S. Huang and C.H. Lee, “Motion and Structure from Orthorgraphic Projections”, IEEE Transactions on PAMI, 1989, vol. 2, no. 5: pp. 536-540.

[11] T. Sim, S. Baker, and M. Bsat, "The CMU Pose, Illumination, and Expression (PIE) Database", Proc. the 5th IEEE International Conference on Automatic Face and Gesture Recognition (FG'02), Washington, DC, May 2002.

[12] V. Blanz and T. Vetter, “Face Recognition based on Fitting a 3D Morphable Model”, IEEE Transactions on PAMI 2003, vol. 25, pp. 1063-1074.

[13] W. Gao, B. Cao, S.G. Shan, D.L. Zhou, X.H. Zhang and D.B. Zhao, “The CAS-PEAL Large-Scale Chinese Face DataBase and Evaluation Protocols”, Technique Report No. JDL-TR_04_FR_001, Joint Research & Development Laboratory, CAS, 2004.

[14] W. Zhao and R. Chellappa, “SFS Based View Synthesis for Robust Face Recognition”, In Proceedings of the International Conference on Automatic Face and Gesture Recognition, Grenoble, 2000, pp. 285-292.