Pose Invariant Face Recognition Under Arbitrary Illumination Based on 3D Face Reconstruction

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Abstract. Pose and illumination changes from picture to picture are two main barriers toward full automatic face recognition. In this paper, a novel method to handle both pose and lighting condition simultaneously is proposed, which calibrates the pose and lighting condition to a pre-set reference condition through an illumination invariant 3D face reconstruction. First, some located facial landmarks and a priori statistical deformable 3D model are used to recover an elaborate 3D shape. Based on the recovered 3D shape, the "texture image" calibrated to a standard illumination is generated by spherical harmonics ratio image and finally the illumination independent 3D face is reconstructed completely. The proposed 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 virtual views of a given face image and enhance the performance of face recognition. The experimental results on CMU PIE database show that this method can significantly improve the accuracy of the existed face recognition method when pose and illumination are inconsistent between gallery and probe sets.

1 Introduction

The face recognition problem has been studied for more than three decades. Currently, the accuracy of face recognition for frontal face under uniform lighting condition is pretty high [12]. However, in some more complicated cases, the recognition tasks suffer from the variations of poses and illuminations.

The appearance of faces may looks quite different when pose or illumination change, and this issues an imperfect task for face recognition when only the 2-D appearance-based method is applied. Although some 2-D-based methods are proposed to tackle pose or illumination variation problem, we believe that 3-D-based method is the final killer of both pose and illumination blending problem.

In the early years, using the low dimensional representation is the mainstream to tackle both pose and illumination problem in face recognition. Eigenfaces [11] and Fisherfaces [2] 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 decreased dramatically when the imaging condition is dissimilar to those of the training images. The Fisher light-fields algorithm [7] proposed by Gross etc tackled the pose and illumination problem by

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estimating the eigen light-fields of the subject's head from the 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 [14], 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.

Since the pose and illumination variations are all related to the 3D face structure, the pose and illumination invariant face recognition can be easily achieved once the 3D face 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 [6] to solve face recognition under varying lightings and poses. Sampling across pose changing, 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 under different lighting condition for each subject, which is impractical for the most of the applications. Zhao introduce the symmetric constraint to shape from shading for 3D face reconstruction and proposed the SSFS (Symmetric Shape from Shading) method [13]. The most successful face recognition system across pose and lighting is the 3D morphable model [3]. 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 [12]. However, the iterative optimization cost too much computational power and the fitting processing takes about 4.5 minutes on a workstation with a 2Ghz P4 processor.

Inspired by the work of the 3D morphable model [3], 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 and a sparse version of the 3D deformable model are used to get the optimal shape coefficients, which can recover the whole elaborate 3D shape. The face region is extracted directly from the input image. Based on the recovered 3D shape, we approximate the "texture image" by relighting the face region to the standard illumination. Then the illumination independent 3D face is recovered completely only from single face image under any pose with arbitrary illumination. 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 which have also been done the same normalization.

The remaining parts of the paper are 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 sparse statistical deformable model is described. In subsection 2.2

the illumination independent "texture image" generation with spherical harmonic ratio image is presented. Some synthesized examples based on our algorithm and the experimental 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 pose and illumination calibration for face recognition is given in Fig. 1. First, the irises are located by a region growing searching algorithm [4] and the rude pose class is 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 independent "texture image" is obtained by relighting the face region extracted from the given image with spherical harmonic ratio image strategy. 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 independent "texture image" generation.

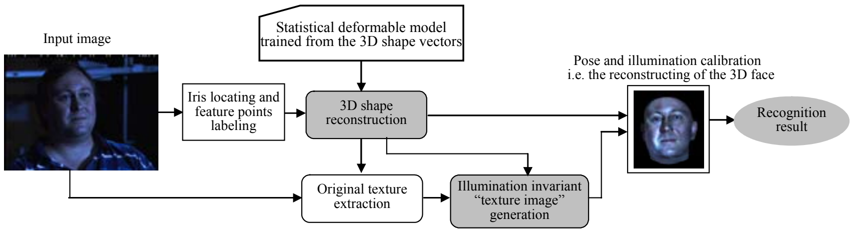

Fig. 1. The framework of pose and illumination calibration for face recognition

2.1 3D Shape Reconstruction from Single View

It is well known that the most direct solution to do pose normalization for a single non-frontal face image is to recover the 3D structure of the specific face. However, without any assumptions, recovering 3D shape from single image is a typical ill-posed problem. The minimal number of the images necessary to reconstruct the 3D face is three [8]. To overcome this, we use the prior knowledge of the 3D face class to describe the specific 3D shape of any novel face. A 3D face data set is used for training to get the statistical deformable model. This training set is formed by 100 laser-scanned 3D faces selected from the USF Human ID 3-D database [3]. 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 paragraphs, the whole 3D facial shape reconstruction procedure will be explained in detail.

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:

$\mathbf{S} = (X_1, Y_1, Z_1, \quad , X_n, Y_n, Z_n)^T \in \Re^{3n}$. Supposing the number of the 3D face training collection is m, each face vector can then be written as $\mathbf{S_i}$, where $i = 1, \quad , m$. These 3D shape vectors have been full correspondence. Each novel 3D shape can be represented as the linear combination of the m exemplar faces shapes by: $\mathbf{S} = \sum_{i=1}^{m} w_\mathbf{i} \mathbf{S_i}$. 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 the matrix composed by these 3D shapes using PCA and we obtain $d \leq (m-1)$ eigen shape vectors according to the descending order, which constitute the projection matrix $\mathbf{P}$. Therefore, the statistical deformable model is formed: $\mathbf{S} = \overline{\mathbf{S}} + \mathbf{P}\boldsymbol{\alpha}$, where $\overline{\mathbf{S}}$ is the mean shape 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 3D face coordinate center. We import a denotation $\mathbf{V^R}$, which represents the operator performing a transformation to a 3D vector $\mathbf{V}$ by right multiplying a rotation matrix $\mathbf{R}$. Therefore, 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 coordinates of k landmarks ($(x_i, y_i), i = 1,2, \quad , k$) 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. These corresponding 3D points constitute the sparse version of the 3D shape. The *x* and *y* coordinates of this sparse 3D shape concatenated to a 2D shape vector called $\mathbf{S_f}$, that is $\mathbf{S_f} = (x_1, y_1, \quad , x_k, y_k)^T \in \Re^{2k}$. 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* from the 3D vector $\mathbf{V}$. So, $\overline{\mathbf{S}}_\mathbf{f}$ and $\mathbf{P}_f$ describe the corresponding parts to the 2D landmarks extracted from the 3D mean shape $\overline{\mathbf{S}}$ and projection matrix $\mathbf{P}$ respectively. $\mathbf{S_f^R}$, which denotes the sparse 2D shape vector extracted from the 3D face under $\mathbf{R}$ 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 of the corresponding coordinate axis. Making use of the 5 key landmarks in a face image and the corresponding 3D facial points of its 3D shape model $\mathbf{S}$, the three rotation angle parameters can be inferred 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 respectively.

In the following, we will describe the iterative algorithm to compute the optimal 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 to get the initial values of the pose parameters. 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) Refine $\mathbf{S}_f^{\mathbf{R}}$ 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 coefficients vector converges or a limit on the iteration times is reached.

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 the given 2D image.

2.2 Illumination Independent "Texture Image" Generation with Spherical Harmonic Ratio Image

With the recovered 3D shape and the pose parameters in subsection 2.1, the face region is extracted from the given image. However, this face region image is influenced by the illumination condition. For the difficulty to get the really intrinsic texture, we transformed to compute the calibrated "texture image" under some standard illumination. Finally, this calibrated "texture image" can be mapped to the 3D shape and the illumination independent 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 [1] 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 $A_l\,(A_0 = \pi, A_1 = 2\pi/3, A_2 = \pi/4)$ [1] 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. The spherical harmonics has already been used in face recognition across illumination, such as [15].

Given a face region image I, for each pixel (x,y), this equation always holds up: $I(x,y) = \rho(x,y)E(\alpha(x,y),\beta(x,y))$. 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. 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 a standard illumination is straightforward [16].

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 illumination calibrated "texture image" are recovered, we can reconstruct the whole 3D face of the specific person. For the invisible points in the texture, the interpolation strategy is exploited. And the pose normalization can be achieved by rotating the 3D face model to any predefined standard pose.

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 illumination independent 3D face. Pose normalization is achieved by rotating the 3D face to a predefined (frontal) pose. Then the calibrated face image is used as the input of the general face recognition system to perform recognition.

3.1 Experimental 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 [10], 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 from the pose set 27, which are all frontal images. Our face recognition method is Gabor PCA plus LDA, whose idea is similar to the GFC [9]. The training images are selected from the CAS-PEAL Database [5], totally 300 persons, and each person has 6 pose images, 10 frontal images averagely. In our experiment the feature points are labeled manually. Some pose normalization results based on the 3D face reconstruction are presented in Fig. 2 to give a visualize evaluation. The recognition results are listed in Fig. 3, which has intensively shows the good performance of the pose normalization based on our 3D face reconstruction. The recognition match scores for the 4 pose sets are improved significantly compared with the original recognitions, and the rank-1 recognition rate reaches to 94.85% averagely after pose normalization.

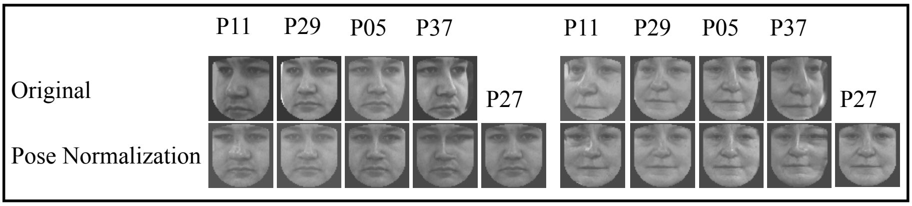

Fig. 2. The pose normalized images. The first row is the original masked images. The second row is the corresponding pose normalized images, and right to which are the gallery images in 27 to be references

3.2 Experimental 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 frontal 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 examples of the pose and illumination normalized images are given in Fig.4. The normalized images in (b) are more similar to the gallery image as (c) in vision than the original images shown in (a). The experimental results of face recognition with correlation matching strategy across pose and lighting are listed in Table 1.

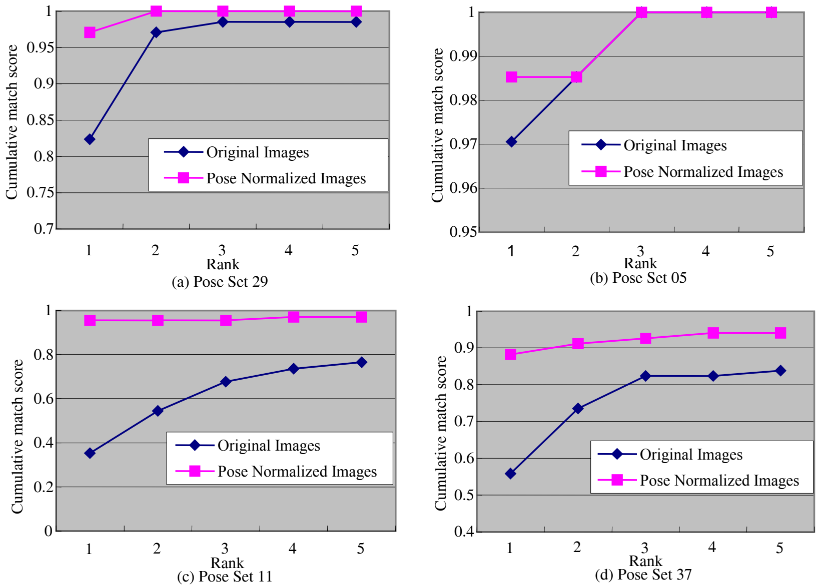

Fig. 3. The recognition results on the original and the pose normalized images in the 4 different pose sets of CMU PIE database with Gabor PCA plus LDA recognition strategy

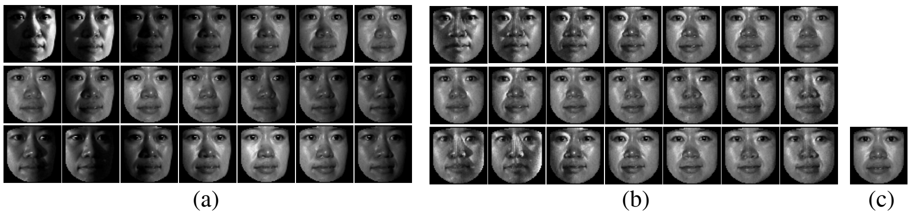

Fig. 4. The pose and illumination calibrated results. (a) the original images. (b) the corresponding pose and lighting calibrated results. (c) the gallery image

4 Conclusion

In this paper a novel illumination independent 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 independent facial "texture image" is achieved with spherical harmonic ratio image. The experimental 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.

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

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.

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