Reconstruction of sensible 3D Face Counterpart From 2D Images - A hybrid approach

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Abstract:
In this paper, we are going to implement a, realistic algorithm, for the reconstruction of, three dimensional head model, from a two dimensional image, using a hybrid method. The proposed system, reconstructs the, 3D head model, is the combination of, two components that are, cubical ray projection method and weighted normalization linear - based algorithm. for the first part, we propose a, new cubical ray projection algorithm that uses the linear equation, to recover the texture and shape parameters irrespective of lighting conditions and the pose of the input face image. By matching the recovered shape and texture parameters, the face recognition is implemented. In addition, we apply the weighted normalization linear-based technique, to establish the dense correspondences, between each three dimensional face model, and the reference face model. For the reconstruction of 3D face, from a single image, the proposed algorithm finds the, best combination of the output values. An investigational result shows that the, proposed 3D face reconstruction algorithm provides, adequate result and takes less time on a regular PC.

Keywords – 2d to 3d conversion

1 INTRODUCTION

3D Model based techniques, have been broadly used in a, variety of fields, in computer graphics. For example, Dalong Jiang et al. [14] proposed, cubical ray projection method, to construct the, realistic 3d Head model. Pentland and Turk [1] proposed, the eigen-face procedure, to recognize faces from images, by projecting face images into a PCA (Principal component analysis) technique. This PCA technique, extracts the features that are, not stable for, face recognition. Later, Taylor and Cootes, [2] presented a, statistical shape modeling technique, to describe 2D shape of an object, by an Active Shape Model(ASM). In addition, Vetter and Blanz, [3] developed a, morphable model, for modeling textured 3D faces, that is accomplished by transforming the texture, and shape into a, vector space representation. They used this morphable model, to reconstruct, 3D face model, from a single image. More recently, this 3D morphable model was, also useful to achieve, high-accuracy face recognition, with various poses and a wide range of illumination changes.

In most of the statistical techniques, one of the most essential aspects is, to represent the shape of the object, by a setting the landmark points. A numerous approaches, have been proposed to, register the landmark points. Some methods [3, 5, and 6] resolved, the 3D point correspondence problem, by applying 2D registration techniques, on a 2D projected space. Since the human head shape is, closely matched with a 3D ellipsoid, the data sets of 3D face can be, easily maps with a, cylindrical coordinate. 3D head models, by transforming the data sets, onto a cylindrical coordinate. This proposed method, principally based on, modifying the method, in [14], to achieve higher accuracy in finding, correspondences of 3D face, data points. Most of the previous, 3D face reconstruction techniques, require more than one image, to achieve, satisfying 3D human face modeling. Though, several different approaches for, 3D reconstruction from an image, such as shape from texture and shape from focus, these approaches are, not well suited for, 3D face reconstruction, due to limited texture information, in the human face images. Another approach for, 3D face reconstruction from an image is, to simplify the problem, by using a prior head model, of statistical. For example, Atick et al. [11] combined the, shape from shading constraint, with prior eigenhead model, to reconstruct a, 3D face model, by minimizing the, corresponding energy function. since the energy function to be minimized is independent of the illumination condition.

2 CONSTRUCTION OF POINT DISTRIBUTION MODEL

The PDM provides the, earlier knowledge of 3D human face models. The training 3D face models are, collected from two sources. The first part contains 79 face models acquired from a 3D laser scanner. There are 75 in males and 4 in females with ages between 22 and 25. In the second part of the 3D data set, we used 65 face models, which contain 43 male and 22 female of ages between 18 and 40, provided by GAVAB [11]. The flow chart is shown in Figure 1.

2.1 ITERATIVE ALIGNMENT

To estimate correspondences between 3D face models, we need to align the faces first, to a reference face model. The iterative closest point (ICP) method has been, used to determine the, pose parameters, From the correspondences of these 29 landmark points, we can determine an initial estimate of the scale, rotation and translation parameters by minimizing the following energy function,

$$\sqrt{\arg\min_{R,t} \sum_{i=1}^{n} \left\| x_i^r - (Rx_i + t) \right\|^2} \quad (1)$$

Where xi means, ith feature point, in a face data set, and xi r denotes the, feature points in the, reference 3D face model, and n is the number of feature points. Thus, the initial 3D alignment is compiled by, minimizing the above energy function [8]. After the initial alignment of 3D face models, we have to find more point correspondences automatically, to refine the 3D alignment. Instead of choosing the closest points between 3D head models for point correspondence, we do it by transforming the 3D head models, into a cylindrical coordinate by equation (2) as depicted in Figure 3.

Fig. 2. The generic 3D head model and the corresponding feature points.

(a) Generic head model in two views and (b) the 29 facial landmark points used in the system.

$$(\theta, h, r) = \begin{pmatrix} \tan^{-1}\left(\frac{X - X_C}{\sqrt{(X-X_C)^2 + (Z-Z_C)^2}}, \frac{Z - Z_C}{\sqrt{(X-X_C)^2 + (Z-Z_C)^2}}\right), Y - Y_C, \\ \sqrt{(X - X_C)^2 + (Z - Z_C)^2} \end{pmatrix} \quad \textbf{(2)}$$

Now the corresponding pairs can be determined easily. We first discretize the cylindrical coordinate space, with the co-ordinate of (θ, h) with a regular grid. Then we have to find the correspondence, for each point of the reference face model, from cubical ray projection of the sample head model, at the same (θ, h) coordinate, in the cylindrical space. Thus, extreme correspondence between the 3D face models can be, established to improve the 3D model alignment. The proposed alignment algorithm iteratively refines the 3D alignment.

2.2 Refined Correspondence through Transformation of Weighted Normalization Linear -Based Registration

After the above 3D alignment iteration, each face model is aligned, to a reference face model. But we do not simply use the correspondence pairs, as the training data sets, because the 3D transformations, used in the compiled, 3D face model alignment, cannot provide satisfactory matching, of facial feature points. Therefore, we can apply the, weighted normalization linear based approximation [13] to determine, an elastic transformation that manipulates the, pairs of correspondent landmark points. Then they are mapped to the, cylindrical space, in order to find the, corresponding points, in the other face models. Then we can apply linear interpolation, to find the weighted modes, of variations in the, 125 training data set. Some of the examples are depicted in Figure 4.

3. 3d Face Reconstructions

In this section, we present an algorithm for, reconstructing the, 3D head model from a single face image, by using the combination of, cubical ray projection method and weighted normalization linear based method, combining facial feature and contour matching. Both are using the method of 3D cubical ray projection method. The flow chart is shown in Figure 5.

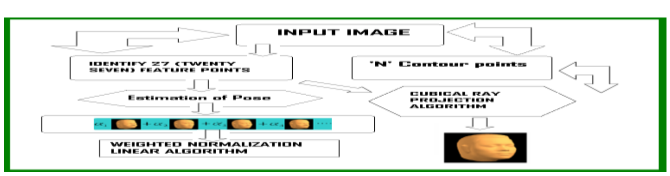


Fig. 5. Flow diagram of 3D faces reconstruction.

Then we can apply LM method, to optimize the final results, by considering both feature points and contour information simultaneously.

3.1 Initialize 3D Face from 2D Feature Information

In this work, we focused on the, 3D reconstruction from a near frontal, human face image. We assume that the 29 facial feature points have been extracted. These feature points include four corners of eyebrows, four corners of eyes, tip and two sides of nose, corners of mouth, top of upper lip and the bottom of lower lip shown as Figure 2(b). To initialize a 3D face model, we first estimate the pose of, human head by 29 feature points, and the pose information can be obtained by minimizing the energy function:

$$E = \sqrt{\sum_{i=1}^{n} \left\| u_i - (sR\bar{x}_i + t) \right\|} \tag{3}$$

Where ui is the ith feature point, on the 2D image, and xi denotes the ith feature point on the mean face. The rotation matrix R and translation vector t can be estimated by minimizing the, total re-projection errors with LM algorithm. We restrict the angle of rotation, within 5 degrees since we are mainly capturing the frontal face image. Let a 3D face model M be, represented by the mean head model, and a linear combination basis vectors (v1, v2, v3, …, vn) as follows:

$$M = \bar{M} + \sum_{i=1}^{e} \alpha_i v_i \tag{4}$$

Where α1,α2,…,αn are the, weights associated with the cubical ray projection basis vectors. To obtain an initial face model from the, 2D-3D correspondences, of the 29 facial feature points, we can formulate this model estimation problem, as the linear system:

$$\begin{bmatrix} \bar{x}_1 & v_{1,1x} & v_{1,2x} & \cdots & v_{1,ex} & 1\,0 \\ \bar{y}_1 & v_{1,1y} & v_{1,2x} & \cdots & v_{1,ey} & 0\,1 \\ \vdots & \vdots & \vdots & \cdots & \vdots & \vdots \\ \bar{y}_{fn} & v_{fn,1x} & v_{fn,2x} & \cdots & v_{fn,ey} & 0\,1 \end{bmatrix}_{2fn\times(3+e)} \begin{bmatrix} s \\ \alpha_1 \\ \vdots \\ \alpha_e \\ t_x \\ t_y \end{bmatrix}_{(3+e)\times 1} = R^{-1} \begin{bmatrix} u_{1,x} \\ u_{1,y} \\ u_{2,x} \\ u_{2,y} \\ \vdots \\ u_{fn,x} \\ u_{fn,y} \end{bmatrix}_{(2fn)\times 1} \tag{5}$$

Where R is the, concatenation of the, estimated rotation matrix, s is the scale, where as vi,j denotes the ith element of jth linear cubical ray projection based vector, and ‘n’ is the total number of linear modes, used in the face reconstruction, and ui is the ith 2D feature point coordinate. We can simply solve the above linear system to obtain the weights, of the linear cubical ray projection based vector, thus an initial 3D head model is determined.

3.2 Detail Refinement of 3D Face Model

In this refinement step, we apply the initial 3D face model and combine the feature points, and contour information, to reconstruct a 3D human face model, by using LM method optimization. One of the most consistent information for, 3D face reconstruction, from a single image is the, 2D face contour. Based on the 29 feature points, we simply apply a spline based contour extraction method, to detect the face contour, in a face image by, fitting a contour with, local maximal image gradients. In addition, we also proposed a 3D face contour extraction algorithm given as follows:

1. Normal direction of each vertex is approximated, by computing the, normal direction in the 3D face surface.
2. The vertices are viewed the orthogonally, to define the contours.
3. Splitting the space of all contour, into several bins, and choosing one from each bin with the maximum value ‘z’ as the 3D contour control point.

After the extraction of the projected contour, of 3D face model, the problem of how to define the, distance between the re-projected contour, and the extracted 2D image contour, is crucial. Here we apply a modified Hausdorff distance, to measure the distance between, two face contours, which is called one-way Hausdorff distance:

$$H(A,B) = K^{th}_{a \in A} \min_{b \in B} \|a - b\| \quad (6)$$

where the Kth largest value of, the minimum distance, from the location of, point set A to, point set B is used as the, distance between, the two point sets. We use a fractional value 'f' to determine, an appropriate value K to be

$$f = K^{th}_{a \in A} / |A|$$

Note that f = 0.901 to prevent some outlier effect. The idea is depicted in Figure 6.

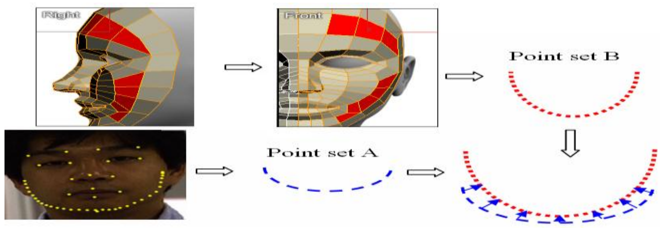


Fig. 6. One-Way Hausdorff Distance: Sparse point set A contains the sparse points on a 2D contour, and Dense point set B contains 2D re-projected contour points from a 3D model

Because the detected 3D face contour, is a set of dense points, we only compute the, Hausdorff Distance in the way, from 2D image contour to the, re-projected contour, as depicted in Figure 6. This distance becomes an additional error term:

$$E = \sum_{i=1}^{16} \left\| u_i - (sR\bar{x}_i + t) \right\| + H(C_I, C_{pj}) \quad (7)$$

To be more specific, the 3D face model reconstruction problem is, resolved by minimizing the, following energy function:

$$E = \sum_{i=1}^{n} \left\| u_i - (sR(\bar{x}_i + \sum_{j=1}^{e} \alpha_j v_{j,i}) + t) \right\| + H(C_I, C_{pj}(M)) \quad (8)$$

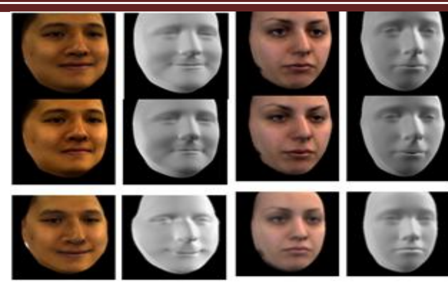
where CI is the contour point set, extracted from a 2D face image, and Cpj means the re-projected contour point sets, computed from the reconstructed 3D face model M. We take both the matching of facial feature points and facial contours, into account simultaneously, and minimize the total error by using the LM algorithm [9].

4 Experimental Results

We compiled and implemented the proposed system in C++ language, and all experiments are conducted on a PC with Intel Pentium IV, 2.8GHz CPU with 1 GB of RAM. To estimate the accuracy of the 3D face reconstruction, we define the following error measures.
one-way Hausdorff Distance of 2D contour error with f = 0.901.

4.1 Simulation Experiments

We took four different 3D face models, which are not included in the training set, to test the accuracy of reconstructed face models. The test 3D sample models are labeled with, 29 feature points in 3D space. Table 1 gives the average errors in 2D and 3D space, and the error are actually relatively small enough.



Real and Reconstructed 3D face models

Fig. 7. The comparison of 3D faces and the reconstructed faces displayed at a near-profile view after getting the result

4.2 Real Images Experiments

We tested the proposed, 3D face reconstruction algorithm, on the face images in the database [10]. All the individuals in the experiments are, not included in the set of, 3D face models for constructing the statistical 3D face model.

Fig. 8. The reconstruction process: the upper is real and the lower is the reconstructed profile

We selected some of the, frontal face images from the database, for testing the images. The corresponding profile face images, are used to perceptually compare the, difference between the real face images and the face images, which are rendered from the, reconstructed 3D face models as shown in Figure 8 and 9. showing the accuracy of our system. The reconstructed time also demonstrates the efficiency of our algorithm.

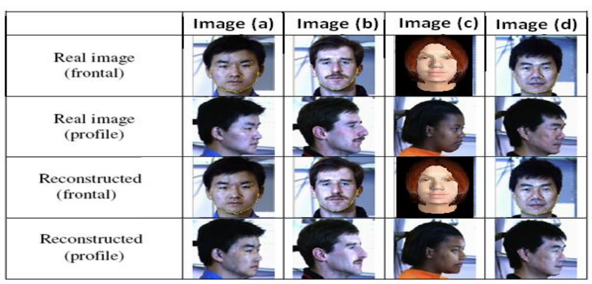


Fig. 9. The comparison of 3D face reconstructions in four numbers

Table 2. Reconstruction results on the real images

	Reconstruction time (sec)	E_f^{2D} (pixels) Max / Min / Avg			E_c^{2D} (pixels)
Image #1	8.938	4.573	0.0339	1.635	7.611
Image #2	4.000	4.778	0.2159	1.887	11.988
Image #3	5.905	3.255	0.2208	1.352	11.267
Image #4	6.656	3.760	0.2654	1.675	6.351
Ratio (error/Image size)		0.010 | 0.0159	0.0001 | 0.0008	0.004 | 0.0062	0.021 | 0.0399

5 Conclusions

In this paper, we developed a novel efficient algorithm by combining the 3D linear cubical ray projection method and the gradient method, to reconstruct the detailed 3D face model, from a single 2D face image. This proposed 3D face data alignment process achieves accurate 3D result. The experimental results on simulated and real images not only show the accuracy of the reconstruction process but also demonstrate its computational efficiency.

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