

Facial Modeling from an Uncalibrated face Image Using a Coarse-to-fine Genetic Algorithm

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Abstract

This paper presents a genetic algorithm-based optimization approach for facial modeling from an uncalibrated face image using a flexible generic parameterized facial model (FGPFM). The FGPFM can be easily modified using the facial features as parameters of FGPFM to construct an accurate specific 3D facial model from only a photograph of an individual with a randomly yawed face based on the projection transformation. The facial modeling problem is formulated as a parameter optimization problem and the objective function is also given. Moreover, a coarse-to-fine approach based on our intelligent genetic algorithm which can efficiently solve the large parameter optimization problems is used to accelerate the search for an optimal solution. Furthermore, experimental results with texture mapping demonstrate the effectiveness of the proposed method.

Keywords: Facial modeling, Genetic algorithm, Generic facial model, Pose determination, Optimization

1. Introduction

Face images have received considerable attention, particularly in the fields of computer vision and signal processing communities. For instance, model-based image coding methods have been proposed for future videophone and video conference services. However, the images in these applications are complex and highly variable, even for a specific individual. An important problem is how to create a 3D model of a specific individual. Automatic creation of a 3D facial model of a specific individual plays an important role in many applications, such as model-based coding for narrow-band visual communication^(1,2,3,4), view independent face recognition tasks^(5,6), and image synthesis problems in areas like virtualized reality⁽⁷⁾ and synthesis of novel views^(8,9).

3D facial models can be categorized into two classes: those based on the view-independent 3D facial structure and those considering only view-dependent facial models. The view-dependent facial model uses multiview representation in which a set of 2D image-based example facial models are combined into a flexible 3D facial model by a weighted sum of given example facial models^(9,10). The limitations of view-dependence narrow the scope of 3D facial model-related applications. The approaches used to automatically create 3D facial models with a view-independent 3D facial structure can be applied more

extensively⁽³⁾. Approaches capable of creating a view-independent 3D facial model of a specific individual can be categorized into two groups: use of an actual 3D face of a specific individual and use of a generic facial model with 2D face images of an individual. Among the approaches that need an actual 3D face include active vision⁽²⁾, 3D digitizer⁽⁸⁾, and vision-based methods⁽¹¹⁾.

Approaches belonging to the second group in which the 3D facial model of a specific individual is constructed consist of two steps. First, select a generic model representing the topological structure of a typical face and a typical front-viewed 2D face image of the individual and, then, adjust the geometrical shape of the generic model to that of the actual face image through 3D transformation and modification according to the positions of some facial features such as eyes, mouth, nose, and facial contour. Akimoto *et al.*⁽¹⁾, Tang and Huang⁽¹²⁾, and Ip and Yin⁽⁷⁾ use two orthogonal face images of an individual's head to acquire the features deemed necessary for fitting a generic model to an individual's head. Luo and King⁽¹³⁾ developed a facial-feature-extraction algorithm to automate the process of fitting the general facial wire frame model to the actual face image. Pei *et al.*⁽⁴⁾ used the transformation of the generic facial model with an affine mapping for model-based image coding by tracking 3D contour feature points. Aizawa *et al.*⁽¹⁴⁾ used multiple face images to adjust a flexible three-dimensional facial model for a particular face. Eisert and Girod⁽¹⁵⁾ changed the texture and control points' position using information from 3D laser scans to adjust the generic 3D model to a specific individual.

Given only a photograph of an individual with a front-viewed randomly yawed face, can one automatically create an accurate 3D facial model of the individual? For this purpose, assessing the effectiveness of the above approaches is relatively difficult since no work has reported on the generalization performance to automatically create 3D facial models which takes the pose of the face and the depth information in the fitting process into consideration from only a photograph. How to accurately modify the generic facial model to fit the specific face image from an uncalibrated face image is investigated in the work. Two fundamental problems which must fully cooperate with each other are the establishment of the generic facial model and the model modification method described as follows.

(a) Used as an optimization technique, genetic algorithms (GAs) have proven to be an effective way to search extremely large or complex solution spaces. Since genetic algorithms do not rely on problem-specific knowledge, they can be used to discover solutions that would be difficult to find by other methods. Due to the

complexity large variance of face images, there are many GA-based approaches are applied to the applications about human face⁽¹⁶⁻²⁶⁾. A. Guarda, *et al.*⁽¹⁶⁾ used GA techniques to learn visual feature and proposed a program which combines and integrates the features in non-linear ways to design a face detector. J. Ohya and F. Kishino⁽¹⁷⁾ detected deformations of facial parts from a face image regardless of change in the position and orientation of a face using a genetic algorithm. In addition, GAs are also used in the facial feature extraction⁽²¹⁻²³⁾, human face detection⁽¹⁸⁻²⁰⁾, human face location in images sequence⁽²⁴⁾, human posture estimation⁽²⁵⁾, and automated face recognition⁽²⁶⁾.

(b) An effective generic facial model is in general problem-dependent. In addition, the establishment of the generic facial model depends on the modification method for facial modeling. Parameterized facial model can produce realistic and manipulable face images with a small number of parameters^(27,28). Although parametric facial modeling has received considerable interest, the inverse problem of extracting parameters from face images has seldom been addressed. Therefore, developing a complete parameter set which can be automatically and easily manipulated is extremely difficult, especially from a monocular face image. Various kind of the wire frame facial models are adopted in various applications^(1,4,12,29,30). The larger the number of triangle elements implies a better quality of the synthesis image, however, the complexity of modeling grows.

In light of above two problems, this paper presents a GA-based optimization approach for facial modeling from an uncalibrated face image using a flexible generic parameterized facial model (FGPFM). The microstructure information can be expressed using the structural FGPF with representative facial features that can be accurately found in the image. The reconstruction procedure can be regarded as a block function of the FGPFM, and the input parameters are the 3D face-centered coordinates of control points. Once the control points are given, the desired 3D facial model is determined based on the topological and geometric descriptions of the FGPFM. How to reconstruct the 3D facial model is transformed into a problem of how to acquire the accurate 3D control points. More information about the construction of the FGPFM can be found in⁽³⁵⁾.

Since the solution space is large and complex considering the large number of control points in 3D space, the proposed coarse-to-fine approach based on our intelligent genetic algorithm IG⁽³¹⁾ is used to efficiently solve the optimization problem. IGA is an efficient general-purpose algorithm capable of solving large parameter optimization problem. Coarse-to-fine approach can efficiently adjust control points in 3D space. The fitness function takes into account the evidence from the face image and human perception. A coarse-to-fine IGA can effectively construct an optimal facial model. Merits of the proposed method are summarized as follows. (1) FGPFM is presented that the good parameters, the control points of the FGPFM can yield the good facial model for a specific person. (2) An analytic solution for the pose determination of human faces (PDF)⁽³²⁾ from a monocular image is used to obtain the initial 3D control points and make the coarse-to-fine IGA more efficient. (3) The reconstruction problem is formulated as a parameter optimization problem based on the ability of the FGPFM and PDF. Furthermore, a coarse-to-fine IGA is also proposed to speed up the search

for an optimal solution which is a set of the control points of FGPFM.

The rest of this paper is organized as follows. Section 2 formulates the facial modeling problem as an optimization problem and also outlines the reconstruction procedure. Section 3 summarizes the sensitivity analysis and shows the experimental results with texture mapping. Conclusions are finally made in Section 4.

2. Facial Modeling as an Optimization Problem

As widely recognized, accurate 3D control points based on the FGPFM can lead to an accurate 3D facial model of a specific individual. Herein, the reconstruction problem is formulated as a parameter optimization problem as follows.

Find a set of control points V_1^* , such that

$$F(V_1^*) = \text{Min. } F(V_1) \quad (1)$$

where V_1 is the set of control points of the FGPFM. The two major problems are:

- (a) How to construct the fitness function $F(V_1)$? And
- (b) How to search for the optimal solution V_1^* ?

2.1 Fitness function

The formulation of fitness function $F(V_1)$ closely corresponds to the quality of the 3D constructed model. Two criteria for evaluating the quality of the facial model are presented as follows

- (1) Projection of the facial model from some viewpoint must coincide with the features of the face image.
- (2) The facial model must adhere to the general knowledge of human faces accepted by the human reception.

Let $R = \{r_1, r_2, \dots, r_l\}$ denote the set of model ratios and $S = \{S_1, S_2, \dots, S_c\}$ where S_i is a control point/vertex or a point which may be projected on the silhouette of the transformed FGPFM. R and S can be determined from V_1 . According to the two criteria, we define

$$F(V_1) = f_p(S) + w_1 f_y(V_1) + w_2 f_z(V_1) + w_3 f_r(R) \quad (2)$$

where w_1 , w_2 and w_3 are weighting constants. Three error estimation functions are described as follows.

$$(1) \text{Projection function } f_p(S) = \frac{1}{c} \left(\sum_{i=1}^c \text{Dist}(s_i, s'_i) \right)$$

s_i and s'_i are the projection of S_i and its corresponding feature point in the face image, respectively.

$$(2) \text{Symmetry function } f_y(V_1) = \frac{1}{m} \sum_{i=1}^m S_{ym}(v_i)$$

control point $v_i = (x_i, y_i, z_i)$ and the symmetry point of v_i be $v'_i = (x'_i, y'_i, z'_i)$.

$$S_{ym} = \begin{cases} X_i^2 & \text{if } v_i \text{ should be on the} \\ & \text{symmetry axis,} \\ \left((x_i + x_i')^2 + (y_i + y_i')^2 + (z_i + z_i')^2 \right) & \text{otherwise.} \end{cases}$$

(3) Depth value function

$$f_z(V_1) = \frac{1}{|V_1|} \left(\sum_{i=1}^{|V_1|} \text{Dist}(z_i - \hat{z}_i) \right), \quad z_i \text{ and } \hat{z}_i \text{ are the}$$

depth values of control points in FGPFM and the estimated depth values, respectively.

(4) Model ratio function

$$f_r(R) = \frac{1}{I} \sum_{i=1}^I \left\{ 1 - \sqrt{2\pi} \sigma_i \left[\frac{1}{\sqrt{2\pi} \sigma_i} \exp\left(-\frac{1}{2} \left(\frac{r_i - \mu_i}{\sigma_i}\right)^2\right) \right] \right\}$$

where σ_i and μ_i are the means and standard deviation of model ratios r_i of the FGPFM, respectively.

2.2 Chromosome representation

Theoretical analysis, experimental studies and the application of IGA can be found in our recent work^(31,36). IGA has demonstrated the capabilities of solving the large parameter optimization problems with fast convergence and high accuracy. Due to the huge search space of adjusting 3D control points, IGA is indispensable for obtaining optimal solutions in the facial modeling procedure. coarse-to-fine approach using IGA is used to obtain an optimal facial model.

Based on the ability of PDF and FGPFM, the initial control points can be estimated by using the backprojection technique. Through a coarse-to-fine approach based on IGA, it is easy to adjust the initial control point set to an optimal control point set of FGPFM. Since the optimal control point set is the optimal solution for FGPFM, a best 3D facial model for a specific individual can be reconstructed accurately.

Chromosome is encoded as a string $((m_1, d_1), (m_2, d_2), \dots, (m_{|V_1|}, d_{|V_1|}))$ with $2 \cdot |V_1|$ parameters, where $|V_1|$ is the number of control points, m_i is an integer from 0 to 26, and d_i is an integer from 1 to N_{part} , $i=1, 2, \dots, |V_1|$. Where m_i represents the moving direction in the 3D space and $m_i=0$ means that the i^{th} control point is unadjusted. Where N_{part} represents the partition number of search space in each direction. Let D_i represent the radius of search space for the i^{th} control point. The moving step size S_{tep} is equal to $\frac{D_i}{N_{part}} \cdot d_i$. The new position of control points $C_i=(x_i, y_i, z_i)$

is $C_i + S_{tep} \cdot V_{m_i}$. Where V_{m_i} means the moving vector for direction m of i^{th} control point, listed in Table 1. For example: the first control point $C_1=(20,30,-5)$, $(m_1, d_1)=(17,4)$, $N_{part}=5$, and $D_1=3$. Then, $S_{tep_1}=2.4$ and $v_{17}=(1,-1,-1)$. Therefore, new control point $C_1=(22.4,27.6,-7.4)$.

2.3 Backprojection method for obtaining 3 control points

We have successfully presented an analytic solution for the PDF from an uncalibrated monocular face image using a generic facial model⁽³²⁾. PDF plays an important role in automatic facial modeling. Only four stable facial feature points, the far corners of the eyes and mouth that can be extracted by deformable templates⁽³⁷⁾, in an image are needed in PDF procedure. It can provide an exact and analytic solution for facial plane equation determined by the four feature points via a perspective projection inversion approach.

Generally, the iterative process without predetermining the pose is adopted to modify the 3D facial model until the superimposed face contours resemble those on the face image^(27,29). However using the iterative process to solve the combination problems of the pose and depth is not only difficult but also inefficient. Herein, we solve this difficult problem based on the ability to separate the pose and depth problems. The estimated initial control points are helpful for IGA to accelerate the search process.

2.4 Coarse-to-fine approach

Due to the huge search space for adjusting 3D control points, the search process of optimal control points consists of many steps using various partition resolutions of search space. We present a coarse-to-fine approach using IGA to efficiently find the optimal control points. The coarse and fine searches can be regarded as global and local searches, respectively. The parameter D_i , radius of search space, serves as the tuning parameters. Call one adjustment of all control points using one run of IGA one *step*. Let the radius

of search space for the j^{th} step be $D_i^j = \frac{D_i}{j}$ where

D_1^1 contains all the global search space. The stopping condition for one step can be determined by an improving factor E_{step} :

$$E_{step} = \frac{|X_i - X_{i-1}|}{X_{i-1}}, \quad (3)$$

where X_i represents the fitness function evaluation value of the i^{th} generation in IGA. If E_{step} is smaller than a threshold value ρ , it means that the optimal control point set has been obtained in the given search window. Once the control points are adjusted by moving one step according to the derived moving direction and step size, the radius of search window for next move must be adjusted in order to refine the solution. Notably, an elitist strategy is adapted in the coarse-to-fine IGA a specific chromosome $((0,0),(0,0), \dots,$

(0,0) into the initial population for the next step. The stopping condition of the entire coarse-to-fine algorithm can be determined b

$$E_{\text{stop}} = \frac{|Y_i - Y_{i-1}|}{Y_{i-1}}, \quad (4)$$

where Y_i represents the fitness function evaluation value of i^{th} step in IGA. If E_{stop} is smaller than a threshold value λ , the stop condition is met.

2.5 Overview the algorithm

Input data of the reconstruction procedure is a 2D face image with the visibility of the eyes and mouth corners and a FGPFM. Output is the 3D face-centered facial model. The entire facial modeling procedure is designed as follows.

- Step 1. Extract facial feature points by deformable templates, such as mouth contour, eye contours, head contour and nose feature (if possible).
- Step 2. Obtain face pose using PDF procedure.
- Step 3. Derive the initial 3D control points by backprojection technique.
- Step 4. Derive initial 3D control points by backprojection technique and a learning *priori* knowledge.
- Step 5. Set starting set of control points using elitist strategy.
- Step 6. Perform one generation of IGA to obtain an optimal solution for one step.
- Step 7. If stopping condition of one step is not met, i.e. $E_{\text{step}} > \rho$, goto Step 6.
- Step 8. Adjust the control points for one step.
- Step 9. If stopping condition of coarse-to-fine procedure is not met, go to Step5.
- Step 10. Use the coarse-to-fine IGA to obtain an optimal solution of $F(V_i)$ and the control point set V_1^* of FGPFM.
- Step 11. Reconstruct facial model using V_1^* and FGPFM.

3. Experimental results

In this section, three experiments using FGPFM, synthetic face images and actual face images are analyzed to demonstrate the feasibility of the proposed method. The first experiment demonstrates the effectiveness of the proposed fitting function and the high performance of coarse-to-fine IGA. In the second and the third experiments, an application applies our algorithm to obtain optimal control points in the reconstruction of a 3D facial model from a monocular face image and two uncalibrated face images, respectively. In all experiments, the parameters of IGA and the simple genetic algorithm with elitist strategy (ESGA) are: the population size = 20, mutation rate = 0.1, and the crossover rate = 0.5. The number of control points $|v_1|$ is 24 and $L_e=100$.

3.1 Experiment 1

An additional synthetic test image is generated by projecting the unperturbed FGPFM from some known view point and focal length. The used fitness function is

described in Section 2.1. The aim of the GAs is to adjust the perturbed 3D control points to fit the 2D image of the transformed FGPFM and simultaneously take the human perception of human face into consideration. The simulation results of ESGA, IGA, coarse-to-fine ESGA and coarse-to-fine IGA under various perturbation conditions are illustrated in Fig. 1. The N_{part} values used in GAs without coarse-to-fine procedure and GAs with coarse-to-fine procedure are 250 and 5, respectively. The performance in Fig. 1 is average measurement using ten independent runs. From these figures, it can reveal that coarse-to-fine IGA is still superior to other GA approaches using only a single 2D face image.

Define the relative error E_{rr} as follows

$$E_{\text{rr}} = \frac{\text{Fit}}{|v_1| \cdot L_e}. \quad (5)$$

After executing 400 steps of coarse-to-fine IGA the final Err values are 0.44%, 1.4304%, and 4.5529% corresponding to $w=4$, $w=10$, and $w=20$. From these accurate results, it demonstrates the effectiveness of the proposed fitness function for the coarse-to-fine IGA.

3.2 Experiment 2

Two uncalibrated face images, one front-viewed and one yawed face images, are used to examine the applicability of the proposed algorithm to actual facial images with unknown focal length of the camera and optical center of the image, as shown in Figs. 2(a) and 2(b).

Using PDF to obtain the initial control points of FGPFM, the coarse-to-fine IGA is applied to obtain an optimal set of control points. The fitness function used in the coarse-to-fine IGA is described in Section 2.1. Fig. 3(a) and Fig. 3(b) display the convergence from the input images Fig. 2(a) and 2(b), respectively. Let the optimal control point sets of coarse-to-fine IGA derived from the initial control point set using Fig. 2(a) and Fig. 2(b) be $\{ p_{f_1}, p_{f_2}, \dots, p_{f_{|v_1|}} \}$ and $\{ p_{y_1}, p_{y_2}, \dots, p_{y_{|v_1|}} \}$, respectively. Define the relative error E_{ref} as follows

$$E_{\text{ref}} = \frac{\sum_{i=1}^{|v_1|} \text{Dist}(p_{f_i} - p_{y_i})}{|v_1| \cdot L_e}. \quad (6)$$

After executing 400 steps of coarse-to-fine IGA, the error E_{ref} is 1.7002%. Notably, the model ratios of FGPFM are average measurement from sample face images and may be different to those in the given actual face.

Fig.4(a) shows the initial facial model constructed from the initial control points of FGPFM using image Fig. 2(b). Fig. 4(b) and Fig. 4(c) show the optimal facial model obtained using coarse-to-fine IGA in various poses. The texture-mapped face images using the reconstructed facial model Fig. 4(b) in various poses are illustrated in Fig. 5.

3.3 Experiment 3

In this experiment, we examine the effectiveness of the proposed algorithm for facial modeling from two uncalibrated face images Fig. 2(a) and Fig. 2(b). To make use of the evidence from two face images, the projection function $f_p(S)$ of the fitness function $F(V_i)$ is modified. The optimal facial model should be optimally superimposed with all the given face image. Therefore, the projection function takes all the feature points in the given face images into consideration.

The error E_{ref} is 0.95% after 400 steps of coarse-to-fine IGA. It reveals that the proposed algorithm can find the optimal solution using various initial control points. In other words, the proposed algorithm is robust for various poses of human faces. Compare the error E_{ref} of Experiment 3 and 4, 1.7002% and 0.95%, it demonstrates that two face images can obtain the better facial model than a single face image. Fig. 6 illustrates the optimal facial model which is the best fitting of Figs. 2(a) and 2(b) simultaneously.

4. Conclusions

This study has presented a novel genetic algorithm-based optimization approach for facial modeling from an uncalibrated monocular face image using flexible generic parameterized facial model. The proposed method has the following features. (1) FGPFMs are presented so that the good parameters, the control points, of the FGPFM can yield a good facial model for a specific individual. (2) An analytic solution for the pose determination of human faces (PDF) from a monocular image is applied for efficient facial modeling. (3) The reconstruction problem is formulated as a parameter optimization problem based on the ability of the FGPFM and PDF. Furthermore, the coarse-to-fine IGA is proposed to accelerate the search for an optimal solution that is a set of control points. Finally, sensitivity analysis and experimental results demonstrate the effectiveness of the proposed method.

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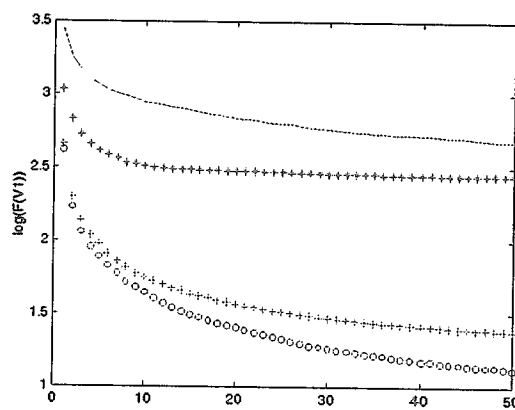
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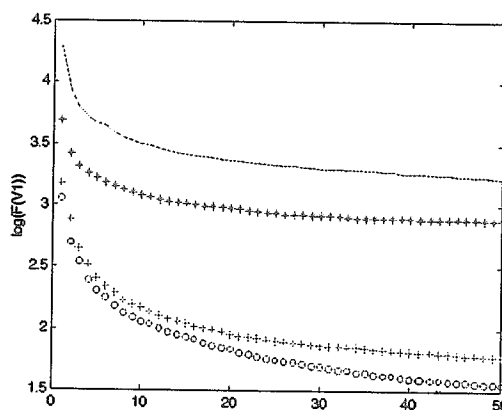
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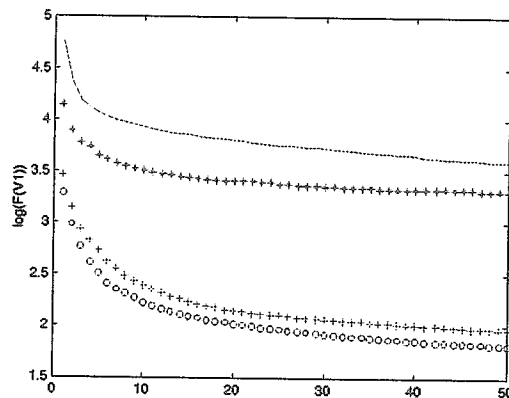
facial feature detection, *Pattern Recognition* 26, 1739-1755 (1993)



(a)



(b)



(c)

Figure. 1 Simulation results of various GA approaches. (a) $w=4$, (b) $w=10$, (c) $w=20$. Notation: -;ESFA, *;IGA

+ : coarse-to-fine ESGA, and o : coarse-to-fine IGA.



Figure. 2 Two input actual faces images with different poses.

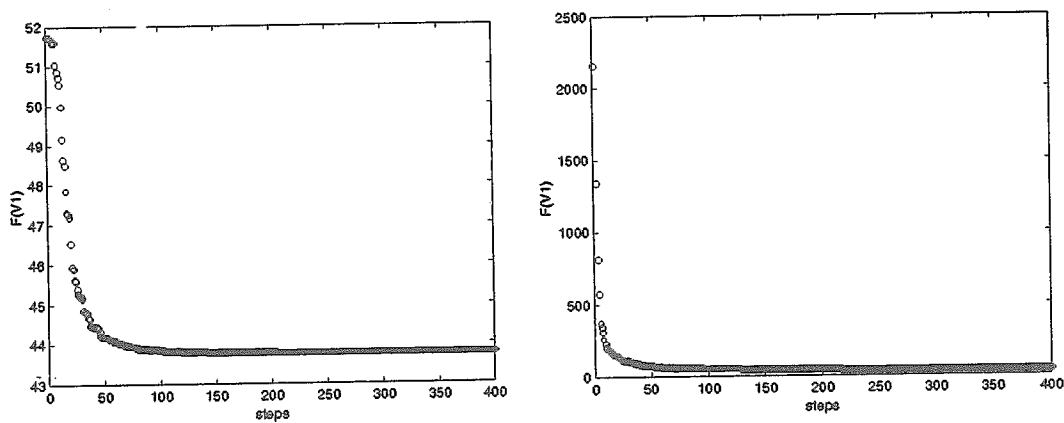


Figure. 3 The convergence speed and accuracy of Figure 2(a) and Figure 2(b), respectively

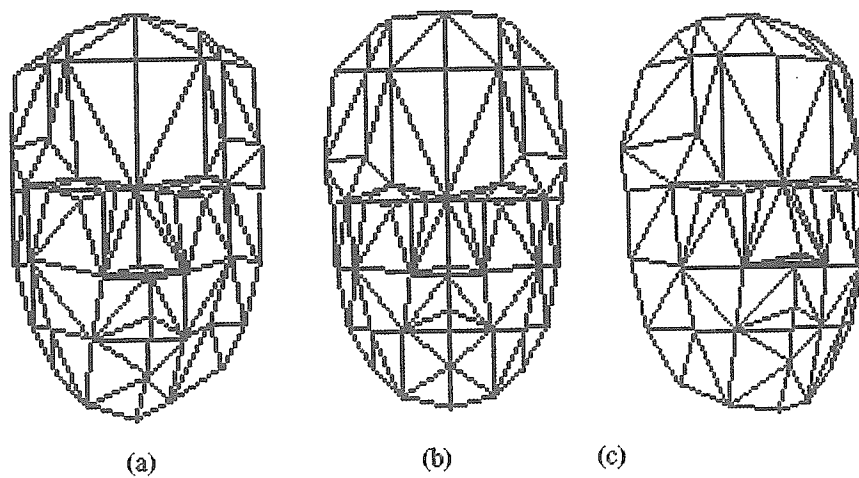


Figure. 4 (a) The initial unadjusted facial model in front view. (b) The adjusted facial model using coarse-to-fine IGA. (c)

The yawed facial model of Figure 4(b).

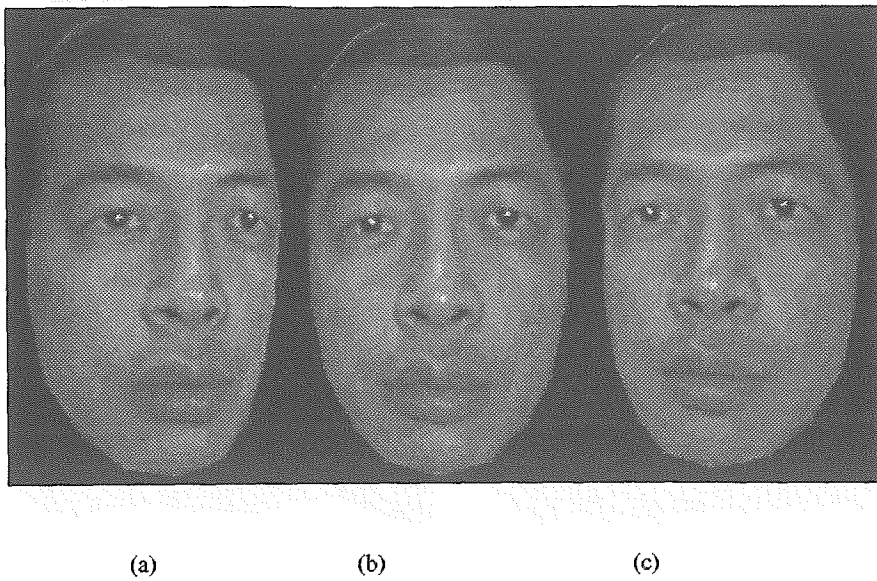


Figure. 5 The texture-mapped face images using the reconstructed facial model Figure 4(b) in various poses.

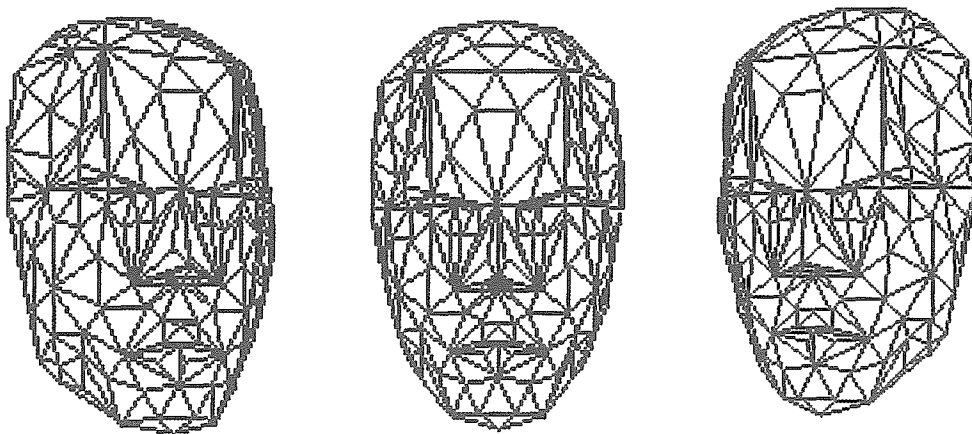


Figure. 6 The optimal tow-leveled in various poses facial model Figure 2.

Table 1. Moving vectors of control points 3D space.

direction m	moving vector v_m								
0~8	0,0,0	0,0,1	0,0,-1	0,1,0	0,-1,0	0,1,1	0,1,-1	0,-1,1	0,-1,-1
9~17	1,0,0	1,0,1	1,0,-1	1,1,0	1,-1,0	1,1,1	1,1,-1	1,-1,1	1,-1,-1
18~26	-1,0,0	-1,0,1	-1,0,-1	-1,1,0	-1,-1,0	-1,1,1	-1,1,-1	-1,-1,1	-1,-1,-1