A Vision-based Approach for Facial Expression Cloning by Facial Motion Tracking

Junchul Chun[1] and Oryun Kwon[2], *Members*
[1]Department of Computer Science, Kyonggi University,
Yui-Dong, Yongtong-Gu, Suwon, Gyeonggi-Do 443-760, South Korea
[e-mail: jcchun@kgu.ac.kr]
[2]HanSoft Co., Prime Center 554-6 Guui-Dong, Kwangjin-Gu, Seoul, South Korea
[e-mail: kor5663@kgu.ac.kr]
*Corresponding author: Junchul Chun

Received February 22, 2008; revised March 28, 2008; accepted March 31, 2008; published April 25, 2008

Abstract

This paper presents a novel approach for facial motion tracking and facial expression cloning to create a realistic facial animation of a 3D avatar. The exact head pose estimation and facial expression tracking are critical issues that must be solved when developing vision-based computer animation. In this paper, we deal with these two problems. The proposed approach consists of two phases: dynamic head pose estimation and facial expression cloning. The dynamic head pose estimation can robustly estimate a 3D head pose from input video images. Given an initial reference template of a face image and the corresponding 3D head pose, the full head motion is recovered by projecting a cylindrical head model onto the face image. It is possible to recover the head pose regardless of light variations and self-occlusion by updating the template dynamically. In the phase of synthesizing the facial expression, the variations of the major facial feature points of the face images are tracked by using optical flow and the variations are retargeted to the 3D face model. At the same time, we exploit the RBF (Radial Basis Function) to deform the local area of the face model around the major feature points. Consequently, facial expression synthesis is done by directly tracking the variations of the major feature points and indirectly estimating the variations of the regional feature points. From the experiments, we can prove that the proposed vision-based facial expression cloning method automatically estimates the 3D head pose and produces realistic 3D facial expressions in real time.

***Keywords*:** Head pose estimation, facial expression cloning, Radial Basis Function, optical flow

Digital Object Identifier 10.3837/tiis.2008.02.004

1. Introduction

Realistic animated facial modeling and facial expression control of a 3D face model has been an important research field for diverse application areas such as virtual character animation for entertainment, 3D avatars in the internet, and 3D teleconferencing. Therefore, there has been a growing interest in developing more intuitive and natural interaction between the user and the computer based on facial expressions. The vision-based approach for face motion tracking and facial expression recognition is therefore an attractive input mode for better human-computer interaction. However, facial motion tracking is a tough challenge particularly in varying lighting conditions and when there is a moving, clustered background image. Facial expression retargeting is considered to be particularly critical for designing a human-centered interface and for generating facial expression animation. The analysis of facial information from the sequential video images has been an additional challenging problem that must be resolved to cope with the problems caused by facial motion tracking.

Recent studies of vision-based facial motion tracking and facial expression control have been done to develop a real time facial animation system and facial expression cloning [1][2][3][4][5]. While developing such a system, face pose estimation and tracking are tough challenges particularly in varying lighting conditions and with a moving, clustered background image. To solve such problems, many research methods have attempted to recover face motion from image sequences [6][7][8][9][10][11]. One method uses distinct image features [6], and this method works well when the features may be reliably tracked over the image sequence. When good feature correspondences are not available, tracking the entire facial region using a 3D head model is more effective. Both generic and user-specific models have been used for head motion recovery [8]. Much simpler geometric models such as the planer model and the ellipsoidal model, which are effective and robust against initialization errors, have been introduced [9].

In this paper, we propose automatic model-based 3D head pose estimation along with facial expression cloning for vision-based animation. The proposed approach consists of two parallel phases. The first phase is to estimate the 3D face pose from video images and the second phase is to synthesize a realistic facial expression. At the initial stage, a candidate facial region is determined from an input face image by using an HT skin color model, and the exact face is extracted from the candidate facial region by using template matching. The template face image is generated by making an average face image from training face images, and Principal Component Analysis (PCA) is applied to the average face image. The PCA can reduce the high dimensional data set to a low dimensional data set. When the face is detected, the two phases are processed in a parallel fashion. In the phase of motion estimation, a cylindrical head model is created and projected onto the detected face image. The head motion is tracked by using optical flow and the exact head pose is recovered by dynamically updating the projected template. In the phase of synthesizing the facial expression, the facial features are extracted and the variations of the major facial feature points of the input face images are tracked by using optical flow, and the variations are retargeted to the 3D face model. At the same time, in synthesizing the facial expression, a Gaussian RBF (Radial Basis Function) is used to deform the local region of the 3D face model around the detected major feature points.

The rest of the paper is organized as follows. Section 2 presents motion estimation methods for face detection, facial feature extraction, and head pose tracking. Section 3 describes a facial expression synthesizing method based on scattered data interpolation with the Gaussian RBF (Radial Basis Function). Experimental results of face pose estimation and synthesized facial expressions created by the proposed method are provided in Section 4. In Section 5, the conclusion and future work is discussed.

2. Face Pose Estimation Method

Estimating the exact head pose is critical for extracting and tracking the variations of the facial expression from the video image. Face detection is the first step before tracking the varying head motion from the sequential input images. It is proven that the nonparametric HT skin color model proposed by authors [12][13] is efficient in detecting the facial region rather than using the existing parametric skin color model when light variation is involved. Based on the HT skin color model, we can extract the candidate facial region. In this work, we consider minimal numbers of feature points that are needed to recognize a facial expression. We extract only 12 major feature points such as the eye and mouth positions that are defined in MPEG 4 [4][5]. For extracting facial features, the geometric information of the face is used. The standard proportions for the human face can be used to determine its proper feature positions and find their orientation [14].

For head pose estimation, we first project a cylindrical 3D model on the detected facial area. Using the projected cylindrical 3D model, the full head motion from the sequential input images is estimated by tracking the cylindrical template model [15] rather than tracking the facial region itself [16]. **Fig. 1** illustrates a schematic flow for head pose estimation.

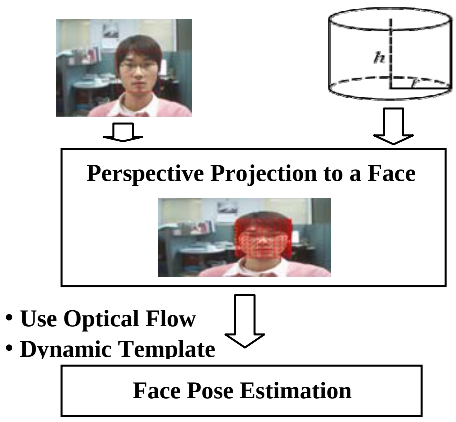


Fig. 1. Projection of the cylindrical model to a face for head pose estimation

Head motion tracking using a cylindrical 3D template can be described as follows. If we are given an image $I(u,t)$ at time t where $u=(x,y)$ is a pixel in the image, at $t+1$, u moves to $u' = F(u,\mu)$, where μ is the motion parameter vector and $F(u,\mu)$ is the parametric model that maps u to the new position u'. The motion vector μ can be obtained by minimizing the following function when the illumination condition is unchanged.

$$\min E(\mu) = \sum_{u \in \Omega} (I(F(u,\mu), t+1) - I(u,t))^2 \qquad (1)$$

where Ω is the region of the template at t. By using the Lucas-Kanade method [17][18], the problem of equation (1) can be solved as follows:

$$\mu = -\left(\sum_{\Omega} (I_u F_\mu)^T (I_u F_u) \right)^{-1} \sum_{\Omega} (I_t (I_u F_u)^T) \qquad (2)$$

where I_t and I_u respectively are the temporal and spatial image gradients. F_μ is the partial differential of F with respect to μ, which depends on the motion model and is computed at $\mu = 0$. To present the geometry of the entire head, the 3D cylindrical model is projected to the input face model and the head pose is estimated using the projected face model. If the location of the head pose at t is $X = [x, y, z]^T$, then the location of the head pose at $t+1$ becomes

$$X(t+1) = M \bullet X(t) = \begin{bmatrix} R & T \\ 0 & 1 \end{bmatrix} \bullet X(t) \tag{3}$$

when R is the rotation matrix with 3 degrees of freedom and T is the 3D translation vector. Then the image projection μ of $X = [x, y, z]^T$ at $t+1$ can be defined as

$$u(t+1) = \begin{bmatrix} x - y\omega_z + z\omega_y + t_x \\ x\omega_z + y - z\omega_x + t_y \end{bmatrix} \cdot \frac{f_L}{-x\omega_y + y\omega_x + z + t_z} \tag{4}$$

where $\lfloor \omega_x, \omega_y, \omega_z \rfloor$, $\lfloor t_x, t_y, t_z \rfloor$, and f_L represents the rotation, translation, and focal length respectively. Consequently, the motion model $F(u, \mu)$ with the parameter $\mu = \lfloor \omega_x, \omega_y, \omega_z, t_x, t_y, t_z \rfloor$ is defined by

$$F_\mu\big|_{\mu=0} = \begin{bmatrix} -xy & x^2+z^2 & -yz & z & 0 & -x \\ -(y^2+z^2) & xy & xz & 0 & z & -y \end{bmatrix} \cdot \frac{f_L}{z^2}(t). \tag{5}$$

In the real application, however, the occlusion caused by hands or other material frequently occurs and it makes the face pose tracking fail. In this work, the occlusion-induced problem can be resolved by dynamically updating the template while tracking the head pose. The single template through the entire image sequence is not adequate for coping with the problems like light change and self-occlusion. If any occlusion occurs in a certain frame, then the current template is removed and the most recently used template is recovered as a new template for the next frame. This improves the robustness of the head pose estimation.

3. Facial Expression Cloning Method

3.1 Local Model Deformation Using RBF

Synthesizing a facial expression uses two fitting processes: one fits the estimated feature points in the generic model, which correspond to the major feature points obtained by optical flow, and the other modifies the non-major points, which are the points around the estimated facial feature points that correspond to the major facial features in the generic model using the interpolation technique. In previous works, in order to retarget the facial expression to a specific facial model, several methods such as scattered data interpolation, anthropometry techniques, and projection onto the cylindrical coordinates incorporated with a positive Laplacian field function have been introduced [17][18].

In this work, we have used scattered data interpolation to create a deformed shape of the non-major feature points in the 3D face model. Scattered data interpolation refers to the problem of fitting a smooth surface through a scattered or non-uniform distribution of data points. We have considered the problem of scattered data interpolation as follows:

Given,

$$(p_i, q_i) \in \Re^3 \times \Re^3, \quad i = 1..N \tag{6}$$

find a continuous function $f : \Re^3 \rightarrow \Re^3$

$$f(p_i) = q_i, \quad i = 1..N \,. \tag{7}$$

The points (p_i, q_i) are corresponding feature point pairs and the points in $\Re^3$ are denoted either by $\vec{x}$, or $\vec{x} = (x, y, z)$. The class of solutions to the scattered data problems is classified into five categories based on the form of the solutions: polynomial or piecewise continuous polynomial parametric solutions, algebraic solutions, radial basis function methods, Shepard's methods, and subdivision. Radial basis functions are used to define the interpolation function as a linear combination of radially symmetric basis functions, each centered on a particular feature point. In general, an RBF is a smooth, continuous function that interpolates the given data and provides at least C^1 continuity [19]. An RBF is capable of closely interpolating a smooth hyper-surface such as human facial structures. Scattered data interpolation methods that are based on an RBF have some advantages. First, the deformation process does not require an equal number of nodes in the target meshes since missing points are interpolated. Second, mathematical support ensures that a deformed mesh approaches the target mesh if appropriate correspondences are selected [4].

An RBF generally consists of two functions. Given *N* corresponding feature point pairs, they can be described by the following equation, where $\vec{x} = (x, y, z)$;

$$f_k(\vec{x}) = P_{mk}(\vec{x}) + \sum_{i=1}^{N} A_{ik} \Phi \left(\|\vec{x} - \vec{x}_i\|\right), \qquad k = 1,2,3 \tag{8}$$

A_{Nk} is the weight associated with the N^{th} RBF, centered at $\vec{x}_i$. $P_{mk}(\vec{x})$ is a polynomial of degree *m*, or is not present. Φ is a radial function and $\| \ \|$ denotes the Euclidean norm, such that:

$$\|\vec{x} - \vec{x}_i\| = [(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2]^{\frac{1}{2}} \tag{9}$$

It is necessary to determine a proper basis function, weight, centers, and width parameter for interpolation. The nonlinear basis function Φ can be formed using a number of different functions: multiquadric, inverse multiquadric, Gaussian, thin-plate spline, shifted-LOG, and Cauchy. The choice of a basis function is determined by the dimension of the interpolation problem, the interpolation conditions, and the desired properties of the interpolation [19].

In this work, we adopt a Gaussian function as a basis function for facial expression control since it can exist without polynomial precision and it can be used to deform a complex structure like a face. Moreover, it is localized in a neighborhood near the center in comparison to other functions that have a global response. The basis function of the Gaussian can be expressed by:

$$\Phi(\|\vec{x}-\vec{x}_i\|) = e^{(-(\vec{x}-\vec{x}_i)^2/\sigma)} \tag{10}$$

The synthesized facial expression is made by tracking the direct changes of the major feature points and by creating the appropriate variations of the minor facial feature points that may be affected by the change of each major feature point. We regard such an area as a local facial cluster. In this research, the extracted 12 major feature points are considered as centers of each local facial area. Therefore, we need to decide only the weight and width parameter for each cluster. Since we know the 3D coordinates of feature points $\vec{x}$ and vertices positions $\vec{y}$ of the 3D face model that corresponds to the feature points, we can evaluate the weights by solving the following equations:

$$f_k(\vec{x}_i) = \vec{x}_i - \vec{y}_i,\ f_k(\vec{x}_i) = \sum_{j=1}^{N} A_{ik}\Phi(\|\vec{x}_i - \vec{x}_j\|)\ k=1,2,3 \tag{11}$$

The range of influence of the basis function can be controlled by regulating the σ parameter of the RBF. σ is called the width or locality parameter. This parameter gives more weight to near feature points and less weight to far feature points. If the value of the width parameter increases, it induces a smooth and more global interpolation. In this research, because the basis function must be localized, we select an appropriate small parameter, but it is large enough to adequately represent the basis function's range of influence. A few methods of selecting the width parameter have been introduced [19][20]. However, the currently used selection methods determine the width parameter experimentally and they apply the parameter to the face model globally. Thus, when we set the same parameter values at different points, it can induce an inaccurate interpolation result because the vertices of the 3D face model are scattered. Thus, different parameter values at different points can improve the accuracy of the interpolation.

In this work, we propose a new parameter decision rule that is applicable to scattered data interpolation such as the generic face model. We make clusters of feature points to detect points under the influence of each width parameter. The width parameters of each cluster are determined by use of the mahalanobis distance between the major points of the major feature and the furthest non-major points from the feature point, and it can be obtained by

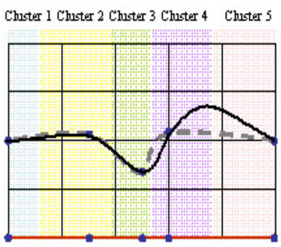
$$\sigma_i = \max_i([(\vec{x}_k - \vec{x}_i)' S^{-1} (\vec{x}_k - \vec{x}_i)]^{\frac{1}{2}}) \tag{12}$$

In formula (12), $\vec{x}_k$ is a point in the k^{th} cluster and S is the covariance matrix.

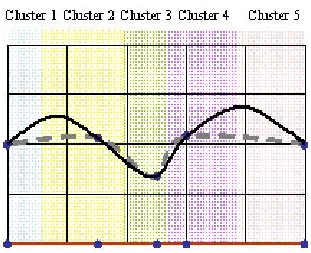
In order to verify the efficiency of the proposed parameter decision rule for scattered data interpolation, we make a comparison between the proposed method and currently used methods. A common way to determine the width or locality parameter is to obtain it experimentally. Since the experimentally determined single parameter is usually used for the interpolation of all of the scattered data, it is inappropriate to control the data locally. Meanwhile, the average distances between the feature points and the distributions of the feature points are also used for determining the width parameter [21][22]. These decision rules are expressed by

$$\sigma_i = \frac{\sum_{k=1}^{N} (\vec{x}_k - \vec{x}_i)^2}{N}, \quad \sigma_i = \frac{\sum_{i=1}^{N} \sum_{k=1}^{N} (\vec{x}_k - \vec{x}_i)^2}{N} \tag{13}$$

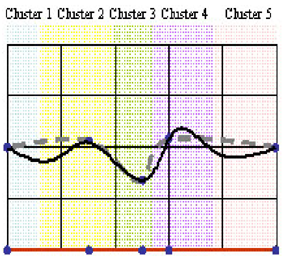
In the experiment, we have applied the parameter decision methods to the randomly generated data set. Since Gaussian functions presented in 2D are easily extendible into 3D, we can verify the efficiency by using a 2D graph. We generate 100 points randomly and arbitrary select 5 feature points as cluster centers among these data points. The transformed positions of non-selected points are measured when the selected feature points are moved. **Fig. 2** shows RBF interpolation results when each width parameter decision rule is used. The dotted line is the desired shape and the solid line is the transformed shape from a straight baseline by use of the scattered interpolation with a different parameter decision rule.



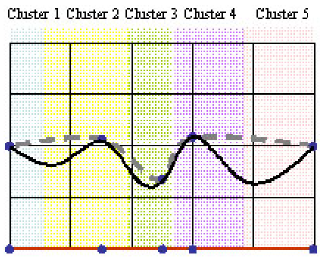
(a) Results by the proposed method



(b) Result by the experimental method



(c) Result by average distance



(d) Result by distributions

Fig. 2. RBF interpolation results using various width parameter decision rules

In **Fig. 2**, we can find gaps between the transformed line and the desired line especially in-between the fourth and fifth feature points. However, the line that is transformed by the proposed method is more similar to the desired line than the lines obtained by using the other decision rules. **Fig. 3** shows the classification results based on the 12 major feature points. The local clusters that can be affected by the variations of major feature points are determined by the K-means clustering algorithm. For each cluster, a different width parameter is assigned for the scattered data interpolation during model deformation.

Fig. 3. Twelve major facial feature points (left), their corresponding clusters (middle) and areas to be affected by the width parameters (right)

3.2 Estimation of Animation Parameters

In the facial expression cloning of a 3D face model, the geometric positions of the 3D model depend on both the facial features variation and the head pose variation from the input video image. The transformed positions of the facial feature points can be obtained from the feature positions of a frontal face image when the initial feature positions and the changed positions due to the head pose and facial variation are defined by $\vec{v}_0$ and $\vec{v}_p$. Then the relationship between $\vec{v}_0$ and $\vec{v}_p$ is defined by

$$v_p = T \bullet R \bullet \vec{v}_f,\ \ \vec{v}_f = \delta\vec{v} + \vec{v}_0 \tag{14}$$

where $\vec{v}_f$ is the positions of the features from the front of the face, $\delta\vec{v}$ is the animation parameter that represents the variation from an initial feature point to a changed feature point, T is the transform matrix, and R is the rotation matrix. T and R are defined by

$$T = \begin{bmatrix} 1 & 0 & 0 & T_x \\ 0 & 1 & 0 & T_y \\ 0 & 0 & 1 & T_z \\ 0 & 0 & 0 & 1 \end{bmatrix}\ R = \begin{bmatrix} u_x & u_y & u_z & 0 \\ v_x & v_y & v_z & 0 \\ w_x & w_y & w_z & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{15}$$

Thus, the animation parameter $\delta\vec{v}$ is simply the difference between $\vec{v}_0$ and $\vec{v}_p$. Thus, we can define it as

$$\delta\vec{v} = \vec{v}_f - \vec{v}_0 \tag{16}$$

where $\vec{v}_f$ can be calculated by

$$\vec{v}_f = R^{-1} \bullet T^{-1} \bullet \vec{v}_p \tag{17}$$

4. Experimental Results

All of the proposed methods are integrated into developing a real time facial expression synthesizing system for vision-based animation. **Fig. 4** depicts the overall steps for generating facial expression cloning from input video images. The facial motion cloning can be obtained by performing two parallel phases concurrently. In the phase of head pose estimation, a cylindrical head model is projected onto the face image. Subsequently, the head motion is tracked and the exact head pose is recovered by dynamically updating the projected template. For facial expression cloning, major facial features are extracted and the variation of the facial feature points is traced and retargeted to the 3D avatar model. At the same time, RBF is used to deform the local region around the major feature points.

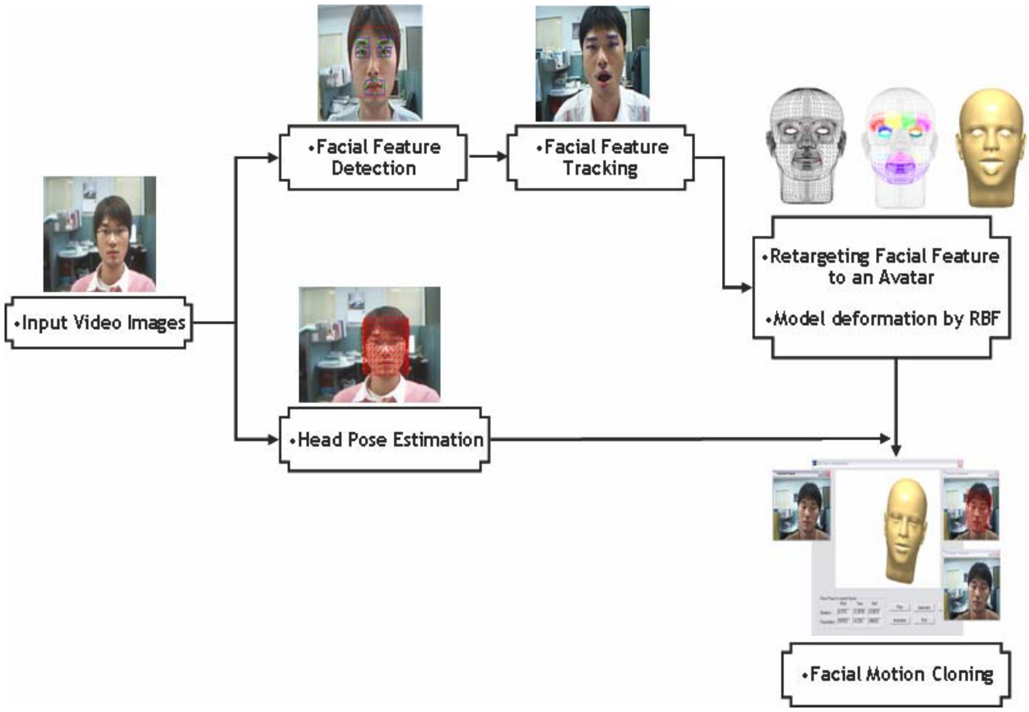
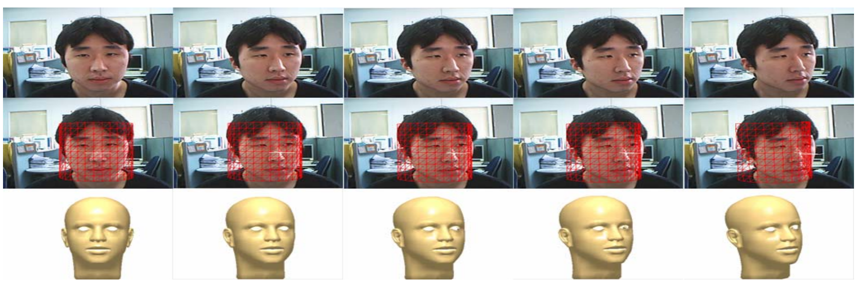


Fig. 4. Overall steps for vision-based facial motion cloning system

The results of face tracking and head pose estimation by projecting the cylindrical head model onto the detected face and tracking the face pose by using the optical flow method are illustrated in **Fig. 5**. The experiments show that head motion is fully recovered using the three different types of head pose variations consisting of translation, rotation, and back and forth movement. In this experiment, we have processed 10 frames per second for facial motion tracking and facial expression cloning.



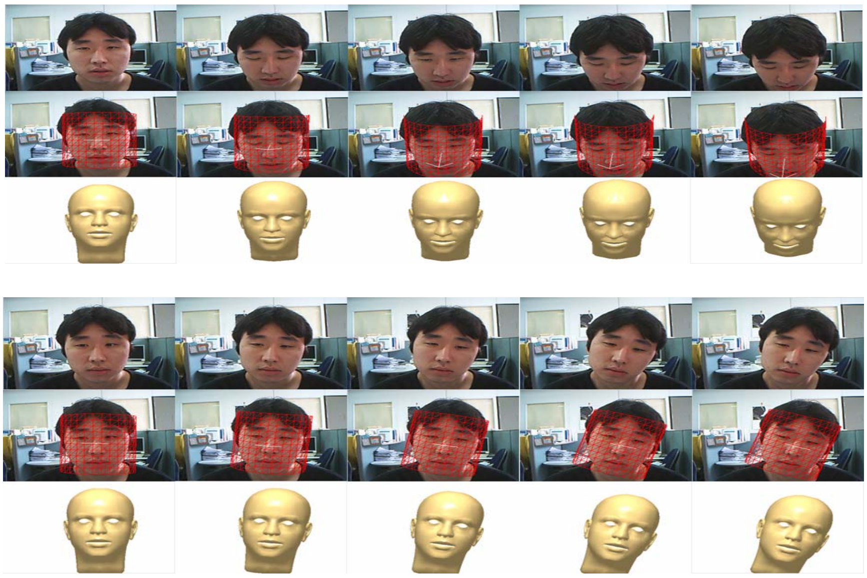


Fig. 5. Three different types of head pose estimation

The robustness of the developed face pose estimation is also proven against the partial occlusion caused by some objects. As shown in **Fig. 6**, the head pose is successfully recovered when facial area is partially occluded by hand or paper during tracking the facial region.

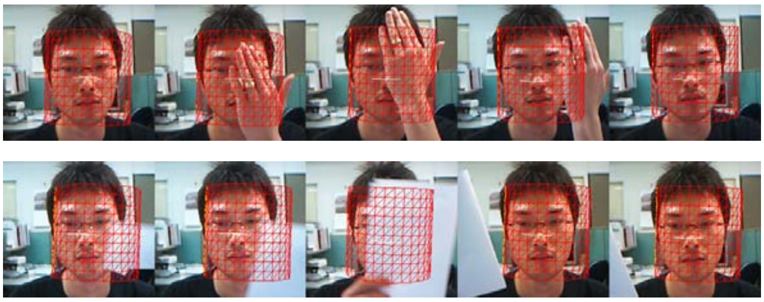
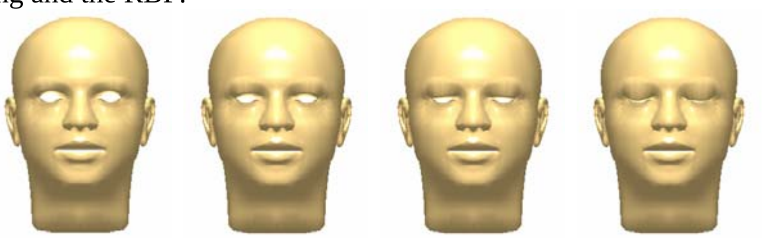
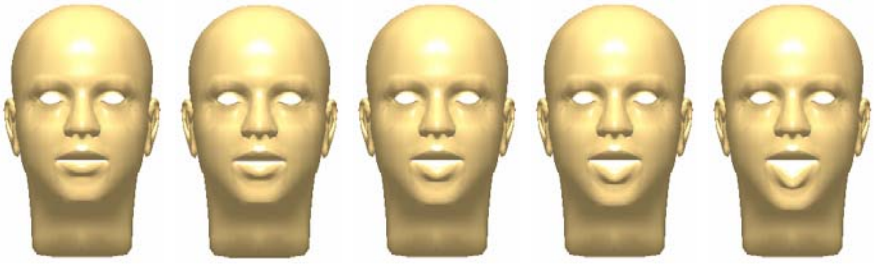


Fig. 6. Head pose recovery from the partial occlusion

Fig. 7 shows the synthesizing results of facial feature variations of the 3D face model according to the variation of facial features from the video images using the proposed facial feature clustering and the RBF.



(a) The results of retargeted eye blinking



(b) The results of retargeted smiling

Fig. 7. Results of facial expression cloning

We have compared the motion vectors (translation and rotation) between the proposed head motion estimation method and the feature-based method [16]. As illustrated in **Fig. 8**, the proposed method can estimate head motion in a stable fashion rather than using the feature-based method when the degree of rotation is relatively high.

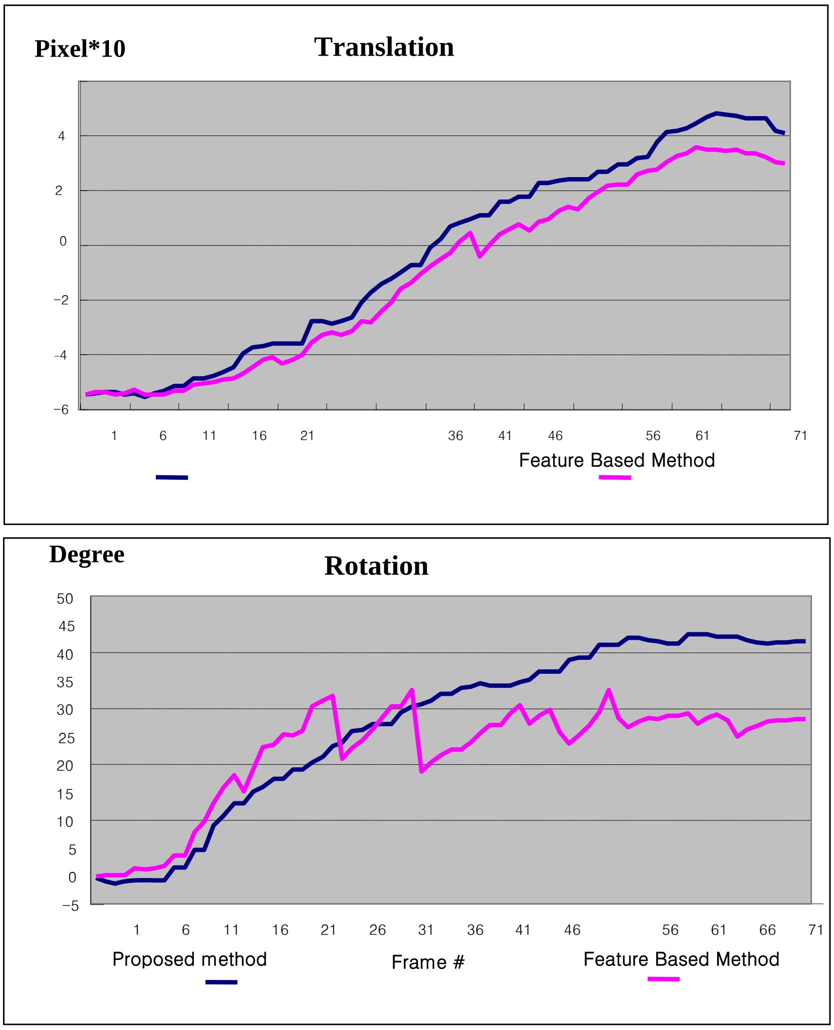


Fig. 8. Comparative result between the proposed method and feature-based tracking

We also use other 3D avatars such as a professor model and a wolf model for real time facial expression control. The head pose estimation and facial motion variation results for the professor and wolf models according to the change of facial features points and head pose estimation are illustrated in **Fig. 9**.

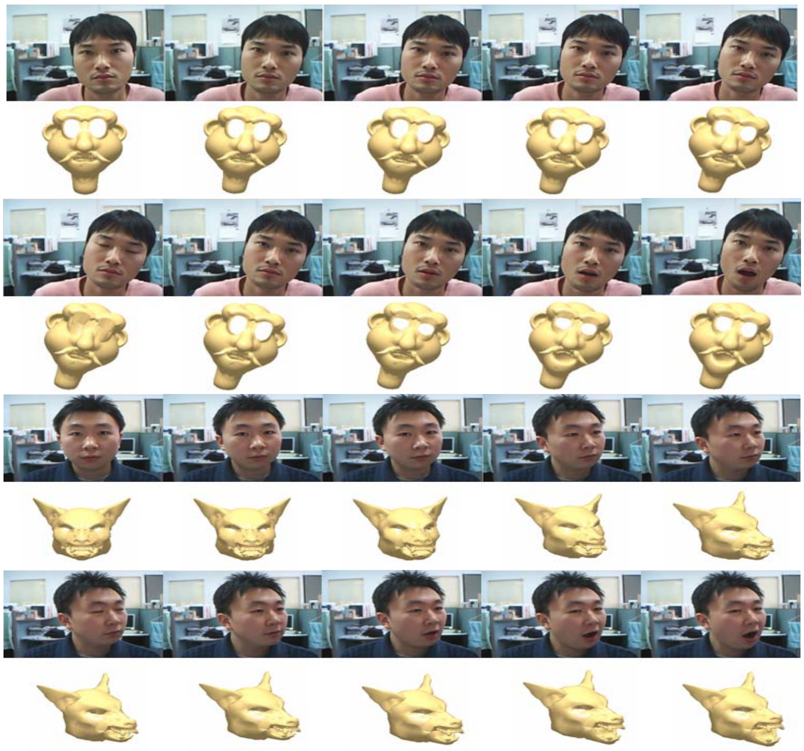


Fig. 9. Facial expression cloning of 3D avatar models

5. Conclusion and Future Work

In this paper, we proposed a real time vision-based approach for 3D head pose estimation and facial expression control for the face animation of a 3D avatar. For head pose estimation, a cylindrical head model was created and projected onto the detected face image. Then the head motion was tracked by using optical flow, and the exact head pose was recovered by dynamically updating the projected template. From the experiments, we showed that the proposed method can effectively recover the head pose fully even when self-occlusion occurs in the sequences of input images. The result of head pose estimation was used for real time facial expression retargeting to a virtual 3D avatar. For synthesizing the facial expression, the variations of the major facial feature points of the face images were tracked by use of optical flow, and the variations were retargeted to the 3D face model. At the same time, by applying scattered data interpolation with the RBF to the local deformation of the scattered facial features, points around the estimated major feature points of the 3D model were created. In this stage, we proposed a new width parameter decision method and showed how to use the locally applicable width parameters in the scattered facial feature point interpolation. From the experiments, we proved that the proposed vision-based facial expression cloning method automatically estimates the 3D head pose and produces realistic 3D facial expressions from an input video image in real time. As for future work, the next step is to improve the realism of the synthesized facial expressions by detecting more meaningful feature points automatically and by applying them to synthesis of facial expressions.

Acknowledgement

This research is supported by Foundation of Ubiquitous Computing and Networking (UCN) Project, the Ministry of Knowledge Economy (MKE) 21st Century Frontier R&D Program in South Korea and a result of subproject UCN 08B3-O3-40S.

References

[1] J.X Chai, J. Xiao and J. Hodings, "Vision-based Control of 3D Facial Animation," *Proceedings of the 2003 ACM SIGGRAPH/Eurographics Symposium on Computer Animation*, pp. 193-206 (2003)
[2] X. Wei, Z. Zhu, L. Yin and Q. Ji, "A Real time Face Tracking and Animation System," *IEEE Conf. on CVPR 2004*, Vol 5, pp. 71-78, 2004.
[3] J.Y. Noh and U. Neumann, "Expression Cloning, Computer Graphics," *Proceedings of ACM SIGGRAPH*, pp. 277-288, 2001.
[4] J. Noh and U. Neumann, "A survey of facial modeling and animation techniques," Technical report, USC 99-705, 1998.
[5] A. Wojdel and L. J. M. Rothkrantx, "Parametric Generation of Facial Expressions Based on FACS," *Computer Graphic Forum*, Vol. 24, pp. 743-757, 2005.
[6] J. Xaio, T Kanade and J. Cohn, "Robust full-motion recovery of head by dynamic templates and re-registration techniques," *Proceedings of the IEEE International Conference on Automatic Face and Gesture Recognition*, pp. 163-169, 2002.
[7] C.C Chien, Y.J Chang and Y.C Chen, "Facial Expression Analysis Under Various Head Poses," *Proceedings of 3rd IEEE Pacific-Rim Conf. on Multimedia* (*PCM2002*), Vol. 2532, pp. 1193-1200, 2002.
[8] I.A. Essa and A.P. Pentland, "Coding analysis, interpretation, and recognition of facial expressions," *PAMI*, Vol. 19, No. 7, pp. 757-763, 1997.
[9] G.D. Hager and P.N. Belhumeur, "Efficient region tracking with parametric models of geometry and illumination," *PAMI*, Vol. 20, No. 10, pp. 1025-1039, 1998.
[10] O.Kwon, JC Chun, P. Park, "Cylindrical Model-Based Head Tracking and 3D Pose Recovery from Sequential Face Images," *ICHIT '06*. pp. 135-139, 2006.
[11] JC Chun, OR Kwon, KP Min, "A Robust 3D Face Pose Estimation and Facial Expression Control for Vision-Based Animation," *LNCS 4351*, pp 700-708, 2007.
[12] K. Min, J. Chun, G. Park, "A Nonparametric Skin Color Model for Face Detection from Color Images," *LNCS 3320*, pp. 115-119, 2004.
[13] JC Chun, KP Min, "A Realistic Human Face Modeling from Photographs by Use of Skin Color and Model Deformation," *LNCS 3480*, pp 1135-1143, 2005.
[14] Bill Fleming, Darris Dobbs, "Animating facial features and expressions," Jenifer L. Niles, MA:Charles River Media, 1999.
[15] OR Kwon, K.P Min, JC Chun, Peom Park, "Real-Time Face Pose Tracking and Facial Expression Synthesizing for the Animation of 3D Avatar," *LNCS 4469*, pp. 191-201, 2007.
[16] OR Kwon, KP Min, JC Chun, "A Robust Head Pose Estimation and Feature Based Facial Expression Control," *Proceeding of the 1st APICT/IST*, pp. 53-58, 2006.
[17] J.L. Barron, D.J. Fleet and SS. Beauchemin, "Performance of Optical Flow Techniques," *Int. Journal of Computer Vision*, pp. 43-77, 1994.
[18] J.L Barron, N.A Thacker, "Tutorial: Computing 2D and 3D Optical Flow," Tina Memo No. 2004-012, 2005.

[19] M.A. Wirth, "A Nonrigid Approach to Medical Image Registration: Matching Images of the Breast," Ph.D. Thesis. RMIT University, Melbourne Australia. 2000.
[20] T. Lyche, L. Schumaker, "Scattered Data Interpolation in Three or More Variables, Mathematical Methods in Computer Aided Geometric Design," Academic Press, 1989.
[21] R. Franke, "Scattered data interpolation: Tests of some methods," *Mathematics of Computation*, Vol. 38, pp. 181-200, 1982.
[22] D. Ruprecht and H. Muller, "Image Warping with Scattered Data Interpolation," *IEEE Computer Graphics and Applications*, Vol. 15, No. 2, pp. 37-43, 1995.

Junchul Chun is currently a professor in the department of computer science and a principal investigator in the Graphics and Image Processing Research Laboratory at Kyonggi University, Suwon, South Korea. He received a B.S degree from Chung-Ang University majoring in computer science. He also received MS and Ph.D degrees from the department of computer science and engineering at the University of Connecticut, CT., U.S.A, in 1992 and 1995, respectively. He was a visiting research scholar in PRIP (Pattern Recognition and Image Processing) at Michigan State University from 2001 to 2002. He has served as an IEEE workshop chair of AITA (Advanced Internet Technology and Application) in 2007 and 2008. His current research fields are 3D face modeling, vision-based animation, and human computer interaction.

Oryun Kwon is a Research Engineer at the Hansoft Co., Seoul, South Korea. He received a BS degree and an MS degree in Computer Science from the Kyonggi University, South Korea, in 2002 and 2006, respectively. His research fields are computer animation, vision-based motion tracking, and face recognition.