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基于形状外观关联映射的动态脸部纹理生成*

杜杨洲+, 林学訚

(清华大学 计算机科学与技术系,北京 100084)

Dynamic Facial Texture Generation Based on Shape-Appearance Dependence Mapping Strategy

DU Yang-Zhou+, LIN Xue-Yin

(Department of Computer Science and Technology, Tsinghua University, Beijing 100084, China)

+ Corresponding author: Phn: +86-10-62782590, E-mail: dyz99@mails.tsinghua.edu.cn, http://www.tsinghua.edu.cn

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Abstract: The subtle details on an expressional face, such as creases and furrows, are very important visual cues, but they are difficult to model and synthesize as they vary dynamically from one frame to another while people speak and make expression. A novel strategy, which is different from the traditional texture mapping methods, is proposed for generating such a kind of dynamic facial textures according to the motion of facial feature points. Based on the observation that shape and appearance on face images are highly correlated, a mapping is designed to transfer one image to the other. The mapping is called SADM (shape-appearance dependence mapping). The experimental results show that the synthesized faces with SADM are very close to the real ones. The proposed SADM strategy can be integrated into a wire-frame based head model to generate the realistic animation effects, or applied to a model-based video coding to produce more efficient bit-rates.

Key words: realistic face animation; flexible models; dynamic texture generation; dependence mapping

摘 要: 脸部表情的变化细节(例如皱纹)是很重要的视觉线索,但是它们难以建模与合成.这是由于人们说话和作表情时,脸部纹理也在动态地改变.与传统的纹理映射方法不同,提出一种根据脸部特征点运动来生成脸部动态纹理的新方法.基于形状和外观在表情脸部图像上高度相关这个观察,设计建立了从形状到外观的映射关系.这个映射被称作“形状外观的关联映射(shape-appearance dependence mapping,简称 SADM)”.实验结果表明用,SADM 合成出的人脸与真实的人脸十分近似.提出的 SADM 方法可以集成到基于线框模型的人头模型中产生真实的动画效果,也可

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DU Yang-Zhou was born in 1977. He is a Ph.D. candidate at the Department of Computer Science and Technology, Tsinghua University. His current research areas include computer vision, image processing and pattern recognition. **LIN Xue-Yin** was born in 1940. He is a professor and doctoral supervisor at the Department of Computer Science and Technology, Tsinghua University. His research areas are computer vision, image processing and pattern recognition.

以应用于基于模型的视频编码来进一步节省传输带宽.

关键词: 真实感人脸动画;可融通模型;动态纹理生成;关联映射

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1 Introduction

Psychology research shows that a significant contribution to realistic expression comes not only from facial feature shape, but also from texture variations generated from expression. There have also been literatures on facial expression recognition, reporting that it would greatly improve recognition results by considering texture feature such as Gabor-wavelet feature rather than simply taking geometric feature into account[1,2]. The significant expression details on face include forehead wrinkles, dimple and cheekbone shadows, visibility of teeth and tongue due to mouth opening, fine and subtle variation on eye area, and so on. Since they vary frame by frame we call them the dynamical facial texture, and all of them are important cue in visual perception.

To illustrate this intuitively, Fig.1 shows a comparison of expressional face with and without expression details. The left face is warped from a neutral face, while the right one is a real expressive face. Though both faces take exactly the same shape and position of facial features, it is obvious that the left one is looked less believable for lacking essential expressive texture. In particular, it can be seen that in the mouth area, both the shapes of the outside contours are exactly the same, but the visual perception is extremely different.

Fig.1 A comparison of expressional face with and without expression details

Realistic facial animation has gained an increased attention in recent years. Its typical applications can be found in the scenario of talking heads, such as virtual news reporter, computer-aided instruction, visual telephone and so on. In order to pursue realistic animation effects, researchers adopt different methods and achieve a varying degree of success.

Most works in the field of facial animation adopt a 3D wire-frame head model. Although some researchers have devoted a great deal of efforts to the model development[3] and its animation[4], the dynamic facial textures such as furrows caused by different expressions turn out to be very difficult to model. The creation of these features using geometric methodology would require an extremely high polygon count in the 3D model with an intensive computation. In spite of this, complex models generally produce animation with an artificial look while rendering highly deformable facial parts such as mouth.

If facial texture can be updated for every frame, a realistic facial animation result can be achieved. However, direct texture updating is an expensive approach, requiring a high transmitting bandwidth or a large memory storage. To solve this kind of problem, Yin and Basu[5] propose a scheme of partial texture updating to cope with the requirement of very low bit-rate coding. Cosatto *et al*.[6] decompose the whole face into parts to reduce the total number of required sample images in their talking head system. As an alternative technique for expression generation, Liu *et al*. [7] capture the illumination changes due to expression in a ratio image and then map it to anyone else's face to generate a realistic facial expression.

In this paper, we propose a novel strategy for generating a dynamic facial texture according to the motion of facial feature points. To represent the variation of a facial appearance, we have built a compact parametric facial model by performing a statistical analysis over a video sequence of facial expressions. Based on the observation that the parameter variations of shape and appearance parts in the face model are highly correlated, we design a mapping to transfer the former to the latter. The mapping is called SADM (shape-appearance dependence mapping). With SADM, a proper dynamic expressive facial texture can be generated according to the shape of face feature. The work reported in this paper handles dynamic facial texture generation under constant lighting for a specific person. This condition is commonly satisfied in the most scenarios of talking head.

The rest of this paper is organized as follows. Section 2 describes a parametric model for the face appearance used in our experiments. Sections 3 and 4 give the principle and implementation of shape appearance dependence mapping on face images respectively. Experimental results and evaluation are presented in Section 5. Finally, we conclude our work and discuss the limitation and some potential application of our method.

2 Face Appearance Modeling

In order to implement the dynamic facial texture generation, we should firstly represent face images with a proper model. For convenience the flexible model proposed by Cootes *et al*.[8] has been adopted in our method. The model has achieved a great success in face modeling applications, for it is built by performing a statistical analysis over a training set and is capable of capturing all the sources of variability on face images.

The flexible model consists of a shape part and a grayscale part. They are complementary to each other and are used together to describe the overall appearance of each face example. For generating a shape model, a number of key feature points must be extracted from each face. A column vector s is used to record coordinates of these feature points. After that, a principle components analysis (PCA) is applied on the set of vectors to obtain a representation with reduced dimensionality. Thus, a training example can be approximated by

$$s = \bar{s} + P_s b_s \tag{1}$$

where $\bar{s}$ is the mean shape vector, P_s is a matrix of unit eigenvectors of the covariance deviations, b_s is a column vector of weights and referred to as shape model parameters.

To build a grayscale model, each example face image must be warped first so that the whole face matches with a reference face shape (commonly the mean shape is selected). This operation guarantees that each training example aligns its feature points with the reference one. It also ensures the number of pixels for each example is identical. The intensity values of pixels along a scanning line order are recorded using a column vector, g. Similar to the shape model, by performing the PCA on these grayscale vectors, a shape-normalized grayscale patch of the training example can be estimated as

$$g = \bar{g} + P_g b_g \tag{2}$$

where $\bar{g}$ is the mean grayscale vector, P_g is a matrix of unit eigenvectors, b_g is a weight vector and referred to as grayscale model parameters. Thus, each training example is fully represented by its corresponding b_s and b_g. Correspondingly, given these two vectors, the full appearance of the corresponding example face image can be well reconstructed.

In our work, the video sequence, Mario, used in Ref.[5] is taken as experimental data, in which the actor displays a set of facial expressions with rich dynamic textures. The size of the face area on the frame is about 120×120 pixels and the total number of frames is 128. All the face images in the video are taken to build the flexible model for face and the number of face model parameters is chosen empirically. As a result, the derived model needs 5 variables for the shape part and 15 variables for the grayscale part to explain most of the variations over all face in the video sequence.

3 Principle of SADM

As mentioned in introduction, a dynamic texture on an expressive face is a very important visual cue. It can be observed that if a synthesized face tends to be more realistic, the problem of dynamic texture generation should be considered. A dynamic texture is defined as a texture on the face that varies dynamically with different expressions. For example, furrows in the forehead may appear while a person is raising eyebrows, wrinkles on canthus may turn to be deeper, and cheekbone may become lighter while one is smiling. Especially, the texture inside the mouth may vary due to the motion of teeth and tongue while a person is talking.

In order to render these dynamic textures properly and efficiently, we develop a Shape Appearance Dependence Mapping (SADM) strategy. Our idea is inspired by the observation that the variations of facial shape and facial texture occur simultaneously. Furthermore, their variations are highly correlated. In fact, this phenomenon has been noticed by Cootes *et al*. and used to make the flexible model more efficient. In later work on their statistical model for appearance, they concatenated the b_s and b_g vectors (see Eqs.(1) and (2)), applied a further PCA to remove correlations between the shape and grayscale variations, and obtained a more compact representing model.

Based on the observation that the variation of a dynamic texture is caused by the shape variation of a related facial feature, the shape variation can be used as a handle for manipulating the dynamic texture correspondingly. For a specific person, shape and texture on the face can be corresponded one by one in some extent. In the flexible model building, we know that the shape and shape-normalized grayscale are complementary parts for describing the overall facial appearance, but they are certainly dependent on each other. By using their dependence, a special mapping (SADM), is designed to transfer the shape parameters onto the grayscale model parameters. Thus, given a face shape configuration, we can generate a proper texture on face with the dependence mapping. To take the shape and texture parameters as a pair of variables, the mapping can be derived with function regression by using a training set.

The approach presented in this paper is an extended version of our previous work[9]. In our previous work, we first proposed the strategy of SADM and applied it to do realistic mouth animation with a great success. It is well known that the texture inside mouth, teeth and tongue would present and disappear according to different expressions, and lip appearance would change as well. Since the specific textures on mouth opening and closing are associated with the corresponding mouth shapes, the proper appearance of overall mouth can be generated with a given mouth shape. Therefore the mouth animation can be easily handled under the SADM strategy, and its success has been verified by our experiments. In this paper, we intend to generate various dynamic textures for the whole face under the original SADM framework. Furthermore the detail of the implementation method and its robustness are also discussed.

4 Implementation of SADM

In this section, we describe the implementations of the SADM. We have tried different implementing methods, from the simplest linear mapping to the more complex non-linear ones.

In our experiment linear mapping has been conducted first for its simplicity. In that case, the relation of the corresponding b_g and b_s of frame in the video sequence is supposed to be linear and can be expressed as

$$b_g^{(i)} = A b_s^{(i)},\ \ i = 1,\dots,M \tag{3}$$

where $b_g^{(i)}$ and $b_s^{(i)}$ are parameter vectors for grayscale and shape model parameters, respectively, A is a matrix, and M is the total number of frames in the video sequence. If we arrange all the vectors for the shape model in a matrix

$$S = \left(b_s^{(1)},\dots,b_s^{(M)}\right),$$

and all the vectors for the gray-level model in a matrix

$$G=\left(b_g^{(1)},\ldots,b_g^{(M)}\right),$$

we may write Eq.(4) as

$$G=AS \tag{4}$$

Since the exact solution would not exist, we can solve A by minimizing an approximated error. According to the pseudo-inverse theories in a matrix, the solution is as follows:

$$A=GS^T\left(SS^T\right)^{-1} \tag{5}$$

As the linear regression has a limited fitting capability, we also tried three other non-linear methods to simulate the relationship between b_s and b_g. They are the second order polynomial regression, forward-feed neural network and SVM regression. These non-linear regression methods are expected to give a better estimation than the linear one.

In order to evaluate the performance of the different regression methods, Normalized Cross Correlation is adopted to evaluate the consistency between the estimated and real values for each element of the grayscale parameter vector b_g. The evaluation results for different regression methods are summarized in Table 1. It can be seen that (1) the significant principle components are estimated generally better than the insignificant ones; (2) the first four components in b_g are well estimated from b_s even with the linear method; (3) Though insignificant components are estimated poorly with the linear and second order polynomial, they are improved with the neural network and SVM. This result shows it is true that variations of shape and texture on expressional face are highly correlated and their relationship are approximate to form a mapping. Thus, the SADM strategy is confident to generate a facial texture with good results.

Table 1 Correlation coefficients for evaluating different regression methods

b_g	Linear mapping	2-order polynomial	Neural network	SVM regression
1	0.9956	0.9984	0.9941	0.9993
2	0.9913	0.9952	0.9905	0.9986
3	0.9816	0.9843	0.9838	0.9954
4	0.9157	0.9819	0.9822	0.9888
5	0.4876	0.8362	0.9485	0.8653
6	0.6608	0.7762	0.9512	0.9896
7	0.4017	0.9260	0.9015	0.9207
8	0.2828	0.5300	0.7410	0.8267
9	0.2260	0.4290	0.5581	0.6096
10	0.1302	0.4288	0.6975	0.8125
11	0.2404	0.5852	0.8048	0.8475
12	0.1767	0.6031	0.7235	0.8628
13	0.0751	0.2225	0.4181	0.4263
14	0.0689	0.4712	0.5772	0.7699
15	0.0972	0.3907	0.6559	0.6424

We have just addressed how to establish Shape Appearance Dependence Mapping with function regression methods. As a result, given a face shape configuration, the proper texture can be generated on face. The full procedure is conducted as follows:

(1) Give feature points on expressive face, s;

(2) Calculate b_s according to Eq.(1);

(3) Get b_g with the SADM, e.g., Eq.(3);

(4) Get g according to Eq.(2);

(5) Warp image patch g to match for shape s.

Now, the derived g is just related to the image patch of the main facial part. To synthesize a full face, we stretch and rotate the image patch properly, paste to the original neutral face image and then smooth the patch boundary area. Although this operation is very simple, it can achieve good effects on the near frontal pose.

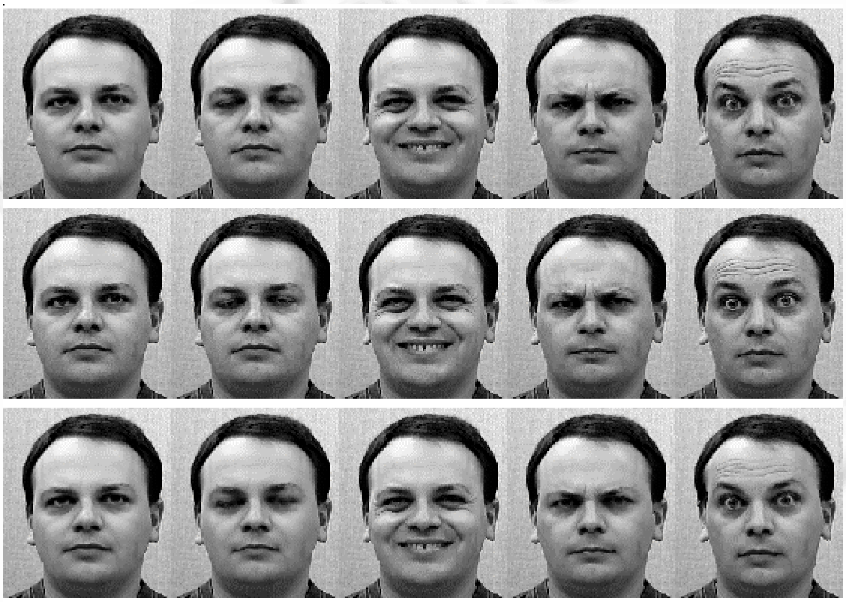
Before the algorithm is performed we need restrict model parameters b_s and b_g within a valid range. This operation prevents the terrible facial appearance to be constructed when the given shape vector is far away from the training samples. This limitation stems from the PCA and takes the form below[10]:

$$-3\sqrt{\lambda_i} \le b_i \le +3\sqrt{\lambda_i} \tag{6}$$

where λ_i is the eigenvalues derived in PCA, b_i denotes the i-th element of vector b_s or b_g.

5 Experimental Results

In order to exhibit the performance of the SADM strategy, some results will be shown. Figure 2 presents some synthesized faces with SADM. The SADM is implemented with neural network and the feature point positions of the real face are taken as inputting data. It can be seen that the synthesized faces are very close to the real one. All essential dynamic textures due to expression such as forehead wrinkles, cheekbone shadows are properly generated with the SADM.



Top: Ground truth

Middle: Synthesis with accurate shape

Bottom: Synthesis with disturbing shape (adding Gaussian noise to shape points with variance δ=2 pixels)

Fig.2 Synthesized faces with SADM

These synthesized faces with the generated texture are visually good. Moreover, to have a look of the numerical metric, we adopt the Peak Signal-to-Noise (PSNR) measures to estimate the quality of a reconstructed image and compare it with that of an original image. PSNR in decibels (dB) is computed by using

$$PSNR = 10\log_{10}\left(\frac{255^2}{MSE}\right) \tag{7}$$

where MSE is the Mean Squared Error between the reconstructed image and the original one. Typical PSNR values range between 20 and 40. Figure 3 shows the PSNR of the reconstructed sequence over 128 frames with SADM.

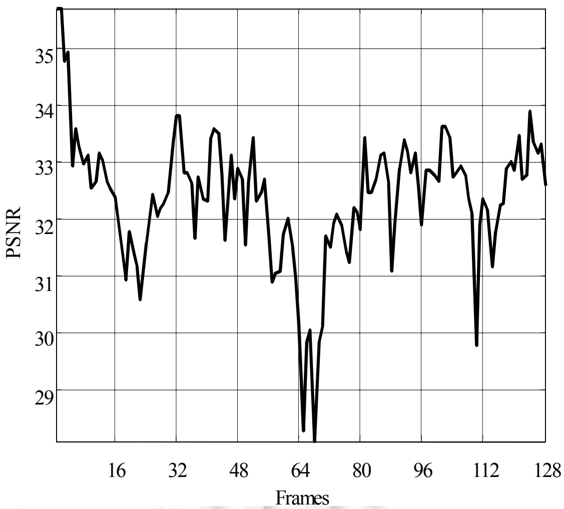


Fig.3 PSNR of reconstructed sequence with SADM

Next, we will test the accuracy requirement of the shape data input required for SADM. Since the whole face appearance is completely determined by the inputting shape parameters, the sensitivity of appearance variation with respect to shape disturbance should be of concern. If the appearance variation is very sensitive to the value variations of the corresponding shape parameters, the synthesized results will be unstable.

In order to inspect this sensitivity, we add Gaussian noise with $\mathcal{N}(0,\delta^2)$ to the coordinates of facial feature points and generate the facial texture with SADM by using the disturbed shape data input. Then we observe the synthesized results and evaluate them with PSNR. When different noise level is added to the shape data input, the results are listed in Table 2. The synthesis faces with shape disturbing are specially shown in the bottom row of Fig.2. It can be seen that the noise level is up to δ=2 pixels and the synthesized results are still accepted. This anti-noise capability is due to the face model building, for it can not only represent a valid shape configuration but also correct an inaccurate face feature location in some extent. This is a very good property, for it relaxes the accurate requirement of locating facial feature points when using the SADM strategy.

Table 2 Sensitivity analysis for SADM

Noise level (δ)	Subject evaluation	Average PSNR (dB)
0 pixel	Good	32.3
1 pixel	Good	31.2
2 pixels	Fair	28.6
3 pixels	Poor	26.1

6 Conclusions and Discussions

We have presented a novel approach for generating a dynamic facial texture according to the motion of facial feature points. To describe the variation of facial appearance, we have built a compact parametric model of face by performing a statistical analysis over a video sequence of expressive face. Although the shape and shape-normalized grayscale are complementary parts for describing the overall appearance of the face, they are certainly dependent on each other. By using their dependence, a special mapping (SADM) is designed to transfer images from one to the other. The experimental results show that the essential expressional details are indeed generated with the SADM and the synthesized faces are very close to the real ones. In addition, when using SADM, the input data – the position of feature points do not need to be very accurate. This tolerance makes SADM easy to use in practice.

It should be pointed out that the current SADM could only be applied to a specific person. As the SADM is trained on the data collected from just one person, it cannot be used directly to generate a proper expressive texture for other people. People would show individual characters even though they show the same kind of expression. So it is not expected that a single SADM will be able to generate all types of variation of facial expression exhibited in all persons. Based on this consideration, we are planning to train a set of SADMs instead. We hope that each of them will reflect one kind of typical mappings between the shape and the facial appearance variation. Therefore a suitable SADM can be selected to make a realistic facial expression for a new person based on some criterion.

Another limitation of the current approach is in dealing with facial pose variation. It is well-know that head gestures such as nodding or shaking are accompanied with talking in the natural interaction, so SADM needs to consider the problem of pose variation. There may be two solutions: one is the putting of the frontal and non-frontal face images together and the training of the mapping directly, and the other is the generation of the proper texture for the frontal face first and then is warping into the non-frontal pose. However, the former choice might be confronted with a more complex relationship between shape and appearance and a more difficult mapping training, while the latter one needs to find the suitable warping method and solve the possible occlusion of facial features. We will explore the better solution in our future research work.

In some applications, one may hope to generate a facial animation under various illuminations. As a SADM is trained under a well-controlled photographic condition, its synthetic results will be faith for in the special illumination. The problem, however, can be solved by utilizing some kind of face relighting methods to make the synthetic face image adapted to the required illumination. A number of image-based relighting techniques were proposed recently and were successfully applied to realistic image synthesis, such as Quotient Images[11] and Photometric Image-Based Rendering[12].

Finally, we would like to say a few words about the potential applications of SADM. There are many 3D head models with fine animation structures[3,4], but they lack texture updating mechanism and generate animation with less realistic effects. If our SADM strategy is integrated into these head models, more natural and realistic animation results can be achieved. The SADM strategy would also be useful in the area of very low bit-rate coding of videos. If only the face shape parameters are transmitted and the whole face appearance is reconstructed with SADM at the receiver end, more efficient coding results with less image quality loss may be achieved.

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第 5 届中国计算机图形学大会(Chinagraph 2004)

征 文 通 知

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