A Novel Visualization System for Expressive Facial Motion Data Exploration

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Abstract

Facial emotions and expressive facial motions have become an intrinsic part of many graphics systems and human computer interaction applications. The dynamics and high dimensionality of facial motion data make its exploration and processing challenging. In this paper, we propose a novel visualization system for expressive facial motion data exploration. Based on Principal Component Analysis (PCA) dimensionality reduction on anatomical facial sub regions, high dimensional facial motion data is mapped to 3D spaces. We further rendered it as colored 3D trajectories and color represents different emotion. We design an intuitive interface to allow users effectively explore and analyze high dimensional facial motion spaces. The applications of our visualization system on novel facial motion synthesis and emotion recognition are demonstrated.

Keywords: Motion Visualization, Emotion, Facial Expression, Facial Motion Capture, Principal Component Analysis, High Dimensional Data Visualization.

Index Terms: H.5.2 [Information Interfaces and Presentation]: User Interfaces—Graphical user interfaces

1 Introduction

Facial expressions and realistic facial motions are not only challenging topics in the computer graphics and human computer interaction community, but also important to other fields, including artificial intelligence, cognitive science, psychology, communication, etc. As facial expressions and digital humans become more and more prevalent in many applications, understanding the visual space of expressive facial motions is clearly a priority. However, despite this growing area of research in the past several decades [23, 21, 10, 4, 8, 7], there currently is not a systematic methodology to understand and visualize expressive facial motion space, which is intrinsically high dimensional and complex.

A human face is arguably the most complex muscular region of the human body, and human facial motion is the consequence of subtle skin deformation supported by the relaxation/stress of tens of hidden facial muscles. The high dimensionality of facial motions and the unresolved interplay between facial emotions and mouth movement impose grand challenges to intuitive visualization of expressive facial motions. Meanwhile, in recent years how to intuitively visualize high dimensional spatial-temporal data has caught a great deal of attention from the visualization community.

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In this work, we propose a novel visualization system for expressive facial motion data exploration. First we collected high-fidelity 3D facial motions of an actress by placing hundreds of facial markers on her face using an optical motion capture system. The captured subject was directed to speak a designed corpus with various facial emotions. We divide the whole face into six anatomical facial sub regions (each facial marker belongs to one sub region). Then for the facial markers in each facial sub region, we apply the Principal Component Analysis (PCA) and 3D rendering technique to create a trail of 3D expressive facial motion space. In the 3D expressive facial motion trail, different emotions are represented as different colors. A recorded facial motion sequence is visualized as an intuitive 3D trajectory by our visualization system, as shown in Figure 1. Figure 1 shows a snapshot of this running visualization system. In this work, we also demonstrate several versatile applications of our novel visualization system, including visually exploring facial expression space, novel facial motion synthesis by visual interaction, and emotion recognition from facial motion sequences. To our knowledge, our proposed visualization system for dynamic and high dimensional expressive facial motions is the first attempt in the field. It opens up a new way to visually explore and understand the sophisticated nature of dynamic facial expressions.

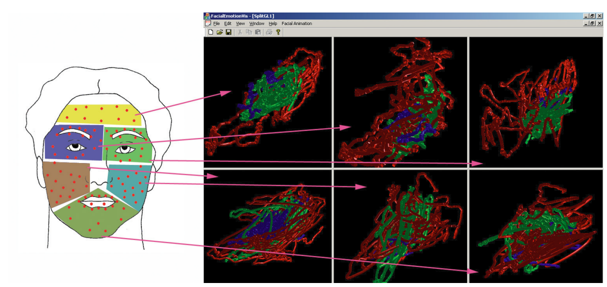

Figure 1: A snapshot of the running 3D visualization system for expressive facial motion data exploration. The six windows (from top to bottom, from left to right) are for forehead region, left eye region, right eye region, left cheek region, right cheek region, and mouth/jaw region. Here, red for anger, green for happiness, and blue for sadness.

The remainder of this paper is organized as follows: Section 2 reviews related work on facial animation and temporal-spatial data visualization. Section 3 briefly introduces how expressive facial motion data are acquired in this work. Section 4 describes the details of our approach, including region-based data reduction and the 3D visualization generation. Section 5 demonstrates several applications of our visualization system, including visually exploring facial expression space, novel facial motion synthesis by visual interaction, and emotion recognition from facial motion sequences. Section 6 discusses advantages and limitations of our system and concludes this paper.

2 Related Work

Since the computer facial animation was introduced in 1972 [22], various facial animation and modeling techniques have been developed. In particular, in recent years data-driven facial animation has drawn a lot of interests from the community. The data-driven facial animation generally makes use of a pre-collected facial motion database for novel animation synthesis and editing applications, including learning statistical models from facial motion dataset [10, 4, 8] or recombining recorded frames to satisfy novel acoustic speech input [2, 19, 7]. For example, the Facial Action Coding Systems (FACS) proposed by Ekman and Friesen [9] is a widely used system to represent various human expressions by combining basic facial action units. Wang et al. [24] have proposed a framework for the facial expression embedding and the style separation across different persons. The embedding in their work is based on the LLE techniques.

Since each frame of the captured facial motion data contains hundreds of 3D markers, such data can also be regarded as time-varying, high dimensional or multivariate data. Many techniques, such as glyphs [1, 18], scatterplot matrices [5], parallel coordinates [12, 13, 25], and pixel-oriented methods [15], have been developed to visualize and explore high dimensional data sets. In such techniques, dimensions are positioned in one- or two-dimensional arrangements on the screen.

Multi-resolution approaches [28, 11, 30] are used to group the data into hierarchies and display them at a desired level of detail. These approaches do not retain all the information in the original data, since many details will be filtered out at low resolutions.

High dimensionality is another source of clutter. Many approaches currently exist for dimension reduction. Principal Component Analysis [14], Multi-dimensional Scaling [17, 26], and Self Organizing Maps [16] are popular dimensionality reduction techniques used in data and information visualization. Yang et al. [31, 32] proposed a visual hierarchical dimension reduction technique that creates meaningful lower dimensional spaces with representative dimensions from the original data space instead of generating new dimensions. These techniques generate a lower dimensional subspace to reduce clutter but some information in the original data space is also lost.

Visualizing time varying data sets is common for volumetric data [20]. Recently researchers have developed methods for visualizing time varying volume data without relying on animation [29]. Raniel and Chen [6] use volume rendering techniques to visualize videos. In our work, we first convert high dimensional data to multiple 3D points with PCA. The resulting points form a 3D trail which can be rendered for a variety of applications.

3 Expressive Facial Motion Data Acquisition

To acquire high-fidelity expressive facial motion data, we captured facial motions of an actress using a VICON motion capture system (the left panel of Fig. 2). The actress with 102 markers on her face was directed to speak a designed corpus several times, and each repetition was spoken with a different facial emotion. In this work, totally three basic emotions are considered (happiness, anger and sadness).

The facial motion data was recorded with a 120 frames/second rate. Because of tracking errors caused by rapid, large head movement and the removal of unnecessary facial markers, we used only 90 of 102 markers for this work. The 90 markers were fully tracked. Figure 2 shows a facial motion capture system, the 102 captured markers and the 90 kept markers. The motion frames for each corpus repetition are labeled with the intended emotion.

After data capture, we normalized the facial motion data (removed head movement from the data). All the markers were translated so that a specific marker was at the local coordinate center of each frame. Then a statistical shape analysis method [3] was used to calculate head motion. A neutral pose with closed mouth was chosen as a reference frame and was packed into a 90×3 matrix, y. For each motion capture frame, a matrix x_i was created using the same marker order as the reference. After that, the *Singular Value Decomposition* (SVD), UDV^T, of matrix $y^T x_i$ was calculated.

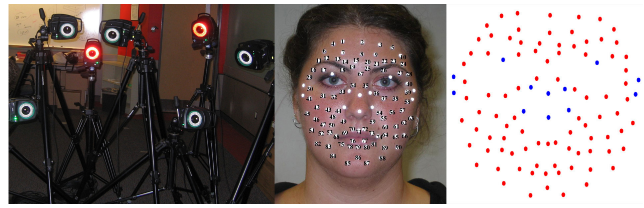

Figure 2: The left shows a facial motion capture system, the middle is a snapshot of the captured actress. In the right panel, blue and red points represent the 102 captured markers, where the red points are the 90 markers used for this work.

$$y^T x_i = UDV^T \tag{1}$$

Finally, the product of VU^T gave the rotation matrix, R.

$$R = VU^T \tag{2}$$

4 Our Approach

In this section, we describe how to transform the original 270 (90×3) dimensional facial motion data to a 3D interactive visualization system. This approach consists of two major steps: *region-based dimension reduction* and *3D visualization*. In the region-based dimension reduction step, we first partition the whole face into six anatomical facial sub regions. The 3D positions (xyz) of the markers in each facial sub region is concatenated to form a single vector whose dimensionality is further reduced using the principal component analysis. In this work, we experimentally set the reduced dimensionality to three, as such, each concatenated vector is transformed to a 3D point at the space spanned by the largest three eigen-vectors. In the 3D visualization stage, given the transformed 3D points (each point corresponds to a facial motion on a specific facial region), we use efficient visualization techniques to characterize different expressive facial motions in colors (red for anger, green for happiness, and blue for sadness respectively). Finally, users can navigate through this 3D visualization system interactively and perform dynamic data explorations (Section 5).

4.1 Region-based Dimension Reduction

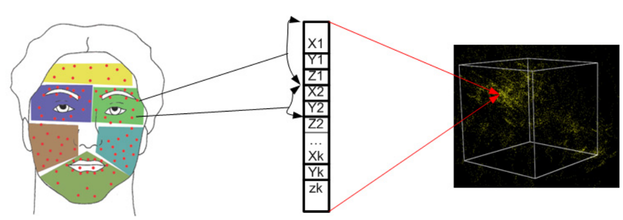

Figure 3: Illustration of region-based dimension reduction for expressive facial motion data. The left panel shows how the face is divided into six regions, the middle panels shows the 3D position of markers in one region is packed into a vector, and the right panel shows the concatenated vector is reduced to a 3D point in the reduced PCA space.

Figure 3 shows the process of region-based dimension reduction for the recorded expressive facial motion data. In this step, we divide all the markers into six groups - each corresponds a facial region (refer to the left panel of Fig. 3). These six facial regions are forehead region, left/right eye region, left/right cheek region, and mouth region. Some markers are not positioned in symmetry. Then, we concatenate 3D positions of markers in one facial region into a vector. These vectors $\{X_i\}$ are put as a matrix D, and X_i is a column of D. Singular Value Decomposition to generate three new matrices of U, S, and V, as shown in Eq. 3 to Eq. 5 is then used. The result of this process is that one high dimensional vector X_i (motion for a facial sub region) is transformed into a 3D point, C_i (refer to the right panel of Figure. 3).

$$\begin{pmatrix} X_1 \\ X_2 \\ \dots \\ X_n \end{pmatrix}^T = U.S.V^T = \begin{pmatrix} U_1^T \\ U_2^T \\ . \\ U_m^T \end{pmatrix}^T \times \begin{pmatrix} s_1 & 0 & . & 0 \\ 0 & s_2 & 0 & . \\ . & . & . & . \\ 0 & . & 0 & s_m \end{pmatrix} \times V^T \quad (3)$$

$$EigMX = \begin{pmatrix} U_1 & U_2 & U_3 \end{pmatrix} \quad (4)$$

$$C = EigMX^T.(X_i - \mu) \quad (5)$$

Here, μ represents the mean vector of $\{X_i\}$, each column of $EigMX$ is a retained eigen matrix, and C is the reduced vector (PCA coefficient). In this work, we experimentally set the reduced dimensionality to three due to the following reasons:

- Because we apply PCA to an anatomical facial sub region (not the whole face), and hence reducing dimensionality to three still can keep more than 90% of the motion variation.

- It is much more intuitive to interactively navigate and explore a 3D visualization space than higher dimensional spaces.

4.2 3D Visualization

In this section, we describe how to use efficient 3D rendering techniques to create an intuitive 3D space for expressive facial exploration and interaction. Now we have transformed a facial motion frame to six 3D points and each of them represents its motion at a specific facial sub region. If these 3D points are simply plotted as dots in 3D spaces, their results will be like the right panel of Fig. 3. To provide intuitive interfaces for data exploration, we convert point clouds to more appealing representations.

We are aware the emotion category of any recorded motion capture sequence (the captured subject was directed to intentionally speak with specified emotions), therefore, we know the emotion label for any recorded facial motion capture frame. In this 3D visualization step, we assign a different color for each emotion (red for anger, green for happiness, and blue for sadness). We conducted experiments on three different visualization techniques: simple line, volume rendering, and 3D tube rendering.

For simple line, we only connect points of the same motion sequence together as a line and color them based on their emotion categories (Figure 4 (a)). We will discuss in more details on 3D Volume rendering and 3D Tube rendering in the follow-up subsections.

4.2.1 3D Volume Rendering

In the volume rendering technique (Figure 4 (b)), first, we divide the 3D data into a 3D volume grid. In the implementation of this work, we use $200^3 = 8{,}000{,}000$ grids. From assigned colors (red for anger, green for happiness, and blue for sadness), we also assume that each 3D point (located in a specific grid) will affect (or propagate to) its neighboring grids with an attenuation function. This attenuation function is modeled as a Gaussian function. As such, the intensity of any grid is the summation of propagation from its neighboring 3D points. Each grid is colored by blending of the

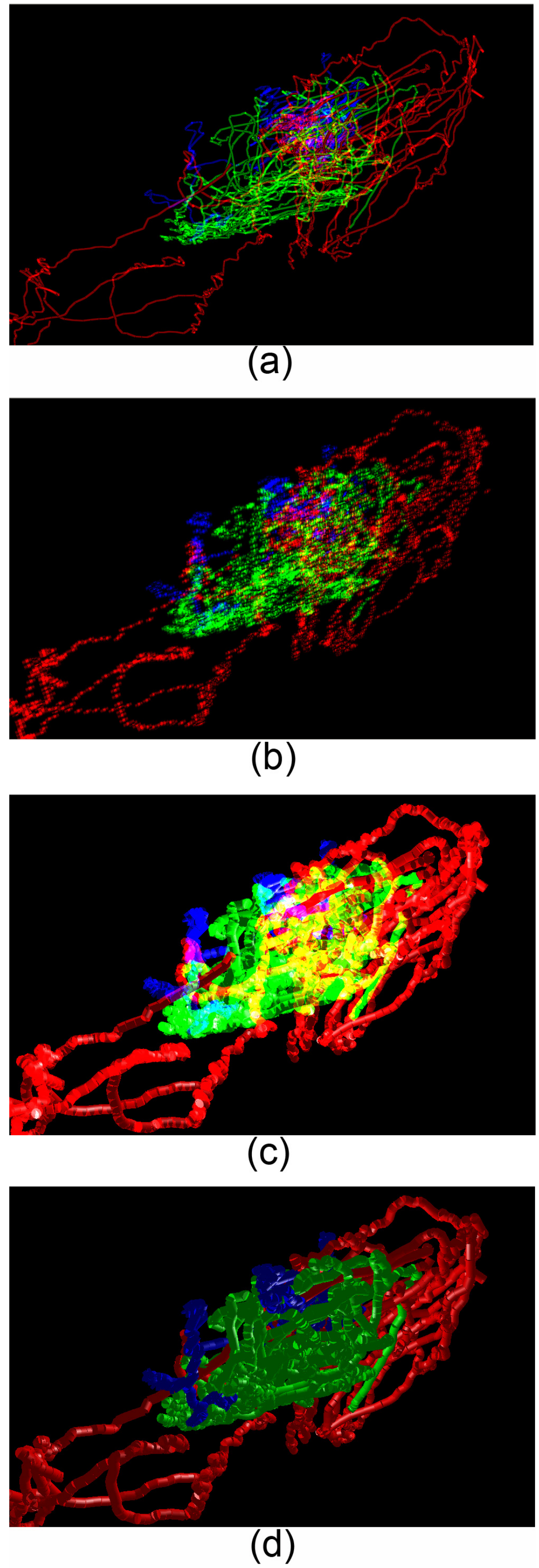

Figure 4: A comparison result of three visualization techniques of (a) simple line, (b) volume rendering, (c) 3D tube rendering with alpha values, and (d) solid 3D tube rendering.

colors of all points located in the grid and the propagations from neighboring points. For color blending, we use the alpha blending technique. Each time when a point identified to be in a voxel it will color the grid with its emotion color and also the alpha value. Hence, in the final volume visualization results, color of each voxel represents the meaning of emotion, and its intensity is proportional to the probability of the occurrence of this voxel.

4.2.2 3D Tube Rendering

In the 3D tube rendering technique (Figure 4 (c) and (d)), we shield each simple line connection with a cylinder and shade it with the Phong shading to make it more visually intuitive.

We use the cylinder with constant radius along all trajectories. Each cylinder is placed on each line segment by rotating the cylinder with the same angle as the line segment aligned on a 3D space. For shading style, we use simple Phong shading. Each cylinder is rendered by color material assigned by emotion colors with proper ambient, diffusion and specular parameters. In our experiment, we use one light source located on the top with 0.2 for ambient parameter (K_a), 0.7 for diffusion parameter (K_d), and 0.7 for specular parameter (K_s). All the parameters are the same for each RGB channel.

For this 3D tube rendering, we did two different experiments: one uses alpha values and the other uses solid material. Both semi-transparent and opaque alpha values for 3D tube rendering have been test, as shown in Figure 4(c) and (d) respectively. In Figure 4 (c), we use 3D tube with alpha values. Also, in Figure 4 (d), we apply solid material instead of using alpha values. As we can see in the figure, the solid material-based rendering tube yields more tangibility on the colored trail trajectory.

4.2.3 Result comparison

Through experiment comparisons, we found that the solid 3D tube rendering generates the most appealing visualization as shown in Figure 4. The 3D trails with shading generated by the 3D tube rendering technique also clearly illustrate the trajectory trend of each data set. Figure 5 shows final visualized results for one facial region. The tubes color coded with red, green and blue correspond to the emotion of angry, happy and sad respectively. The white dots are selected frames shown at the bottom row.

5 Applications of Our Visualization System

In this section, we describe how to explore expressive facial motion space based on this developed 3D visualization system. Specifically, we will describe the following applications: visually exploring facial expression space, novel facial motion synthesis by visual interaction, and emotion recognition from facial motion sequences.

5.1 Visually Exploring Facial Expression Space

As shown in Figure 1 and 5, recorded facial motions of each facial region are visualized in a separate 3D window. Hence, users can conveniently employ standard 3D navigation interfaces to interactively explore the visualized facial expression spaces. For example, users can rotate and zoom the 3D trajectories in any of the above visualization windows. Given a new facial motion sequence, the users can intuitively check its corresponding 3D trajectories in the six visualization windows. Additionally, users can visually see how different facial expressions are differentiated in these spaces, and visually tell which emotion pairs are often intersected each other. If a pair of emotions is always easily intersected, it means that facial motions (of these two emotions) are visually similar and may cause visual confusions.

5.2 Novel Facial Motion Synthesis by Visual Interaction

Generating novel expressive facial motions has been one of challenging topics in the animation community for decades, and most of the proposed approaches heavily rely on some optimized search or machine learning models; however, little work can synthesize novel expressive facial motions via intuitive and simple visual operations. This novel visualization system can be employed for generating novel expressive facial motions by intuitive visual operations. Users can pick any 3D motion trajectory from the six visualization windows. These six selected motion trajectories (each point of these trajectories represents three retained PCA coefficients) can be transformed back to the motion marker space, and finally motion markers are put together to generate a novel facial animation frame.

Conceptually, this mapping can be regarded as the inverse of the process illustrated in Figure 2. Taking into consideration that the frame numbers of the selected trajectories are different, we use a motion time-warping technique [27] to normalize all selected trajectories to have the same number of frames. In this work, a facial animation preview window shows its synthesized facial animation when the six 3D trajectories are picked (Figures 6 and 7). It should be noted that users not only can pick any of existing 3D trajectories in the six visualization windows, but also can use 3D drawing tools to create novel 3D trajectories in each of the visualization windows.

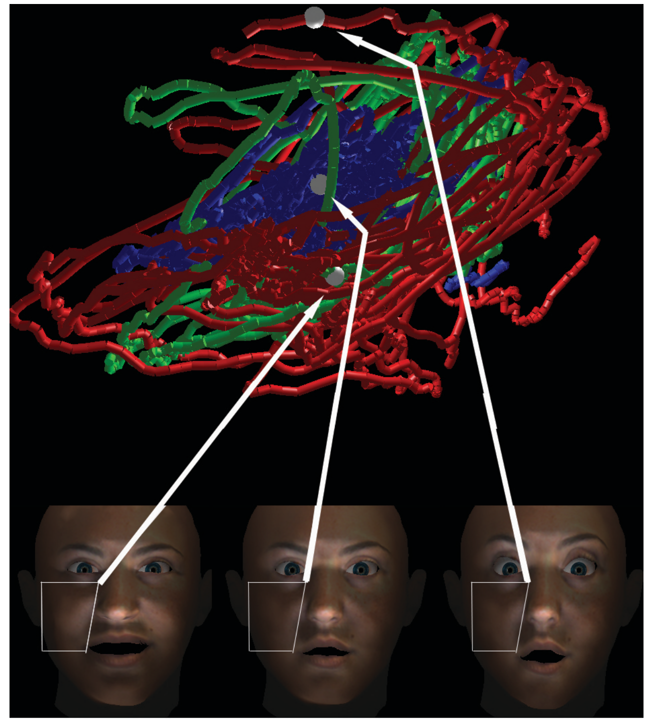

Figure 5: Visualization results for one facial region (right cheek) using the solid 3D tube technique. Red, green and blue correspond to the emotion of angry, happy and sad respectively.

5.3 Emotion Recognition via Visual Inspection

With our visualization system, users can recognize emotion category of novel captured facial motions via intuitive visual inspection. In motion capture practice, typically hundreds of thousands of motion frames are recorded. However, not all of motion data have clear emotion labels or the emotion labels of some facial motion sequences are lost. In this case, various pattern recognition and machine learning methods certainly can be tried. Our visualization system provide an alternative to recognize emotion category of any facial motion sequence by intuitive visual inspection. After loading a new facial motion sequence and visualizing it as a 3D trajectory (with a different color), users can visually inspect which emotion

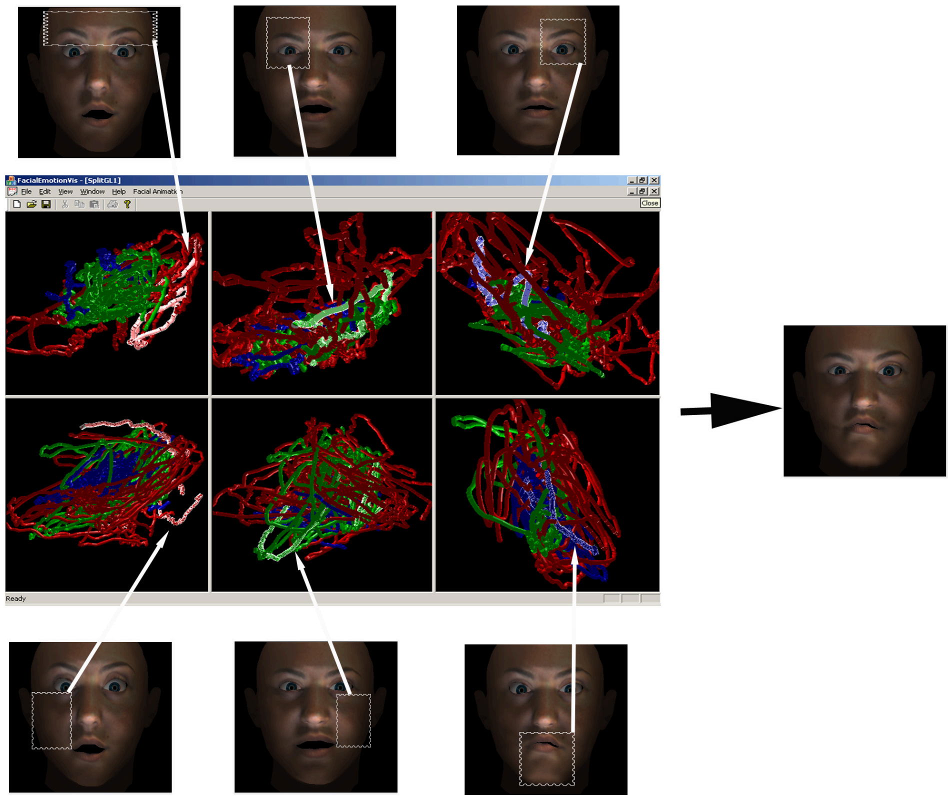

Figure 6: The first example of novel facial motion synthesis by visually picking 3D trajectories in visualization windows. Here heavy white trajectories represent selected ones. The right shows the synthesized face.

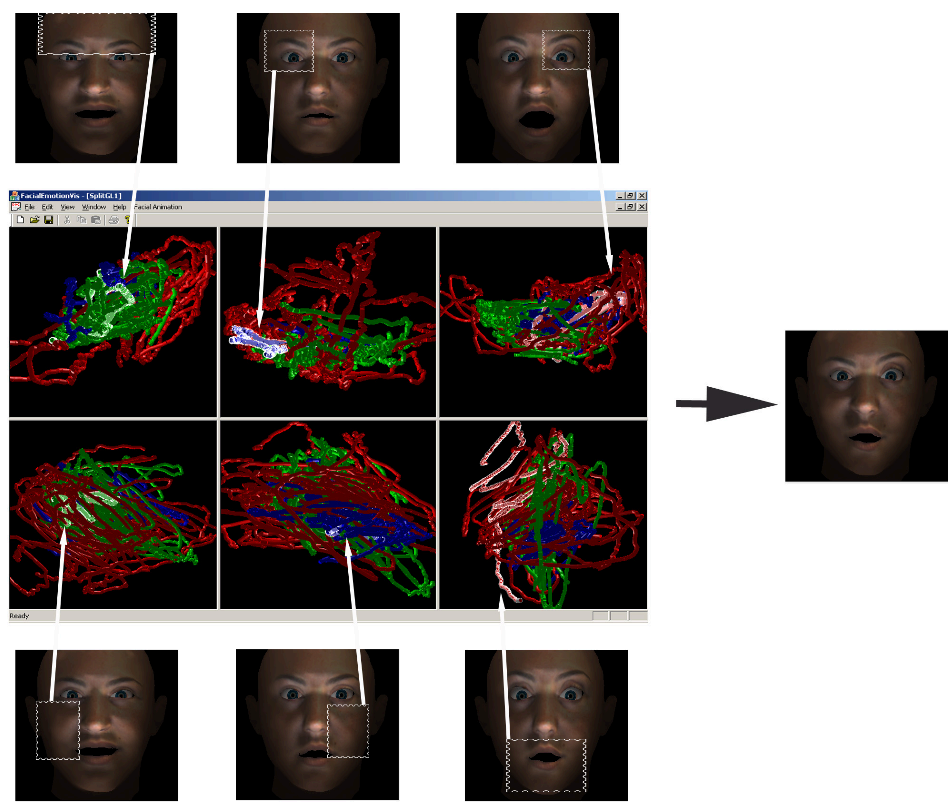

Figure 7: The second example of novel facial motion synthesis by visually picking 3D trajectories in visualization windows. Here heavy white trajectories represent selected ones. The right shows the synthesized face.

(colored) space this trajectory pass through in the six visualization windows (Figure 1). Finally, the users can easily judge its emotion label. This conceptually intuitive visualization offers a novel way for emotion perception and recognition applications. Figure 8 shows a snapshot of the running visualization system for emotion recognition, where the white trajectories are the ones corresponding to a test facial motion sequence. To illustrate the consistency, as shown in figure 9, we use 80% of the original data set as the training set and the remaining 20% as the testing facial motion sequences. The testing facial motion sequences used in the experiment are the happy emotion. The experiment shows that the locations of the testing facial motion trajectories are highly overlapped with the happy emotion of the training facial motion trajectories.

6 Discussion and Conclusions

In this paper, we propose a region-based 3D visualization system for expressive facial motion data exploration. We collected high-fidelity 3D facial motions of a selected human subject using a motion capture system. We divide the data into six anatomical sub regions, and project data into 3D spaces, which are further rendered as 3D tubes. In this visualization system, different emotions are represented as different colors.

Based on this visualization system, we demonstrated several important applications including navigating the 3D facial expression spaces, novel facial motion synthesis by visual interactions, and emotion recognition from facial motion sequences via visual inspection. The visual cue provided by our system can greatly facilitate the users to handle highly difficult tasks.

We are aware that the three basic emotions (anger, sadness, and happiness) studied in this work are not enough to cover all types of emotions [9], e.g. fear, surprise, and disgust are not covered in this work. In future we plan to examine a wider array of emotions. Furthermore, a major limitation of the current work is that we only collected expressive facial motion data from a single subject. In order to fully generalize our findings, we plan to extend this work with a number of male and female subjects. However, the purpose of this work is to validate our methodologies, and we found novel and intuitive applications for our approach.

A number of questions remain open. For example, if expressive facial motion data of multiple subjects are captured and rendered into one space, how different would these visualizations be? And does our visualization system reflect the personalities of captured subjects somehow? In the future, we plan to try other type of visualization techniques, such as parallel coordinate [12, 13, 25] for visualizing captured expressive facial motion data. In this work, the motion embedding is based on a linear PCA technique. As the facial skin deformations are non-rigid, we plan to consider non-linear techniques in the future research.

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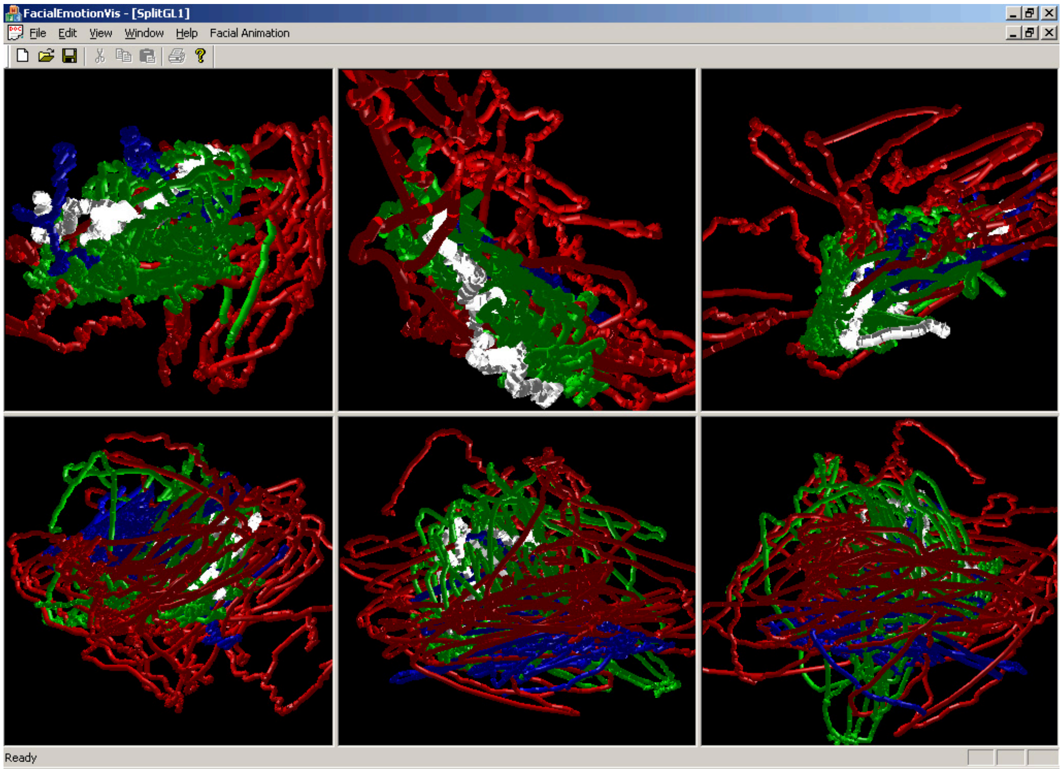

Figure 8: A snapshot of the running visualization system for emotion recognition, where the white trajectory is the one corresponding to a novel test facial motion sequence (happy).

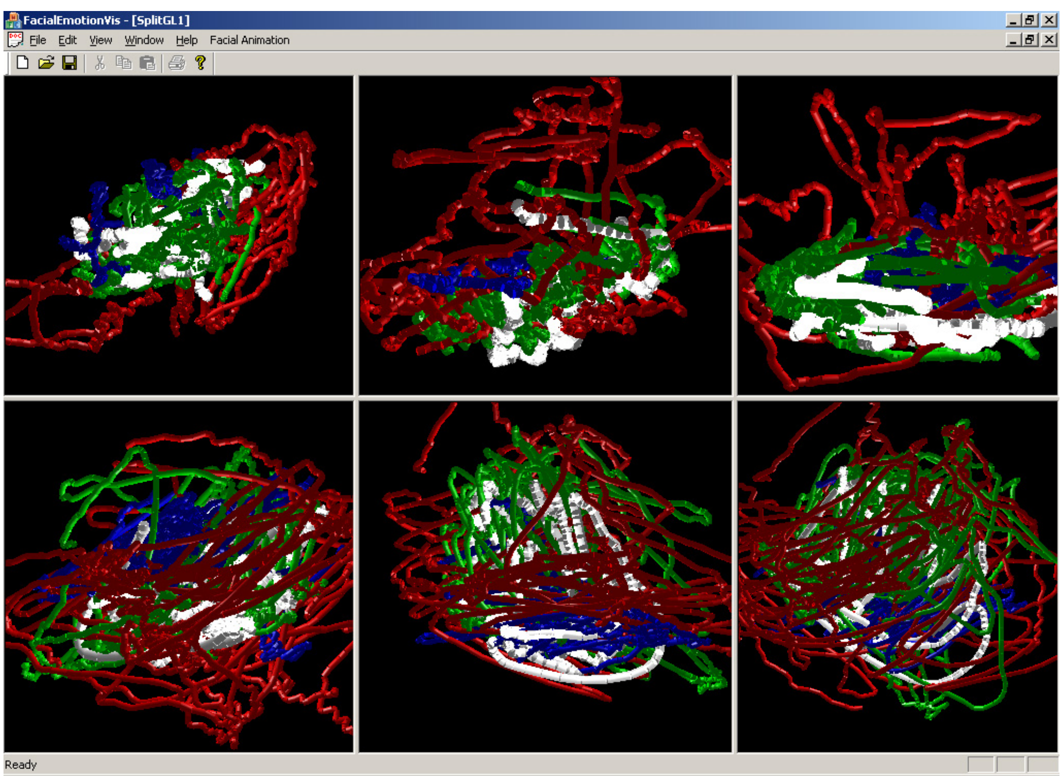

Figure 9: A snapshot of the running visualization system for emotion recognition, where the white trajectories are the another 20% of the data set corresponding to a novel test facial motion sequence (happy).