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SPECIAL ISSUE PAPER

Characteristic facial retargeting

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ABSTRACT

Facial motion retargeting has been developed mainly in the direction of representing high fidelity between a source and a target model. We present a novel facial motion retargeting method that properly regards the significant characteristics of target face model. We focus on stylistic facial shapes and timings that reveal the individuality of the target model well, after the retargeting process is finished. The method works with a range of expression pairs between the source and the target facial expressions and emotional sequence pairs of the source and the target facial motions. We first construct a prediction model to place semantically corresponding facial shapes. Our hybrid retargeting model, which combines the radial basis function (RBF) and kernel canonical correlation analysis (kCCA)-based regression methods copes well with new input source motions without visual artifacts. 1D Laplacian motion warping follows after the shape retargeting process, replacing stylistically important emotional sequences and thus, representing the characteristics of the target face. Copyright © 2011 John Wiley & Sons, Ltd.

KEYWORDS

facial animation; motion retargeting; facial style transfer; machine learning

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1. INTRODUCTION

Facial expression represents the most significant features of human communication [1] and the same principle holds for digital characters in movies and animations. Therefore, generating good facial animation is one of the most important factors in the creation of appealing, believable, and attractive characters. Most facial motion retargeting techniques have concentrated on recreating a realistic facial motion with high accuracy [2–4]. However, for a cartoon style character or a non-human face, previous retargeting methods based on position matching [5,6] are not always suitable, as they fail to produce the desired results. In addition, the timing of the motion is too realistic to express the unique individuality of such characters. For these reasons, traditional manual key-framing is still favored for the creation of highly characteristic facial animation.

We pursue a complementary direction to create characteristic target facial motions while preserving the original dynamics of the source input. In terms of facial characteristics, non-linearly deformed facial shapes and stylistic timings should be recreated in a target face. Therefore, this paper proposes a semantically similar but stylistically different motion retargeting and warping technique.

We begin by manually defining a range of expression pairs between morphologically different but semantically similar facial shapes. After obtaining a range of expression pairs, we utilize a hybrid retargeting method to transfer a source animation into a target character properly. The challenge of this retargeting task is to choose a powerful regressor such that the non-linearly mapped expression pairs can cope with new input sequences while preserving the characteristic shapes of the target face. By combining radial basis function (RBF) and kernel canonical correlation analysis (kCCA)-based regression, we achieve convincing results that interpolate the target face very well within the range of expressions.

To convert the retargeted target motion and make it more stylish, the timing of the retargeted motion is adjusted based on emotional sequence pairs. We detect emotionally important intervals (e.g., surprise and anger) with our heuristic function to warp the retargeted motion so that it can respects the relevant target intervals correctly. Using 1D Laplacian motion warping, we place emotionally fluent motion intervals into the retargeted motion while preserving the details of the original motion.

With our method, human face motion from captured data is effectively and stylistically retargeted onto several character faces.

2. RELATED WORK

This work is mainly related to two research fields: facial retargeting and stylized character animation. Facial motion retargeting has had a rich history since the initial work by [7]. Most of the ensuing methods transfer the source motion using sparse correspondence and position matching. Element-wise transformation was conducted in References [2,7] obtained desired target facial animation by formulating facial dynamics. Example-based retargeting methods are a popular choice as shown in References [3,8,9]. These approaches generally work well when the source and the target model have similar shapes, but they have limitations when the shapes are significantly different which is common in the case of cartoon animation characters.

In contrast to the above retargeting methods, the technique in Reference [10] took a different approach. RBF regression between the position of the source markers and the target facial expressions was applied during the training phase and employed throughout the retargeting phase. The process is similar to our method, but it often fails when the cross-mapping becomes complicated. In contrast, our method intelligently solves the problem through the blending of linear and non-linear retargeting models.

Timing is one of the most important factors in creating stylistic animation. However, in the facial motion retargeting domain, adjusting the timing during retargeting has never been suggested. This issue can be found in the area of motion stylizing. Witkin and Zoran [11] introduced a simple and interactive motion editing method based on parametric curve interpolation with some constraint points. Hsu *et al*. [12] performed motion warping iteratively for the entire human body to create a stylized motion. A pair of different style of animations is learned during the training phase and is used to produce a desired motion when a new input motion is given. Wang *et al*. [13] presented a simple method to produce a cartoon style animation by filtering the input animation. These methods are considered to be effective in making stylized human motions, but they only focus on full-body animation. Moreover, the range of generated animation style is limited. Our method was inspired by the above approaches, but is the first work that addresses the issue of stylized animation in the domain of facial retargeting.

3. RANGE OF EXPRESSION

The quality of facial animation retargeting depends on how the source and target correspondences are defined. To retarget morphologically varied but semantically identical facial expressions, we first build a range of expression pairs. The pairs consist of semantically identical face expressions between a source and a target model.

We assume that the source model has a sufficient number of blendshapes and that desirable expressions can be fully represented. To increase the performance of the retargeting model as described in Section 4, the target expressions should also be capable of representing the full range of source expressions. Each range of expression pair is constructed as $\mathrm{Source}_{\mathrm{exp}} = \sum_{i=1}^{\mathrm{ns}} (w_i b_i)$ and $\mathrm{Target}_{\mathrm{exp}} = \bigcup_{i=1}^{\mathrm{nt}} \mathbf{cv}_i$, where b_i is the blendshape with the corresponding weight w_i and where the subscript exp refers to the semantically identical facial expression of the source and the target model. ns is number of blendshapes of the source model, and nt is dimensions of $\mathbf{cv}$ of the target model. In this case, target expressions are generated with a more general basis $\mathbf{cv}$, which denotes the *control vector* of the target model when the target model utilizes non-blendshape functionalities such as skeleton-driven methods, and geometric deformers. All of the numerical factors from these methods can be encoded into the elements of $\mathbf{cv}$s.

After an animator creates the range of expression pairs manually, the range of expression matrix $\mathbf{S}$ and $\mathbf{T}$ can be constructed as follows:

$$\mathbf{S} = \begin{pmatrix} w_1^1 & w_2^1 & \dots & w_{\mathrm{ns}}^1 \\ \vdots & \vdots & \ddots & \vdots \\ w_1^{\mathrm{np}} & w_2^{\mathrm{np}} & \dots & w_{\mathrm{ns}}^{\mathrm{np}} \end{pmatrix} \tag{1}$$

$$\mathbf{T} = \begin{pmatrix} \mathbf{cv}_1^1 & \mathbf{cv}_2^1 & \dots & \mathbf{cv}_{\mathrm{nt}}^1 \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{cv}_1^{\mathrm{np}} & \mathbf{cv}_2^{\mathrm{np}} & \dots & \mathbf{cv}_{\mathrm{nt}}^{\mathrm{np}} \end{pmatrix} \tag{2}$$

where np denotes the number of the range of expression pairs.

4. HYBRID RETARGETING MODEL

As the numerical correspondence between the source and target face models contains similar patterns but complex relationships, we chose the RBF and kCCA based regression method to interpolate the new input powerfully.

While RBF respects the training data effectively, kCCA outperforms in the case of dense correspondence, thus avoiding over-fitting artifacts. By combining these two methods in a hybrid manner, our retargeting model can cope with dramatically changing source inputs to predict visually appealing and characteristic facial shapes.

4.1. RBF-Based Retargeting

RBF is one of the most powerful interpolation methods [2,4] to learn the best weight values between source and target data pairs. The RBF network is of the following form:

$$F(w_i) = \sum_{j=1}^{\mathrm{np}} r_j \phi_j(w_i) \tag{3}$$

We employ Hardy multi-quadrics for the basis function, $\phi_j(w_i) = \sqrt{\|w_i - w_j\|^2 + s_j^2}$. The variables r_j denote the RBF weight to be computed, np is the number of the range

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of expression pairs, w_i denotes the input vector, and $F(w_i)$ is the estimated output. The distance s_j is measured between w_j and the nearest w_i, leading to less deformations for widely scattered feature points and greater deformation for closely located points [2]. This network is trained np times with source correspondences as $w_i(i = 1, 2, \ldots \text{ns})$ and target correspondences as $\mathbf{cv}_i(i = 1, 2, \ldots \text{nt})$, respectively.

After the training of network of RBF, we obtain the linear operator $\mathbf{M_{RBF}} = [\mathbf{r_1}|\mathbf{r_2}|\ldots|\mathbf{r_i}|\ldots|\mathbf{r_{nt}}]$ where $\mathbf{r_i}$ is ith np-dimensional weight vector. Here, we can exploit $\mathbf{M_{RBF}}$ to find an output vector as follows:

$$\mathbf{t}_{\text{RBF}} = \mathbf{M_{RBF}}^T \cdot \phi(s_{\text{new}}) \tag{4}$$

RBF-based regression cannot outperform in the case of non-linearly corresponding data samples. When an animator constructs the range of expression pairs, if two source expressions that are almost identical are mapped to the significantly different target expressions, it will cause conflicts in training step [10].

4.2. kCCA-Based Retargeting

CCA is a statistic analysis method [14] that is used for defining the correlation between two sets of multivariate data. kCCA is a nonlinear version of CCA that uses kernel function [15]. It is a well-known tool for analyzing non-linear data pairs. kCCA finds bases pair while maximizing correlation between reduced input and output data.

From the result of Section 3, each expression can be represented by two sets of variables as $\exp = (\mathbf{s}, \mathbf{t})$ where $\mathbf{s} \in \mathbb{R}^{\text{ns}}$ and $\mathbf{t} \in \mathbb{R}^{\text{nt}}$.

Using $\mathbf{S}$ and $\mathbf{T}$ as described in Section 3, the kCCA equation that maximizes the correlation coefficient ρ is as:

$$\max_{(\mathbf{h_s}, \mathbf{h_t})} \rho = \max_{(\mathbf{h_s}, \mathbf{h_t})} \frac{\mathbf{h_s}^T \hat{\mathbf{S}} \hat{T} h_\mathbf{t}}{\sqrt{\mathbf{h_s}^T (\hat{\mathbf{S}})^2 \mathbf{h_s} \mathbf{h_t}^T (\hat{\mathbf{T}})^2 \mathbf{h_t}}} \tag{5}$$

where $\mathbf{h_s}$, $\mathbf{h_t}$ are coefficient vectors that are used to obtain the basis pair $\{\mathbf{b_s}, \mathbf{b_t}\}$, and $\mathbf{b_s} = \Phi(\mathbf{S})\mathbf{h_s}$, $\mathbf{b_t} = \Phi(\mathbf{T})\mathbf{h_t}$. $\hat{\mathbf{S}}$ and $\hat{\mathbf{T}}$ are the matrices of the source and target samples on the feature space by the kernel function k, respectively. Details of the kernel function and the derivation of kCCA are described in Reference [15].

After generating the reduced data pair from kCCA, we build the retargeting model using standard linear regression. This model minimizes errors in the least square sense as:

$$\min_{\mathbf{M_s}} \sum_{i=1}^{\text{np}} \left\| \mathbf{M_s} \mathbf{s_r^i} - \mathbf{t_r^i} \right\|^2 \tag{6}$$

and

$$\min_{\mathbf{M_t}} \sum_{i=1}^{\text{np}} \left\| \mathbf{M_t} \mathbf{t_r^i} - \mathbf{t}^i \right\|^2 \tag{7}$$

where $\mathbf{s_r}$, $\mathbf{t_r}$ are reduced data pair. The linear operator $\mathbf{M_{kCCA}} = \mathbf{M_t M_s H_s}$ can be formulated using Equations (6) and (7). An output vector can be found using

$$\mathbf{t}_{\text{kCCA}} = \mathbf{M_{kCCA}} \cdot \hat{\mathbf{s}}_{\mathbf{new}} \tag{8}$$

from the new input vector $\mathbf{s_{new}}$. A kernelized vector $\hat{\mathbf{s}}_{\mathbf{new}}$ can be obtained using the kernel function k.

4.3. Hybrid Retargeting Model

We use the advantages of both the RBF-based and kCCA-based retargeting models by combining the two. The combined retargeting model is formulated as:

$$\mathbf{t}_{\text{final}} = \alpha(\mathbf{t}_{\text{RBF}}) + (1 - \alpha)(\mathbf{t}_{\text{kCCA}}) \tag{9}$$

where $\mathbf{t}_{\text{final}}$ is the final retargeted output vector, and $\mathbf{t}_{\text{RBF}}$ and $\mathbf{t}_{\text{kCCA}}$ are the regression results utilizing RBF in Equation (4) and kCCA in Equation (8), respectively. We use α as a blending parameter. A user can control the α value in the range of [0,1] along the entire retargeted sequence for the most desirable result.

As the retargeting model matrices $\mathbf{M_{RBF}}$ and $\mathbf{M_{kCCA}}$ are calculated once in the training stage, the computation in the runtime stage requires only two matrix-vector multiplications. Consequently, we can show a blended result in real time.

5. CHARACTERISTIC MOTION WARPING

After the initial retargeting process, the characteristic motion warping extends the target animation to express the unique individuality of the target face model. Without this extension, while resembling the expressions of the source face in terms of the overall motion, the target motion does not respect its extreme poses and timings which reveal the characteristics of only the target face. A cartoon style target face contains many more characteristic features [16] such as squashes, stretches, and exaggerations. We designed a heuristic search function to detect semantically identical intervals using pairs of source and target expressions. At each detected interval, the source motion was smoothly transformed into the target pair using 1D Laplacian coordinates [17,18]. Our method regenerates the final target animation with plenty of emotional appeals in the detected intervals and prevents non-emotional sequences being transformed with artifacts.

5.1. Emotional Sequence Pair

In contrast to the range of expression pairs, an emotional sequence pair includes both characteristic facial shapes and timings. For a specific emotional sequence of the source motion, such as ''expressing surprise.'' ''crying,'' and ''laughing,'' we first create the target facial motion manually. When we create the emotional pair for the target face, the new pair sequence is not restricted to the source sequence. The total number of frames for the pair motion can differ and the timing flow can vary in each case along the sequence. The only factor that emotional pair should observe is the semantic identity. This provides a considerable benefit when the target facial expression greatly deviates from the source expression.

5.2. Heuristic Search Function

With the emotional sequence pair, we detect the most suitable interval to transform using a heuristic search function. The detection step uses the sum of the inner products (for each frame) for the current interval of interest to describe the absolute error between the source motion and the source interval of the emotional sequence pair. Given consecutive start frames f_k along the entire source motion, we detect the start frames to transform F_{st} as follows:

$$F_{st} = \left\{ f_k \middle| \sum_{i \in I} \sqrt{\|S^{rt}_{k+i} - S^{pair}_i\|^2} \leq \delta \right\} \tag{10}$$

where, S^{rt}_{k+i} is the current start frame of the retargeted source motion, S^{pair}_i is the start frame of the interval of source pair, and δ is a user threshold. We used $\delta = 1.0$ in our experiments; this detects motion intervals similar to those in the source pair reasonably well. When we have more than two f_ks within the same interval frames, we simply use the average of them as a start frame, as this occurs only at the beginning of the intervals when the motion of the source pair changes very smoothly.

5.3. 1D Laplacian Motion Warping

After obtaining the most suitable intervals to transform, we perform motion warping for the original retargeted motion curves to fit the target motion intervals using 1D Laplacian coordinates. The final motion correctly matches when the emotional target intervals are issued while still resembling the original retargeted motion. We first convert our key values $f(t)$ in the entire n number of frames for every target control dimension nt into 1D Laplacian coordinates in order to preserve the original retargeted motion. Let F_o be the $n \times$ nt matrix storing all the key values for every control dimensions. Then, Laplacian coordinates L are generated with:

$$L = \Delta F_o \tag{11}$$

where Δ is the $(n-1) \times n$ 1D Laplacian matrix with elements:

$$\Delta_{ij} = \begin{cases} -1 & \text{if } i = j \\ 1 & \text{if } i = j-1 \\ 0 & \text{otherwise} \end{cases}$$

Using the Laplacian coordinates, we encode all of the details of key value changes from the original retargeted motion. In addition, this allows us to constrain a subset of key values in the target interval and the original retargeted motion such that the remaining key values are appropriately interpolated. We recover the key values F from the Laplacian coordinates and the key value constraints by solving the following linear least squares system:

$$\underset{F}{\operatorname{argmin}} \left(\|\Delta F - L\|^2 + \|C_T F - T\|^2 + \|C_P F - P\|^2 \right) \tag{12}$$

In this system, the $m \times$ nt matrix T contains the target interval key values of m constrained frames with the rows of the $m \times n$ matrix C_T having 1's at the corresponding columns. Similarly, the $l \times$ nt matrix P contains the original non-interval key values of l constrained frames, with the $l \times n$ constraint matrix C_P. For the target interval constraint matrix C_T and T, we constrained every key values along the interval frames to respect the emotional sequences defined in Section 5.1. To preserve the original retargeted motion excluding the target interval sequences, we added additional l constraints as described in Figure 1. The first

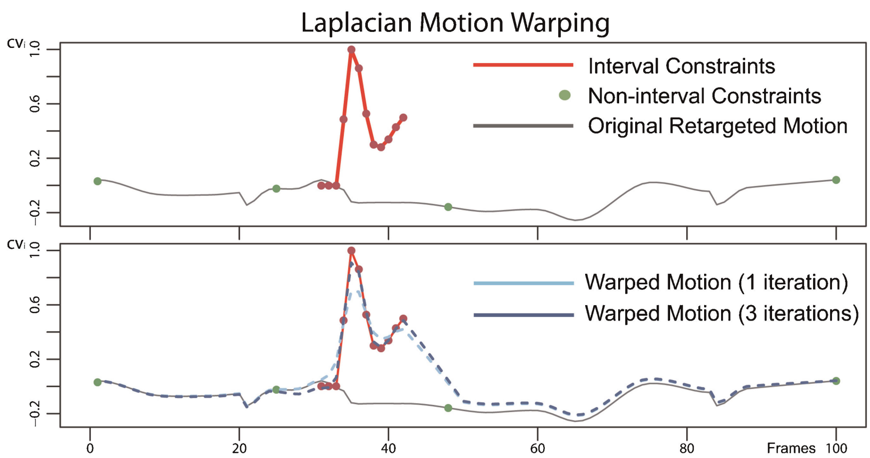

Figure 1. Original retargeted motion with a target interval and a non-interval constraints (top) warped to match the target interval while preserving the original retargeted motion (bottom).

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and the third terms ensure detailed preservation of the original retargeted motion. The second term ensures that the emotional time intervals are satisfied. We use soft constraints rather than hard ones so that the user can modify the final result by including values other than 1.

6. RESULTS

We tested our method on several characters that have morphologically different faces compared to a human source face. We evaluated our method according to two criteria: computation efficiency and robustness of the hybrid retargeting method.

6.1. Experimental Setup

We have one human face model with two motion sequences. We used a *verbal* sequence to test the retargeting performance and a *surprise* sequence to test the characteristic motion warping.

Target models have to be rigged, but our method is not restricted to a rigging method. Table 1 shows the source face and the target faces, their rigging method and the number of control vectors (degree of freedom).

6.2. Performance

The processing was done on a 2.67 GHz Intel Quad Core CPU with 8 GB of RAM. As described in Section 4.3, most of the computation time elapsed in the training stage. We improved our computational time dramatically using sparse matrix solving system so that it took less than 20 seconds to build both the kCCA and RBF regression model for the most characters. In the runtime stage, as we can represent both regression models into the matrix forms described in the Equations (4) and (8), a new target motion is updated using only matrix vector multiplication. Given that the blending of the two regression models is also very simple, every operation in the runtime stage is performed in real time.

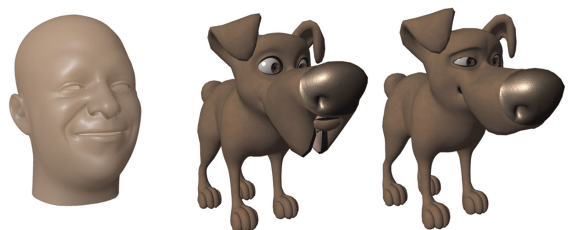

Figure 2. A comparison between position matching and our method.

6.3. Evaluation

To verify robustness of our method, we evaluate our final retargeting result with the result from the previous approach based on the position matching method. As shown in Figure 2, while the position matching method which exploits the non-negative least square (NNLS) [8] produces visual artifacts around a dog's mouth, our method generates a good result on target faces regardless of the morphological difference.

To evaluate the hybrid retargeting method quantitatively, we adopt a cyclical process similar to the Noh and Neumann's [2] evaluation method. We perform the motion retargeting from the original human motion to various target faces, and then do the same process in reverse way as shown in Figure 3. We assess an average vertex displacement error between the original and the retargeted human motion (Figure 4).

The RBF-based regression shows a plausible result in many cases as shown in the left graph of Figure 5. However, when a non-linear mapping occurs as additional range of expression pairs are added intuitively by an animator, the error of RBF-based regression is dramatically increasing while the error of kCCA-based regression remains unchanged (See the middle graph of Figure 5).

To obtain a better retargeting result, as mentioned in Section 4.3, a user can combine the two different retargeting results on specific intervals by key-framing different α values. In our experiments, we reduce the error by specifying only seven α values as shown in the right graph of Figure 5.

Table 1. Source and target faces used in our experiments. Three rigging methods are used in our target faces, and we used their parameters as control vectors. The number of the range of expressions are same for all characters, 34 pairs.

Face model	Vertices	Blend shapes	Skeletons	Deformers	Control vectors
Human (source)	11 510	33	–	–	–
Cartoon	1777	24	–	6	34
Dog	2260	28	8	36	220
Dragon	7434	4	15	28	77
Camel	2061	44	–	–	44
Crocodile	14 701	30	6	–	48
Cyclops	937	39	–	–	39

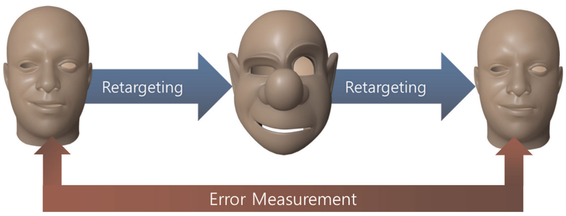

Figure 3. Explanation of our evaluation process.

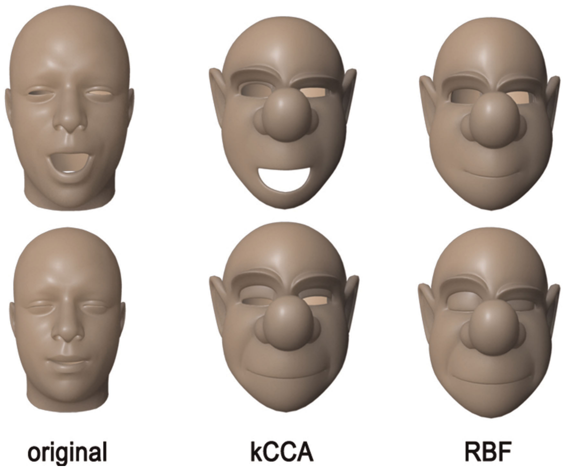

Figure 4. A comparison between kCCA and RBF based retargeting results. Each row shows the same frames of an animation sequence.

7. DISCUSSION

Our framework is very helpful to transfer captured motion data into various type of characters (Figure 6). In this work, however, we do not use the motion capture markers directly as input data. Instead, the blendshapes of a human model with captured motion data already suitably retargeted were used [19]. This assumption is associated with two advantages. First, this helps animators to create the range of expression pairs intuitively. Second, any facial motion data can be used for the source if it consists of blendshapes.

Our characteristic motion warping stage can be improved by automatically detecting the intervals with emotionally classified. It will be a challenging problem to define certain intervals requiring motion warping only using emotional target sequence.

Another challenging direction is to incorporate our method with an intuitive editing technique that helps animators. This can also be a powerful application, when used in industry.

8. CONCLUSION

We presented a novel facial retargeting method that faithfully represent the characteristics of the target model. Our contribution includes a hybrid retargeting method based on RBF and kCCA, which transfers the source animation into target faces regardless of the linearity of the sample data pairs. In addition, for more stylistic timing of the target animation, our method sums the sample

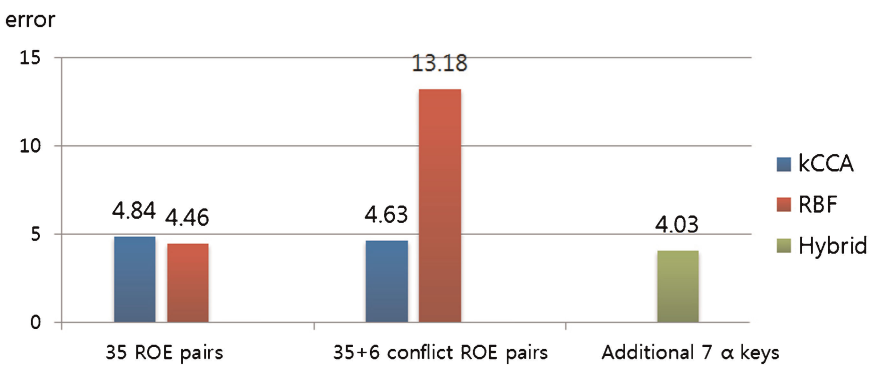

Figure 5. Robustness of hybrid retargeting model.

Figure 6. One source motion to various characters.

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animation pair, and warps the timing and spacing of target animation using these emotional sequences. Laplacian motion warping enhances the characteristics of the target facial motion while preserving the details of the input source motion.

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