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RESEARCH ARTICLE

Pose space parameterization and style transfer of skin deformation

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ABSTRACT

We present a technique to parameterize skin deformation by skeletal motion and to transfer the deformation style from one character to another. We decompose skin deformation into time-varying signals and basis matrices by using dimension reduction techniques and then approximate the time-varying signals by using radial basis functions with respect to joint angles that define skeletal motion. This decomposition reduces the size of deformation data to a small number of time-varying signals that represent the complex role of muscle action. The subsequent parameterization yields a fast and intuitive control of characters; thus, it allows us to construct faithful skin deformations quickly as skeletal bones move. The representation of our parameterization allows us to capture and transfer a derived deformation style to another skeleton–skin structure without considering the input dimension of the deformation data. This style transfer can be used as a basis for realistically animating variants of sample characters that have the same skeletal topology. Parameterization of skin deformation and its style transfer can be performed within a small amount of error once the preprocessing time and control of the deformation is carried out in real time by our graphics processing unit implementation. Copyright © 2011 John Wiley & Sons, Ltd.

KEYWORDS

skin deformation; parameterization; style transfer

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1. INTRODUCTION

Faithful skin deformation enhances the realism of virtual characters in interactive animation environments such as games. Skin deformation has numerous degrees of freedom because it is affected nonlinearly by complex motions of underlying structures such as bones and muscles. The complex and nonlinear dependence makes it hard to achieve realistic skin deformations.

Traditionally, well-trained artists spend much effort on setting up a realistically looking and moving character. Motion capture and physical simulation techniques have greatly reduced the required amount of manual effort and resulted in computational tools for generating realistic skin deformation. However, those methods require a large amount of storage space or execution time and lack convenient controls for computing appropriate skin deformations. Therefore, those methods have a limited role in particular interactive environments. In game applications, for example, fast execution with small amounts of data and simple control methods are crucial yet must achieve a credible degree of realism. It is clear that these requirements cannot be met easily and that a trade-off may be needed. We present a method to parameterize skin deformation by skeletal motion in order to represent the deformation with a small amount of data and to provide a fast and intuitive control. We also present a method to transfer the deformation style from one character to another using simple matrix computations.

We assume that skin deformation is represented by a sequence of vertex motions over time. This data can be obtained either by motion capture devices or by computationally demanding physical simulation of muscles with skin. First, we decompose the skin deformation into two parts, one of which represents a local basis matrix and the other represents time-varying signals, using existing dimension reduction techniques such as principal component analysis (PCA) or independent component analysis (ICA). Time-varying signals model virtual muscle actions that affect the vertex motions in a local coordinate system. Projecting the signals into time-corresponding joint angles and approximating the signals using radial basis functions

(RBFs), we have a parameterization of skin deformation with respect to skeletal motion. Although it is not easy to define the style of skin deformation mathematically, the notion of style is often considered as the intrinsic difference between two deformations. The style captured by the difference between deformations can be transferred to another deformation so that it follows the style. Because the skin deformation is represented by the matrix multiplications in our parameterization, we can easily capture the deformation style between two deformations and transfer the style to another using simple matrix computations.

2. RELATED WORK

There are many research results aiming to represent realistic skin deformation as the human body moves. We briefly review the subspace parameterization and data-driven approaches that are closely related to our method.

The subspace parameterization approach parameterizes skin deformation by a certain underlying structure—typically bones (joints). In a skeleton subspace deformation (SSD) model, a vertex on the skin is attached to a few joints, and the motion of the vertex is computed as a weighted combination of joint angles [1]. Because of its simplicity, this method executes extremely fast and is easy to implement, and hence this technique is widely adopted in many real-time applications such as games. Unfortunately, this method cannot avoid artifacts near joints such as collapsing elbows and candy wrap effects. To resolve such artifacts, Lewis and colleagues [2] proposed a pose space deformation technique, in which they represented the deformation as a function of a high-dimensional pose space spanned by a set of skeletal joints using scattered data interpolation techniques. Sloan and colleagues [3] interpolated an articulated figure using example shapes scattered in an abstract space. Kry and colleagues [4] presented the practical EigenSkin technique where they used a PCA to represent the displacements locally. Mohr and Gleicher [5] modified erroneous regions with additional bones for better approximation of skin deformation. Kurihara and Miyata [6] used the weighted pose space deformation for more accurate example interpolation. Wang and Philliphs [7] instead used multiple weights for each bone. James and Twigg [8] suggested a method to determine a virtual skeleton from example deformation data, seeking to find a single weight envelope method. Wang and colleagues [9] proposed a rotational regression model with deformation gradient prediction. Kavan and colleagues [10] presented a dual quaternion blending scheme for skinning.

Data-driven approaches are able to produce realistic results because they capture the deformation from real examples. Most of them take a large volume of the deformation data obtained by range scan [11], or by a motion capture device with a large number of markers [12], and so on. Anguelov and colleagues [13] presented a method for building a human-shape model that spans variation in both subject shape and pose by learning a pose deformation model and a separate model of variation based on body shape. Park and Hodgins [14] presented a method to represent the deformation due to dynamic effects as well as skeletal motion. Several research results have been proposed to resolve the high-dimensional difficulties of the deformation data by reducing the dimensionality of the parameter spaces using reduced deformation models, modal techniques, and so on [4,15–18].

Sumner and Popović [19] presented a method to transfer the deformation from a source mesh to a different target mesh using a user-defined correspondence map between the source triangles and the target ones. Baran and colleagues [20] proposed an automatic transfer method that uses several example mesh pairs by inferring a correspondence between the shape spaces of the two characters. Those methods so proposed are to produce target mesh deformation from source mesh deformation by exploiting the correspondence of triangles or poses. In this paper, we aim to produce target skin deformation that follows source deformation style by capturing and transferring the difference of two source deformations without considering any shape or pose correspondence between the source and the target.

3. PARAMETERIZATION OF SKIN DEFORMATION

It is well known that PCA and ICA can be used to reduce the input dimension within a specified amount of error [21,22] and that RBF can be used to parameterize the scattered data with respect to desired parameters [23]. By means of these mathematical tools, we describe the overall parameterization method briefly as shown in Figure 1. We assume that the skin deformation is represented by a sequence of n vertex motions over time whose frame length is m such that $P(t) = \{\vec{p}_i(t) | 0 \le i < n, 0 \le t < m,$ and $\vec{p}_i \in \mathbf{R}^3\}$ and that the corresponding joint angles $\Theta(t) = \{\vec{\theta}_j(t) | 0 \le j < l,\ 0 \le t < m,$ and $\vec{\theta}_j \in \mathbf{SO}(3)\}$ are known, where l is the number of joints.

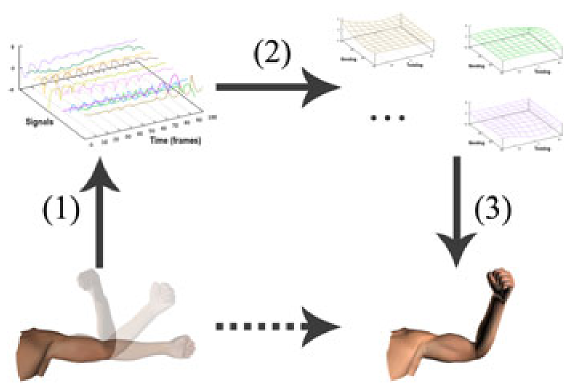

Figure 1. Parameterization of skin deformation with respect to joint angles by means of (1) dimension reduction, (2) projection, and (3) radial basis function approximation.

First, we extracted the nonrigid deformation $X(t)$ by eliminating the contribution of the rigid and possible SSD motion from the rest pose such that $X(t) = P'(t) - P(0)$, where $P'(t)$ is the vertex positions measured in the space that defines the rest pose $P(0)$ [4,24]. The vertex displacements X so obtained was anatomically considered to be influenced mainly by muscles between skeletal bones and the skin. Instead of modeling the influence from the muscles directly, we reduced the dimensionality of $X(t)$ in order to make the subsequent parameterization simple by dimension reduction techniques such as PCA or ICA; then, we have

$$X(t) = A\,S(t) \tag{1}$$

In Equation (1), within a specified amount of error, we can take k largest eigenvalues in PCA or specify k independent signals in ICA. In the case of $k < m, n$, the size of deformation X is reduced from $(n \times m)$ to $(n \times k) + (k \times m)$ by decomposed matrices A and S.

By means of dimension reduction techniques, we have time-varying signals $S(t)$ with respect to a basis matrix A, which defines the linear combination of signals for all vertex motions in X. Each column vector of $S(t)$ represents a k-dimensional position on a curve parameterized by time. At the same time, for each column vector of $S(t)$, we also have its corresponding joint angles at the corresponding column of $\Theta(t)$. For any column vector $\vec{s}$ in $S(t)$ and its corresponding column vector $\vec{\theta}$ in $\Theta(t)$, an ordered pair $(\vec{s}, \vec{\theta})$ represents a position in $(k + l)$-dimensional space. Projecting all the m positions onto an l-dimensional subspace (skeletal space), we have scattered m point samples of a k-dimensional surface. Using a thin plate spline as the kernel function of RBF, we can approximate the surface that maps from joint angles onto signals. Once the approximation is performed successfully, we can represent the vertex displacements on the skin with respect to arbitrary joint angles such that

$$X(\vec{\theta}) = A\,S(\vec{\theta}) \tag{2}$$

where $\vec{\theta}$ stands for joints angles of length l. Equation (2) gives an intuitive control to produce a nonrigid skin deformation from the joint angles that define skeletal motion.

There has been research to parameterize the motion of points on the skin by approximating X with respect to Θ. The parameterization has taken place directly in a higher-dimensional parameter space with $(n + m)$ dimension. In contrast, our parameterization is indirect and takes place in a $(k+l)$-dimensional space of much lower dimensionality. Even though the approximation problems are recognized as underdetermined linear system, the approximation in this low-dimensional space can avoid the over-fitting problem, and hence it generates a smooth surface with respect to desired parameters.

Our parameterization method seems to be quite similar to that of the EigenSkin [4], which also takes PCA and RBF interpolation into account for the parameterization of skin deformation. They defined the *joint support* that is significantly affected by a joint motion, computed an *eigendisplacement* for each vertex of a joint support using PCA, and then blended the eigendisplacements of all the joints that support a single vertex using RBF interpolation. However, we are not required to find a set of vertices that are affected by each joint explicitly and take all the possible joints that affect a single vertex into account simultaneously. The consequence representations of [4] and ours are quantitatively equivalent for a vertex displacement, but our representation is suitable for the style transfer operation described in Section 4. It is also obvious that a vertex of skin is not always influenced from all the joints when we consider the whole-body skin deformation. Hence, the explicit segmentation of skin is helpful to reduce the size of parameterization problem of skin deformation.

4. STYLE TRANSFER

Given two input skin deformation data X_1 and X_2, we present a method to capture and transfer the style between X_1 and X_2 into another input deformation Y_1 in order to produce a new skin deformation Y_2 that follows the style by simple matrix computations (Figure 2). We show that our style transfer can be carried out without considering any shape or pose space correspondence but considering the intrinsic conditions between input deformations such as the number of vertices of the skin, time-varying signals, and examples. We assume that input skin deformations are obtained from the same skeletal topology, that is, the same skeletal hierarchy but not the same bone length to each other.

Let the matrix $T : X_1 \to X_2$ be the transformation from X_1 to X_2, which plays a role in capturing the style between X_1 and X_2, such that

$$T = A_2 S_2 S_1^{+} A_1^{+} \tag{3}$$

where M^{+} stands for the pseudo-inverse matrix of M. Applying T to X_1 allows us to obtain the transformed signals of X_1 with respect to the same basis A_2 of X_2 because T is the change of coordinate transformation matrix from X_1 to X_2. Let n_1 and n_2 be the numbers of vertices, k_1 and

$$\begin{tikzcd}
X_1 = A_1 S_1 \arrow[r, "T"] & X_2 = A_2 S_2 \arrow[d, "U^{+}"] \\
Y_1 = B_1 R_1 \arrow[u, "U"] \arrow[r, dotted, "T'"'] & Y_2 = B_2 R_2
\end{tikzcd}$$

Figure 2. Skin deformation style transfer: computing the skin deformation Y_2 that follows the style between X_1 and X_2 from Y_1.

k_2 be the numbers of time-varying signals, and m_1 and m_2 be the numbers of example frames in the deformation data X_1 and X_2, respectively. The transformation matrix T can be obtained only if $k_1 = k_2$ and $m_1 = m_2$, irrespective of the number of vertices n_1 and n_2. It is easy to make $k_1 = k_2$ by specifying the same number of independent signals in ICA or taking the same number of eigenvalues in PCA when computing Equation (1). Note that we can always reconstruct new input skin deformation X_1 and X_2 of the length m by specifying the same m sequence of joint angles $\vec{\theta}$ for S_1 and S_2 in Equation (2), once we obtained the parameterization of the original skin deformation.

Similarly, let the matrix $U : Y_1 \to X_1$ be the transformation from Y_1 to X_1, which plays a role in matching the space between X_1 and Y_1, such that

$$U = A_1 S_1 R_1^+ B_1^+ \tag{4}$$

Let n_1', k_1', and m_1' be the number of vertices, time-varying signals, and frames in Y_1, respectively. Regardless of n_1 and n_1', the matrix U can also be obtained only if $k_1 = k_1'$ and $m_1 = m_1'$, which can be achieved as easily as described in Equation (3).

Finally, we can obtain the desired deformation Y_2 such that

$$\begin{aligned} Y_2 &= T' Y_1 \\ &= U^+ T U Y_1 \end{aligned} \tag{5}$$

Only the additionally required condition to obtain the deformation data Y_2 using the Equation (5) is $n_1 = n_2$ but not necessarily $n_1 = n_1'$. That is to say, if we prepare two example deformations X_1 to X_2 carefully for a character X with the same number of vertices, we can transfer the style between X_1 and X_2 to any variant Y_2 of Y_1 for a character Y without having to consider the number of vertices between X and Y.

One of the advantages in our parameterization is providing a mathematic way to interpret geometric meaning of skin deformation using a simple matrix computations. We can represent $Y_1 = Y_1 S_1^+ S_1$, which describes Y_1 with respect to the same time-varying signals S_1 of X_1 in a transformed basis $Y_1 S_1^+$. Similarly, let $X_2 = A_1 A_1^+ X_2$; then, X_2 is described by a transformed time-varying signals $A_1^+ X_2$ in the same basis matrix A_1 of X_1. Therefore, X_2 and Y_1 can be described in the same style space of X_1 with transformed basis and signals simultaneously. For the verification purpose, let $A^* = Y_1 S_1^+$ be the transformed basis matrix and $S^* = A_1^+ X_2$ be the transformed time-varying signals; then, the style-transferred deformation can be described by the multiplication of the transformed basis matrix and time-varying signals such that $Y_2 = A^* S^* = Y_1 S_1^+ A_1^+ X_2 = U^+ A_2 S_2 = U^+ T A_1 S_1 = U^+ T U B_1 R_1 = T' Y_1$, which produces the same result in Equation (5).

5. EXPERIMENTAL RESULTS

We implemented our proposed method on a PC with 2.4-GHz core 2 quad processor, 4GB main memory, and GeForce 8800 Ultra (768MB) graphics subsystems. For our graphics processing unit implementation purpose, we set the maximum number of signals to 12 for each x, y, and z coordinate of a single vertex deformation. If a vertex of the skin has more than 12 signals within a specified amount of error, we make the skin partitioned into several parts manually.

Table I shows the quantitative experimental result of our parameterization and style transfer of skin deformation. For input skin deformation shown in Figure 3(a), we applied either PCA or ICA to parameterize the deformation with the same RBF shown in Figure 3(b). Then, we compared the parameterization results in terms of root mean square error (RMSE) and the maximum error (MAXE) with respect to the original input deformation. The RMSE and MAXE are measured relatively to the size of the model, which is set to 100. When using the same number of signals in both PCA and ICA, there is no meaningful or noticeable difference quantitatively between PCA and ICA for a given example deformation. Therefore, Table I does not show whether we apply either PCA or ICA.

The amount of parameterization error is mainly affected by the quality of input example deformation as shown in Table I. Note the result for the male character of Figure 5(a). As the number of example frames m increases, the number of selectable signals increases, and hence the amount of RMSE and MAXE decreases rapidly. Given the same number of example frames, the more signals selected, the smaller error obtained. However, the impact of the number of signals is limited and saturated at a certain number of signals. The amount of processing time includes computing time for the matrices A and S in Equation (2), which is also primarily affected by the number of input examples but not by the number of signals. Once Equation (2) is obtained by our parameterization, the evaluation performs very quickly.

To measure the performance of our style transfer method, we designed deformation examples for simple geometry objects as shown in Figure 4. There are input skin deformation X_1 and X_2 for a cube shape X and another input skin deformation Y_1 for a cylinder shape Y. The input deformation X_1 and Y_1 are generated using a simple SSD, and X_2 are generated using the dual quaternion technique [10] for the comparison purpose. The number of vertices in X and Y differ to each other(402 vs. 290 or 482), but the number of examples and signals have to be the same in order to capture and transfer the style between X_1 and X_2 into Y_1. The result deformation Y_2 after style transfer from Y_1 is compared with the ground truth deformation that is generated using the dual quaternion technique to the same cylinder shape Y. The amount of error in Figure 4(b) includes the parameterization error relative to the ground truth deformation. The amount of error in Figure 4(d) includes the style transfer error between the

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Table I. Quantitative result of parameterization and style transfer, where n stands for the number of vertices on skin, m for the number of frames in a given example, k for the number of signals obtained by principal component analysis, and R for the radius of the bounding sphere for a given model.

Model	n	m	k	R	RMSE	MAXE	Time	FPS
Arm (Figure 3(b))	9071	20	68	770.56	0.00216	0.09127	4.403	8325.16
Cube (Figure 4(b))	402	9	7	12.00	0.04671	0.32829	0.015	64448.49
Cylinder (Figure 4(d))	290	9	7	12.00	0.40031	2.59442	0.034	65530.20
	482				0.40086	2.59489	0.038	62844.75
Male (Figure 5(a))	39808	11	312	1720.78	0.05218	1.31168	13.058	4133.19
		28	493		0.00500	0.22317	19.622	2191.03
		55	512		0.00345	0.10871	33.275	1225.22
		55	265		0.00354	0.10870	33.369	1369.48
		55	176		0.00420	0.15525	33.189	1785.24
		55	71		0.01811	0.48350	32.938	2034.79
Male (Figure 5(b))	39808	55	512	1720.78	0.03673	1.01821	19.364	1244.93
Female (Figure 5(c))	38389	55	512	1584.53	0.00369	0.12671	9.852	1232.16

Note: The execution time for parameterization or style transfer is measured in seconds.
FPS, frames per second; MAXE, maximum error; RMSE, root mean square error.

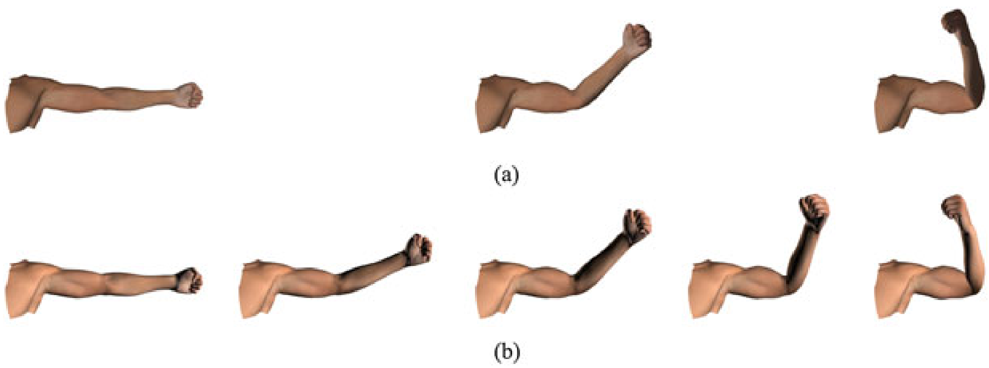

Figure 3. (a) For an input deformation data X with 20 example frames, (b) our parameterization can generate the same deformation at the same input posture (first, third, and fifth) within a very small amount of error and new deformation at desired skeletal postures (second and fourth).

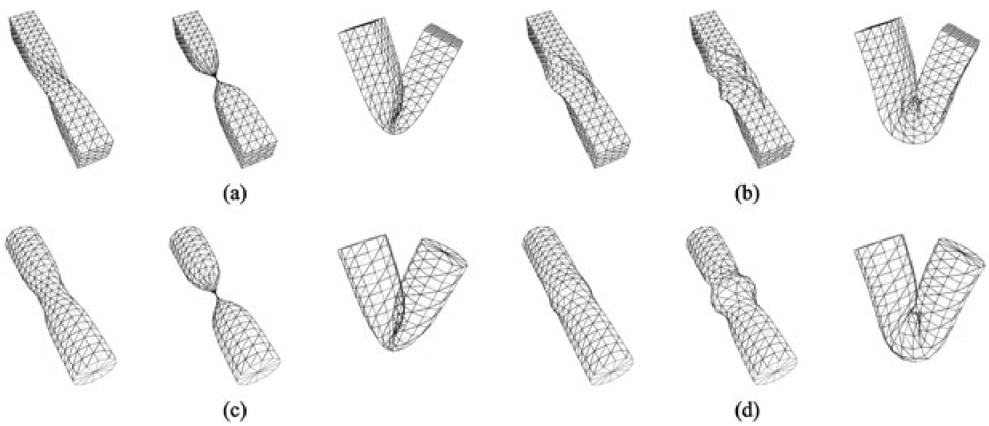

Figure 4. Style transfer of skin deformation from cube to cylinder. (a) X_1, (b) X_2, (c) Y_1, and (d) Y_2.

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ground truth deformation and the style-transferred deformation from Y_1 by the matrix U in Equation (4) as well as by the matrix T in Equation (3). The amount of errors for style transfer is approximately 10 times larger than that for parameterization error, which is mainly due to the amount of residual errors of the matrix T and U. The sum of residual errors of the matrices T and U appears in RMSE and MAXE of Figure 4(d) in the performance table.

For the whole-body skin deformation of a given male human character X as shown in Figure 5(a) and (b) and that of a female character Y in Figure 5(c), we can generate faithful skin deformation only from 55 frames long examples and 512 computed time-varying signals without considering the difference between the number of vertices. Note that the time for Figure 4(d) and Figure 5(b) and (c) includes the processing time to compute the matrices T and U but not the parameterization time.

6. DISCUSSION AND FUTURE WORK

We have presented a method to parameterize the skin deformation by skeletal motion. We presented skin deformation by matrix multiplication of two matrices, one of which encodes the basis matrix that deformation takes place and the other does the time-varying signals that capture the virtual muscle action. The time-varying signals are then parameterized by joint angles using RBF, which gives us a fast and intuitive way to control the skin deformation. Furthermore, given a set of two skin deformations, we capture the style between the deformations and transfer the style into another deformation data using only matrix computations.

There are a few limitations to capture and transfer the style of skin deformation from one to another. Differently from the traditional deformation transfer techniques, our method can transfer the style but not the deformation itself when the number of vertices in source and target differs to each other. When capturing the style between two deformation data X_1 and X_2, the number of vertices should be the same to compute Equation (5). Furthermore, for X_1, X_2, and Y_1, the number of signals and the number of example frames should be the same to compute Equations (3) and (4). Mathematically, it is relatively easy to achieve those conditions as described in the style transfer section. However, the quality of example deformation in X_1, X_2, and Y_1 matters at the same skeletal pose. If the original input deformation data X_1 and X_2 do not contain enough example skeletal posture, because of the possible extrapolation, the reconstructed deformation by Equation (2) may very differ from the other deformation Y_1. This makes the resulting deformation Y_2 unfaithful, because either X_1 or X_2 can be. According to our experiments, our style transfer method works well when input deformation contains enough length of examples, that is, the primary reason that we apply our parameterization and style transfer method to generate the variants of a character from existing example deformations of another character.

In this paper, we considered skin deformation as caused by the action of the structure between the skin and the skeleton. So far, we have interpreted the time-varying signals as muscle actions. In conventional animation software,

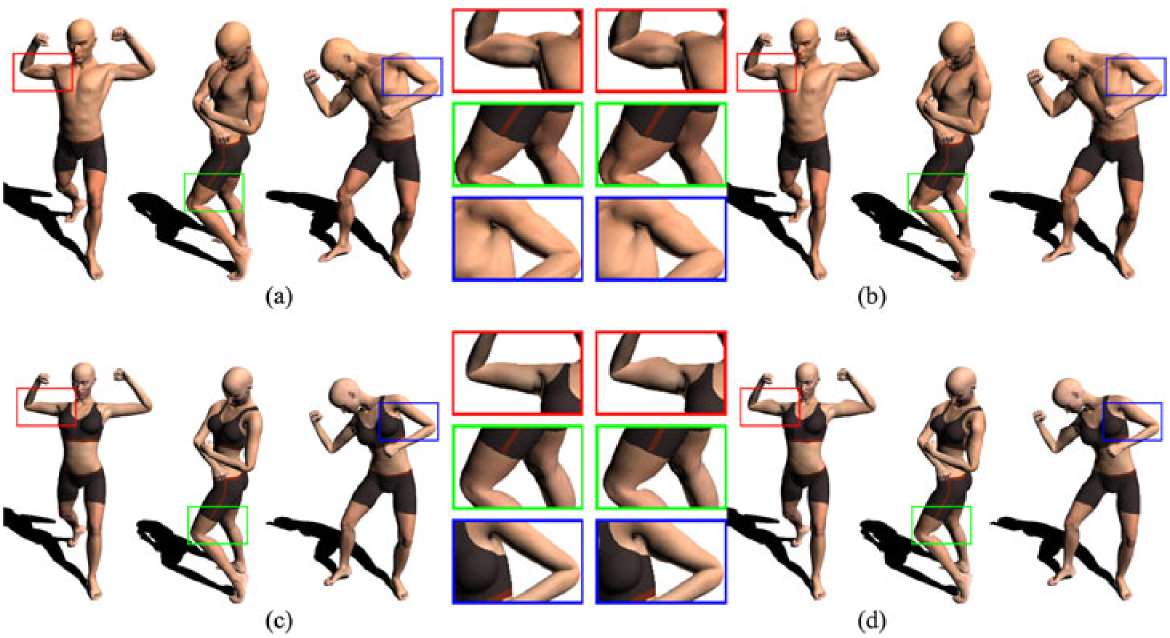

Figure 5. Style transfer of skin deformation from male to female. (a) X_1, (b) X_2, (c) Y_1, and (d) Y_2.

skin deformation is controlled using simplistic parameters of muscles, such as a "bulging rate", which seems to be intuitive to the deformation. In contrast, changing the value of a single signal or a small set of signals is not meaningful and does not result in realistic shapes of the characters. Thus, signals are qualitatively different than the bulging rates of individual muscles, and given realistic deformation data, we cannot expect that direct, manual control of the signals is intuitive. Therefore, the use of RBF that map signals to joint-space coordinates of the skeleton is an important aspect of the reported work, because control of joint angles is the easiest and fastest way of character control affecting the skin deformation. Observed muscle shape depends not only on skeletal pose but also, for example, on loads when lifting heavy objects or on the secondary action when moving fast. Our method cannot parameterize or transfer the style effectively for those dynamic skin deformation by external force.

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