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Motion Style Retargeting to Characters With Different Morphologies

M. Abdul-Massih[1], I. Yoo[2] and B. Benes[1]

[1]Department of Computer Graphics Technology, Purdue University, West Lafayette, IN, USA
michel.abdul@gmail.com, bbenes@purdue.edu
[2]NVIDIA Corporation, OpenGL Chips and Core, San Jose, CA, USA
iyoo@nvidia.com

Abstract

We present a novel approach for style retargeting to non-humanoid characters by allowing extracted stylistic features from one character to be added to the motion of another character with a different body morphology. We introduce the concept of groups of body parts (GBPs), for example, the torso, legs and tail, and we argue that they can be used to capture the individual style of a character motion. By separating GBPs from a character, the user can define mappings between characters with different morphologies. We automatically extract the motion of each GBP from the source, map it to the target and then use a constrained optimization to adjust all joints in each GBP in the target to preserve the original motion while expressing the style of the source. We show results on characters that present different morphologies to the source motion from which the style is extracted. The style transfer is intuitive and provides a high level of control. For most of the examples in this paper, the definition of GBP takes around 5 min and the optimization about 7 min on average. For the most complicated examples, the definition of three GBPs and their mapping takes about 10 min and the optimization another 30 min.

Keywords: animation w/constraints, motion control, animation systems, animation retargeting, different morphologies

ACM CCS: I.3.7 [Computer Graphics]: Three-Dimensional Graphics and Realism—Animation

1. Introduction

The motion of animated characters is determined by their actions, but also by the style in which those actions are being performed. For example, a person can walk from one location to another and the action can be done with a sad or happy mood. It is important for a character animator to be able to change the style of a particular action without significantly modifying the actual motion. However, the style definition is often a challenging task that might result in having to redo the animation from scratch. Characters with non-humanoid morphologies present an even greater challenge because it is very difficult to find or capture motion of characters with non-humanoid morphology performed in a certain style.

A common technique for style editing is its transfer from another motion. This is usually possible for characters with similar morphologies (e.g. [UAT95, ABC96, BH00, SCF06]), but animated characters used in movies or videogames are often non-humanoid. Research exists aimed at synthesizing or editing non-humanoid animations [HRE*08, DYP03, YAH10], but these works are not concerned with retargeting stylistic features. As such, it is difficult to provide motion capture with a desired style (for example, of a sad cow or a happy dragon) or to find characters with similar morphologies from which stylistic features can be transferred. Instead, animators are left with the task of tedious manual editing or even redoing the animation from scratch.

The key observation of our work is that the stylistic features present in a character animation are composed of identifiable, coordinated motion of body parts, and the style of the animation can be described as the combination of these individual body parts. For example, a sad character will have a small sway of the shoulders, low inclination of the head, nearly no swing of the arms, as well as the overall low amplitude of joint rotations and speed relative to a neutral motion. Furthermore, some of these body parts rotate as a whole around a fixed point on the body. The style can be expressed in terms of these larger structures. Moreover, if we could express the style of the motion of each body part, we could map the style between body parts that do not present the same skeletal topology, shape or correspond to the same part in both characters, i.e. to be able to match an arm and a tail, even though their structure and function might be different.

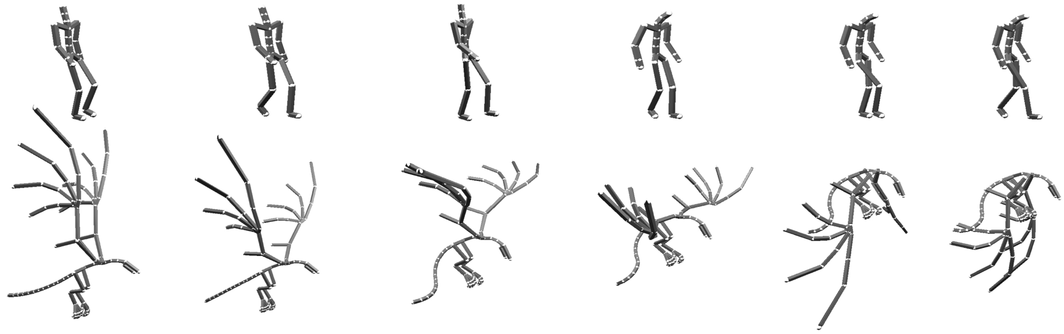

Figure 1: *(Top) A sequence of humans changing from a neutral to a sad motion style. (Bottom) A sequence of dragons changing from a neutral to a sad style. The stylistic features from the sad human were transferred to the dragon, resulting in a dragon showing a sad style.*

We introduce an approach for intuitive motion style retargeting to non-humanoid characters. Our work is aimed at editing existing motions of characters that present topologically different skeletal structures. We introduce the concept of Group of Body Parts (GBPs). The user defines the GBPs in the source and target characters and the system then extracts motion features from the source GBPs and transfers them to the target. In order to achieve style transfer, a full body per frame optimization is performed to enforce the constraints set by the features while aiming to keep the motion as similar as possible to the original.

Manual work is required from the user for temporally aligning the source and target motions, as well as spatially aligning GBPs if automatic alignment is not satisfactory. The user also has the option to specify the stiffness of GBP joints for the optimization stage. There exists the option to save GBPs and their mappings in case the results of the style transfer needs to be improved by adding or removing GBPs, changing parameters and rerunning the transfer operation.

The main contributions of this work are:

(1) the decomposition of the motion style into a set of features present in separate GBPs,
(2) a methodology for transferring stylistic motion features between characters with different skeletal topologies by using GBPs and
(3) a data representation that allows for reuse of stylistic features on different characters without the need of extracting them for every new character.

We show the results on a set of characters that present a wide range of topological differences with the source characters from which stylistic motion features are extracted. An example in Figure 1 shows sadness style retargeted to a dragon. The final animations present the features extracted from the source stylized character and conserve the content of the original motion. We show examples of human style retargeted to a T-Rex, a dragon, a three-headed creature, a snake and to a human. The overall time for transferring the style for the most complicated examples in this paper, the definition of three GBPs, and their mapping takes about 10 min and the optimization another 30 min, however, for most examples the GBP definition is around 5 min, and the optimization about 7 min. Usually three to four GBPs have been sufficient to express style in our examples.

2. Related Work

Transferring human motion to characters with different morphological structures has been addressed in the context of motion puppetry and synthesis, but the transfer of *stylistic features* to characters with different morphologies has not been the main focus of previous research.

Motion Retargeting for Skeletal Animation allows for the reuse of motion data by transferring animation from a source to a target character. Gleicher [Gle98] showed motion retargeting between characters with the same joint hierarchy, but potentially different bone lengths. The system uses a modified version of the space time optimization from [WK88] to keep the properties of the original motion while enforcing constraints. Popović and Witkin [PW99] used a space time constraints model with dynamics and a simplified human model to edit motion by changing dynamic constraints and Lee and Shin [LS99] did a per-frame optimization with spatial constraints and hierarchical B-splines fitting to smooth the motion. We use their approach for enforcing the motion constraints in our system.

The works of [MBBT00] and [KMA05] focus on retargeting motion to characters with different humanoid topologies. While their research allows for different skeletal structures, it is not meant for highly varied topologies.

Motion Retargeting to Non-humanoid Characters has been addressed by Hecker *et al.* [HRE*08] who used their results in the game of Spore™ in which animators create semantically annotated motion which is transferred to user-generated characters of varied morphologies. However, the system allows for a limited set of clearly annotated topologies with pre-defined mapping.

Dontcheva *et al.* [DYP03] developed a system based on motion captured data that allows for inferred mapping between the actor and the character and Yamane *et al.* [YAH10] presented a method for retargeting human motion capture data to non-humanoid characters semi-automatically. Their system learns a mapping between the motion capture data and the target character through a Shared

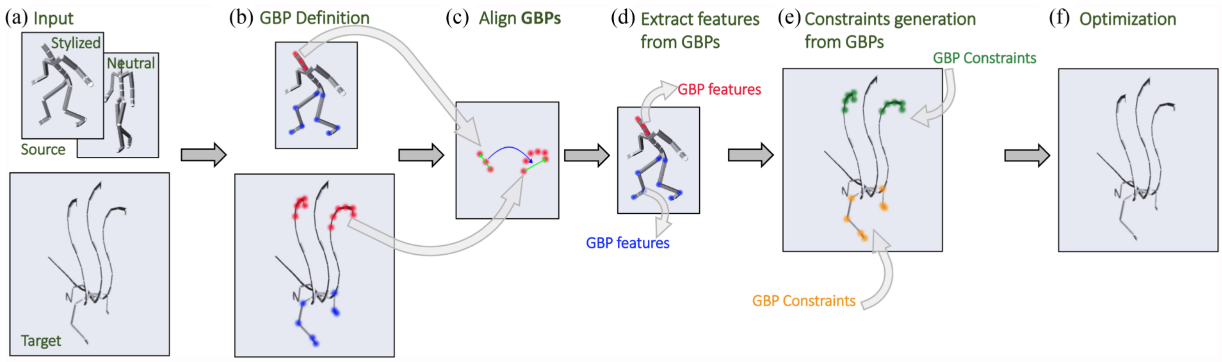

Figure 2: *Overview of the motion style retargeting framework. (a) The input are two animated characters (stylized and neutral), and a target animated character. (b) Matching Groups of Body Parts (GBPs) are defined for the source and target characters. (c) The GBPs are aligned. (d) Positional and angular amplitude features are extracted from the source character. (e) Features from the source are turned into constraints by the system. (f) Constraints are fed into a mathematical optimization to obtain the final stylized animation.*

Gaussian Process Latent Variable Model. Seol *et al.* [SOL13] presented a method for online puppetry of non-humanoid characters. A mapping is created between features of the human motion and a classifier learns the motions performed by the actor so this information can be used in the puppetry stage. These methods, while powerful for performing puppetry on non-humanoid characters, need to either carefully pose the target character or a live actor to match the pose of the target character. In our work, the alignment of body parts is much simpler, and furthermore provides the user with a lot of flexibility and control over the transfer. While the main works in this area have principally focused on motion puppetry and motion synthesis, our approach is retargeting stylistic features instead of generating motion from scratch.

One of the first works in 'Motion Style Retargeting in Animation' to perform style extraction from motion data is [UAT95] in which the authors interpolate and extrapolate periodic human locomotion with emotion from Fourier expansions of motion data. Signal processing techniques were also exploited by Amaya *et al.* [ABC96] who used the difference between a normal and an emotional motion to stylize a neutral animation. A method for interpolating between motions was presented by Rose *et al.* [RCB98] who separate motions into expressiveness and control behaviours. Interpolation is done on a space of radial basis functions. They call motions 'verbs' and their parameters are their 'adverbs'.

Many techniques for motion style extraction and translation use statistical methods to learn stylistic features of motions and apply learned poses to a target character. Brand and Hertzmann [BH00] generated motion sequences in different learned styles through parameter manipulation. They learn style by using a Hidden Markov Model of joint motions through time. Vasilescu [Vas02] and more recently, Min *et al.* [MLC10], use multi-linear models to learn and synthesize stylistic motion. Other statistical methods for style extraction and translation include Gaussian Processes, as in the work of Grochow *et al.* [GMHP04], Principal Component Analysis, as shown by Urtasun *et al.* [UGB*04], self-organizing mixture network of Gaussians used by Wang *et al.* [WLZ06] and Bayesian networks, as in [MXH*10]. Hsu *et al.* [HPP05] translate a motion style into an existing motion that potentially changes in speed and direction. They use a linear time-invariant model to learn a style and transfer it online to other motions.

Realistic physics-based character animation presenting different styles was introduced by [LHP05]. In this work, parameters like muscle, tendon, shoe elasticity and joint preference represent different styles. Changes to the style can be made by changing body and dynamic properties of the character.

Motion style can also be learned and synthesized through edits made by the user, as in the work of Neff and Kim [NK09]. They transform the joint angles into different parameters used for editing which they call motion drives. Another user edit-based method was introduced by Ikemoto *et al.* [IAF09]. Their system learns edits that artists make to an animation and later applies those operations to different animations. The system builds a function from user-generated changes to an animation using Gaussian Process. This function is applied by the system to a new character using traditional retargeting.

Relevant to our work is the research of Shapiro *et al.* [SCF06] who use Independent Component Analysis (ICA) to extract style from motions and then apply the style component selected by the user to a base motion. The ICA is applied to concatenate the stylized and base motion. The result from this operation allows the user to see all the components separated by ICA and can select and apply one or more components to the base motion. We use ICA as one possible technique for motion style identification and extraction.

The above works have in common that stylistic features must be transferred between characters with similar morphologies, and in many cases, the methods are targeted specifically to humans. Our method focuses on the translation of these features to characters with completely different body structures.

3. Overview

Our motion style retargeting method is performed in two main steps (Figure 2): *motion feature extraction* and *motion feature transfer*. In the first stage, GBPs are defined by the user on input characters

(Figure 2b). GBPs from the source and the target characters are manually aligned. Positional and angular features are obtained from the motion of the source characters. During the motion transfer stage, constraints on the target motion are computed from the values of the extracted features. These constraints are then used in an optimization for obtaining the final animation.

Motion Feature Extraction Motion features in this work are defined by the way individual GBPs move, and the way the overall rotation ranges of the joints of the stylized character behave compared to a neutral motion. The *input* of our retargeting framework consists of two character animations used as source motion and one character animation used as target motion. One of the source characters contains stylized motion and the other source character contains a neutral version of the same action (Figure 2a).

Groups of Body Parts belonging to the source and target characters are defined by the user for transferring the desired motion features. This is illustrated in Figure 2(b). The red GBPs on the source character are matched to the red GBPs on the target character, and the blue dots on the source character are matched to the blue dots on the target. Note that the number of joints in each group can be different. Matching and alignment of the groups between source and target characters will be used as the means of passing data between the feature extraction and transfer stages (Section 4.1).

Spatial alignment of the GBPs is necessary so that the target GBPs move in the correct direction when the features are transferred from the source groups (Figure 2c). An interface is provided for the user to perform the alignment of GBPs.

Temporal alignment of the two characters is also necessary for the transferred motion features to be coordinated with the target character (Section 4.2).

Motion feature extraction is performed after GBPs have been created for the source and target characters (Figure 2d). We categorize the motion features into positional and angular amplitude features. Positional features are used to transfer motion directly from the source to the target, and they are represented by relative paths of specific joints on the source character. Angular amplitude features are used to scale and offset the angles of the target motion based on the difference between the stylized and neutral source motions (Sections 4.3 and 4.4).

Motion Feature Transfer is performed after all motion features from the source have been identified and extracted. Features from source GBPs are used to create positional and angular constraints on joints on the target groups. Positional constraints are created by mapping the motion of the source GBPs to joints on the target groups and angular constraints are created by scaling and offsetting the range of rotation of joints on target GBPs. Figure 2(e) shows the groups created on the target character in a different colour to highlight that by this point, constraints have been created for those GBPs.

A full body optimization is performed on the target character using the positional and angular constraints mentioned above, which results in the transfer of the source character's selected features while conserving the content of the target animation (Figure 2f and Section 5).

4. Motion Feature Extraction

Our input consists of three animated characters: the source character is represented by its neutral motion $\mathbb{S}_\mathrm{N}$ and the stylized motion $\mathbb{S}_\mathrm{S}$ that contains the stylistic features that we intend to transfer to a character's target motion denoted by $\mathbb{T}_\mathrm{N}$. Character $\mathbb{S}_\mathrm{N}$ contains the same skeletal structure as $\mathbb{S}_\mathrm{S}$, while $\mathbb{T}_\mathrm{N}$ skeleton can be different.

We represent a character motion as a discrete set of poses, each of which is composed of the position of a root joint and the rotations of l joints: $\mathbf{m} = \{\mathbf{p}, \mathbf{q_1}, \ldots, \mathbf{q_l}\}$, where $\mathbf{p}$ is a vector of positions $p(t)$ of the root joint in 3D, $\mathbf{q_1}$ is a vector of the rotations of the root joint represented as quaternions and $\mathbf{q_i}$ are vectors of rotations $q_i(t)$ of the rest of the joints represented as quaternions, where $2 \leq i \leq l$.

4.1. Groups of body parts

The first step in the process of feature extraction is selecting which joints of the source character contain stylistic information and creating GBPs that will later be matched to groups on the target character during the motion transfer stage.

The GBPs are defined by the user by simply interactively selecting the joints that belong to each group. After creating the GBPs on the source character, each group is matched by the user to a GBP on the target character, where the motion style will be transferred. The ith GBP on the source character's set of GBPs $g_\mathrm{S}^i \in G_\mathrm{S}$ is defined as

$$g_\mathrm{S}^i = \{J_\mathrm{S}, F_\mathrm{S}\},$$

where $J_\mathrm{S} = \{j_\mathrm{S}^1, j_\mathrm{S}^2, \ldots, j_\mathrm{S}^n\}$ is the set of joints in the group, $F_\mathrm{S} = \{f_\mathrm{S}^1, f_\mathrm{S}^2, \ldots, f_\mathrm{S}^w\}$ is the set of features of the group, n is the number of joints in the group and w is the number of features describing the motion of the group.

Joints belonging to a group do not need to be topologically adjacent; for example, a group can be composed of a joint on the spine, the shoulder and the hand, depending on the features that the user intends to extract from the motion of this group. Instead of transferring the stylistic features for the whole body at once, the motion transfer is done on a per group basis, thus allowing for one group on the source character to be matched to more than one group on the target. A joint can belong to several groups at the same time.

Once the joints of a GBP have been selected, the GBPs are processed. We measure the topological distance between each pair of joints inside the group. The joints with the highest topological distance form a *representative vector* (RV) of the group that is a unique representative of it. The end of the RV will be the closest joint to a leaf in the structure and it is called the *leading* joint in the group. The starting point of the RV is called the *base* of the GBP. The intuition for the RV is that the leading joint should be representative of the stylistic motion feature within the joint group and the base joint should be fixed relative to the GBP. The leading joint will rotate around the base joint, and this rotation will be used by our method to achieve the motion transfer. An automatic selection assigns the base as close to the spine as possible, but the user can override this choice. An example in Figure 3 shows that the RV for a shoulder would be defined by a spine joint as the base and the shoulder as a lead.

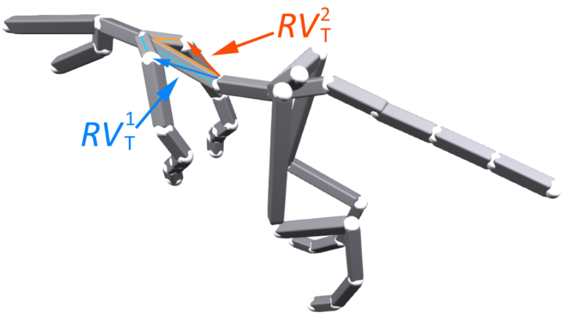

Figure 3: *Several joints from a stylistically important part of the body form a GBP. The representative vector (RV) is extracted from the GBP.*

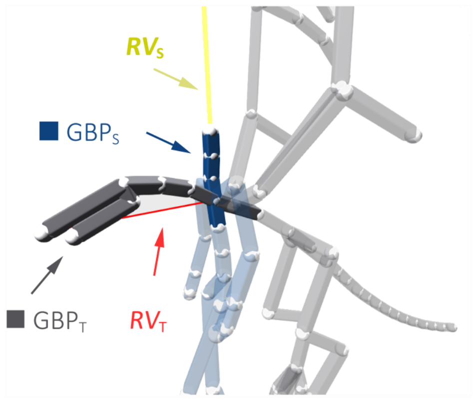

Figure 4: *Alignment of two GBPs lead to the alignment matrix $\mathcal{M}$.*

4.2. GBP alignment

Before the GBPs are used for extracting positional features from the source character, they need to be aligned with groups on the target. The alignment is performed semi-automatically. The base points of both RVs are matched as well as the directions. The corresponding characters are then displayed and the user rotates them to the desired match. This operation yields an alignment matrix $\mathcal{M}$ for each GBP pairs matched by the user. Figure 4 shows an example of two RVs before matching. The RV_S will be aligned with RV_T and the matrix $\mathcal{M}$ generated. These matrices are used in the transfer stage as a pre-rotation of the extracted source features to create the target motion.

4.3. Positional features

The GBPs (Section 4.1) on the source character contain part of a set of stylistic features that the user wants to transfer; each GBP on the source character represents a certain *part* of the motion. By combining all of these parts together on the target character, we aim at reproducing the motion style of the source. We do so by extracting positional and angular amplitude from each group.

Positional features refer to the path created by the RV throughout the duration of the source motion $\mathbb{S}_S$. At every frame of the motion, the RV of the source character will perform a rotation around its base joint. Let us denote the set of all the RV rotations for a GBP g_S^i by A_S^i. This set of rotations will be used in the motion transfer stage to transfer the source GBP's motion to the target character (Section 5).

The output of this stage for each GBP that contains positional features is a set of rotations $\alpha(t)$ that will be used to compute the positional constraints in Section 5.1.

Positional features are called this way because even if they are obtained by rotating the RV's leading joint around the base joint, what is ultimately used as constraints for the solver are the positions of the leading joint.

4.4. Angle amplitude features

It is a well-studied property of human motion that emotions present different amplitude patterns [NLK*13]. For example, sadness or sorrow causes the GBPs to contract, while anger and happiness causes them to extend. Our angle amplitude features attempt to describe the average contraction or extension of body parts relative to the neutral input motion $\mathbb{S}_N$. In order to extract angle amplitude features from a stylized source character $\mathbb{S}_S$, we use the input character that presents neutral motion $\mathbb{S}_N$, so the amplitudes of the angles of both characters can be compared.

Extraction of angle amplitude features from a user-identified GBP $g_S^i \in G_S$, where $1 \leq i \leq m$ and m is the total number of GBPs on the source, is done as follows:

(1) For each joint in g_S^i, find all pairs of the maxima and minima of their angle amplitudes.
(2) Calculate the average difference d_j between these extrema for every joint in g_S^i.
(3) Compute the average of the differences $\bar{d}_S = \frac{1}{n}\sum_{j=1}^{n} d_j$.
(4) Compute the average value, $\bar{d}_N$, for the corresponding GBP in the neutral input motion.
(5) Calculate the ratio between these quantities as $r_i = \bar{d}_S / \bar{d}_N$.

We also compute the midpoint of the average difference between the extrema for the stylized and neutral sources for each GBP. Let $\bar{m}_S^i$ be the average minimum of the angles of the joints in g_S^i, we obtain

$$o_S^i = \bar{m}_S^i + \frac{\bar{d}_S}{2}$$

and

$$o_N^i = \bar{m}_N^i + \frac{\bar{d}_N}{2}.$$

Finally, we subtract both values $o_i = o_S^i - o_N^i$.

The output is a set of ratios $R = \{r_1, r_2, \ldots r_m\}$ and a set of offsets $O = \{o_1, o_2, \ldots, o_m\}$ that are used for scaling the amplitudes and to offset the range of the corresponding joints in the target character $\mathbb{T}_N$.

5. Motion Feature Transfer

When the motion features from the source character have been extracted and necessary alignment operations have been performed, motion feature transfer to the target character can be carried out.

Each GBP in the set of groups G_{S} from the source character is mapped to one or more GBPs in the set of groups G_{T} on the target character. Every motion feature in a group will be later transformed into a constraint on the target character's motion and the constraints will be enforced through a full-body constrained optimization.

5.1. Positional constraints

Our goal is to move certain parts of the target character's body in a similar way to the source character matching parts without losing the underlying motion of the target. In this stage, we generate rotations of body parts around a base joint that yield a position in space of the leading joint of an RV. These positions will be used in an Inverse Kinematics solver to achieve the rotation of the whole body part. The motion of the RV in the source GBP is transferred to the target character. The joints in the GBP that do not belong to the RV are used to control the rigidity of the motion of the GBP of the target (rigidity can be user defined).

Recall that the result of extracting positional features for a GBP g^i_{S} in Section 4.3 is a set of rotations $\alpha(t)$ of an RV around its base joint. We also have an alignment matrix $\mathcal{M}$ for each matched pair of GBPs between the source and target characters. By using these data, we obtain a set of points in space $p(t)$ for every target GBP as follows:

- Rotate the normalized source RV by its corresponding $\mathcal{M}$. This will serve as a pre-rotation to align the source RV with the target.
- For every time-step t, rotate the source RV by $\alpha(t)$, and multiply the result by the magnitude of the target RV.
- Scale the result by the ratio between the current length of the source RV and its length at $t = 0$. This will have the effect of stretching the vector and finally yield a new point $p(t)$.

Points $p(t)$ are the positional constraints for the leading joint of the target's RV.

5.2. Angular amplitude constraints

The positional constraints directly map the motion of a source to a target GBP. This mapping is important because much of the stylistic motion can be transferred in terms of rotations of whole GBPs. However, stylistic features exist that may be present as the amount that joints are contracted or extended on average throughout the motion.

Let us recall that the average angle amplitude ratio between the stylized and neutral motions is denoted by R (Section 4.4). This controls the range of rotation on specific target character's GBP joints by multiplying the value of the joint rotation angle on every frame by the corresponding $r^i_{\mathrm{S}} \in R$. Similarly, we use the angular offset between the stylized and neutral source motions O to offset the rotation of specific target character's GBP joints by adding the value of the joint rotation angle on every frame to the corresponding $o^i_{\mathrm{S}} \in O$.

5.3. Optimization

When we transfer features to a target character, we aim at conserving the underlying motion as much as possible, while enforcing the constraints set by the transfer as closely as possible. We use the space time approach presented by Lee and Shin [LS99] for solving the final motion using the constraints generated in the previous sections. This approach minimizes at sparse frames the objective function:

$$
\begin{aligned}
&\min \qquad f(\mathbf{x}) = \frac{1}{2}\mathbf{x}^T M \mathbf{x} \\
&\text{subject to} \quad c_i(\mathbf{x}) = 0, i \in N_e, \qquad c_i(\mathbf{x}) > 0, i \in N_i,
\end{aligned}
$$

where $\mathbf{x}$ is a vector containing the position of the root and the rotations of all the joints, M is a rigidity matrix, which we modify when the rigidity of the joints in a GBP is changed (see [LS99] for details) and c_i are equality and inequality constraints. In this work, we only use equality constraints: the positional constraints (Section 5.1) and the axis of rotation of the angle amplitude constraints (Section 5.2). After all constrained frames have been calculated, we further smooth the motion curves to account for the discontinuities. Similar to Lee and Shin's work [LS99], the optimization and smoothing are done repeatedly with increasing precision and in our experiments we needed up to six iterations.

Intuitively, solving the optimization minimizes the difference between the original target motion and the edited target motion, while enforcing the constraints on positions and rotations generated in the previous sections. The result of the constrained optimization is the final animation.

6. User Interaction

The input to the retargeting system are the stylized source $\mathbb{S}_{\mathrm{S}}$, neutral source $\mathbb{S}_{\mathrm{N}}$ and target $\mathbb{T}_{\mathrm{N}}$. Temporal alignment of the motions is necessary, but it is possible within the application and takes just a few seconds to temporally align two motions by use of sliders that scale timing. The reverse process can be performed when the style transfer has been completed.

Once the motions are temporally aligned, creation of GBPs is performed by identifying source and target joints for the style transfer. First, the user creates GBPs by selecting joints on the source character. These joints are not necessarily adjacent. The user then indicates if the GBP should be used for its positional features (as described in Section 4.3), or angle amplitude features (as described in Section 4.4), or both. If positional features, an RV is generated automatically for the user between the most inner and outer joints of the GBP, but the user is free to change this. The user is also presented with the option to select the start and end time for the feature to be extracted. GBPs can be saved for future use to transfer style to other characters.

GBPs on the target character are created the same way. For each GBP, the user decides if it should be used for positional constraints (as described in Section 5.1), angular constraints (as described in Section 5.2), foot placement constraints or if the motion of the joints in the GBP should be kept as similar as possible to their original

Table 1: *Statistics for the examples show comparisons of character joint count, number of frames, number of GBPs created, number of GBP joints and time to compute the new motion.*

Clip	Joints	Frames	GBPs	Joints	Time
Dragon	177	1200	3	26	30 min
T-Rex	43	1200	3	22	5 min
Three heads	70	900	7	16	20 min
Snake	53	1000	1	9	<1 min
Human	30	900	4	16	10 min

target character's motion. At this stage, the user has the option to assign stiffness to joints in the GBP (as described in Section 5.3).

After creating GBPs for source and target characters, the user assigns each source GBP to one or more target GBPs. Each pair of GBPs is automatically aligned by matching RV points and rotations, but the user has the option to correct the alignment manually, which in general takes a few seconds. Finally, the user indicates that the operations are done and the optimization takes place.

Whenever the user is not satisfied with the results, the process described above can be repeated by reloading and rematching GBPs, and changing stiffness values of the GBP joints. It is possible that the optimization does not converge given a high number of constraints, in which case, it is necessary to remove some of these constraints. In some cases, like with foot constraints, these can be added later on a second pass.

In our examples, the whole setup process has taken between 5 and 10 min. It was necessary in some cases to iterate the process for increasing or decreasing the GBP joint stiffness to achieve the desired results.

7. Implementation and Results

Our framework is implemented in C++ and uses OpenGL with GLSL for visualization, and the Qt library for user interface. All tests have been performed on a PC equipped with Intel Core i7 920 running at 2.67 GHz and nVidia Quadro K4000 with 4 GB RAM. All animations in this paper took at most 30 min to compute and they contain between 900 and 1200 frames. The set of constraints is subsampled, so not all of the frames need to be evaluated. Note that the animations can be found in the Supporting Information video S1. Table 1 shows statistics for the number of character joints, number of frames, number of GBPs, total joints inside all GBPs and calculation time per character. The Supporting Information includes additional tables with details for examples from this section.

Temporal alignment, when necessary, was performed manually between the source and the target characters. This could be done with an external tool or within our system.

Figure 6(a) shows an example of a sad dragon. We used positional and angle amplitude constraints extracted from joints on a depressed human animation and applied them to the winged character. We defined two GBPs on the human character (left), and three on the dragon (middle). The coloured legend on the figure corresponds to the GBPs on the source. Note that two groups on the dragon have the same colour because they correspond to the same group on the source. The resulting animation shows that the range of rotation of the wings is smaller than the original; furthermore, the rotations have also been offset, so they start further down. The tail of the character shows significant contraction with respect to the original, and its head is positioned similar to the source character. Creating and mapping the GBPs took less than 5 min, while computation of the final animation took around 30 min.

The second example shows an angry T-Rex in Figure 6(b). For this animation, we used the arm and head motion of an angry human (left). Three GBPs were defined on the human and another three GBPs were defined on the target character. Figure 6(b) in the middle shows the T-Rex swinging its arms and shaking its head in the same manner as the source character. The creation and mapping of the GBPs took less than 5 min, and the final animation was computed within 5 min.

Next, in Figure 6(c), we show a three-headed creature moving in the same manner as the source macho human character. The source character was divided into four GBPs and the target character into six. We use positional, as well as angular, features to transfer the movement style of the source character to the creature. The sway of the shoulders from the source character is mapped to the shoulders of the creature, and we also transfer the motion of the source's head to two of the target character's heads. We took angle amplitude features from the arms of the source character, which are wider compared to the source neutral character. The computation of the final animation was about 20 min given that we also add foot placement constraints so the character's feet do not slide. Foot placements can be added as just one more GBP and by setting positional constraints at sparse frames.

In the example in Figure 6(d), we generate the motion of a drunk snake. The animation was very quick to accomplish with a few seconds to create and match the GBPs and less than a minute to perform the optimization. We used only one GBP on the source and one on the target character. The resulting motion shows a strong sway of the snake's body.

The last example shows a spider for which our method fails (Figure 5). This character has a root joint to which all of the legs and head are connected directly. The current framework does not allow changes to the position of the root joint because modifying the values of this joint transforms to the entire character and destroys the animation.

Table 1 shows statistics for all examples from this paper. It includes the number of joints, frames, number of GBPs and the time for computation of the new animation. The maximum number of GBPs was 7, the average time for the extraction of the GBPs and their alignment was around 7 min. Once the GBPs have been created, it is possible to reuse them with another animation, simply by performing a new alignment. The computation time depends on the number of joints, as well as the number of joints in each GBP. The maximum time for computation was 30 min for the dragon, and the computation for the Snake of less than a minute was the quickest.

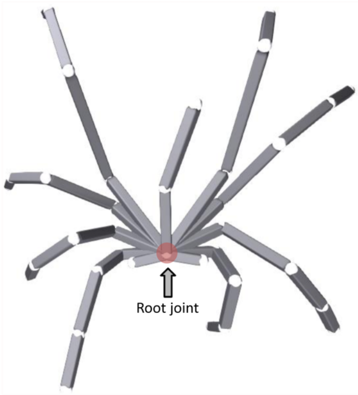

Figure 5: *A failure case of a spider with no torso except for one root joint. Making changes directly to the root joint would break the motion.*

7.1. Evaluation

Rating the naturalness of motions is difficult and sensitive to user perceptions of what a natural motion looks like, as well as the rendering style of the characters being evaluated. Chaminade *et al.* performed a user study that aimed to compare naturalness ratings of motion capture data compared to hand animation of human motion and several rendering styles [CHK07]. It was found that the hand animations were consistently rated lower than the motion capture, even though only the in-betweens were hand animated. Also, it was found that more rendering details on the human character reduced the naturalness. Methods for evaluating the naturalness of an animation are limited, and in general, user studies have proven to be the most effective to achieve this task. A motion Turing test is often used, in which the participants are presented with human motions and asked if the motion looks artificially generated or if it was performed by a human [VWVBE*10]. Artificially generated human motions and motion capture were studied in [JvW09] to discern good user test paradigms for motion of virtual humans. Three types of questions were asked to users in order to rate the naturalness of human motion:

- Asking the participants if the motion presented to them was real human motion data or a computational model,
- after showing artificially generated motion, as well as motion capture, asking the participants to decide which one showed natural motion,
- rating the naturalness of motions from 1 to 10.

In this research, ambiguity might arise if users are asked the above set of questions referring to motions of non-humanoid characters. Asking participants if the motion of non-humanoid characters is real or a computational model could create confusion since no one has seen a real T-Rex moving.

Few previous works on style retargeting and synthesis have performed user tests, or other form of evaluation to measure the success of the transfer or synthesis of stylistic motion. Style synthesis was evaluated by [Vas02] through an automatic method. Etemad and Arya [EA13] performed a survey for evaluating their style recognition and synthesis framework on 10 participants. Tilmanne and Dutoit [TD12] performed a survey for evaluating interpolation of synthesized styles through comparison with original styles and inquired about their naturalness. The result of style retargeting and synthesis is generally verified purely by visual inspection of the researcher. The output of the method is generally shown next to the motion from which the style is extracted. Another way of showing the quality of results in related works is by comparing graphs representing certain joint angles through time of stylized motion and neutral motion with a style applied to it.

In this research, in order to measure the success of the proposed methodology of style translation to non-humanoid characters, a survey was applied to 100 participants, 18 years of age or older. The study was carried out in the platform Amazon Mechanical Turk or MTurk (www.MTurk.com) that is an Internet-based service where people get paid for completing tasks such as surveys, writing or other activities. According to [BKG11], the population that provides services through the website is significantly more diverse than American College samples. After stating their age and their animation expertise (1 = no expertise, 5 = professional), 16 movie clips are presented to the user separately. Six clips show *target characters* after motion style transfer (resulting animations), five clips show the *target characters* in a neutral style and five clips show the five *source human characters* acting the styles transferred. Each of the clips contains two camera perspectives, e.g. side and front, presented one after another. Each clip repeats 20 times for convenience of the user, and can be replayed, rewinded or stopped. After watching a clip, the participants were invited to respond four questions (see Figure 7 for a screenshot of the survey layout):

- What is the *style* of the motion in the video presented above? Style refers to your perceived mood, behaviour or physical properties of the motion.
  Angry/Frustrated
  Sad
  Drunk
  Mummy
  Confident
  Neutral/No style
  Other (an area for adding text to this answer is provided)
- Rate *how clearly* the style is expressed in the video (1 = not clear at all, 10 = very clear)
- Rate *how naturally* the action in the video is carried out (1 = not natural at all, 10 = very natural)
- *Optionally*, please make any comments that you feel necessary

The questions were selected such that if the participant is confused about the term naturalness used with non-humanoid characters, a question about how clearly the style is transferred supports the user response to the question of which style is being transferred.

Participants have the option of not responding to questions, prompted a reminder if a question is not responded and they must read a consent form and agree to it before starting the study.

7.2. Analysis of survey answers

Tables 2, 3 and 4 summarize the answers provided by 102 participants of the survey. They rated how the styles are expressed in the

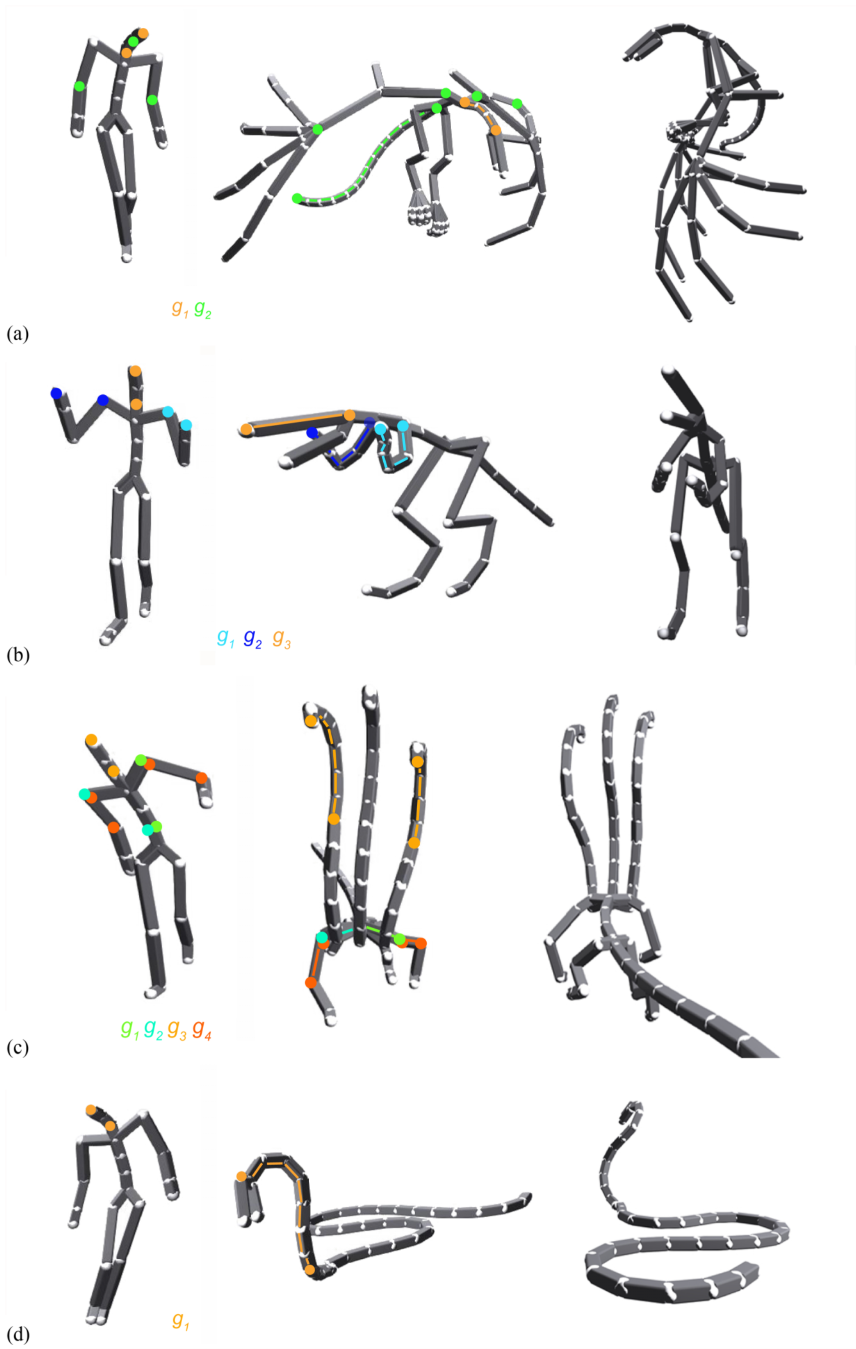

Figure 6: *Examples of style transfer. The left column shows the source character with colour-encoded GBPs. Lines indicate that all the joints in the middle of two other joints belong to a group. The middle and the right column show the target characters in different angles. Part (a) is an example of a sad dragon, (b) shows the transfer of anger to a T-Rex, (c) shows a macho style on a three-headed creature and (d) shows a drunk snake.*

animations, as well as how natural they look compared to the neutral versions. Two sets of *t*-tests ($\alpha = 0.05$) were performed to analyse the data. The first was between the ratings of each edited animation and its neutral counterpart (for example, sad dragon vs. neutral dragon as in Table 4). The second was between the edited animation and the source stylized animation (for example, sad dragon vs. sad human, as in Table 3). The motions of the sad dragon, the angry T-Rex, the confident three-headed monster and the drunk snake did not present statistically significant difference to their neutral versions in regards to how well the style is expressed. However, the

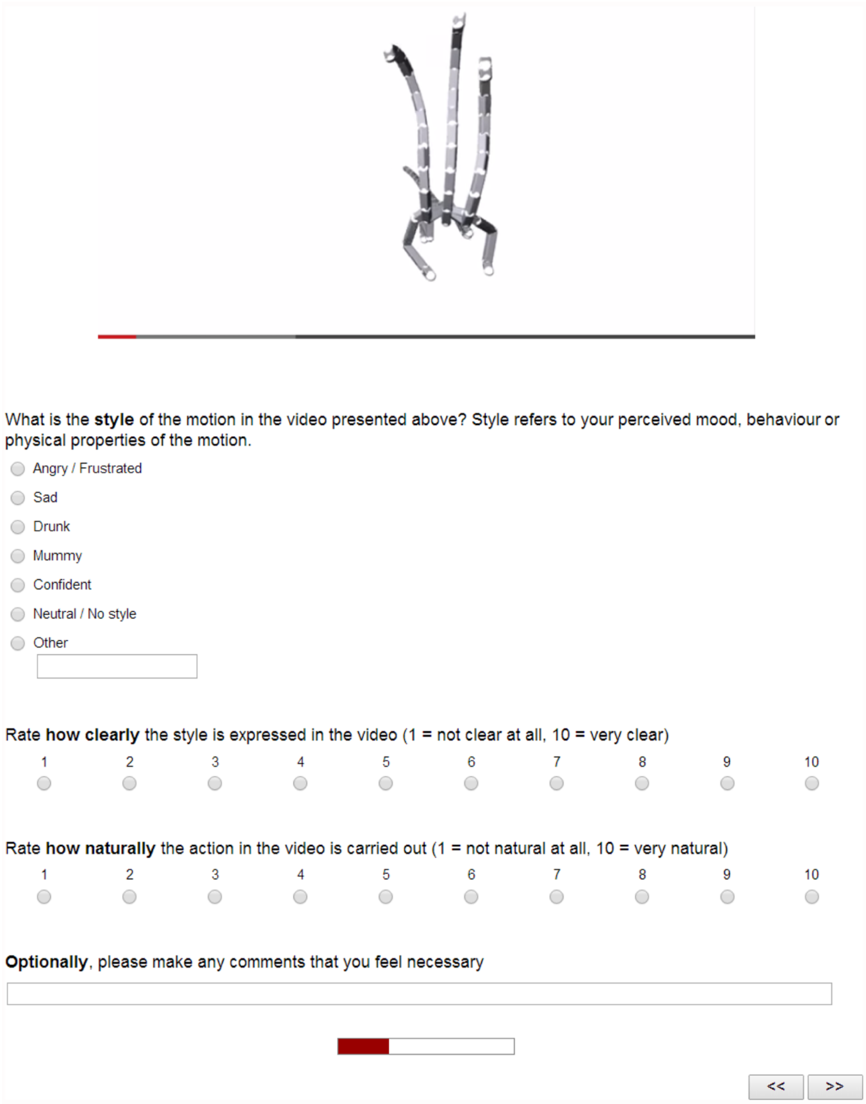

Figure 7: *A screenshot of the survey layout.*

angry human and mummy T-Rex did present a statistically significant difference with respect to their neutral versions. The mummy T-Rex animation mimicked the arm raising action from the original stylized character, but did not present any of the torso sway and its tail did not appear stiff. This is likely the cause of the low recognition rate of the style (15%) and the low values in the ratings questions. Adding stiffness and sway to the character's body might increase the recognition rate. The angry human animation was successfully recognized 51% of the time, but it still was rated lower than its neutral counterparts. This animation presents similar arm and torso motions to the source angry human character, but the arm movements are slower and lower than the original motion. Most of the participants that provided comments about the angry human motion described it as someone talking to themselves and solving a problem (see Table 6). The source anger animation does present this behaviour, but due to the higher speed of the movements, this animation is perceived as expressing the style better than the target animation.

When rating the naturalness of the target stylized motions compared to their neutral counterparts, the results are similar to the above expressiveness results, except for the confident three-headed monster, which was rated less natural than its neutral counterpart (mean stylized $= 6.99$, mean neutral $= 7.63$, $p = 0.03$), see Table 4 for details. This is likely due to the fact that two of the three heads of the character move in exactly the same way because the motion comes from the same positional feature. Even though most of the people rated the motion as being confident, the next highest rating was for neutral. However, in several cases, the neutral motion was described as confident motion, so it naturally follows that the confident style was sometimes perceived as neutral.

Table 2: *Percentage of people in survey that correctly classified the style of the target character versus the percentage of people that correctly classified the style of the source character.*

Style	*Character*	*Correct userclassification (target)*	*Correct userclassification (source)*
Sad	Dragon	61%	68%
Angry	T-Rex	63%	81%
Confident	Three-headed	48%	73%
Drunk	Snake	19%	99%
Angry	Human	51%	81%
Mummy	T-Rex	15%	89%

Table 3: *Participant ratings of naturalness, as well as how well the style was expressed on the character edited with the framework versus the original stylized character. A t-test was performed between the results for each stylized character and its neutral counterpart to test if a difference exists between their mean values.*

Style	*Character*	*Target expressed*	*Original expressed*	*Significant difference*	*Target naturalness*	*Original naturalness*	*Significant difference*
Sad	Dragon	6.9607	7.7941	Y ($p = 0.005$)	6.9901	7.5000	Y ($p = 0.09$)
Angry	T-Rex	6.7352	8.1568	Y ($p < 0.001$)	6.8529	8.0000	Y ($p < 0.001$)
Confident	Three-headed	6.3627	8.6960	Y ($p < 0.001$)	6.2843	7.3529	Y ($p = 0.001$)
Drunk	Snake	6.6372	9.1372	Y ($p < 0.001$)	6.6862	8.3333	Y ($p < 0.001$)
Angry	Human	6.7647	8.1568	Y ($p < 0.001$)	6.8921	8.0000	Y ($p < 0.001$)
Mummy	T-Rex	6.2540	9.1176	Y ($p < 0.001$)	6.5392	8.0882	Y ($p < 0.001$)

Table 4: *Participant ratings of naturalness, as well as how well the style was expressed on the character edited with the framework versus its neutral counterpart. A t-test was performed between the results for each stylized character and its neutral counterpart to test if a difference exists between their mean values.*

Style	*Character*	*Stylized expressed*	*Neutral expressed*	*Significant difference*	*Stylized naturalness*	*Neutral naturalness*	*Significant difference*
Sad	Dragon	6.9607	6.8823	N ($p = 0.82$)	6.9901	7.6372	Y ($p = 0.03$)
Angry	T-Rex	6.7352	6.9607	N ($p = 0.46$)	6.8529	7.2843	N ($p = 0.14$)
Confident	Three-headed	6.3627	6.4117	N ($p = 0.87$)	6.2843	6.9313	N ($p = 0.054$)
Drunk	Snake	6.6372	6.3725	N ($p = 0.45$)	6.6862	7.2843	N ($p = 0.06$)
Angry	Human	6.7647	7.9019	Y ($p < 0.001$)	6.8921	8.4019	Y ($p < 0.001$)
Mummy	T-Rex	6.254	6.9607	Y ($p = 0.03$)	6.5392	7.2843	Y ($p = 0.17$)

In most of the cases, the edited animations received a lower rating than the source humanoid animations, as shown in Table 3. In a user study on purely human motion by [CHK07], motions that were generated by hand as opposed to motion capture were consistently rated lower on naturalness than motion captured data. The results in this work also present this phenomenon; animations of target characters, even without being edited, were rated less natural and less expressive than the motion captured data. However, the motions edited with the presented method, in several cases, were rated *no significantly different than their neutral counterparts*. This is an encouraging result that suggests that the visual quality of the source animations is not being lost. Instead, the original non-humanoid animations were not viewed as natural and expressive as the human motion capture data.

During the survey, participants were encouraged to provide comments on each of the animations presented. Fourteen percent of participants provided written responses. Tables 5 and 6 show for each animation, what was the main feature or features that provided a clue towards the *correct* recognition of the style, and what was the main feature or features that provided a clue towards the *incorrect* recognition of the style. Perception of the animations was varied; some participants provided detailed explanations of their responses, which in general showed understanding of the concept of style used in this work. For other participants, the task of discerning stylistic motion on the non-humanoid characters was more challenging, and some responses were of the kind: 'no dragon experience.' Other participants pointed to the correct motion of, for example, a snake, for which they might have a clearer picture. The opinion gap between participants indicates that even if they recognize the character as a dragon, or a T-Rex, more queues might be needed when rendering the characters to indicate the 'cartoonish' nature of the edited animations. One way to accomplish this could be to attach to the characters a cartoonish skin that would persuade

Table 5: *Participant responses to the open question of the survey for the sad dragon, angry T-Rex and the three-headed monster.*

Style/Character	Sad/Dragon
Features —correct	Head down, slow wing movement
Features —incorrect	Head down looks unnatural, no dragon experience
Style/Character	Angry/T-Rex
Features —correct	'The figure is pumping its fist so it seems frustrated.'
Features —incorrect	'It seems frustrated' '...but I don't know how natural that is.'
Style/Character	Confident/Three-headed monster
Features —correct	Swagger, on the lookout
Features —incorrect	Just walking along, no recognizable style, wobbling shows anger

Table 6: *Participant responses to the open question of the survey for the drunk snake, the angry human and the mummy T-Rex.*

Style/Character	Drunk/Snake
Features —correct	'The snake just a touch to much', 'It looks like a sad cartoon snake'.
Features —incorrect	'Snake seems wobbly–not sure if that's intended to convey drunkenness...it's hard to see human emotion portrayed clearly in a non-human figure', looks active, so confident
Style/Character	Angry/Human
Features —correct	Pumping fists, shaking fists
Features —incorrect	Figuring out a problem, slow motion, talking to self, could be stronger movement, walking with swagger
Style/Character	Mummy/T-Rex
Features —correct	Stretches out like mummy, but no change in walk pattern
Features —incorrect	Hands up in frustration, hands up stalking prey, no style, angry with fists in the air

participants to view the characters as fantastic creatures with humanoid 'personalities.'

8. Conclusion

We have presented a framework for motion style transfer between characters with different morphologies. The underlying idea of our approach is that the stylistic features can be separated into blocks—GBPs—that can be mapped individually. We use the rotation of the overall group to drive the motion on the target character, as opposed to handling individual joints. The user selects the GBPs in the source and target character and aligns them. RVs of each GBP are identified and features are extracted from the input source animation as a sequence of GBP rotations, angular scaling factors and offsets. These values are used as the constraints for an optimization that attempts to preserve the input animation while matching the predefined constraints.

Our results show that we can perform style transfer to a wide variety of character morphologies with ease. Generation of the animations for complex characters in our examples took more than 20 min to compute while the simplest ones took less than a minute. Another advantage of our method is that it is possible to keep the extracted motion features from source characters and reuse them.

Our approach is not without limitations. The most important one is that the GBPs are treated separately. The user could, for example, map the left arm to the left and right arms of the target, which would lead to an unrealistic animation. While such global dependencies among different GBPs can be solved by careful mapping of logical features from the source to the target animation, a full automatic solution could and should be found.

A potential problem is that with a high number of constraints, the optimization is less capable of enforcing them all. The target characters in this work usually contain a high number of joints. This problem could be alleviated by using a simplified version of the character skeleton as the input for the optimization. This would also alleviate convergence times for the optimization problem, which would make it easier to make iterations on the results.

Another limitation is the requirement of source neutral and stylized animations when angular amplitudes are transferred. A solution that extracts the feature vectors from a single animation would be preferable. However, it should not be difficult to find a neutral counterpart for motions. For example, for a stylized walk, a normal walk would serve as the neutral motion. For other motions where a person is standing and performing some action, an idling motion could work as a neutral counterpart.

In this work, the user needs to temporally align the motions, even if it is a rough alignment. Temporal alignment could be automated with Dynamic Time Warping, using steps or cyclic points of the motion as reference.

It would be beneficial to apply learning techniques to generalize the transfer of the features to learned target poses. Finally, conducting a user study that provides information about the ease of use of the method would provide further information as to the usefulness of transferring the style, as opposed to manually performing motion editing.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's web site:

Table S1: Human and Dragon joint count and GBP information.

Table S2: Human and T-Rex joint count and GBP information.

Table S3: Human and Three headed creature joint count and GBP information.

Table S4: Human and Snake joint count and GBP information.

Video S1