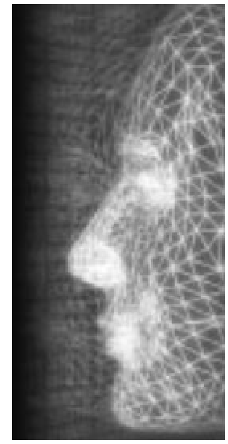
COMPUTER ANIMATION AND VIRTUAL WORLDS
Comp. Anim. Virtual Worlds 2008; **19**: 211–221
Published online 12 August 2008 in Wiley InterScience
(www.interscience.wiley.com) DOI: 10.1002/cav.260



Emulating human perception of motion similarity

By Jeff K. T. Tang, Howard Leung, Taku Komura and Hubert P. H. Shum*

Evaluating the similarity of motions is useful for motion retrieval, motion blending, and performance analysis of dancers and athletes. Euclidean distance between corresponding joints has been widely adopted in measuring similarity of postures and hence motions. However, such a measure does not necessarily conform to the human perception of motion similarity. In this paper, we propose a new similarity measure based on machine learning techniques. We make use of the results of questionnaires from subjects answering whether arbitrary pairs of motions appear similar or not. Using the relative distance between the joints as the basic features, we train the system to compute the similarity of arbitrary pair of motions. Experimental results show that our method outperforms methods based on Euclidean distance between corresponding joints. Our method is applicable to content-based motion retrieval of human motion for large-scale database systems. It is also applicable to e-Learning systems which automatically evaluates the performance of dancers and athletes by comparing the subjects' motions with those by experts. Copyright © 2008 John Wiley & Sons, Ltd.

Received: 27 June 2008; Accepted: 28 June 2008

KEY WORDS: 3D human motion similarity; human perception; pattern recognition

Introduction

Evaluating the similarity of motions is useful for motion retrieval, motion blending, and performance analysis of dancers and athletes. The requirements to evaluate the similarity of motions are application oriented. In the performance training tool proposed by Chan *et al.*,[1] the posture similarity between the trainee and the teacher at every instance is evaluated by the cosine similarity of joint angles. In the Tai-chi training system proposed by Chua *et al.*,[2] the error made by the student were evaluated by measuring the distance between the corresponding joints of the subject and the teacher. In the motion graph,[3–5] postures were compared by calculating the difference of the 3D coordinates of the joints or the generalized coordinates of the body. So and Baciu[6] retrieve motions and evaluate similarity between key postures by the dot product of orientation vectors between corresponding body parts. However, these similarity measures do not necessarily conform with those of humans when they perceive movements of humans.

Blake and Shiffrar[7] explained that the human perception of human motion depends on (1) visual sensation, (2) how people imitate a motion that they perceived, and (3) affective processes, which is related to social interaction. Here, we focus on the factor of visual sensation. Johansson[8] discovered humans can perceive the nature of the subject just from the movements of dot lights attached to different parts of the body. Kozlowski and Cutting[9] found people can recognize the sex of the subjects. Boyd and Little[10] synthesized gait-like optical flows based on point light data. Harada *et al.*[11] proposed a measure to emulate the similarity of postures based on human perception by weighted distance between the 3D coordinates of joints. They extended their method to compute the similarity of motions by applying dynamic time warping. On the other hand, Miura *et al.*[12] investigated some features that affect the human judgment to motion similarity. They have studied several measures based on (1) joint angles, (2) joint angular velocity, (3) joint position, and (4) joint velocity. They found that in general a measure based on both joint angles and joint velocities best correlates

*Correspondence to: H. Leung, Department of Computer Science, City University of Hong Kong, 83 Tat Chee Ave., Kowloon, Hong Kong. E-mail: howard@cityu.edu.hk

with human perception. Müller *et al.*[13] proposed boolean features, such as whether one joint is in front/back of a plane composed by a plane defined by multiple other joints, to calculate the similarity of motions. It is useful for searching motions logically similar to the query motion. However, the boolean features are manually selected and the combinations of features which are important can be application oriented.

In this paper, we propose a new method to evaluate the similarity of human postures based on human perception. The approach is general enough to be applied to all sorts of motions. We use the relative distance between joints as the basic measure to evaluate the similarity of postures. Based on the questionnaire results of whether two motions are similar or not, we find out which set of relative distances affects the motion similarity in human perception the most. We compare our method with other measures based on Euclidean distances to show that our method outperforms them.

Perception-Based Criterion of Motion Similarity

Here, we propose to use the closeness of joints in each posture as a criterion to calculate the similarity of two postures. We use the distance between arbitrary joints in each posture as the basic features to distinguish postures. We then provide subjects with a number of motion pairs and ask them to fill in questionnaires to answer whether the two motions look similar or not. Using the results of questionnaires as the ground truth, the features which are most influential are found and are given larger weights in the confidence measure which is used to evaluate whether two postures are similar or not.

Data Preparation

Twenty dance motion sequences performed by two dancers are used as the training dataset. Each motion sequence contains 2000 to 3000 frames. The data contains four types of dances: waltz box steps, pop, hip-hop, and house. The motions were captured by the Eagle MotionAnalysis optical motion capture system.

Firstly, numerically similar and dissimilar patterns are extracted by the method proposed by Tang *et al.*[14] Each motion pair is labeled as either perceptually similar or perceptually dissimilar by the subjects. A tool shown in Figure 1 is built so that the subjects can view a pair of motions from different viewpoints including the front, back, left, and right views, simultaneously. Among all the given pairs, 428 were annotated similar and 428 were annotated as dissimilar. Then, the corresponding postures of the two motions were found by scaling their durations to the same length, and resampling. Hence, 43 620 posture pairs were annotated as similar and 35 300 posture pairs as dissimilar.

Similarity Based on Joint Relative Distance

In this subsection, we explain about the concept of joint relative distance, and how it is used to judge whether two given postures appear similar or not.

We use a hierarchical structure of the body as shown in Figure 2. The body is composed of 20 segments. Let P_1 and P_2 be the two postures to be compared. The position of the joints and end-sites in each posture are defined by $p_1^i = \left(x_1^i, y_1^i, z_1^i\right)$ and $p_2^i = \left(x_2^i, y_2^i, z_2^i\right)$ $(i = 0, 1, \ldots, n-1)$ where n is 25 in this research. The joint relative distance of a pair of joints (i, j) between posture p_1 and p_2 is calculated by

$$\mathrm{JRD}_{p_1,p_2}(i, j) = \left| D\left(p_1^i, p_1^j\right) - D\left(p_2^i, p_2^j\right) \right| \qquad (1)$$

where $D(x, y)$ represents the Euclidean distance of x and y in the Cartesian space. We calculate the weighted sum of the joint relative distance to compute a confidence measure which evaluates whether two postures appear similar or not. Since we want the weights of the symmetric pair of joints to be equal, we use the average of the symmetric pair of joints as the element of the feature:

$$f_{p_1,p_2}(i,j) = \begin{cases} \frac{1}{2}(\mathrm{JRD}_{p_1,p_2}(i, j) + \mathrm{JRD}_{p_1,p_2}(i', j')), & \text{if } (i, j) \text{ has a symmetric pair } (i', j') \\ \mathrm{JRD}_{p_1,p_2}(i, j), & \text{(otherwise)} \end{cases} \qquad (2)$$

Finally, the confidence measure is calculated as the weighted sum of the features:

$$y_{p_1,p_2} = \sum_{(i,j)\in P} w_{i,j} f_{p_1,p_2}(i, j) \qquad (3)$$

where P is the set of joint pairs used to evaluate the similarity of two postures and $w_{i,j}$ is the weight for joint

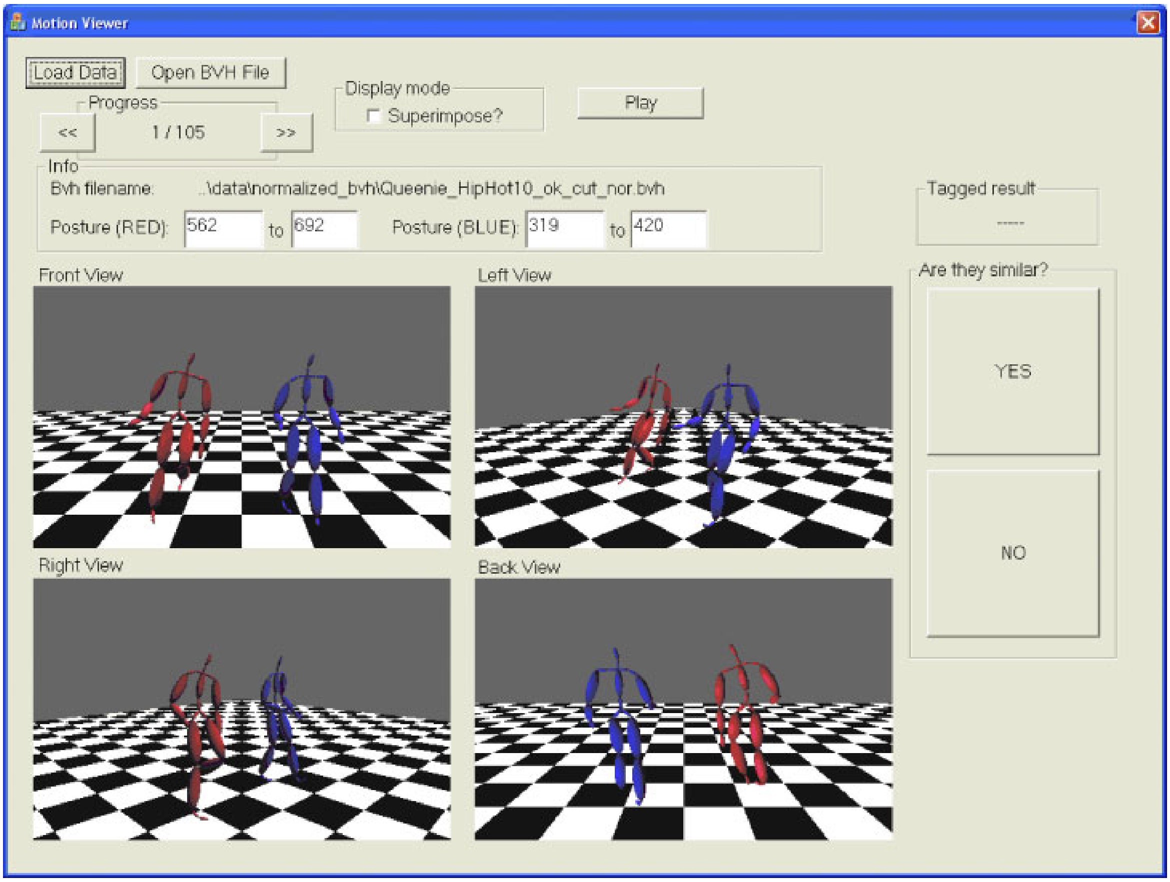


Figure 1. The interface for the users to tag similar/dissimilar motion pairs.

pair (i, j). We classify the pair as similar when $y_{p_1,p_2} > 0$ and dissimilar when $y_{p_1,p_2} < 0$. The weights are trained using tagged samples. The details are explained in the next section.

The joint relative distance can capture features to which humans are sensitive, such as the contacts between the end effectors and other parts of the body. For example, when we see a person putting his/her hands together, we will focus more on the fact the hands are attached to each other rather than the joint angles of the elbows or the shoulders. Therefore, in this research, we search for the most influential combination of joints which humans are more sensitive to, and adjust their weights according to their importance.

Some pair of joints, such as (1) both belonging to the same segment and (2) both are in the area of torso, are excluded from the set to calculate the joint relative distance. This is because the distance between such pair of joints usually stay constant and do not give any cue of the posture.

Training the Weights by Examples

We use the weighted sum of the joint relative distance to emulate the human perception of motion similarity. The weights of each combination of joints are computed using the tagged set of postures.

Let us assume we have n pair of postures which are tagged either "similar" or "dissimilar." A vector of labels based on manual tagging is formed as $Y = (y_1, y_2, \ldots, y_n)$, where $y_k = 1$ if the posture-pair k are similar and $y_k = -1$ if dissimilar. Equation (3) for all y_k can be written in a matrix form as follows:

$$Y = WA \tag{4}$$

where W is the vector of weights composed of $w_{i,j}$, and A is a feature matrix which is composed of the joint relative distance features. An extra constant term of value 1 is inserted as the last element of A to bias the results such that the dividing plan does not have to intersect with (0,0).

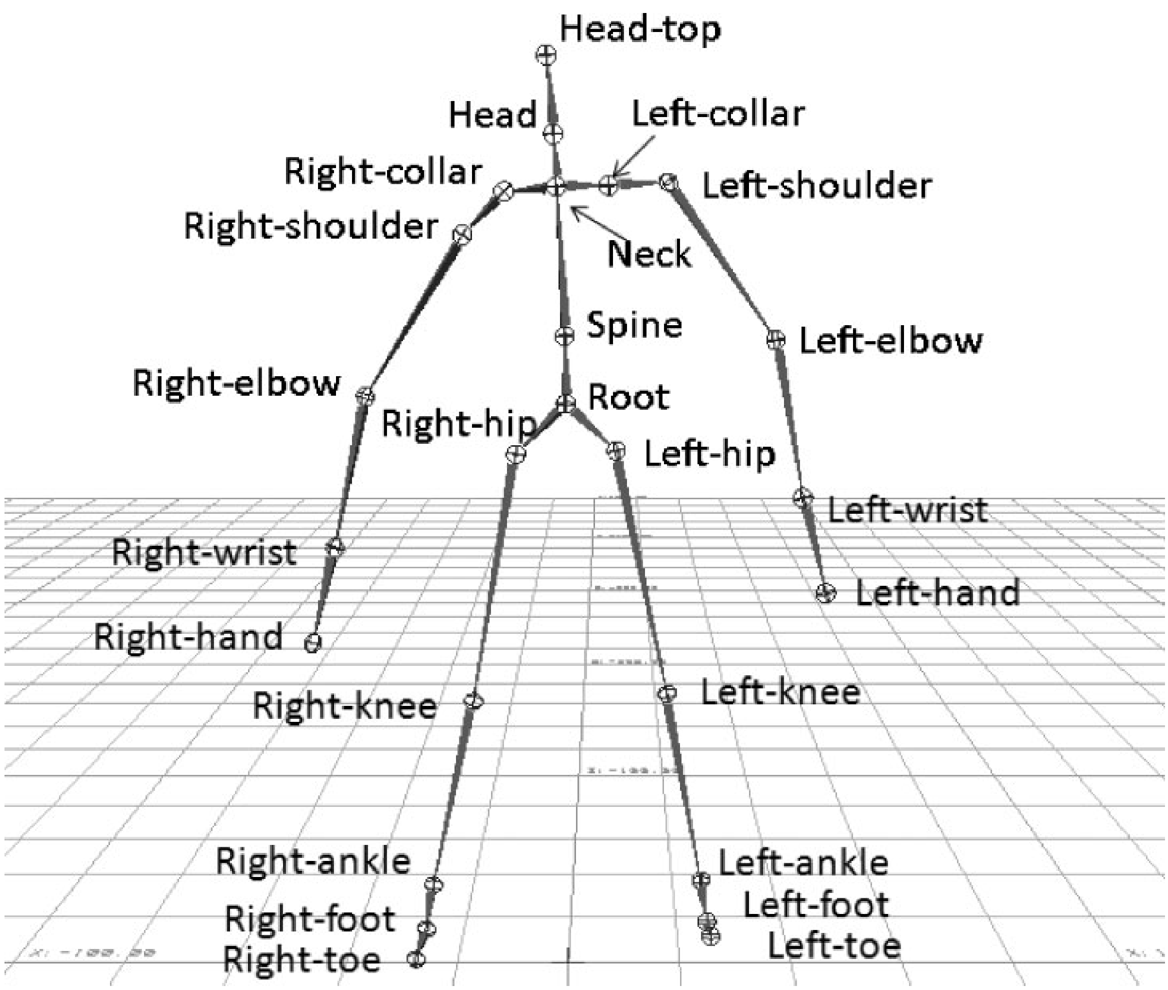


Figure 2. The human body structure used in this study.

Here, our objective is to calculate the weight from the training samples. As the number of samples ($n = 7892$) is much larger than the size of the feature vector, we compute the pseudo-inverse matrix of A to obtain the weight with the least square error:

$$W = YA^{+} \tag{5}$$

where A^{+} is the pseudo-inverse of feature matrix A, which can be calculated by $A^{+} = A^{T}(AA^{T})^{-1}$. The magnitudes of the feature weights sorted in descending order are shown in Figure 3. The features with larger weights have more influence to the perceptual similarity of human motions. Table 1 shows the top 30 features and Table 2 shows the last 10 features.

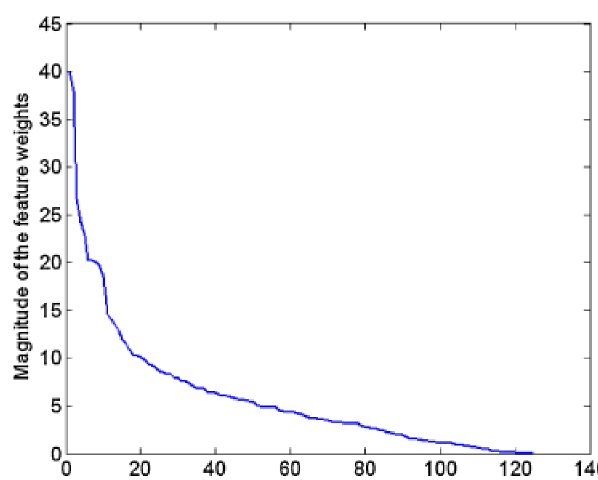


Figure 3. Magnitude of weights of different relative distance in the descending order.

Rank	Absolute weight	Joints considered in the measure			
		Joint pair 1		Joint pair 2 (symmetric pair)	
1	40.006395	Right-knee	Head	Head	Left-knee
2	37.954929	Right-knee	Neck	Neck	Left-knee
3	26.680455	Right-foot	Left-collar	Right-collar	Left-foot
4	24.165646	Right-ankle	Spine	Spine	Left-ankle
5	22.823449	Right-foot	Head-top	Head-top	Left-foot
6	20.229034	Right-ankle	Neck	Neck	Left-ankle
7	20.210250	Neck	Left-elbow	Neck	Right-elbow
8	20.059475	Root	Right-ankle	Root	Left-ankle
9	19.725673	Right-foot	Neck	Neck	Left-foot
10	18.535401	Right-foot	Head	Head	Left-foot
11	14.617462	Right-knee	Head-top	Head-top	Left-knee
12	14.162427	Right-knee	Spine	Spine	Left-knee
13	13.616902	Right-ankle	Left-collar	Right-collar	Left-ankle
14	12.864232	Right-foot	Left-wrist	Right-wrist	Left-foot
15	12.019233	Right-ankle	Left-wrist	Right-wrist	Left-ankle
16	11.589273	Right-toe	Head-top	Head-top	Left-toe
17	10.903691	Right-toe	Spine	Spine	Left-toe
18	10.392072	Right-foot	Left-elbow	Right-elbow	Left-foot
19	10.265179	Root	Right-knee	Root	Left-knee
20	10.146129	Left-collar	Right-elbow	Left-elbow	Right-collar
21	9.838014	Left-collar	Left-elbow	Right-collar	Right-elbow
22	9.368392	Right-ankle	Left-shoulder	Right-shoulder	Left-ankle
23	9.311758	Root	Head-top	Root	Head-top
24	8.980815	Right-knee	Left-foot	Right-foot	Left-knee
25	8.620271	Right-foot	Right-collar	Left-collar	Left-foot
26	8.520379	Right-toe	Right-elbow	Left-elbow	Left-toe
27	8.332012	Right-knee	Left-ankle	Right-ankle	Left-knee
28	8.327948	Right-toe	Right-wrist	Left-wrist	Left-toe
29	7.899120	Head-top	Left-collar	Head-top	Right-collar
30	7.867494	Right-toe	Right-shoulder	Left-shoulder	Left-toe

Table 1. The features of top 30 weights

Calculating the Similarity of Motions

The similarity of motions is calculated by counting the number of corresponding postures which are perceptually similar. The corresponding postures are found by normalizing the duration of the two motions and resampling. We adopt this method because it is reported that scaling is more efficient and accurate than dynamic time warping in many cases.[15] If the ratio of similar postures in the motions is above a cut-off threshold, the motion is evaluated as perceptually similar.

The value of the cut-off threshold is calculated using the training data. When the threshold is high, the false positive rate (dissimilar pairs wrongly classified as similar) drops but the false negative rate (similar pairs wrongly classified as dissimilar) increases. When the threshold is set low, the opposite will happen. Therefore, we set the threshold to the equal error rate (EER), where the false positive rate and false negative rate become equal. An example of plotting the false positive rate and false negative rate when changing the threshold is shown in Figure 6. This example is based on the joint relative distance measure, and the threshold is set to 73.40%, where the false positive and false negative rates are the same.

DOI: 10.1002/cav

Rank	Absolute weight	Joints considered in the measure			
		Joint pair 1		Joint pair 2 (symmetric pair)	
116	0.235311	Right-foot	Left-toe	Right-toe	Left-foot
117	0.197283	Left-shoulder	Left-wrist	Right-shoulder	Right-wrist
118	0.177502	Right-knee	Right-shoulder	Left-shoulder	Left-knee
119	0.165024	Right-ankle	Left-ankle	Right-ankle	Left-ankle
120	0.115780	Right-ankle	Right-toe	Left-ankle	Left-toe
121	0.087828	Right-toe	Left-hand	Right-hand	Left-toe
122	0.085672	Left-collar	Right-hand	Left-hand	Right-collar
123	0.085563	Right-foot	Left-hand	Right-hand	Left-foot
124	0.068980	Left-elbow	Left-hand	Right-elbow	Right-hand
125	0.029300	Right-knee	Left-shoulder	Right-shoulder	Left-knee

Table 2. The features of least 10 weights

Experiments

In this section, we explain the experiments conducted to analyze and evaluate our methodology to compute the similarity of motions. We used the training data composed of similar and dissimilar pairs to compute the weights of joint relative distance. Firstly, we have computed the weights of the features and examined which ones are more influential to the perceptual similarity of the motions. Secondly, we computed the cut-off threshold using the EER of the training data. Finally, using the weight and threshold calculated with the testing data, we examined how well the proposed joint relative distance scheme emulates the human perception regarding the similarity of motions.

Relative Distance Feature Analysis

Here, we explain which pairs and joints are more influential to the confidence measure that evaluates the similarity of two postures based on the joint relative distance. First, we divide the joints and end-sites into the following four groups based on their region in the body:

- Leg: knee, ankle, foot, toes.
- Body: hip, collar, neck, spine, root.
- Arm: hand, wrist, elbow, shoulder.
- Head: head, head-top.

In Figure 4, the group of joint pairs which are influential to the perceptual similarity of human motions are shown in descending order. The absolute weights of each group are summed and plotted. It can be observed that those pairs that include the joints/end-sites of the legs are most influential to the perception. The weights for pairs of limbs, such as Leg–Leg or Arm–Arm, are small. This can be due to the dataset; we had little motions in which the subjects stick their hands together.

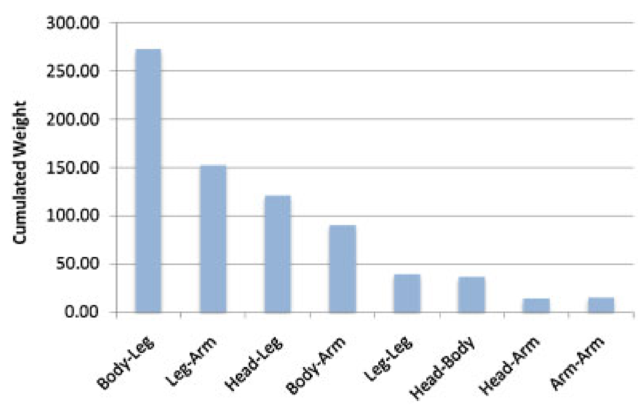


Figure 4. The group of joint pairs which are influential to the perceptual similarity of human motions shown in descending order. The absolute weights of pairs belonging to different groups are summed. The pairs in which the leg joints take part are more influential.

The importance of each individual joint/end-site to the perceptual similarity of human motion is shown in Figure 5. The absolute weights of joint pairs in which the corresponding joints/end-sites take part are summed and plotted. Here, we can see those most influential are the legs, second the body, third the arms, and finally the head. Joints such as ankle, foot, and toes, which are closer to the end effector of the leg, have large influence on the results. The fact that movements of the end effectors are more influential on the perceptual similarity of human motions matches our empirical knowledge. For example,

Comp. Anim. Virtual Worlds 2008; **19**: 211–221
DOI: 10.1002/cav

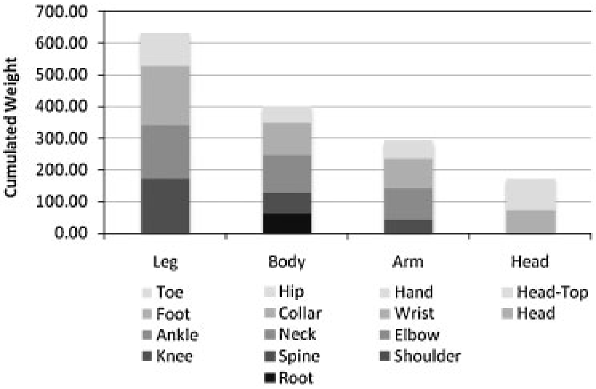


Figure 5. The importance of each individual joint/end-site to the perceptual similarity of human motion. The absolute weights of each group are summed and plotted.

in computer animation, we are very sensitive to artifacts such as foot sliding.

Evaluation of the Performance

In this subsection, we evaluate the performance of the joint relative distance by examining how much it emulates the human perception of motion similarity. We compare its performance with another scheme based on Euclidean distance of the same joints in the two postures, which is often used for comparing the similarity of postures such as in Motion Graph.[4] In the Euclidean distance scheme, the confidence measure of the similarity of two postures p_1 and p_2 is computed by the following equation instead of Equation (3):

$$e_{p_1,p_2} = \sum_{i}^{N_j} w_i^e D(p_1^i, p_2^i) \tag{6}$$

where N_j is the total number of joints and end-sites which is 25, and w_i^e are the weights which are calculated using the pseudo-inverse of the feature matrix based on Euclidean distance.

We first computed the threshold based on the EER using the training data and then used the computed threshold to examine how the joint relative distance scheme emulates the human perception of motion similarity with the test data. The same experiment was conducted with the Euclidean distance scheme for comparison of the performance. In our experiment, 75% of the data is used for the training and the remaining 25% is used for testing. Different sets of training data are rotated with a fourfold cross-validation.

The results are shown in Tables 3 and 4. The performance of joint relative distance scheme (average

	Euclidean distance		Joint relative distance	
Trials	EER (%)	Threshold (%)	EER (%)	Threshold (%)
1	12.15	83.00	7.17	73.60
2	13.08	82.80	7.63	73.40
3	16.82	83.40	8.72	74.00
4	17.13	84.00	9.66	72.20
Average	14.80	83.30	8.30	73.30

Table 3. Training result

	Euclidean distance		Joint relative distance	
Trials	False negative (%)	False positive (%)	False negative (%)	False positive (%)
1	21.50	23.36	12.15	11.21
2	16.82	20.56	11.21	11.21
3	9.35	8.41	7.48	4.67
4	10.28	7.48	1.87	8.41
Average	14.50	15.00	8.18	8.88

Table 4. Testing result

DOI: 10.1002/cav

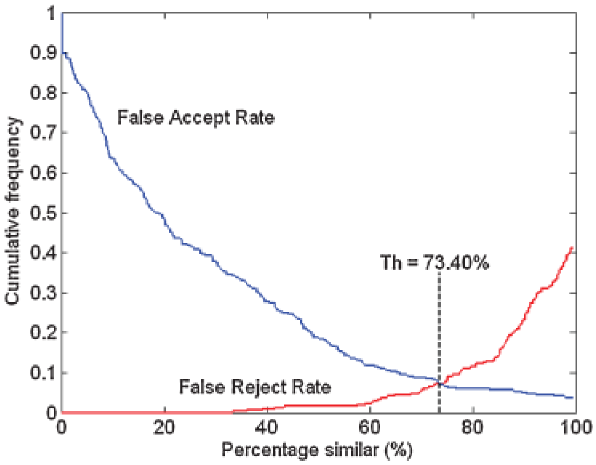


Figure 6. The curve showing how the false negative and false positive rates change when the cut-off threshold is shifted.

false positive rate of 8.88% and average false negative rate of 8.18%) is much better than joint Euclidean distance feature (average false positive rate of 15.0% and average false negative rate of 14.5%). This is because the absolute positions of the corresponding joints are not necessarily similar for perceptually similar motions. Hence, the results show that Euclidean distance measure is not effective for modeling the human perception of motion similarity.

Applying the Scheme to the Example Motions

From the results above, it is clear that there exist pairs of motions which are perceptually similar, although the Euclidean distance between them is large. Also, there are pairs of motions which are perceptually dissimilar although their Euclidean distance is small. Here, we show such examples.

Figure 7 shows two cases that a pair of motions which are perceptually similar although their Euclidean distance is large. In Figure 7(a), the arms in the two motions are bent to different extents but the perceptual difference is limited. In Figure 7(b), the posture of the arms and legs are different in the two motions, but the perceptual difference is again limited.

Figure 8 shows two cases that the joint Euclidean distances are small although the motions are perceptually dissimilar. In Figure 8(a), the trajectories of the right arms appear quite different. In the upper sequence, the right arm is driven by the shoulder and is translating horizontally to the right; while in the lower sequence, it is driven by the elbow. In Figure 8(b), the arms are bent in different ways. In the upper sequence, the right arm is bent outwards, while it is kept straight in the lower sequence. The trajectories of the legs are perceived different as well; the right leg is stretched in the upper sequence although it is bent in the lower sequence. However, they are recognized as similar in the Euclidean

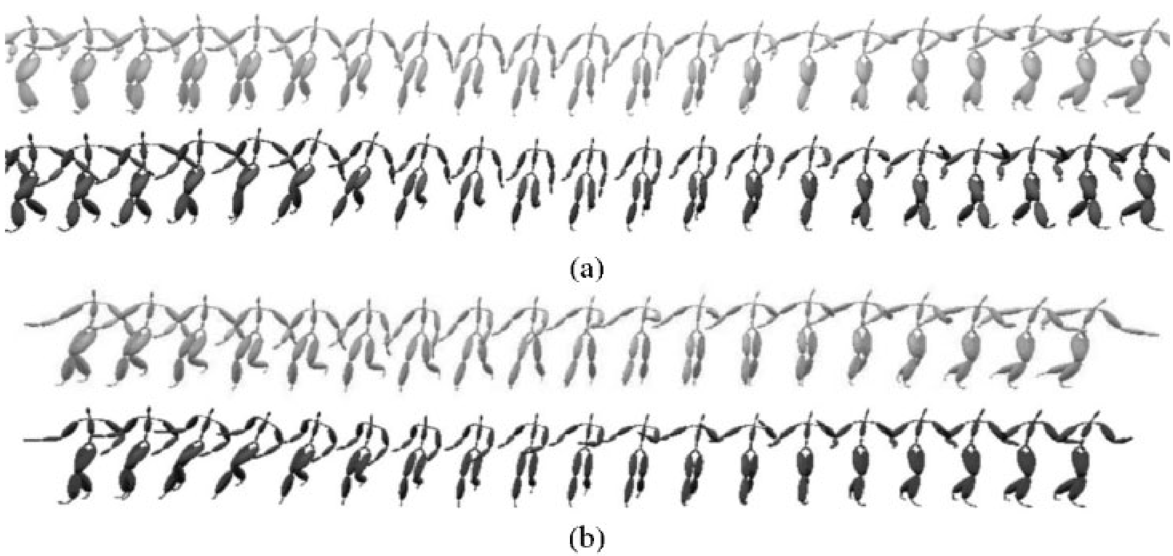


Figure 7. Motions which are perceptually similar but are dissimilar under the Euclidean distance scheme. (a) The arms are bending in different extent but show a small perceived difference. (b) The lower sequence shows a slight delay with variations in limb positions.

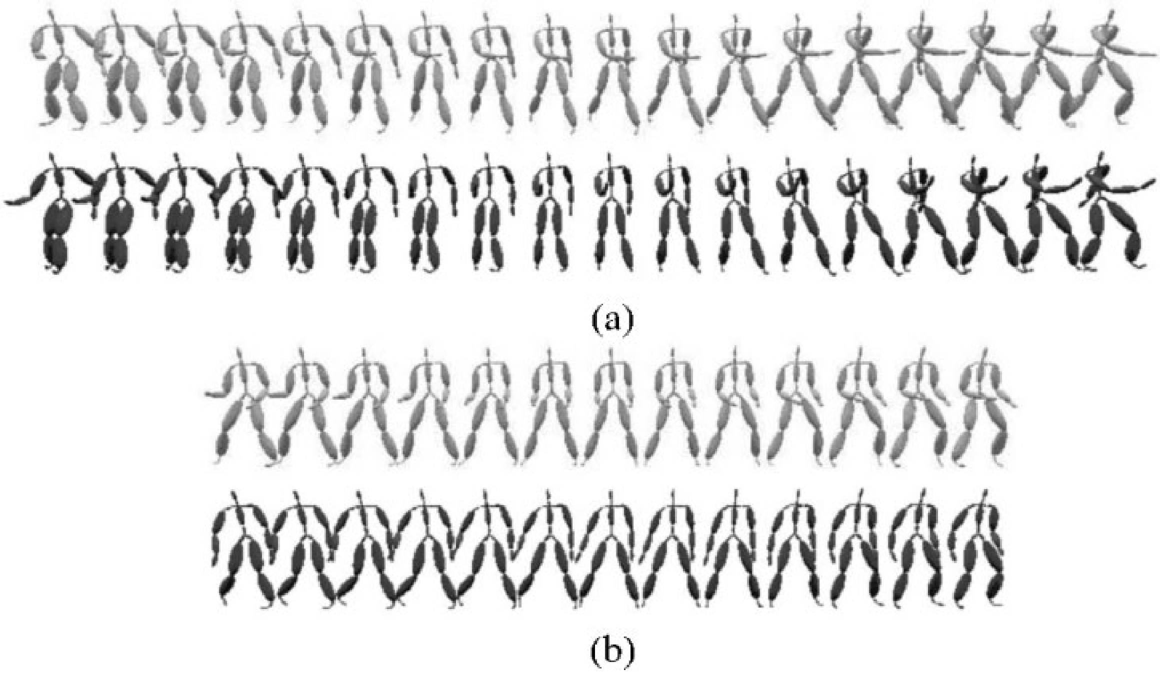


Figure 8. Motions which are similar under the Euclidean distance scheme but are perceptually dissimilar. (a) The trajectories of right arm are different. (b) Legs and arms are bending differently in two sequences, but the joints are at similar positions.

distance scheme because the joint positions are very similar in both sequences.

Figure 9 shows two cases that our method fails. In Figure 9(a), the postures of the body are similar but the orientation of the torso is different. Therefore, the joint relative distance between the joints of the legs and arms become large. As a result, the joint relative distance scheme cannot recognize the two motions as similar, although the motions are perceived as similar. Figure 9(b) shows another case. The left shoulder is used to rotate the

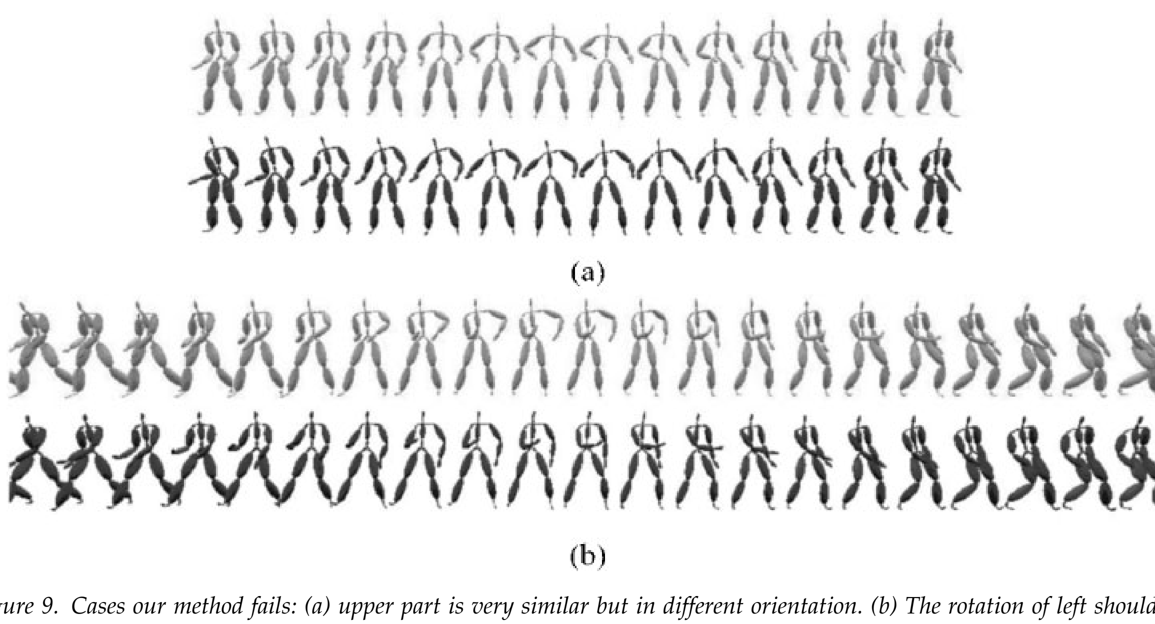


Figure 9. Cases our method fails: (a) upper part is very similar but in different orientation. (b) The rotation of left shoulder of upper movement has not been recognized as a difference.

arm in the upper sequence while it is simply translated horizontally in the lower sequence. This example shows that the joint relative distance scheme is not sensitive to joint rotation which is a weakness that has to be overcome by introducing some concepts of rotation.

Conclusion and Future Work

In this paper, a scheme to emulate the perceptual similarity of 3D human motions has been studied. To overcome the limitations of existing measures such as those based on Euclidean distance between corresponding joints, a novel approach called joint relative distance is introduced. We have shown that the joint relative distance scheme can emulate the perceptual similarity of human motions much better than the Euclidean distance scheme. We also calculated the weights of the features based on the questionnaire answered by subjects. We have found the pairs composed of the spine joints and limb joints are more influential to the human judgment. Moreover, relative distance measures are independent of body translation and rotation, and hence no normalization of posture is needed. Despite the advantages, some weak points of the method were found: first of all, the experiment results show our proposed measure fails to identify the perceived difference made by joint rotation. Secondly, as we do not take into account the velocity information, the proposed scheme can acknowledge movements in different speed and direction as similar as far as their joint relative distance feature have similar profiles.

As future work, we are interested in taking into account features such as the angular velocity or angular momentum to overcome the weakness of our scheme. We are also interested in exploring the stationary patterns in a motion that usually occur in human motion such as walking or climbing. Understanding factors such as the difficulty of motions and effort required to perform the motion are also interesting topics to explore.

ACKNOWLEDGEMENTS

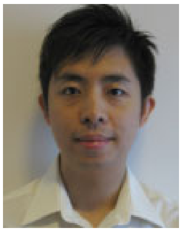
The work described in this paper was fully supported by a grant from the Research Grants Councils of the Hong Kong Special Administration Region, China (Project No. CityU 1167/05E).

References

1. Chan J, Leung H, Tang K-T, Komura T. Immersive performance training tools using motion capture technology. In *Proceedings of the 1st International Conference on Immersive Telecommunications (IMMERSCOM'07)*, Verona, Italy, October 2007, 2007.
2. Chua P-T, Crivella R, Daly B, *et al*. Training for physical tasks in virtual environments: Tai chi. In *Proceedings of the IEEE Virtual Reality (VR'03)*, 2003; 87–94.
3. Lee J, Chai J, Reitsma PSA, Hodgins JK, Pollard NS. Interactive control of avatars animated with human motion data. *ACM Transactions on Graphics (TOG)* 2002; **21**(3): 491–500.
4. Kovar L, Gleicher M, Pighin F. Motion graphs. *ACM Transactions on Graphics (TOG)* 2002; **21**(3): 473–482.
5. Arikan O, Forsyth DA. Motion generation from examples. *ACM Transactions on Graphics (TOG)* 2002; **21**(3): 483–490.
6. So CK-F, Baciu G. Entropy-based motion extraction for motion capture animation: motion capture and retrieval. *Computer Animation and Virtual Worlds* 2005; **16**(3–4): 225–235.
7. Blake R, Shiffrar M. Perception of human motion. *Annual review of Psychology* 2006; **58**: 47–73.
8. Johansson G. Visual perception of biological motion and a model for its analysis. *Perception and Psychophysics* 1973; **14**(2): 201–211.
9. Kozlowski L-T, Cutting J-E. Recognizing the sex of a walker from a dynamic point-light display. *Perception and Psychophysics* 1997; **21**(6): 575–580.
10. Boyd JE, Little JJ. Shape of motion and the perception of human gaits. In *Proceedings of the IEEE Workshop on Empirical Evaluation Methods in Computer Vision (CVPR'98)*, Santa Barbara, CA, United States, 1998; 155–171.
11. Harada T, Taoka S, Mori T, Sato T. Quantitative evaluation method for pose and motion similarity based on human perception. In *4th IEEE/RAS International Conference on Humanoid Robots*, Vol. 1, November 2004; 494–512.
12. Miura K, Furukawa H, Shoji M. Similarity of human motion: congruity between perception and data. In *IEEE International Conference on Systems, Man and Cybernetics (SMC'06)*, Vol. 2, October 2006; 1184–1189.
13. Müller M, Röder T, Clausen M. Efficient content-based retrieval of motion capture data. *ACM Transactions on Graphics (TOG)* 2005; **24**(3): 677–685.
14. Tang K-T, Leung H, Komura T, Shum H-P. Finding repetitive patterns in 3D human motion captured data. In *Proceedings of the 2nd International Conference on Ubiquitous Information Management and Communication (ICUIMC'08)*, 2008; 396–403.
15. Keogh EJ, Palpanas T, Zordan VB, Gunopulos D, Cardle M. Indexing large human-motion databases. In *Proceedings of 30th VLDB Conference*, 2004; 780–791.

DOI: 10.1002/cav

Authors' biographies:



Jeff K. T. Tang received his BEng in Computer Engineering from City University of Hong Kong in 2003, and MSc in Information Technology from Hong Kong University of Science and Technology in 2005. He is currently an MPhil student in the Department of Computer Science at City University of Hong Kong. His research interests include human motion analysis, human computer interaction, and pattern recognition.

Howard Leung is currently an Assistant Professor in the Department of Computer Science at City University of Hong Kong. He received his BEng degree in Electrical Engineering from McGill University, Canada, in 1998, MSc and the PhD degrees in Electrical and Computer Engineering from Carnegie Mellon University in 1999 and 2003, respectively. Howard's current research projects include 3D Human Motion Analysis, Intelligent Tools for Chinese Handwriting Education, Chinese Calligraphic Image Analysis, and Automatic Content Adaptation for PDA Viewing of E-Comics. Howard has also been actively involved in various professional activities. He is currently a member of the Multimedia Systems & Applications Technical Committee (MSATC) which is a subsidiary organization of the IEEE Circuits and Systems (IEEE-CAS) Society. He is also a member of the IEEE Signal Processing Society. He is the Treasurer of the Hong Kong Web Society and the Treasurer of the ACM Hong Kong Chapter.

Taku Komura is currently a Lecturer in the School of Informatics at University of Edinburgh. He received his PhD (2000), MSc (1997), and BSc (1995) in Information Science from the University of Tokyo. His research interests include human motion analysis and synthesis, physically based animation, and real-time computer graphics.

Hubert P. H. Shum received his Bachelor's and Master's degree in the City University of Hong Kong. He is currently a PhD student in the School of Informatics of the University of Edinburgh. His research interests include computer animation and human motion analysis.

Comp. Anim. Virtual Worlds 2008; **19**: 211–221
DOI: 10.1002/cav