

基于 SOM 特性和 PCA 索引的三维运动检索*

李玉梅, 张强⁺, 魏小鹏, 姚书磊

(先进设计与智能计算省部共建教育部重点实验室 (大连大学), 辽宁 大连 116622)

3D Motion Retrieval Measure Based on SOM Feature and PCA Index

LI Yu-Mei, ZHANG Qiang⁺, WEI Xiao-Peng, YAO Shu-Lei

(Key Laboratory of Advanced Design and Intelligent Computing (Dalian University), Ministry of Education, Dalian 116622, China)

+ Corresponding author: E-mail: zhangq@dlu.edu.cn

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Abstract: A novel approach for 3D motion capture data retrieval based on the Self-Organizing Map (SOM) and PCA index is proposed. Firstly, the Self-organizing map topological features are enhanced before learning. Characteristic will be mapped to a main surface after training every motion. Then, principal component analysis (PCA) is applied to deal with the surface characteristics. To improve the retrieval efficiency, an indexing scheme based on the principal eigenvector is constructed. Introduction of SOM avoid directing contact with the raw data, Follow-up work are only based on the main surface. It eliminate the position information influence of different frame length of the motion characteristics. Experimental results show that the algorithm is effective.

Key words: CMU motion capture database; SOM; PCA

摘要: 提出了一种基于自组织特征映射(SOM)和 PCA 索引的三维运动数据检索方法.首先利用每一个运动序列来进行拓扑特性加强的 SOM 的学习,其运动特性被映射到一个主曲面,然后利用主成分分析方法(PCA)提取主曲面的主成分来建立一个基于主成分的索引机制,加快检索速率.SOM 的引入避免了与原始数据的直接接触,后续的工作只是在主曲面的基础上展开,消除了不同骨架长度的位置信息对运动特性的影响.实验结果表明了算法的有效性.

关键词: CMU 运动捕捉数据库; SOM; PCA

1 Introduction

In recent years, capture equipment and technology become constantly improved, access to a large number of 3D motion capture data can be more easily, and a large database of 3D movement has been widely used in computer animation, games, computer special effects and the areas of medical simulation^[1,2], so movement database retrieval becomes a huge problem for urgent solution. In order to enable more effective use of large scale 3D motion

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databases, we need to study the efficient movement of data retrieval technology which can facilitate editing of the movement and synthesis processing. However, there are still the following issues^[3] when retrieving the data on the three-dimensional motion:

(1) Human motion data's structure is complex. Each motion is a combination of each joint's timing signals. We need to extract the essential attribute which can represent the characteristics of human motion information of the whole body movement.

(2) Motion feature dimension from the original motion data is very high, if the dimension is not effectively reduced, it will produce high dimension disaster. The distance between each data becomes almost the same because of the central limit theorem, and they can not distinguish each other.

(3) It is very difficult to compare the similarity of movement sequence's timing signal, which consider not only the data in the space of similarity, but also the similarity of the time.

In order to resolve these challenges, Liu Feng, Yue-Ting Zhuang from Zhejiang University put forward a retrieval method of three-dimensional motion based on examples^[4]. The algorithm use dynamic clustering algorithm to establish the movement search tree based on hierarchical motion description, then classify the motion examples to employ the k nearest neighbor rule according to the movement search tree and determine the retrieval subset. At last, elastic matching algorithm is used to calculate the similarity between motion examples and a subset of retrieved and get a subset of search. Retrieval algorithm efficiency has increased, but the retrieval performance has to be perfect. Xiang jian etc in Zhejiang University have proposed the 3D motion retrieval method based on the Characteristics of 3D transformation rules about 3D transform space and time^[5]. Algorithm can be dealt with each local space-time characteristics of the joints separately. It can avoid direct contact with the raw data, retrieval performance is high, but the spatial characteristics extracted can not eliminate the impact of location information with different frame length. Literature^[6] have propose a new motion retrieval algorithm based on content. Firstly, feature are extracted accordance with the distribution of each movement sequence, and dimension were reduced using the singular value decomposition. Then double-indexing mechanism is constructed based on stratified SOM and used to speed up retrieval rate. The algorithm combines two technology about the feature vector extraction and fuzzy queries. But it can be prone to error feature when extracted directly on the raw data. Literature^[7] have proposed a motion data retrieval algorithm based on SOM and the Smith-Waterman string similarity metric. Existing motion clips are first used to train a self-organizing map and then indexed by the nodes of the map to get the motion strings. The Smith-Waterman algorithm is used in clustering the motion strings. Then the motion motif of each cluster is extracted for the retrieval of example-based query. The posture distortion problem also exists in the SOM training and indexing of the algorithm.

This paper presents a method using of the self-organizing feature map (SOM) to do the feature mapping. SOM has a role in feature extraction, because it has a topological order characteristic and the result is non-linear mapping, so motion data features will be mapped to a primary surface through SOM who's topological features enhanced to handle the original motion data. Thus it can not only avoid extracting both the time and the space feature, but also avoid direct contact with the original data, and the follow-up work is only based on the main surface. It can largely avoided the curse of dimensionality. Then, principal component analysis (PCA) is used to extract principal component about the main surface of each movement, and an indexing mechanism is established based on principal component. It make follow-up search conveniently. Figure 1 is the flow chart of the index matching.

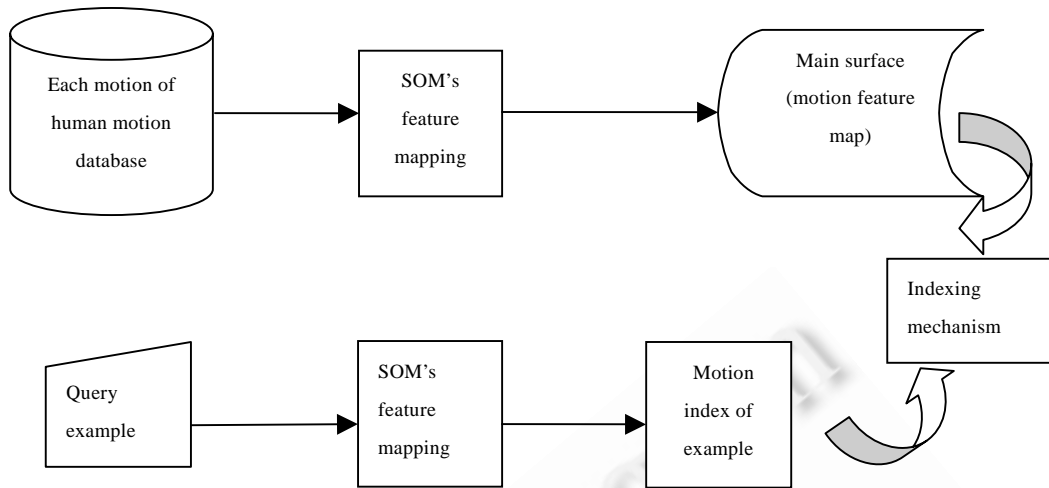


Fig.1 The flow chart of the index matching

2 Human Body Model

The Motion data format file in this paper are all BVH format file. The expression of the human body structure is the skeleton model structure, which using nodes to show joint, a connection to show body. As shown in Figure 2, is the human skeleton model. The model is composed of 32 joints (because some nodes is closers and almost overlap, so the graph does not see all nodes). All the joints organized by tree structure, *root* is the root node of the tree of human skeleton, various subtrees are formed by extension from the *root* joint point to each end node of the human skeleton step by step. *Root* joint is represented by 3D joint positions and joint rotations, other joints without *root* are only represented by 3D rotations. Translation of *root* decides the current location of human motion, rotation of *root* decide direction of the body. Rotation of other joints represent direction of the joint in the parent's local coordinate system, they jointly decide human posture.

Human motion data obtained by motion capture are sequence of human body posture by the discrete time sampling^[8], each sample point is a frame, posture of each frame is decided by 32 joints together. Therefore, in any i frame, human posture is shown as: $F_i = (p_i^{(1)}, r_i^{(1)}, r_i^{(2)}, \dots, r_i^{(32)})$, where $p_i^{(1)} \in P^3$ and $r_i^{(1)} \in R^3$, they express the position and orientation of *root*, that is, translational and rotational quantity. $r_i^{(j)} \in R^3, j = 2, \dots, 32$, express orientation of joints without *root* (rotational quantity). In the BVH file, 'CHANNEL' is included in the 'MOTION' section of each motion data frame, it is translation and rotation values in their respective local coordinate system. This nature could make 'CHANNEL' corresponding to all motion data frame to identify different posture and even different motion solely. In our paper, we all choose 'CHANNEL' in 'MOTIOM' section as the main features of movement identity. Feature extraction using SOM is this part of the data.

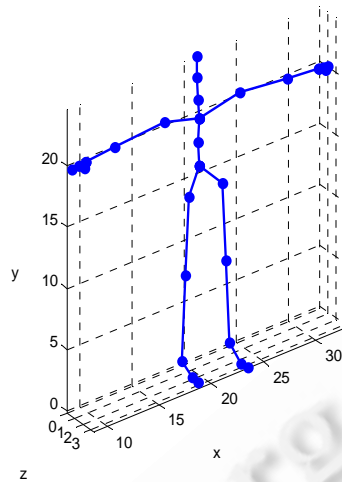


Fig.2 Human skeleton model

3 Feature Extraction Using SOM

3.1 SOM introduction

The self-organizing map (SOM) algorithm^[9] is a clustering and visualization of high dimensional unsupervised learning algorithm. It is an artificial neural network developed by simulating characteristics which the human brain deals with the signal processing. It can make any dimension nonlinear data space mapped into one-dimensional or two-dimensional graphics, and maintain its topology change.

SOM makes up of input layer and competitive layer (output layer). The number of input layer neurons is n , competitive layer is formed by m neurons of one-dimensional or two-dimensional planar array. The network is fully connected, that is, each input node connects with all output nodes. Network can make the weight vector space and probability distribution of input patterns consistent through learning the input mode repeatedly. After mapping, not only dimension reduces, but also curve or two-grid constituted could describe the characteristics and distribution situation of the original sample. Neurons on network competition level compete the opportunities respond to the input mode, weight of the winning neuron adjusted toward the more favorable orientation for its competition. "That is, winning neurons as the center of the neighboring neurons showed excitatory feedback side, while far from adjacent neurons show inhibitory lateral feedback, neighbors who inspire each other, much adjacent to each other and inhibition." This mode of the interaction curve is similar to the Mexican hat, so it is also known as "Mexican hat".

The specific process of SOM algorithm is as follows:

- (1) The weight w_{ij} is given to the initial value, set a large initial neighborhood N_c , and set the cycle number of network T ;
- (2) A new input mode: $X_k : X_k = \{ X_{1k}, X_{2k}, \dots, X_{nk} \}$, were normalized and then input to the network.
- (3) Calculate the distance d_{ik} between mode X_k and all output neurons, and select the neurons c , who has the smallest distance to X_k , that is:

$$\| X_k - W_c \| = \min \{ d_{jk} \},$$

Then c is the winning neuron;

(4) The process of updating connection weights between node c and its neighbor nodes is:

$$W_{ij}(t+1) = W_{ij}(t) + \eta(t)(X_i - W_{ij}(t))$$

which $0 < \eta(t) < 1$ is the neighborhood function, it is decreasing with time.

(5) Select another mode of learning provided to the network input layer, return to step (3), until all input patterns are provided to the network;

(6) Order $t = t + 1$, return to step (2), until $t = T$.

The key problem of SOM to maintain topological relations is to determine the neighborhood relations. The proximity of the neighborhood relations in the SOM is determined based on the distance between best matching neuron (BMU) and the other elements. When the weight vector of each unit is updated, the areas closer relationship, the greater the updates done. However, unsupervised learning is not yet ripe for development, so SOM algorithm also has some limitations, such as: network structure fixed, the network training emerge "dead neuron", Network initial state and the algorithm parameters have more influence on the convergence performance of the network and so on. So if you want to enhance the SOM topological properties, SOM must be improved.

3.2 Feature mapping

Human motion data is usually expressed as two forms: 3D position information and rotation angle information [10]. In a large motion database, the skeleton length of different motion capture subject are changed largely. Extracting features when using 3D position information will generate a lot of mistakes. Therefore, we select the angle rotation of joints in the motion data to describe the movement of information. The angle rotation of joints in each motion input to SOM as input sample. A frame of motion data in a motion can be expressed as: $F_i = (p_i^{(1)}, r_i^{(1)}, r_i^{(2)}, \dots, r_i^{(32)})$. here, we get rid of $p_i^{(1)}$ to eliminate the influence of root position information. So each frame of motion data is a 96-dimensional vector and a sequence of motion can be represented by matrix $M \in \mathfrak{R}^{m \times n}$, where m is the number of frames, and n equals 93.

Setting the first initial values and enhancing the network's topological characteristics [11] should be carrying out before SOM feature mapping. In this paper, we use the field of rectangular topology and the midpoint weight initialization function to set the initial input data processing weights. Neuron node Weights update process is:

$$W_{ij}(t+1) = W_{ij}(t) + \eta(t)(X_i - W_{ij}(t)).$$

General neighborhood function $\eta(t)$ can all choose Gaussian function:

$$\eta(t) = \alpha(t)e^{-d^2/2\sigma^2(t)}.$$

where $0 < \alpha(t) < 1$, is learning rate function, here it is as a learning rate factor. The width of it and $\eta(t)$ decreases with the number of training steps increasing. d is the minimum distance between input mode and all the output neurons. It use to identify the best matching unit (BMU), viz:

$$\alpha(t) = 0.5 \times \exp(-2 \times (t/t_m)),$$

$$d = \min(d_{jk}).$$

t_m is the total number of training. Once identified the BMU, it is necessary to update the BMU and the adjacent weight vector to narrow the gap between them and the input samples. Update to BMU for the center, the adjusted amount will be reduced when the distance between each neuron to BMU increased. However, update according to the distance between neurons and BMU, can not fully describe the position relationship between them and topological relations of the input sample data are not well maintained. In order to make the input mode of topology get better mapping, Switch to update x coordinates and y coordinates of the difference between neurons and BMU. When the input space is two-dimensional, use the formula is:

$$W_{i1}(t+1) = W_{i1}(t) + \eta_1(t)(X_1(t) - W_{i1}(t)),$$

$$W_{i_2}(t+1) = W_{i_2}(t) + \eta_2(t)(X_2(t) - W_{i_2}(t)),$$

$$\eta_1(t) = \alpha(t)e^{-(x_i - x_c)^2 / 2\sigma^2(t)},$$

$$\eta_2(t) = \alpha(t)e^{-(y_i - y_c)^2 / 2\sigma^2(t)}.$$

where x_i and y_i is represented as the horizontal and vertical coordinates in the topological neighborhood respectively. $\sigma(t)$ is shown as formula(10). a express dimension about the first layer of network competition, b express dimension about the second layer of network competition.

$$\sigma(t) = 2 \times r \times \exp(-4 \times (t / t_m)),$$

$$r = 0.5 \times \sqrt{(a-1)^2 + (b-1)^2}.$$

Experimental results show that the method can maintain the topological properties^[11]. It should be noted that, in the learning process, the location of each neuron is fixed, and the value of weight is in the change (the learning process is amend weight, study results also reflect in the value of the weight)^[12]. It can be also understand that, If the weight vector of each node is as a cluster center after learning, it should be the center of the class it represents while these cluster centers are projected to the samples before. If two cluster centers corresponding node in the mapping space is directly adjacent, connect them with a line, The final connections result is that maps. This is equivalent to see the output layer as a flexible network whose location of the node determined with its weight vector, So, the network has a topological ordering. In addition, n dimensional space is mapped to the one-dimensional by SOM, it is exactly mapped to a curve in n dimensional space; when mapped to two-dimensional ,it is mapped to a two-dimensional surface in n dimensional space. Moreover, results of SOM mapping is non-linear, here, we can considered that it is mapped to the main surface.

As mentioned above, after network training is completed, the information contained in the movement will be mapped to the main surface, it also reflected in the weight vector space. Therefore, the work of the follow-up only need to deal with weight vector space. Figure 3 shows the main surface figure of the movement walk .

4 Indexing Mechanism Based on PCA and Retrieval

4.1 Indexing based on PCA

Principal component analysis (PCA) method^[8] is the most mature algorithm in the machine vision, pattern recognition. PCA is a subspace method. Suppose given a D -dimensional sample points x_i of the number of n , it is not distributed in the whole space R^D and just distributed in one of the subspace of R^D .Subspace method is to find the number of d basis vectors $w_i, i=1\dots d, w_i \in R^D$ of the subspace who consistent with some kind of criteria. Then high dimensional data will need to be dealt with are projected onto the the coordinate system ($y_i = W^T x_i, W = (w^1, w^2, \dots, w^n)$), which is defined by d basis vectors. So the purposes of dimensionality reduction and feature extraction will be achieved.

Index aims to be excluded movement which is not related to vast majority of cases from the motion database, so that it can avoid the unnecessary large-scale database traversal. Because the movement in motion database has multiple attributes, they all have different length an speed. Therefore, indexing directly on the original motion data is very difficult and low efficiency. In this paper, PCA method is used to extract feature vector which represent approximately and can be representative of the whole movement, from the main surface through the SOM training .The feature vectors indexed all single kind of movement of the motion database.

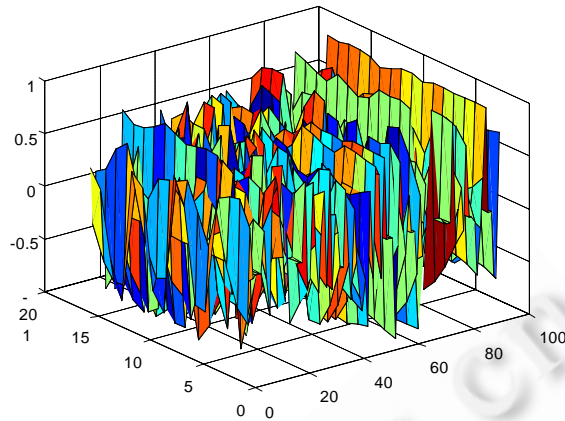


Fig.3 The main surface figure of the movement walk

How to use PCA to feature extraction describe specifically as follows:

- (1) Computer the average motion M_{avg} of each motion sequence's data:
- (2) The difference $\Delta M = M - M_{avg}$ produce a matrix D , and

$$D = [\Delta M_1, \dots, \Delta M_n].$$

- (3) Calculate the covariance matrix $C_M = DD^T$, then it could to be eigenvalue decomposition $C_M W = W \Lambda$, Where $W = (w_1, w_2, \dots, w_n)$, $\Lambda = \text{diag}(\lambda_1, \dots, \lambda_n)$, after eigenvalue decomposition, the corresponding eigenvalue array by size. Previous d feature vectors is the largest d eigenvalue vectors. Using previous d eigenvalue as the base subspace, high dimensional data $X = (x_1, x_2, \dots, x_n)$ can be used projection of x_i based on d base subspace to obtain, $y_i = W_d^T x_i$, $W_d = (w_1, w_2, \dots, w_d)$. Using y_i to reconstruct x_i , can be obtain as $\hat{x}_i = W y_i$. d base subspace obtained from PCA algorithm is optimal base-dimensional subspace which has the minimum error in the reconstruction of the sense. Previous d principal axis eigenvalue vectors about covariance matrix S of X is previous d principal axis of data X 's distribution. Corresponding eigenvalue is the variance of these principal axis.

Generally, eigenvalue decomposition carried out against the PCA are based on the singular value decomposition (SVD). For any size $m \times n$ of real matrix A , The existence of orthogonal matrix is $U = [u_1, u_2, \dots, u_m]$ and $V = [v_1, v_2, \dots, v_n]$ to make

$$A = U \Sigma V^T.$$

Here, $\Sigma = \text{diag}(\sigma_1, \sigma_2, \dots, \sigma_{\min(m,n)}) \in R^{m \times n}$.

α_i is the i eigenvalue, u_i, v_i is the i left eigenvector and right eigenvector about A , where $i = \min(m, n)$.

According to similar motion for different lengths, their left eigenvectors have different length, but the corresponding right eigenvectors are equal. The number of feature vectors are number of features extracted from the movement. Therefore, for convenience, we referred to the feature vector as the follow-up right eigenvectors.

Experiment have found that if the two movements is similar to the feature matrix, they should have similar geometric features. Because PCA can reveal the geometric characteristics of the data, that is, the inner structure of movement. Using PCA method produces representative feature vector, and then use these feature vectors to index the corresponding movement. According to movement data for PCA subspace, when the first one of the largest eigenvalue is much larger than other characteristic value, it has a dominant position and its corresponding feature vector contains most of the information about the motion on the geometric characteristics. We tested more than 200

features of surface movement sequences which extracted from the database, and the results have confirmed that the proportion of the largest eigenvalue are all more than 60%. Therefore, the first eigenvector corresponding to the largest eigenvalue is that we are looking for. If the two motions are similar, the angle correspond to their first eigenvector should be small, they are similar to parallel in the geometric sense, we can also similar to consider that $|u_1 v_1| = |u_1| |v_1| \cos \theta = |u_1| |v_1| = 1$, where u_1 and v_1 is the first eigenvector of the two motions, θ is the angle between two feature vectors. Because they are all orthogonal matrix, it can be get $|u_1| = |v_1| = 1$. Similarly, if the two motions are not similar, the angle of their first eigenvector corresponding to is large.

This article is using the first feature vector to to create indexing mechanism. Human motion database contains many of the motions, here we use the standard motion database: the database collected at Carnegie Mellon University (CMU). Each motion before feature mapping have already been marked, so that every motion index established with the database will correspond to the specific motion. This can effectively improve the efficiency.

4.2 Motion retrieval

Firstly, for any query example we use SOM to feature mapping according to steps of Section 3.2. Then using PCA to extract feature vector for the main surface which also means the weight vector. The first eigenvectors as the index, compare similarity with the index database established in the previous section. If the angle of feature vectors about two motions is in our error range of allowable, we consider that these two motions are similar. In this paper, we set up a threshold ε . It is a adaptive value based on the stability of the network and other factors. In the similarity results about each motion, any angle maximum difference of the cosine about two feature vectors is less than ε , we think they are the results of inquiries. Here, ε is set to different values depending on different network. SOM also have different topological properties because various networks have the performance difference with the randomness, when to set you should consider a number of factors. Figure 4 is Precision and Recall change according to the threshold increased in our paper. We chose appropriate threshold ε by referring to the graph. It should be clear that: the number of frame on search examples and any motion sequence of the database are not fixed, no matter how many frames, as long as they are the same type, they are similar.

5 Experimental Results and Analysis

The method mentioned in this paper is carried out in the Matlab simulation environment. We carried out the experiment based on the CMU database which are provided by Carnegie Mellon University. The motion database used to test contains more than 800 motion sequences which include jump and dance and so on. Motion data sequences are from dozens of frames to thousands of frames. Users can carry out similarity retrieval for different types of movement examples.

Each movement of the motion database is marked before motion index constructed. An index is corresponding to a motion and comparison of the similarity are based on them. So the efficiency of retrieval improved more than other methods. Table 1 is the retrieval time performance statistic after the index of database and query example are constructed.

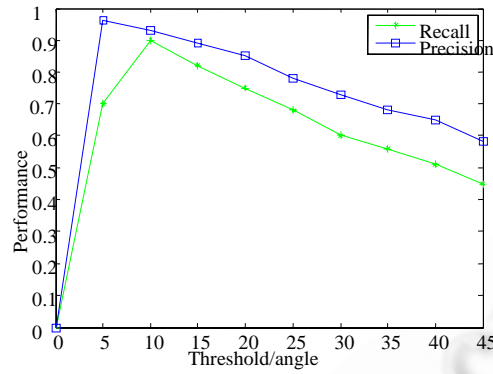


Fig.4 The performance changes with threshold changing

Table 1 The retrieval time performance statistic

Motion database scale	100	200	400	600	800
Retrieval time/s	0.004 81	0.006 70	0.010 3	0.065 6	0.102

The standard of measuring the performance of a data extraction system is mainly rate of recall and precision. Their formula as follows:

Recall=the number of the correct motion examples extracted/the number of motions related to the query examples in the motion database

Precision=the number of the correct motion examples extracted/all the number of motion examples extracted

SOM as a neural network has uncertainty. Therefore, the final performance statistics were tested 100 times, and then obtained the average. Table 2 shows the performance comparison in same database of method in this paper proposed [SOM] to retrieve motions and the 3D motion retrieval methods based on examples [LZ]^[4], we can find that recall rate and accuracy rate have improved greater. The results verify that the algorithm have achieved better results. It reflects the effectiveness of the algorithm.

Table 2 Retrieval performance comparison

Motion sequence	Recall		Precision	
	LZ	SOM	LZ	SOM
Walk	0.85	0.90	0.90	0.94
Run	0.70	0.84	0.85	0.91
Dance	0.75	0.80	0.90	0.90

6 Conclusion

In order to carry out retrieval and synthesis processing about large-scale 3D motion database gained from motion capture equipment effectively, We proposed a new retrieval method on 3D motion according to the timing characteristics of motion capture data such as the nonlinearity of motin sequence. We get a feature surface through SOM feature mapping, then use PCA to extract the first feature vector from the feature surface and establish indexing mechanism to speed up the retrieval rate. SOM have gone through treatment on topological features enhanced, so the feature surface can cover the characteristics of information of motions. Because the length of human skeleton is different and spatial feature extracted will lead to many errors, feature extraction in this paper avoided spatial location information and use the angle of rotation information to extract more effective motion characteristics. Experimental results have shown that the algorithm is effective and the efficiency can improve.

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李玉梅(1981—),女,山东胶南人,硕士,主要研究领域为计算机动画.



魏小鹏(1959—),男,博士,教授,主要研究领域为计算机辅助设计,动画.



张强(1971—),男,博士,主要研究领域为智能计算,计算机动画.



姚书磊(1983—),男,硕士,主要研究领域为计算机动画.