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Analysis of Limb Motion Training and Rehabilitation Capture based on Human Motion Capture

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ABSTRACT

This article studies the rehabilitation capture analysis method for limb motion training based on human motion capture. This method aims to improve the effectiveness of exercise training and the quality of rehabilitation by capturing the motion characteristics of the human body and conducting training and rehabilitation analysis on limb movements. On this basis, this article proposes a limb motion rehabilitation analysis method based on fuzzy decision trees. This method utilizes fuzzy set theory and decision tree algorithm to evaluate and predict the rehabilitation effect of limb movements. Specifically, a series of fuzzy rules are first set based on experience, and then the membership degrees of each rule are calculated based on the collected motion data. Finally, a decision tree model reflecting the rehabilitation effect is constructed using the decision tree algorithm. The experimental results indicate that the rehabilitation capture analysis method for limb motion training based on human motion capture can accurately evaluate and predict the rehabilitation effect of limbs, providing strong support for exercise training and rehabilitation treatment.

Keywords: Human Motion Capture, Data Retrieval, Data Segmentation, Motion Data Retrieval and Segmentation

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1. Introduction

With the continuous development of motion capture, its applications in film, television, game animation, virtual reality, and other industries are changing rapidly [1]. Because the acquisition process is too delicate, a large amount of motion capture data can't be directly analyzed to determine movement characteristics and semantic information in the reuse process, as it needs to meet the requirements of motion animation retrieval from these vast datasets [2]. Current retrieval methods usually from similarity retrieval and similarity based on logic two aspects of retrieval based on the value, the former considers the differences in the value of the motion data, this method is simple, the distance between the frame-by-frame calculation can calculate the similarity value; logical similarity retrieval is the difference of motion data based on the characteristics of the embodiment of action, usually called content-based retrieval [3]. In the processing of motion capture data, motion segmentation is a crucial part [4]. When human motion data is collected, these movements are preserved in the human motion database. Then, automatically, motion segmentation will be vital for the human motion capture data type [5]. The segmented data should contain unique behavioral semantics, that is, only one behavior type. Currently, motion sequence segmentation methods can be categorized into two types: manual segmentation involving human participation and automatic segmentation without human intervention. Manual segmentation can be divided into pure manual segmentation and semi-automatic segmentation with preprocessing segmentation. Overall, the artificial segmentation speed is slow and inefficient, with a high error rate. Automatic segmentation is the process of automatically categorizing motion sequences into distinct behaviors through unsupervised learning, allowing for full automation.

2. Early Work

In biomechanics research, motion capture systems have been used to capture the spatiotemporal stride length, stride rate, contact time, swing time, and angular kinematic measures of joint angles. [6] These measures are used in diagnosing diseases/conditions, injury prevention, and sport performance analyses. [7-12] Inertial Measurement Units mounted on the foot could work to improve the positioning accuracy of the human motion capture system. [13] describes a design with a low-cost, lightweight, and wireless inertial motion capture system for simultaneously reconstructing body attitude and displacement. [13].

The existing motion capture datasets are largely short-range and cannot yet meet the need for long-range applications. Therefore, in [14], a design is proposed that considers the obsolescence of LiDARHuman26M, a novel human motion capture dataset captured by Lidar at much longer ranges. Over the past few years, flexible and stretchable strain sensors have emerged as potential candidates for wearable devices for humans. However, the existing strain sensors often neglect multi-performance development and various challenges in practice. In a study, with the perspective on conservation and versatile material performance, a composite film was prepared using water as the solvent, based on high elasticity natural rubber latex (NR), multi-walled carbon nanotubes, and silver nanowires. [15]

3. Material and Methods

3.1 Motion Model

The University of motion capture database serves as the experimental data, utilizing a capture data file format for BVH. The hierarchical structure and motion data files, composed of human skeleton points, are divided into two parts, including a skeletal joints model as shown in Figure 1. Each joint consists of two parameters: position and rotation. 3-dimensional space vectors represent the position parameters. The rotation parameters are defined by rotation matrix, Euler angle or four element number; The human skeleton hierarchy definition part describes each joint relationship and coordinate position, except the root node of the Hips, each joint has three rotational parameters [6]. to describe motion information, Hips joint points have six parameters, respectively, the location of the root node and the angle of rotation, in the motion data part, the joint point motion data corresponding to each frame and the joint point level is given in frame, using these data, the motion of human skeleton model can be realized thus, the motion of N frames with K joint points is represented as

$$M=\{f_1,f_2,f_3,\ldots,f_n\} \quad f_i=\{J_{1i},J_{2i},J_{3i},\ldots,J_{ki}\} \qquad (1)$$

Each joint (joint root point) has three parameters, so the motion data required by M N (3(K 1) + 6) is determined by the data dimensions of both joint motion data points and moving frames. The former selects the joint points or joint chains that can reflect the motion features, and the latter obtains the key frames that can reflect the motion characteristics by merging similar frames, thus reducing the amount of data and improving retrieval speed.

Figure 1. The structure of human motion

3.2 Motion Feature Extraction

In human action recognition, human motion detection, human behavior analysis, and motion data retrieval, high-dimensional human motion data processing primarily focuses on the visual features of sports as the basis of the search [7]. The movement posture is the most basic manifestation of movement. The main posture, which can represent human movement, is selected as the movement characteristic, thereby improving retrieval speed and accuracy. The segmentation of the human body is an effective way to extract local body characteristics.

Feature vector selection. Motion feature extraction can enhance the accuracy of motion data retrieval, improving recall and precision. Because the motion data itself is the motion data of each joint point of the body, it cannot describe the characteristics of movement directly, so that the part of joint points that can reflect the characteristics of human movement constitute the feature vector, which is used to identify the motion characteristics of the gesture, and then describe the motion semantically, it not only preserves the motion characteristics of data, but also reduces the amount of motion data.

Determine the direction of the torso, as shown in Figure 2, the plane composed of points $P_{LHipjoint}$、$P_{RHipjoint}$ and P_{Hips} is selected as the datum plane to determine the front and rear postures of limbs, The vectors $V_1 = P_{RHipjoint} - P_{Hips}$, $V_2 = P_{Hips} - P_{LHipjoint}$, $V = V_1 \times V_2$ are chosen as the normal vectors of the datum plane. Set the positive axis of the Y axis in the world coordinate system to indicate the standing direction of the human body V_y , Determining

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the posture of human torso using the angle between V and V_y, Select $V_{LeftArm} = P_{LeftShouder} - P_{LeftForeArm}$、$V_{LeftLef} = P_{LHipjoint} - P_{LeftLeg}$ as the direction vector of left arm and left leg, $V_{RightArm} = P_{RightShouder} - P_{RightForeArm}$、$V_{RightLef} = P_{RHipjoint} - P_{RightLeg}$ as the right arm and right leg direction vector, The angle vector between the direction vector of the limbs and the normal vector V of the datum plane is used as the criterion for judging the front and rear postures of the limbs; The limbs are divided into two parts: the upper and the lower parts, the detailed features of the limbs are described by the relative positional relationship between the two segments. The selected vectors are shown in Table 1. Determine the specific posture of the limbs by measuring the angle between the upper and lower two parts.

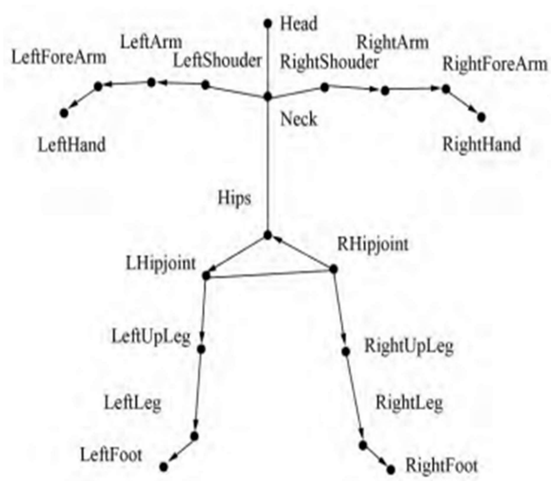

Figure 2. Nine segments of major bone

Vector	Selection method	Description
V_{LArm}	$P_{Left\ Shoulder} - P_{LeftArm}$	The movement posture of the left arm
V_{LArm}	$P_{Left\ Shoulder} - P_{LeftArm}$	The movement posture of the left forearm
V_{RArm}	$P_{Right\ Shoulder} - P_{RightArm}$	The movement posture of the right arm
V_{RFrm}	$P_{RightArm} - P_{RightForeArm}$	The movement posture of the right forearm
V_{LUleg}	$P_{LHipjoint} - P_{LeftUpLeg}$	The movement posture of the left thigh
V_{LUleg}	$P_{LeftUpLeg} - P_{LeftUpLeg}$	The movement posture of the the left leg
V_{RUleg}	$P_{RHipjoint} - P_{RightUpleg}$	The movement posture of the right thigh
V_{RLeg}	$P_{RightUpLeg} - P_{RightLeg}$	The movement posture of the right leg

Table 1. Pose Feature Vectors of Limb

Feature dimension reduction. selected 11 feature vectors, V_y、$V_{LeftArm}$、$V_{LeftLeg}$、$V_{RightArm}$、$V_{RightLeg}$ determines the state of body torso changes (upright, forward, backward), Changes of limbs state (front and back swinging), the limb posture vector V_{LArm}、V_{LFArm}、V_{RArm}、V_{RFArm}、V_{LLeg}、V_{LULeg}、V_{RLeg}、V_{RULeg} determines the detail postures of the limbs. According to the selected feature vectors , the geometric relations between the feature vectors are analyzed, and the dimension reduction function is defined to realize the automatic dimensionality reduction of the motion data, thus the data representation of the motion semantic features is completed. Geometric relations of motion. In addition to the above 11 feature vectors, a datum plane composed of point $P_{LHipjoint}$、$P_{RHipjoint}$ and P_{Hips} is also constructed, the geometric relation is determined by the relation between its normal vector V and other vectors, therefore, the angle between the feature vectors can reflect the detail features of motion, and analyze the kinematics characteristics of human body, each human joint point has a specific motion limit, that is, the maximum angle range of the closing node activity. The angle between them determines the geometric relationship between the vectors. The A *and* B are used to represent the feature vectors and the angle between A *and* B is

$$\theta = \langle A, B \rangle = \arccos\left(\frac{A \bullet B}{|A||B|}\right) \qquad (2)$$

The angle and geometric relationship between the feature vectors are shown in table 2.

Body parts	**Included angle of vector**	**Angle range**	**Geometric relation**
Torso direction	$\theta = \langle V_y, V \rangle$	90°	Erect
		>90°	Flexion
		<90°	Hypsokinesis
		90°	Erect
Limb direction	$\theta = \langle V', V \rangle$	>90°	Swing backward
	$V' \in \{V_{Left\ Arm}, V_{Left\ Leg}, V_{Left\ Leg}, V_{Left\ Leg}\}$	<90°	Swing forward
Limb posture	$\theta = \langle V_{LArm}, V_{LFArm} \rangle$	-10°~150°	Range of motion in the upper and lower extremities
	$\theta = \langle V_{RArm}, V_{RArm} \rangle$		
	$\theta = \langle V_{LULeg}, V_{LLeg} \rangle$		
	$\theta = \langle V_{RULeg}, V_{RLeg} \rangle$		

Table 2. Vectorial Angle and Geometrical Relation

Dimension reduction function. After extracting the motion features, the motion data dimensionality reduction function is determined, and the relationship between the angle of the feature vector and the geometric motion simplifies the motion content. Taking into account the precision and recall of retrieval, as well as the differences of performers' activities in capturing motion data, the function is defined as follows

$$f(\theta)=\begin{cases}0 & 90^\circ-\varepsilon\le\theta\le 90^\circ+\varepsilon\\ 1 & \theta<90^\circ-\varepsilon\\ -1 & \theta>90^\circ+\varepsilon\end{cases} \tag{3}$$

Taking into account the movement of the captured data, there may be some movement deviation, such as when the human body stands, it cannot be completely straight; therefore, a minimal angle correction value ε is applied, by reducing the dimension function, the N frame motion with *K* joint points can be simplified to the following nine eigenvalues $M=\{f_1,f_2,f_3,\ldots\ldots,f_n\},f_i=\{C_{i1},C_{i2},C_{i3},\ldots\ldots,C_{i9}\},C_1\sim C_5$ As the directional eigenvalues of the trunk and limbs, *X* is the characteristic value of the limb posture.

2.3 Key Frame Extraction

To improve retrieval speed and extract key frames, the K-means clustering method is a common approach for extracting key frames from the original motion data. Because the feature dimension of motion data has been reduced, the fast computation Hamming distance is used to extract the key frame, the process is as follows:

Step 1. The initialization set the key frame collection $M',i=0$

Step 2. Put the i frame M of the motion f_i into the M' ;

Step 3. $j=i+1$, Hamming distance $D(i,j)=\sqrt{\sum_{k=0}^{9}(C_{ik}-C_{jk})^2}$ or computing f_i and f_j ,If $D(i,j)=0$, then abandon f_j,

if $D(i,j)>0$ $D(i,j)>0$, then $i=j$, go back to **Step2:** until $j>n$

Step4. A new description motion set is obtained from the above 3 steps. The set only retains the motion feature encoding of the key frame, so the motion *M* is compressed to the *K* frame as:

$$f_{encode}(\mathrm{M})=\{f_1',f_2',f_3',\ldots\ldots,f_k'\},\quad f_i'=\{C_{i1},C_{i2},C_{i3},\ldots\ldots,C_{i9}\} \tag{4}$$

4. Results

4.1 The First Stage is Action Segmentation

Phase action segmentation. In the first stage, the purpose is to find out the motion of the 3 dimensions of each end joint and merge the whole joint segmentation point. The velocity zero crossing point and zero point in a one-dimensional motion are collectively called the segmentation points of the motion. The number of segmentation points in each dimension is usually large, and there is a large number of false positives. This problem will be solved in the subsequent fusion operation. For each end joint, the segmentation points of the whole joint are fused from the segmentation points of the 3D motion. If there is a close distance between 3 points in the 3 dimensions (the maximum gap is less than 20 frames), that is, the motion of the 3 dimensions almost zero at the same time or zero, called the 3 points align, it is also considered that there are 1 points at the end of the 3 segments, at the end of the joint segmentation point is the weighted average of each dimension on the segmentation point, here is the dividing point of weight movements between the 2 segmentation points before and after the segmentation, the joint segmentation point is more inclined to exercise larger dimensions of the split point. On the other hand, if the 3 points on the 3 dimensions of an end joint cannot be aligned, it can be considered that there is no segmentation point of the end joint in the interval defined by the 3 points

Second stage action segmentation. After each end joint segmentation point in the second stage, the paper tries to integrate all movements of the segmentation points from each end joint segmentation, local limit segmentation points corresponding to the body posture is to mining. There are 2 cases, first cases, if the 4 segmentation point to align 4 end joint movement, means that the 4 ending joint movement almost at the same time zero or zero, is that the interval in the body motion segmentation point must lie in the 4 division in the limited, is at the end of each joint segmentation weighted average point, here is the weight end joint segmentation point in the 3 dimension and range of motion and body segmentation point is more inclined to larger movement joint segmentation.

4.2 Experimental Results

The experimental data from the university sports capture database, including “walking”, “jumping”, “playing golf”, “playing football”, “swimming”, “boxing” 12941 frames of data. Five students were invited to manually segment the data and integrate their opinions, and finally 203 separate points were obtained. For each segmentation point automatically detected, the segmentation point can be correctly detected if the segmentation points are less than 10 frames in the manually segmented points. The accuracy and recall of the proposed segmentation method are obtained by comparing the automatically detected segmentation points with the manually segmented ones. This method and other 2 methods were compared, the 2 methods are rate-based methods, but the use of different features, one is to use all the joint rotation angle as the feature, and the other is with the characteristics of end joint position relative to the root joint. Figure 3 and Figure 4 show the accuracy and recall of various methods for segmenting all kinds of actions.

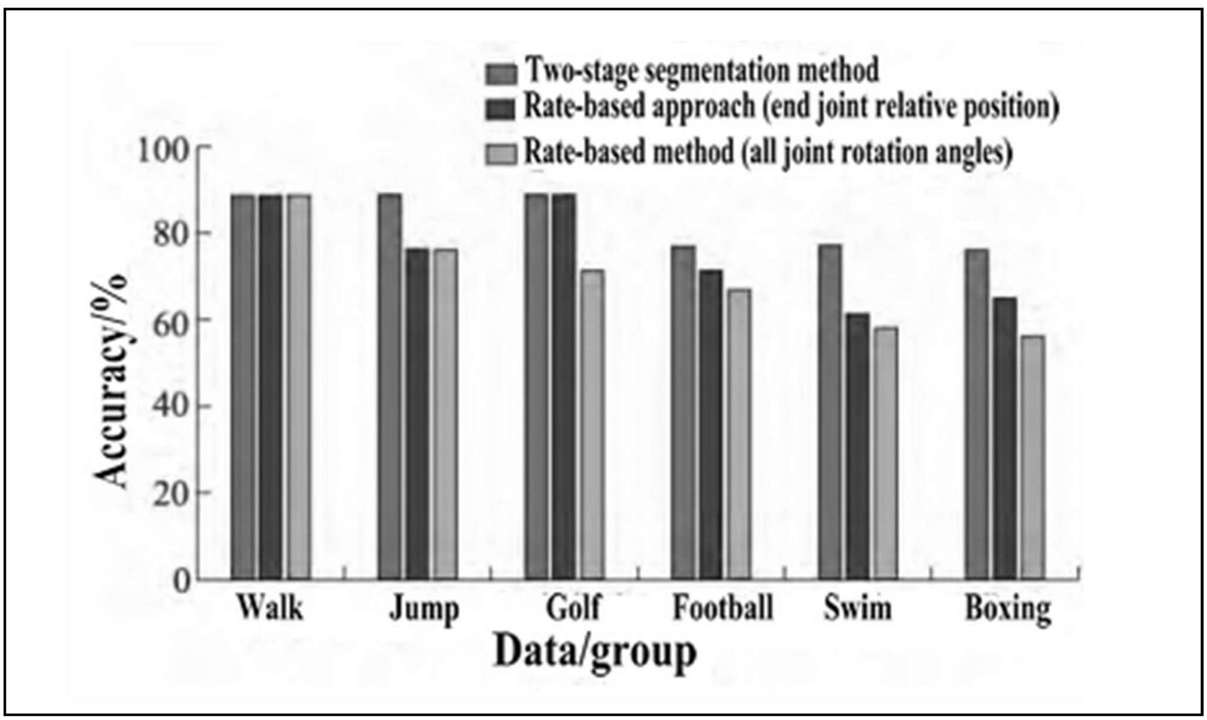

Figure 3. The accuracy of the various segmentation methods is compared

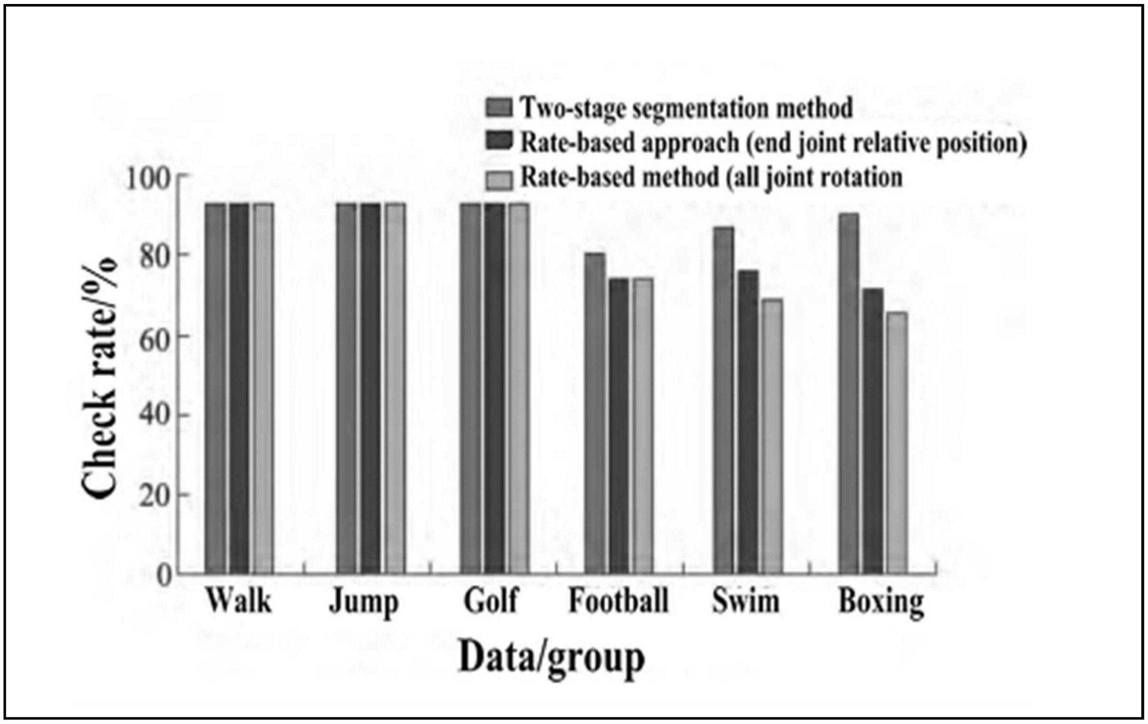

Figure 4. A comparison of all kinds of segmentation methods

5. Discussions

5.1 Database Index Establishment

For the existing motion in the database through the feature extraction and dimensionality reduction of motion of a copy of each movement, by observing the movement of copy found, some feature extraction in some sort of movement value remains unchanged, namely the movement only involves a part of motion feature extraction but not full. As shown in Table 3, the characteristics of the 4 movements show that in the walking movement, the trunk direction and the limbs state do not change during the whole movement, therefore, the index of motion is removed, and the speed of searching is accelerated by removing the interference of the invariant eigenvalues in the 9 eigenvalues. For moving M', its indexing function is as follows

$$f_{index}(M) = \{E_1, E_2, E_3, E_4, E_5, E_6, E_7, E_8, E_9\} \qquad E_i \in \{0,1\} \tag{5}$$

E_i indicates whether the characteristic i is related to motion in the process of motion. If the coding of the characteristic i does not change in motion, then $E_i = 0$; otherwise $E_i = S_i / k$, Where k is the current key frames, S_i said I is the number of distinct values in the current key frame, this ratio can reflect the characteristics of the I frequency change in the whole movement of. The index stored in the motion database, and the database is sorted according to the index, motion features, database indexing and original motion database are 3 forms of the same motion data which index ensure the retrieval speed, motion features guarantee accuracy of retrieval, similarity of original data is used to measure the movement of the sample and the search results.

Motion	Feature coding		
	Torso direction	Limb direction	Limb posture
walk	1	1 -1 -1 1	0 0 0 0
	1	-1 1 1 -1	0 0 0 0
	1	2 -1 -1 1	0 0 0 0
	1	-1 1 -1 1	0 0 0 0
	1	1 -1 -1 1	0 0 0 0
jump	0	-1 -1 1 1	0 0 0 0
	0	-1 -1 1 1	0 0 -1 -1
	0	1 1 -1 -1	0 0 -1 -1
	0	1 1 -1 -1	0 0 0 0
	0	1 1 -1 -1	-1 0 0 0
run	1	1 -1 1 -1	-1 0 0 0
	1	1 -1 1 -1	-1 0 -1 0
	1	-1 1 -1 1	-1 -1 -1 0
	1	-1 1 -1 1	0 -1 -1 0
	1	-1 1 -1 1	0 -1 0 0
cartwheel	0	1 1 -1 1	0 0 0 0
	-1	1 1 -1 1	0 0 0 0
	-1	-1 -1 -1 1	0 0 0 0
	-1	-1 -1 -1 1	0 0 -1 0
	-1	-1 -1 -1 1	0 0 0 -1

Table 3. The Feature Coding of Four Motions

5.2 Analysis of Experimental Results

The test data from the University Laboratory of sports graphics database, the frame rate is 120Hz, the length ranging from motion data, using Matlab as a development tool to verify the validity of hierarchical posture feature encoding retrieval based on PC machine with 8Gbyte of memory. A total of 150 sports segments including walking, running, dancing, boxing and a small amount of other movements were established as test databases, among them, there are different styles of walking, running and dancing. This paper holds that different styles of walking, running and dancing are logical similar movements, while others are logical non similar movements. In this paper, a hierarchical search method is used to retrieve the motion data. Table 4 compares the precision and recall of retrieval time and retrieval results by using hierarchical retrieval method and single retrieval method. When a single retrieval strategy is implemented, the highest precision is achieved based on similarity of motion values, and the longest running time of the algorithm; the similarity ratio based on motion feature is the highest recall, which is the further extraction of feature coding, and the amount of data is reduced. The similarity between the recall based on the recall and the precision is slightly higher than that based on the data index. This is because the description precision data of low actuating cable; moreover, the hierarchical retrieval method is based on the similarity of motion numerical similarity and the similarity of motion features, and improves the retrieval efficiency while guaranteeing the precision and recall of the retrieval results. With the increase of the amount of data, the execution time of the algorithm decreases continuously, and the hierarchical retrieval method can provide guarantee for the large-scale motion database retrieval.

Retrieval method	**Walk**			**Run**			**Dance**		
	Precision ratio /%	**Recall ratio/ %**	**Time/ s**	**Precision ratio %**	**Recall / ratio/%**	**Time / s**	**Precision ratio /%**	**Recall ratio /%**	**Time / s**
Motion numerical retrieval	94	78	2137.2	81	77	2135.7	77	100	2153.9
Motion feature retrieval	85	95	4.8	73	85	2.6	50	100	12.9
Data index retrieval	83	91	5.0	71	82	3.7	10	100	14.0
Hierarchical retrieval	100	95	1259.3	98	85	1197.2	100	100	1179.

Table 4. Comparison of Retrieval Results of Different Retrieval Strategies

Taking walking movement as an example, figure 5 is the 4 movements of different styles in the retrieval results, and selects the tenth, thirtieth, fiftieth, 70 and 90 frame motion postures of each motion sequence. As shown in Fig. 5, in the retrieval results of each sample motion, although the same moving frame is selected, the motion attitudes of different retrieval results on the same moving frame are not the same, the motion information of the whole movement is the same, which shows that the hierarchical retrieval algorithm can well retrieve the logic similar motion.

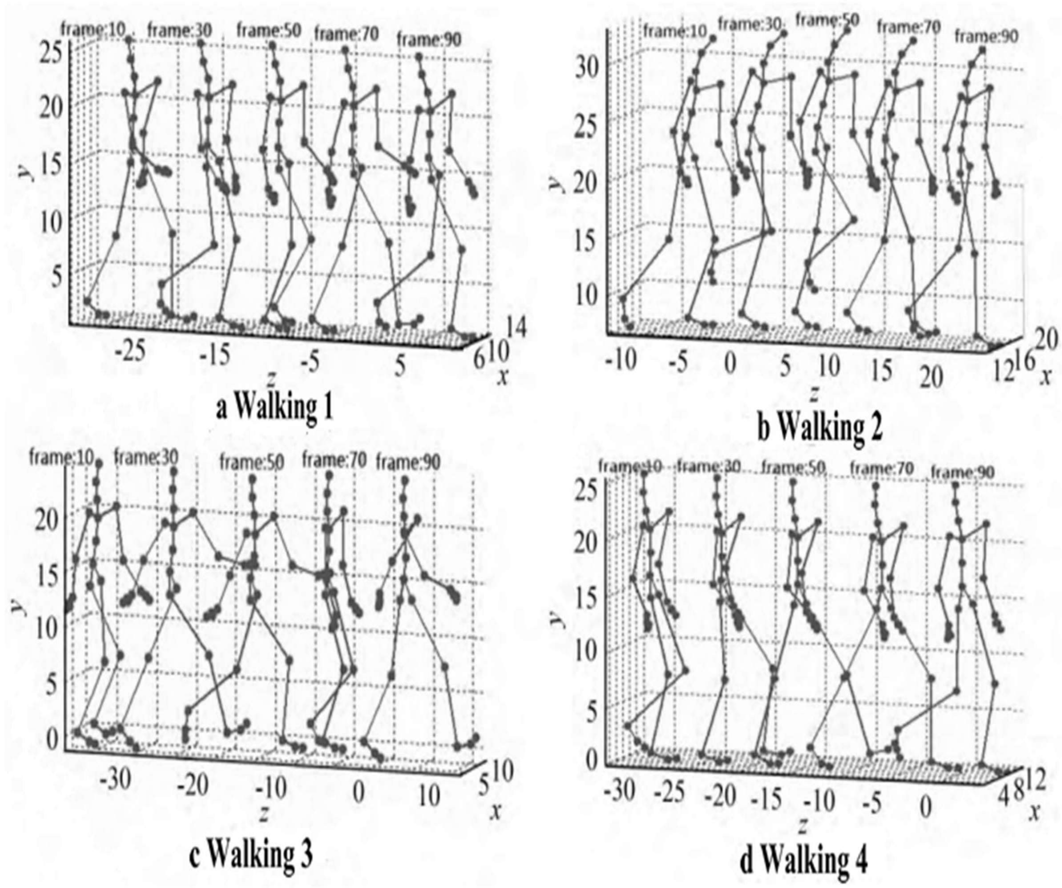

Figure 5. Logical similarity retrieval results of walk motion

6. Conclusion

With the rise of the movement of the motion capture data, large amounts of data are used in computer animation, games and film stunt simulation, medical and other fields, the capture device by using optical and mechanical, has gained the massive data capture movement. In this paper, the retrieval and segmentation technology of athletes' motion capture data is studied, aiming at the shortcomings of high error rate and low efficiency of artificial segmentation motion sequences, a new method of motion reduction based on maximum variance expansion is proposed. The results also show that the hierarchical retrieval method based on gesture feature coding can improve the retrieval speed and retrieval quality.

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