Research on Trend Analysis Model of Movement Features Based on Big Data

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Abstract. The motion feature data capture can well preserve the details of the motion and truly record the trajectory of the motion. It has been widely used in many fields such as virtual reality, three-dimensional games, film and television effects, and so on. With the widespread application of motion feature capture, how to analyze the trend data of sports features has become a hot topic. The main purpose of the trend analysis of the research motion characteristics is to better understand and describe the motion process of the objects so as to manage and reuse the motion capture data in the motion capture database. For the existing motion feature capture data in the motion capture database, the motion feature data behavior is precisely segmented, the motion template is extracted and calculated more quickly and efficiently, the motion behavior is identified, and the motion behavior in the motion sequence segment is automatically identified.

Keywords: Big data · Motion feature · Human motion information

1 Introduction

With the development of sports science research, the use of computer motion features for modeling and simulation and sports diagnosis has become an inevitable trend. In order to better analyze the trend of movement characteristics, the human movement characteristics are taken as an example. With the help of knowledge of sports biomechanics, the movement characteristics of athletes are simulated and tested. This method has a high theoretical and practical value, many scholars at home and abroad have carried out in-depth and meticulous research work [1]. The traditional athlete modeling method is based on Newton's law of motion. By simplifying the human body structure, writing the equation of motion, setting the initial conditions, and solving the equation, the simulation results are finally obtained. This method uses a simplified model, inevitably there will be a larger calculation error, and the model is difficult to modify. In order to solve these problems, based on the analysis of the human motion modeling and simulation research methods, a new idea of the trend information fusion modeling based on big data is proposed [2]. Starting from the acquisition and analysis of the motion information, it focuses on the feature extraction and classification of the

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ground reaction force information in the human body movement process, the surface electromyographic information of the human body, and the relevant parameters of the motion image analysis, and adopts a multi-source information fusion method to realize the motion. Automatic decomposition and identification of feature extraction process, and establish a trend analysis model of movement characteristics, in order to improve the accuracy of movement feature trend modeling and simulation, and lay the foundation for the construction of movement feature trend analysis system.

2 Motion Feature Parameter Calculation Method

The gesture of the movement can be represented by the global coordinates of each joint, or it can be expressed by the translation of the root joint and the rotation of the remaining joints [4]. The translation in three-dimensional space can be simply represented by the translation matrix, so the motion feature trend is analyzed using the calculation method of the human body joint global coordinates [3]. In the process of motion, the motion characteristic matrix can be regarded as a vector. When multiplied by the matrix, only the feature parameter information will affect the direction of the vector but will not change the size of the vector matrix. When you rotate a certain angle around the coordinate axis, you must first determine the positive direction [5]. It is specified that in the right-hand coordinate system, the counterclockwise rotation direction is positive when viewed from the positive end of the coordinate axis. In the same way, in the left-handed coordinate system, the clockwise rotation direction is positive when viewed from the positive end of the coordinate axis. This definition ensures that the same rotation matrix is used in either the right-handed or left-handed coordinate system. In the right-handed Cartesian coordinate system, the rotation matrix that rotates the α angle about the X axis is:

$$U_x(\alpha) = \begin{bmatrix} 1 & 0 & 1 \\ 0 & \cos\alpha & -\sin\alpha \\ 0 & \sin\alpha & \cos\alpha \end{bmatrix} \tag{1}$$

The rotation matrix that rotates by α degrees around the Y axis is:

$$U_y(\alpha) = \begin{bmatrix} \cos\alpha & 0 & \sin\alpha \\ 0 & 1 & 0 \\ -\sin\alpha & 0 & \cos\alpha \end{bmatrix} \tag{2}$$

The rotation matrix rotated by α degrees around the Z axis is:

$$U_z(\alpha) = \begin{bmatrix} \cos\alpha & -\sin\alpha & 0 \\ 0 & 1 & 0 \\ -\sin\alpha & 0 & \cos\alpha \end{bmatrix} \tag{3}$$

For an arbitrary rotation axis n that circumvents the origin, when rotating the e-angle, the vector n can be decomposed into three directions of x, y, z, and then obtained by cascading a simple rotation matrix of three components nX, ny, n. The final rotation matrix is:

$$U_i(\alpha) = \begin{bmatrix} i_x^2(1-\cos\alpha)+\cos\alpha & i_xi_y(1-\cos\alpha)-i_x\sin\alpha & i_xi_z(1-\cos\alpha)-i_y\sin\alpha \\ i_xi_y(1-\cos\alpha)+i_z\sin\alpha & i_y^2(1-\cos\alpha)+\sin\alpha & i_yi_z(1-\cos\alpha)-i_x\sin\alpha \\ i_xi_z(1-\cos\alpha)-i_y\sin\alpha & i_zi_y(1-\cos\alpha)+i_x\sin\alpha & i_z^2(1-\cos\alpha)+\sin\alpha \end{bmatrix} \quad (4)$$

In combination with the above algorithm, the data features of any rotation axis in the human body motion are extracted. If the movement is selected and moved around a rotation axis n, the movement feature data is expressed in the form of: The formula rotating around the n-axis is rotated, and finally the rotary axis is translated to the original position [6]. The value of the human motion gesture is captured and recorded, and the Euler angle representation method is used to calculate the motion feature relationship. Finally, the Euler angle's motion gesture feature calculation result is converted into a corresponding three-dimensional space coordinate system display diagram, as shown below (Fig. 1).

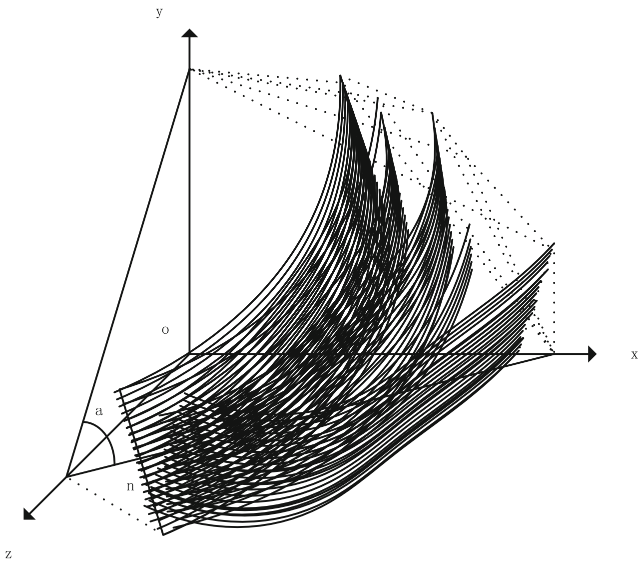

Fig. 1. Graphical display of human movement gesture features

3 Motion Characteristics Trend Analysis Model Design

The hardware part of the motion feature information acquisition system consists of PIR sensor, Fresnel lens, signal conditioning circuit, and digital-analog conversion device. The software part is programmed by Lab-VIEW software [7]. The design principle is as follows: When the walking human body passes through the PIR sensor, the PIR sensor receives the infrared radiation emitted by the human body, the Fresnel lens is added on the front end to increase the detection distance, and the electrical signal output by the sensor is processed through the amplifying and filtering circuit, and the data acquisition card is used. Perform A/D conversion and then access the computer for data analysis (Fig. 2).

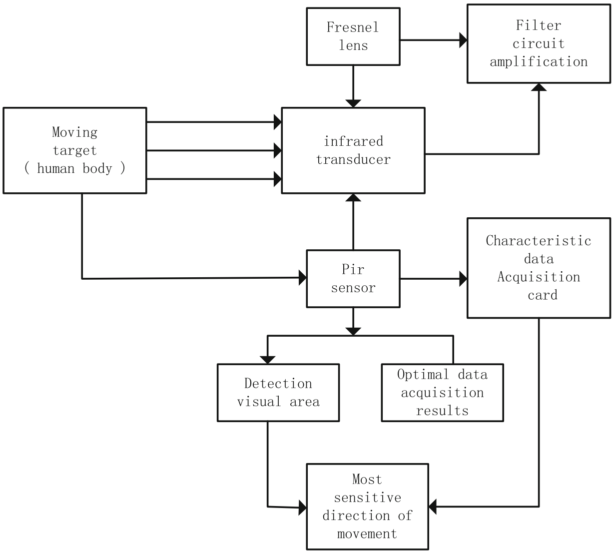

Fig. 2. Motion data feature acquisition system

After the collection of the motion feature data, combined with the motion template extraction calculation method, the original relationship feature function is improved, and a motion feature trend extraction method based on the improved motion relation template is realized [8]. This method proposes a relational matrix based on the relationship between human joints and spatial geometry to describe the spatial position relationships of the various joints of the human body. The relationship feature matrix of the same category of motion behaviors is aligned with the time axis by the method of dynamic time rounding. And record the time deformation process of the DTW, the aligned matrix is averaged and inverse transformed according to the recorded time deformation process, and finally quantized to obtain the category of motion behavior, so as to correspond to the movement trend template [9]. In the aspect of motion behavior recognition, a motion analysis feature trend analysis model based on motion templates is proposed to automatically identify the motion segments obtained by behavioral segmentation of the original motion data sequence [10]. The method divides the motion of the root node in the human skeleton model corresponding to the motion sequences to be identified into two types: root node motion and root node motionless. Based on the DTW method, the motion sequences to be identified are sequentially performed with motion templates of different motion behaviors. The similarity matching calculation achieves the automatic recognition of the motion behavior in the motion sequence segment. The trend analysis model of sports features is as follows (Fig. 3).

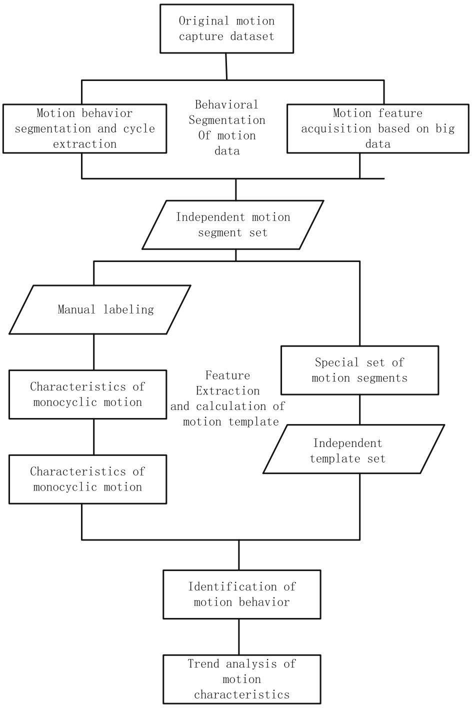

Fig. 3. Trend analysis model of movement features

As shown in the figure, the model can automatically perform behavior segmentation, cycle extraction, and motion behavior recognition on the original motion data sequence containing basic motion behaviors, and realize an important role in effective analysis and management of motion feature trends.

4 Experimental Results and Analysis

In order to verify the operational effect of the trend feature analysis model proposed in this chapter, the model was run in the software environment of Matlab2011. In the experiment, let the feature parameter be a value that can make the average number of neighbors per point account for 1% of the total points. Thirty-four motion sequences containing different behaviors were selected from the CMU database. Each motion sequence contained different behavior and complexity, including walking, running, jumping, boxing, and stretching. These sequences were segmented using the previous method. One volunteer who was healthy and had no abnormal gait was randomly selected as the study subject. Anthropometric parameters of volunteers were measured, including height, weight, forearm length, upper arm length, and hand length; The length of the forearm was the distance from the radial stem to the epicondyle, the upper arm was the shoulder to the epicondyle, the hand was the distance from the radial stem to the middle fingertip, and the length of the arm was the shoulder to the radius styloid process.

The motion capture system of the model was used to capture the movement of the upper extremities during walking. It was found that each rigid body was composed of at least three Marker points and was consolidated on the outside of the forearm and the upper arm by a gauze, Another rigid body is attached to the sternum to calculate the upper arm swing angle. Since the wrist joint has a small movement during walking, the handle and the forearm can be regarded as the same rigid body. For each key anatomical feature point that is not easy to collect, a virtual tool of the motion feature capture system is used to set the virtual Marker, and the three-dimensional motion feature track attached to the active light emitter Marker point of the test subject is obtained as shown in the following Fig. 4.

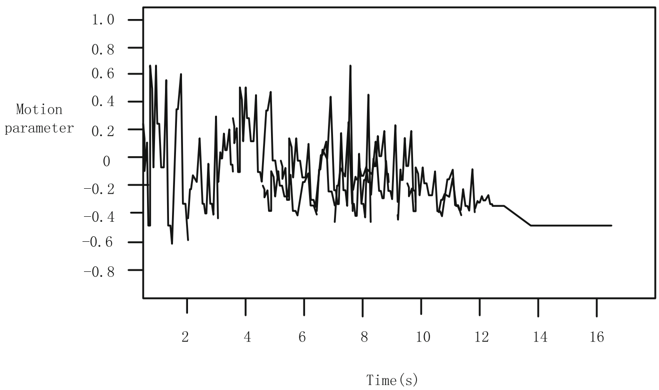

Fig. 4. Three-dimensional movement characteristics

Deltoid around the shoulder joint, the clavicle of the pectoralis major muscle, the biceps brachii, the latissimus dorsi, the major round muscle, and the posterior deltoid muscle during the swing arm are performed synchronous measurement and exercised on the main EMG signals of the anterior, also, their trends are analyzed. First, the test subjects were measured for ergonomic parameters, and then adhered in sequence according to the Marker points and the electromyography plan formulated above. Adjust the speed of the treadmill to 2 m/s before the start of the capture test. Each tester will perform at least several adaptive exercises to suit the laboratory's light, temperature, treadmill and other equipment. The testers are required to walk in a naturally relaxed state and then begin to capture measurements; each tester also performs multiple cycles of the same action. The test data is as follows (Fig. 5):

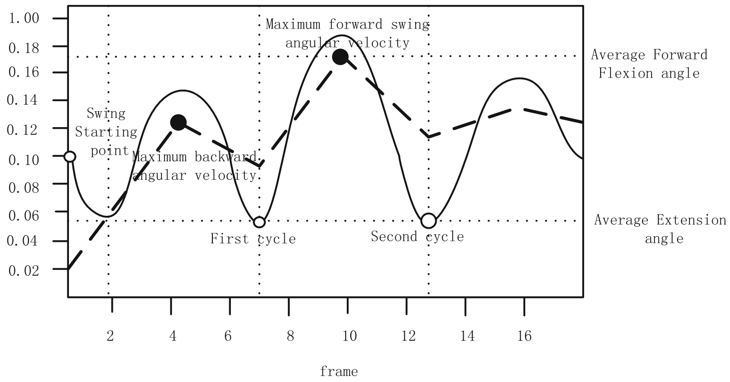

Fig. 5. Trend analysis of sports features

As can be seen from the figure, the method of folding and cross-validation is used to classify and recognize the motion feature data samples under slow, medium, and fast conditions, and it is found that the experimenter's motion features are accurately acquired and calculated. The tendency of the trend data of sports features confirms the effectiveness of the model. In summary, the trend analysis model based on big data can be effectively applied to the human motion trend classification and identification system.

5 Conclusion

Although there are certain regularities in the movement process, the complexity of the movement characteristics is still relatively high. The information describing the freedom of the movement model and the structure of the kinematic chain is too complex, resulting in the traditional movement modeling method in the structure of the human lower limb movement model. Due to the high complexity, it is impossible to accurately model the motion of human lower limbs. Therefore, a method for modeling human lower limbs kinematic chain motion combining human body dynamics is proposed. The problem of the motion curve simulation of the human kinematic chain is converted into the basic variable set. The variables include the zero-point moment of the human lower limbs, the gravity point and the posture relationship of the movement. The accurate analysis of human lower limb movement characteristics trends is achieved through the constraints of the human lower limb movement dynamics model. It is best to show through experiments that using the improved algorithm to analyze the trend model of the movement characteristics, which has a better running effect.

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