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Capturing and Analyzing Volleyball Player Training Trajectory Data Based on Mean Shift Algorithm

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ABSTRACT

To address the challenges of complex backgrounds and incomplete trajectory capture due to the fast movement of the target, this study proposes a data capture method for volleyball player training trajectories based on the mean shift algorithm. The human body model is considered a skeleton model with 51 degrees of freedom and 16 joints to digitize the training trajectory data, and dimensionality reduction is applied to reduce computational complexity. To reduce the dependency of the mean shift algorithm on environmental parameters, a probability density function from the gradient iterative estimation algorithm is selected, and the target's color information is used as a feature to complete the trajectory data capture. The experiment demonstrates that the method can capture the motion of each athlete's joint, achieving more accurate training trajectory data capture without depending on relevant parameters.

Keywords: Training Trajectory Data Digitization, Data Dimensionality Reduction, Mean Shift Algorithm, Gradient Iteration

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1. Introduction

With the development of globalization, strengthening research in sports science has become increasingly important. The VSAM monitoring system was developed by researchers at Carnegie Mellon University in the 1990s and was initially used in the military field but has now become a widely applied technology. In recent years, with technological advancements, more scholars have utilized SpaceMocap systems to develop more accurate monitoring technologies for capturing the motion states of astronauts in space. Li et al. used the SpaceMocap system to first scan astronauts on the ground, precisely adjusted camera parameters based on the model, and then used neural network technology to accurately detect the positions of each joint of the human body for real-time tracking of joint angles [2]. Shen X proposed a knee joint motion capture measurement method based on MATLAB, effectively solving the problem of traditional knee joint extension calculation and volunteer walking measurement at a lower cost to meet the aerospace field's needs better and capture knee joint motion more accurately [3]. However, this method still needs to improve capturing overall trajectory motion data. Chi X and his team built a motion energy-driven human motion model based on the theory of "entropy". They used DTW matching technology to determine the relative positions of test and reference sequences, grouping them to detect motion behaviours effectively [4]. Park Y utilized decision tree technology to study each key part of the human body and its interactions, constructing a new dataset that can accurately capture and describe body motion for further identity authentication [5]. Zhang H developed a semantic-based human motion classification system integrating multiple datasets to form a motion model with specific semantics. This model can accurately detect motion behavior based on different features by associating the detected motion sequences with DTW [6]. Jiand his team used a two-dimensional hidden variable method and human activity complexity to construct a new model for better capturing and analyzing joint position information, and based on this model, a series of motion templates can be built for more accurate prediction and analysis of joint position information [7]. Yuan and other researchers used the geometric structure of human joints and planes to construct a feature matrix for capturing and analyzing various complex motion states and a pattern for accurately defining and analyzing complex motion states, thus automatically detecting any uncertain motion trajectory [8]. This paper proposes a novel sports training trajectory capture method, which utilizes the mean shift algorithm to convert the motion status of the human body into visual images and uses the color information of the target object as a feature to effectively capture motion trajectories [10].

2. Volleyball Player Training Individual Modeling

To present motion data more clearly, the human body model is abstracted as a skeleton structure consisting of 16 joints, each with its coordinate system connecting them. In this skeleton structure, the motion state of child joints can be related to parent joints or freely adjusted based on their characteristics. In contrast, the motion of parent joints is entirely independent of external factors [11,12]. To reduce the complexity caused by Euler angle representation, quaternions are adopted to describe the rotation state of each joint, and m(t) is defined as the motion data for each frame of volleyball player training to reduce the possibility of anomalies in the model.

$$M(t) = \left(p_1(t), q_1(t), q_2(t), \cdots, q_n(t)\right) \tag{1}$$

In this formula, M represents the number of joints that will appear during training, $p(t)$ refers to the specific position of each joint, $q{:}(t)ES$ represents the direction of each joint during rotation, and $qn(t)$ refers to the rotation state of the nth joint. By mapping quaternions, we can map them to three numbers in $R3$, resulting in the numerical model of y.

$$\hat{f}_{G(x)} = \frac{C}{nh^d} \sum_{i=1}^{n} K\left(\frac{x - X_i}{h}^2\right) \tag{2}$$

To better understand the motion status, we map quaternions to $R3$ space and use a linear time-invariant system for data dimensionality reduction. The state equation of this method can be represented as follows:

$$X_{t+1} = A x_t + w_t$$
$$Y_t = Cx_t + V_t \tag{3}$$

In Equation 3, w and v are Gaussian noises, followed by w:$N(0,Q)$ and $VN(0,R)$, respectively, and p represents the dimension of the data. xt is the state variable in a low-dimensional space k with k< transition matrix, i.e., dim[A]-$k \times k$.C represents the input matrix, where dim[C]-p×k.

2.2 Effectively Capturing Trajectory Data Using Mean Shift Algorithm

In sports training, capturing fast-moving targets in a complex background is necessary. Therefore, this study adopts the mean shift algorithm to track the motion trajectory of the target [13-15]. The mean shift algorithm is a non-parametric kernel density estimation method that calculates the probability density through gradient iteration. It can quickly match and does not rely on relevant parameters. The kernel density estimation method of the algorithm is as follows:

After tracking the target position, the trajectory data capture is completed based on the feature information of the mean algorithm. Color information does not change when the target undergoes translation, rotation, or deformation. Therefore, color information is one of the most reliable features in the image. This study uses the color histogram method to describe it. The specific process is as follows: define a set of N samples in the set X-{$X1$,..., Xt}, and its probability density function is $p(x) = N(x, 0, N)$, where 0 is the mean vector, and V is the covariance matrix. Assuming the training target is elliptical, the initial selection of the target for the current frame is initialized, and X represents the pixel position possessed by the athlete as a whole, with 0 as the initial position, and T as the motion cycle.

In recent years, with the development of software and hardware technology and the reduction of costs, motion capture systems have become increasingly popular. Optical-based 3D human motion capture methods have become an important means of obtaining human motion information, leading to the emergence of large-scale human motion capture databases, gradually growing in size [16-18]. Human motion capture data can effectively preserve motion details and realistically record the trajectory of human motion. It has the characteristics of high data accuracy and good quality, making it widely used in computer animation.

Motion capture integrates mechanical, electronic, optical, and computer graphics technologies to capture performers' actions and directly drive virtual character technology through this motion data. It has a wide range of applications in medical science, gaming, film, and animation. Motion capture technology can effectively measure and record the movement of objects in three-dimensional space. This technology records the positions of multiple joints and bones of the human body by installing sensors on key parts of the moving object. The data is then processed by a computer and saved in a usable format. General motion capture devices mainly consist of four parts: sensors, signal capture devices, data transmission devices, and data processing devices. Sensors are used to track moving objects' trajectories and are installed on specific parts of the object as needed. The signal capture device is responsible for capturing the spatial position signals of the object. Data transmission devices transmit the captured position signals to the computer for real-time processing. The data processing device processes the captured data through software and hardware for analysis.

2.3 Description of Motion Capture Data Behavior Sequence

By constructing a model that can describe human motion behavior, we can use the method shown in Figure 1. Firstly, we need to take a set of high-dimensional data points as input to the model and record their positions and sizes. Next, we can construct a model that describes human motion by comparing the density and distance of two models based on their positions and sizes. Finally, we can combine the inputs and outputs of these models to construct a model that describes human motion. By acquiring the original motion records, we can transform them into a series of texts to better explain and understand human activities.

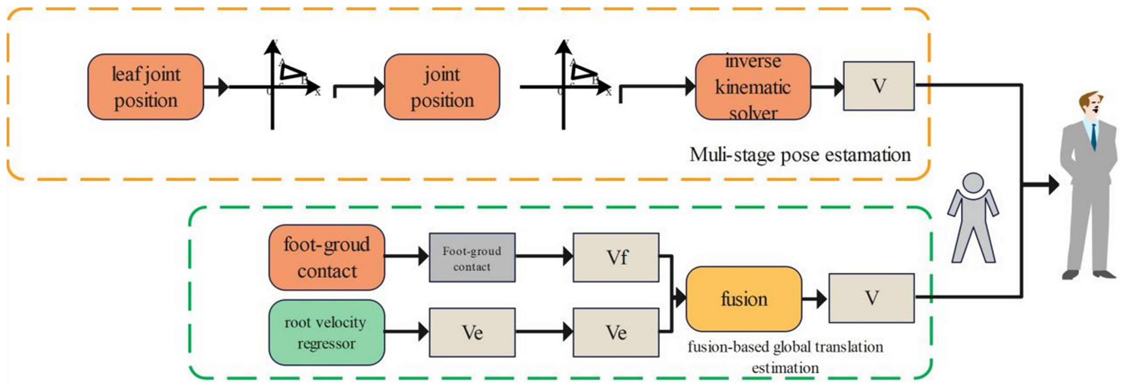

Figure 1. Process Diagram of Behavior Sequence

Through the adoption of clustering techniques, a complete behavior sequence can be effectively constructed. Specifically, the original motion frames can be treated as high-dimensional spaces. The frame number and the distance to the other two spaces are recorded, thus building a complete behavior sequence. Sub-I found that traditional methods of measuring the distance between two frames are limited to measuring the positions of two key points, needing more measurements of other key points, making it unable to identify more complex movements accurately. Therefore, by using the technology of MotionField, we can measure the posture and velocity of two frames to more accurately describe the similarity between the two points. The human body structure is a complex framework consisting of 31 parts, each with 62 independent degrees of freedom. The posture of the i-th frame is independent, and its size depends on the size of each part, which is an Euclidean distance. In this case, the motion of the final frame will be the same as the motion of the previous frame.

3. Experimental Design and Results Analysis

3.1 Experimental Design

Feature extraction of human motion capture data has significant application value for reusing and managing motion capture data. With the continuous development of motion capture technology, the increasing amount of data in the library may lead to difficulties in managing a large amount of relevant data. For the existing action capture data in the database, how do we select the human demand action class data? The feature extraction of human motion capture data can obtain the action features of the corresponding actions. According to the different action characteristics extracted, the action sequence can be analyzed, retrieved, recognized, and marked, thereby enabling the reuse and management of action class data. In this article, we draw on Muller's technology and develop a new computer vision technology that uses the principles of DTW to construct a correlation feature matrix containing 32 Boolean types to reflect the geometric positions of each part of the human body. It can rearrange the feature matrix of similar behaviors in a certain period to better understand their connections.

After the reconstruction, we can use a new method to describe each movement's behaviour. First, we need to calculate their square and negative phases and then use our mathematical method to compute them. After the reconstruction, we can use a new method to describe each movement's behaviour.

3.2 Results Analysis

Through real-time monitoring of the athlete's training trajectory in two sets of image sequences, we have discovered a new motion trajectory capture method that can accurately capture the athlete's motion trajectory with low and false detection rates. We compared this method with the SpaceMocapand MATLAB-based trajectory capture methods to prove its effectiveness. According to the results in Figure 2, the accuracy and error rate of the SpaceMocap method are significantly better than the MATLAB method. Still, the accuracy and error rate of the mean shift method proposed in this article are higher. This is because it does not require any parameter adjustment and can effectively capture external factors such as object deformation and motion speed.

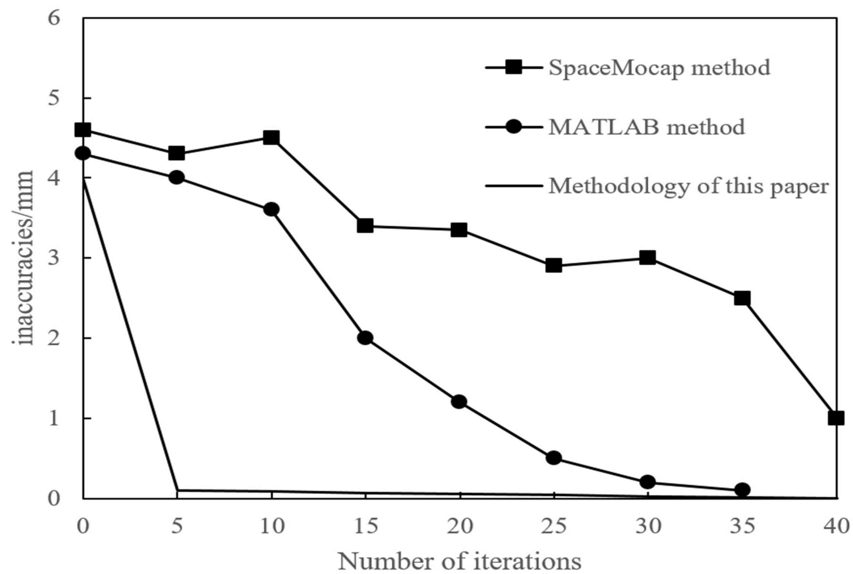

Figure 2. Differences in Accuracy and Error Rates of Trajectory Data Trained with Different Methods

We can obtain their average value by calculating the DTW distance between each motion template and its corresponding sequence. For example, when we use the "walking" motion template, we can calculate its average distance to the "chopping" motion behavior given in Figure 2, resulting in 29.12. Through calculations, we found that the distance of a motion template on the main diagonal of the two images is smaller than its distance at other positions, indicating that the average distance of a motion template in multiple sequences of the same behavior is smaller than that in multiple sequences of different behaviors. After research, it was found that there is little difference between a motion template and sequences of the same type of motion behavior. Still, there is a significant difference between it and sequences of different motion behaviors. This indicates that this algorithm can capture specific types of motion behaviors well. "Unknown" behaviors can be divided according to their positions and can be divided into two categories: one is basic activities, such as squatting, single-leg jump, stationary rotation, and jumping; the other is basic static behaviors, such as chopping, lifting, drinking, sideways waving, etc., and their activity paths can be referenced in Figure 3. The "motion sequence" in the figure represents 110 human motion capture data sequences to be recognized. "Manual recognition" represents the recognition results obtained through manual methods, which serve as the ground truth in the experiment. "Original template" means the recognition results obtained based on the original motion templates, where the original motion templates are obtained by calculating 39 relational feature functions proposed by Muller. “Improved template” represents the recognition results obtained based on the improved motion templates, where the improved motiontemplates are obtained by calculating 32 relational feature functions. The diagonal line in the “manual recognition” results indicates that the motion behavior contained in this sequence does not belong to a complete motion behavior semantically; it may be a transitional part between two behaviors or a meaningless motion segment. This is caused by the segmentation method. Because the motion behavior segmentation method used in this article cannot achieve 100% accuracy, incorrect segmentation results in motion segments that do not represent a complete motion behavior. Therefore, if these sequences obtained from incorrect segmentation are used as the motion sequences to be recognized, the correct recognition result should be “unknown.”

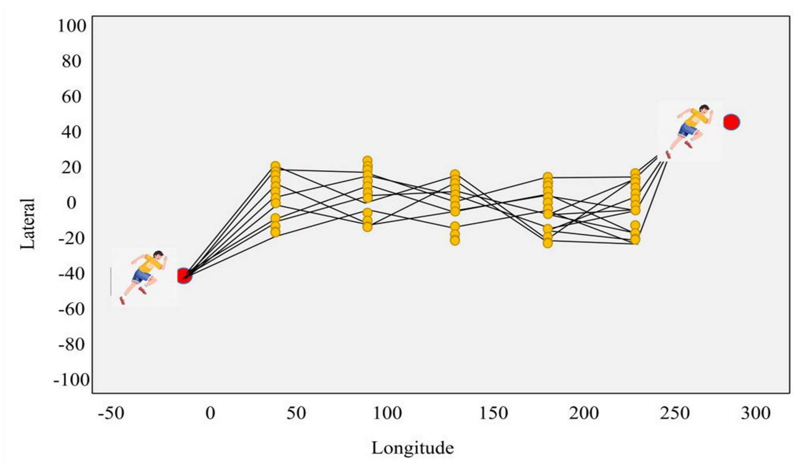

Figure 3. Movement Trajectories of Volleyball Players

4. Conclusion

When we watch training videos, we find that the athlete’s body posture may undergo drastic transformations and be hidden. Therefore, monitoring the athlete’s walking path is very challenging. To solve this problem, we adopted the mean shift algorithm and analyzed it using color information. Through testing, we found that the accuracy of this algorithm is high, and the probability of errors is small. We discovered that this new technique is efficient. It can finely divide digital patterns of various human activities and quickly identify active states and times consistent with previous patterns.

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