



Digitization and Analysis of Sports Training Trajectories Using Dimensionality Reduction

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ABSTRACT

This paper presents an innovative method for digitizing and analyzing sports training trajectory data using the mean shift algorithm combined with color histogram features for robust motion tracking. The authors model the human body as a 16 joint skeletal framework, representing joint rotations via quaternions mapped in to $\mathbb{R}^3$ space to avoid singularities associated with Euler angles. To manage high dimensional motion capture data, they apply a linear time invariant system for dimensionality reduction. The mean shift algorithm chosen for its non parametric nature and resilience to object deformation, rotation, and speed variations is used to track athletes' motion paths by leveraging consistent color features across video frames. Experimental results demonstrate that this approach outperforms both Space Mocap and MATLAB based trajectory methods in accuracy and error rate. The study also integrates Dynamic Time Warping (DTW) to compare motion sequences, showing that intra class motion distances are significantly smaller than inter class ones, thereby enabling effective behavior classification. Motion sequences are categorized into dynamic (e.g., jumps, squats) and static (e.g., lifting, waving) actions. The system achieves precise segmentation and recognition of human activities, even under conditions of occlusion or changes in posture. Supported by motion capture databases and validated through comparative analysis, the proposed technique offers a reliable, parameter-free solution for real time athlete tracking and motion behavior analysis in sports science applications.

Keywords: Training Trajectory Data Digitization, Data Dimensionality Reduction, Mean Shift Algorithm, Gradient Iteration, Human Motion Capture, Quaternion Representation, Dynamic Time Warping (DTW), Sports Performance Analysis

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1. Introduction

As globalization continues to evolve, enhancing research in sports science has gained significant importance. The VSAM monitoring system was created by researchers from Carnegie Mellon University in the 1990s and was initially employed in military applications, but has since become a commonly used technology. In recent

years, advancements in technology have led to a growing number of scholars utilizing Space Mocap systems to devise more precise monitoring technologies for tracking the motion states of astronauts in outer space. Li et al. employed the Space Mocap system to initially scan astronauts on Earth, accurately fine tuning camera settings based on the model, and then utilized neural network technology to effectively identify the locations of each joint in the human body for real time tracking of joint angles [2]. Shen X introduced a method for measuring knee joint motion capture grounded in MATLAB, successfully addressing the challenges associated with traditional calculations of knee joint extension and volunteer walking measurements at a reduced cost, thereby better catering to the needs of the aerospace sector and capturing knee joint motion with greater accuracy [3]. Nonetheless, this method still requires enhancements in capturing comprehensive trajectory motion data. Chi X and his team developed a human motion model driven by motion energy, based on the “entropy” theory. They implemented DTW matching technology to ascertain the relative positions of test and reference sequences, effectively grouping them to identify motion behaviors [4]. Park Y applied decision tree technology to investigate each critical part of the human body and its interactions, creating a new dataset that can accurately capture and articulate body motion for further identification verification [5]. Zhang H devised a semantic based human motion classification system that integrates multiple datasets to establish a motion model with specific semantics. This model can precisely identify motion behaviors based on varying features by linking the detected motion sequences with DTW [6]. Ji and his team utilized a two dimensional hidden variable approach and the complexity of human activities to build a new model for more effectively capturing and analyzing joint position data, enabling the creation of a series of motion templates for enhanced prediction and analysis of joint position information [7]. Yuan and fellow researchers leveraged the geometric structure of human joints and planes to develop a feature matrix for capturing and analyzing various complex motion states, alongside a framework for accurately defining and evaluating complex motion states, thus allowing for the automatic detection of uncertain motion trajectories [8]. This paper introduces an innovative method for capturing sports training trajectories, which employs the mean shift algorithm to transform the motion status of the human body into visual images and utilises the colour information of the target object as a feature to track motion trajectories effectively [10].

2. Physical sports Player Training Individual Modeling

To enhance the clarity of motion data, the human body is represented as a skeletal framework comprising 16 joints, each connected by its own coordinate system. Within this skeletal framework, the movement state of child joints can be associated with parent joints or adjusted independently based on their specific traits. Conversely, the motion of parent joints is completely unaffected by external influences [11, 12]. To simplify the complexities associated with Euler angle representation, quaternions are utilized to depict the rotational state of each joint, while $m(t)$ denotes the motion data for every frame during physical training of athletes, minimizing the likelihood of irregularities in the model.

$$M(t) = (p_1(t), q_1(t), q_2(t), \dots, q_n(t)) \quad (1)$$

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 n^{th} joint. By mapping quaternions, we can map them to three numbers in R^3 , resulting in the numerical model of y .

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

To better understand the motion status, we map quaternions to R^3 space and use a linear time invariant system for data dimensionality reduction. The state equation of this method can be represented as follows

$$\begin{aligned}x_{t+1} &= Ax_t + w_t \\ y_t &= Cx_t + v_t\end{aligned}\quad (3)$$

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

2.2 Effectively Capturing Trajectory Data Using Mean Shift Algorithm

In athletic training, it is essential to capture swiftly moving targets against intricate backgrounds. Consequently, this research employs the mean shift algorithm to monitor the motion path of the target [13-15]. The mean shift algorithm serves as a non parametric method for kernel density estimation, determining probability density through gradient iterations. It facilitates rapid matching without reliance on specific parameters. The kernel density estimation method utilized in the algorithm is as follows: Upon tracking the target's position, the trajectory data collection is finalized based on the feature information derived from the mean algorithm. The color information remains consistent even when the target experiences translation, rotation, or deformation, making it one of the most dependable features within the image. This study employs the color histogram technique to depict this. The detailed procedure is as follows: define a collection of N samples within the set $X = \{X_1, \dots, X_T\}$, with its probability density function expressed as $p(x) = N(x, o, N)$, where o represents the mean vector and V denotes the covariance matrix. Assuming the training target is elliptical, the initial selection of the target for the current frame is set up, where X indicates the pixel positions occupied by the athlete as a whole, starting at o , and T represents the motion cycle.

In recent years, advancements in software and hardware technology, combined with decreasing costs, have led to a surge in the popularity of motion capture systems. Optical based 3D human motion capture techniques have become a significant method for acquiring human motion data, resulting in the creation of extensive human motion capture databases, which are progressively expanding in size [16-18]. Human motion capture data effectively retains movement details and accurately documents the trajectory of human actions. This data is characterized by high accuracy and quality, making it widely utilized in computer animation.

Motion capture amalgamates mechanical, electronic, optical, and computer graphics technologies to record performers' movements, subsequently driving virtual character technology through this motion data. It finds diverse applications across medical science, gaming, film, and animation. This technology is capable of precisely measuring and documenting the movements of objects within three dimensional space, recording the positions of multiple joints and bones in the human body by affixing sensors to critical locations on the moving object.

The information is subsequently analyzed by a computer and stored in a format that can be utilized. Standard motion capture systems are primarily comprised of four components: sensors, signal capture units, data transmission units, and data processing units. Sensors are employed to monitor the paths of moving objects and are positioned on specific areas of the object as required. The signal capture unit is tasked with acquiring the spatial position signals of the object. Data transmission units relay the captured position signals to the computer for immediate processing. The data processing unit analyzes the gathered data using both software and hardware for further examination.

2.3 Description of Motion Capture Data Behavior Sequence

By creating a model that can depict human motion behaviors, we can implement the approach illustrated in Figure 1. Initially, we must input a collection of high dimensional data points into the model and document their locations and dimensions. Then, we can develop a model that represents human movement by assessing the density and distance between two models based on their locations and dimensions. Ultimately, we can merge the inputs and outputs of these models to formulate a model that characterizes human motion. By obtaining the original motion data, we can convert them into a sequence of texts to enhance the explanation and comprehension of human activities.

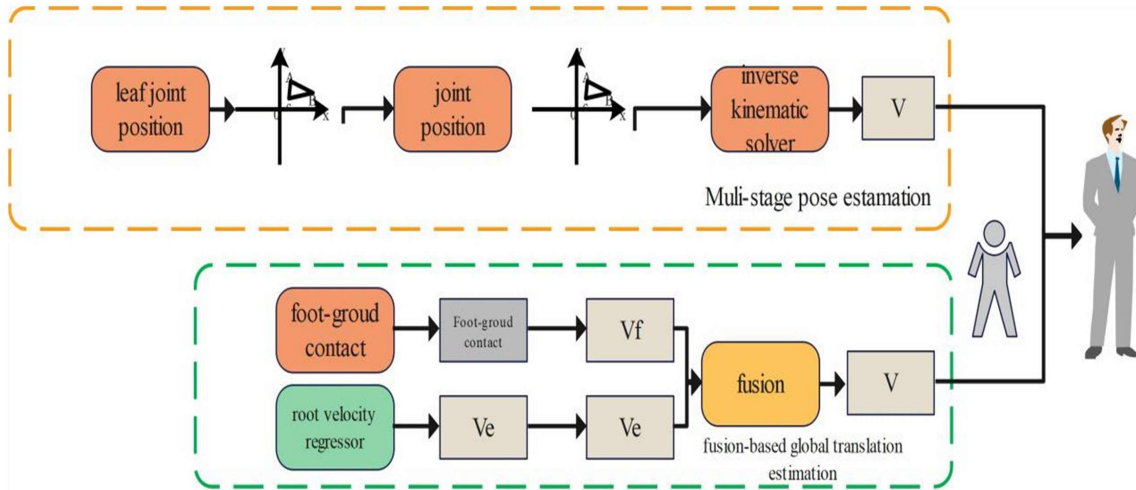


Figure 1. Process Diagram of Behavior Sequence

Through the utilization of clustering techniques, a comprehensive sequence of behavior can be efficiently established. Specifically, the original motion frames may be viewed as high dimensional spaces. The frame number and the distance to the other two spaces are recorded, thereby constructing a complete behavior sequence. Sub-I discovered that conventional methods for evaluating the distance between two frames are restricted to assessing the positions of just two key points, lacking additional measurements of other critical points, which inhibits the accurate identification of more intricate movements. Consequently, by employing Motion Field technology, we can assess the posture and speed of two frames to delineate the similarity between the two points more precisely. The human body structure comprises a complex framework consisting of 31 segments, each possessing 62 independent degrees of freedom. The posture of the i^{th} frame operates independently, and its dimensions are determined by the size of each segment, which is an Euclidean distance. In this scenario, the motion of the final frame will mirror the movement of the preceding frame.

3. Experimental Design and Results Analysis

3.1 Experimental Design

The extraction of features from human motion capture data holds considerable value for the reuse and management of such data. As motion capture technology continues to advance, the growing volume of data in the repository may create challenges in handling a significant amount of pertinent information. For the existing action capture data within the database, what methods can be employed to choose the required action class

data for humans? By extracting features from human motion capture data, we can identify the characteristics of specific actions. Based on the various features extracted, action sequences can be analyzed, retrieved, recognized, and annotated, which facilitates the reuse and management of action class data. In this paper, we leverage Muller's technology to create a novel computer vision technique utilizing the principles of DTW to establish a correlation feature matrix comprising 32 Boolean types that represent the geometric positions of different body parts. This allows for the rearrangement of feature matrices of similar actions over a set period, enhancing our understanding of their interrelations. Following this reconstruction, we can apply a new approach to characterize each movement's behavior. Initially, we must compute their square and negative phases, then use our mathematical methodology to the calculations. After the reconstruction phase, we can utilize a fresh technique to articulate each movement's behavior.

3.2 Results Analysis

By continuously monitoring an athlete's training path across two sets of image sequences, we have identified a new method for capturing motion trajectories that accurately records the athlete's movements while maintaining low false detection rates. We compared this approach with Space Mocap and MATLAB-based trajectory capturing techniques to validate its efficiency. The results depicted in Figure 2 indicate that while the accuracy and error rate of the Space Mocap method are considerably superior to those of the MATLAB approach, the accuracy and error rate of the mean shift method introduced in this article surpass both. This advantage arises from its lack of necessity for parameter adjustments and its capability to effectively account for external influences such as object deformation and motion speed.

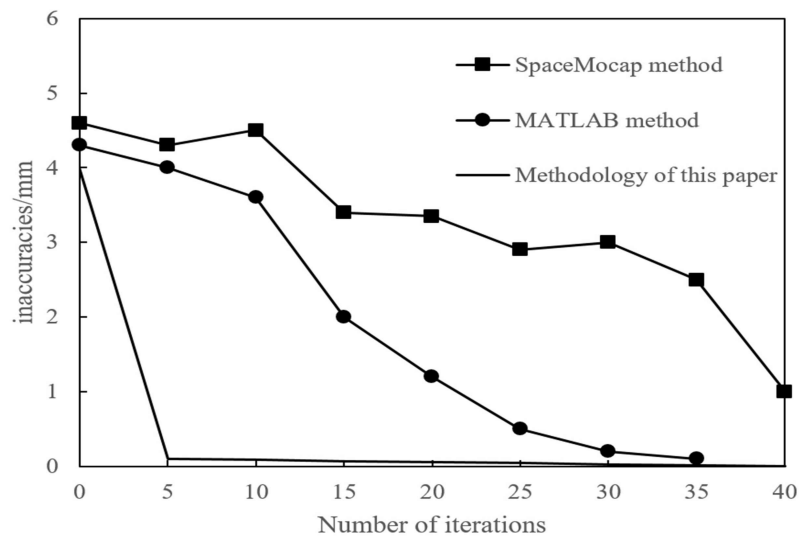


Figure 2. Differences in Accuracy and Error Rates of Trajectory Data Trained with Different Methods

To derive their average value, we calculate the DTW distance between each motion template and its corresponding sequence. For instance, when utilizing the “walking” motion template, we can determine its average distance to the “chopping” motion behavior presented in Figure 2, yielding a result of 29.12. Our calculations reveal that the distance of a motion template along the main diagonal of the two images is less than its distance at other locations, suggesting that the average distance of a motion template across multiple sequences of the same behavior is smaller than that across multiple sequences of differing behaviors. Research findings indicate that there is minimal disparity between a motion template and sequences of the same type of

motion behavior. In contrast, a notable difference exists when compared to sequences of various motion behaviors. This suggests that the algorithm is effective in capturing specific types of motion behaviors accurately.

“Unfamiliar” behaviors can be categorized based on their positions and are split into two main groups: the first consists of fundamental activities like squatting, single leg jumps, stationary rotations, and jumping; the second encompasses basic static actions, including chopping, lifting, drinking, sideways waving, and so forth. Their activity pathways are illustrated in Figure 3. The “motion sequence” depicted in the figure illustrates 110 human motion capture data sequences targeted for recognition. “Manual recognition” denotes the results obtained through manual methods, which act as the benchmark in the experiment. “Original template” refers to the recognition outcomes derived from the initial motion templates, which are created by calculating 39 relational feature functions proposed by Muller. “Improved template” signifies the recognition results based on the enhanced motion templates, which are formulated by calculating 32 relational feature functions. The diagonal line in the “manual recognition” outcomes indicates that the motion behavior present in this sequence does not semantically correspond to a complete motion behavior; it might represent a transitional phase between two actions or an irrelevant motion segment. This occurrence arises from the segmentation technique used. Since the motion behavior segmentation method applied in this study cannot guarantee 100% accuracy, erroneous segmentation leads to motion segments that fail to represent a complete motion behavior. Consequently, if these sequences obtained from inaccurate segmentation are utilized as the motion sequences to be recognized, the correct identification should be “unknown.”

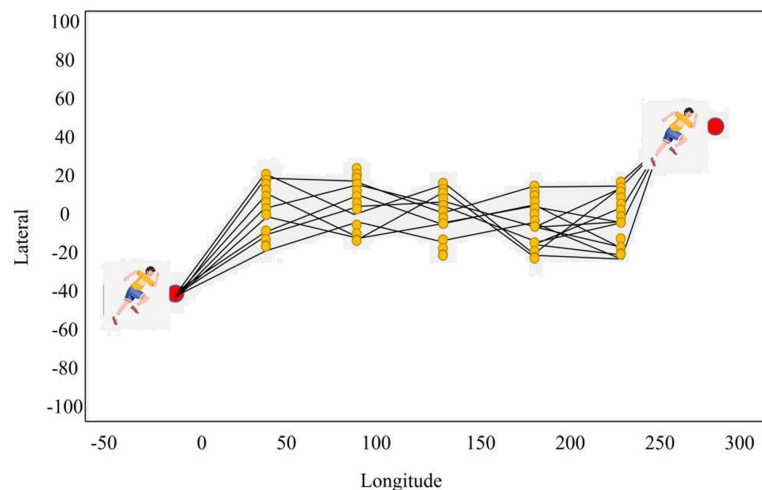


Figure 3. Movement Trajectories of Physical Sports Players

4. Conclusion

While observing training videos, we notice that an athlete’s body posture may undergo significant changes and become obscured. Thus, tracking the athlete’s walking path poses considerable challenges. To address this issue, we employed the mean shift algorithm and conducted an analysis using color information. Testing revealed that this algorithm has a high accuracy rate with minimal error probability. We found this novel technique to be effective, as it can finely segment digital representations of various human activities and swiftly identify active states and durations that align with previous patterns.

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