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Research progress on model and analysis method of jumping posture in figure skating

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Abstract:

This paper reviews the human skeletal dynamics model employed in figure skating pose analysis. The prevailing contemporary technological framework is predicated on the integration of artificial observation assistance, miniature wearable unit data, and dynamic human pose recognition, a suite of technical methodologies. This paper assesses the technical tools and advantages and disadvantages of these three approaches, with a focus on neural network-based multi-fusion 3D pose recognition. Finally, the study offers a discussion of the potential for hardware and software performance improvements to facilitate more accurate analysis of various figure skating models. This, in turn, could guide and train athletes to achieve more difficult movement breakthroughs. Moreover, such improvements could enhance the enjoyment of sports competitions.

Keywords: Figure skating; human posture recognition; multi-view fusion.

1. Introduction

The figure skating has grown relatively rapidly during the past decades, especially in the area of singles skating jumps. Since the 2022 Winter Olympics, athletes who have completed more than two distinct quadruple jumps have been awarded medals in the senior competition[1].

It is worth of mentioning that jumps constitute one of the most highly-scored maneuvers in the context of high-level skating performances. Skaters accrue points for each maneuver[2], with the number of spins completed in a jump maneuver being a significant factor in determining the number of points awarded. The capacity to execute a series of rotations around the longitudinal axis of the body is of paramount importance to the performance of a figure skater. The execution of these jumps necessitates not only technical expertise but also the capacity to withstand significant forces. The study of posture in figure skating enables the implementation of more objective judging standards[3] across a range of events. It facilitates the reduction of scoring ambiguities and judging errors that are often introduced by human observation, and it enhances the audience's entertainment experience. Furthermore, the data-based analysis of jumping posture plays a significant role in enhancing athletes' training posture, which is conducive to understanding athletes' behaviors and ultimately leads to improved performance in competition.

The analysis of figure skating stances has undergone significant evolution over several decades, progressing through three distinct stages of development. The initial approach was primarily based on manual observation of event videos and image recordings, which gradually evolved into a more sophisticated posture analysis technique involving the collaboration of athletes wearing sensor devices and manual video recordings. Currently, the most prevalent application is three-dimensional(3D) posture analysis based on multi-sensor fusion, integrating data from images, computer-aided visual analysis, and posture sensors, among other sources. In 2005, Deborah L. King et al. employed image and video analysis[4] of competitions to ascertain athlete performance. This process entails meticulous observation of the figure skater's movements, frame-by-frame determination of successful completion of the jump, and biomechanical analysis of triple and quadruple jumps. The insights derived from this analysis are then employed to assess the athlete's strength and to inform the development of their training program.

The standardization of skating movements is predominantly influenced by the angular velocity, rotation angle, and rotation circumference of the athlete. Typically, these parameters are analyzed through the utilization of calibrated multi-camera capturing of the movements, complemented by human eye observation[5]. This approach is employed to procure the necessary data for a comprehensive assessment. Manual analysis of images and videos is more convenient, but figure skating involves unusual postures that differ from those of common sports. Firstly, the presence of abnormal posture is indicative of multiple body movements that are easily confused and difficult to recognize, even by the human eye. Secondly, figure skating competitions are typically held in large venues, allowing for ample range of motion by the athletes. However, in certain instances, the target may be situated at a considerable distance from the camera, resulting in unclear and difficult-to-detect content projected onto the screen.

To rectify these issues, Waseda University organized an inaugural test for members of its Tian Figure Skating Club. Athletes were permitted to wear the sensors during weekly jumping exercises. The testers then collected and analyzed data from the sensors. Wearable devices impose no supplementary demands on the athlete and are more oriented towards the human form. This, when combined with high-speed video capture, engenders a clearer and more comprehensive image[6]. Local confidence estimates for each articulation point are obtained by acquiring video and image data in conjunction with the node localization of the motion sensors. These maps reflect the two-dimensional(2D) gesture structure of each movement.

In order to enhance the precision and reliability of postural movements, the researchers implemented computer vision techniques as an alternative to the manual analysis of individual frames. These techniques involved the identification of discrete points in the view through the use of heat maps, the acquisition of sufficient discrete points to confirm the precise position of each joint and the reduction of the impact of low-strength confidence maps on the overall data set to improve the accuracy of the data analysis. However, despite the integration of the wearable device and the computerized view to modify the human eye observation, there are still some unavoidable problems. For example, the visual dead space in the 2D view will make the image ambiguous[7]. In order to resolve the aforementioned issue, the researchers' primary focus has been on the implementation of a combination of a three-dimensional view and wearable devices, utilizing six monocular cameras to the greatest extent possible in order to circumvent the utilization of 360-degree views in dead space. The integration of binocular stereo vision, which emulates the visual effect experienced by the human eye, is intended to facilitate the formation of stereoscopic vision. The wearable device has been shown to determine the 2D/3D posture of the athlete and confirm the angular velocity difference between body parts during the jump. The device then analyzes all parameters to derive the optimal jump preparation position. Despite their extensive implementation in action recognition, yielding favorable outcomes, the limitations imposed by low feature dimensionality and inadequate time scale have significantly constrained the advancement of these methodologies. In the context of gesture recognition algorithms, early recognition algorithms relied on hand-designed feature operators to locally characterize the target.

The advent of neural network theory has precipitated the rapid evolution of numerous neural network methodologies for human movement recognition. These methodologies leverage skeletal points as features, exhibiting superior accuracy compared to conventional manual features[8]. The aforementioned recognition algorithms can be classified into the following categories: recursive neural network-based, convolutional neural network-based, and graph convolutional neural network-based, among others. A significant number of classical recurrent neural network algorithms[9], including LSTM and RNN, are frequently employed to model subclassification of skeletal point sequences characterized by dynamic durations. In the context of human action recognition using graph convolution, the deep learning network model necessitates a shift in focus from the content information of the image to the movement information of the human body. The ability to recognize key markers in an image facilitates the enhancement of the recognition effect.

In this paper, we reviewed human-bone dynamics models

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utilized in traditional pose analysis and summarized three dominant technical approaches to pose analysis, while more focusing on multi-fusion 3D posture recognition. The continuous development of machine vision and hardware has led to significant advancements in multi-fusion 3D view motion analysis, resulting in enhanced precision. The refinement of algorithmic performance has enabled more accurate analysis of various motion models.

2. Basic human model of figure skating

2.1 Human dynamics simulation methodology

Figure skating is an ice sport that originated in the Netherlands during the 12th century[10], from which it underwent rapid development in Europe and North America, including Germany, the United States, Canada, and other European nations. The sport of figure skating is typically characterized by a state of dynamic equilibrium; therefore, the dynamics method stands as a particularly apt approach for its analysis.

Human dynamics is a branch of study that emerged from multibody dynamics, with the human being in motion serving as the primary object of investigation. Multibody system dynamics is chiefly the study and analysis of the kinematic and dynamic characteristics of multibody systems subject to specific constraints. Multibody systems are comprised of multiple rigid and flexible objects interconnected by hinges. The earliest studies of the dynamics of multi-rigid-body systems, such as the method proposed by Hooker[11] and Margulies in 1965, evolved on the basis of the Newton-Euler equations. Yeadon employed a systematic approach[12] in his study of freestyle skiing, utilizing dynamics to analyze its spatial motion and torsion. He integrated these research theories with those of other sports, including diving, gymnastics, ice skating, and wrestling, among others.

Presently, researchers are focusing on enhancing the biomechanical model of human movement. These efforts aim to augment the model's realism, thereby ensuring its closer alignment with actual human movement. Additionally, there is a focus on refining multi-body dynamics algorithms to enhance computational efficiency. Additionally, others employ the analysis of human motion data to design human models that exhibit motion responses corresponding to the structural characteristics of the human body. This approach has been demonstrated to achieve successful simulation of the motion represented by the data through empirical examples. A plethora of methods have been employed, including user evaluation[13], which is predicated on the subjective experience and sentiments of observers (e.g., high-level athletes, coaches, etc.) with extensive experience in the field. These observers are tasked with assessing the veracity of the simulation results. Subsequently, a comparison is made between the simulation results and the original motion capture data. This comparison is used to verify the characteristics of the human body movement being simulated. Additionally, it is used to analyze the forces on various body parts during movement. Finally, a comparative test is carried out with the help of Newtonian mechanics. In order to achieve non-invasive, simple, and accurate detection of real-time dynamic changes in musculoskeletal loads during exercise, as well as to compare and validate muscle force measurements with modeling simulation results, the following research directions are recommended for future investigation.

2.2 Movements in figure skating

The technical movements of figure skating include jumps[14], spins, lifts, footwork and turns, and swallow steps. In the discipline of Single Skating, these elements include jumps, spins, steps and turns, and swallow steps, among others. Among all disciplines, single skating demands the highest level of jumping proficiency, thus representing the pinnacle of jumping complexity that a skater can attain.

The ability to differentiate between various jumps is predicated on the analysis of movement patterns during the jump, while the capacity to discern between skating jumps[15] is contingent on the identification of specific body postures, such as the pointing foot and the utilization of the blade, concurrent with the jump. The fundamental distinction between rotational movements and other forms of movement lies in the recognition of the spatial characteristics inherent in human postures. The recognition of rotational technical movements in skating also requires rating recognition[16], and the majority of rating points are contingent on the transformations between underlying rotational movements. These transformations can be interpreted as a piece of sequential information in the time dimension.

The challenges associated with recognizing figure skating movements can be categorized into two primary aspects. Firstly, the ability to discern more intricate spatial characteristics in the movement, grounded in the localized human body segments, is paramount. A notable illustration of this is the utilization of the inner and outer edges during jumps, which plays a pivotal role in the assessment of movement type. Secondly, there is a necessity to adopt an alternate scale of perception regarding the temporal dimension. In the categorization of technical movements, such as jumps, it is imperative to pay greater attention to the key frames of the jump.

2.3 Human structural analysis and modeling

The human body is a highly intricate system, necessitating the analysis of its biomechanics through modeling to comprehend the underlying mechanisms governing movement. The human skeleton is an effective model for representing the dynamics of the musculoskeletal system. This model is employed to analyze the human system, and it is simplified for the purpose of comprehension. The human body is composed of a macroscopic structure that can be primarily categorized as either bones, joints, or muscles. Bones are regarded as rigid bodies that collectively form the robust human skeleton. The bones are interconnected by joints, with muscles acting as the primary force that enables movement of the bones around the joints, as illustrated in Figure 1 a.

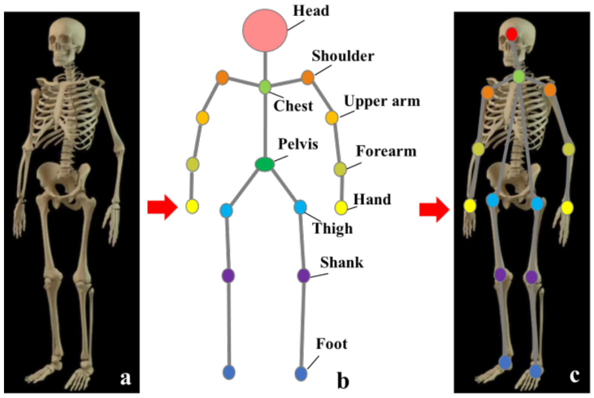

Fig. 1. Modelling step of human structure. (a) Origin data(photo); (b)Sample caption.

Bony structures within the human body are interconnected by joints, which can be conceptualized as various forms of hinges, contingent upon the degree of freedom exhibited by these joints during particular movement patterns. Influence of these factors on human motion is direct, and their concern lies outside the realm of involuntary muscles governed by human consciousness (e.g., the cardiac muscles that comprise the heart's pacemaker conduction system). As illustrated in the figure, the skeletal model can be conceptualized as a multi-rigid-body system, thereby enabling the facilitation of modeling calculations in the context of specific movement studies. These calculations can be streamlined into various hinges according to the joint degrees of freedom (Fig. 1b), and commonly employed algorithms can be distilled into a 14-node model (Fig. 1c). Consequently, the simplified human skeletal joints can be utilized as the focal point of mechanical analysis to investigate their forces and responses during the performance of figure skating. In the domain of figure skating, the conventional approach entails the utilization of high-speed cameras and assorted equipment to assess and analyze the stability of the jumping technique. This methodical process facilitates the determination of optimal jumping speed, time, air height, stopping time, turning speed, successful landing body angle, and other sports technical indicators. This technical approach facilitates the analysis of figure skating jump technical principles, the exploration of its action structure, and the identification of underlying laws.

3. Posture recognition methods

3.1 Posture estimation by manual observation

In the domain of figure skating, the conventional approach entails the utilization of high-speed cameras[17] and assorted equipment to assess and analyze the stability of the jumping technique. This methodical process facilitates the determination of optimal jumping speed, time, air height, stopping time, turning speed, successful landing body angle, and other sports technical indicators. This technical approach facilitates the analysis of figure skating jump technical principles, the exploration of its action structure, and the identification of underlying laws.

Typically, a high-speed camera is employed to capture the start-finish frames of an athlete's jumping action within a calibrated space. The captured motion video is then processed using the Ariel Parsing System (APAS System), and the raw data is smoothed using low-pass filter smoothing. The analysis of the athlete's technical movements is obtained objectively based on the skeletal node model. Secondly, an experienced referee is sought to obtain an aesthetic score based on a combination of video judgments and scores given by the parsing system.

Secondly, in order to facilitate the evaluation of the video system, an electromyography (EMG) tester can be employed to synchronize the EMG signals with angular velocity, acceleration, as well as transverse and longitudinal velocities during the jump. These EMG signals are then synchronized with the kinematic data obtained from the high-speed camera, thereby ensuring a comprehensive and precise data set. The analysis of the kinematic parameters, including torso center of gravity (CoG) displacement, angular velocity, and longitudinal torso velocity is of paramount importance to the scoring system, affecting the geometric edges, mass, and position of the landing site.

3.2 Posture estimation based on wearable sensors

In the context of figure skating jumps, researchers predominantly utilize Inertial Measurement Unit (IMU sensors), which are wearable devices that facilitate the

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measurement of attitude and position. These Inertial Measurement Unit (IMUs), which comprise accelerometers and gyroscopes, serve to monitor three critical parameters in the domain of figure skating: the number of jumps executed, the height achieved during each jump, and the rotational velocity of the skater. To mathematically describe the motion of each limb, it is necessary to construct a series of coordinate systems[18]. The three primary coordinate systems employed in wearable human motion capture systems are as follows: a reference coordinate system, a sensor measurement coordinate system, and a human limb coordinate system.

In figure skating, the angular velocity of an athlete's rotation exhibits variability during jumps of uniform rotational circumference. The magnitude of the angular velocity is contingent on the angular momentum accumulated during the cushioned jump, which is derived from two sources: the moment of momentum gained by agitating the ice, and the moment of momentum formed by the initial horizontal velocity around the longitudinal axis of the body. Adequate cushioning has been shown to enhance the force exerted by the stirrups; however, it concomitantly results in a reduction in horizontal velocity. Consequently, in order to ensure a stable jump, it is imperative to minimize the reduction in horizontal velocity, thereby maximizing the efficiency of energy conversion.

Luinge et al. combined a Kalman filter[19] based on a human kinematic model in order to separate gravitational acceleration and linear acceleration from accelerometer measurements. They used the gravitational acceleration estimate in order to compute the tilt angle of the limb. This method is superior to processing that employs a low-pass filter[20].

Due to the effect of linear acceleration, accelerometer-based human motion capture systems are only suitable for stationary or slow-moving occasions. Furthermore, the measurement error of such systems increases significantly when the human body moves vigorously. Consequently, numerous technology companies have dedicated significant efforts to the development of inertial motion capture systems, which have been successfully commercialized. The most notable systems include the MVN inertial motion capture system developed by Xsens in the Netherlands and the 3DSuit inertial motion capture system designed by Innalabs in the United States.

Shown in Figure 2, the MVN winda is a wireless inertial capture version with sensor nodes and cables embedded in a straitjacket for optimal ease of wear. The complete system consists of 17 MTx inertial measurement modules and one Xbus Master module. Each MTx inertial measurement module contains a 3-axis gyroscope, a 3-axis accelerometer, a 3-axis magnetometer, and a thermometer, which are integrated with a multi-sensor fusion algorithm to facilitate the acquisition of precise 3D attitude measurements.

Fig. 2. MVN winda 3DSuit on motion capture and action recognition.

The accuracy of the inertial motion capture system is influenced by numerous factors. Firstly, high-precision and low-latency limb attitude measurement is paramount for human motion capture and reconstruction. Consequently, it is essential to integrate it with multi-sensor fusion algorithms to ensure the acquisition of accurate and stable attitude measurements. Secondly, due to the irregularity of the human body's limb surface, it is difficult to ensure that the sensor's measurement coordinate system is completely overlapped with the human body's limb coordinate system when the sensor is worn. Therefore, it is necessary to convert the sensor's measurements to the human body's coordinate system through initialization calibration.

Consequently, the inertial sensor-based system can reflect the trajectory and attitude by measuring the biological events in figure skating jumping. Specifically, the system measures the contact and flight time from picking the tip to landing, and secondly, it measures the rotational speed during the flight. Finally, the system analyzes the attitude change by using computer software algorithms. The sensor comprises an accelerometer and a miniature three-axis gyroscope affixed to the athlete's back, with a sensitivity ranging from 4000 to 5000°/s.

3.3 3D Posture establishment and estimation

The jumping posture of figure skating can be decomposed into multiple motion frames. For the space corresponding to each frame, 3D points are output, which are composed of joints of human skeleton structure. The multi-view 3D human pose estimation scheme is fundamentally predicated on a machine-learnable triangulation method[21], whereby the 3D characteristics/ information of the overall target are obtained by extracting multiple 2D information. Multi-semantic annotation can be used to synthesize 3D poses of the human body through 2D poses[22] and multi-view recordings, as shown in Figure 3.

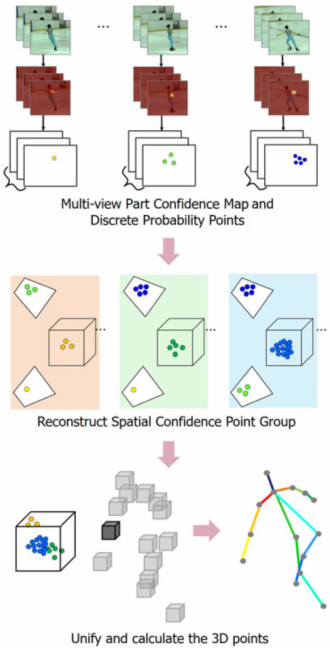

Fig. 3. Reconstruction schematic for multi-view 3D pose estimation [ref [23]].

Multi-view fusion techniques have been demonstrated to be superior to monocular vision methods for 3D pose estimation. This is due to the ability of multi-view fusion techniques to extrapolate the geometric effects of multiple views[24]. Consequently, multi-view fusion techniques have been utilized in many research efforts for pose estimation by 3D inference methods. Neural network (CNN) algorithms build 3D models from multiple perspectives, focusing on human body shape and human movement. Based on multi-view 3D fusion, a spatial/temporal filtering is required to smooth the human motion data[25] and obtain accurate human motion analysis.

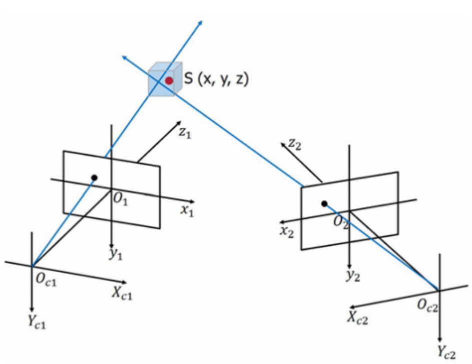

Fig. 4. Typical binocular stereo vision principles.

In 3D pose estimation, camera-based stereo vision is an important part of the system. Binocular stereo vision is based on the structure of the human eye, imitating the human eye to capture three-dimensional information of images and objects. Shown in Figure 4, binocular stereo vision consists of two cameras (CCDs) that form a triangular relationship with objects in space[26]. When two cameras shoot an object at the same time, different images of the same scene can be obtained, and the position deviation of the projected image can be calculated through triangulation, and the depth information in the three-dimensional coordinate system can be restored. The binocular stereo vision structure uses the calibration theory of the camera to calculate the relationship between the space point and the corresponding pixel point and uses this to estimate the depth value of the space point. Finally, according to the calibration matrix of the camera and the two-dimensional pixel projection of the spatial point in the viewing angle, we can calculate the three-dimensional point coordinates in the space. In larger spatial distributions, such as those associated with skating rinks, the use of multiple cameras for projection capture was employed with the objective of maximizing data. As illustrated in Figure 5, this approach was implemented to ensure the comprehensive collection of relevant information.

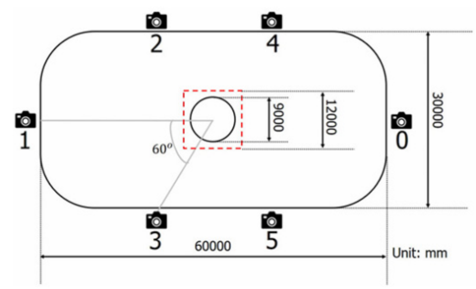

Fig. 5. Typical schematic of a multi-camera based on rink site definition

Graph Convolutional Networks have achieved considerable success in a variety of applications and have demonstrated enhanced accuracy in human movement recognition. The temporal sequence is fully acquired, and the coordinates of the skeleton information are processed by vectorization to effectively extract the features of the video or image[27]. Furthermore, the incorporation of a multi-scale sptial-temporal graph convolutional network, augmented by an attention mechanism, has been demonstrated to enhance the extraction of temporal features, thereby facilitating a more comprehensive and nuanced understanding of human movement.

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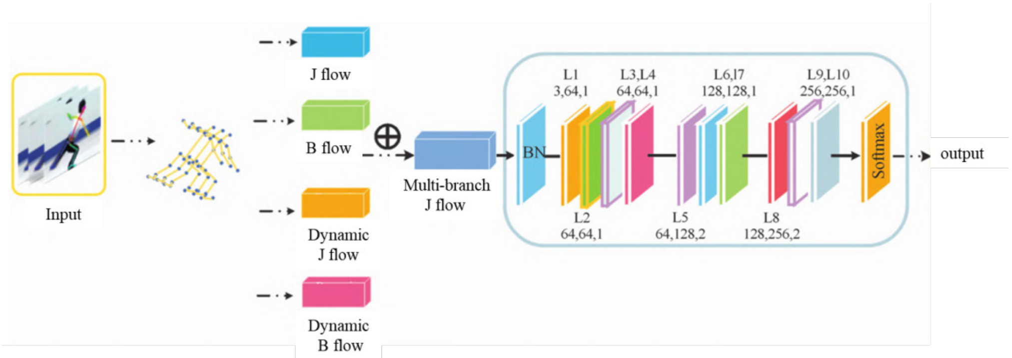

Fig. 6. Network schematic of spatial temporal graph convolutional networks, ST-GCN.

As illustrated in Figure 6, the process of establishing a pose typically unfolds as such: initially, the skeleton sequence of the action samples is extracted through the implementation of the human pose estimation algorithm Open Pose[28]. Subsequently, the extracted sequence is then introduced into the network for the purpose of feature extraction, with the objective of eliminating background noise interference. The network model extracts four branches of features from the skeleton sequence: joint static flow (J flow), bone static flow (B flow), joint dynamic movement flow (Dynamic J flow), and bone dynamic movement flow (Dynamic B flow). These features are then fused into a shared feature block of Multi-branch flow. In the subsequent stage, the deep temporal characteristics and key spatial information of human motion are captured by a multi-scale spatial-temporal graph convolutional network fused with attention to the Multi-branch flow. The network comprises attention spatial -temporal graph convolution modules arranged in 10 layers (L1-L10). The three parameters of each layer, designated as Li (i:1-10), denote the number of input channels, the number of output channels, and the step size, respectively. Finally, Softmax is utilized to discriminate the more accurate actions. This approach enables the capture of multi-scale timing characteristics, facilitating the recognition of more precise actions.

4. Conclusion

The recognition of human motion represents a significant frontier in the field of computer science, with considerable research importance. The development of algorithms for this purpose has led to their application in various domains, including motion content analysis, human-computer interaction, video synthesis, and video retrieval. The simulation and analysis of sports biomechanics constitute a multidisciplinary and comprehensive research topic, with investigations encompassing sports biomechanics, multi-body system dynamics, robot dynamics and control, numerical optimization, and related fields. In order to enhance the performance of young figure skaters, it is essential to comprehensively understand the human body structure and motion control model. The complete figure skating jumping action can be restored by utilizing multi-sensor data. The obtained data holds greater significance as a reference, facilitating more targeted research on figure skating sports technology and enabling the development of optimal technical movement guidance.

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