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Research Article

Evaluation Algorithm of Fencing Athletes' Strength Distribution Characteristics Based on Gait Tracking

Zhengwei Fei and Chuanjie Zhao

Shanghai University of Sports, Shanghai 200438, China

Correspondence should be addressed to Zhengwei Fei; feizhengwei@sus.edu.cn

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Human motion capturing techniques are used in various fields such as surveillance, healthcare, and sports to analyze, understand, and synthesize kinematic and kinetic data. Among the mentioned application areas of motion recognition techniques, sport is an essential sector in which it is extensively used. The dynamic and kinematic performance of the three joints of the lower limbs in lunge movement is the main factor affecting the lunge speed of the fencers. Fencing is an open-skill combat sport in which complicated body movements and effective game techniques are required. The extremely nonlinear human movements, muscle dynamics, and foot-ground contact make athletic gait analysis a difficult topic in biomechanics. At present, there are no comprehensive and systematic research results on the impact of the dynamic and kinematic performance of the ankle, knee, and hip joints of lower limbs on the lunge speed. Based on the gait tracking algorithm, this study compares and analyzes the dynamic and kinematic performance of lower limbs ankle, knee, and hip joints in the lunge of fencing athletes at different levels and discusses the influence of the dynamic and kinematic performance of the three lower limbs joints of fencing athletes on the lunge speed. This study mainly focuses on, (1) exploring the dynamic and kinematic influencing factors of the peak horizontal speed of the center of gravity of fencing athletes' lunge movement, (2) to verify whether there is a difference in the lunge speed of fencing athletes at different levels and analyzes the reasons for the differences, (3) to explore the ankle, knee, and the differences of hip joint dynamics and kinematics, the causes of the differences, and to analyze the influence of the differences on the lunge speed. In this paper, we have used a gait tracking algorithm that evaluates the fencing athletes' strength distribution characteristics. With the help of gait recognition algorithm based on artificial intelligence (AI) technology, the movement posture and gait of fencers can be recognized automatically in real time which is helpful to realize the automatic evaluation of power distribution. The experimental results prove the significance of the proposed model.

1. Introduction

Fencing is a high-end competitive sport that requires high stamina, focus, and a sharp mind. Fencing, the art of using a sword to attack and defend oneself, is presently seeing a renaissance. It is a sport that needs extreme physical and mental stamina. The lunge is the fastest approach to close the gap between the two opponents in the fencing sport [1]. The lunge can start at the tip of the Foil. Because if someone has grabbed the Foil's tip and is dragging it forward, causing the Foil arm to extend quickly and the body to follow. As a result, the athletes believe the blade directs the body's movement [2]. The lunge is performed by flexing and extending the elbow, knee, and hip to propel the body forward and maintain body balance in the guard position. There are many changes in attack and defense. The ability to respond and react to the opponent's quick and unexpected movements is one of the most important characteristics of fencing. The ability of the fencer to manage the attack is greatly reliant on the fencer's agility, quickness, and ability to grasp the chance when the opponent is unprepared [3]. In the face of the opponent's changeable attack, athletes need to adjust their defensive countermeasures all the time and then grasp the opportunity to defeat the opponent. In this process, the athletes need to be highly focused, flexible, and coordinated [4]. So, athletes need strong mental and physical health conditions in order to perform better in the field. In fencing, the role of core force is very important. Therefore, this paper discusses the role of fencing athletes' core strength training and its scientific and reasonable training methods.

Fencers should complete a series of flexible offensive and defensive actions in fierce combat, which requires having good physical quality, professional skills, especially excellent reaction speed, and coordination [5]. In order to maintain their balance, fencers must overcome instability. In this process, the coordination of the upper and lower limbs on the opposite side plays an important role. The athlete's core muscle group plays a connecting role in fencing by maintaining the balance [6]. In addition, improving the coordination of neuro-muscles and the stability of ligaments, ankles, and knees plays an important role in improving the balance ability. The upper and lower limbs of the human body coordinate movement through the core area, which can control the posture of the human body and then affect the flexibility of the limbs. For fencers, the stability of lower limbs and trunk is very important which directly affects the performance of fencers [7]. Strengthening the strength of the core area can improve the stability of the fencers' pelvis, greatly increase the strength of the body, improve the coordination of the body, and make their fencing movements more flexible and orderly. Therefore, the stability of the core area of fencers is conducive to the control of the distal and proximal ends of the body, and can also promote the stability of the lower limbs, which has a great significance to achieve excellent results.

Fencing athletes exerts their power under unbalanced conditions which requires very high physical coordination ability of athletes [8]. The actual combat posture of fencing is special which include when standing, one side of the body is forward, the knees are abducted, the arms and wrists holding the sword face outward, the joints face inward, when moving, and the forefoot moves forward. If the athletes have poor coordination, it is difficult to complete the above actions. The fencing sports is different from conventional sports and does not conform to human normal behaviors or habits. Fencing is based on a variety of technical and tactical combinations [9]. If athletes want to achieve good results, they must have good coordination, technology, and integrated sports. They show their strongest strength only when the athletes' footwork, technique, attack, and defense reach the coordination, unity and perfect cooperation, and their fencing action meets the standard. To complete the fencing movement with high quality, athletes must have good core strength, enhance the stability and flexibility of various parts of the body, reduce the energy consumption of limbs, and coordinate the body movements to achieve perfect unity [10].

The development of machine learning (ML) and deep learning (DL) brought many different research directions in the academic field such as image processing, computer vision, forecasting, and predictions [11]. The development of these technologies allows computers to perceive human movements through cameras and other devices. The most critical technology in the process of human action recognition is human body posture estimation. A series of features obtained based on human body posture estimation are compared with some standard actions, so as to guide people's motion posture during the exercise [12]. Therefore, the human motion evaluation system has been greatly developed and people's eyes are gradually shifting from professional to portable. Portable is a human motion evaluation system that is not affected by venues and environment, and can improve the quality of people's daily exercise. However, the current human motion evaluation systems do not meet the standards and there are still some shortcomings in the existing systems. One of the commonly used and existing human motion capturing equipment is Kinect [13], but it itself is a device developed for somatosensory games which is expensive and insufficiently developed. The academic community uses Kinect and other equipment as external hardware devices to have good results in the field of human posture estimation and human motion recognition, but these systems are still in the development stage and the accuracy of estimation is unable to reach a good balance [14]. Early human action recognition required the assistance of external equipment to perceive changes in the human posture.

The main contributions of this study include;

(i) In this paper, we have proposed a gait tracking algorithm which evaluates the fencing athletes' strength distribution characteristics. With the help of gait recognition algorithm based on AI technology, the movement posture and gait of fencers can be recognized automatically in real time which is helpful to realize the automatic evaluation of power distribution.

(ii) We summarized the dynamic and kinematic performance of the three joints of the lower limbs in the lunge movement of fencing athletics.

(iii) We also compared and analyzed the dynamic and kinematic performance of lower limbs ankle, knee, and hip joints in the lunge of fencing athletes at different levels and discussed the influence of the dynamic and kinematic performance of three lower limbs joints of fencing athletes on the lunge speed.

(iv) We attained promising results, which proves the significance of the proposed gait tracking algorithm.

The remaining article is organized as follows; Section 2 demonstrates the related work. The material used and the methods followed for the conduction of this study are represented in Section 3, while the experimental results are discussed in Section 4. Section 5 illustrates the overall theme and findings of this article.

2. Related Work

Fencing is an arduous sport in which athletes have more injuries. Due to the characteristics of the event and the particularity of competition, the injured parts of athletes are mostly ankle, knee, and waist etc. [15, 16]. Through core strength training, improving the strength of fencers' muscle groups can reduce their injuries in sports or training. The improvement of core strength makes the athlete's body more and more stable, and the pressure on the spine and related soft tissues in the process of fencing is reduced, so as to reduce the occurrence of lower limb injuries [17]. The enhancement of athletes' core strength is mainly reflected in the speed and accuracy of movement.

Zhang et al. [18] proposed a gait analysis-based walking rehabilitation assessment system. In their proposed model, the accelerometer sensors are used and placed on the subject's body, and then the data generated is collected from the gait cycle. After smoothing, they used it as an input signal for gait features extraction, and then after feature extraction, they forwarded it for classification. In order to evaluate and improve walking therapy, it is necessary to categorize normal and abnormal gait. Using Long Short Term Memory (LSTM) networks and a Bio inspired Algorithm (BIA) framework, Chen et al. [19] created a model that recognizes a sportsperson's activity and motivates an individual to enhance the sports abilities. Action detection and categorization can also be utilised to automatically provide matching or practice statistics. Felipe et al. [20] provide a methodology for evaluating the accuracy of a multi-camera tracking system for tracking top football players' movements in real time. Zhang et al. [21] proposed a research to examine four female top Epee fencers' lunge technique. During a trial match versus Jiang Su Team, the motion was captured using a video camera (50 Hz). A Peak Performance System (PPS) was used to gather and analyze data. The lunge was studied in terms of attacking technique. The kinematic characteristics that were determined were lunge stride length, response time, horizontal velocity of the center of gravity, and time to reach the target. A. Suchanowski et al. [22] presented a research to assess the dynamic model of a fencing lunge performed by a professional athlete using electromyography (EMG) recordings of muscle activity in the extensor carpi radials of the right arm and the rectus femoris of the lower extremities. Żelawski and Hachaj [23] introduced and evaluated a novel motion capture (kinematic) processing and human action detection approach based on topological data analysis (TDA). They described human behavior in terms of topological characteristics. The recognition procedure was based on topological persistence which was stable to perturbations.

2.1. Basic Theoretical Knowledge of Fencing. Fencing sport has a history of hundreds of years. People began carrying swords for the first time in the late 15th century, from which modern fencing began. In 1896, fencing became one of the official events of the first Olympic Games for the first time [24]. Since that time, it has been popularized all over the world. The development of fencing in China began in 1955. Scholars from the former Soviet Union introduced fencing into China [25]. Fencing has achieved rapid development in China and Chinese fencers have repeatedly made good achievements in recent world competitions. Luan Jujie won the first Olympic gold medal for the Chinese fencing team in 1984. Zhongman won the men's fencing championship at the Beijing Olympic Games in 2008. In 2012, Li Na, sun Yujie, Xu Anqi, and Luo Xiaojuan won the women's Epee team championship at London Olympic Games, and Lei Sheng won the men's Foil championship at London Olympic Games. Tan Xue, Wang Lei, and Li Na won the individual events at the world championships. With the emergence of world champions of Chinese fencing team, fencing has also achieved extensive development and popularity in China [26].

2.2. Gait Analysis

2.2.1. Normal Gait. Normal gait refers to the position of the human body when moving from one place to another or walking. Walking is primarily powered by the muscles of the lower limbs and trunk. As a result, central nervous system-controlled walking is also relying on the human body [27]. A sequence of actions is done by combining the pelvis, hip, knee, ankle, and toes. Gait analysis is a way of studying walking rules that uses biomechanics and kinematics to show the essential linkages and influencing elements of gait irregularity in order to guide rehabilitation evaluation and treatments.

2.2.2. Parameters of Gait Analysis. Gait analysis is a sub-branch of biomechanics. Its characteristics can be categorized into the following groups: step length, step breadth, speed, stride, cadence, foot angle, and gait cycle are all time-distance factors. Its kinematics parameters include knee, walking mid-hip, ankle joint motion law, angle-angle diagram, and pelvic position change law. The most often used dynamic characteristics are ground response force measurement and a force platform that can measure the vertical, front, rear, and side force components of the ground reaction force. Walking gait can be accurately detected using a combination of biomechanics and kinematics [28]. Improving the extraction accuracy of human key point coordinates in the image as much as possible and efficient and accurate motion evaluation methods are the top priority of motion-aided evaluation system. Human posture recognition technology based on deep learning is the main method of motion-aided evaluation system in the recent years.

3. Materials and Methods

3.1. Sword Types of Fencing. Fencing events are divided into three different sword types, namely, Foil, Sabre, and Epee. In Epee and Foil events only sword spikes are allowed, and splitting and chopping actions are not allowed. When the sword tip contacts the effective part of the other party and reaches a certain pressure, the spring device at the sword tip is compressed which connects the circuit between the sword body and the athlete's fencing suit, and then makes the referee light on. In terms of sword body weight, Foil has the smallest weight among the three sword types, and the effective part in the competition is the athlete's trunk. Foil has high technical content and strict technical and tactical requirements for athletes. The weight of Epee is the largest among all kinds of swords, and the effective stabbing part is also the largest in the competition [29]. It is effective for athletes to stab any part of the opponent's body in the

Table 1: Basic information of different swords in fencing.

Number	Foil fencing	Heavy sword	Walking rapier
Weight (g)	<660	<890	<450
Sword Body Length (cm)	110	110	105
The blade length (cm)	90	90	88
The sword shape	Quadrilateral prism	Triangular pyramid	Triangular pyramid
Effective target	trunk	the whole body	Head, torso, upper limbs, loves
Available parts	Sword tip	Sword tip	Sword blade and sword tip
Effective stabbing force (N)	>5.32	>8.56	Contact is effective
Preferential hit rule	Yes	No	Yes

competition, and there are few referee factors in Epee that affect the competition. When both sides stab at the same time, if the time interval is within 1/4 second then both sides will score. If it is beyond 1/4 second, stab one side first to score, it is not necessary to judge according to the principle of priority like other sword competitions. Sabre is quite different from Foil and Epee. In Sabre competition, athletes are not only allowed to use sword spikes, but also allowed to use sword blades to chop. The effective hitting parts are athletes' trunk and upper limbs. On the whole, the Foil event has high requirements for the use of athletes' technology and tactics and the flexible use of tactics in the competition, which requires athletes to have exquisite technology and clear mind at the same time [30]. Epee has high requirements for athletes' strength and confrontation. The Sabre competition is the most flexible, requiring athletes to dare to attack, and the use of the blade increases the intensity of the competition. The visual impact of the Sabre competition is more obvious, and the frequency of wonderful confrontation and attack actions of athletes are higher in the competition.

In addition, there are differences in competition venues between different sword types. The length of Epee and Sabre competition venues is 18 meters, and the length of Foil venue is 14 meters. Before the start of the competition, the athletes of both sides hold swords at two meters outside the center line and wait for the referee to announce the start of the competition. After any player of either side scores, both sides suspend the competition, and both sides return to two meters outside the center line to prepare to restart the competition. The rules of the three kinds of swords in fencing are different, but they all require athletes to stab the opponent with the sword at the fastest speed before the opponent takes effective defense and counterattack. Therefore, there are high requirements of speed to attack within the specific time of attack. When the timing of attack appears, then the bow step stab is often the first choice for athletes to attack the opponent. In Epee competition, the use frequency and scoring frequency of lunge are very high. It can be said that the level of Fencers' lunge affects their competitive level to a great extent. Therefore, whether in the daily training of professional athletes or in the fencing research, lunge is an extremely important part. Basic information of different swords in fencing is shown in Table 1.

3.2. Fencing Lunge Stages. The fencing lunge moves from the preparation position to the landing of the front leg, which is fast, coherent, and complete in one go. The fencing lunge is divided into six action phases that, respectively, represent the starting point or ending point of each stage of the lunge, and is shown in Figure 1. The phases are briefly described below.

(a) Preparation posture: in this phase, the lower limbs of the swordsman are the front legs, the opposite side is the rear legs, the body's center of gravity is between the two legs, the elbow of the swordsman is slightly bent, and the sword tip points to the opponent.

(b) Posture with the sword: in this phase, the elbow joint is extended, the hind leg begins to pedal the ground, and the hip joint of the front leg is bent to lift the front foot off the ground.

(c) In this phase, the hind legs continue to push on the ground, and the body's center of gravity begins to move forward.

(d) In this phase, when the athlete's hind leg kicks on the ground, the rear knee joint extends to the maximum, the front leg swings forward quickly, and the body center of gravity moves forward greatly.

(e) In this stage, the hind legs of the athletes are off the ground, the body is in the flying stage, the knee joint of the front leg is stretched as far as possible, and the physical center of gravity continues to move forward.

(f) In this stage, when the athlete's front foot lands then the above steps enter the landing buffer stage.

According to the change of the ground reaction force, the whole lunge is divided into three stages including ground stage, flying stage, and stable stage. The ground stage consists of the front leg and hind leg pushing and stretching. From the hind leg off the ground to the front foot landing is the flying stage. The stable stage is from the front foot landing to the center of gravity stabilization. The stage division of fencing lunge movement is helpful to understand and analyze the lunge movement more clearly because the fencing lunge movement is fast and involves many main joints of lower limbs. Schematic diagram of stage division of fencing lunge is shown in Figure 1.

3.3. Fencer's Lunge Preparation. The preparation posture of the lunge is the same as that of fencing. The distance between the athlete's feet is close to the shoulder width. As shown in Figure 2, the toe direction of the front foot of the Fencer

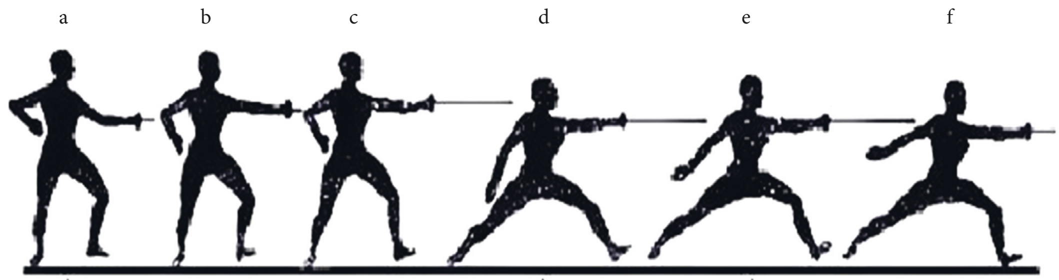

Figure 1: Schematic diagram of stage division of fencing lunge.

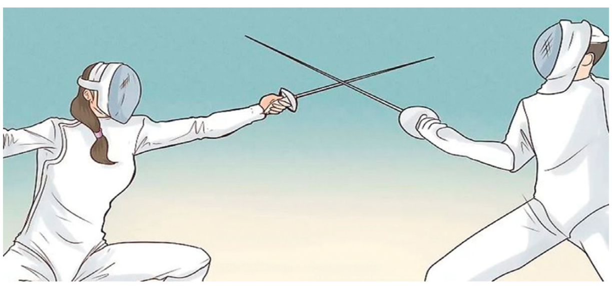

Figure 2: Schematic diagram of feet position of Fencer's lunge preparation posture.

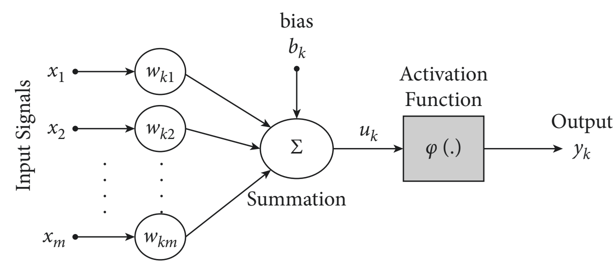

Figure 3: Artificial neuron structure.

points to the opponent and the position of the rear foot is basically perpendicular to the direction of the front foot. The elbow joint of the sword-holding arm bends naturally and the sword tip points to the opponent. The preparation action in this posture can provide the best balance and stability for athletes. It allows athletes to quickly and flexibly switch between attack and defense in the competition. In competition, when the athlete decides to launch the lunge action for the attack, the athlete starts from the preparation position, and the rear foot quickly pushes onto the ground to provide power for the lunge forward. After the front foot leaves the ground, the athlete's body center of gravity begins to move forward, and the lunge action enters the acceleration stage which ends when the rear foot leaves the ground. The acceleration stage is the most critical stage in the lunge. The peak values of power and angular velocity of the ankle, knee, and hip before and after the landing of the athlete's front foot appear in this stage. For the timing of the athlete's movement at the beginning of the fencing lunge, the traditional view is that the swordsman moves ahead of other parts of the body, and the whole lunge is pulled forward by the hand. In the lunge movement of elite athletes, the movement of the swordsman is not ahead of other parts of the body and the movement of the swordsman is synchronized with the center of gravity of the athlete's body. Schematic diagram of feet position of Fencer's lunge preparation posture is shown in Figure 2.

3.4. Artificial Neural Network (ANN). Neural network is a special branch of AI. ANN is a naturally inspired structure which has many similarities with the human brain. A natural neuron consists of neuronal nuclei, dendrites, and axons. Axons are divided into many branches which are connected with the dendrites of other neurons to form synapses. Both the artificial and natural neuron has almost the same structure. It also possesses an operating unit (nucleus), input (dendrites), and output (similar to an axon). Figure 3 depicts the structure of the artificial neuron.

The input part of artificial neuron can be text, sound, image, signal, video, and other meaningful information. The weight is a variable set to expand or compares the strength of the input information. The signal transmitted in the network is changed by changing the weight, so as to realize the effect of modifying the output signal. Bias is an independent element which can add external signals to the activation function, and bias also has a corresponding weight. The function of activation function is to filter the signal and send the signal.

3.4.1. Convolutional Neural Network (CNN). Convolutional neural network (CNN) is a subfield of artificial neural network, which introduce convolution operation on the basis of neural network. CNNs meet transformers (CMT) performs well in many fields especially in image related tasks such as computer vision problems, image classification, semantic image sharing, image restoration, and object detection. It has also been applied in natural language processing (NLP) which can classify text and spoken words in much the same way human beings can. CNN consists of the following subparts.

(i) Basic structure: Generally, CNN has multiple levels, and the content initially transmitted into the input layer can be photos in RGB format or original audio and video materials. In the process of data transmission, CNN processes it through multi-layer mode to extract features. The convolution layer performs convolution processing, the pooling layer performs

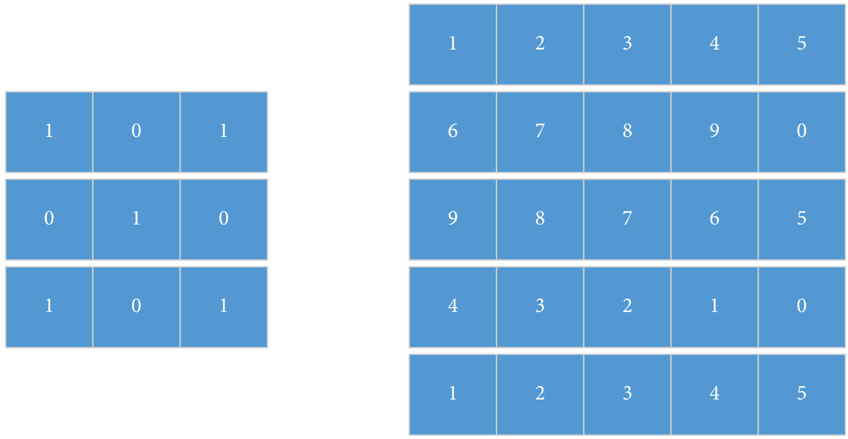

Figure 4: Convolution kernel (left) and input data (right).

confluence processing, the activation function layer performs feature filtering, and the full connection layer performs feature classification processing. The convolution network can output the loss value of each iteration, feed this value back to the network for repeated iteration, and this value will become smaller and smaller.

(ii) Basic components: Convolution operation is the focus of CNN. In the process of network training, data sampling is completed by the convolution layer. In CNN, discrete convolution operation is adopted, assuming that the original data 5×5, and the specification of the corresponding convolution kernel is 3×3. The moving step of convolution kernel is 1, as shown in Figure 4.

Expand the convolution operation on the upper left of the original image. The detailed convolution operation and the results are shown in Figure 5.

The values in the convolution kernel matrix are not artificially specified in the actual training but obtained by the network self-learning. The shape of the convolution kernel can be designed according to the actual scene.

4. Results and Discussion

In the machine learning, the feature extractor is selected, and the parameters of the classifier are trained with data. In high-dimensional space, decent features are not easy to be seen directly by humans in many cases. Convolutional neural network literally includes two parts, convolutional and neural network. In which convolution is the feature extractor and neural network can be regarded as a classifier. Training a CNN model is to train both the feature extractor (convolution) and the subsequent classifier (neural network). From the perspective of function, the traditional classification model can be written as follows.

$$y = f(x, \theta\,\text{classifier}). \quad (1)$$

In equation (1) f illustrates the feature extractor, x depicts the original data, and θ represents the classifier. As a feature

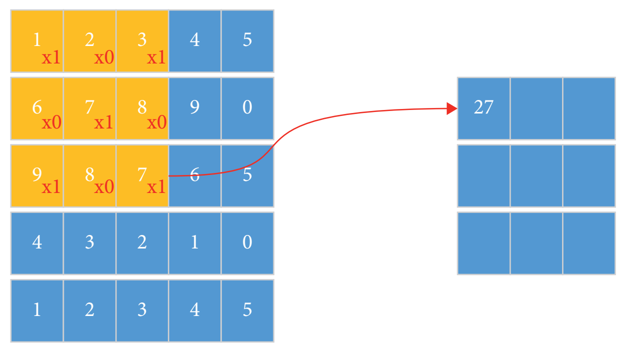

Figure 5: Convolution operations and its results.

extractor, the classification model of convolution can be described as follows:

$$y = f(x, \theta\,\text{filter}, \theta\,\text{classifier}). \quad (2)$$

In equation (2) θ filter illustrates the parameters in the feature extractor.

4.1. Human Joint Point Extraction and Tracking. For the detected human foreground, this study will track the joint points and skeleton in it. The traditional joint point extraction methods are optical marking and manual annotation. Optical marking is not conducive to the movement of limbs, and manual annotation is not conducive to the automation of the system. Therefore, this paper proposes an automatic joint point initialization method based on multifeature fusion that uses the fusion algorithm of vertical integral projection, horizontal line scanning, index lookup table, and length proportion constraint to extract the joint points. This method is fast and accurate, does not rely on manual annotation, and can improve the intelligence of the system. In the process of human motion, one tracking method cannot accurately obtain the motion position of joint points and tracking will be wrong and lost due to the influence of occlusion, motion speed, and other factors. Therefore, in this research work, Lucas Kanade optical flow tracking algorithm is used to track the motion of joint points and then combined with Kalman filtering algorithm to

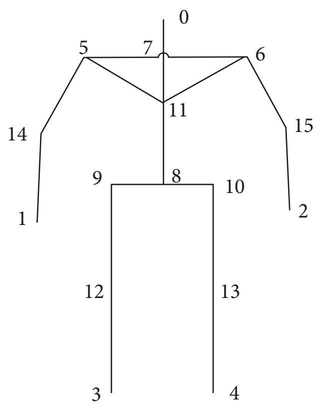

Figure 6: Human 2D bone model.

Table 2: Corresponding relationship between human joint points and labels.

Label of human skeleton model	Corresponding joint point
0	Abdomen
1	Left hip
2	Right hip
3	Chest
4	Left knee
5	Right knee
6	Left elbow
7	Right elbow
8	Head
9	Left-hand
10	Right-hand
11	Left-foot
12	Right-foot
13	Left shoulder
14	Right shoulder
15	Neck

predict the change of motion, so as to correct the wrong points and improve the accuracy of tracking.

4.1.1. Human Skeletonization. After obtaining the human silhouette image, it is difficult to extract human joint points directly, and the extraction algorithm has large amount of calculation and low accuracy. Therefore, it is necessary to skeleton the silhouette image to find out the position of joint points. The joint points are connected according to a certain sequence to form the human joint point model as shown in Figure 6.

The labels in Figure 6 are from 0 to 15 and the corresponding relationship with each joint point of the human body is shown in Table 2.

Bone is a feature that describes the underlying information of an image, which was first proposed by Blum. Skeletonization also known as thinning refers to the stripping of human targets layer by layer to reduce redundant information, while maintaining the basic topology of the shape unchanged and extract bone structure features. Image thinning can reduce the redundant data information in the original image and reduce the amount of calculation in the

P9	P2	P3
P8	P1	P4
P7	P6	P5

Figure 7: Schematic diagram of eight neighborhoods.

process of joint point extraction. At present, there are two commonly used skeletonization methods: distance transformation method and eight neighborhood method. The distance transformation method has a large amount of calculation, low accuracy, and cannot ensure the connectivity of the image. The eight neighborhood method is used for skeletonization in this paper to improve the accuracy of the bone model. For a pixel P1 in the image, its eight neighborhoods are shown in Figure 7.

The principle of the eight neighborhood method is when the eight neighborhoods of $p1$ pixel meet the following three conditions at the same time, it indicates that the point is not on the bone, so set its pixel value to 0 and delete it from the image. The three conditions are: (1) there is only one point with a value of 1 in the eight neighborhoods (i.e., p is the endpoint) and there are 7 or 8 points with a value of 1 (i.e., p is the target internal point); (2) The line segment itself is single pixel wide to prevent further skeletonization from breaking the bone; (3) p is the point on the silhouette boundary which must not be a bone point. The formula expression of the three conditions is shown in the below equations.

$$2 \leq N(p_1) \leq 6, \tag{3}$$

$$z(p_1) = 1, \tag{4}$$

$$p_2 \cdot p_4 \cdot p_8 = 0 \text{ or } Z(p_2) \neq 1, \tag{5}$$

$$p_2 \cdot p_4 \cdot p_6 = 0 \text{ or } Z(p_4) \neq 1, \tag{6}$$

where $N(p1)$ represents the number of black pixels (value 0) in the eight neighborhoods of $p1$ and $Z(p1)$ represents the number of changes of pixel values from 0 to 1 in the order of $p2$, $p3$, . . . , $p9$. According to the conditions of equations (1)–(4), navigate each pixel in the image. If at least one condition is not met, it indicates that the pixel is a bone point. Set its value to 1, and finally get a binary bone image, as shown in Figure 8.

It can be seen that the human bone image extracted by the eight-neighborhood method is more accurate. Different from the distance transformation method, it can ensure the connectivity of bones, single pixel width, no burr, and its extraction process is simple and fast which provides a reliable basis for the extraction of joint points.

4.2. Camera Projection Model. The process of camera imaging is essentially a process of space-to-image-plane

Figure 8: Human bone image extracted by the eight-neighborhood method.

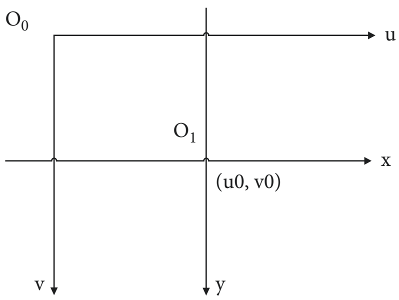

Figure 9: Image coordinate system.

projection, which can be represented as a transition between several coordinate systems such as the image frame, camera frame, and world coordinate systems. Image coordinate system refers to the coordinate system on the electrical display device. In image coordinate system (u, v), the horizontal axis is represented by u that goes from left to right and the vertical axis is represented by v that goes from top to bottom the in pixels. The center of the image coordinate system (x, y) is located (u_0, v_0) in the UOV plane as shown in Figure 9.

The association between the image coordinate systems (u, v) and (x, y) can be calculated via the following equation .

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} \frac{1}{k} & 0 & u_0 \\ 0 & \frac{1}{l} & v_0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}, \quad (7)$$

where the size of the pixel is $K \times 1$, and the time calculation unit is millimeter (mm). The origin of the camera coordinate system (X_C, Y_C, Z_C) is the optical center of the lens, the X_C axis is parallel to the X axis of the image coordinate system, the Y_C axis is parallel to the Y axis of the image coordinate system, and the Z_C axis is perpendicular to the image plane and parallel to the optical axis. If $P(X, Y, Z)$ is an object point in the world coordinate system then C is the center of the camera lens, and x, y is the image plane. In order to facilitate observation, we transform point P to the side of the same lens as the image plane. Equations (8) and (9) show the relationship between image and camera coordinate systems.

$$\left\{ \begin{aligned} u &= f_x \frac{X_C}{Z_C} + c_x, \\ v &= f_y \frac{Y_C}{Z_C} + c_y, \end{aligned} \right\} \quad (8)$$

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} X_C \\ Y_C \\ Z_C \end{bmatrix}, \quad (9)$$

where $f_x = f_{sx}$, $f_y = f_{sy}$, f is the actual focal length of the camera. $s_x = 1/dx, s_y = 1/dy$, respectively, represents the number of pixels in the unit physical size in the x and y directions of the image plane, and dx and dy are the physical size of a pixel. c_x, c_y are the offset of the optical axis and (f_x, f_y, c_x, c_y) is called the internal parameter of the camera. The association between the world and the camera coordinate system can be expressed via the following formula.

$$\begin{bmatrix} X_C \\ Y_C \\ Z_C \\ 1 \end{bmatrix} = \begin{bmatrix} R_{3\times3} & T_{3\times3} \\ 0 & 1 \end{bmatrix} \begin{bmatrix} X_C \\ Y_C \\ Z_C \\ 1 \end{bmatrix}. \quad (10)$$

In the above equation, $R_{3\times3}$ is the rotation matrix and $T_{3\times3}$ is the translation matrix, representing the external parameters of the camera. The perspective projection association from the world coordinate system to the image coordinate system can be calculated as follows.

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = s \begin{bmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} R_{3\times3} & T_{3\times3} \\ 0 & 1 \end{bmatrix} \begin{bmatrix} X_W \\ Y_W \\ Z_W \\ 1 \end{bmatrix}, \quad (11)$$

where s is the scale factor. The above proportional projection formula is verified for the two-dimensional human bone image using the following steps.

Step 1: select human limb length. First, the human limb length is determined according to the joint length of the initial action in the image.

Step 2: solve the scale factor s. Calculate the s of each joint according to the derivation formula, and finally select the maximum value as the scale factor.

Step 3: determine the first frame depth symbol.

Step 4: calculate the relative depth.

Step 5: reconstruct 3D point coordinates. Take the abdominal joint point as the reference point, calculate the Z coordinate of each joint point according to the depth, and calculate the X and Y coordinates.

Step 6: calculate the relative depth of joint points in subsequent frames.

Table 3: Human limb length.

Corresponding depth of the human skeleton model	The human skeleton model corresponds to the joint	Relative length of skeleton
Z0	8~11	16.56
Z1	11~7	36.06
Z2	7~0	16.00
Z3	7~5	37.48
Z6	12~7	29.12
Z4	7~6	14.04
Z7	12~8	20.08
Z5	12~5	16.28
Z8	10~6	21.14
Z9	12~3	37.48
Z12	8~12	25.58
Z10	5~8	14.04
Z13	13~5	56.08
Z11	10~6	20.56
Z14	1~14	25.36

Table 4: Comparison of joint angle between test action and standard action.

Articular angle	Test action (angle)	Standard action (angle)	Improvement recommendations (angle)
Left shoulder ∠ 5	87	78	-9
Right shoulder ∠ 6	56	85	+29
Neck ∠ 7	152	165	+13
Left hip ∠ 9	106	112	+5
Right hip ∠ 10	125	108	-17
Chest ∠ 11	175	167	-8
Left knee ∠ 12	175	164	-11
Right knee ∠ 3	158	168	+10
Left elbow∠ 14	165	156	-9
Right elbow ∠ 15	172	165	-7

Step 7: reconstruct 3D point coordinates. According to the principle of motion coherence, the positive and negative values of the relative depth of subsequent frames select the depth of the joint point closer to the Z coordinate of the previous frame.

The length of selected human limbs is shown in Table 3.

After obtaining the three-dimensional coordinates of the human body node, the angle between each node can be calculated to correct the mobilization swing. Comparison of joint angle between test action and standard action is shown in Table 4.

Through the three-dimensional modeling of human joint points, we can intuitively see the athletes' posture that helps the coach to analyze the athletes' actions and problems, so as to better guide the training athletes.

5. Conclusion

One of the most basic movements in fencing and other high stamina consuming sports is lungeing. The accurate and fast execution of lungeing and its succeeding movements (return to the original position or change of route) has a crucial role in athletes' success. The most critical technology in the process of human action recognition is human body posture detection. In this paper, a human motion recognition and posture analysis system based on gait technology is proposed. Several factors including foreground detection, morphological processing, human skeletonization, node extraction, motion tracking, motion prediction, similarity evaluation, and the three-dimensional motion information of human nodes are considered in this study, which provides guidance for sports movement training. According to the characteristics of fencing, choosing appropriate core strength training methods and resources not only improves athletes' professional skills and fencing strength but also reduces athletes' injury probability in fencing competition or training. According to this study, different core strength training means and methods need to be adjusted according to the training purpose. Furthermore, coaches need to formulate different training programs according to the training requirements and physical conditions of athletes, and carry out training in combination with the individual abilities of athletes. In this paper, we used a gait tracking algorithm that evaluates the fencing athletes' strength distribution characteristics. Further, using the gait recognition algorithm based on AI technology, the movement posture and gait of fencers can be recognized automatically in real time which is helpful to realize the automatic evaluation of power distribution.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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