Research Article

Application and Analysis of Taekwondo Techniques, Tactics, and Movement Trajectories Based on Multi-Intelligent Decision Making

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The aim of this study is to compare the trajectory of cross-kick technical movements of excellent taekwondo players in different weight classes and to investigate the relationship between weight class differences and the characteristics of cross-kick technical movements and the extent to which they affect the speed of movements. To this end, an artificial intelligence system is proposed for taekwondo field decision making, combining computer and applied mathematics knowledge. The angles, angular velocities, and moments of the joints of the lower limbs, as well as the movement time, displacement, and speed of the lower limbs, of the athletes in the three weight classes were significantly different ($P < 0.05$).

1. Introduction

Artificial intelligence (AI) is a branch of computer science, which is a new technical science that studies and develops theories, methods, techniques and application systems for simulating, extending, and extending human intelligence [1]. One of its main goals is to enable machines to perform complex tasks that would normally require human intelligence. It has developed rapidly in recent years and is widely used in many fields such as military, economy, and management. The main objective of this idea is to build an artificial intelligence-assisted system for taekwondo field decision making based on a database and through an expert system platform (data mining, online analysis, artificial intelligence, and virtual reality) [2].

Taekwondo, as one of the more typical skill-driven same-field confrontation events in the East [3], was first listed as an official event of the Sydney Olympic Games in 2000. Due to the relatively few weight classes established, competition is relatively fierce. In competition, the horizontal kick technique has the advantages of speed, power, difficulty, short range of motion, and less cushioning, and has become the most frequently used technical movement by athletes [4]. In the cross-kick technique, the body accelerates and brakes according to the major and minor links in sequence so that the momentum moment is transferred to the end links, which is a typical whipping action [5]. Because of the great speed and power that can be generated at the end of the kinetic chain, the horizontal kick technique has become an important scoring tool in Taekwondo and a key technique in determining the winner of a match. In order to improve the effectiveness of this technique, some scholars have studied the scoring effect [6], training methods [7], structural characteristics [8], biomechanical characteristics [9], as well as the body composition [10], sports injury, and prevention [11] of the athletes [12], the results of which have laid the foundation for improving the effectiveness of the use of the cross-kick technique. In recent years, due to new rules and the use of electronic protective gear [13], the speed of the cross-kick technique plays a decisive role in improving the effectiveness of striking [14] and has once again become a new hot spot of common concern among researchers.
However, a review of domestic and foreign research literature on the movement speed of the horizontal kick technique reveals that the research mainly focuses on individual weight classes [15], gender differences [16], regional differences [17], training methods [18], the effect of old and new rules on movement speed, and its comparison with the speed of other technical movements [19]. As there is a distinction between weight classes in taekwondo competitions, there are individual differences in the height and mass of athletes. Therefore, the key to improving the speed of horizontal kicks and the effectiveness of the strikes is to find out the intrinsic connection between the weight class differences and the speed of the athletes’ movements. Based on this, the biomechanical characteristics of cross-kick movements of athletes in different weight classes were analysed and compared with the weight class set in the men’s taekwondo competition at the Summer Olympic Games, using a 3D motion capture system and analysis software.

The aim is to provide theoretical reference for the improvement of cross-kick movements, increase the speed of movements, and enhance the hitting effect of taekwondo players of different weight classes.

The contributions of this paper are as follows:

We propose to establish an artificial intelligence assistant system for taekwondo on-site decision making. Using a Vicon Nexus three-dimensional motion capture system, we can collect the motion trajectories of athletes of different weight levels when hitting the target position.

Based on D-H modelling, we can describe the posture angle of Taekwondo trainer ontology with the Euler angle.

In this experiment, according to the weight level set in the men’s Taekwondo competition of the summer Olympic Games, all subjects did not carry out high-intensity training within 24 hours. Under the knowledge of this system, the training effect was improved.

2. Feasibility Analysis

The basis of the artificial intelligence assisted system for taekwondo field decision making is data. It is the large amount of data and information accumulated during daily training and competition that provides a solid foundation for the system, and the rich knowledge and experience of the coaches in field command that provides a reliable support for adjusting and optimising the system. The data mining, online analysis, and virtual technology involved in this system are all relatively mature technologies and have been widely used in many fields such as military, economy, and management, and have been successful. The application of artificial intelligence in various industries is also becoming more and more widespread, and the robot football simulation game has become quite mature. Artificial intelligence is of course based on data and models, which can be built on the basis of data mining analysis of various relationships and laws, or combined with basketball expertise and the experience of coaches and experts. The model can be used to obtain valuable information from a large amount of data and to display this information in an intuitive form so that the data can be used to benefit, and the model can be dynamically added to or subtracted from and improved through practical application. In addition, tactical rehearsals, virtual arenas, and virtual pavilions are becoming more sophisticated.

A literature search shows that as early as the 1990s, about 20 NBA teams in the US used the advanced scout system, a data mining application developed by IBM, to provide relevant game data information to optimise their tactical combinations and predict game formats. Some of the technical and tactical research in China has also started to move towards informationization and digitalization, such as the use of the “transfer matrix” for table tennis simulation and diagnosis; the video analysis and rapid feedback system for diving technical training and diving training data management and analysis system of Tsinghua University; the multimedia database for basketball techniques and tactics developed by Chen Jian of Shanghai Sports Institute, etc. research and development, etc.

By providing a wealth of data and a large number of analysis tools, the artificial intelligence assisted system can assist coaches in making on-site analysis and decisions, and can also propose targeted training objectives for daily training.

3. Based on D-H Modelling

Based on the principles of conservation of momentum and conservation of angular momentum, the conceptual model of the SR system with n degrees of freedom is studied based on the kinematic and model transformation, where the posture angles of the taekwondo trainer’s body are described by $z - x - y$ Euler angles $\alpha, \beta$, and $\gamma$, and the relevant notation is agreed as follows:

$$\sum A_i: \text{inertial coordinate system; } \sum 0: \text{coordinate system fixed to the center of mass } C_0 \text{ of the taekwondo trainer’s body; } n: \text{number of degrees of freedom of the system } \sum i: \text{the coordinate system defined on the link } i \text{ whose } z\text{-axis coincides with the axis of the joint } i; m_i: \text{the mass of the link } i$$

$$^{A}R_{i} \in \mathbb{R}^{3 \times 3}: \text{coordinate transformation matrix from } \sum i \text{ to } \sum A_{i} ; k_{i}: \text{unit vector along the } z\text{-axis of } \sum i$$
$$^{A}R_{0} \in \mathbb{R}^{3 \times 3}: \text{the posture matrix of the taekwondo trainer’s body relative to } \sum A_{i} ; C: \text{the whole system center-of-mass position vector (PV)}$$
$$C_{i}: \text{center of mass of the composite subsystem formed by the } i\text{-th link to the end effector link } n$$

And the vector product matrix of vector $r = \begin{bmatrix} r_x \ r_y \ r_z \end{bmatrix}^T$ is defined as

$$\bar{r} = \begin{bmatrix} 0 & -r_z & r_y \\ r_z & 0 & -r_x \\ -r_y & r_x & 0 \end{bmatrix}.$$  \hspace{1cm} (1)

The superscript to the left of the symbol (e.g., A in symbol $^{A}R_{i}$) indicates the coordinate system in which the
vector is described. $\sum A$ this superscript is omitted when the vector is represented in the coordinate system $G_{ua}$.

3.1. Single-Degree-of-Freedom Models. We consider first the SR system with a single DOF at $n = 1$, which consists of the body of the taekwondo trainer (link 0) and a link (link 1) connected by a rotating joint.

First, the total system momentum $P$ and the total angular momentum $L$ with respect to the $\sum A$ origin can be expressed as

$$
\begin{align*}
\text{gathered} P &= \sum_{i=0}^{1} m_i \dot{r}_i = m_C \dot{r}_C, \\
L &= \sum_{i=0}^{1} (I_i \omega_i + m_i r_i \times \dot{r}_i) = I_C \omega_C + m_C r_C \times \dot{r}_C.
\end{align*}
$$

According to the $D\ H$ method, the velocity relationship between chain rod 0 and chain rod 1 is

$$
\begin{align*}
\dot{r}_1 &= \dot{r}_0 + \omega_0 \times (p_l - p_0) + \dot{\theta}_1 k_1 \\
\omega_1 &= \dot{\omega}_0 + \dot{\theta}_1 a_1,
\end{align*}
$$

where $\dot{\theta}_1$ is the angular velocity of link 1 and $a_1$ is the linear acceleration of link 1.

Based on the above relationship, the equation $v_0$ can be derived for the proprioceptive speed of a taekwondo trainer:

$$
v_0 = J_0 \dot{\theta}_1 + H_0 v_C,
$$

where

$$
J_0 = \begin{bmatrix} k_1 \times \left( \frac{m_l}{m_C} a_1 \right) + p_0 I_C^{-1} I_1 k_1 \\
- I_C^{-1} I_1 k_1 \end{bmatrix},
$$

$$
I_1 = I_1 - m_1 p_1 a_1,
$$

$$
H_0 = \begin{bmatrix} E_3 - p_0 \\
0 & E_3 \end{bmatrix}.
$$

In turn, wood-end effector speeds can be obtained as $v_E$:

$$
\dot{r}_E = \dot{r}_0 + \omega_0 \times (p_E - p_0) + \left( \dot{\theta}_1 k_1 \right) \times \dot{\theta}_1 a_1,
$$

$$
\omega_E = \dot{\omega}_0 + \dot{\theta}_1 a_1,
$$

thus obtaining the end effector speed:

$$
v_E = J_E \dot{\theta}_1 + H_E v_C,
$$

where

$$
J_E = \begin{bmatrix} k_1 \times \left( I_{E,1} - \frac{m_l}{m_C} a_1 \right) + p_E I_C^{-1} I_1 k_1 \\
- I_C^{-1} I_1 k_1 \end{bmatrix},
$$

$$
H_E = \begin{bmatrix} E_3 - p_E \\
0 & E_3 \end{bmatrix}.
$$

Equations (5) and (10) are the equations of motion for a single white yawl SR, matrices $J_E$ and $J_0$ in equations (6) and (11) are the generalized Jacobi moments (GJMs) of the $6 \times 1$ underdetermined instanton and end effector.

3.2. Multidegree-of-Freedom Models. The kinematic equations of the multidegree SR can be derived recursively from the conservation equations for linear and angular momentum and from the $D\ H$ method. In general, the equations for the SR of $n$ degrees of freedom can be described by the plant-meaning Jacobi matrix (GJM)$[1] J_E^*= R_n^{6 \times n}$, which represents the relationship between the end-effector velocity $v_E$ and the joint velocity $\dot{\theta}_M$ of the manipulator:

$$
v_E = J_E^* \dot{\theta}_M + h_E,
$$

where

$$
h_E = H_E \cdot v_C,
$$

$$
H_E = \begin{bmatrix} E_3 - p_E \\
0 & E_3 \end{bmatrix},
$$

where $H_E$ represents the end effector velocity when $\dot{\theta}_M = 0$, which only occurs when the system has nonzero momentum. Clearly, the key to kinematic modelling is the calculation of the Jacobi matrix. Based on the formulation proposed by Orin and Schrader for the fixed-base Jacobi, the $i$-th column of the generalized Jacobi matrix $J_E^*$ in equation (13) can be interpreted as the end-effector velocity $v_E$ when $H_E = 0$, and only the $i$-th element of $\dot{\theta}_M$ has value $\dot{\theta}_i$ of 1. Therefore, in order to derive the $i$-th column element of the GM, the system can be viewed as consisting of only two composite link sub-systems connected by the $i$-th joint, and its $i$-th column element can be calculated using the results of the previous section, thus allowing a multidegree-of-freedom SR model to be built.

Let $J_E^* = [ J_{IE} \ldots J_{JE} ]$, where the column element $J_{IE} \in R_n^{6 \times 1}$ represents the contribution of the joint velocity $\dot{\theta}_i$ to the end effector velocity, and using the section to obtain the result, corresponding to equation (13), yields $J_{IE}$:

$$
J_{IE} = \begin{bmatrix} k_i \times \left( I_{E,i} - \frac{m_l}{m_C} a_i^* \right) + p_E I_C^{-1} I_1 k_i \\
k_i - I_C^{-1} I_1 k_i \end{bmatrix},
$$

where

$$
I_i = I_i^* - m_l^2 p_i^* A_i^*.
$$

The kinematic equations of SR with the reference point on the end effector can be derived in the same way as the kinematic equations of other forms with the reference point not on the end effector but on the body of the taekwondo trainer. This kinematic equation can be expressed as...
\[ v_0 = J_0^* \dot{\theta}_M + h_0, \]
\[ h_0 = H_0 \cdot v_C, \]
\[ H_0 = \begin{bmatrix} E_3 & -P_0^* \\ 0 & E_3 \end{bmatrix}, \]
\[ J_0^* = \begin{bmatrix} J_{10} & \cdots & J_{n0} \end{bmatrix} \in \mathbb{R}^{6\times n}, \]
\[ J_{i0} = \begin{bmatrix} k_i \times (m_i^T a_i^*) + \frac{1}{2} I_i^{-1} \dot{I}_i k_i \\ -I_i^{-1} \dot{I}_i k_i \end{bmatrix}, \]
\[ v_0 = J_0^* \dot{\theta}_M + h_0. \]

4. Continuous Motion Trajectory Control (Continual Motion Trajectory Control)

This section investigates the continuous motion trajectory control algorithm for SR. When the linear and angular momentum are conserved and the initial momentum is zero, the end-effector velocity can be expressed as

\[ v_E = J_E^* \cdot \dot{\theta}_M. \]

To the aid of the GJM, the relationship between the velocity of the SR end effector and the angular velocity of the joint is formally the same as that described for the ground robot. If \( J_E^* \) is invertible, then

\[ \dot{\theta}_M = (J_E^*)^{-1} \cdot v_E. \]

The solution of the inverse kinematics at the velocity level of SR is obtained by (17), according to which the continuous motion trajectory control algorithm based on the visual feedback and RMRC method is proposed. Let the \( \theta \) be the desired position of the spatial target \( T_c = \begin{bmatrix} a_c \times 1 \end{bmatrix} \)

and the position of the end effector of the manipulator measured by the vision system installed on the body of the SR be \( T_d = \begin{bmatrix} a_d \times 0 \times 1 \end{bmatrix} \), and the position error of the end effector is \( e_p \), and the attitude error is \( e_R \).

\[ e_p = r_d - r_e, \]
\[ e_R = \frac{(n_c \times n_d + o_c \times o_d + a_c \times a_d)}{2}, \]
\[ \dot{\theta}_M = (J^*)^{-1} v_E, \]
\[ v_E = \frac{e_p}{\Delta t}, \]

where \( \Delta t \) is the sampling period.

5. Subjects and Methods

5.1. Test Subjects. Thirty Korean taekwondo athletes in three weight classes, 58 kg, 68 kg, and 80 kg, were selected for testing according to the weight class set for the men’s taekwondo competition at the Summer Olympic Games. Of these, 12 were from the Taeyeong Village (4 players/class) and 18 from the Yongin University team (6 players/class), all of whom were athletes at the rank of athlete and above. All subjects were athletes of fitness level or above. All subjects had not undergone heavy training within 24 h before the test and had not intentionally increased or decreased their body mass or suffered any sports injuries to their lower limb joints within 3 months, and their physical condition and athletic ability were normal. The basic information of the subjects is shown in Table 1.

5.2. Research Process. The signals collected by the 3D motion capture system are set according to the movement characteristics of the cross-kick technique, observing the moment when the supporting foot and the attacking leg touch the ground reaction on the force measuring table, the movement of the reflective marker ball attached to the target, the minimum flexion and maximum extension of the knee joint angle of the attacking leg, etc. The time interval from one moment to the next is the time periods shown in Figure 1.

Ready moment (E1): the moment the supporting foot touches the floor of the dynamometer

Moment of flexion (E2): the moment of minimum knee flexion when the attacking leg is flexed

Moment of strike (E3): the moment of maximum extension of the knee joint during the strike of the attacking leg

Moment of recovery (E4): the moment the attacking leg is recovered and touches the floor of the dynamometer

P1: from the end of the preparation period to the beginning of the knee flexion period (E1 --- E2)

Striking time (P2): from the end of the knee flexion to the beginning of the striking time (E2 --- E3)

Recovery (P3): from the end of the strike to the beginning of the recovery (E3 --- E4)

The results of the one-way RMANOVA are shown in Figure 2. The amplitude and direction of motion of the hip joint vary to varying degrees. At the moment of preparation (E1), the amplitude of flexion on the X-axis for the 58 kg and 68 kg, 68 kg and 80 kg weight classes, and the amplitude of abduction on the Y-axis for the three weight classes; at the moment of flexion (E2), the amplitude of flexion on the
X-axis for the 58 kg and 68 kg weight classes, and the amplitude of rotation on the Z-axis for the 68 kg and 80 kg weight classes; at the moment of strike (E3), the amplitude of flexion on the X-axis for the 58 kg and 68 kg weight classes, and the amplitude of rotation on the Z-axis for the 58 kg and 80 kg weight classes. At the moment of strike (E3) the flexion amplitude of the 58 kg and 68 kg weight classes on the X-axis, the abduction amplitude of the 58 kg and 68 kg, 68 kg and 80 kg weight classes on the Y-axis and the rotation amplitude of the three weight classes on the Z-axis; at the moment of recovery (E4), the flexion amplitude of the 68 kg and 80 kg weight classes on the X-axis and the inversion amplitude of the 58 kg and 68 kg weight classes on the Y-axis were different ($P > 0.05$), but not statistically significant. The differences were not statistically significant.

The angular velocities and moments of the knee joints of the athletes in the three periods were 58 kg > 68 kg > 80 kg, and the maximum moments of the 58 kg and 68 kg weight classes differed in the striking period (P2) ($P > 0.05$) but were not statistically significant.

In order to verify the effectiveness of the kinematic modelling method proposed in this paper and its GJM and continuous motion trajectory control algorithms, a computer simulation study of the trajectory control of a failed taekwondo trainer was carried out using a 6DOF PUMA type SR model as an example. Figures 5 and 6 show the time course of the SR taekwondo trainer’s body posture angle and the change of the robot’s joint angle.

6. Discussion

The aim of the study is to investigate the similarities and differences in the movement trajectories of cross-kick technical movements of athletes of different weight classes, the angles, angular velocities, and moments of the joints of the lower limbs, as well as the displacement and speed of the technical movements at the four set moments and three time periods, and the degree of their influence on the speed of the movements. The study explores the biomechanical characteristics of the cross-kick technical movements of athletes of
different weight classes and identifies the links between the differences in weight classes and movement speed, using theoretical knowledge of kinesiology and physiology and the author’s training practice [20]. The results of the test revealed that there were significant differences in the biomechanical characteristics of the cross-kick movements of athletes in different weight classes. At the start of the horizontal kick, the trunk and supporting leg first rotate around the longitudinal axis, with the magnitude of rotation being 58 kg > 68 kg > 80 kg. The smaller the weight class, the greater the magnitude of rotation around the axis. It has been suggested that the rotation of the trunk and lower limb joints around the axis is consistent with the anatomy of the human body and that the supporting leg should be abducted first in order to facilitate the attacking leg movement [21]. The movement trajectory of the attacking leg is similar to that of the supporting leg in terms of flexion and extension, adduction and abduction, and internal and external rotation, starting from the preparation moment of the technical movement, with the overall performance of
58 kg > 68 kg > 80 kg. This shows that the difference in weight class has a direct effect on the rotation of the trunk and support leg as well as the attacking leg, especially on the knee flexion of the attacking leg.

7. Conclusions

The weight difference between the weight classes of the best taekwondo athletes has a significant effect on the speed of the cross kick technique; the lower the weight class of the athlete, the less agility of the body, although the distance of the strike is relatively long, but the effect on the speed of the movement is relatively obvious. The greater the weight class the less agile the athlete is, and although the distance is longer, the effect on speed is more pronounced.

When formulating training plans or carrying out special training, coaches should improve body agility and standardise cross-kick technical movements according to the differences in the characteristics of cross-kick technical movements of athletes of different weight classes and the degree of influence on movement speed, combining the characteristics of cross-kick technical movements and the principle of whipping movements, and according to the individual differences in athletes’ agility, in accordance with the training principle of low weight and fast speed.

Data Availability

The experimental 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 regarding this work.

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