Study on the Intelligent Muscle Force Monitoring System Assisting Elite Hurdle Athletes in Personalized Take-off Point Selection and Muscle Force Precision Improvement

Li Wang[1], Haiping Sun[2], Qi Liu[3]*, Qi Sun[4], Taifu Xie[5]

1.Department of Physical Education and Sport, Shanghai Ocean University, Shanghai 201306, China

2.Hurdling Group, National Track and Field Team of China, Beijing 100763, China

3.Shanghai Sports Science Society, Shanghai 200030, China

4.School of Athletics Performance，Shanghai University of Sport, Shanghai,200438,China

5.College of Information Technology, Shanghai Ocean University, Shanghai 201306, China

Abstract: The rationality of the takeoff point and the precision of muscle strength are key factors determining elite hurdlers' hurdling efficiency, rhythm between hurdles, and injury risk. Current training relies on coaches' subjective experience (e.g., step counting/visual estimation) to determine the takeoff point, while muscle strength parameters (e.g., electromyographic activation timing, peak force) lack real-time quantification. This hinders the development of personalized training programs (tailored for lower-body strength, flexibility, etc.), limiting athletic performance while increasing the risk of muscle injuries (quadriceps/hamstrings) during the takeoff phase. This study employed a proprietary lightweight monitoring system to analyze 22 elite national/provincial hurdlers (15 males, 7 females; including 8 National Athletes and 14 First-Class Athletes). By integrating multimodal data and applying machine learning, the system overcomes traditional empirical limitations to enable personalized quantification of takeoff points. This approach enhances muscle force precision and athletic performance while reducing injury risk. The findings demonstrate that the “data collection-model prediction-intervention-outcome validation” framework is replicable for complex track and field events, validating the feasibility of integrating sports technology with competitive training.

Keywords: Intelligent Muscle Force Monitoring System; Elite Hurdle Athletes; Personalized Take-off Point; Muscle Force Precision; Multimodal Data Fusion

1 Introduction

1.1 Research Background

In the development of contemporary competitive sports, the Olympic spirit of "Citius, Altius, Fortius" drives all events to continuously break performance boundaries. The in-depth integration of technological innovation and scientific training has become the core driving force for elite athletes to achieve leaps in competitive performance. As a fundamental event in competitive sports, track and field includes hurdle events that combine speed, strength, technique, and rhythm, making them an important indicator of a country’s comprehensive track and field strength. The technical complexity of hurdle events is reflected in multiple links, among which the take-off phase, as a key node connecting the approach run and hurdle clearance, directly determines hurdle clearance efficiency, inter-hurdle rhythm stability, and overall competitive performance. The precision of muscle force is the core element ensuring the quality of take-off technology and reducing injury risks.

With the rapid iteration of sports science and technology, the traditional training model relying on coaches' subjective experience has gradually exposed limitations. In elite hurdle training, coaches mostly determine take-off points based on experience-based methods such as "step counting + visual observation". Although this method has accumulated certain effects in long-term practice, it is difficult to avoid judgment deviations caused by individual differences—elite athletes vary significantly in lower limb strength distribution, flexibility, and step frequency. A unified take-off point standard or judgment based on majority experience often fails to adapt to each athlete's physiological and technical characteristics, leading to problems such as muscle compensation, insufficient force, or excessive load during take-off for some athletes. At the same time, muscle force is a dynamic and abstract process, and key parameters such as activation timing, force peaks, and muscle group coordination are difficult to quantify through visual observation. Coaches can only infer force effects indirectly through athletes' technical performance (e.g., hurdle clearance height, landing stability). This "result-driven cause inference" model lacks real-time performance and precision, making it impossible to detect and correct force deviations in a timely manner or develop refined training plans for individuals.

In recent years, the application of intelligent monitoring technology in competitive sports has provided a new path to address this pain point. The maturity of multimodal data collection methods such as surface electromyography (sEMG), inertial measurement, and plantar pressure sensing has made it possible to capture real-time physiological and kinematic parameters of athletes during training; the development of artificial intelligence technologies such as machine learning and big data analysis has provided algorithmic support for in-depth interpretation of data and personalized decision-making output. Against this background, constructing an Intelligent Muscle Force Monitoring System integrating multimodal data collection, intelligent analysis, and real-time feedback functions, and applying it to the take-off training of elite hurdle athletes, can not only realize the quantification and personalization of take-off point selection but also precisely regulate the muscle force process, promoting the transformation of hurdle training from "experience-driven" to "data-driven". This is not only an inevitable trend of sports science and technology empowering competitive training but also a practical need to enhance the competitiveness of China's elite hurdle events.

1.2 Research Significance

The significance of this study is reflected in three dimensions: theory, practice, and industry development. At the theoretical level, this study will fill the theoretical gap in the in-depth integration of intelligent monitoring technology and specialized hurdle training. Current research on sports intelligent monitoring mostly focuses on macro competitive performance evaluation or general muscle force analysis, with few specialized studies on the take-off phase of hurdle events—especially studies combining multimodal data with machine learning to construct a "take-off point - muscle force - competitive performance" correlation model are even scarcer. By systematically sorting out the technical characteristics and muscle force mechanisms of the hurdle take-off phase, clarifying the core functional modules and data collection dimensions of the intelligent monitoring system, and establishing an optimal take-off point prediction model based on individual data, this study can enrich the theoretical system of interdisciplinary disciplines such as sports training science, sports biomechanics, and sports information technology, and provide a theoretical framework and research paradigm for the subsequent application of intelligent technology in specialized track and field training.

At the practical level, the results of this study will provide an operable intelligent solution for elite hurdle training. For athletes, the Intelligent Muscle Force Monitoring System can provide real-time feedback on take-off point deviations and muscle force problems, helping them establish a closed-loop awareness of "force perception - technical adjustment", transforming from passive acceptance of coach guidance to active optimization of technical movements, and improving training autonomy and efficiency. For coaches, the quantitative data output by the system can provide an objective basis for formulating training plans, avoiding subjective deviations in experience-based judgment, realizing "one-on-one" personalized training, and tracking athletes' training progress through data to adjust training intensity and focus in a timely manner. For training teams, the system's injury risk early warning function can reduce the incidence of training injuries, ensure the continuity of athletes' training and the stability of their competitive state, and provide safety guarantees for preparing for major competitions.

At the industry development level, this study will promote the in-depth integration of sports science and technology with competitive training, providing references for other technical sports. As a representative of technically complex track and field events, hurdle events have strong radiating effects in their intelligent training research results—the "multimodal data collection - intelligent modeling - training intervention" framework constructed in the study can be migrated to other technical track and field events such as high jump and long jump, and even applied to sports requiring both technique and strength such as gymnastics, fencing, and wushu, promoting the intelligent upgrading of training models in the entire competitive sports field. At the same time, the exploration of system lightweight, real-time performance, and multi-scenario adaptability in the study will also provide directions for the research and development of intelligent sports equipment, promoting the innovative development of the sports science and technology industry and forming a virtuous cycle of "technology R&D - training application - industrial upgrading".

1.3 Research Status at Home and Abroad

1.3.1 Foreign Research Status

Foreign research on sports intelligent monitoring technology started early, and certain accumulations have been formed in the application exploration of hurdle training. In terms of muscle force monitoring, sports science and technology developed countries such as the United States and Europe have widely applied surface electromyography (sEMG) technology to the evaluation of athletes' muscle function, with research focusing on the activation characteristics of key muscle groups in different sports phases—for example, a research team from the German Institute of Sports Biomechanics analyzed the activation timing of muscle groups in the take-off leg and swing leg of hurdle athletes using sEMG technology, and found that the coordinated activation time difference between the quadriceps femoris and hamstrings was negatively correlated with hurdle clearance efficiency. This conclusion provides a theoretical basis for the regulation of muscle force precision. At the same time, the integrated application of inertial measurement units (IMUs) and plantar pressure sensing technology is also relatively mature. For example, a sports technology company in the United States has developed wearable devices that can collect real-time joint angles, angular velocities, and plantar pressure distribution data of athletes, and generate kinematic analysis reports through a cloud platform. These devices have been tested in professional track and field teams in some European and American countries, mainly for technical movement correction and injury risk early warning.

In terms of intelligent decision-making, foreign research focuses more on the application of machine learning algorithms in the interpretation of training data. A research team from Loughborough University in the United Kingdom constructed a technical movement classification model based on support vector machines (SVM) using training data of hurdle athletes, which can identify the types of technical deviations during the take-off phase. However, this model only relies on kinematic data and does not include muscle force parameters, resulting in insufficient adaptability to individual differences. In addition, foreign research on take-off point selection mostly starts from the perspective of sports biomechanics, calculating the optimal take-off point range by establishing mechanical models. However, these models are mostly based on general physiological parameters and lack personalized adjustments for each athlete, making it difficult to meet the refined needs of elite training. Overall, foreign research has advantages in the maturity of technical application and algorithm advancement, but there is still room for improvement in specialized adaptation (e.g., multimodal data fusion for the hurdle take-off phase) and personalized decision-making.

1.3.2 Domestic Research Status

Domestic research on sports intelligent monitoring technology began in the early 21st century, and in recent years, under the promotion of national policies such as "Integration of Sports and Education" and "Sports Development Driven by Science and Technology", relevant research has shown a rapid development trend. In the field of hurdle events, domestic research mainly focuses on two directions: one is traditional sports biomechanical analysis, which studies the technical characteristics of hurdle athletes through high-speed photography, 3D motion capture, and other technologies. For example, a research team from Beijing Sport University conducted a biomechanical analysis of the take-off technology of China's elite hurdle athletes and proposed reference ranges for technical indicators such as take-off angle and ground reaction force. However, most of these studies are offline analyses and cannot provide real-time guidance for training; the other is the application exploration of intelligent monitoring technology. Research teams from universities such as Shanghai University of Sport and Wuhan Sports University have attempted to combine sEMG technology with IMU technology to develop monitoring devices suitable for hurdle training. However, existing devices mostly have problems such as single function (e.g., only capable of data collection, lacking analysis and feedback functions) and insufficient lightweight design (large sensor size, affecting athletes' movements), and have not yet formed a complete "collection - analysis - feedback" closed loop.

In terms of personalized training, domestic research mostly emphasizes the combination of experience and data, but experience still dominates in practical application. Although some provincial and municipal track and field teams have introduced intelligent monitoring devices, the frequency and effect of device use are limited due to coaches' insufficient data interpretation ability and poor adaptability of devices to training scenarios. In addition, there are few intelligent studies on take-off point selection, and existing studies mostly establish general models based on group data, lacking quantitative analysis of individual differences among elite athletes. In general, domestic research has continuously improved the tightness of technical R&D and specialized integration, but there is still a certain gap with advanced foreign levels in system integration, algorithm precision, and practical application implementation, and there is an urgent need to construct a complete Intelligent Muscle Force Monitoring System adapted to elite hurdle training.

1.4 Research Content and Methods

1.4.1 Research Content

The core content of this study revolves around the construction, application, and value verification of the Intelligent Muscle Force Monitoring System, specifically including four aspects: first, theoretical analysis of the technical characteristics and muscle force mechanisms of the hurdle take-off phase, clarifying the core influencing factors of take-off point selection and muscle force, and determining the key parameter dimensions to be collected by the system by sorting out the theories of hurdle sports biomechanics and training science; second, functional design and technical integration of the Intelligent Muscle Force Monitoring System, including the design of multimodal data collection modules (sEMG sensors, IMUs, plantar pressure sensors), data transmission and processing modules (5G transmission, cloud platform), and intelligent analysis and feedback modules (machine learning models, real-time feedback interface), ensuring that the system meets the requirements of real-time performance, lightweight design, and precision; third, construction of a personalized take-off point prediction model based on the system, determining the input features and output indicators of the model by analyzing the correlation between multimodal data and hurdle clearance efficiency, selecting suitable machine learning algorithms to realize the quantitative prediction of personalized optimal take-off points; fourth, analysis of the application value of the system in improving muscle force precision and competitive performance, expounding the empowering effect of the system on hurdle training from three dimensions (technical optimization, injury prevention, and athlete awareness improvement), and proposing paths for system promotion and optimization.

1.4.2 Research Methods

This study adopts interdisciplinary research methods to ensure scientificity and logic. First, the literature research method: by searching databases such as CNKI, Wanfang, Web of Science, and PubMed, collecting domestic and foreign literature on hurdle training, intelligent monitoring technology, sports biomechanics, and machine learning, sorting out the research status and theoretical basis, and clarifying the entry point and innovation of this study. Second, the theoretical analysis method: combining sports biomechanics theory to analyze the mechanical principles and muscle force mechanisms of the hurdle take-off phase, deriving the correlation logic between take-off point selection and muscle force parameters, and providing theoretical support for system design and model construction. Third, the technology design method: based on existing achievements in multimodal data collection technology and artificial intelligence technology, designing the hardware architecture and software functions of the Intelligent Muscle Force Monitoring System, and clarifying the technical parameters and collaborative logic of each module. Fourth, the logical reasoning method: by sorting out the logic of the system application process, analyzing the mechanism of the system in personalized take-off point selection and muscle force precision regulation, deriving the influence path of the system on competitive performance and injury prevention, and forming a complete research logic chain.

2 Technical Characteristics and Muscle Force Mechanisms of the Hurdle Take-off Phase

2.1 Analysis of Technical Characteristics of the Hurdle Take-off Phase

The complete technical process of hurdle events includes five phases: approach run, take-off, hurdle clearance, landing, and inter-hurdle run. Among them, the take-off phase, as the end of the approach run and the beginning of hurdle clearance, is the key to technical connection, and its technical quality directly determines the fluency and efficiency of subsequent hurdle clearance movements. From the perspective of technical structure, the take-off phase can be divided into three sub-links: take-off preparation, ground reaction force application, and take-off for hurdle clearance, each with clear technical requirements and characteristics.

The take-off preparation link starts from the last two steps of the approach run. At this stage, athletes need to adjust their step frequency and stride length to store kinetic energy for take-off ground reaction force. During this link, athletes' center of gravity should remain stable and slightly forward-leaning, with the trunk forming a certain angle with the ground, and the swing amplitude of the arms increasing to maintain body balance and accumulate force for ground reaction force application. The stride length of the last step of the approach run is usually slightly shorter than that of the previous step, aiming to shorten the support time, increase the ground reaction force speed, and ensure that the take-off leg lands accurately on the predetermined take-off point—the distance between the take-off point and the hurdle should adapt to the athlete's lower limb length and approach speed. An excessively long distance will lead to insufficient ground reaction force application, while an excessively short distance will easily cause the "hurdle jumping" phenomenon, increasing the difficulty of hurdle clearance and injury risks.

The ground reaction force application link is the core of the take-off phase and the stage where muscle force is most concentrated. After the take-off leg lands on the ground, athletes need to quickly transfer their center of gravity to the take-off leg and simultaneously activate the coordinated force of the take-off leg and swing leg—the quadriceps femoris, hamstrings, gastrocnemius, and other muscle groups of the take-off leg contract rapidly, generating a resultant force that is vertically upward and horizontally forward to push the body off the ground; the swing leg swings rapidly forward and upward under the action of the iliopsoas, biceps femoris, and tibialis anterior, with the knee lifted to a height similar to the hurdle to prepare for hurdle clearance. During this link, the timing and intensity of muscle force need to be precisely controlled: the ground reaction force application of the take-off leg should be synchronized with the swing movement of the swing leg to avoid force delay or premature force application, which would disrupt body balance; at the same time, the intensity of ground reaction force application should match the approach speed—excessive intensity will easily lead to excessive muscle load, while insufficient intensity cannot provide enough kinetic energy to support hurdle clearance.

The take-off for hurdle clearance link is the end of the take-off phase. At this point, the athlete's body is completely off the ground and enters the hurdle clearance phase. At the moment of take-off, the take-off leg should remain in an extended state until the knee joint is fully extended to maximize the use of ground reaction force kinetic energy; the swing leg should continue to swing forward, with the sole of the foot remaining relaxed when passing over the hurdle to avoid excessive muscle tension leading to increased hurdle clearance height or reduced speed. At the same time, the trunk should maintain a moderate forward lean, and the arms should swing in coordination with the leg movements to maintain body balance in the air and prepare for landing buffer in the landing phase. From the perspective of technical characteristics, the quality of the take-off for hurdle clearance link depends on the technical completion of the previous two links—only with reasonable take-off point selection and precise muscle force can the body achieve stable take-off and efficient hurdle clearance; otherwise, problems such as rigid hurdle clearance movements and unstable landing will easily occur.

2.2 Muscle Force Mechanisms of the Hurdle Take-off Phase

Muscle force during the hurdle take-off phase is a complex process of coordinated work of multiple muscle groups. Different muscle groups perform different functions in different links, and their force timing, intensity, and coordination mode jointly determine the quality of take-off technology. According to the location and functional differences of muscle groups, the key muscle groups in the take-off phase can be divided into three categories: take-off leg muscle groups, swing leg muscle groups, and core muscle groups. The coordinated force of these three categories of muscle groups constitutes the muscle force mechanism of the take-off phase.

As the main force source of the take-off phase, the take-off leg muscle groups are responsible for supporting the body and generating ground reaction force kinetic energy, mainly including the quadriceps femoris, hamstrings, gastrocnemius, and tibialis anterior. The quadriceps femoris, located on the front of the thigh, is the main muscle group for ground reaction force application of the take-off leg. During the ground reaction force preparation phase, the quadriceps femoris is in a pre-tensioned state to store elastic potential energy; during the ground reaction force application phase, the quadriceps femoris contracts concentrically rapidly to promote knee joint extension, generating vertically upward force and simultaneously coordinating with hip flexors to provide forward kinetic energy for the body. The hamstrings, located on the back of the thigh, form an antagonistic relationship with the quadriceps femoris. During the take-off preparation phase, the hamstrings relax moderately to cooperate with the pre-tension of the quadriceps femoris; during the ground reaction force application phase, the hamstrings first contract eccentrically to control the speed of knee joint extension, avoiding injury caused by excessive extension, and then switch to concentric contraction to assist the quadriceps femoris in completing the ground reaction force application action while maintaining the balance of the muscles on the back of the thigh. The gastrocnemius, located on the back of the lower leg, contracts rapidly at the moment of take-off, promoting ankle plantar flexion, further enhancing ground reaction force intensity, extending the ground reaction force time, and providing additional upward kinetic energy for the body. The tibialis anterior, located on the front of the lower leg, mainly functions to control the landing angle of the sole of the foot during the take-off preparation phase, avoiding excessive inversion or eversion of the sole of the foot, maintaining the support stability of the take-off leg, and assisting in ankle movement during the ground reaction force application phase to ensure the precision of the force direction.

The main function of the swing leg muscle groups is to provide forward inertia for the body through rapid swinging and maintain body balance in the air, mainly including the iliopsoas, biceps femoris, rectus femoris, and tibialis anterior. The iliopsoas, located inside the hip joint, is the main power source for lifting the swing leg. During the take-off preparation phase, the iliopsoas contracts slowly to accumulate force for the swing movement; during the ground reaction force application phase, the iliopsoas contracts concentrically rapidly, pulling the swing leg hip joint to flex, so that the knee is quickly lifted to the predetermined height to prepare for hurdle clearance. The biceps femoris, located on the back of the thigh, contracts eccentrically moderately during the swing movement of the swing leg to control the swing speed of the swing leg, avoiding body imbalance caused by excessive swing speed, and simultaneously coordinates with the iliopsoas to adjust the swing angle of the swing leg to ensure that the sole of the foot can pass over the hurdle smoothly. As part of the quadriceps femoris, the rectus femoris participates in hip joint flexion during the swing phase of the swing leg, assisting the iliopsoas in lifting the knee, and at the same time maintaining the tension of the muscles on the front of the thigh to avoid muscle relaxation caused by the swing movement. The tibialis anterior contracts during the swing phase of the swing leg to cause ankle dorsiflexion, keeping the sole of the foot in a neutral position and avoiding the sole of the foot drooping and touching the hurdle, ensuring the fluency of the hurdle clearance movement.

Although the core muscle groups do not directly participate in the ground reaction force application or swing movement of the take-off phase, they play a key role in maintaining body balance and transmitting force kinetic energy, mainly including the rectus abdominis, external oblique muscles, erector spinae, and gluteus maximus. The rectus abdominis and external oblique muscles, located in the abdomen, maintain trunk stability through contraction during the take-off phase, avoiding excessive forward or backward leaning of the trunk caused by leg force; at the same time, the contraction of the abdominal muscles can transmit the kinetic energy generated by the lower limbs upward to provide support for arm swinging, enhancing the coordination of overall force. The erector spinae, located on both sides of the spine, functions to maintain the physiological curvature of the spine. During the take-off phase, the erector spinae is moderately tense to avoid spinal curvature caused by the transfer of the center of gravity, protecting the spine from injury and simultaneously coordinating with the abdominal muscles to maintain the vertical stability of the trunk. The gluteus maximus, located in the buttocks, contracts to maintain the stability of the hip joint during the take-off preparation phase, avoiding excessive extension of the hip joint; during the ground reaction force application phase, the gluteus maximus coordinates with the quadriceps femoris of the take-off leg to enhance the intensity of ground reaction force application, and adjusts the pelvic position through contraction to ensure the reasonable distribution of the body’s center of gravity.

2.3 Correlation Logic Between Take-off Point Selection and Muscle Force

There is a close dynamic correlation between take-off point selection and muscle force. A reasonable take-off point can create optimal biomechanical conditions for muscle force, while precise muscle force is the basis for realizing take-off point adaptation. The two influence and restrict each other, jointly determining the technical quality of the take-off phase.

From a biomechanical perspective, the position of the take-off point directly affects the angle, moment, and efficiency of muscle force. When the distance between the take-off point and the hurdle is excessively long, athletes need to increase the ground reaction force angle of the take-off leg (i.e., the extension angle of the knee and hip joints) to complete hurdle clearance, which will cause the quadriceps femoris and hamstrings of the take-off leg to be in an overextended state. The initial length of muscle contraction exceeds the optimal range, thereby reducing the efficiency of muscle force—according to the length-tension relationship principle of muscle contraction, muscles can only generate maximum tension at a moderate initial length; both overextension and overshortening will lead to a decrease in tension. At the same time, an excessively long take-off point will also increase the swing distance of the swing leg, causing the iliopsoas and biceps femoris of the swing leg to bear a greater load, which easily leads to muscle fatigue or force delay, disrupting the coordinated force rhythm of the take-off leg and swing leg.

An excessively short take-off point will lead to another type of biomechanical imbalance: at this time, the ground reaction force angle of the take-off leg is too small, the extension range of the knee and hip joints is insufficient, the vertically upward component of the muscle force is reduced, and the horizontally forward component is too large, which easily causes the body to take off prematurely, resulting in the "hurdle jumping" phenomenon—the trajectory of the body in the air is too high, which not only increases the hurdle clearance time but also increases the impact force during landing, increasing the risk of injuries to the knee and ankle joints. At the same time, an excessively short take-off point will limit the swing space of the swing leg, making it impossible for the iliopsoas to contract fully, resulting in insufficient lifting height of the swing leg, which easily causes the sole of the foot to touch the hurdle, affecting the fluency of hurdle clearance.

On the contrary, a reasonable take-off point can put the muscles in an optimal force state: the quadriceps femoris and hamstrings of the take-off leg are at a moderate initial length, which can generate maximum tension during contraction; the ratio of the vertically upward and horizontally forward components of the ground reaction force is balanced, which can not only provide sufficient kinetic energy to support hurdle clearance but also maintain the stability of the body's center of gravity; the swing distance and angle of the swing leg are moderate, the force load of the iliopsoas and biceps femoris is within a reasonable range, and rapid and stable swinging can be achieved to form coordination with the ground reaction force of the take-off leg. This state of "take-off point adapting to muscle force" is the key to improving hurdle clearance efficiency and reducing injury risks.

At the same time, the precision of muscle force also affects the stability of take-off point selection. Even if the coach sets a reasonable take-off point range based on experience, if the athlete's muscle force deviates during training (e.g., premature or delayed ground reaction force application of the take-off leg, unstable swing speed of the swing leg), the actual take-off point will deviate from the predetermined range—for example, delayed activation of the quadriceps femoris of the take-off leg will delay the ground reaction force application time, making the athlete's actual take-off point closer to the hurdle than the predetermined position; excessive force of the iliopsoas of the swing leg will increase the swing speed, making the actual take-off point farther from the hurdle than the predetermined position. This phenomenon of "muscle force deviation leading to take-off point deviation" further indicates that take-off point selection and muscle force are a dynamic balance process. It is impossible to optimize take-off technology by only relying on experience to set take-off points or only focusing on muscle force while ignoring take-off point adaptation.

3 Design and Construction of the Intelligent Muscle Force Monitoring System

3.1 Core Principles of System Design

The design of the Intelligent Muscle Force Monitoring System should be guided by the actual needs of hurdle take-off training, combined with the characteristics of multimodal data collection technology and artificial intelligence technology, and follow four core principles: real-time performance, precision, lightweight design, and personalization. These principles ensure that the system can provide high-quality monitoring and feedback services for training without interfering with athletes' training.

The real-time performance principle is the primary requirement for system design, with its core being to ensure the timeliness of data collection, transmission, analysis, and feedback. In hurdle take-off training, the technical movement of athletes is completed in a short time (the take-off phase only lasts 0.3-0.5 seconds). Coaches and athletes need to obtain force deviation and take-off point information in a timely manner to quickly adjust technical movements in subsequent training. Therefore, the system's data collection module should have a high sampling frequency to capture the dynamic changes of muscle force and kinematic parameters; the data transmission module should adopt high-speed transmission technology to reduce data latency; the data analysis module should be equipped with efficient algorithms to quickly complete data processing and decision-making output; the feedback module should transmit information to coaches and athletes in an intuitive form (e.g., real-time pop-ups, sound and light prompts), ensuring that the feedback time interval is controlled within 1 second to meet the real-time adjustment needs of training.

The precision principle is the basis for ensuring the system's monitoring effect, covering the accuracy of data collection and the reliability of analysis results. The accuracy of data collection requires sensors to accurately capture key parameters—the surface electromyography sensor should accurately record muscle activation timing and root mean square (RMS) amplitude, with errors controlled within an acceptable range; the inertial measurement unit should accurately measure joint angles and angular velocities, avoiding data deviations caused by device vibration or external interference; the plantar pressure sensor should accurately obtain the pressure distribution and peaks of ground reaction force, ensuring that the data can truly reflect the force intensity. The reliability of analysis results requires the machine learning model to have a high prediction accuracy, which can accurately identify take-off point deviations and muscle force problems based on multimodal data, avoiding incorrect feedback information caused by algorithm errors that affect training effects or even increase injury risks. To achieve precision, the system should select high-precision sensors in hardware selection, optimize model parameters through a large amount of data training in software algorithms, and establish a data calibration mechanism to regularly calibrate sensors and models.

The lightweight design principle aims to reduce the system's interference with athletes' training and ensure that the device can adapt to actual training scenarios. Hurdle events have high requirements for athletes' movement flexibility. If the system equipment is too large, heavy, or cumbersome to wear, it will limit the range and speed of athletes' movements, affecting the authenticity of training. Therefore, the hardware design of the system should pursue miniaturization and lightweight—sensors should select products with small size and light weight, such as patch-type surface electromyography sensors and micro inertial measurement units; the fixing method of sensors should be convenient and firm, using breathable and elastic straps or stickers to avoid irritation to the skin or falling off during movement; the data transmission module should be integrated to reduce the number of wires and avoid wire entanglement affecting movements. At the same time, the software operation of the system should be simple and easy to understand, so that coaches and athletes can master the basic usage methods without complex training, ensuring that the system can be quickly integrated into the daily training process.

The personalization principle is the key to the system adapting to elite hurdle training, emphasizing that the system can provide customized services according to the individual differences of each athlete. Elite hurdle athletes vary significantly in physiological characteristics (e.g., height, weight, lower limb length), technical characteristics (e.g., approach speed, step frequency), and training needs (e.g., improving hurdle clearance speed, correcting force deviations). A unified monitoring standard and feedback mode cannot meet individual needs. Therefore, the system should have personalized data collection dimensions—adjusting the attachment position and collection focus of sensors according to the athlete's technical weaknesses; personalized model parameters—training an exclusive optimal take-off point prediction model based on each athlete's basic data; personalized feedback content—outputting targeted correction suggestions for the athlete's specific problems, such as some athletes needing to focus on adjusting the ground reaction force time of the take-off leg, and others needing to optimize the swing angle of the swing leg. Through personalized design, the system can truly realize "one-on-one" refined training support.

3.2 Hardware Architecture Design of the System

The hardware architecture of the Intelligent Muscle Force Monitoring System adopts a "distributed collection - centralized processing" mode, consisting of four parts: a multimodal data collection module, a data transmission module, a cloud processing module, and a terminal feedback module. Each module works collaboratively to realize the complete process from data capture to information output.

The multimodal data collection module is the "perceptual organ" of the system, responsible for real-time capture of muscle force and kinematic parameters of the hurdle take-off phase. Its core includes a surface electromyography (sEMG) sensor sub-module, an inertial measurement unit (IMU) sub-module, and a plantar pressure sensor sub-module. The surface electromyography sensor sub-module is used to collect the electrophysiological signals of key muscle groups to reflect the muscle activation state—according to the muscle force mechanism of the hurdle take-off phase, the sensors should be attached to 6 groups of muscle groups: the quadriceps femoris (lateral head), hamstrings (biceps femoris), and gastrocnemius (medial head) of the take-off leg, and the iliopsoas (inguinal region), biceps femoris (lateral head), and tibialis anterior (middle front of the lower leg) of the swing leg; the sensors adopt a patch-type design, with a thickness of less than 1mm and a weight of less than 5g, and a sampling frequency set to 1000Hz, which can accurately capture the timing changes and RMS values of muscle activation, and has anti-interference functions to reduce the impact of sweat and skin friction on signals during movement.

The inertial measurement unit (IMU) sub-module is used to collect athletes' kinematic parameters, including joint angles, angular velocities, and accelerations, to reflect the state of body movements—the IMU adopts a miniaturized design, with a volume of approximately 1cm×1cm×0.5cm and a weight of less than 3g, and is fixed to 5 positions of the athlete's body via elastic straps: the waist (L3-L4 vertebral region), the lateral side of the take-off leg's knee joint, the lateral side of the take-off leg's ankle joint, the lateral side of the swing leg's knee joint, and the lateral side of the swing leg's ankle joint; the sampling frequency of the IMU is set to 200Hz, which can real-time record the tilt angle of the trunk, the extension/flexion angles and angular velocities of the knee and ankle joints during the take-off phase, providing data support for analyzing body balance and movement coordination; at the same time, the IMU has a built-in temperature compensation function to avoid measurement errors caused by temperature changes in the training environment.

The plantar pressure sensor sub-module is used to collect the plantar pressure distribution and peaks at the moment of take-off ground reaction force, reflecting the intensity and symmetry of ground reaction force—the sensor adopts a flexible film design, with a thickness of less than 0.5mm and a weight of less than 10g, which can be directly embedded in the insole of the athlete's training shoes, covering the forefoot, midfoot, and hindfoot regions of the sole; the sampling frequency of the sensor is set to 500Hz, which can capture the pressure change curve at the moment of ground reaction force, and calculate parameters such as pressure peaks, pressure center trajectory, and pressure distribution uniformity; the sensor has high sensitivity, with a pressure measurement range of 0-2000kPa, which can accurately reflect ground reaction force of different intensities.

The data transmission module is the "nerve center" of the system, responsible for real-time transmission of data captured by the multimodal data collection module to the cloud processing module. Its core adopts a combination of 5G wireless transmission technology and edge computing nodes. Since hurdle training is mostly conducted outdoors or in large venues, wired transmission has limitations. The 5G technology has the characteristics of high bandwidth (peak rate up to 10Gbps), low latency (end-to-end latency ≤ 100ms), and wide coverage, which can meet the needs of simultaneous data transmission from multiple sensors and is not limited by the training venue. A miniaturized edge computing node (with a volume of approximately 5cm×3cm×2cm and a weight of less than 50g) is equipped on each athlete. This node is connected to each sensor via Bluetooth Low Energy (BLE) technology, receives data collected by the sensors, and performs preliminary preprocessing (such as data filtering and format conversion) to reduce the amount of original data transmission; subsequently, the edge computing node uploads the preprocessed data to the cloud processing module via the 5G module, and also has a data caching function. In case of temporary 5G signal interruption, data can be temporarily stored and uploaded continuously after the signal is restored to ensure no data loss.

The cloud processing module is the "brain" of the system, responsible for in-depth analysis and intelligent decision-making of the transmitted data, and consists of a server cluster and an algorithm model library. The server cluster adopts a distributed architecture, with high-performance data processing capabilities, which can simultaneously receive training data from multiple athletes and perform parallel processing; the server is equipped with large-capacity storage devices, which can store athletes' training data for a long time, providing data support for subsequent training progress analysis and model optimization. The algorithm model library is the core of the cloud processing module, including data preprocessing algorithms, feature extraction algorithms, machine learning prediction models, and result generation algorithms—the data preprocessing algorithms are used to further clean the data (such as removing noise and filling missing values) to ensure data quality; the feature extraction algorithms are used to extract key features from multimodal data (such as the RMS value of sEMG, the peak angular velocity of joints from IMU, and the peak time of plantar pressure); the machine learning prediction models (such as random forest, neural network) predict the optimal take-off point of each athlete based on the extracted features and identify muscle force deviations; the result generation algorithms convert the model output results into intuitive analysis reports and feedback suggestions, such as take-off point deviation values, muscle activation delay time, and force correction directions.

The terminal feedback module is the "output interface" of the system, responsible for transmitting the analysis results and feedback suggestions generated by the cloud processing module to coaches and athletes, including two sub-modules: the coach terminal and the athlete terminal. The coach terminal uses a tablet computer or laptop as the terminal device, and receives the analysis report sent by the cloud via dedicated software. The report content includes the athlete's take-off point selection deviation, the change trend of muscle force parameters, and the evaluation of training effects. Coaches can view real-time data and historical data comparisons via the software to formulate or adjust training plans; at the same time, the coach terminal software has a data visualization function, displaying data in the form of charts (such as line charts, heat maps) to facilitate coaches to quickly understand the athlete's technical problems. The athlete terminal uses a smart watch or bracelet as the terminal device, which is small in size and convenient to wear, and can receive concise feedback information sent by the cloud in real-time, such as take-off point deviation prompts ("The current take-off point is too close, please move back 5cm") and muscle force correction prompts ("Hamstring activation is delayed, please apply force 0.2s earlier"). The feedback information is presented in text or sound and light form to ensure that athletes can obtain adjustment suggestions in a timely manner during training breaks.

3.3 Software Function Design of the System

The software functions of the Intelligent Muscle Force Monitoring System revolve around the entire process of "data collection - analysis - feedback - management", and are divided into four modules: data collection software, cloud analysis software, terminal feedback software, and system management software. The functions of each module are connected to form a complete software ecosystem.

The data collection software is the control core of the hardware module, with main functions including sensor management, real-time data collection, and preprocessing, running on the edge computing node and locally on the sensors. The sensor management function allows users to configure sensor parameters (such as sampling frequency, signal gain, and transmission mode) via the software interface, and can detect the connection status and battery level of the sensors. If a sensor is disconnected or the battery level is low, the software will issue an alarm prompt in a timely manner to ensure the continuity of the collection process; for surface electromyography sensors, the software also has a skin impedance detection function to help users confirm whether the sensors are attached properly, avoiding data deviations caused by poor contact. The real-time data collection function can simultaneously receive data from 6 groups of sEMG sensors, 5 IMUs, and 1 group of plantar pressure sensors, and uses time stamp synchronization technology to ensure that data from different types of sensors are consistent in the time dimension, with an error controlled within 1ms; the collected data are displayed in real-time on the software interface in the form of data streams, allowing users to intuitively view data waveforms and judge data quality. The data preprocessing function performs preliminary processing on the collected data locally, including signal filtering (using a Butterworth filter to remove 50Hz power frequency interference and motion artifacts), data dimensionality reduction (extracting feature parameters such as the RMS value of sEMG and the mean value of IMU angles and angular velocities), and data format conversion (converting raw data into JSON format recognizable by the cloud analysis software), reducing the amount of data transmission and improving the efficiency of subsequent analysis.

The cloud analysis software is the intelligent core of the system, undertaking the functions of in-depth data analysis and intelligent decision-making, and running on the cloud server cluster. The data receiving and storage function is responsible for receiving preprocessed data from the edge computing node, storing the data using a distributed database (such as Hadoop HDFS), supporting long-term storage and fast retrieval of massive data; at the same time, the software establishes an exclusive database for each athlete, recording their multimodal data from each training session to form a complete training data file. The feature extraction function further extracts more representative feature parameters based on the preprocessed data—for sEMG data, extracting parameters such as muscle activation latency, peak RMS value, and activation duration; for IMU data, extracting parameters such as peak joint angle, peak angular velocity, and angle change rate; for plantar pressure data, extracting parameters such as pressure peak, pressure center offset, and pressure distribution uniformity; these feature parameters serve as inputs to the machine learning model for subsequent analysis and prediction.

The machine learning analysis function is the core of the cloud analysis software, including an optimal take-off point prediction model and a muscle force deviation identification model. The optimal take-off point prediction model adopts the random forest algorithm, with the athlete's basic physiological parameters (height, weight, lower limb length), feature parameters during training (such as approach speed, knee joint angular velocity of the take-off leg, and plantar pressure peak), and historical hurdle clearance efficiency data (hurdle clearance time, referee score) as input features, and "optimal take-off point position" as the output label. The model optimizes parameters through a large amount of training data to realize accurate prediction of the personalized optimal take-off point for each athlete; the model has a dynamic update function, and will retrain the model regularly as the athlete's training data accumulates to ensure that the prediction results always adapt to the athlete's latest state. The muscle force deviation identification model adopts the support vector machine (SVM) algorithm, which compares real-time collected feature parameters with feature parameters in the normal force state to identify the type (such as activation delay, insufficient force, coordination imbalance) and degree of muscle force deviation, and analyzes the possible causes of deviation (such as muscle fatigue, irregular technical movements) to provide a basis for subsequent feedback suggestions.

The result generation function converts the analysis results of the machine learning model into intuitive and operable feedback content, including a take-off point analysis report, a muscle force evaluation report, and a training suggestion report. The take-off point analysis report displays the deviation value and direction between the current take-off point and the optimal take-off point, as well as adjustment suggestions; the muscle force evaluation report evaluates the precision of muscle force in the form of a score (100-point scale), focusing on analyzing the force parameters of key muscle groups and pointing out existing deviations; the training suggestion report proposes specific training adjustment plans based on the deviation analysis results, such as suggesting additional targeted explosive training for hamstring activation delay, and suggesting adjusting the landing angle of the sole of the foot during take-off for uneven plantar pressure distribution.

The terminal feedback software is responsible for transmitting the results generated by the cloud analysis software to users, divided into the coach terminal and the athlete terminal, with functional designs focusing on different priorities. The coach terminal software runs on a tablet computer or laptop, with data visualization, multi-athlete management, and training plan formulation functions. The data visualization function displays the athlete's real-time and historical data in the form of charts, such as a trend chart of take-off point deviation changes, a comparison chart of muscle force parameters, and a curve chart of hurdle clearance efficiency improvement, helping coaches quickly grasp the athlete's training progress and technical problems; the multi-athlete management function allows coaches to monitor training data of multiple athletes simultaneously, switching between the analysis results of different athletes via the software interface to facilitate the overall management of team training; the training plan formulation function provides coaches with training plan templates based on the athlete's evaluation report, allowing coaches to adjust the training content, intensity, and frequency according to actual needs, and synchronize the plan to the athlete terminal software to realize accurate transmission of training guidance.

The athlete terminal software runs on a smart watch or bracelet, with functions designed to be concise and real-time, including real-time feedback, training records, and a personal center. The real-time feedback function transmits brief adjustment suggestions to athletes in text or sound and light form during training, such as "The take-off point is too close, move back 5cm" and "Hamstring force is delayed, speed up ground reaction force", ensuring that athletes can adjust in a timely manner during training; the training record function automatically saves the evaluation report and feedback suggestions of each training session, allowing athletes to view them after training to review their technical problems and progress; the personal center function displays the athlete's basic information, total training duration, hurdle clearance efficiency score, and other data, helping athletes establish training goals and enhance training initiative.

The system management software is used to ensure the stable operation and security of the entire system, with main functions including user management, permission control, data security, and system maintenance. The user management function allows administrators to create user accounts for different roles such as coaches, athletes, and system maintenance personnel, and set the validity period and login password of the accounts; the permission control function assigns different operation permissions to different roles, such as coaches can view and manage the data of their affiliated athletes, athletes can only view their own data, and system maintenance personnel can perform sensor calibration and software updates, avoiding data leakage or incorrect operations; the data security function uses encryption technology (such as AES-256 encryption) to protect transmitted and stored data, preventing data from being stolen or tampered with, and at the same time establishes a data backup mechanism to regularly back up the database to ensure data security; the system maintenance function allows administrators to remotely monitor the operation status of each module of the system, such as sensor connection status, server load, and network transmission speed. If an abnormality is found, remote repair can be performed in a timely manner or a maintenance prompt can be issued to ensure the stable operation of the system.

4 Application Mechanism of the Intelligent Muscle Force Monitoring System in Hurdle

Training

4.1 Application Mechanism of the System in Personalized Take-off Point Selection

The application of the Intelligent Muscle Force Monitoring System in personalized take-off point selection follows a closed-loop mechanism of "data collection - model prediction - real-time adjustment - dynamic optimization". Through in-depth integration and intelligent analysis of multi-dimensional data, it realizes the transformation of take-off point selection from "experience-based judgment" to "quantitative adaptation", ensuring that each elite hurdle athlete can obtain the most suitable take-off point position for themselves.

In the data collection and basic modeling phase, the system first comprehensively captures the athlete's individual basic data and initial training data through the multimodal data collection module, providing basic support for the personalized take-off point prediction model. The individual basic data includes the athlete's physiological parameters (height, weight, lower limb length, flexibility, lower limb strength distribution) and technical parameters (approach speed, step frequency, stride characteristics), which are obtained through special tests in the early stage—such as measuring physiological parameters via physical testing equipment and analyzing approach technical parameters via high-speed photography and motion capture technology; the initial training data refers to the multimodal data of the athlete completing take-off training under traditional coach guidance without accessing system feedback, including muscle activation parameters recorded by sEMG, kinematic parameters recorded by IMU, ground reaction force parameters recorded by plantar pressure sensors, and the coach's score of hurdle clearance efficiency. The system uploads these data to the cloud analysis software, extracts key features (such as the stride length of the last step of the approach run, the maximum extension angle of the take-off leg's knee joint, and the occurrence time of the plantar pressure peak) via the feature extraction algorithm, and then correlates these features with the hurdle clearance efficiency score to train the initial optimal take-off point prediction model. The core goal of this phase is to establish the correlation logic of "individual data - hurdle clearance efficiency - take-off point" and lay the foundation for subsequent personalized prediction.

In the real-time prediction and feedback phase, the system enters normalized training application, providing dynamic take-off point suggestions for athletes through real-time data collection and model calculation. When the athlete conducts take-off training, the multimodal data collection module captures real-time multimodal data during training, and the edge computing node performs preliminary preprocessing on the data before quickly transmitting it to the cloud analysis software; the cloud software first compares the real-time data with the athlete's basic data to determine whether there is an abnormality in the current training state (such as whether the approach speed decreases due to fatigue). If an abnormality exists, the model parameters are temporarily adjusted to ensure the adaptability of the prediction results; subsequently, the software inputs the real-time extracted feature parameters into the optimal take-off point prediction model, calculates the personalized optimal take-off point position under the current state, and compares it with the athlete's actual take-off point position (jointly positioned via IMU and plantar pressure data) to obtain the deviation value and direction. The system transmits this result to coaches and athletes in real-time via the terminal feedback module—the coach terminal software displays a detailed deviation analysis, such as "The current take-off point is 8cm closer than the optimal position, which may lead to insufficient hurdle clearance height"; the athlete terminal device provides a concise prompt, such as "The take-off point is too close, please move back 8cm", helping the athlete adjust the approach rhythm and optimize take-off point selection in subsequent training. The core of this phase is to realize real-time quantitative feedback of take-off point selection and help athletes quickly correct deviations.

In the dynamic optimization and iteration phase, the system continuously improves the accuracy of personalized take-off point prediction through long-term data accumulation and model updates, ensuring that the take-off point selection always adapts to the athlete's technical progress and state changes. As training continues, the system automatically stores the real-time data, prediction results, and actual hurdle clearance efficiency data of each training session, forming a large personal training database. The cloud analysis software regularly (e.g., weekly) conducts review and analysis of these data to evaluate the accuracy of the prediction model—if a deviation is found between the model-predicted optimal take-off point and the actual take-off point that produces the best hurdle clearance efficiency, the model is retrained via machine learning algorithms to adjust feature weights and model parameters, such as increasing the weight of recent muscle force parameters and reducing the influence of early basic data; at the same time, the system also analyzes the influence of the athlete's technical progress on the take-off point, such as automatically adjusting the range of the optimal take-off point when the athlete's approach speed increases to ensure that the take-off point adapts to the new approach speed. In addition, when the athlete encounters special situations (such as post-injury rehabilitation, technical movement improvement), the system triggers an emergency model update, quickly adjusting the prediction model by supplementing the collection of special test data to avoid inaccurate take-off point suggestions caused by model lag. The core of this phase is to realize dynamic adaptation of take-off point prediction and ensure the long-term effectiveness of personalized suggestions.

4.2 Application Mechanism of the System in Improving Muscle Force Precision

The Intelligent Muscle Force Monitoring System helps elite hurdle athletes improve muscle force precision during the take-off phase from three dimensions (muscle activation timing, force intensity, and muscle group coordination) through a progressive mechanism of "real-time monitoring - deviation identification - precise feedback - training reinforcement", realizing the transformation from "ambiguous force" to "controllable force".

In terms of muscle activation timing regulation, the system accurately captures the time nodes of muscle activation, identifies problems of activation delay or premature activation, and provides targeted feedback and training suggestions. Muscle activation timing is the key to determining the quality of take-off technology—the activation of the quadriceps femoris of the take-off leg needs to be synchronized with the activation of the iliopsoas of the swing leg. If the quadriceps femoris is activated delayed, it will lead to delayed ground reaction force application and affect take-off speed; if the iliopsoas is activated prematurely, it will cause the swing leg to lift too early and disrupt body balance. The system's surface electromyography sensors record the activation signals of 6 groups of key muscle groups in real-time, and the cloud analysis software calculates the activation latency (the time from the landing of the last step of the approach run to the start of muscle activation) and activation duration of each group of muscle groups via the feature extraction algorithm, and compares them with the athlete's "optimal activation timing template" (established based on historical best training data) to identify timing deviations. For example, if the analysis finds that the activation latency of the hamstrings of the take-off leg is 0.2s later than the optimal template, the system transmits this deviation information to coaches and athletes—the coach terminal software displays a change curve of hamstring activation timing to help coaches analyze the cause of the deviation (such as whether the reaction speed decreases due to muscle fatigue); the athlete terminal device provides a real-time prompt of "Hamstring activation is delayed, please speed up the ground reaction force response". At the same time, the system recommends a targeted timing training plan based on the type of deviation, such as adopting the "sound-controlled trigger" training method, allowing athletes to activate hamstring force according to specific sound signals, and shortening the activation latency through repeated training to optimize activation timing.

In terms of force intensity regulation, the system quantifies the intensity parameters of muscle force, identifies problems of insufficient or excessive force, and helps athletes adjust force intensity to realize "on-demand force application". Different take-off phases have different requirements for muscle force intensity—during the take-off preparation phase, moderate force accumulation is required, and the force intensity should not be too large to avoid premature energy consumption; during the ground reaction force application phase, full force is required to generate sufficient kinetic energy to support hurdle clearance; during the take-off for hurdle clearance phase, moderate relaxation is required to avoid muscle tension affecting movement fluency. The system quantifies muscle force intensity in real-time via the RMS value of surface electromyography sensors (reflecting muscle force intensity) and the pressure peak of plantar pressure sensors (reflecting ground reaction force intensity), and compares it with the "phased force intensity standard" (formulated based on sports biomechanics theory and individual best data) to identify intensity deviations. For example, if the analysis finds that the RMS value of the iliopsoas of the swing leg during the ground reaction force application phase is only 70% of the optimal standard, it indicates insufficient force, which will reduce the lifting speed of the swing leg and affect hurdle clearance efficiency; the system feeds this information back to the user and recommends an intensity training plan, such as adopting "resistance band-assisted swing" training to increase the resistance of the swing leg, enhance the force intensity of the iliopsoas, and simultaneously monitor changes in the RMS value in real-time via the system to ensure training effects. For cases of excessive force, such as when the RMS value of the quadriceps femoris of the take-off leg during the ground reaction force application phase exceeds 120% of the optimal standard, the system prompts "Excessive force of the quadriceps femoris, please reduce the force intensity to avoid excessive muscle load" and recommends relaxation training to help athletes adjust their force habits.

In terms of muscle group coordination regulation, the system analyzes the force correlation parameters of multiple muscle groups, identifies coordination imbalance problems, and helps athletes optimize the cooperation between muscle groups to realize "coordinated force application". Muscle force during the hurdle take-off phase is the result of coordinated work of multiple muscle groups, and any deviation in the force of a single muscle group will affect the overall coordination effect—for example, excessive force of the quadriceps femoris of the take-off leg and insufficient force of the hamstrings will lead to excessive extension of the knee joint, increasing injury risks; coordination imbalance between the iliopsoas and biceps femoris of the swing leg will cause deviation in the swing angle of the swing leg, affecting the hurdle clearance trajectory. The system calculates the force parameter ratios between different muscle groups (such as the RMS ratio between the quadriceps femoris and hamstrings, and the activation time difference between the iliopsoas and biceps femoris) via the cloud analysis software, and compares them with the "optimal coordination parameter range" to identify the type of coordination imbalance. For example, if the analysis finds that the RMS ratio between the quadriceps femoris and hamstrings of the take-off leg is 3:1, far exceeding the optimal range of 2:1, it indicates that the quadriceps femoris is relatively over-forceful and the hamstrings are insufficiently coordinated; the system generates a coordination imbalance analysis report, points out the problem, and recommends a coordination training plan, such as adopting "bilateral synchronized force" training, allowing athletes to focus on the force of both the quadriceps femoris and hamstrings during training, and adjusting the force intensity of the two muscle groups through the ratio changes fed back by the system in real-time to gradually reduce the ratio to the optimal range. At the same time, the system also analyzes the influence of muscle group coordination imbalance on kinematic parameters via IMU and plantar pressure data, such as whether it causes joint angle deviation or uneven plantar pressure distribution, helping coaches and athletes more comprehensively understand the hazards of coordination problems and enhance the targeting of training.

4.3 Application Mechanism of the System in Injury Risk Prevention and Athlete Awareness Improvement

4.3.1 Injury Risk Prevention Mechanism

The take-off phase of hurdle races is a high-risk link for injuries, with common injuries including strains of the quadriceps femoris in the take-off leg, hamstring tears, and ankle sprains. These injuries are mostly caused by muscle force deviations (such as excessive load and compensatory force) and movement imbalances (such as abnormal joint angles and uneven plantar pressure distribution). The Intelligent Muscle Force Monitoring System realizes proactive prevention of injury risks through a "risk early warning - cause analysis - intervention suggestion" mechanism, eliminating injury risks in their infancy.

In terms of risk early warning, the system establishes an "Injury Risk Assessment Model" to monitor key injury-related parameters in real time and identify potential risks in advance. Based on sports medicine and sports biomechanics theories, the Injury Risk Assessment Model selects parameters highly correlated with injuries as early warning indicators, including muscle force parameters (e.g., the number of times muscle activation intensity exceeds the individual tolerance threshold, the duration of muscle group coordination imbalance), kinematic parameters (e.g., the frequency of the knee joint's maximum extension angle exceeding the safe range, the number of abnormal ankle inversion angles), and plantar pressure parameters (e.g., the time when the local plantar pressure peak exceeds the safety threshold, the pressure center offset). The system captures these parameters in real time through the multimodal data collection module, and the cloud analysis software inputs them into the assessment model to calculate the injury risk score (0-100 points, with higher scores indicating higher risks). Risk level thresholds are set (e.g., 0-30 points for low risk, 31-70 points for medium risk, and 71-100 points for high risk). When the risk score reaches medium risk or above, the system immediately issues an early warning through the terminal feedback module: the coach-side software displays specific early warning indicators and risk levels, such as "The activation intensity of the quadriceps femoris in the take-off leg has exceeded the tolerance threshold 5 consecutive times, with a risk score of 75 points (high risk)"; the athlete-side device provides an audio-visual alarm prompt, such as "Excessive load on the quadriceps femoris, it is recommended to pause training and relax", ensuring the timely termination of high-risk training behaviors.

In terms of cause analysis, while issuing a risk early warning, the system conducts an in-depth analysis of the root causes of the risk to provide a basis for subsequent interventions. The causes of injury risks can be divided into technical factors (e.g., muscle force deviations, irregular movements), physiological factors (e.g., muscle fatigue, insufficient flexibility), and external factors (e.g., excessive training intensity, poor venue conditions). The system identifies the main causes through multi-dimensional data comparison. For example, if the early warning indicator is "abnormal ankle inversion angle", the system first analyzes the plantar pressure data to determine whether the uneven plantar pressure distribution causes ankle force imbalance; if the pressure distribution is normal, it analyzes the muscle force data to determine whether the coordination imbalance of calf muscles (such as the tibialis anterior and gastrocnemius) leads to a decrease in ankle control ability; if the muscle force data is normal, it combines training records to analyze whether recent excessive training intensity causes muscle fatigue or whether hard venues increase ankle force. The system outputs the cause analysis results in the form of a report, helping coaches and athletes identify the root cause of the risk and avoid blind training adjustments.

In terms of intervention suggestions, based on the cause analysis results, the system provides targeted risk intervention plans, including immediate intervention and long-term intervention. Immediate intervention plans are used to quickly reduce current injury risks: for example, for excessive muscle load, it is recommended to immediately perform static stretching or cold compresses; for movement imbalances, it is recommended to pause take-off training and conduct specialized technical correction exercises (such as simulating take-off movements without hurdles). Long-term intervention plans are used to fundamentally eliminate risk factors: for example, for muscle coordination imbalance, a 2-week coordination training plan is recommended, including specific training movements (such as lunges and side leg lifts), training frequency (3 times a week), and training duration (30 minutes per session); for insufficient flexibility, a 15-minute daily dynamic stretching training is recommended, focusing on stretching the key muscle groups of the take-off and swing legs. At the same time, the system tracks the implementation of the intervention plan through the terminal feedback software and regularly evaluates risk changes. If the risk score does not decrease, the intervention plan is adjusted to ensure effective risk control.

4.3.2 Athlete Awareness Improvement Mechanism

An athlete’s awareness of their own technical and force characteristics directly affects the autonomy and efficiency of training. In traditional training, athletes mostly understand their own problems indirectly through coaches’ verbal feedback, resulting in vague awareness. The Intelligent Muscle Force Monitoring System helps athletes establish a clear understanding of their own techniques and force through a "data visualization feedback - active exploratory learning - closed-loop awareness construction" mechanism, realizing the transformation from "passive acceptance of guidance" to "active technical optimization".

In terms of data visualization feedback, the system converts abstract muscle force and kinematic parameters into understandable information through intuitive charts, helping athletes establish a correlative awareness of "parameters - techniques - performance". Both the athlete-side and coach-side software have rich data visualization functions, such as muscle activation timing charts (showing the activation timeline of 6 muscle groups to help athletes understand the coordination of muscle groups), force intensity heatmaps (indicating the distribution of muscle force intensity through color depth to help athletes identify areas of excessive or insufficient force), and take-off point deviation trend charts (showing changes in take-off point deviation over a period to help athletes recognize their progress). For example, by viewing the muscle activation timing chart, athletes can clearly find that "their hamstrings are always activated 0.2 seconds later than the quadriceps femoris", thereby understanding why coaches point out "incoherent ground force application"; by viewing the force intensity heatmap, athletes can intuitively see that "the force intensity of the iliopsoas in the swing leg is lower than the optimal standard", and further understand why the swing leg lifting speed is slow. This visualized feedback transforms abstract technical problems into specific data differences, helping athletes establish clear awareness and avoid vague understanding of coaches' feedback.

In terms of active exploratory learning, the system allows athletes to actively adjust their technical movements during training and verify the adjustment effects through real-time data feedback, cultivating their ability of independent exploration. In traditional training, athletes mostly adjust their techniques according to coaches' instructions, lacking the process of independent trial and verification. With the support of the system, athletes can independently try to adjust the take-off point position, muscle force timing, or intensity under the guidance of coaches, and judge the effectiveness of the adjustments through real-time parameter feedback from the system. For example, athletes can try to move the take-off point back by 5 cm, and check through the system whether the hurdle clearance time is shortened and whether the muscle force parameters are closer to the optimal standard to verify whether this adjustment is suitable for themselves; they can also try to activate the hamstrings 0.1 seconds earlier and check through the system whether the muscle group activation timing is more coordinated, thereby finding the force timing that suits them. This process of active exploration not only enables athletes to gain a deeper understanding of their own technical characteristics but also cultivates their ability to analyze and solve problems independently, improving the autonomy of training.

In terms of closed-loop awareness construction, through long-term training data tracking and feedback, the system helps athletes establish a "awareness - adjustment - verification - re-awareness" closed loop, realizing the continuous improvement of their awareness level. As training continues, the system automatically records the technical parameters, adjustment measures, and training effects of each training session for athletes, forming a personal training file. Athletes can review the file regularly to analyze the changing trend of their own technical problems, such as "after 2 weeks of timing training, the activation delay of the hamstrings has been reduced from 0.2 seconds to 0.1 seconds", thereby verifying the effectiveness of the training method and strengthening correct awareness; at the same time, athletes can compare parameters of different stages to identify new technical problems, such as "the recent decrease in the uniformity of plantar pressure distribution may be caused by insufficient ankle strength", and then initiate a new process of awareness and adjustment. This closed-loop awareness model enables athletes' awareness level to deepen continuously with training: from initially "understanding the problem" to "comprehending the cause", and then to "solving the problem independently", ultimately achieving the simultaneous improvement of technique and awareness.

5. Research Conclusions and Prospects

5.1 Research Conclusions

This study focuses on the application of the Intelligent Muscle Force Monitoring System in assisting elite hurdle athletes with personalized take-off point selection and muscle force precision improvement. Through theoretical analysis, system design, and application mechanism research, the following core conclusions are drawn:

First, the Intelligent Muscle Force Monitoring System, relying on multimodal data fusion and artificial intelligence technology, breaks through the limitations of traditional hurdle training—where take-off point selection depends on experience and muscle force is difficult to quantify—and constructs a new "data-driven" paradigm for hurdle training. In traditional training, coaches' judgment of take-off points and evaluation of muscle force are mostly based on subjective experience, lacking objective data support and making it difficult to adapt to the individual differences of elite athletes. However, the system designed in this study realizes the real-time quantification of muscle force and kinematic parameters during the take-off phase by integrating multimodal data collection technologies such as surface electromyography, inertial measurement, and plantar pressure sensing; it also achieves accurate prediction of the optimal take-off point and intelligent identification of muscle force deviations by constructing a personalized prediction model using machine learning algorithms. This provides an objective basis for the formulation and adjustment of training plans, promoting the transformation of hurdle training from "experience-led" to "a combination of data and experience".

Second, the application mechanism of the system in personalized take-off point selection realizes the transformation of take-off points from "unified standards" to "individual adaptation", laying a foundation for improving hurdle clearance efficiency. Through a closed-loop mechanism of "data collection - model prediction - real-time adjustment - dynamic optimization", the system first establishes an exclusive optimal take-off point prediction model based on the athlete's individual basic data and initial training data; then captures real-time data during training to predict the optimal take-off point under the current state and feed back deviation information; finally, continuously optimizes the model through long-term data accumulation to ensure that the take-off point always adapts to the athlete's technical progress and state changes. This mechanism effectively solves the problem of individual deviations in traditional experience-based judgment, enabling the take-off point selection to fully adapt to each athlete's physiological characteristics and technical strengths, and creating optimal biomechanical conditions for subsequent muscle force optimization and hurdle clearance efficiency improvement.

Third, the application mechanism of the system in improving muscle force precision achieves refined regulation of muscle force from three dimensions—activation timing, force intensity, and muscle group coordination—directly promoting the improvement of hurdle clearance technical quality and competitive performance. In terms of activation timing regulation, the system helps athletes optimize force timing by identifying problems of delayed or premature muscle activation; in terms of force intensity regulation, it helps athletes achieve "on-demand force application" by quantifying force intensity parameters, avoiding excessive or insufficient force; in terms of muscle group coordination regulation, it helps athletes optimize coordination by analyzing the correlation parameters between muscle groups, reducing compensatory force. The coordinated regulation of these three dimensions jointly improves muscle force precision, which is further transformed into improved competitive performance—such as shortened hurdle clearance time and enhanced inter-hurdle rhythm stability—verifying the practical value of intelligent monitoring technology for technical optimization.

Fourth, the application of the system in injury risk prevention and athlete awareness improvement expands the value boundary of intelligent technology in hurdle training, realizing multi-dimensional empowerment of "technical optimization - injury prevention - awareness improvement". In terms of injury risk prevention, the system effectively reduces the incidence of injuries during the take-off phase by establishing an injury risk assessment model to issue real-time early warnings of potential risks and provide targeted intervention plans; in terms of athlete awareness improvement, it helps athletes establish a clear understanding of their own techniques and force through data visualization feedback, active exploratory learning, and closed-loop awareness construction, improving the autonomy and efficiency of training. These two aspects of application make the system not only a tool for technical optimization but also an important support for ensuring training safety and cultivating athletes' comprehensive abilities, enriching the connotation of intelligent training.

Fifth, the "multimodal data collection - intelligent analysis - real-time feedback - dynamic optimization" system framework and application mechanism constructed in this study provide a replicable paradigm for the application of intelligent technology in specialized track and field training (especially for technically complex events). As a representative of technically complex track and field events, hurdle races have typical demands for intelligent monitoring in training—requiring accurate capture of dynamic muscle force and kinematic parameters, adaptation to significant individual differences, and real-time feedback and adjustment. The system designed in this study fully considers these specialized demands in terms of hardware architecture, software functions, and application mechanisms, forming a complete solution. The core logic of this solution (such as multimodal data fusion, personalized model construction, and closed-loop application mechanism) can be migrated to other technical track and field events (such as high jump and long jump) or other sports with high technical requirements (such as gymnastics and fencing), providing theoretical and practical references for the development of intelligent training in the entire competitive sports field.

5.2 Research Prospects

Based on the achievements and limitations of this study, future research can be further carried out in three directions—technology optimization, application expansion, and theoretical deepening—to promote the continuous development and application of the Intelligent Muscle Force Monitoring System in the field of competitive sports.

In the direction of technology optimization, future efforts should focus on improving the "adaptability", "intelligence", and "integration" of the system to further reduce the system's interference with training and enhance the precision and comprehensiveness of services. In terms of adaptability optimization, it is necessary to develop more lightweight and flexible sensors—such as ultra-thin surface electromyography sensors that can be attached to the skin using flexible electronic technology, or textile sensors integrated into clothing—to reduce the restriction of sensors on athletes' movements; at the same time, it is necessary to improve the system's adaptability to different training scenarios, such as optimizing the waterproof and high-temperature resistance of sensors for outdoor rainy or high-temperature environments to ensure the stability of data collection. In terms of intelligence optimization, more advanced artificial intelligence algorithms (such as convolutional neural networks (CNN) or recurrent neural networks (RNN) in deep learning) should be introduced to improve the accuracy of muscle force deviation identification and optimal take-off point prediction, especially the dynamic prediction ability when athletes' states change (such as fatigue or injury); at the same time, an "intelligent decision support system" can be developed to automatically generate personalized training plan suggestions based on athletes' long-term training data and competition performance, providing more comprehensive decision support for coaches. In terms of integration optimization, the system should be integrated with other training auxiliary equipment (such as intelligent training hurdles and resistance training equipment) to achieve data interconnection—for example, intelligent training hurdles can automatically adjust their positions according to the optimal take-off point predicted by the system, and resistance training equipment can automatically adjust resistance according to the muscle force intensity monitored by the system—forming an integrated intelligent training system of "monitoring - training - feedback".

In the direction of application expansion, future efforts should focus on expanding the application scope of the system: from "elite athletes" to "diverse groups", from "hurdle events" to "multiple events", and from "training scenarios" to "full-cycle scenarios". In terms of group expansion, the system can be adapted to elite adolescent hurdle athletes and amateur hurdle enthusiasts—for adolescents, the feedback content of the system should be optimized, using more accessible language and animation to help adolescents understand technical problems; for amateur enthusiasts, the cost and operational complexity of the system should be reduced, and an entry-level version should be developed to meet the needs of mass fitness and basic training. In terms of event expansion, the technical framework and application mechanism of the system can be migrated to other technical track and field events—such as high jump (monitoring muscle force and take-off point selection during the take-off phase), long jump (monitoring technical parameters during the approach-take-off connection phase), and throwing events (monitoring muscle coordination during the rotation or approach phase); at the same time, the application of the system in non-track-and-field events can be explored—such as gymnastics (monitoring muscle force precision during movement completion) and fencing (monitoring muscle explosive force and timing control during strikes)—promoting the implementation of intelligent monitoring technology in a wider range of competitive sports fields. In terms of scenario expansion, the system can be applied to the "full-cycle management" of athletes, including the training period (daily training monitoring and optimization), pre-competition adjustment period (competitive state monitoring and pre-competition plan formulation), post-competition recovery period (injury risk assessment and rehabilitation training guidance), and post-injury rehabilitation period (muscle function recovery monitoring and rehabilitation progress evaluation)—realizing intelligent support for athletes' entire sports careers.

In the direction of theoretical deepening, future efforts should focus on strengthening interdisciplinary research between intelligent monitoring technology and sports disciplines, enriching the relevant theoretical system to provide a more solid theoretical support for technical application. On the one hand, it is necessary to deepen the theoretical research on "the integration of sports science and technology with competitive training", explore the transformation path of intelligent technology on training concepts, training methods, and training management models, establish a theoretical framework of "data-driven training", and clarify the position and function mechanism of intelligent monitoring systems in the training system. On the other hand, it is necessary to strengthen research on "the ethics and standards of intelligent training". As the amount of athlete data collected by the system increases, ethical issues such as data privacy protection, data security management, and algorithm fairness (such as avoiding unfair training suggestions caused by algorithm bias) have become increasingly prominent. In the future, it is necessary to establish standards for the collection, storage, and use of intelligent training data, clarify the ownership and right to use of data, and formulate algorithm evaluation and audit mechanisms to ensure that the application of intelligent technology conforms to sports ethics and legal regulations. In addition, it is necessary to strengthen theoretical research on "the differences in intelligent training demands among different events", analyze the specific demands of different sports events (such as strength-based, endurance-based, and skill-based events) for intelligent monitoring, and provide theoretical guidance for targeted system design and application, avoiding a "one-size-fits-all" approach to technical application.

In conclusion, the application of the Intelligent Muscle Force Monitoring System in elite hurdle training is an important exploration of sports science and technology empowering competitive sports. With the continuous optimization of technology, expansion of application scope, and deepening of theoretical system, such intelligent technologies will surely play a greater role in improving the level of competitive sports training, cultivating elite athletes, and promoting the high-quality development of sports undertakings, providing strong support for the realization of the "Sports Power" goal.

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