

Physiological Monitoring and Technical Diagnostic System for Track and Field Training Integrating Intelligent Sensing and Artificial Intelligence

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ABSTRACT Real-time physiological monitoring and technical diagnosis in track and field training are often constrained by fragmented multimodal data acquisition, insufficient sensor synchronization, and limited intelligent analysis capabilities. To address these issues, this study proposes an integrated physiological monitoring and technical diagnostic system based on intelligent sensing and artificial intelligence. A distributed sensing architecture incorporating inertial measurement units (IMUs), electromyography (EMG), heart rate (HR), and plantar pressure sensors is established, where timestamp synchronization and edge computing enable millisecond-level alignment of heterogeneous signals. Sliding-window feature extraction, Long Short-Term Memory (LSTM) networks, and Spatiotemporal Graph Convolutional Networks (ST-GCNs) are jointly employed for physiological load estimation and technical action deviation diagnosis, while a hierarchical feedback mechanism provides real-time training guidance. Experimental results demonstrate an overall action recognition accuracy of 90.2%, an F1-score of 0.859, an average end-to-end latency of 40.6 ms, and a physiological load prediction highly correlated with blood lactate measurements ($r > 0.96$). The proposed framework establishes an efficient multimodal sensing and intelligent decision-making paradigm for wearable monitoring systems and provides valuable engineering references for electromagnetic sensing networks, wireless signal acquisition, antenna-enabled wearable devices, and intelligent information processing in next-generation human-centered monitoring applications.

INDEX TERMS multimodal intelligent sensing, physiological monitoring, spatiotemporal graph convolutional network, electromagnetic sensing network, wearable antenna systems

I. INTRODUCTION

TRAINING for track and field events relies heavily on the physical condition and the technical nature of the athlete's movement. Alterations to the level of stress used during workouts, inconsistency in movement patterns and change in recovery times have an effect on both performance when competing and the prevention of injuries [1-2]. Training analysis is most commonly conducted via one device (e.g., heart rate monitors, blood lactate monitors, action video cameras), with multiple sources for the data and major differences in how the data is sampled. There is no universal time stamp or consistent spatial reference between the different systems of measurement used, thereby creating a long-term disconnect between the physical signals exhibited by the athlete and the movements demonstrated by the athlete [3-4]. The vast majority of training analysis is done on an after-the-event basis with a manual method of organizing the data and evaluating it based on subjective

assessment experience leaving a long time between the point at which an athlete receives feedback about their training and the events that led to the feedback. Timing of changes in training load and the presence of technical errors is difficult to present in the appropriate time frame and there is often a lack of continuity associated with fluctuations of athletes' conditions. The frequency of regulating training is typically in a delayed reaction mode [5-6]. Multimodal data has no consistent format from the time of acquisition until the time it is transmitted or analysed meaning it is difficult to identify the relationship between the complex movements associated with motion and the physiological responses that result from them. Training related decisions often depend on results of individual observations of athletes, and there is a shortage in overall capability to perform analysis across all gathered data [7-8].

Regarding the issue of sports training monitoring, the academic community has conducted extensive research on

multi-source data collection and sports state analysis. At the level of technical action analysis, DANG's research [9] pointed out that artificial intelligence has been widely applied in key aspects such as motion recognition, tactical modeling, and fatigue monitoring in football training. Through the fusion of computer vision and sensor data, real-time capture and deviation warning of athletes' movements and postures can be achieved. To achieve such precise analysis, stable and long-term data collection is the foundation, which drives the development of new sensing technologies. For example, Parashar et al. [10] developed a self powered wearable sensing system based on frictional nanogenerators, which can collect energy from biomechanical movements such as gait and generate signals. By combining with machine learning algorithms, the system achieved an accuracy of 99.6% in tasks such as user identity recognition, providing a hardware foundation for long-term, passive physiological and behavioral monitoring. Zhou et al. [11] provided a comprehensive review of the use of artificial intelligence across all areas of sports science, including major current challenges and indications as to where the application of AI technology is expected to progress in the future. These authors address the many different aspects of sport in relation to AI application, including skill development and assessment, injury prevention, and many more. As an example, some researchers have explored the use of wearable technology for data collection during training, including techniques such as heart rate monitoring and inertial sensors for assessing exercise intensity levels [12-13]. Other researchers have integrated electromyographic data and motion analysis into the same study in order to apply advanced statistical models to the collected data to help identify patterns in muscle activation that indicate both fatigue and motion stability, for example [14-15]. In recent years, researchers have applied several different types of technology to accomplish action recognition tasks, including applying convolutional neural networks to extract features from a video sequence of a particular action that was performed and classifying that action according to a predefined set of technical criteria. Similarly, researchers have developed statistical time series models to analyze continuous motion data in order to quantify the extent of variation of the rhythm of a given action over time [16-17]. These studies have resulted in a progression of knowledge regarding the analysis of single sources or types of data; however, the interrelatedness of the different data sources collected has been shown to be weak, and there is currently no standardized, universally-accepted model for applying to multi-source data sets, which has resulted in difficulties in determining dynamic relationships between physiological states and changes in actions [18].

For multimodal data fusion, part of the research proposes a method based on feature stitching, which maps different sensor signals to a unified feature space for training the load assessment model. There are also studies introducing recursive neural networks to process time series data, using

historical information to predict future exercise states, and achieving certain results in fatigue recognition and exercise intensity prediction [19-20]. Regarding spatial structure modeling, some studies have used graph structures to express human joint relationships, with action skeletons as node structures input into the model for analyzing differences in action patterns [21-22]. Partial methods combining graph structure and time models are used to process continuous action sequences, and perform well in action recognition accuracy [23-24]. However, these methods still have shortcomings in terms of sensor synchronization accuracy control, multi-source signal coupling expression, and real-time analysis response. The unified modeling ability between physiological signals and action information is limited, and the feedback delay problem on the training site has not been effectively improved [25-26]. There are significant limitations in the expression of multi-source data consistency and real-time training decision-making in existing research.

Based on the above issues, this article constructs a track and field training physiological monitoring and technical diagnosis system that integrates intelligent sensing and artificial intelligence. The system is equipped with inertial measurement units, electromyography sensors, heart rate monitoring devices, and plantar pressure acquisition devices in key body parts of athletes. Multiple sources of physiological and mechanical signals are incorporated into a unified acquisition network structure, and a time synchronization mechanism is used to calibrate the data stream uniformly, so that different types of signals can be aligned and processed on the same time axis. After the training data enters the edge computing node, the sliding time window is used to segment the time sequence of multidimensional signals, extract the characteristics of heart rate variability, EMG frequency and impact load, and construct a combined description vector of physiology and mechanics to describe the dynamic changes of training load. For action analysis tasks, the human joint structure is mapped into a graph structure model, and a spatiotemporal graph convolutional network is introduced to structurally encode the action sequence. Technical action pattern features are extracted from the relationship between joint motion trajectories and temporal changes to identify action deviations and abnormal behaviors. Based on the results of load monitoring and action diagnosis, a physiological load and technical deviation discrimination interval is set, and the analysis results are mapped into graded feedback information, which is immediately output at the training site to form a closed-loop mechanism for training state perception and action correction. The system forms an overall framework for unified expression of multi-source signals, dynamic characterization of training loads, and analysis of action structures, reflecting the value of method improvement in real-time training monitoring and multimodal information correlation expression.

II. METHODS

A. SYNCHRONOUS COLLECTION OF DISTRIBUTED PHYSIOLOGICAL TECHNICAL SENSOR NETWORKS

This article constructs a multi-source heterogeneous sensing acquisition network at key nodes of the athlete's body movement chain, fixing six axis inertial measurement units in the foot, tibia, and trunk areas respectively, to record three-axis acceleration and three-axis angular velocity signals; the four channel surface electromyography sensor is arranged on the surfaces of the rectus femoris, biceps femoris, gastrocnemius and tibialis anterior muscles to collect changes in the original electromyographic potential; The chest strap type heart rate sensor is placed at the lower edge of the chest to record the electrocardiogram interval sequence; Distributed plantar pressure insoles are embedded inside the shoe body, and pressure sampling is performed on the left and right soles to output a pressure matrix sequence [27-28]. All types of sensors are equipped with independent sampling clocks, but there are clock drift and inconsistent sampling starting points between different devices. Therefore, a unified timestamp calibration mechanism is introduced before data enters the transmission link.

The main clock driven timestamp alignment protocol is used for time synchronization, and the edge computing node is used as the time reference source to mark the access time of each sensor data packet. The sensor adds a local timestamp t_i^{local} when generating data, and the edge nodes receive it and modify it based on the network transmission delay estimation function to form a unified timeline mapping relationship:

$$t_i^{sync} = t_i^{local} + \Delta t_i^{network} \quad (1)$$

$\Delta t_i^{network}$ represents the average transmission delay compensation value introduced by the 2.4 GHz wireless communication link, which is estimated from the periodic handshake signal and used to eliminate time offsets between different nodes. The data transmission link adopts a 2.4 GHz wireless gateway for centralized aggregation. Each sensing node sends data packets to the gateway in a low-power periodic broadcast manner. The gateway performs cache rearrangement and time sorting operations, and structurally aligns data from different sources according to a unified time index. The alignment process is segmented into fixed time windows, each containing synchronized sampling segments from all sensors, forming a unified multimodal temporal data structure.

Assuming the sensor set is $S = \{s_1, s_2, \dots, s_n\}$, the sampled data within any time window is defined as:

$$X(t) = \{x_{s_1}(t), x_{s_2}(t), \dots, x_{s_n}(t)\} \quad (2)$$

$x_{s_i}(t)$ represents the observation vector of the i -th type sensor at synchronization time t . After time alignment, various modal signals form a multidimensional joint observation matrix on the same time axis, which enables consistent mapping relationships between step frequency changes, joint angular velocity evolution, electromyographic

integration changes, heart rate interval fluctuations, and plantar pressure center trajectories in the time dimension. To eliminate the problem of uneven data density caused by differences in sampling frequency, high-frequency signals are downsampled and low-frequency signals are interpolated and reconstructed, so that all channel data are uniformly mapped to a fixed sampling rate sequence. The interpolation function is defined in a piecewise linear manner:

$$x(t) = x(t_k) + \frac{t - t_k}{t_{k+1} - t_k} (x(t_{k+1}) - x(t_k)) \quad (3)$$

t_k and t_{k+1} represent adjacent sampling moments. After interpolation and resampling, each sensing modality forms a structurally consistent temporal input at a unified time scale, providing a unified data foundation for subsequent feature extraction and multimodal fusion calculations.

All of the synchronized data in the buffer queue at the edge computing terminal are stored in a streaming format, then chronologically sliced into windows through a sliding window technique. The data from each window is transferred to the next processing module as a single time unit. This results in the spatially-distributed acquisition system being transformed into a strong time consistent multi-mode sequence structure and physically aligning observations from the different sensors so that they have an identical temporal reference point. This eliminates timing offsets between heterogeneous data.

To address the time offset issue caused by the accumulation of wireless transmission delay under high-speed motion conditions, this system introduces a dynamic drift compensation mechanism into the timestamp calibration protocol, stabilizing the theoretical synchronization accuracy at the millisecond level. The 15-30 millisecond offset represents the residual uncompensated error under extreme high-dynamic conditions. This error has been strictly limited within the tolerance threshold of the sliding window feature extraction, ensuring the integrity of the multimodal joint representation. For cross-band synchronization between 1000 Hz electromyography, 200 Hz inertial, and 1 Hz heart rate, the system employs a feature-level asynchronous extraction and time-level unified mapping strategy. High-frequency signals undergo time-frequency feature calculation (e.g., median frequency, peak impact, joint angular velocity) at the original sampling rate, followed by linear interpolation resampling to match the low-frequency physiological baseline. This process effectively preserves the key patterns of muscle bursts and joint transient responses, avoiding high-frequency information attenuation caused by direct global downsampling. It ensures that the spatiotemporal graph convolutional network and the long short-term memory network, when inputting node features, possess both high-frequency kinematic details and maintain the structural consistency of multimodal data along the time axis.

B. DYNAMIC FEATURE EXTRACTION AND REAL-TIME MODELING OF LOAD STATUS

After completing the time alignment and unified sampling of multimodal sensing data, the continuous time-series data is input into a sliding window structure for serialization processing. The window length is set to a fixed time span T_w , and the sliding step size is set to Δt , forming an overlapping set of time segments. The use of this overlap provides for the simultaneous capture of short-duration motion variability and continuous load variability. Each individual window contains synchronously recorded inertial measurement data, electromyography signal sequence data, heart rate interval sequence data, and plantar pressure matrix sequence data. Each channel's data represent temporally consistent data within the sliding window to form a single unified multivariate time-series input data set.

Channel-wise time-domain feature extraction can be performed on the data within each sliding window, and the differential rate of change between adjacent heart rate intervals can be calculated for the heart rate sequence. The recovery phase interval can be exponentially fitted to obtain the heart rate recovery slope; it can perform full wave rectification and low-pass filtering on electromyographic signals to calculate integrated electromyographic values. At the same time, fast Fourier transform is used in the frequency domain to obtain power spectrum distribution, and the median frequency is extracted as a representation of muscle fatigue changes; A contact force matrix sequence can be constructed for plantar pressure data to calculate the cumulative distribution of impact peak values per unit time, which is used to describe the intensity of impact load changes [29-30]. The inertial data is fused with angular velocity and acceleration signals to obtain the rate of change in joint angular motion, which is used to characterize the trend of motion load changes. In the process of frequency domain feature extraction, define the power spectral density function $P(f)$ for electromyographic signals and calculate the median frequency f_{med} :

$$\int_0^{f_{med}} P(f) df = \frac{1}{2} \int_0^{f_{max}} P(f) df \quad (4)$$

This indicator is used to describe the spectral shift characteristics caused by muscle fatigue, expressing the time-domain intensity changes and frequency-domain structural changes in a unified feature space. Normalize the impact load and construct a unit time impact rate function:

$$I(t) = \frac{1}{T_w} \sum_{k=1}^n F_k \quad (5)$$

F_k represents the peak force of the k th foot contact within the window, used to characterize the cumulative level of ground reaction force during movement.

In the multimodal feature fusion stage, all time-domain and frequency-domain features are concatenated into a unified feature vector sequence and input into a long short-term memory network for temporal modeling. The LSTM

structure is used to learn cross window load variation dependencies, and the hidden state is used to record the cumulative effect of historical training loads. Its state update process is defined as:

$$h_t = \text{LSTM}(x_t, h_{t-1}) \quad (6)$$

x_t represents the current window feature vector, and h_t represents the load state representation corresponding to the time step. To construct an individualized training load threshold model, an online update mechanism is introduced to recursively adjust the historical training state and current output error, so that the model parameters can be dynamically adjusted during the training process. The load threshold update adopts an exponential weighting method:

$$\theta_t = \alpha \theta_{t-1} + (1 - \alpha) \hat{y}_t \quad (7)$$

θ_t represents the current load threshold state, $\hat{y}_t$ represents the real-time load estimation value output by the model, and α represents the historical memory weight.

In the output stage, the hidden state of LSTM is mapped to a fatigue index scalar, which is compressed from a multidimensional feature space and used to describe the comprehensive relationship between the accumulated training load and physiological consumption state. The mapping process is completed by fully connected transformation, which transforms high-dimensional temporal features into a single continuous evaluation quantity, thereby forming a real-time updated load state curve.

The whole calculation process is carried out in a streaming mode within the edge computing node, and the window sliding and feature updating process are carried out synchronously, so that multimodal physiological signals and mechanical signals are continuously analyzed on the continuous time axis, so as to build the dynamic evolution sequence of training load and provide an input basis for the subsequent action diagnosis and early warning module.

C. ACTION DEVIATION DIAGNOSIS BASED ON GRAPH CONVOLUTIONAL NETWORK TECHNOLOGY

After completing the construction of multimodal time series features, the athlete's skeletal joint structure is mapped uniformly with sensor observation points to establish a human motion topology model, as shown in Figure 1. The node set is composed of key joint points and sensor installation positions, while the edge set is defined based on the anatomical connection relationship and motion dynamics coupling relationship of the human body, thus forming a time-varying spatial graph structure. Each time step corresponds to a snapshot of the graph, and the node features consist of inertial measurement data, angular velocity information, and fusion features of electromyography and pressure, allowing structural information and motion state information to be expressed in the same graph domain.

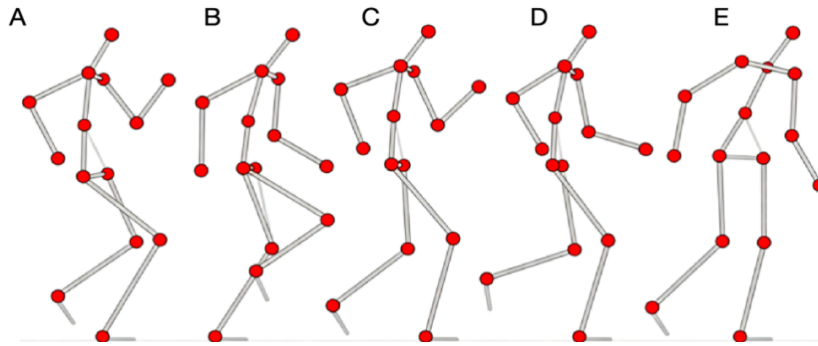


FIGURE 1. Topological model of human motion

Let the graph structure be represented as $G_t = (V, E, X_t)$, where V represents the set of nodes, E represents the topological connection relationship, and X_t represents the node feature matrix corresponding to time t . To depict the temporal dependencies during the motion process, a temporal dimension extension is introduced on the basis of the graph structure to construct a spatiotemporal graph sequence, which enables continuous propagation of node states between adjacent time frames, thus forming a three-dimensional structural expression. In the process of feature propagation, graph convolution operation is used to aggregate the neighborhood information of nodes, so that the motion associations between local joints are encoded into a high-dimensional feature space [31-32]. The process of graph convolution update is defined as:

$$H^{(l+1)} = \sigma \left(D^{-\frac{1}{2}} A D^{-\frac{1}{2}} H^{(l)} W^{(l)} \right) \quad (8)$$

A represents the adjacency matrix, D represents the degree matrix, $H^{(l)}$ represents the node state of the l -th layer, $W^{(l)}$ represents the learnable weight parameter, and σ represents the nonlinear transformation function. This process is used to integrate the spatial constraint relationships between joints, so that local motion changes propagate in the global structure.

The standard movement trajectory relied upon for movement deviation diagnosis is not a single rigid template, but a personalized reference benchmark constructed based on the individual biomechanical characteristics of the athlete. During system initialization, standardized training data of the athlete under fatigue-free conditions is collected, spatially normalized, and then confirmed by professional coaches to generate an initial reference graph sequence. In subsequent training cycles, this reference sequence undergoes dynamic iteration using an exponentially weighted moving average mechanism to adapt to the natural evolution of the athlete's technical style and fluctuations in competitive performance. This individualized benchmark strategy effectively avoids misjudgments caused by differences in body shape or force application habits, enabling the deviation scoring function to accurately focus on abnormal joint movements that deviate from the individual's optimal technical pattern, significantly

reducing the false positive rate in complex movement scenarios.

In time dimension modeling, a time convolution module is introduced to serialize the continuous graph structure, encoding the evolution relationship of joint states at different time steps into temporal feature representations. The spatiotemporal joint modeling structure simultaneously performs spatial aggregation and temporal recursion on each joint node, expressing changes in motion trajectory, angle, and force within a unified framework. To calculate the difference between the standard action mode and the measured action, the standard action trajectory is constructed as the reference graph sequence G_t^{ref} , and the measured action at time t is constructed as the observation graph sequence G_t^{obs} . The difference between the two is mapped in the node feature space to form an error coding matrix:

$$\Delta X_t = X_t^{obs} - X_t^{ref} \quad (9)$$

After the difference vector is input into the spatiotemporal graph convolutional network, it is amplified or suppressed layer by layer during the propagation of the multi-layer graph structure, making local biases explicit in the spatial structure and enhancing the ability to identify abnormal joints.

In the anomaly localization stage, a deviation scoring function is output for each node, and the joint motion error is cumulatively calculated over time to form a sequence of deviation intensity. This process maps abnormal knee adduction angles, hip rotation offsets, and ankle landing timing changes to a unified scoring space, allowing structural abnormalities to be expressed synchronously with temporal abnormalities [33-34]. After spatial reconstruction of the deviation sequence, a heat distribution matrix is generated to represent the degree of deviation of different joints at different time periods.

The process of generating heat maps is based on normalizing node deviation values, mapping the deviations of each joint to a unified scale space, so that local abnormal areas present a continuous distribution pattern in the spatial structure, thereby completing the structured calibration of action abnormal areas. The result is output in the form of a graph structure to the feedback module, which is used as the

input source for the subsequent load technical joint analysis module.

Figure 2 shows the distribution characteristics of action deviation based on spatiotemporal graph convolutional network output in the time and joint dimensions. The horizontal axis represents time frames, reflecting the evolution of action sequences during training, and the vertical axis represents joint nodes, corresponding to key joint positions in the human body. The higher the value of normalized deviation intensity, the more obvious the deviation of the joint from the standard action mode at the corresponding time. It can be observed that there are continuous high deviation areas in the left knee (LKnee) between frames 8 and 15, indicating significant joint motion abnormalities at this stage. At the same time, the deviation of the left ankle (LAngle) is slightly higher, reflecting the cumulative effect of unstable landing control. The system can identify the location and duration interval of abnormal actions in a unified spatiotemporal structure, providing direct basis for technical correction during the training process.

D. LOAD TECHNOLOGY JOINT WARNING AND ON-SITE FEEDBACK OUTPUT

After completing the multimodal load modeling and graph convolution action deviation diagnosis, the two types of output results are aligned uniformly on the time axis to form a sequence of state vectors under the same time index, which is used to construct a joint discrimination mechanism. The physiological load output is composed of the fatigue index sequence generated by LSTM network, and the technical action output is composed of the joint deviation score sequence generated by graph convolution network. Both of them are synchronously cached inside the edge computing node, and frame level matching is performed according to the unified timestamp, thus forming a joint state matrix.

Set a threshold discrimination function for physiological load status, normalize the maximum heart rate sequence, and calculate the time difference of electromyographic fatigue slope to form a composite load discrimination condition. The discrimination process adopts a logical combination structure to label time slices that meet high load conditions. Its expression is defined as:

$$L_t = I \left(\frac{HR_t}{HR_{max}} > \tau_1 \wedge \frac{dEMG_t}{dt} > \tau_2 \right) \quad (10)$$

HR_t represents the current heart rate value, HR_{max} represents the maximum estimated heart rate value, $dEMG_t/dt$ represents the slope of electromyographic fatigue change, τ_1 and τ_2 are set thresholds, and $I(\cdot)$ represents the indicator function used to mark the high load state interval. The technical action deviation part is composed of the joint error scoring sequence output by the graph convolutional network. The key motion nodes are subjected to angle deviation calculation, and the trunk forward tilt angle, knee adduction angle, and ankle landing angle are mapped into a unified angle error space. Deviation threshold

constraints are set, and time slices that exceed the threshold are marked and processed. Its expression form is:

$$T_t = I \left(\sum_{i=1}^n w_i |\theta_{i,t} - \theta_i^{ref}| > \tau_3 \right) \quad (11)$$

$\theta_{i,t}$ represents the observation angle of the i -th joint at time t , θ_i^{ref} represents the standard action reference angle, w_i represents the joint weight coefficient, and τ_3 represents the technical deviation threshold. In the joint discrimination layer, the physiological load marker sequence and the technical deviation marker sequence are logically fused to form a multi-level risk discrimination structure. A hierarchical output mechanism is constructed based on the superposition relationship between the two, and mapped to a preset hierarchical structure according to different combination relationships, so that high load and high deviation states correspond to higher-level feedback.

Figure 3 shows the joint discrimination results and distribution characteristics of physiological load and technical deviation during the training process. Figure 3(a) depicts the evolution of risk status throughout the training process, with time as the horizontal axis and warning level as the vertical axis. A continuous high-risk period occurs between approximately 170-210 seconds, corresponding to the synchronous occurrence of load accumulation and technical degradation. Figure 3(b) shows the scatter distribution with physiological load index L_t as the horizontal axis and technical deviation score T_t as the vertical axis. The normal samples are concentrated in the low load and low deviation area, while high-risk points are mainly distributed in the upper right quadrant, indicating a significant decrease in technical stability under high load conditions. This result reflects that the system can achieve joint modeling of load and technology in a unified feature space, and effectively classify and identify abnormal states.

The feedback output component maps the results from joint discrimination onto the communication channel's low-latency output via 2.4 GHz wireless links and a local edge broadcast mechanism for transmitting graded status data between the bone conduction earphones and wrist display. Using bone conduction headphones, warning signals may be output acoustically through varying frequencies and intervals dependent on the risk assessed, while the wrist display shows athletes and coaches synchronized colour-coded status indicators that enable them to receive status information simultaneously at the training site.

The training process thus allows for their use in prior training backtracking to update models. All time slices during which a warning signal has been triggered at the data recording layer shall be segmented and stored synchronously with their associated multimodal raw signals as well as model output results on time index forming an organized abnormal sample archive of all recorded samples. This historical archives provide an organized structure for performing future offline analysis calls to facilitate consistent

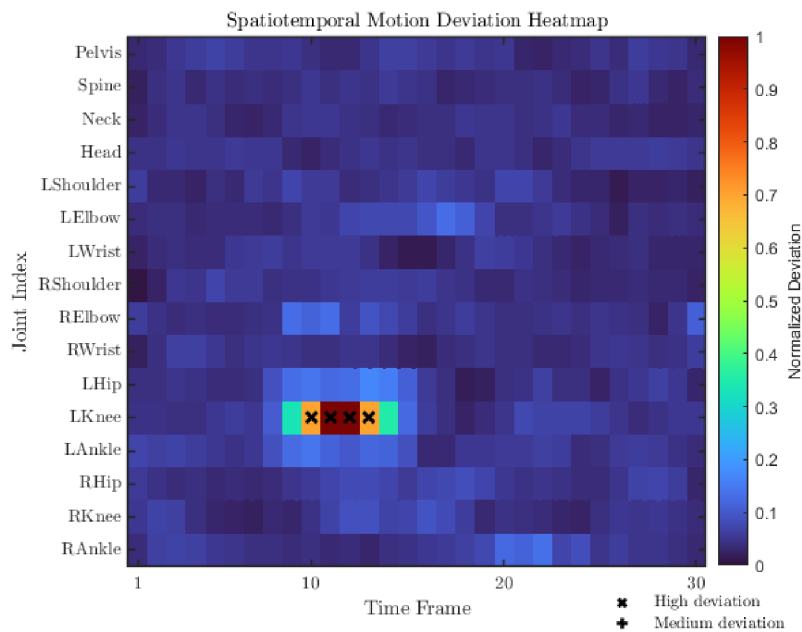


FIGURE 2. Heatmap of spatiotemporal distribution of technical action deviation

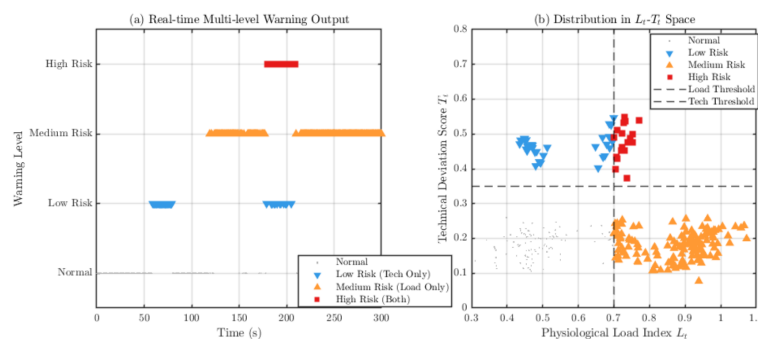


FIGURE 3. Results of physiological technical joint warning: (a) Real time multi-level warning status change diagram; (b) Spatial distribution of physiological load technical deviation characteristics

recording structure of both physiological abnormalities and technology deviations within specific timeframes.

III. EXPERIMENTS AND EVALUATION

A. DATASET SOURCE AND COMPOSITION DESCRIPTION

A collection of two forms of data were obtained for this research project: (1) A publicly available database of sports physiology and movement data, and (2) an established database containing common data documenting the movement analysis of athletics. In the physiological database, data include continuous recordings of heart rate intervals, surface electromyography (EMG) data, and corresponding annotated data collected during exercise measurements of blood lactate levels during physical activity. The range of sampled frequencies include 1000 Hz for all EMG data, 200 Hz for all inertial sensor sample frequency data, and 1 Hz for all physiological metabolic markers. The motion data was recorded using a multi-camera synchronous capture system

and produced as a 3D model containing a sequence of 3D skeletal keypoints with a sampling rate of 120 fps, and were spatially calibrated with millimeter precision. The plantar surface pressure data collected used a partitioned pressure sampling insole system divided into 8 pressure zones for each foot and the output from this system was an 8×8 time series matrix.

The data set consists of three common movements used in track and field: running, jumping and throwing; each movement has two types of labels, which are labelled as either standard movement or deviation movement, with deviation movements being labelled by experienced coaches using their knowledge of each technical specification. The duration of the various training samples represents different stages associated with varying intensity levels: low intensity warm-up, moderate intensity training and high intensity sprint training. The range of heart rates collected during training tapped to the interval between 90 and 190 beats per minute, while the amplitude of EMG signals were collected

within ± 5 mV. Prior to collection, data were denoised and time-synchronized and subsequently provided as continuous data to be uniformly organized into a standard time line format, so that when entering into multimodal fusion modeling, this data can be accurately integrated across modalities and comprehensively analyzed.

Prior to entering the experimental process, data are organized and treated according to individual athlete numbers. Therefore, each data set has records encompassing the complete cycle of training and is maintained as continuous time series data. A common timestamp alignment strategy is applied across the various modalities of data to ensure all physiological signals, motion trajectories and pressure distributions can be analyzed at the same timestamp; thereby achieving consistency within the dataset between the data sets geometrically and temporally.

B. EXPERIMENTAL DESIGN AND EVALUATION INDICATORS

The experimental design utilizes a phased experiment comparison process, and compares the multi-mode fusion model to the single mode analysis. Input data is set up in sliding windows by time, with each sliding window being an independent sample input of data for model training and testing. The model training portion of the experiment is structured that the training set is divided into training set and validation set, while during the test portion independent athlete data are used for a generalization evaluation to avoid data leakage. The tasks of physiological load forecasting and action deviation identification calculate their output results independently, with a unified timeline alignment analysis being performed between the two output results.

The evaluation indicators consist of four dimensions: synchronization error, load forecasting deviation, action recognition error, and system delay. Synchronization error is used to evaluate multiple sensor temporal alignment consistency; load forecast error is used to evaluate precision of physiological state estimation; action recognition error is used to evaluate precision of technical action diagnosis; and system delay assesses feedback capability in real-time.

The experimental system consists of a multi-sensor acquisition terminal, edge computing nodes, and a feedback execution module. The inertial measurement unit employs a six-axis MEMS (Micro-Electro-Mechanical Systems) sensor, the electromyography (EMG) acquisition module is equipped with a four-channel high-gain amplifier circuit, the heart rate module uses a chest-strap photoplethysmography (PPG) sensor structure, and the plantar pressure system comprises a 16-zone pressure-sensitive array. The edge computing terminal uses a multi-core embedded processor to run real-time data processing and model inference tasks. The communication module uses a 2.4 GHz wireless transmission protocol to achieve multi-node data aggregation. The feedback terminal includes bone conduction headphones and a wrist-worn OLED (Organic Light-Emitting Diode) display device for real-time output of graded warning information.

IV. RESULTS AND ANALYSIS

A. EVALUATION OF MULTI-SOURCE DATA TIME SYNCHRONIZATION ERROR

In this paper, the output time stamps of all sensors are matched with the master clock of the edge computing node one by one, and the offset between the sampling start point of each device in the same training segment and the master clock is extracted to form an error sequence. The time offset distribution is counted for different sensor channels, and the offset value in each training cycle is squared to calculate the mean value, and then the square is extracted to obtain the synchronization deviation level. The evaluation process is divided into training stages and is used to analyze the synchronous stability differences between static standing, starting, and high-speed motion stages, and to screen out abnormal offset data before recalculating the stable interval results.

These sensors correspond to different sources of physiological and kinematic information, used to construct a multimodal motion monitoring system. IMU-Chest refers to the inertial measurement unit installed in the chest, mainly used to collect acceleration and angular velocity information of the torso, thereby reflecting overall posture and upper body stability; IMU-Thigh is an IMU placed in the thigh, used to capture the movement state of the lower limbs, such as gait, acceleration and deceleration; sEMG-RF refers to the surface electromyography signal of the rectus femoris muscle, used to characterize the activation level of the muscles on the front of the thigh, often used to analyze knee extension and explosive movements; sEMG-BF refers to the surface electromyography signal of the biceps femoris, reflecting the involvement of the posterior thigh muscles in knee flexion and stability control; HR (Heart Rate) Sensor is a heart rate sensor used to monitor heart rate changes, thereby indirectly reflecting exercise intensity and physiological load; Plantar Pressure is a plantar pressure sensor used to record the force distribution on the sole of the foot, which can analyze landing pattern, balance, and gait characteristics.

Figure 4 shows the time synchronization performance of a multi-source sensing system under different motion states. The horizontal axis in Figure 4 (a) represents the sensor type, and the vertical axis represents the average time offset (ms). The three sets of bars correspond to the static, acceleration, and high-speed stages, respectively. The results show that as the motion intensity increases, the overall time offset of each sensor increases. Among them, the offset values of HR Sensor and sEMG-RF significantly increase in the high-speed stage, indicating the delay accumulation phenomenon in wireless transmission and signal processing under high dynamic conditions. Figure 4 (b) The horizontal axis is the movement phase, and the vertical axis is the root mean square (RMS) error. Different colors represent different sensors. The overall trend also shows a gradual increase from static to high-speed. The RMS error of heart rate signals reaches a high level in the high-speed phase,

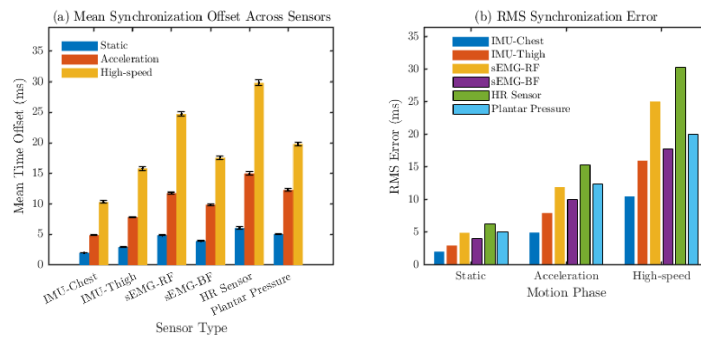


FIGURE 4. Time synchronization error analysis of multi-source sensors: (a) Average time offset of different sensors in each movement phase; (b) RMS time synchronization error at different stages of motion

reflecting the decline of synchronous stability of multimodal signals in severe movement. This result indicates significant stage differences in time alignment errors under complex motion conditions, which have a direct impact on subsequent feature extraction and action diagnosis.

The time synchronization error distribution characteristics for a single physiological signal during the acceleration phase can be seen in Figure 5. The time offset (horizontal) is a measure of how much the time at which the sensor collects data is different from the system master clock. The probability density (vertical) reflects how often one would expect to see each possible time offset value in the data set. The overall data set follows a Gaussian distribution with an overall average of approximately 15 ms, which is consistent with the established mean value ($\mu = 15$ ms). The system has a fixed but non-zero delay between signals; therefore, the standard deviation (σ) of approximately 2.5 ms means that most data points fall within a range of about 10 ms - 20 ms, meaning that the level of fluctuation in the way in which time synchronization errors occur remains relatively small and stable. If these errors remain uncorrected and instead utilize their respective distance from the average value of all data collected by the same sensor to determine how closely aligned they are with one another (multimodal fusion), then their respective distances from their averages can impact their accuracy in determining an action recognition of any particular signal. Thus, this figure illustrates nonvisually how well time synchronization error data follow a statistical model that can serve as an impetus for subsequent development of timing alignment and timing compensation processes.

B. CONSISTENCY EVALUATION OF PHYSIOLOGICAL LOAD PREDICTION

This article selects the results of blood lactate testing as the reference sequence, aligns the fatigue index output by the system with the corresponding physiological detection values at each time point, and constructs a time matching comparison table. The relative deviation between predicted and measured values can be calculated for each time slot, and the error distribution of all samples can be statistically analyzed. To reduce the impact of individual differences,

the data of different athletes were normalized and the error levels were calculated separately. Then, the overall consistency evaluation results were summarized to reflect the stability of the model in different load stages.

Figure 6 shows the temporal relationship between the predicted physiological load and the measured blood lactate values of a single athlete during the entire training process. The horizontal axis represents time points, and the vertical axis represents normalized physiological index values. The blue solid line represents the trend of the measured blood lactate values, the red dashed line represents the fatigue index prediction results based on the model output, and the shaded area corresponds to the high-intensity training stage. From the perspective of data changes, the two curves remain consistent in overall trend, showing a gentle increase in both low and moderate intensity stages, a significant rise and peak in the high-intensity stage, and then gradually decline in the recovery stage, indicating that the predicted results have good follow-up to load changes; There is a slight deviation between the two, reflecting the response lag and amplitude difference of the model under severe load fluctuations, but the overall fluctuation range remains consistent, indicating that the system has a high level of consistency in dynamic load monitoring and fatigue assessment, which can support real-time load discrimination and regulation during the training process.

Figure 7 shows the consistency relationship between the fatigue index predicted by the model and the measured blood lactate values in different subjects. The horizontal axis represents the normalized measured blood lactate values, and the vertical axis represents the predicted fatigue index values output by the model. At each time point, there is a distribution of scatter that represents a corresponding relationship between the two. The scatter plot shows that the majority of all the data points are distributed closely around the diagonal line of best fit, which tells us that there is a strong correlation between the predicted modelled values and the actual physiologic loads. The correlation coefficients for each of the diagrams are also relatively high (i.e., 0.96 or greater); therefore, they indicate that this model provides an increased ability to capture the dynamic change of blood lactate with the intensity of training. Figure 7 shows that

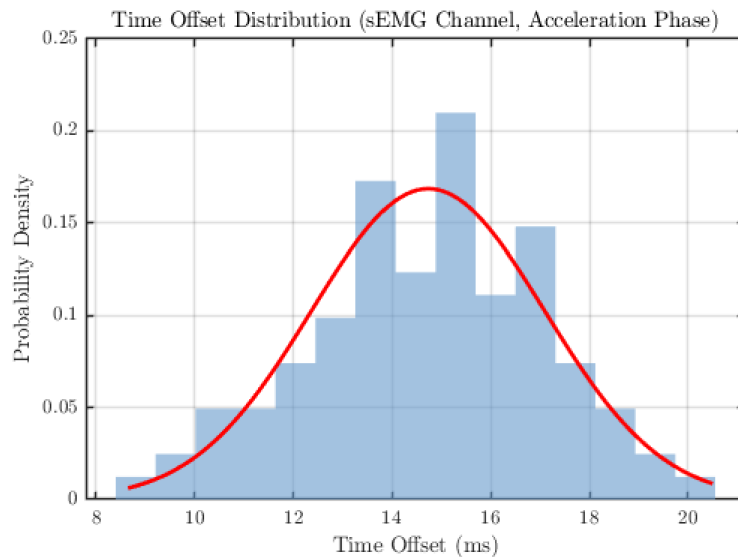


FIGURE 5. Time offset distribution and probability density fitting diagram

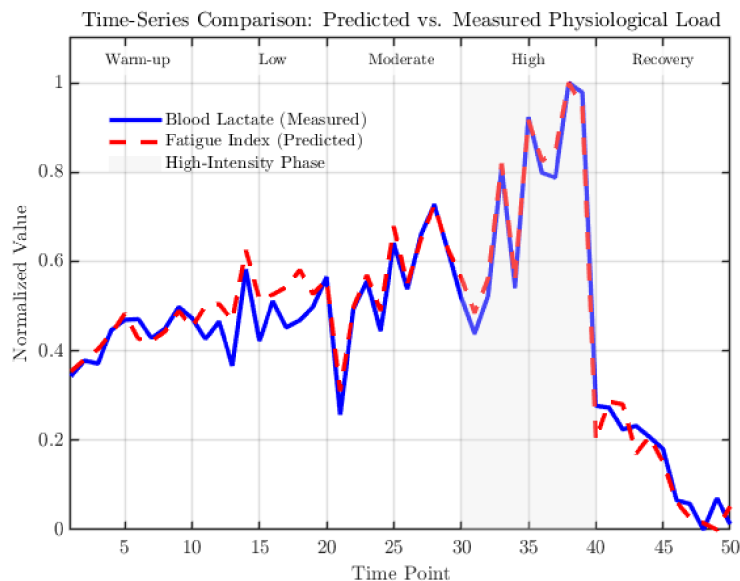


FIGURE 6. Comparison of consistency time series for physiological load prediction

this model has shown consistency in its ability to capture changes in physiologic load, under multi-subject conditions, thus providing a valid basis for continued use in personal assessments of fatigue and monitoring in real time.

C. TECHNICAL ACTION MISDETECTION

This article constructs a standard reference sequence based on manually annotated action anomaly time slices, and matches the abnormal segments detected by the system with time indices. It is possible to determine whether each frame of data appears simultaneously in both manual annotation and system output sets, forming a frame by frame comparison matrix. This article presents a statistical analysis of false positives and false negatives in different types of

movements, including accuracy, F1 Score, and false alarm rate. The results are grouped and analyzed according to the type of movement, and the deviation distribution is calculated for the takeoff, landing, and arm swinging stages to observe the recognition stability of the system under different movement structures.

Table 1 shows the performance of the technical action anomaly detection model under different types of movements, and evaluates the model's recognition ability in various types of movements comprehensively through accuracy, F1 Score, and False Positive Rate. From the overall results, the model's overall accuracy reached 90.2%, F1 Score was 0.859, and false positive rate was 5.6%, indicating that the model has good stability and practicality in multi-action

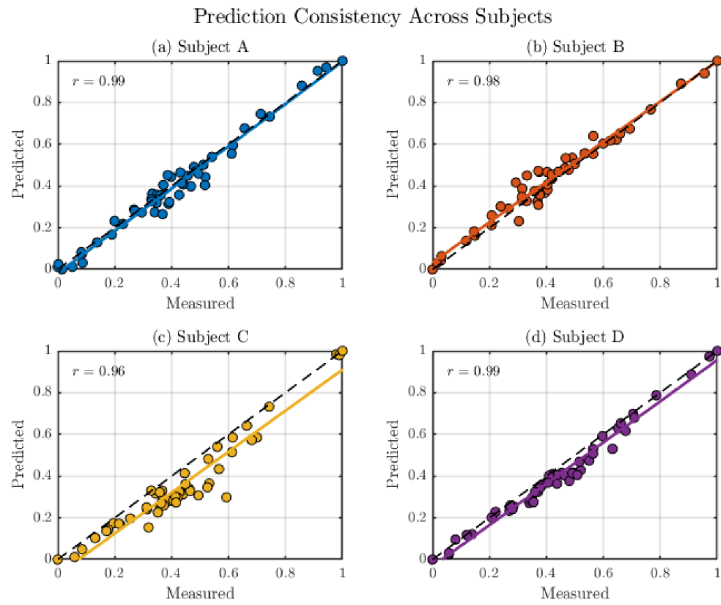


FIGURE 7. Consistent scatter plot of physiological load prediction for four subjects

TABLE 1. Analysis results of technical action misdetection for different action types

Action Type	Accuracy (%)	F1-Score	False Positive Rate (%)
Take-off	94.7	0.898	3.1
Landing	89.3	0.838	5.8
Arm Swing	92.1	0.896	4.2
Direction Change	85.6	0.795	8.5
Acceleration	91.5	0.884	4.9
Deceleration	87.8	0.843	7.1
Overall	90.2	0.859	5.6

scenarios; Specifically, the take-off movement performed the best, with an accuracy rate of 94.7%, F1 Score of 0.898, and a false alarm rate of only 3.1%, indicating that this type of movement has obvious characteristics and is easy for the model to recognize. However, the directional movement is the weakest performance type, with an accuracy rate of only 85.6% and F1 Score reduced to 0.795. At the same time, the false alarm rate increased to 8.5%, reflecting that the model is more prone to misjudgment in complex motion patterns. In addition, the F1 Score of arm swing and acceleration actions reached 0.896 and 0.884, respectively, and the false alarm rate was controlled between 4% and 5%, indicating that the model still maintains high consistency in actions with strong rhythmicity or linear changes, while landing and deceleration actions performed moderately. The F1 Score was about 0.838 and 0.843, with false alarm rates of 5.8% and 7.1%, respectively, reflecting the impact of increased signal fluctuations on detection accuracy during impact or deceleration stages.

D. REAL TIME RESPONSE DELAY EVALUATION OF THE SYSTEM

This paper inserts a time stamp at the time of sensor data generation, records the termination time when the edge computing node outputs the feedback signal, and constructs a complete processing link time series. This article calculates the difference between the start and end times for each data stream to form a set of delayed samples. This article separately calculates the time consumption of data collection, transmission processing, and model inference in three stages, and accumulates and analyzes the results of each stage to identify the bottleneck of system response and evaluate the overall real-time performance.

Table 2 reflects the latency composition of each processing stage of the system and its impact on overall real-time performance. The overall end-to-end average latency is 40.6 ms, and the P95 (95th Percentile) is 61.2 ms, indicating that the system basically meets the real-time response requirements. Among them, the ST-GCN (Spatial-Temporal Graph Convolutional Network) and LSTM in the model inference stage are the main bottlenecks, with an average latency of 18.3 ms, accounting for 45.00% of the total latency, which is significantly higher than data acquisition (12.80%) and transmission preprocessing (21.40%). At the same time, the computational correlation stage accounts for a cumulative 79.2%, indicating that the system latency is mainly concentrated in the data processing and model computation stages. It is worth noting that feedback output still accounts for 20.80% (about 8.4 ms), while the transmission preprocessing stage P99 (99th Percentile) reaches 19.8 ms, indicating that link fluctuations can also affect overall stability. Overall, although the system has good real-time performance, the optimization focus should be on model

TABLE 2. Stage decomposition statistics of real-time response delay of the system

Processing Stage	Mean $\pm$ Std (ms)	Median (ms)	P95 (ms)	P99 (ms)	Contribution to Total Latency (%)
Data Acquisition	5.2 $\pm$ 2.1	4.8	8.9	11.5	12.80%
Transmission & Preprocessing	8.7 $\pm$ 3.5	7.9	15.1	19.8	21.40%
Model Inference (ST-GCN & LSTM)	18.3 $\pm$ 6.2	16.9	29.7	35.2	45.00%
Subtotal (Computation)	32.2 $\pm$ 9.8	30.1	48.5	55.8	79.2%
Feedback Output	8.4 $\pm$ 2.8	7.7	13.5	16.3	20.80%
End-to-End Total	40.6 $\pm$ 11.5	38.3	61.2	70.5	100%

inference and data processing efficiency.

The system's end-to-end average latency of 40.6 milliseconds and P95 latency of 61.2 milliseconds only characterize the processing time for data acquisition, edge computing, and warning signal generation. Considering the human neuromuscular response time to bone conduction audio cues is approximately 150 to 250 milliseconds, the total latency of the complete feedback loop is controlled within the range of 200 to 300 milliseconds. While this latency is insufficient for instantaneous correction within a single step cycle in high-speed track and field, it is sufficient to provide near-real-time intervention within one to two gait cycles of a continuous movement flow. Warning information is output synchronously via graded acoustic frequencies and wrist visual indications, aiming to influence technical fine-tuning and load redistribution in subsequent movement cycles, aligning with the cognitive and executive principles of immediate feedback within continuous movement sequences in exercise physiology. Therefore, in this context, real-time graded warning specifically refers to continuous low-latency closed-loop intervention within the training flow, with its engineering latency highly matched to the biomechanical response window, ensuring logical consistency and practical feasibility of on-site technical correction.

E. MULTIMODAL FUSION STABILITY ASSESSMENT

In this paper, the data from different sensors are divided into synchronous windows, and the change consistency of each modal signal in the same time slice is calculated. It calculates the fluctuation trends of inertial data, electromyographic signals, heart rate sequences, and plantar pressure data, and compares their correlation changes within continuous time windows. This article can statistically summarize the degree of deviation between various modalities, analyze the differences in performance between high-intensity and low-intensity training conditions, and evaluate the stability and consistency of multi-source data fusion structures.

Table 3 reflects the correlation and fusion stability between different sensing modes under low intensity and high intensity training conditions, reflecting the consistency and reliability of multi-source data fusion in motion state modeling. Overall, the average correlation coefficient of each modal pair is 0.73 ± 0.11 , corresponding to a fusion stability index of 7.24, indicating a moderately high coupling relationship between multimodal data; Among them, IMU and sEMG showed the most stable performance, with a correlation of 0.85 ± 0.08 in low-intensity training, and the

highest fusion stability index of 10.63 under high-intensity conditions, indicating strong consistency and complementarity between kinematic and electromyographic signals. IMU and pressure data also showed good performance (0.80 ± 0.09 , stability 8.89), indicating that lower limb dynamics information can better support action state recognition; In contrast, the overall correlation of modal combinations involving HR is relatively low, with HR and pressure only at 0.60 ± 0.13 , and the lowest stability index at 4.62, reflecting a certain time delay and nonlinear difference between physiological signals and mechanical signals, especially under high-intensity exercise. Overall, this result indicates that the effectiveness of multimodal fusion depends on the degree of physical correlation between signals, with the combination of IMU and sEMG being the most representative and stable.

V. CONCLUSION

This article focuses on the problems of disconnection, feedback delay, and insufficient joint analysis ability between multi-source physiological signals and technical action data during track and field training, and constructs a monitoring and diagnostic method system that integrates intelligent sensing and spatiotemporal graph learning. This article achieves unified temporal synchronization of physiological signals, motion trajectories, and plantar pressure data through a multimodal sensing synchronous acquisition and time alignment mechanism. It combines sliding window feature extraction and sequence modeling structure to dynamically estimate the training load; This article introduces spatiotemporal graph convolutional networks to model human joint structures, achieving spatial localization and temporal tracking of technical action deviations; On this basis, a joint discrimination mechanism for physiological load and action deviation is established, and the graded feedback output of the training site is completed, thus forming a closed-loop system framework covering data collection, analysis, and decision-making. The research results indicate that this method forms a unified modeling path in terms of consistent expression of multi-source data, dynamic characterization of training load, and recognition of action deviation, improving the continuity and structuring of information parsing during the training process. The system completes real-time processing and feedback output under the edge computing architecture, which enhances the response ability of the training scene to the change of the movement state. The limitation lies in the physiological differences among different athletes, which still affect the generalization ability

TABLE 3. Stability evaluation of multimodal fusion under different training intensities

Modality Pair	Low-Intensity Training Correlation (Mean ± Std)	High-Intensity Training Fusion Stability Index
IMU ↔ sEMG	0.85 ± 0.08	10.63
IMU ↔ HR	0.75 ± 0.10	7.5
IMU ↔ Pressure	0.80 ± 0.09	8.89
sEMG ↔ HR	0.70 ± 0.11	6.36
sEMG ↔ Pressure	0.65 ± 0.12	5.42
HR ↔ Pressure	0.60 ± 0.13	4.62
Average	0.73 ± 0.11	7.24

of the model, and the stability of recognizing complex movements under extreme fatigue conditions still fluctuates. Future research can further expand the ability of cross project training data fusion and optimize lightweight model structures to adapt to higher frequency real-time application scenarios. Simultaneously, further research is needed on how to more efficiently construct and update individualized “standard movement templates,” such as introducing few-shot learning or transfer learning techniques to reduce the requirement for collecting large amounts of initial standard movement data for each athlete.

AUTHOR CONTRIBUTIONS

X.L. was the sole contributor to this article.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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