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PAPER

Development and Optimization of a Physiological Data-Driven Mobile Interactive Feedback System for University Physical Education

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ABSTRACT

Traditional university physical education instruction has remained largely dependent on instructors' experiential observation and subjective evaluation, resulting in delays and imprecision in physiological load monitoring, movement technique analysis, and personalized guidance. With the advancement of the Internet of Things (IoT) and mobile communication technologies, the development of data-driven intelligent instructional support systems has emerged as a critical pathway for educational reform in physical education. However, existing studies have primarily focused on single-parameter physiological monitoring, lacking integrated multimodal data fusion analysis. In addition, the reliability of network transmission under dynamic classroom conditions with high concurrency has often been neglected, leading to substantial feedback delays and limited practical applicability. To address these limitations, a study was conducted on the construction and instructional optimization of a mobile interactive feedback system driven by physiological data, specifically designed for university-level physical education. The principal contributions of this work are threefold. First, a full-chain optimization framework was proposed, encompassing the entire process from data acquisition to pedagogical application, thereby achieving deep integration between information technologies and physical education practices. Second, a perception network deployment and data fusion model adaptable to dynamic instructional scenarios was designed, resolving challenges associated with the collaborative processing of multi-node and multimodal data. Third, a network optimization mechanism integrating channel equalization and latency control was introduced, significantly enhancing the real-time performance and reliability of mobile interactive feedback. These innovations provide the core technical foundation for a practical and intelligent physical education classroom system.

KEYWORDS

physiological data-driven, mobile interaction, information fusion, instructional optimization, university physical education, network transmission control

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1 INTRODUCTION

With the continued advancement of educational informatization initiatives [1] and the full implementation of the "Healthy China" strategy, university physical education curricula have been increasingly urged to transition from traditional, experience-based teaching models toward digital, intelligent, and personalized instructional paradigms [2–5]. At present, the instructional process in university-level physical education largely depends on instructors' visual observation, subjective judgment, and students' self-reporting. This conventional approach is inherently constrained by latency and subjectivity, particularly in assessing physiological load [6], evaluating the correctness of motor skills [7], and preventing sports-related injuries [8]. In parallel, the rapid development of IoT technologies [9], wearable sensing devices [10], and mobile communication systems [11] has established a robust technological foundation for the real-time acquisition, transmission, and analysis of physiological data from both students and instructors. Against this backdrop, the construction of an intelligent feedback system that integrates physiological data sensing, mobile interaction, and instructional decision-making has emerged as a critical frontier in the reform of university physical education. Through data-driven approaches, such systems are expected to achieve greater instructional precision and pedagogical optimization.

Although the potential of technology in physical education has been increasingly acknowledged, several key deficiencies remain in current methodologies. First, at the data sensing layer, the majority of studies [12–14] have focused on monitoring isolated physiological parameters, lacking coordinated perception and fusion analysis of multimodal physiological data. This deficiency has limited the comprehensiveness and accuracy of assessments regarding complex physical activity states. Second, at the network transmission layer, existing systems [15, 16] have often failed to account for the challenges posed by high concurrency and mobility in actual instructional settings. For example, the system model proposed by Si et al. [17] did not incorporate optimized allocation of network channel resources, thereby increasing the risk of data congestion and loss. Similarly, the design described by Ke et al. [18] lacked effective multipath transmission strategies and latency control mechanisms, resulting in significant delays in feedback and making real-time interaction and timely intervention difficult to achieve. Consequently, the practical applicability and reliability of such systems have been substantially compromised.

To address the aforementioned limitations, the core scope of the present research can be divided into two principal components. The first component focuses on the deployment of physiological data sensing nodes and information fusion within mobile interactive networks for university physical education. A node deployment strategy, tailored to the evolving topologies of real-world instructional scenarios, is proposed. In addition, a fusion algorithm for multi-source heterogeneous physiological data is developed, with the objective of resolving fundamental challenges related to the comprehensiveness, stability, and effectiveness of physiological data acquisition at the source level. The second component involves the optimization of instructional monitoring and feedback mechanisms within mobile interactive networks used in university physical education. Emphasis is placed on the study of channel balancing strategies and transmission delay control mechanisms, aiming to ensure low-latency and high-reliability transmission of critical instructional data streams.

Ultimately, a closed-loop system comprising sensing, fusion, transmission, and feedback is constructed. The significance of this research lies not in the mere aggregation of advanced technologies, but in the systematic resolution of core bottlenecks encountered throughout the full chain—from physiological data sensing to interactive feedback—guided by the authentic demands of physical education instruction. By doing so, a comprehensive and practical solution is provided to enable precision teaching, personalized learning, and intelligent management in university physical education settings.

2 METHODOLOGY

2.1 Deployment of physiological data sensing nodes and information fusion in mobile interactive networks for university physical education

Traditional physical education has long relied on instructors' experiential observation and students' self-reporting. This subjective and delayed mode of feedback has proven inadequate for supporting personalized instruction and precise intervention. As a result, the deployment of wearable devices or embedded environmental sensing nodes to facilitate real-time acquisition of multimodal physiological and movement data—including heart rate, heart rate variability, electromyographic signals, motion trajectories, and acceleration—has become a core element in system construction. Such deployment involves more than a simple accumulation of devices; rather, it necessitates a topology-optimized network architecture that accounts for the specific scenarios of university-level physical education and the characteristics of various sports activities. This ensures the comprehensiveness, stability, and minimal intrusiveness of data acquisition, thereby providing a high-quality and time-sensitive data source for subsequent information fusion and feedback processes.

In this study, the deployment of physiological data sensing nodes for university physical education is conceptualized as the physical foundation of a reliable mobile interactive feedback system. The core principle involves predictive network topology optimization and resource planning, tailored to the dynamic nature of physical education scenarios and instructional interaction demands. Initially, core monitoring zones are delineated based on course content, followed by a preliminary topology design adopting a hybrid tree-mesh structure. In this configuration, each wearable device worn by instructors and students is designated as a source node (*SN*), each wireless access point or edge server pre-installed on-site is defined as a relay node (*RN*), and the instructor's smart terminal serves as the sink node (*Sink*). This design ensures both the high-efficiency data aggregation of tree structures and the path redundancy and reliability characteristic of mesh networks. Furthermore, a fuzzy partitioning strategy is employed to segment the physical space into logical sub-regions X_j based on the functional zones of movement. Within each sub-region, a cluster head is dynamically elected. To prevent communication collisions, a Maximum Independent Set (MIS) strategy is implemented, enabling efficient utilization of node energy and preliminary balancing of network load, thereby establishing a solid foundation for stable and energy-efficient data transmission in subsequent stages.

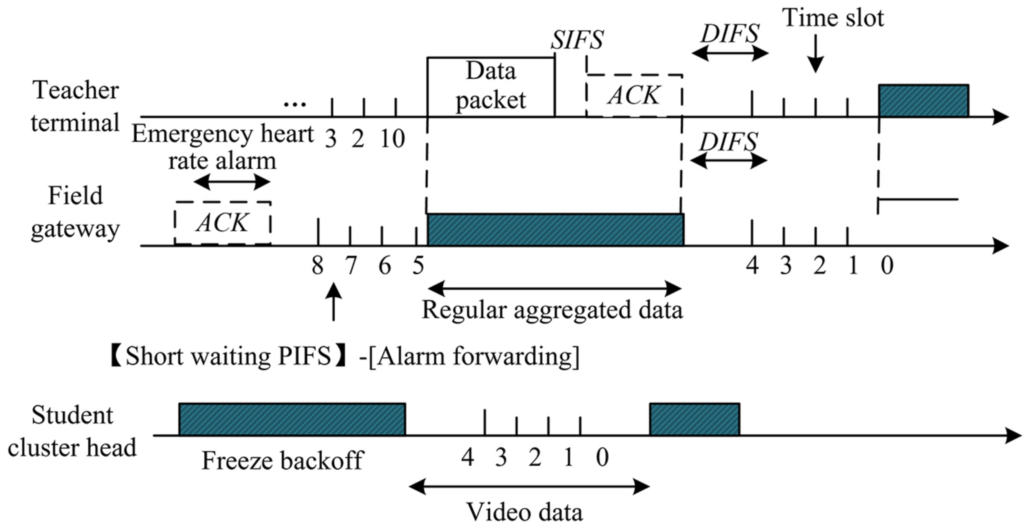

Fig. 1. Dynamic priority channel access mechanism of a two-layer relay network for interactive physical education instruction

Building upon the initial deployment, a more critical aspect of node deployment lies in the implementation of an adaptive regulation and data aggregation strategy based on real-time status, designed to fulfill the real-time responsiveness required for instructional optimization. Figure 1 illustrates the dynamic priority channel access mechanism in a two-layer relay network tailored for interactive physical education. Within the diagram, each network node is assigned a clearly defined functional label, visually representing the proposed two-layer relay network topology. The complete data transmission path is depicted, extending from individual students to cluster heads, then relayed through gateways, and ultimately reaching the instructor terminal. Furthermore, the abstract term "data packet" is contextualized into specific data types relevant to instructional scenarios, thereby providing a practical foundation for introducing a differentiated priority mechanism. Critically, the channel access mechanism diverges from fixed Distributed Inter-Frame Space (DIFS) and Short Inter-Frame Space (SIFS) by adopting a priority-based dynamic scheduling paradigm. Behavior-specific operations, such as freeze backoff, are also explicitly annotated within the scheduling framework.

To prevent channel congestion, time window partitioning is employed for temporal scheduling of data transmissions. More importantly, the system continuously monitors network status, triggering adaptive mechanisms when insufficient residual capacity $EZ(n_k)$ is detected at any relay node along a transmission path, or when increased latency is observed. Based on a linear weighted algorithm, the data forwarding strategy is dynamically adjusted. For example, paths with lighter loads and higher-quality links are preferentially selected, or data from a cluster head t_j located farther from *Sink* are aggregated at an intermediate node along the path, with the condensed results subsequently forwarded to the instructor terminal. Assuming the existence of j disjoint paths within the network and an edge (n_u, n_k) connecting nodes n_u and n_k, the characteristic distribution of network deployment can be described by the following equations:

$$d(n_u, n_k) = 0 \tag{1}$$

$$\sum d(n_0, n_j) = 0 (1 \le j \le v + l) \tag{2}$$

$$\sum d(n_u, n_j) = 0(1 \le j \le v) \tag{3}$$

$$\sum (d(n_k, n_j) - d(n_g, n_k)) = 0$$
$$(v+1 \le j \le v+l, 1 \le g \le v+l) \tag{4}$$

This edge–cloud collaborative data processing model significantly reduces the volume of raw data transmitted to *Sink*, thereby alleviating communication pressure on core network links and lowering overall energy consumption. As a result, physiological data can be transformed into real-time instructional feedback with low latency and high reliability, directly supporting precision teaching optimization decisions such as classroom pacing and personalized instruction.

Upon completion of sensing node deployment and acquisition of massive volumes of raw data, information fusion serves as the critical intelligent processing layer through which raw data are converted into actionable instructional insights and instructional optimization is achieved. Data originating from individual nodes are often limited in scope or affected by noise, rendering them insufficient for accurately and comprehensively characterizing the complex physiological load states, motor skill execution, or interaction effectiveness of both instructors and students. Given that the primary objective of this study is instructional optimization, the system is required to extract pedagogically meaningful information from multi-source, heterogeneous data. The application of information fusion technologies is therefore aimed at the collaborative analysis and integration of fragmented, low-level physiological signals to generate high-level, interpretable assessment indicators. These may include students' real-time exercise intensity, fatigue levels, and movement accuracy, as well as instructors' instructional load and classroom management efficiency. Through this form of deep fusion, the mobile interactive feedback system advances from mere data presentation to intelligent feedback, enabling the delivery of scientific decision support to instructors and personalized exercise prescriptions and safety alerts to students. Ultimately, a closed-loop cycle of data sensing → intelligent fusion → real-time interaction → instructional optimization is established.

The fusion processing of physiological data sensing nodes in mobile interactive networks for university physical education is primarily grounded in a spatially clustered distributed data aggregation mechanism. Following system initialization and the delineation of the monitoring scope, the student nodes (*SN*) are ranked in descending order based on their communication distance to the teacher terminal (*Sink*). The regions containing the furthest nodes—those incurring the highest transmission cost—are then dynamically elected as cluster heads $T = \{t_1, t_2, \dots, t_v\}$. In the context of physical education, this corresponds to logically grouping students engaged in similar activities across a sports field into clusters. Each cluster functions as a local computational unit, within which quantitative fusion-based tracking and recognition are performed across the multimodal physiological data of its members within a defined radius f_0. This process involves the derivation of group-level feature indicators such as average physiological load and movement synchrony. The application of this cluster-based aggregation strategy substantially reduces the volume of data requiring direct transmission to the teacher terminal by compressing large-scale raw inputs into pedagogically meaningful group-level feature information. As a result, bandwidth demands are alleviated and computational overhead at the central node is minimized, enabling an efficient data preprocessing pipeline for real-time feedback.

Furthermore, the deeper principle of information fusion lies in the dynamic selection of fusion paths and intelligent optimization based on network state. The algorithm is not fixed; rather, it is designed to iteratively and adaptively refine both data aggregation and forwarding strategies. A critical decision point is the assessment of the residual capacity $EZ(n_k)$ of each relay node. When sufficient capacity is available, $EZ(n_k) \geq 0$, a shortest-path-first algorithm is applied to ensure efficient transmission of aggregated data. In contrast, when capacity is insufficient, $EZ(n_k) < 0$, a more complex multipath routing protocol is activated, mobilizing additional nodes to participate in forwarding in order to prevent data loss. In real-world instructional settings, this means that the system can intelligently select the most robust data aggregation paths based on real-time conditions such as wireless channel quality and device battery levels. For instance, if student movement in a given area results in an unstable link, the system automatically switches to a redundant path to ensure the reliable and timely delivery of group-aggregated data to the teacher terminal. Through this form of dynamic optimization, the information fusion process not only distills data into high-value insights but also ensures the robustness and low latency of critical instructional information transmission. Consequently, the fusion results can be directly transformed into scientifically grounded feedback to support instructors in making real-time pedagogical interventions, thereby closing the loop from sensing to instructional optimization.

2.2 Instructional monitoring and feedback optimization in mobile interactive networks for university physical education

The optimization of instructional monitoring and feedback mainly aims to elevate the physiological data–driven mobile interactive feedback system from merely functional to highly efficient, reliable, and practical. Within this context, network channel resource allocation and transmission delay are the critical bottlenecks determining system effectiveness. In university physical education environments, the inherent mobility of students and instructors leads to frequent changes in network topology. Dozens or even hundreds of physiological sensing nodes may simultaneously attempt to connect with the teacher terminal and transmit data. In the absence of proactive channel balancing mechanisms, network congestion and channel collisions are highly likely to occur near data aggregation points, resulting in the loss of key physiological data packets or severe delays. For instance, during high-intensity interval training, if peak heart rate data from multiple students cannot be uploaded in a timely manner due to channel contention, the system may fail to accurately assess the group's physiological load threshold. Consequently, any instructional decisions made by the teacher based on incomplete data may be rendered ineffective or misinformed. Through the application of the channel balancing technique, communication slots and bandwidth can be dynamically allocated to data streams of different priorities and to nodes at varying locations, ensuring the integrity and timeliness of high-value instructional information. This constitutes a prerequisite for building a trustworthy feedback system capable of supporting precision pedagogical interventions.

The proposed channel balancing strategy for mobile interactive networks in university physical education is grounded in a priority-based channel allocation mechanism, dynamically evaluated according to both data value and node state. In the dynamic physical education environment, the system quantifies data value by calculating the univariate entropy and spatial features of each node's data stream.

For example, heart rate anomalies are assigned higher entropy values than routine step count data. When the composite feature distribution n'_u satisfies the following conditions:

$$f(n_u, n_0) = f(n'_u, n_0) \tag{5}$$

$$f(n'_u, n_k) > \frac{1}{2} f(n_{u+1}, n_k); f(n'_u, n_k) = \frac{1}{2} f(n_{u+1}, n_k); f(n'_u, n_k) < \frac{1}{2} f(n_{u+1}, n_k) \tag{6}$$

In addition, a node variation function $d(s)$ is defined to continuously evaluate the communication stability of each node. Based on this metric, the algorithm sets a dynamic threshold group $\{M, G\}$ and establishes a channel allocation control function as follows: (a) $f(n_{u+1},n_k)/f_0 = m$, $f(n_u,n_k)/f_0 \rightarrow \eta$, and $[f(n_u,n_k)/f_0] + 1 = \eta + 1$. (b) $f(n_{u+1},n_k)/f_0 = \eta$. ε. When a node is transmitting high-value data such that $f(n_{u+1}, n_k) > 1/2f(n_{u+1},n_k)$ and the communication channel is deemed stable, it is assigned to a high-priority channel. Otherwise, it is allocated to a standard channel. This design ensures that during concurrent physical activities involving multiple participants—where data competition occurs—critical instructional information such as exercise load warnings is prioritized for transmission. As a result, value-driven intelligent allocation is achieved within the constraints of limited wireless spectrum resources.

Moreover, the core mechanism of channel balancing lies in the refined management of linear-shift frame-level scheduling in combination with joint probability density control. To facilitate real-time feedback, transmission time is divided into fine-grained frame sequences $L = [l_1, l_2, \ldots, l_v]$, with the allocation of each frame position determined by the joint probability density l_u, which reflects the data burst characteristics. Specifically, $l_u = INT(|a_{ou} - y_u|/m)$. For example, real-time video streams are allocated to denser or dedicated time slots for transmission, whereas periodic physiological data are evenly distributed. This linear-shift scheduling strategy, combined with probability-weighted distance considerations among nodes, effectively minimizes interference between heterogeneous data streams, thereby reducing transmission collisions and delays to the greatest extent possible. Such fine-grained frame-level scheduling ensures that the teacher terminal can synchronously and smoothly receive multimodal physiological data and video streams from different students, providing a low-latency, stable communication foundation for implementing accurate, real-time instructional interaction and guidance.

Furthermore, the control of network transmission latency serves as a fundamental technological safeguard for advancing from post-hoc analysis toward real-time interaction and instantaneous feedback. The effectiveness and safety of physical education are highly dependent on temporal responsiveness. When physiological data experience delays of several seconds—or longer—between acquisition, transmission, and presentation at the teacher terminal, the so-called "real-time feedback" becomes illusory. Under such conditions, the system can serve only retrospective analytical purposes, rather than facilitating dynamic regulation during teaching. Through the introduction of a latency control mechanism, the end-to-end delay for critical physiological indicators can be maintained within a millisecond to low-second range, which is considered acceptable for real-time responsiveness. This enables instructors to receive visual or haptic alerts via mobile terminals at the precise moment when a student exhibits signs of physiological overload or improper motor execution. Accordingly, individualized guidance or adjustments to the group training protocol can be issued immediately. This near-instantaneous closed-loop cycle of data-driven decision-making and interaction not only significantly enhances the accuracy and safety of instructional guidance but also fundamentally transforms the traditional physical education model, enabling truly personalized and adaptive instructional optimization.

The proposed transmission delay control mechanism for mobile interactive networks in university physical education is principally based on link-layer optimization using multipath parallel transmission and code-chip segmentation. To meet the real-time demands of instructional feedback, a multipath routing generation algorithm is adopted, wherein multiple concurrent transmission paths $m \in [0, M-1]$ are established for critical physiological data. Each path's hop count β_m and delay π_m are quantified and ranked. In addition, drawing from the concept that each cluster head frame can be segmented into V_z code chips, the system performs packet fragmentation at the transport layer, followed by parallel data transmission across distinct paths. Specifically, let *N_E* represent the node difference between the *Source* and *Sink* nodes, the physical location of a monitoring node *u* be defined as (a_u, b_u), and the physiological data mining coordinates be denoted as (a^u, b^u). Under these definitions, the energy consumption of serial-link nodes can be computed using the following expression:

$$r = \frac{1}{N\_E}\sum_{u=1}^{N\_E} sqrt((a_u - \hat{a}_u)^2 + (b_u - \hat{b}_u)^2) \tag{7}$$

This design not only leverages the bandwidth aggregation effect of multipath transmission to significantly reduce the latency associated with individual paths but also utilizes a code-chip–level segmentation and reassembly mechanism to effectively mitigate end-to-end jitter caused by sudden congestion on any single transmission path. As a result, even in high-mobility physical education scenarios, critical instructional data can be reliably and rapidly delivered to the teacher terminal via the optimal transmission path.

At a deeper level, latency control is governed by a global dynamic scheduling strategy that combines intelligent path optimization with fuzzy adaptive weighting. Using the maximum hop count constraint $H\_C\_MAX(n_u, n_0)$, the system employs a linear-shift adaptive optimization algorithm to evaluate the transmission status of all available paths in real time. When a change in load is detected at a cluster head n_u, or when the path delay π_m exceeds a critical threshold, fuzzy adaptive weighted control is activated. This mechanism dynamically increases the scheduling priority of high-value data flows and reassigns them to low-latency paths in real time, while applying traffic shaping to lower-priority data streams. The expression for $H\_C\_MAX(n_u, n_0)$ is defined as follows:

$$H\_C\_MAX(n_u, n_0) = \left[\frac{f(n_u, n_0)}{f_0} + 1\right] \tag{8}$$

Assuming a global energy balancing coefficient denoted by R_{EL}, the graph model for instructional monitoring and feedback in mobile interactive networks for university physical education can be described as

$$R_{Sa}\left(M, f\right) = \begin{cases} MR_{EL} + M\gamma_{st} f^2, f < f_0 \\ MR_{EL} + M\gamma_{lo} f^4, f > f_0 \end{cases} \tag{9}$$

$$R_{Ea}(M) = MR_{EL} \tag{10}$$

This globally balanced, intelligent scheduling mechanism enables the network to dynamically reallocate resources according to evolving instructional demands. Ultimately, in the abstract graph model of instructional monitoring and feedback, precise control over network-wide transmission delay is achieved. This ensures a millisecond-level response experience for instructors, thereby establishing the technological foundation for data-driven, real-time pedagogical intervention and optimization.

3 EXPERIMENTAL RESULTS AND ANALYSIS

To evaluate the reliability of physiological data sensing node deployment and to ensure the stable and continuous acquisition of high-quality raw physiological data in authentic physical education scenarios, real-time heart rate data were first collected from individual students during instructional sessions. Furthermore, in order to validate the effectiveness of the data fusion algorithm and to demonstrate the system's capacity to transform multisource heterogeneous raw data into higher-level indicators with clear pedagogical significance, targeted experiments were conducted. The real-time heart rate acquisition sequence presented in Figure 2 serves as strong evidence of the high quality and robustness of the constructed sensing network under complex teaching conditions. The time-series data reveal uninterrupted heart rate recordings over the full 3000-second instructional timeline. Heart rate values remained within physiologically reasonable ranges and exhibited smooth transitions—rising from approximately 70 beats per minute during the warm-up phase to 160–180 beats per minute during the main training period, followed by a gradual decline during the cool-down phase. No abnormal spikes or data loss were observed. These findings indicate that the optimized deployment of the mobile interactive network effectively overcame communication challenges posed by student movement and equipment interference, thereby enabling the continuous and stable acquisition of raw physiological signals.

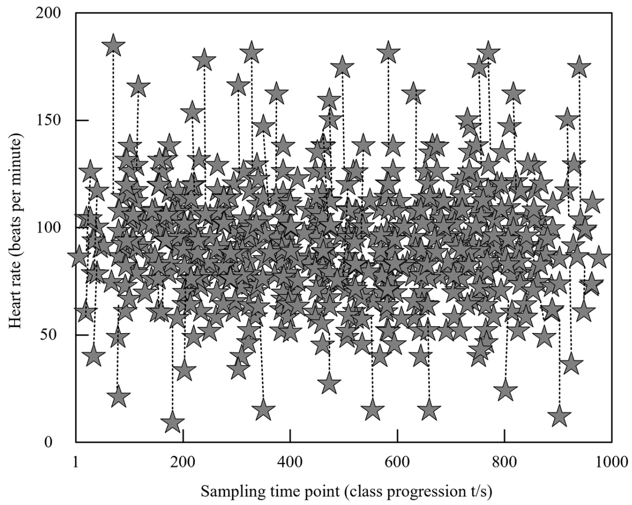

Fig. 2. Real-time heart rate data acquisition sequence for individual students

The exercise load level assessment results based on multisource data fusion, as illustrated in Figure 3, reflect a significant advancement from low-level data presentation to high-level instructional insight. The fused outputs no longer manifest as disordered raw signals; instead, they are clearly quantified into five distinct load levels, ranging from Level 1 to Level 5. The changes correspond closely with instructional segments. For instance, during the E2–E3 interval, load levels consistently remained at Level 4 ("high load"), aligning with the main technical practice phase; during the E5 interval, load levels dropped to Level 2 ("low load"), which coincided with the relaxation and recovery segment. The experimental results directly confirm the effectiveness of the proposed data fusion algorithm. By jointly analyzing heart rate, acceleration, and other multisource inputs, the algorithm effectively filtered noise and output qualitative indicators with clear instructional interpretation. This enabled instructors to intuitively grasp the overall and dynamic distribution of student exercise loads across the entire class, rather than being overwhelmed by massive volumes of unprocessed data. Consequently, the system provided a scientifically grounded and visualized basis for making instructional decisions such as group differentiation, training intensity adjustment, and safety alerts.

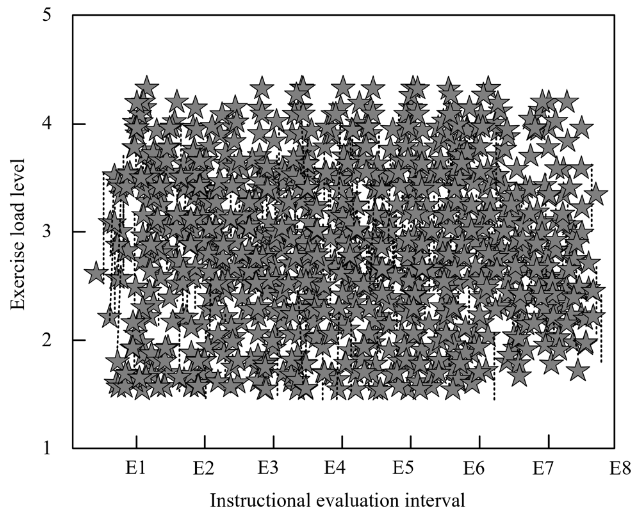

Fig. 3. Student exercise load level assessment based on multisource data fusion

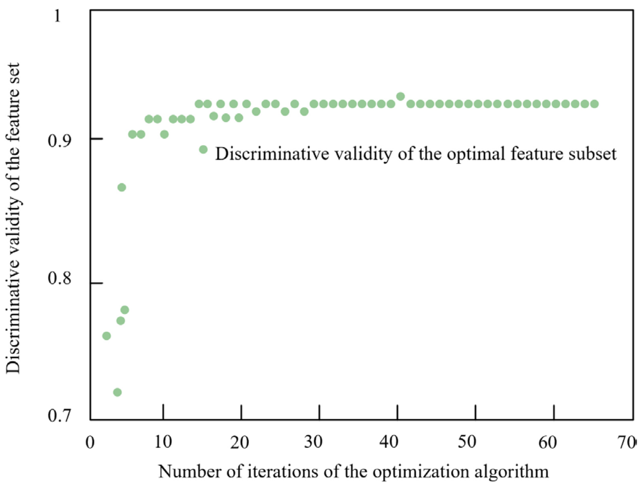

Fig. 4. Optimization process of physiological feature selection based on the maximum entropy model

To intelligently identify the most representative physiological feature subset from a broad array of candidate parameters—thereby enabling the construction of an efficient and accurate instructional evaluation model—a validation experiment was further conducted. As shown in Figure 4, the discriminative validity of the feature subset was observed to increase rapidly from an initial value of approximately 0.70 to a high and stable level of 0.932 after around 70 iterations of the optimization algorithm based on the maximum entropy model. This quantitative outcome clearly demonstrates that the optimization procedure successfully selected a highly discriminative feature combination from a raw feature pool potentially comprising heart rate, heart rate variability, multi-axis acceleration, electromyographic signals, and other physiological indicators. The resulting feature subset exhibited robust classification performance across different physical activity states, thereby confirming the effectiveness of the maximum entropy model in addressing the feature selection problem. This provides a high-quality input foundation for subsequent information fusion processes.

The implications of this experimental result are central to the integrity of the proposed system. First, it substantiates that the "physiological data-driven" approach extends beyond mere aggregation of raw signals and instead entails a refined and distilled process governed by intelligent algorithms. A discriminative validity score of 0.932 indicates that the models for physical load assessment and motion state recognition—built upon this feature subset—will likely achieve superior accuracy and reliability. This ensures that the instructional insights fed back to instructors are not only scientifically grounded but also pedagogically actionable. Therefore, the feature optimization process illustrated in Figure 4 constitutes a critical bridge between "raw data acquisition" and the generation of "high-level instructional insights." By enhancing the intrinsic quality of physiological data inputs, the overall intelligence and practical utility of the mobile interactive feedback system have been fundamentally strengthened.

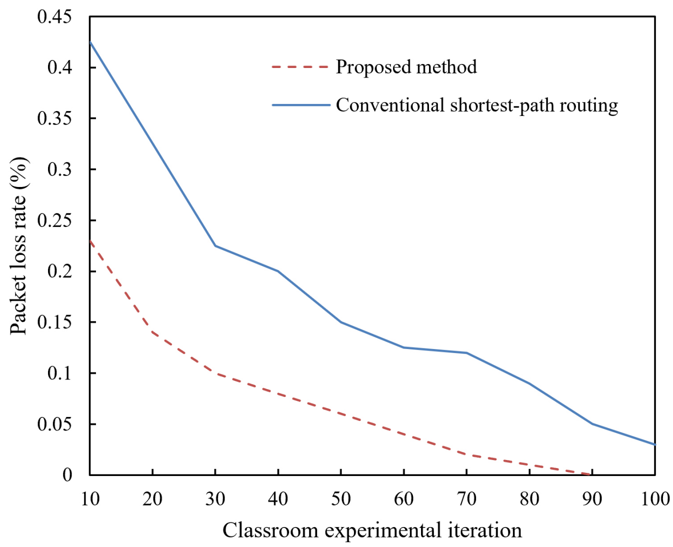

Fig. 5. Comparison of packet loss rate performance under instructional scenarios

To validate the reliability advantages of the proposed adaptive routing algorithm in dynamic physical education environments, a comparative analysis of packet loss rate performance under classroom conditions was conducted. This evaluation aimed to ensure that critical physiological data in mobile teacher-student interactions could be transmitted with minimal loss and high stability. As illustrated in Figure 5, during 100 rounds of classroom simulation experiments representing various teaching phases, the packet loss rate associated with the proposed method remained consistently and significantly lower than that of the traditional shortest-path routing algorithm. In the initial stages of high-intensity, mobility-intensive instructional activities, packet loss rates for the traditional routing method ranged from 0.3 to 0.4. In contrast, the proposed approach maintained the loss rate below 0.1, demonstrating a substantial performance advantage. As the experiments progressed, a decreasing trend in packet loss was observed in both methods, potentially attributable to the stabilization of the network environment. However, the proposed algorithm continued to outperform, eventually achieving a near-zero packet loss rate by the latter stages of the experiments, whereas the traditional method still exhibited a steady-state loss rate of approximately 0.05. This result provides strong evidence that the proposed adaptive mechanism can effectively address the dynamic changes in network topology and fluctuations in link quality caused by student group activities and positional movement during physical education classes, thereby significantly enhancing the reliability of data transmission.

These findings provide critical support at the network communication layer for the overall system framework. The observed low and stable packet loss rate ensures the integrity and authenticity of data supplied to the backend information fusion and decision-making modules. Consequently, any instructional insights derived from the fused physiological data can be regarded as accurate and trustworthy. In contrast, a persistently high packet loss rate would inevitably result in fragmented or distorted feedback, rendering precise pedagogical optimization unattainable. Therefore, the network reliability confirmed by Figure 5 is foundational to the closed-loop functionality of the data-driven system, establishing a technological cornerstone for the practical applicability and effectiveness of the mobile interactive feedback system in real teaching contexts.

To further verify whether the proposed network transmission delay control mechanism can ensure the real-time performance of physiological data and interactive instructions across teaching scenarios of varying complexity, a series of comparative experiments were conducted. As shown in Table 1, the transmission delay of physiological data under all five representative physical education scenarios was significantly reduced by the proposed method compared to conventional shortest path routing. Delay reductions ranged from approximately 65% to nearly 100%, with transmission latency decreasing from 0.67 seconds to 0.14 seconds in Scenario 1 and from 0.13 seconds to a negligible level of < 0.01 seconds in Scenario 5. These results demonstrate the overall superiority of the proposed strategy in minimizing latency across diverse activity conditions. More critically, a clear trend was observed: as scenario dynamics and complexity increased, the latency associated with the baseline method, although slightly reduced, remained at a relatively high level. In contrast, the proposed method exhibited a continuously decreasing latency profile with increasing scenario complexity. This phenomenon highlights the intelligence of the proposed adaptive algorithm, which was able to exploit short-lived high-quality links or parallel paths that frequently emerged in highly dynamic environments. As such, it demonstrated exceptional latency performance precisely under conditions where real-time responsiveness is most essential. These findings confirm that the proposed network optimization strategy is well-suited to the dynamic characteristics of physical education environments, enabling the consistent maintenance of ultra-low transmission delays for critical physiological data. This capability provides a foundational technical guarantee for enabling timely and accurate instructional feedback and safety interventions, thereby strongly supporting the realization of instructional optimization.

Table 1. End-to-end transmission delay of physiological data (seconds)

Instructional Scenario Description	Proposed Method (Adaptive Routing and Channel Balancing)	Baseline Method (Conventional Shortest Path Routing)
Scenario 1: Low-speed stable activity (e.g., gymnastics)	0.14	0.67
Scenario 2: Medium-speed training (e.g., shuttle run)	0.10	0.38
Scenario 3: High-speed intensive activity (e.g., sprinting)	0.05	0.21
Scenario 4: Dense group interaction (e.g., team competition)	0.02	0.18
Scenario 5: Mixed service load (data + instruction)	<0.01	0.13

4 CONCLUSION

A mobile interactive feedback system driven by physiological data was successfully developed and validated for use in university-level physical education settings. The core contributions of this research are centered on two critical components. First, by implementing a dynamic and adaptive deployment strategy for sensing nodes, coupled with a multi-source data fusion algorithm, reliable and high-quality perception and feature extraction of physiological states of instructors and students in complex instructional scenarios have been achieved. Raw physiological data can thus be transformed into evaluative metrics capable of directly informing instructional decision-making. Second, through the integration of channel balancing and intelligent delay control mechanisms, significant improvements in the transmission performance of the mobile interactive network have been realized. Experimental results confirmed that packet loss rates for key instructional data were reduced to nearly zero, while end-to-end latency was maintained at the millisecond level, thereby ensuring the real-time reliability of feedback information. These two components collectively constitute a closed-loop technological framework spanning from "data sensing" to "intelligent integration" and ultimately to "real-time feedback." The effectiveness of the system in enhancing physical education instruction has been empirically demonstrated, enabling accurate insights and timely interventions by instructors. Consequently, a paradigm shift has been facilitated from experience-based teaching to data-driven instruction, representing both a theoretical advancement and a contribution of practical significance.

Despite these advancements, certain limitations remain. Although the system was validated under realistic conditions, the experimental scope was primarily confined to representative physical activities; thus, its generalizability to broader or less structured instructional environments warrants further investigation. In addition, the current study primarily focused on physiological and motion data. Future extensions may incorporate multimodal data such as video-based posture analysis and environmental variables to construct a more comprehensive instructional evaluation model. The system's capacity for personalized adaptive response also remains an area for further enhancement. Accordingly, future research directions include the integration of artificial intelligence to enable more granular personalized instructional recommendations and adaptive learning path planning; the expansion of the system's application to multimodal data fusion in more complex teaching scenarios; and the execution of large-scale, longitudinal empirical studies to systematically evaluate the long-term impact on instructional outcomes and student development. These efforts are expected to further drive the innovation and deep integration of intelligent technologies in the field of physical education.

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