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Article

Analyzing biomechanical force characteristics in sports performance monitoring using biochemical sensors and internet of things devices

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Abstract: This study explores the application of Internet of Things (IoT) devices and biochemical sensors in sports performance monitoring, focusing on the biomechanical force characteristics of athletes to address limitations in traditional methods, such as limited data types, poor real-time accuracy, and insufficient visualization. Emphasizing mechanobiological principles, the analysis targets key force-producing regions of the body—such as the feet, legs, and torso—to optimize energy efficiency, motion precision, and overall athletic performance. Biochemical sensors were employed to monitor real-time biomechanical and physiological data, while IoT devices ensured accurate data transmission, visualization, and feedback. Data accuracy was enhanced through methods such as zero correction, timestamp synchronization, and Kalman filtering, while data transmission efficiency was optimized using a lossless compression algorithm, hierarchical structuring, the MQTT protocol, and encryption via the AES algorithm. Data organization utilized a star-structured MySQL database with composite indexing for swift access. Analytical tools such as the Apriori algorithm for data correlation, linear discriminant analysis for feature extraction, and multi-source data fusion enabled detailed visualization of performance metrics. Experimental applications in football and sprinting demonstrated the effectiveness of IoT-based monitoring. Football experiments captured multi-dimensional data on technical characteristics, while sprint tests recorded precise performance metrics, including real-time speed profiling and timing accuracy. For instance, in a 100-meter sprint test, an IoT system measured an athlete's performance at 12.54 seconds with 100% accuracy, surpassing manual timing methods. These findings highlight the transformative potential of IoT devices and biochemical sensors in sports analytics, offering enhanced accuracy, real-time tracking, and actionable insights to refine athletic performance and decision-making.

Keywords: IoT devices; sports performance monitoring; biomechanical force analysis; mechanobiology; data visualization; data transmission efficiency; MQTT protocol; advanced encryption standard

1. Introduction

With the continuous advancement of competitive sports, the performance levels of athletes have significantly improved, making the monitoring and analysis of sports performance increasingly critical. Accurate tracking of sports performance and understanding its biomechanical patterns not only helps athletes optimize their training outcomes but also provides coaching teams with valuable insights for refining training strategies. However, traditional methods of monitoring and analyzing sports performance often face significant challenges, including reliance on single data types, limited real-time accuracy, and insufficient visualization, which hinder their ability to provide comprehensive and actionable insights.

In recent years, numerous studies have sought to address these limitations by enhancing sports performance monitoring and analysis through advanced technologies and methodologies. For instance, researchers have analyzed key factors influencing athletic performance by monitoring various parameters during training sessions [1–3]. Kocakulak et al. [4] utilized nanobiosensors to collect biological data from athletes, exploring their applications in sports medicine and doping detection. Rana et al. [5] systematically reviewed wearable sensor technologies, focusing on their roles in communication, data fusion, and analysis across various sports disciplines. Plesa et al. [6] examined biomechanical variables such as eccentricity utilization, force-velocity relationships, and response intensity index, demonstrating their potential for evaluating exercise performance, with the exception of eccentricity utilization. Bian et al. [7] introduced wearable surface microfluidic systems for physiological monitoring, addressing the limitations of traditional inspection cycles and laboratory reliance, while enabling continuous monitoring. Raza et al. [8] developed graphene-based fabric sensors for applications like volleyball training, including spike force measurements, detecting receiving errors, and monitoring player positions. Similarly, Barbosa et al. [9] emphasized the contributions of swimming analysts to elite athlete performance, and Clemente et al. [10] tracked professional volleyball players, highlighting the health pressures athletes face as seasons progress. While these studies have significantly advanced the field, challenges related to real-time data accuracy and comprehensive visualization persist.

Emerging technologies like the Internet of Things (IoT) present promising solutions to these challenges by integrating diverse systems and structures capable of connecting and interacting with physical objects through the Internet. IoT systems, comprising sensors, software, and devices, enable real-time data collection, transmission, and processing, creating more intelligent and efficient monitoring systems [11–13]. IoT has been widely applied across various domains. For example, Baucas et al. [14] used IoT devices to provide wireless access to healthcare services, addressing gaps in healthcare delivery. Hadidi et al. [15] leveraged local collaborative networks to utilize the computational power of IoT devices for vision-based applications. In industrial settings, Gungor et al. [16] proposed an ensemble learning framework to enhance maintenance speed and accuracy using Industrial IoT technologies. IoT's ability to enhance system security has also been demonstrated by Cao et al. [17], who developed a remote proof scheme to ensure the integrity of IoT systems. Hubrechsen et al. [18] underscored the importance of flexible testing facilities to improve IoT device performance, while Jusak et al. [19] introduced a semi-automatic heart sound recognition method using IoT for disease detection. Furthermore, Nie et al. [20] analyzed IoT applications in agriculture, demonstrating their effectiveness across perception, transmission, processing, and application layers.

Building on these advances, this study explores the application of IoT technologies to overcome the limitations of traditional sports performance monitoring systems. By integrating IoT with the principles of mechanobiology, this research aims to enhance real-time monitoring capabilities, improve data accuracy, and provide comprehensive visualization. Through multi-dimensional data analysis and innovative methodologies, this study not only advances sports performance analysis but also contributes to the broader understanding of mechanobiological processes, paving the way for future interdisciplinary research and practical applications.

2. Implementation of IoT device

2.1. Application process

Comprehensive monitoring and analysis of athletes' sports performance not only involves analyzing the final results but also focuses on the entire biomechanical process of creating these results. Emphasizing the mechanobiological principles of force generation, such as identifying key regions like the feet, legs, and torso, the monitoring process integrates real-time data collection using IoT devices and biochemical sensors. **Figure 1** summarizes the enhanced workflow of using IoT devices for multi-dimensional sports performance monitoring and detailed biomechanical analysis.

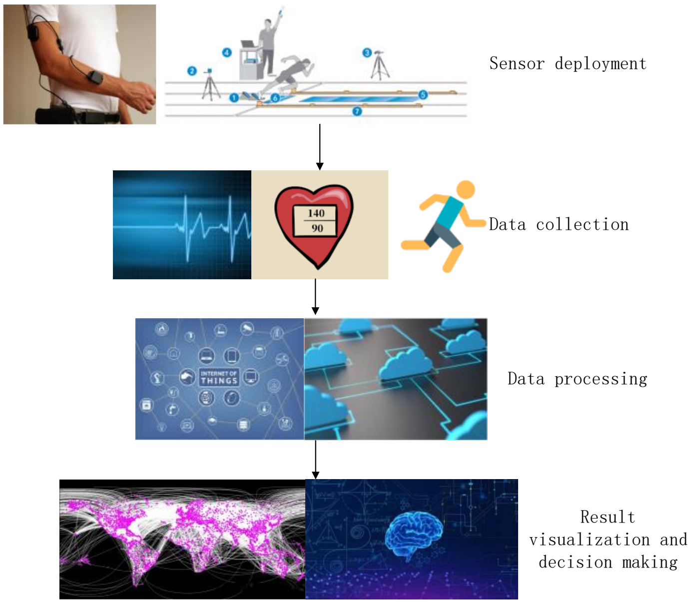

Figure 1. Application process of IoT devices.

Figure 1 illustrates the process of monitoring and analyzing sports performance using IoT devices. First, sensors are selected and deployed according to the specific data requirements for monitoring. Sensors are generally categorized as contact or non-contact types. Contact sensors, worn by athletes, are designed to be lightweight and comfortable to prevent interference with performance. Non-contact sensors, installed in the environment or on-site, require higher precision due to their greater monitoring distances to ensure data accuracy.

During exercise, these sensors capture a variety of data points related to the athletes. Physiological indicators such as heart rate, blood pressure, and body temperature are monitored alongside technical indicators like movement speed, body rotation angles, and pressure distribution across key body regions. These technical indicators provide insights into improving movement efficiency and refining athletic skills. For team sports, additional tactical data, such as movement trajectories and spatial coverage, is also gathered to evaluate and optimize tactical strategies.

The collected data is transmitted to cloud computing platforms via IoT devices, ensuring high-speed and real-time data availability. Once uploaded, the data is standardized into a unified format, processed for analysis, and presented visually. This visualization enables athletes and coaches to interpret results quickly and accurately, driving more effective performance analysis. The insights derived from this process inform training strategies, enhance tactical planning, and contribute to improving overall sports performance.

2.2. Improving the quality of data collection

The advantage of IoT devices over manual recording is that they do not generate human errors, such as typing errors when inputting data or miscalculating results during calculations. However, no matter how precise the equipment is, errors cannot be completely eliminated. In order to ensure the accuracy of motion data as much as possible, first of all, when selecting sensors, select sensors with high accuracy, and it is necessary to calibrate the sensors.

For an ideal sensor, the value of the measured data is the input value of the sensor, and the value read is the output value of the sensor. So, if the input value is set to X_0 and the output value is set to Y_0, the relationship between the input value and the output value can be recorded as:

$$Y_0 = k \cdot X_0 \tag{1}$$

Among them, k is called the sensitivity coefficient of this sensor. According to the equation, the closer the sensitivity coefficient is to 1, the closer the value read by the sensor is to the value of the measured data. Due to environmental impact and aging of equipment inside sensors, sensitivity errors $\Delta\mathrm{k}$ and zero position errors ΔX may occur. At this time, the actual sensitivity coefficient becomes $k + \Delta k$ and the input value becomes $\mathrm{X}_0 + \Delta\mathrm{X}$. The output value at this time is:

$$Y_1 = (k + \Delta k) \cdot (X_0 + \Delta X) \tag{2}$$

The value of error is the absolute difference between Y_0 and Y_1, which is:

$$|Y_1 - Y_0| = |k \cdot \Delta X + \Delta k \cdot X_0 + \Delta k \cdot \Delta X| \tag{3}$$

The final error size, as derived from the equation, is influenced by both sensitivity errors and zero position errors. Sensitivity errors can be mitigated using scaling factor correction [21], while zero position errors are addressed through zero correction methods. By applying these corrections, the overall error can be minimized, significantly enhancing data accuracy.

In motion monitoring scenarios, the use of numerous IoT devices poses the challenge of maintaining data consistency across time points. Without proper synchronization, discrepancies can arise, leading to inaccuracies in analysis. To ensure data synchronization, a combination of timestamp marking and synchronization signals is implemented.

Timestamp marking involves associating each data point with a precise timestamp, indicating the exact moment of data collection. For IoT devices, timestamps are generated using NTP (Network Time Protocol), providing a consistent and accurate time reference. Data points with identical timestamps are considered as being collected simultaneously, ensuring temporal alignment.

Synchronization signals, on the other hand, coordinate the timing of data collection across multiple devices. One sensor is designated as the synchronization source, sending signals to control the initiation or termination of data collection for all connected devices. This study employs electromagnetic wave signals as the synchronization medium due to their superior reliability compared to electrical signals. Electromagnetic waves are less susceptible to interference from conductor materials and cable designs, and their propagation speed—approaching the speed of light—ensures high synchronization accuracy under normal monitoring conditions.

Figure 2 illustrates the waveform of the synchronization signal used to control sensor operation, highlighting the effectiveness of this method in maintaining synchronization and reducing errors during motion monitoring.

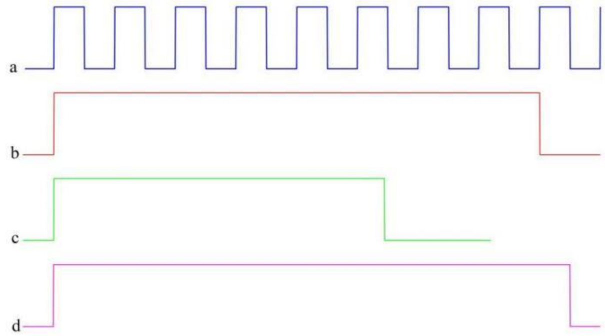

Figure 2. Synchronous signal and sensor working waveform diagram.

Figure 2 illustrates the waveform of a synchronization signal controlling the operation of three sensors. Waveform (a) represents the synchronization signal, while waveforms (b), (c), and (d) correspond to the outputs of three different sensors. The synchronization signal exhibits a periodic pattern, with the rising edge marking the beginning of a new recording cycle. This edge can be adjusted as needed. At the start of a new cycle, all three sensors' waveforms transition from a low level to a high level simultaneously, signaling the commencement of data recording and ensuring synchronization and consistency across sensors.

The ending times of the waveforms for sensors (b), (c), and (d) vary, as each sensor is configured to monitor specific types of data. For example, sensor (b) records blood pressure, sensor (c) monitors speed, and sensor (d) tracks heart rate during the athlete's run. When the athlete finishes running, the speed sensor (c) stops recording since further data collection is unnecessary. However, blood pressure and heart rate sensors (b and d) continue recording to monitor the athlete's recovery. If required, synchronization signals can also be used to align the end times of these sensors for specific analyses.

To ensure the accuracy of data collected by the sensors, a Kalman filter is applied to reduce the effects of environmental noise and abrupt changes during the data collection process. These inconsistencies can compromise data stability and the accuracy of subsequent analyses. The Kalman filter is a recursive algorithm that efficiently processes noise, smooths abrupt variations, and produces stable and reliable data for analysis [22,23].

Figure 3 illustrates the effectiveness of the Kalman filter in processing sensor data, showing a comparison between raw data and filtered data. The filter effectively reduces noise and mitigates sudden fluctuations, providing cleaner and more accurate data for analysis. This not only improves the reliability of the monitoring process but also supports more precise evaluations of athletic performance.

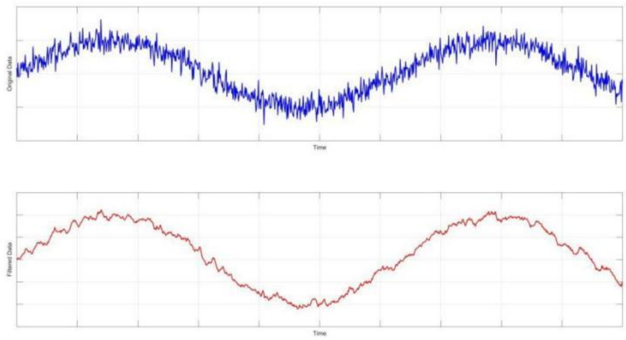

Figure 3. Comparison of Kalman filter processing effects.

Figure 3 presents a schematic diagram comparing the original data with the data processed through Kalman filtering, where the lines represent the trends of the data over time. Observing **Figure 3**, it is evident that the original data contains significant noise and abrupt outliers, resulting in poor stability and inconsistencies throughout the dataset.

After applying the Kalman filter, the noise and outliers are significantly reduced, leading to a much smoother data trend. The processed data exhibits enhanced stability and improved readability, making it more suitable for analysis and interpretation. This improvement ensures that the data can reliably support performance evaluations and decision-making processes.

2.3. Data transmission

Due to the intense nature and strong adversarial nature of sports, the efficiency of data transmission is highly required for real-time monitoring of the sports process. The entire process requires real-time data transmission, and in order to improve transmission efficiency, network bandwidth and network latency need to be considered. So, this article uses compression encoding to reduce the size of data during transmission, specifically using the lossless compression algorithm LZW (Lempel-Ziv-Welch). The LZW [24,25] algorithm uses encoded data to construct new encoding combinations to represent repeated data sequences. This compression method is very suitable for compressing motion data, as there is often a large amount of duplicate data in motion data. For example, the movement trajectory of a football player on the field is continuous and has a large number of overlapping areas. The position data that has already passed through can be represented using encoded data, which improves the efficiency of compression. Table 1 shows the encoding principle of LZW:

Table 1. Encoding principles of LZW algorithm.

Input data	Indexes	Content	Encoded output	Encoding length	Encoding path
12	A	12	A	2	-
567	B	567	B	3	-
90	C	90	C	2	-
12	A	12	-	2	A-2
7	D	7	D	1	-
12	A	12	-	2	A-3
90	C	90	-	2	C-4

Table 1 illustrates an encoding method that assigns indexes to numbers during data compression to improve transmission efficiency. When numbers such as 12, 567, or 90 are encountered for the first time, they are assigned unique indexes (e.g., A, B, and C). For instance, when the number 12 appears again, it is automatically assigned the encoded index A, and represented with a new path, such as A-2, to differentiate it from its initial occurrence. Similarly, a second occurrence of 90 would generate a path like C-4. This approach ensures that continuous data is not mistakenly identified as duplicates when passing through the same location, enhancing the clarity of data encoding and reducing redundancy during transmission.

The focus of data collection differs depending on the sport, and even within the same activity, different types of data hold varying levels of importance. To improve real-time accuracy, prioritizing the transmission of high-priority data is essential. This study applies hierarchical optimization [26] to process motion data, assigning higher priority to more critical data for efficient transmission. Figure 4 illustrates the specific hierarchical optimization process, showcasing how data is categorized, prioritized, and transmitted in a structured manner to ensure timely and accurate delivery of key performance metrics.

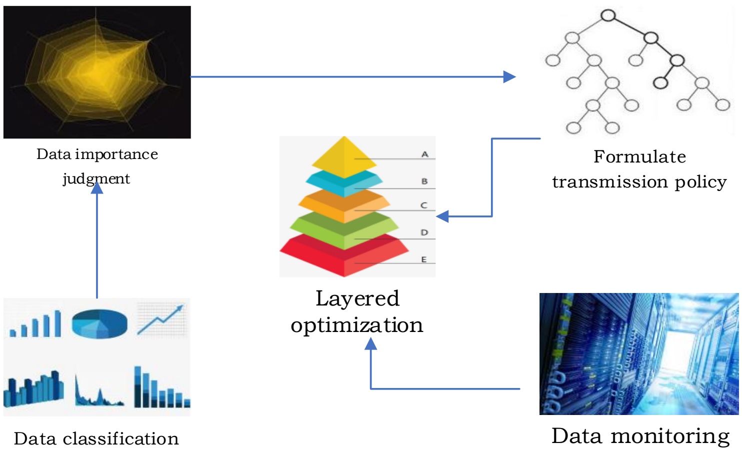

Figure 4. Process of layered optimization.

The process of data layering optimization is illustrated in **Figure 4**. Sports data is categorized into three main types: physiological indicators, technical indicators, and tactical data. The significance of these categories varies depending on the sport and analysis objectives. For instance, in team sports like football and basketball, tactical data is often more critical than physiological indicators. Conversely, in individual sports such as athletics and swimming, technical indicators take precedence over tactical data. By assessing the relative importance of these data types across different sports scenarios, this study prioritizes data transmission in a hierarchical manner, ensuring high-priority data is transmitted first.

During hierarchical optimization, the system continuously monitors the network flow status. In the event of congestion, high-priority data is promptly transmitted to maintain system efficiency and avoid delays in critical information delivery.

Efficient data transmission to the cloud platform requires a reliable communication protocol. This study employs the MQTT communication protocol to connect IoT devices to the cloud. MQTT [27,28] is a lightweight protocol optimized for low-bandwidth environments, making it particularly suitable for IoT devices. It facilitates one-to-many message publishing, minimizes transmission overhead, and uses a streamlined protocol exchange, enabling efficient communication between sensors and cloud systems. Additionally, MQTT features a "Last Will and Testament" mechanism to notify connected clients of abnormal interruptions, enhancing system reliability.

However, MQTT has a notable limitation: it lacks built-in encryption mechanisms, transmitting data in plaintext format, which exposes sensitive athlete data to risks of theft and tampering. To overcome these security challenges, this study integrates the AES (Advanced Encryption Standard) encryption algorithm with the MQTT protocol.

AES [29,30] is a widely adopted encryption standard that succeeds the older DES algorithm. Its ability to process partitioned data aligns well with the hierarchical optimization framework of this study. The AES encryption process for layered data involves two stages: data preparation and encryption. In the preparation stage, the AES algorithm expands its default 128-bit key by generating 10 additional 128-bit keys, resulting in a total of 11 keys. During encryption, plaintext data (e.g., sports motion data) is divided into 128-bit groups. Each group undergoes modulo 2 addition with a corresponding key, producing an intermediate result. This result is transformed by substituting its 16 bytes with values from the S-box and reshaping the data into a 4×4 matrix. Subsequent transformations, including row shifting and column mixing, generate a new 128-bit result. This process is repeated for all keys, producing the final ciphertext, which secures the data for transmission.

By integrating AES encryption with MQTT, the system ensures secure and efficient data transmission, addressing the security vulnerabilities of MQTT while maintaining the advantages of hierarchical optimization. This approach enhances the reliability and integrity of real-time sports performance monitoring systems, offering a robust solution for applying IoT technologies in biomechanical research and sports analytics.

2.4. Data storage and indexing

After data collection is completed, it must be effectively analyzed. The first step involves converting data collected by different IoT devices into a unified format, enabling seamless analysis of all datasets simultaneously. In this study, all data is converted into JSON (JavaScript Object Notation) format, a lightweight and widely used data exchange format. JSON structures data using objects and arrays, with content enclosed within "{}" for objects and "[]" for arrays, providing a simple yet powerful representation for structured data.

Once the data is converted into JSON format, it is stored in a multidimensional database. For managing athlete sports performance data, this study utilizes a relational database, MySQL. Unlike traditional databases that store all data in a single large repository, MySQL organizes data into multiple tables, significantly enhancing query speed and flexibility. To optimize data storage and retrieval, this study employs a star schema model, which includes a central fact table connected to multiple dimension tables. This star schema structure provides efficient organization and accessibility for complex queries and data analysis.

Figure 5 illustrates the star schema model used in this study. The fact table stores core performance metrics, such as speed, heart rate, and pressure distribution, while the dimension tables contain supporting information, such as athlete profiles, event types, and environmental conditions. This structure allows for rapid and flexible queries, enabling detailed analysis of athlete performance from multiple perspectives, such as comparing performance across different events or assessing the impact of environmental factors on results.

The combination of JSON for data unification and the star schema in MySQL ensures efficient storage, retrieval, and analysis of complex, multidimensional sports performance data, supporting comprehensive evaluations and informed decision-making.

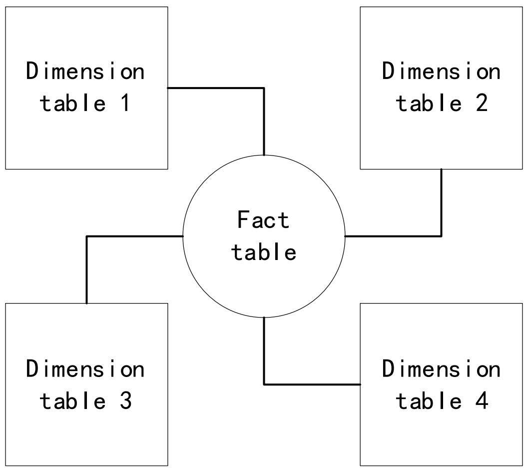

Figure 5. Star model structure diagram.

Figure 5 illustrates the basic structure of the star model used in this study. In the star model, fact tables primarily store numerical data or metrics that can be calculated, such as final scores in athletics or game scores in team sports. Dimension tables, on the other hand, record descriptive or textual data, such as the competition date, athlete names, event types, and other contextual details. This separation between fact and dimension tables facilitates efficient queries and supports multidimensional data analysis.

To enhance query performance, the data stored in the database is indexed. This study employs a composite indexing approach to create optimized indexes for frequently queried data. Composite indexing combines multiple frequently used fields into a single index to streamline query steps and improve retrieval efficiency.

For example, when querying an athlete's performance results over a specific period, a composite index can combine fields such as the athlete's name, competition date, and results into a single information segment. This composite segment can be cached to minimize the number of direct queries to the database, significantly reducing query time and enhancing overall system performance.

By integrating the star schema with composite indexing, the database system supports rapid and flexible queries, enabling detailed and efficient analysis of sports performance data. This approach ensures that large datasets can be processed effectively, supporting comprehensive evaluations and faster decision-making in sports analytics.

2.5. Comprehensive analysis of data

Data analysis is a critical step in enhancing sports performance, as it enables the refinement of training methods and technical movements based on empirical evidence. A fundamental requirement of data analysis is identifying correlations between different types of data. In this study, the Apriori algorithm [31,32] is employed to establish these correlations. In the context of association rule mining, each data type is treated as a dimension. A single-dimensional association rule involves only one type of data, while a multidimensional association rule involves two or more data types appearing together.

The Apriori algorithm relies on two key concepts: support and confidence. Support represents the proportion of a particular data set appearing within the total data set. A higher support value indicates a greater prevalence of that data set. For example, in a 100 m sprint analysis, consider four data sets: A (good starting skills), B (long daily training time), C (strong sprinting ability), and D (sufficient rest before the race). Among 100 athletes, the numbers corresponding to these attributes are as follows: 30 athletes with good starting skills, 40 with long training times, 50 with strong sprinting ability, and 60 with sufficient rest. The support values for A, B, C, and D are 30%, 40%, 50%, and 60%, respectively.

Confidence, on the other hand, represents the likelihood of one data set appearing given the presence of another. For example, among the 60 athletes who had sufficient rest (D), only 15 also had good starting skills (A). Thus, the confidence for the correlation between D (sufficient rest) and A (good starting skills) is 25%. A low confidence value, such as this one, indicates a weak correlation between the two data sets.

Association rules are determined by both support and confidence, which together indicate the strength of the correlation between different data types. For instance, higher support and confidence values suggest a stronger relationship, providing insights into critical factors that influence performance outcomes. By leveraging the Apriori algorithm, this study identifies meaningful correlations in sports data, enabling targeted interventions to improve athlete performance.

After associating the data, it is necessary to extract the features of the data and select meaningful features for fusion. The feature set that affects sports performance is set to a_n, and the equation for calculating the athlete performance feature parameter δ is:

$$\delta = \frac{\sum_{n=1}^{n} a_n}{\mu_n} \tag{4}$$

In the equation, μ represents the proportion of features for each parameter, representing the importance of this feature on the athlete's performance. The feature extraction method used in this article is linear discriminant analysis (LDA). It characterizes two types of data by linearly combining their features, and then performs dimensionality reduction processing on them. Figure 6 shows the analysis principle of linear discriminant analysis.

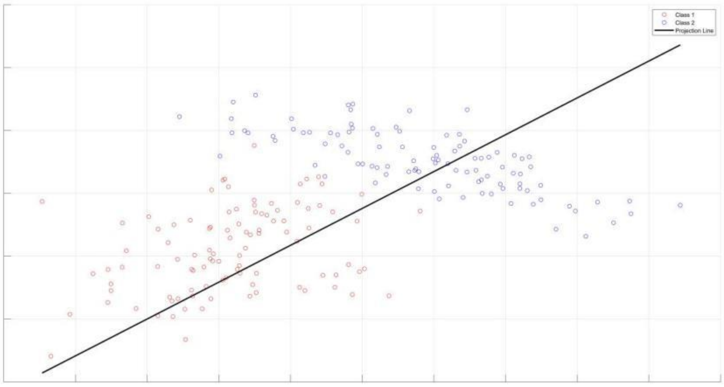

Figure 6. Principle of linear discriminant analysis.

From **Figure 6**, it can be observed that linear discriminant analysis (LDA) projects two types of data onto the same straight line. This projection ensures that data points of the same type are as close to their respective projections as possible, while data points of different types are kept as far apart as possible.

In the context of motion data feature extraction, LDA identifies the most representative features and reduces the dimensionality of the data. By focusing on the most impactful features, LDA minimizes the influence of non-representative data on the analysis results, ensuring a more accurate reflection of the athlete's performance. After feature extraction, the selected features are fused and presented in a visual format. This visualization provides an intuitive and comprehensive overview of an athlete's performance, highlighting key metrics and their contributions to overall sports performance. Such a representation enables coaches and athletes to better understand and interpret performance data, facilitating targeted improvements in training and technique.

3. Experimental monitoring and sports performance

In order to explore the use of Internet equipment on sports performance detection and analysis, different experimental designs were conducted for different sports in this experiment.

Firstly, a football match was selected for the experiment, with 11 randomly selected players on the field as the subjects. Each player wears a system chip to collect physical data of athletes during exercise. The system chip integrates physiological detection and position tracking, and high-speed cameras are installed on the sidelines to record the player's technical data. After the competition, the collected data was collected and the specific results are shown in **Table 2**:

Table 2. Competition data statistics of 11 athletes.

Player number	Running distance (m)	Average running speed (m/s)	Maximum sprint speed (m/s)	Fastest heart rate (times/min)	Mean body temperature (℃)
1	8364	2.3	5.4	178	36.8
2	7643	2.4	6.2	187	37.1
3	8143	2.7	5.9	177	37.3
4	5646	1.6	6.4	182	36.9
5	9773	2.6	5.8	176	37.2
6	5874	2.1	5.2	173	37
7	6743	1.8	7.2	191	36.7
8	2654	1.3	3.6	156	36.5
9	11,347	2	5.9	184	37.4
10	8554	1.7	4.8	173	36.9
11	7647	2.6	5	175	36.8

Table 2 presents the statistical data of 11 football players during the competition, highlighting key performance metrics for each athlete. A detailed analysis reveals significant observations. Athlete 9 recorded the longest running distance, covering 11,347 m, which indicates excellent physical endurance. In contrast, Athlete 8, the goalkeeper, demonstrated the shortest running distance at 2654 m. This aligns with the reduced physical demands of the goalkeeper's role, as also reflected in his lower average running speed and maximum sprint speed.

Athlete 7 achieved the highest sprint speed of 7.2 m/s, showcasing exceptional explosive power. However, his total running distance was relatively short at 6743 m, suggesting a specialized role requiring critical and short bursts of speed during the game. Another crucial metric, the fastest heart rate, provides insights into the players' physical exertion during competition. Extremely high heart rates may signal overexertion, necessitating post-match physical adjustments to mitigate fatigue-related risks such as injuries or illness. Additionally, average body temperature is an important physiological indicator of the players' physical condition. Maintaining a stable body temperature within the normal range is essential for optimal performance throughout the match.

These findings underscore the potential of IoT devices to collect multi-dimensional performance data, enabling a comprehensive analysis of athletic performance. Such insights are invaluable for coaching teams, as they facilitate the development of more scientific and personalized training programs, ultimately enhancing the overall performance of the team.

Beyond the metrics in **Table 2**, this study integrates additional performance data for Athlete 10, including passing accuracy, shooting conversion rate, activity area, and defensive contributions. These metrics were selected as key indicators for in-depth analysis and are visually represented through radar and heat maps. Figure 7 illustrates Athlete 10's performance during the match, offering a clear and intuitive depiction of his contributions across various aspects of gameplay. This visualization enables a more nuanced understanding of the athlete's strengths and areas for improvement, supporting more targeted training and tactical adjustments.

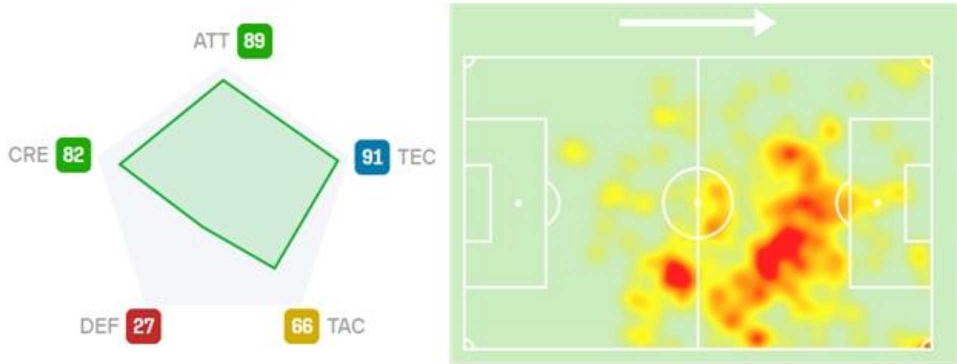

Figure 7. Visualization of football player data.

In **Figure 7**, the metrics ATT (Attack), TEC (Technique), TAC (Tactics), DEF (Defense), and CRE (Creativity) represent the player's offensive ability, technical proficiency, tactical awareness, defensive capability, and creativity, respectively. Additionally, the hotspot map illustrates the player's primary activity areas on the field. Analysis of Figure 7 reveals that the player excels in offensive ability, technical skill, and creativity, but shows weaknesses in defensive ability and tactical awareness. The hotspot map indicates that the player's main activity is concentrated in the attacking second zone, just in front of the opponent's penalty area. These characteristics suggest that the player is particularly effective at creating offensive opportunities, generating threats, and scoring goals. However, their defensive shortcomings highlight the need for targeted defensive training to enhance overall performance.

The visual representation of sports data, as demonstrated in **Figure 7**, provides an intuitive understanding of a player's technical and tactical characteristics. Such visualizations facilitate detailed performance analysis and the development of targeted training plans, as well as more effective competition strategies. These methods are invaluable tools for coaches and analysts, offering actionable insights into athletes' strengths and areas for improvement.

To assess the real-time accuracy and reliability of IoT devices in sports performance monitoring, experiments were conducted using the 100 m sprint as a test scenario. Five professional sprinters and five college students participated in the experiment, wearing smart vests equipped with IoT devices to capture exercise parameters. Sensors were placed at the starting and finishing points of the track to record precise completion times. Simultaneously, ten professional referees manually timed the sprint events to provide a baseline for comparison. The results of this experiment are presented in **Figure 8**.

This experimental setup underscores the capability of IoT devices to deliver high-precision, real-time data in sports monitoring. The findings validate the accuracy of IoT-based monitoring systems and demonstrate their potential to replace traditional manual timing methods, offering superior consistency and granularity. These attributes make IoT devices an invaluable tool for applications in professional sports performance analysis and biomechanical research, enabling enhanced training, competition strategies, and overall athlete development.

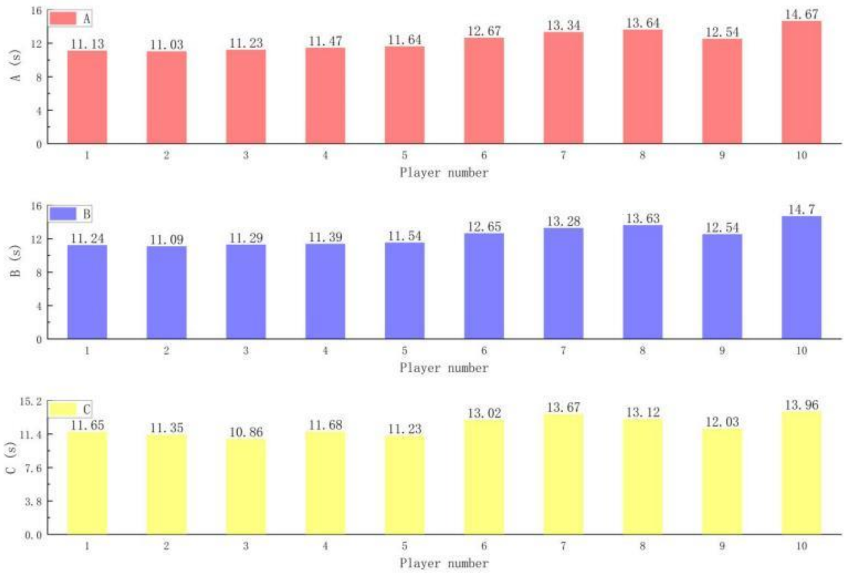

Figure 8. Timing results of 10 contestants in different ways.

In **Figure 8**, numbers 1–5 represent the performance of five professional sprinters, while numbers 6–10 correspond to five ordinary college students. The recorded times are categorized into three data sets: A, the accurate time recorded by sensors placed on the track; B, the time recorded by the IoT smart vest; and C, the time recorded manually by referees. Upon analyzing **Figure 8**, it becomes clear that IoT devices provide times much closer to the accurate values compared to manual recordings. For instance, Contestant 9 achieved 100% accuracy with a recorded time of 12.54 seconds using the IoT smart vest, matching the track sensor's measurement precisely. In contrast, manual timing showed significant inaccuracies, with the smallest discrepancy being 0.21 seconds for Contestant 4, and the largest being 0.71 seconds for Contestant 10.

These experimental results highlight the superior accuracy and reliability of IoT devices over manual timing methods in sports performance monitoring. By minimizing time discrepancies, IoT devices offer a critical advantage in precisely measuring athlete performance, which is beneficial for professional competitions and scientific analysis alike.

In addition to timing data, the speed variation of the five professional sprinters during their 100 m sprint was analyzed, as shown in **Figure 9**. This data provides insights into athletes' speed fluctuations throughout the race, offering a deeper understanding of their performance dynamics and physical capabilities. Key metrics such as acceleration phases, peak speed, and deceleration patterns can be observed, shedding light on biomechanical factors affecting performance.

By integrating precise time measurements with real-time speed monitoring, IoT devices demonstrate their ability to deliver multi-dimensional performance data. This enables coaches and analysts to assess critical factors such as acceleration, peak velocity, and fatigue during a sprint. The application of IoT technology enhances the accuracy of performance assessments and supports the design of targeted training programs and strategies to optimize athletic performance. Such advancements in monitoring and analysis tools pave the way for more effective athletic development and competition preparation.

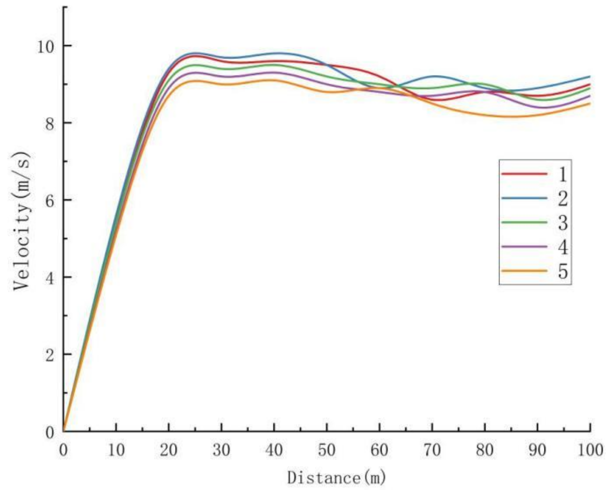

Figure 9. Speed variation diagram of athletes during running process.

Figure 9 illustrates the speed variations of athletes during the 100-meter sprint. Due to the similar professional training backgrounds of the athletes, their speed trajectories follow a generally consistent pattern. Most athletes demonstrate a rapid acceleration phase from the starting point to the 20-meter mark, reaching their peak speed between 20 and 40 meters. Following this peak, a deceleration phase is observed, with its intensity varying based on individual factors such as technique, endurance, and physical condition. In the final segment of the sprint, between 90 and 100 meters, many athletes exhibit a finishing kick, a slight increase in speed resulting from their final exertion.

The capability of IoT devices to record real-time speed variations across the sprint provides unmatched insights into performance dynamics during distinct phases, including acceleration, peak speed, deceleration, and finishing effort. This granular data empowers coaches to develop individualized training programs tailored to the specific strengths and weaknesses of each athlete. For instance, athletes with extended deceleration phases can benefit from targeted endurance training, while those exhibiting slower acceleration may require focused training to enhance explosive power.

This interval-specific, real-time data collection goes beyond the limitations of traditional manual methods, which lack the precision and granularity to capture such detailed performance variations. The experimental results confirm the superior accuracy and responsiveness of IoT devices in tracking athletic performance. Furthermore, these devices are invaluable for preventing abnormalities and injuries by monitoring critical biomechanical data during high-intensity activities.

By leveraging IoT technology, coaches and analysts gain the ability to make data-driven decisions that not only improve athletic performance but also enhance athlete safety. The integration of IoT-based performance monitoring into training and competition settings offers transformative potential for optimizing athlete development and minimizing injury risks, ensuring a more scientific and comprehensive approach to sports analytics.

4. Discussion

The implementation of IoT devices in sports performance monitoring has revolutionized the understanding of individual athlete performance while laying the groundwork for advancing sports science as a discipline. By combining real-time data acquisition, advanced analytics, and visualization tools, IoT devices enable researchers to analyze the intricate relationships between physiological, technical, and tactical factors in greater detail than ever before. For instance, the integration of data such as speed, heart rate, and positional metrics can illuminate how physical and tactical demands during high-intensity intervals influence overall performance. Additionally, cross-athlete analysis allows sports scientists to identify universal performance trends and sport-specific requirements, leading to more refined training methods and competition strategies.

Beyond performance analysis, the widespread adoption of IoT devices presents significant opportunities for predictive and preventive measures in sports. Continuous monitoring of key metrics like heart rate variability, hydration levels, and muscle workload allows these systems to detect early signs of fatigue, injury risk, or performance decline. This proactive approach ensures that athletes receive timely interventions, minimizing downtime and improving long-term health outcomes. Moreover, the integration of machine learning algorithms into IoT systems enhances their predictive capabilities. These algorithms can analyze historical and real-time data to forecast performance trajectories or identify injury risks, enabling a more personalized and data-driven approach to athlete management.

These advancements benefit not only individual athletes but also the broader field of sports science. By incorporating elements of biomechanics, data science, and human physiology, IoT-driven systems foster innovation in performance enhancement and injury prevention. The ability to translate real-time insights into actionable strategies ensures that IoT technology continues to elevate the standards of athlete performance management while contributing to the multidisciplinary growth of sports science.

5. Conclusions

Monitoring and analyzing sports performance is a vital aspect of advancing the sports industry and enhancing athletic achievements. This study successfully demonstrated the application of IoT devices, communication protocols, and feature analysis technologies in collecting, analyzing, and visualizing multi-dimensional sports performance data. Experimental results showed that IoT devices effectively extracted comprehensive data during football matches and presented it through intuitive visual representations. These visualizations provided clearer insights into players' technical and tactical characteristics, facilitating improved assessments. In sprint event tests, IoT devices exhibited exceptional accuracy in timing measurements, significantly outperforming traditional manual methods. Moreover, their ability to monitor real-time speed variations across different sprint phases deepened the understanding of athletes' biomechanical and physiological performance dynamics.

Despite these promising outcomes, this study's focus on specific sports limits the generalizability of its findings. Future research should broaden the application of IoT devices to include a wider range of sports disciplines, particularly those with more complex performance dynamics. Additionally, the integration of advanced machine learning models with IoT systems could enhance data analysis and predictive capabilities, enabling the development of more personalized and precise training programs. These efforts will not only refine the insights gained from this study but also contribute to the broader evolution of sports performance monitoring technologies, further optimizing athletic performance and advancing sports science.

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