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Sensor Automation Technology in Sports Exploration

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ABSTRACT
In recent years, the integration of sensor technology and automation systems has significantly advanced the scientific development of sports. This paper systematically reviews the application of three categories of sensors—physiological monitoring, biomechanical capture, and environmental sensing—in sports contexts. It analyzes the roles of different sensor types in sports scenarios and explores how these sensors function within automation technologies. Through a review of existing literature, the advantages and limitations of various sensors in motion monitoring, data collection, and user experience are identified. Future trends are discussed, predicting the development direction of automation technology in sports scenarios, proposing potential improvement paths and research suggestions, and providing references for subsequent studies.

KEYWORDS
Automation; Sports field; Sensors

1 Introduction

Sensors can be broadly classified into three categories: physiological sensors, biomechanical and posture capture sensors, and environmental sensors. Physiological sensors include heart rate sensors, blood oxygen sensors, electromyography (EMG) sensors, body temperature sensors, and sweat sensors. Biomechanical and posture capture sensors comprise inertial measurement units (IMUs) and pressure sensors. Environmental sensors encompass temperature and humidity sensors, air quality sensors, etc.

Automation technology based on sensor classification is highly significant and promising in the field of sports.

2 Current Applications of Sensor Automation Technology in Sports

2.1 Inertial Measurement Units

Sensor automation technology demonstrates considerable value in football motion analysis. A 3D motion analysis system based on a six-axis IMU enables trajectory reconstruction and motion parameter analysis of kicking actions using a single sensor. The system employs an ICM-20649 sensor to collect acceleration and angular velocity data at a sampling frequency of 100 Hz. Through quaternion-based attitude estimation, coordinate transformation, and gravity compensation algorithms, it achieves precise reconstruction of foot motion trajectories. Experimental results show that for instep kicking actions with an average path length of approximately 3.63 m, the root mean square error (RMSE) of position reconstruction is 0.07 m, and the velocity analysis RMSE is 0.034 m/s, accounting for only 1.93% and 0.45% of the maximum values, respectively. The system is optimized for kicking actions with an acceleration threshold of 0.392 m/s^2 and a velocity threshold of 0.196 m/s, effectively reducing integral error accumulation. Compared to traditional photoelectric motion analysis systems, IMU-based systems offer advantages such as lower cost, fewer environmental constraints, and portability, providing immediate feedback and auxiliary training methods for football players of different skill levels. The study further validates the high consistency between IMU algorithms and high-speed camera results using Bland-Altman plots, offering robust evidence for the reliability of sensor technology in motion analysis.

In fitness activity recognition, sensor automation technology is evolving toward intelligent solutions. Research highlights the application of convolutional neural networks (CNNs) in IMU-based fitness activity recognition, demonstrating the superiority of deep learning through the design of a novel Scaling-FCN architecture and comparisons with traditional machine learning methods. The research team developed a comprehensive data acquisition and preprocessing pipeline using four GSDBLE sensor boards attached to the wrists and ankles of subjects, collecting data for seven types of running exercises at a sampling frequency of 52 Hz. Experimental results show that support vector machines (SVMs) achieve a test accuracy of 99.00% under default configurations, while ResNet attains 97.14% among CNN architectures. Notably, when using only data from the right ankle sensor, the Scaling-FCN architecture achieves an exceptional test accuracy of 99.86%, significantly outperforming traditional machine learning methods. The study also reveals that CNN architectures exhibit stronger robustness with reduced input data, as accuracy decreases by less than 3 percentage points when the time window is reduced from 1.0 s to 0.25 s. The proposed preprocessing pipeline includes data synchronization, timestamp correction, normalization, and sliding window segmentation, providing a feasible

technical solution for real-time fitness applications. These findings indicate that the integration of sensor technology and deep learning effectively addresses challenges such as high action similarity and limited training data in fitness activities, laying a solid foundation for the development of mobile fitness applications.

2.2 Heart Rate Sensors

Heart rate monitoring devices have become essential tools for professional athletes and amateur endurance trainees to assess cardiac function and arrhythmias. Current mainstream HRMs primarily utilize electrocardiogram (ECG) and photoplethysmography (PPG) technologies: ECG captures cardiac electrical signals via electrodes, accurately recording arrhythmias, but often requires chest straps, which may compromise comfort during exercise. PPG detects blood flow changes using optical sensors, offering convenience but suffering from motion artifacts and reduced accuracy in high-intensity or underwater environments. Consensus suggests that ideal HRMs should feature motion artifact resistance, continuous single-lead ECG recording, real-time data transmission, and user-friendly designs to balance medical accuracy and practical utility. However, existing devices still face challenges in diagnosing exercise-induced arrhythmias, as inadequate anti-interference capabilities may lead to false alarms, affecting training decisions. Future optimizations of HRMs should focus on multi-modal sensor fusion and artificial intelligence algorithms to enhance reliability in extreme environments and provide data support for personalized training.

2.3 Blood Oxygen Sensors

Near-infrared spectroscopy (NIRS), as a core technology for muscle oxygenation monitoring, has made significant strides in assessing muscular oxidative metabolism during exercise. NIRS non-invasively measures parameters such as muscle oxygen saturation and oxygenated hemoglobin, reflecting local oxygen supply-demand balance in real time, making it the third key physiological indicator alongside heart rate and power output. The technology has been applied to 37 sports, including cycling, running, and mountaineering, using wearable devices to continuously monitor muscle oxidative capacity, recovery rates, and metabolic thresholds, aiding in defining exercise intensity zones. For instance, in endurance training, dynamic changes in SmO_2 can correlate with lactate thresholds, providing a basis for personalized intensity regimens. The effects of interventions such as ischemic preconditioning or nutritional supplementation can also be quantitatively evaluated via NIRS. However, NIRS is currently limited by shallow measurement depth, interference from subcutaneous adipose tissue, and lack of device standardization. Most applications focus on local muscle groups, failing to comprehensively reflect whole-body exercise states. Future trends include developing multi-channel NIRS systems, multi-modal sensing networks integrated with surface electromyography, and leveraging machine learning to analyze large datasets, ultimately achieving visualized monitoring of full-body muscle oxygenation and advancing training scientificity.

2.4 Sweat Sensors

In sports physiological monitoring, wearable devices that non-invasively track athletes' physiological states in real time have emerged as important alternatives to traditional blood tests. For example, conventional lactate monitoring relies on invasive blood sampling, which is inconvenient, carries infection risks, and lacks continuity. Wearable sweat lactate sensors utilize electrochemical or colorimetric principles, employing biosensors such as lactate oxidase to detect lactate concentration in sweat in real time, with measurement ranges of 0–100 mM, covering key intervals for exercise intensity zoning. These devices are integrated into smartwatches, armbands, or patches, supporting long-term continuous monitoring and correlating sweat and blood lactate levels via algorithms to inform training periodization, fatigue management, and injury prevention. However, challenges remain: the correlation between sweat and blood lactate is influenced by exercise intensity, environmental factors, and individual differences, while sensor accuracy, stability, and anti-interference capabilities require further optimization. Current research primarily focuses on endurance sports; future work should extend to intermittent activities like ball games and combat sports, with multi-center trials validating generalizability. Although commercialization is still in its early stages, sensor automation technology has opened new avenues for personalized training and real-time physiological feedback for athletes.

2.5 Body Temperature Sensors

Research on core body temperature prediction using wearable sensor technology holds significant application value in sports medicine, particularly in preventing exertional heat illnesses. A systematic analysis of 25 prediction algorithms from 20 studies confirms the feasibility of non-invasive temperature monitoring. These algorithms primarily leverage multi-modal sensor data (e.g., heart rate, skin temperature, heat flux) combined with advanced computational methods such as Kalman filtering and machine learning to achieve accurate core temperature predictions during exercise. Experimental data show that 17 of the 18 algorithms reporting root mean square errors meet clinically acceptable standards, with an average error of only 0.28 ± 0.14°C. Notably, single-device algorithms show no significant difference in accuracy compared to multi-device combinations, suggesting that hardware dependencies can be minimized through algorithmic optimization. However, limitations persist: most algorithms are validated in laboratory settings, lacking

adaptability to dynamic real-world conditions; sample diversity is insufficient to cover varied age, gender, and fitness levels; and integration of environmental factors and individual characteristics is limited. Future research should strengthen multi-variable fusion via machine learning, develop personalized prediction models, and promote integration with heat stress indices such as the wet-bulb globe temperature, ultimately building an intelligent temperature management ecosystem encompassing risk assessment, real-time alerts, and clinical decision support.

2.6 Air Quality Sensors

In environmental monitoring, sensor automation technology offers new approaches for air quality assessment and risk management in sports venues through the deployment of medium-cost air quality monitoring systems. Traditional monitoring relies on fixed stations with insufficient spatiotemporal resolution to reflect internal pollution exposure. In contrast, MAQM (Medium-Cost Air Quality Monitoring) systems integrate multiple sensors to collect high-resolution data at 5-minute intervals and analyze pollution sources and diurnal patterns using machine learning methods such as self-organizing maps. For example, a pilot study across six global athletics stadiums showed that sensor data indicated NO_2 and PM peaks coinciding with commuting hours, O_3 concentrations influenced by photochemical reactions and regional transport, and $PM_{2.5}/PM_{10}$ ratios helping identify dust resuspension or combustion sources. Such data can guide event organizers in optimizing training schedules, establishing pollution thresholds, and implementing targeted mitigation measures. However, practical applications face limitations: uncalibrated data may suffer from cross-sensitivities to temperature and humidity, while geographical and climatic variations affect comparability across venues. Future efforts should combine local validation with reference instruments and establish standardized guidelines to ensure fairness in international competitions and athlete health protection. Overall, sensor automation technology is advancing real-time, hyper-local environmental monitoring, fostering deeper integration of sports science and public health.

2.7 Multi-Modal Sensors

Literature analysis indicates that rock climbing imposes unique demands on sensor technology, requiring continuous, multi-dimensional data acquisition without compromising athlete performance. Currently deployed sensors fall into five categories: body motion sensors, respiratory sensors, cardiac activity sensors, eye-tracking sensors, and skeletal muscle characteristic sensors. Body motion sensors, including IMUs, standalone accelerometers, and pressure-sensing insoles, accurately capture 3D motion trajectories and force application patterns on climbing walls. Studies show that elite climbers exhibit superior movement fluidity, with smaller hip acceleration variations and more economical trajectories. Respiratory sensors, using wearable metabolic systems and respiratory inductive plethysmography, monitor oxygen uptake and ventilation in real time, providing key data for assessing exercise intensity and energy expenditure. Notably, integrated devices like the Hexoskin biometric compression garment synchronously capture ECG signals, respiratory parameters, and acceleration data, enabling synergistic analysis of multi-modal physiological signals. Current challenges include data synchronization across multi-source sensors, visualization of massive information, and establishment of sport-specific metrics. Future work could combine artificial intelligence to develop smart coaching systems, further optimizing training strategies.

Alpine skiing, as a high-speed dynamic sport, relies on multi-modal data fusion from IMUs, global navigation satellite systems (GNSS), and video sensors, with computational intelligence enabling in-depth motion pattern analysis. Studies demonstrate that tri-axial accelerometers and gyroscopes mounted on skiers ' ankles at 100 Hz sampling rates accurately capture kinetic characteristics during turns. Signal magnitude calculation and digital filtering preprocessing effectively extract motion features. Notably, the combined application of discrete Fourier transforms and wavelet transforms allows simultaneous analysis of energy distribution characteristics of turning actions in both frequency and scale domains. Future research should focus on embedded processing of multi-sensor systems, deep learning-based motion pattern recognition, and innovative applications of virtual reality in ski training, driving scientific training in alpine skiing to new heights.

3 Development Trends and Future Prospects

3.1 Current Technical Bottlenecks

Sensor technology in sports monitoring faces multiple challenges. Regarding data quality, IMUs are prone to integral drift under high-speed motion or temperature fluctuations, leading to distorted motion trajectories; physiological sensors are significantly affected by motion artifacts and sweat interference, requiring frequent calibration due to reduced signal-to-noise ratios. Sampling rate disparities and coordinate system inconsistencies among heterogeneous sensors further complicate data fusion.

The contradiction between system energy efficiency is prominent: high-precision, multi-channel sensing and complex algorithm processing drastically increase power consumption, with most current wearable devices lasting less than 24

hours, inadequate for all-day monitoring. Environmental adaptability is another issue, as extreme temperatures, humidity, and electromagnetic interference cause sensor baseline drift, while individual physiological variations lead to algorithm generalization fluctuations, with accuracy deviations up to 20% across populations.

Lack of standardization hinders industry development, with disparate data formats and communication protocols among manufacturers, and certification barriers between medical-grade and consumer-grade devices impeding technology dissemination. Privacy and security risks are severe, as multi-modal data fusion may leak sensitive health information, and current data governance frameworks lack robust compliance regulations for cross-border data flows.

3.2 Future Directions in Sensor Technology

Technological evolution shows multi-dimensional innovation trends. At the hardware level, miniaturization and integration are advancing, with multi-modal sensor chips combining IMU, optical, and physiological monitoring functions into millimeter-scale packages. Flexible, stretchable electronics enable seamless integration with human joints. breakthroughs in self-powering technologies, such as kinetic energy harvesting, may extend device battery life to several months.

Intelligent processing capabilities are leaping forward, with embedded AI chips supporting real-time local decision-making. Large-model-based motion posture assessment systems can dynamically correct technical actions. Digital twin technology, by fusing kinematic, physiological, and environmental data, constructs personalized virtual motion models, simulating specific training environments combined with VR/AR.

System architectures are evolving toward adaptability, with smart sensors capable of scenario recognition to automatically adjust monitoring strategies for different user groups. Security and privacy protections are simultaneously upgraded, employing differential privacy and federated learning to ensure data is "usable but not visible," gradually establishing a sustainable development ecosystem balancing technical standards and ethical norms.

4 Conclusion

Sensor automation technology is reshaping sports science with unprecedented depth and breadth. From wearable physiological monitoring and inertial motion capture to environmental sensing and multi-source data fusion, it enables comprehensive quantification of athletic performance, health status, and training load. This paper systematically reviews current mainstream sensor types and their applications in competitive sports, public fitness, and rehabilitation, analyzing key bottlenecks such as data quality, energy consumption, environmental adaptability, standardization, and privacy protection. Looking ahead, synergistic development of highly integrated, miniaturized hardware and intelligent algorithms will propel sensor systems beyond mere data acquisition toward multi-modal fusion and digital twin-driven autonomous decision-making. Concurrent advances in security, privacy, and ethics will provide institutional safeguards for large-scale deployment. Sensor automation technology is not only an auxiliary tool for enhancing athletic performance but also a core engine for building personalized, precise sports health management ecosystems, continually promoting the scientific evolution of human athletic capabilities and healthy lifestyle transformation.

References

[1] Chun Yu, Ting-Yuan Huang, Hsi-Pin Ma (2022) Motion Analysis of Football Kick Based on an IMU Sensor. Sensors, 4–10.

[2] Philipp Niklas Miller, Alexander Josef Miller, Philipp Achenbach, Stefan Gobel (2024) IMU-Based Fitness Activity Recognition Using CNNs for Time Series Classification. Sensors, 2–15.

[3] Robert Gajda, Jacek Gajda, Milosz Czuba, Beat Knechtle, Wojciech Drygas (2023) Sports Heart Monitors as Reliable Diagnostic Tools for Training Control and Detecting Arrhythmias in Professional and Leisure-Time Endurance Athletes: An Expert Consensus Statement. Springer Nature Link, 1–6.

[4] Stephane Perrey, Valentina Quaresima, Marco Ferrari (2024) Muscle Oximetry in Sports Science: An Updated Systematic Review. Springer Nature Link, 1–7.

[5] Geonwoo Yang, Junggi Hong, Seung-Bo Park (2024) Wearable Device for Continuous Sweat Lactate Monitoring in Sports: A Narrative Review. Frontiers, 16–18.

[6] Mar Viana, Kostas Karatzas, Athanasios Arvanitis, Cristina Reche, Miguel Escribano, Edurne Ibarrola-Ulzurrun, Paolo Emilio Adami, Frederic Garrandes, Stéphane Bermon (2022) Air Quality Sensors Systems as Tools to Support Guidance in Athletics Stadia for Elite and Recreational Athletes. International Journal of Environmental Research and Public Health, 1–14.

[7] Miyuki Breen, Taylor Reed, Yoshiko Nishitani, Matthew Jones, Hannah M. Breen, Michael S. Breen (2023) Wearable and Non-Invasive Sensors for Rock Climbing Applications: Science-Based Training and Performance Optimization. Sensors, 5–13.

[8] Aleš Procházka, Hana Charvátová (2015) Wearable Sensors and Computational Intelligence in Alpine Skiing Analysis. IEEE, 2–5.

[9] Conor M. Dolson, Ethan R. Harlow, Dermot M. Phelan, Tim J. Gabbett, Benjamin Gaal, Christopher McMellen, Benjamin J. Geletka, Jacob G. Calcei, James E. Voos, Dhruv R. Seshadri (2022) Wearable Sensor Technology to Predict Core Body Temperature: A Systematic Review. Sensors, 1–5.