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TOPICAL REVIEW

A Review of Intelligent Garment System for Bioelectric Monitoring During Long-Lasting Intensive Sports

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ABSTRACT Bioelectric signals are significant indicators of the state of health of the human body, especially in sports monitoring, where athletes' fatigue state and performance need to be monitored in real-time to develop a proper training plan. Due to the characteristics of sports, it is difficult to obtain the dynamic bioelectrical signals of the human body during exercise. This paper provides a comprehensive overview of the current knowledge on Intelligent Garment Systems (IGS) for long-lasting bioelectric monitoring in sports. This review includes a detailed examination of human bioelectric signals, focusing on ECG, EMG, and GSR signals and their applications in intelligent wearable technologies. The definition and development history of IGS is also discussed, along with a review of the primary research components of IGS, including dry textile electrodes, methods for connecting sensors to IGS, and processing methods for bioelectric signals. The paper concludes by highlighting the current challenges faced by IGS in terms of real-time dynamic monitoring and connection problems and outlining the future directions for this field, including the need for further advancements in bioelectric signal processing and analysis, the development of new materials and connection technologies, and the integration of artificial intelligence and machine learning into IGS.

INDEX TERMS Bioelectric signal, intelligent garment systems, signal processing, long-lasting sports monitoring.

I. INTRODUCTION

Increasingly sophisticated textiles, materials, and microelectronics have enabled wearable technology to be widely accessible and used in diverse ways in recent years [1], [2]. Recent advancements in the field have introduced novel materials and structures that significantly enhance the capabilities of wearable technologies. These include metamaterials for advanced sensing [3], near-zero-index materials for enhanced sensor performance [4], nanoparticles for medical diagnostic applications [5], multifunctional structures offering a metamaterial perspective [6], metasurfaces for surface wave manipulation [7], plasmonics for optical and chiroptical response [8], and graphene-based field-effect transistors for DNA detection [9]. Meanwhile, the miniaturization and integration of signal-monitoring devices into wearable systems are some future development trends [10]. Wearable technologies refer to intelligent electronic

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devices worn on the body to analyze and transmit various forms of data, such as signals connected to human bodies and physical activities [11].

Intelligent garment systems are specialized wearables that integrate information technology and microelectronics into clothing, referring to clothing or accessories with built-in sensors, electronics, and software to monitor, track, or enhance various aspects of human physiology, such as health, performance, or comfort. However, IGS faces challenges in extended athletic activities, such as material rigidity, poor portability, and low stability of fit. These issues complicate real-time acquisition of human bioelectric signals during long-time sports, and problems like signal noise and motion artifacts further reduce the reliability of physiological exercise monitoring.

This technology has transformed our lifestyle and interpersonal relationships in the social aspects, offering us real-time information, communication, and health monitoring like never before. Quite a range of everyday products utilizes wearable technology, including watches, fitness trackers, spectacles, and, in the foreseeable future, clothing. The advanced sensors in these devices endow them with wireless connectivity and processing capabilities, which promise a revolutionary change in how we monitor and manage our health, fitness, and daily activities.

As advanced electronic technologies with a real-time signal sensing function, wearable technology can monitor various human bioelectric signals using multiple sensors integrated into the device. In addition to these sensors, wearable technology utilizes advanced algorithms and tools, such as machine learning to process and analyze the collected bioelectric signals. By providing real-time feedback, these algorithms enable the device to influence the wearer's physical and mental state [12], such as heart rate variability, stress levels, and sleep quality. As human bioelectric signals are consistently detected and monitored, and valuable information is abundantly generated, wearable technology allows individuals to track their progress, make informed decisions, and maintain a healthy lifestyle.

However, in the field of scientific sports training and sports medicine, traditional sports physiological monitoring equipment had problems such as significant material rigidity, poor portability, and low stability of fit. These issues made it more challenging to achieve the function of real-time acquisition of human bioelectric signals during long-time sports and had been a problem that needed to be solved. In addition, problems such as signal noise and motion artifacts also vastly reduce the reliability of physiological exercise monitoring.

Intelligent garment systems (IGS) are a subcategory of wearable technology. It refers to clothing or accessories with built-in sensors, electronics, and software to monitor, track or enhance various aspects of human physiology, such as health, performance, or comfort, as shown in FIGURE 1. The architecture of an IGS primarily consists of embedded sensors designed to monitor bioelectric signals. These sensors

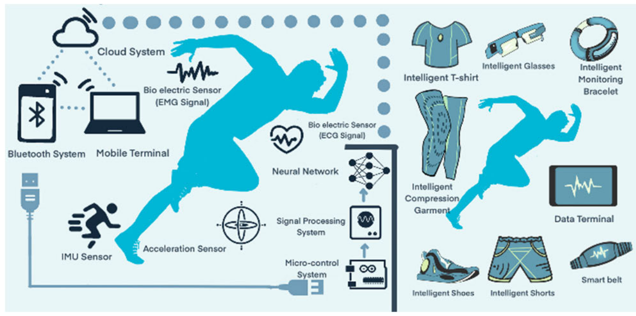

FIGURE 1. Intelligent garment system (IGS).

interface with a controller unit responsible for initial data acquisition and processing. Following initial processing, the acquired data are transmitted to user-specific devices like mobile phones or desktop computers. This transmission can occur through a variety of communication channels, both wired and wireless, with Bluetooth being a commonly employed protocol. Once received, the data can be further uploaded to cloud storage systems for advanced analytical procedures. Examples of IGS products range from smart watches and smart compression garments to smart shoes and smart wristbands. Over the past few years, intelligent garment systems have been one of the hottest research topics as an emerging wearable technology. The evolution of IGS has been marked by significant milestones, such as the integration of IoT (Internet of Things) for seamless data transfer and the use of advanced materials like conductive textiles for improved comfort and functionality [13].

This review provides an overview of the current knowledge on IGS for long-term bioelectric monitoring. The paper is structured as follows: we begin by exploring the fundamental bioelectric signals, including electrocardiography (ECG), electromyograms (EMG), and galvanic skin response (GSR), and their monitoring through state-of-the-art wearable technologies. We then delve into the concept and evolution of the IGS. The subsequent sections address four core research aspects related to IGS: the use of textile dry electrodes for bioelectric signal monitoring, the strategies for sensor integration into IGS, the implementation of AI techniques for bioelectric signal processing, alongside traditional methods, all of which are underpinned by a comprehensive literature review. This is followed by an overview of currently available commercial IGS de-signed for motion monitoring. Thereafter, we identify and discuss the prevailing challenges in the field and propose potential future research directions for intelligent garment systems in sports monitoring. The culminating section of the paper engages in a critical discussion outlining the discrepancies between laboratory-based IGS and their market-oriented counterparts.

II. BIOELECTRIC SIGNALS

Bioelectric signals refer to electrical signals produced by biological systems during biological events [14]. As shown

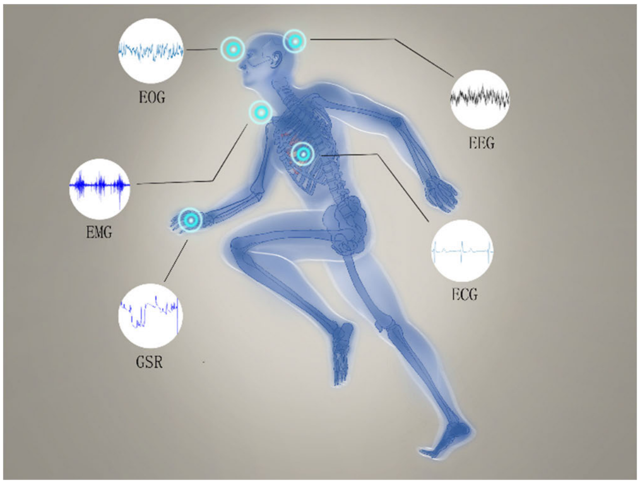

FIGURE 2. **Intelligent garment system (IGS).**

in FIGURE 2, typical human bioelectric signals include electrocardiography (ECG), electromyography (EMG), electroencephalography (EEG), and electrooculography (EOG). Among these signals, electrocardiograms (ECGs), electromyograms (EMGs) and galvanic skin response (GSR) are the most commonly used bioelectric signals in human sport monitoring. These signals are pivotal in sports monitoring, giving precious information about an athlete's physiological state. By measuring these signals, experimenters and coaches can gain insight into an athlete's physical performance, fatigue, and overall health. Recent advancements in Internet of Things (IoT) technologies have facilitated the real-time collection and analysis of these bioelectric signals, particularly in sports environments. Wearable sensor devices can now monitor ECG patterns along with body acceleration, providing a comprehensive view of an athlete's physiological and physical state [15].

These bioelectric signals give precious perceptivity into an athlete's performance, health, and well-being and can help trainers, coaches, and athletes optimize training programs, help injury, and ameliorate athletic performance. For illustration, by measuring EMG, ECG, and GSR during a training session, coaches can acclimate the drill's intensity. This can help to prevent overtraining and reduce the threat of injury. Also, by covering bioelectric signals during competition, trainers can make real-time adaptations to an athlete's strategy grounded on changes in their physiological state. In addition, advances in wearable technology have enabled the nonstop monitoring of bioelectric signals, allowing for the real-time analysis and interpretation of the data.

A. ELECTROCARDIOGRAM (ECG)

Electrocardiogram (ECG) is a bioelectric signal used for vital sign sensing and health monitoring methods and can provide information regarding the electrical activity of the heart [16], [17]. As an efficient non-invasive tool, it can measure the heart rate, examine the rhythm of heartbeats, diagnose heart abnormalities, recognize emotions, and identify biometric information [18]. ECG can be used to collect information about an athlete's heart health in long-last sports monitoring.

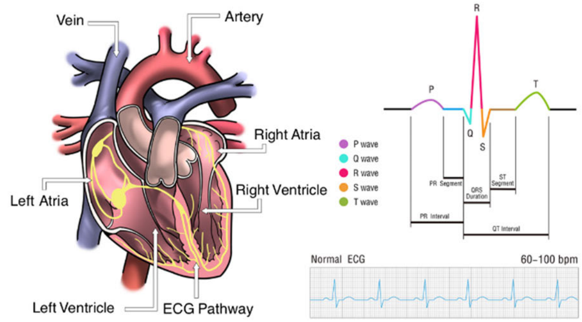

FIGURE 3. **(a) Diagram of heart structure; (b) Schematic diagram of ECG signal wave combination.**

As shown in FIGURE 3(a), the left and right atria, the left and right ventricles, veins and arteries, and the ECG pathway constitute a simplified diagram of the heart. An electrocardiogram (ECG) records the heart's electrical signals as it contracts and relaxes. FIGURE 3(b) shows that each beat is represented on an ECG as a series of moves called P, Q, R, S, and T. A period of ECG generally lasts 10-20 seconds and consists of several beats. The P wave represents the electrical activity of the atria as they contract to pump blood into the ventricles. The QRS complex represents the ventricles' rapid and synchronized electrical activity employed as they contract to pump blood out of the heart. The T wave represents the ventricles as they relax and refill with blood. These heights, ranges, and shapes can give important information about the heart's electrical exertion. It can help diagnose heart-meter diseases, heart attacks, and other heart problems.

The electrocardiogram (ECG) is pivotal in sports monitoring, furnishing precious information about an athlete's cardiovascular health and performance. The integration of ECG into wearable technology has enabled nonstop monitoring and real-time data analysis, allowing for optimized training programs and injury forestallment. The ECG monitors heart rate and detects implicit heart problems during physical exertion, similar to abnormal heart measures or arrhythmias, which may indicate heart conditions. This information is essential for athletes engaged in high-intensity conditioning, as it helps identify implicit health pitfalls and helps prevent severe injury or illness. Also, ECG can track changes in heart rate and meter during physical exertion, furnishing perceptivity into the athlete's heart response to different situations of exertion and the impact of training programs on performance.

Multitudinous experimenters have tried to develop wearable systems that capture and dissect real-time ECG signals. These systems include the Tele-ECG monitoring system with textile electrodes [19], the wireless sensorized belt for simultaneous respiratory and cardiac signal acquisition

[20], and the wearable exercise fatigue detection technology utilizing ECG and inertial sensor signals [21]. The significance of ECG signals in sports and physical activity lies in their potential to provide healthcare professionals with crucial information for health management. However, current wearable systems need a better quality of bioelectric signal acquisition electrodes, which can limit their usefulness in practice. Several studies have been conducted to address these limitations to improve the quality of ECG signals, such as modifying textile electrodes [22]. In this context, a novel ECG classification algorithm has been developed specifically for wearable devices with limited computational resources [23]. The algorithm could greatly improve the feasibility of ECG monitoring in sports.

A multimodal biosensing System-on-a-Chip (SoC) has also been developed to reliably acquire ECG, photoplethysmography, and bio-impedance signals [24]. This innovation could significantly enhance the reliability of wearable systems for ECG monitoring. Furthermore, the feasibility of using sportswear-type wearables for evaluating physical and physiological exercise intensity has been demonstrated [25], indicating the potential for ECG applications in sports to provide valuable insights into athletic performance.

In the field of sports bioelectric monitoring, Electrocardiogram (ECG) sensors play a pivotal role in capturing cardiac electrical activities. These sensors predominantly operate through a mechanism that involves the use of electrodes to detect the electrical potential generated by the heart. The electrodes are often made of conductive materials like silver or gold to ensure high signal fidelity. The signal acquisition ICs in these sensors are designed to amplify the captured signals, providing a gain of around 32 dB and a bandwidth of 370 Hz [26]. Moreover, advancements in electrode structures have been made to suppress motion artifacts, thereby maintaining the stability of the signal quality during non-contact ECG acquisition [27]. It's worth noting that the energy efficiency and transmission delay are also critical factors in the operation of these sensors [28]. The integration of machine learning algorithms has further enhanced the capability to reconstruct ECG signals even under conditions of moderate to heavy movements [29].

The recent advancements in ECG applications in sports have shown the potential to enhance ECG signals and enable multi-dimensional monitoring. Building on recent advancements in wearable technology, ECG monitoring in sports has undergone significant transformations. Notably, sports environments are now benefiting from IoT-based systems specifically designed for real-time heartbeat tracking, employing advanced data classification techniques such as Radial-basis Function Network and Levenberg-Marquardt with Probabilistic Neural Network [15]. Complementing this, a recent study has underscored the diagnostic utility of ECG in sports cardiology, offering a comprehensive review of tailored electrocardiographic monitoring solutions [30]. However, limitations such as processing capacity and movement artifacts remain to be addressed. Future research should focus on improving the stability and reliability of ECG signals, increasing subject comfort, and developing advanced signal processing techniques to maximize the potential of wearable ECG systems. By doing so, it will enhance the ability to detect arrhythmias and accurately estimate exercise fatigue and improve the overall accuracy and practicality of wearable ECG devices.

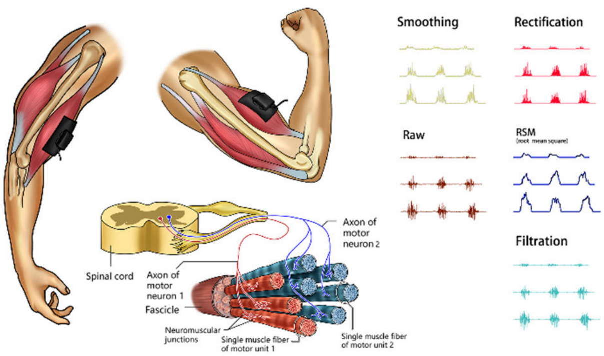

FIGURE 4. Schematic diagram of EMG signal generation and processing flow.

B. ELECTROMYOGRAM (EMG)

Electromyography (EMG) is a technique for recording biomedical electrical signals obtained from neuromuscular activities [31]. In long-last sports monitoring, EMG can be used to gather information about an athlete's muscle health and performance. In addition, EMG signals are further divided into nEMG and sEMG grounded on the system of accession. Needle EMG involves the insertion of a fine line electrode into the muscle to measure the electrical exertion of individual muscle fibers, while the other involves the use of electrodes placed on the skin to measure the electrical exertion of muscles. In comparison with nEMG, sEMG is better suited to the monitoring of sports and recreational activities. As illustrated in FIGURE 4, the contraction or activation of human muscles induces the generation of electrical impulses through muscle fibers and neurons, a phenomenon meticulously recorded through electrodes strategically positioned on the muscle surface. These impulses, innately composed of electrical signals emanated from muscle fibers, are reflective of the intricate dynamics encompassing both the muscles and the governing nervous system, with the intensity and pattern of these impulses providing insightful information into their underlying operational mechanics. Following the acquisition of the Electromyography (EMG) signals, a subsequent step entails the execution of a series of analytical processes including smoothing, rectification, filtering, and root mean square of the raw signals, which are pivotal in delineating the precise status of the muscle condition. These procedural steps aid in the refinement of the data, enhancing the accuracy in understanding the complex interplay of muscular and neural activities, thereby facilitating a more nuanced interpretation of muscle states. In the field of sports science, sEMG has been increasingly adopted for real-time evaluation of muscle state and forecasting of future fatigue trends. Advanced sEMG systems have been developed that are cost-effective, portable, and wearable, specifically designed for sports and healthcare applications [32].

Surface electromyography (sEMG) is increasingly used in sports science to monitor and assess muscular fatigue. By recording and analyzing the electrical activity produced by muscles during contraction via surface electrodes, sEMG enables real-time evaluation of muscle state and forecasting of future fatigue trends. This information is useful for optimizing training and injury prevention strategies. The position of muscle activation measured by sEMG can be used to track changes and give precious feedback to athletes and trainers on areas that bear enhancement. The measurement of muscle activation over time also provides information on muscle fatigue, allowing for timely adjustments in training to prevent further fatigue. In addition to monitoring muscle activation and fatigue, sEMG is also used to assess muscle symmetry and balance, which is essential for optimizing performance by addressing any imbalances or asymmetries in muscle activation. Also, sEMG is used to cover muscle activation during specific exercises and movements, furnishing precious information to optimize training and ameliorate performance.

In parallel to ECG sensors, Electromyography (EMG) sensors are instrumental in the realm of sports bioelectric monitoring, particularly for assessing muscle activities. These sensors primarily function through the detection of electrical potentials generated by muscle contractions. The electrodes in EMG sensors are often fabricated from conductive materials like silver chloride to ensure high signal fidelity [33]. Advanced signal processing techniques, such as PID control algorithms, have been employed to enhance real-time EMG signal interpretation, thereby improving the functionality of upper-limb prostheses [34]. Recent innovations have focused on the robustness of human-machine interactive control for myoelectric prosthetic hands, especially during arm position changes [35]. Moreover, pattern recognition algorithms have been increasingly integrated into EMG sensors to discern user intentions more accurately, thereby enhancing the human-machine interaction [36].

In recent times, there have been significant advancements in the field of sEMG signal accession for sports monitoring operations. Several studies have concentrated on developing cost-effective, movable, and wearable sEMG systems that can be used to cover human exertion during sports and in healthcare assiduity [37], [38], [39]. Another study investigated the extent to which sEMG is adopted by professionals in the field of exercise and human movement [40]. Additionally, Spanu et al. made a significant contribution by developing and validating cost-effective and robust electrodes that provide adequate signal quality in dynamic conditions [41]. Campanini et al. presented educational tools for teaching sEMG detection using electrode pairs and grids [42].

Despite these advancements, there are still limitations and challenges associated with the use of sEMG in wearable applications. One of the key challenges is improving the accuracy and reliability of sEMG signal acquisition in dynamic conditions. Furthermore, current sEMG systems can improve user-friendliness and comfort for long-term wear. Incorporating advanced signal processing techniques and electrode design could improve performance and increase the adoption of sEMG technology in the healthcare and sports industries. To achieve this, further research is needed to address the current limitations of sEMG in wearable applications.

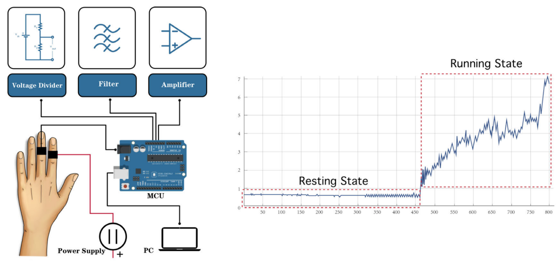

FIGURE 5. **Schematic diagram of GSR and GSR signals during resting and sports states.**

C. GALVANIC SKIN RESPONSE (GSR)

The Galvanic Skin Response (GSR) serves as a crucial bioelectric signal delineating an individual's physiological state during physical activity, demonstrating salient features such as stability, ease of collection, and heightened sensitivity [43]. This physiological metric is regarded as the primary and most responsive indicator of fluctuations in human sympathetic excitability [44]. FIGURE 5 delineates the schematic representation of the GSR (Galvanic Skin Response) measurement process, illustrating a wearable system equipped with GSR electrodes and a microcontroller unit (MCU) that harbors integrated functionalities including a voltage divider, filter, and amplifier. These components are orchestrated to work in unison, transmitting the data to a personal computer for further analysis. Initially, the system acquires raw GSR signals from the fingertips, which are then meticulously processed through the voltage divider, filter, and amplifier to obtain refined information pertaining to skin electrical activity. Complementing this technical overview, FIGURE 5 also exhibits GSR signal graphs corresponding to the resting and running states, vividly illustrating the substantial increase in signal intensity from a stable baseline in the resting state to a pronounced elevation during the running state. GSR effectively captures continuous changes in skin conductance, and a plethora of previous studies have successfully employed this index as an objective measure of stress in their research endeavors [45], [46], [47].

In the context of bioelectric monitoring for sports applications, Galvanic Skin Response (GSR) sensors are indispensable for assessing emotional or physiological arousal. These sensors typically function through a mechanism that measures the electrical conductance of the skin. Unlike some other bioelectric sensors, GSR electrodes are often made of materials that prioritize biocompatibility and conductivity, such as silver/silver-chloride (Ag/AgCl). These electrodes are designed to be in direct contact with the skin to ensure accurate measurements. The sensor's circuitry often includes a constant voltage source to apply a small voltage across the electrodes, thereby allowing the measurement of skin conductance. It's worth noting that the data acquisition system in GSR sensors is calibrated to capture variations in skin conductance levels, which can be indicative of emotional or physiological states.

Regarding the study of GSR in sports, some scholars have done representative studies in recent years. Yang executed a study assessing the impact of daily transportation modes on stress levels, GSR as a reliable, objective surrogate measure.

The research revealed lower stress levels correlated with cycling and walking in comparison to alternate travel methods, while motorized transit exacerbated stress [48]. Serdar Gündoğdu scrutinized the manifestations of stress and mental fatigue in e-sport activities by utilizing a data fusion approach from EEG, GSR, HRV, and eye-tracking information. The investigation discovered e-sport activities exhibited both advantageous effects on attention and focus, as well as partial inducement of stress and mental exhaustion, in addition to distinct emotional processes among participants [49]. Francesco Sessa examined alterations in the human motor cortex and autonomic nervous system dynamics concerning sports training and professional expertise, employing TMS while measuring heart rate (HR) and GSR in both karate athletes and non-athletes. The research identified significant disparities in cortical excitability, HR, and GSR between the two groups, suggesting exercise training impacts autonomic equilibrium, diminishes stress levels, and may contribute to anxiety reduction in athletes [50].

Considering the substantial advancements achieved within the domain, it remains imperative to recognize that the employment of GSR in wearable applications continues to present specific constraints and obstacles. A paramount challenge entails the enhancement of precision and reliability in GSR signal acquisition under dynamic circumstances. Moreover, contemporary GSR systems may gain from the amelioration of user experience and comfort during protracted utilization. The incorporation of sophisticated signal processing methodologies and electrode configuration holds promise in amplifying performance and fostering broader adoption of GSR technology across healthcare and sports sectors. To actualize these prospects, additional investigation is necessitated to surmount the prevailing restrictions associated with GSR in wearable implementations.

III. INTELLIGENT GARMENT SYSTEM (IGS)

Intelligent garment system refers to clothing or accessories embedded with wearable technology components, such as flexible electrodes, sensors, and software, to provide various functionalities such as monitoring vital signs, tracking fitness, providing haptic feedback, and more. Intelligent Garment Systems (IGS) constitute intricate ecosystems that incorporate a diverse array of components, including, but not limited to, flexible electrodes, multi-modal sensors, embedded microcontrollers, and advanced software algorithms. These components synergistically contribute to functionalities such as real-time monitoring of physiological parameters, fitness tracking, haptic feedback provision, and augmented reality experiences.

The IGS is a living system mimic that incorporates perception, feedback, and response functions to sense changes in the external or internal environment and respond to these changes in real-time through a feedback mechanism. In addition to the above-mentioned components, recent advancements have incorporated machine learning algorithms to enhance the real-time data analysis capabilities of IGS. These algorithms are particularly useful in sports applications where immediate feedback can be crucial for performance improvement. For instance, deep learning techniques have been employed to provide more accurate and personalized fitness recommendations [51]. In the field of sport, intelligent garment system provides continuous monitoring of a person's bioelectric signals, such as heart rate, respiration, and muscle activity, during long-term sports programs to provide people with a better understanding of their bodies and how they are performing. Specifically, in sports like marathon running and cycling, IGS has been invaluable in monitoring physiological parameters in real-time, thereby aiding in the prevention of injuries and enhancing athletic performance [52] By collecting and analyzing the accurate real time data provided by the intelligent garment system, it's convenient to access feedback and guidance for improving physical and mental health [53]. As substrates for wearable detectors, e-textile materials are being used more and more constantly in sports, medical, defensive, and military operations, among others, and are of interest to experimenters in various disciplines. Likewise, e-textiles promise to revise how data can be collected, transmitted, and reused, with implicit operations ranging from biomedical diagnostics to environmental monitoring. These garments can be connected to smartphones, tablets, or computers to give real-time data and feedback.

A. TEXTILE DRY ELECTRODE FOR BIOELECTRIC SIGNAL MONITORING

Textile electrodes, a flexible and intelligent skin-friendly textile, can be closely integrated with intelligent clothing systems. Compared to traditional electrodes, textile electrodes offer many benefits when incorporated into intelligent garment systems, including comfort, flexibility, durability, concealment, skin-friendly contact, and washability.

Textile dry electrodes are a better alternative to traditional wet electrodes for bioelectric signal monitoring. Unlike traditional wet electrodes, which rely on a conductive gel to provide electrical connectivity to the skin, dry textile electrodes utilize conductive fibers integrated into the textile

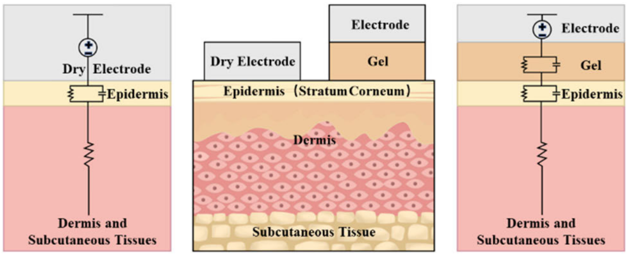

FIGURE 6. Schematic diagram of skin equivalent circuit with the conventional wet electrode and dry textile electrode.

material. The skin equivalent circuit and skin-electrode contact structure of the conventional wet electrode and textile dry electrode is shown in FIGURE 6. Compared with the gel medium of the conventional wet electrode, the dry textile electrode achieves signal transmission with the help of sweat [54], which has advantages in long-term sports. This results in a more comfortable, flexible, and interactive electrode that can be worn for a long time without causing skin vexation or discomfort. Also, the lack of gel reduces the setup time and minimizes the threat of impurity, making the monitoring process more effective and aseptic. These advantages make dry textile electrodes attractive for various bioelectric signal monitoring. In the field of wearable health monitoring, E-textile electrodes have surfaced as a pivotal innovation, harmonizing with the fabric of clothing for unintrusive and continuous bioelectric signal capture. These electrodes are engineered through sophisticated textile technologies, employing conductive fibers and polymers to ensure a high signal-to-noise ratio, rivaling that of conventional gel-based electrodes. The design philosophy behind E-textile electrodes is anchored in biocompatibility, flexibility, and resilience, offering a marked advantage over traditional electrodes that often necessitate skin preparation and are susceptible to motion artifacts. This adaptability renders them particularly invaluable in sports and healthcare scenarios where sustained, long-term monitoring is imperative. As we look to the future, the trajectory of wearable health monitoring is set to be influenced by advancements in sensor miniaturization, energy-efficient technologies, and real-time data analytics. These forthcoming innovations hold the potential to revolutionize both sports training and healthcare by facilitating more precise performance evaluations and enabling timely medical interventions.

Textile dry electrodes can be prepared using various techniques, including stitching, knitting, embroidering, electroplating, and chemical plating. The preparation method is chosen based on the desired properties and applications of the electrode, each offering advantages and challenges. The most common approach is stitching, where conductive yarns are sewn directly onto the textile substrate. For example, Arquilla et al. used silver nanoparticle-coated nylon yarns in an overlapping serrated pattern to create 3 cm x 3 cm textile electrodes with a resistance of 0.3 Ω (FIGURE 7. (a)), which were capable of recording ECG signals with distinguishable R and S peaks [55]. Milad et al. applied

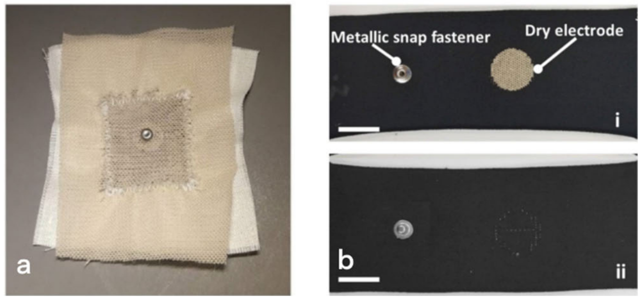

FIGURE 7. (a) Silver nanoparticle-coated nylon electrodes [55]. (b) Schematic diagram of the (i)front and (ii) back of a sample dry electrode [56].

STOLL flat machine to knit plane textile dry electrodes and 3D textile dry electrodes with silver and carbon yarns (FIGURE 7. (b)) and evaluated the performance of these electrodes in long-term electrocardiographic monitoring [56]. Rajanna et al. created knitwear and silver textile electrodes by knitting silver and copper-nickel yarns onto a foam sponge substrate [57]. Both electrodes had a skin contact impedance of less than 1 MΩ/cm^2, with the knitwear electrode having a square resistance of 46 Ω/sq and the silver textile electrode having a much lower square resistance of less than 1 Ω/sq.

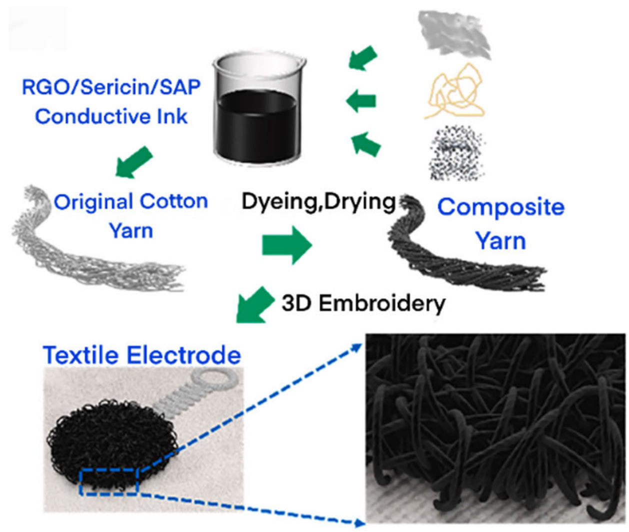

FIGURE 8. Schematic illustration of the 3D textile electrode fabrication process [58].

Further preparation involves embroidering the conductive yarn on the fabric surface to reduce the skin-electrode interface impedance. The research team of Zhao et al. presented a knitted electrode with a mixture of reduced graphene oxide (RGO), sericin, and a water-retention polymer (FIGURE 8) that is capable of monitoring the bioelectric signals of the human body during long-lasting sport [58]. This electrode effectively reduces the electrode-skin interface impedance due to its unique 3D structure and water-retention material properties. Lee et al. used two conductive yarns, stainless steel, and silver, to embroider fabric dry electrodes on the compression garment. At the same time, silicone was applied to the designed embroidery pattern to increase the adhesion between the electrodes and the skin, thereby increasing the effective contact area. His study showed that the application of this method, combined with the appropriate garment pressure, could improve the accuracy of sEMG signal acquisition while increasing the comfort level [59].

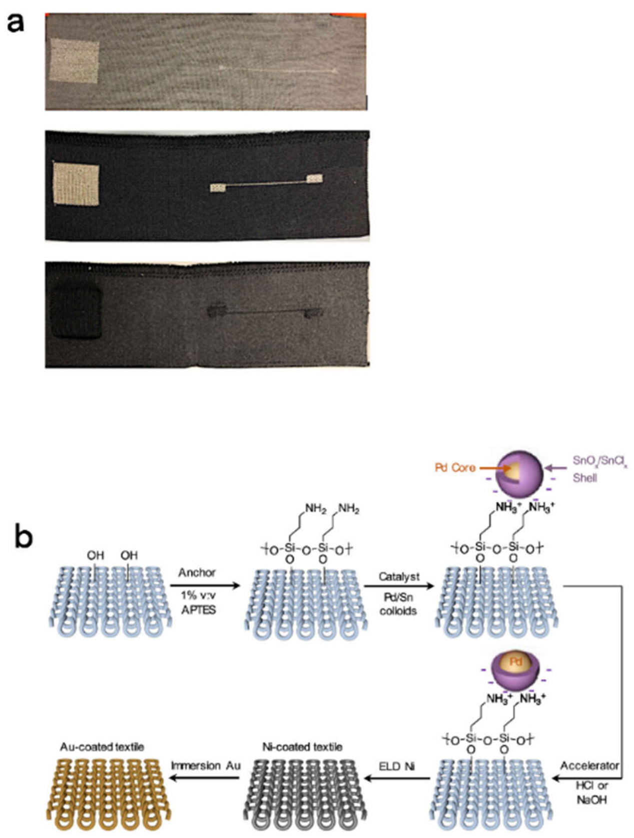

FIGURE 9. (a) Square and line patterns on the circular knitted silver yarn sample, flatbed knitted silver yarn sample, and flatbed knitted carbon yarn sample [62] (b) Schematic of the ENIG process on textiles [64].

Another method of generating electrodes directly on the fabric is electroplating. This particular surface coverage method enables the deposition of conductive metals directly on the textile surface to generate electrodes. Plating technology mainly covers electroplating and chemical plating, the principles of electrolysis and redox respectively [60]. Electroplating allows for control over the thickness of the metallic coating, while chemical plating provides conductivity in all directions of the textile surface and uniformly deposited metallic coatings on complex geometries [61]. Ladan et al. applied silver-plated and carbon-containing nylon yarn to knit electrocardiographic electrodes by electroplating and carbon suffusion methods (FIGURE 9(a)), respectively, and compared them with gold standard hydrogel electrodes for skin impedance before and after washing. The results showed that the performance of these two electrodes is comparable to that of gold-standard hydrogel electrodes and can be effectively used for continuous monitoring of human bioelectric signals [62]. Das et al. fabricated conductive textiles through a chemical plating process, depositing nickel/copper/nickel/gold layers on polyester textiles, resulting in textiles with high electrical conductivity and stability [63]. Wu et al. metalized the "dye bath" by using a method based on chemical nickel-impregnated gold (ENIG), which allows complete penetration of metal ions into the textile structure and deposition of metal coatings on the surface of individual textile fibers (FIGURE 9(b)). This method helps maintain the textile's inherent structure and abrasion resistance and gives e-textiles high electrical conductivity, flexibility, and stretchability [64].

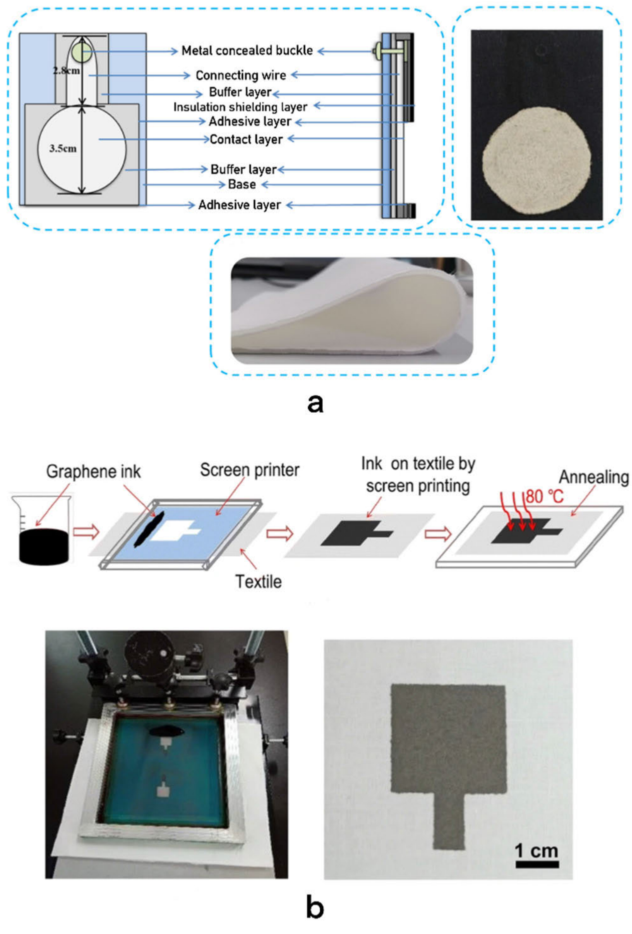

FIGURE 10. (a) Schematic diagram of the structure of the silver-plated fabric electrode [65] (b) Preparation process of screen-printed graphene electrodes, the experimental setup for the screen printing, and photo of the fabricated graphene-coated electrode [66].

Screen printing, which involves applying carbon-based inks to textile substrates to create conductive patterns, is another common approach. Zhang et al. applied the chemical silver-plating method to assemble ECG fabric electrodes from conductive cloth, space wool, and double-sided adhesive conductive foam (FIGURE 10(a)). They discussed the effect of the fabric electrode surface on static and dynamic ECG quality after the conductive media coating. The results showed that the fabric electrode coated with conductive paste could effectively reduce the electrode-skin contact impedance and acquire ECG signals more clearly [65]. Xu et al. used screen printing to apply aqueous graphene ink on cotton textiles(FIGURE 10(b)) and achieved a high Pearson correlation coefficient of 99.47% between the graphene electrode and the commercial Ag/AgCl wet electrode [66].

B. METHODS FOR CONNECTING SENSORS TO INTELLIGENT GARMENT SYSTEM

The interconnection of sensors with intelligent garment systems has garnered significant attention within e-textiles research. To attain the desired level of integration and functionality, a multitude of techniques have been employed for connecting sensors to these systems. Amongst the most widely employed methods, adhesive bonding, snap fasteners, pogo pins, and magnets are the four most prominent.

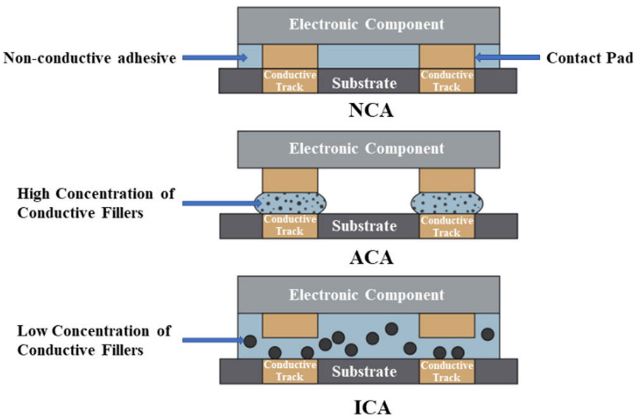

FIGURE 11. **Diagram of NCA, ECA, and ICA bonding.**

Adhesive bonding, the most commonly used method in e-textiles, encompasses several types of bonding, including non-conductive adhesive bonding (NCA), isotropic electrically conductive adhesives (ICA), and anisotropic conductive adhesives (ACA), as shown in FIGURE 11. The NCA bonding method has been adapted to create a connection between rigid circuit modules, and conductive textile interconnects using a thermoplastic film that is sandwiched between the two [67], [68]. ICA bonding involves the addition of a conductive filler to an adhesive material. In contrast, ACA bonding is similar but employs a lower concentration of conductive filler, making it more suitable for fine-pitch connectors [69], [70], [71].

Snap fasteners, also called press studs or poppers, have been extensively employed as connectors in e-textiles. Despite their widespread usage, there is a need for further research to determine their viability as electronic connectors [72], [73]. Ozberk et al. demonstrated that snap fasteners could be used as an electrical interface for graphene-coated fabric electrodes to monitor the sEMG signal in the dynamic state of the human body [74]. For long-lasting sport monitoring, however, we need to assess snap fasteners' durability, reliability, and performance under various conditions to determine whether and how well they are suited for use as electronic fabric connectors.

Pogo pins, typically with a diameter ranging from 1-2 millimeters, have emerged as a standard solution for connecting rigid circuit modules with flexible circuitry in a garment. These pins offer a reliable and efficient way to connect within e-textile systems and have been widely used in various applications. Another method for connecting sensors to intelligent garment systems is to use magnets. Magnets have been used either for alignment or as electrical contacts themselves [75]. This approach presents a unique solution for connecting sensors in e-textile systems, offering a non-contact method for making electrical connections. Further research is needed to explore this approach's feasibility and limitations, particularly its ability to withstand various environmental conditions and its long-term performance.

C. PROCESSING METHOD OF BIOELECTRIC SIGNALS FOR INTELLIGENT GARMENT SYSTEM

1) PROCESSING METHOD OF ECG SIGNALS

ECG signal processing involves preprocessing and feature engineering steps to reduce noise and interference in recorded ECG signals and extract relevant features for analysis. Preprocessing utilizes bandpass, low-pass, high-pass, notch, and median filters to eliminate various types of noise. Feature engineering involves extracting temporal, morphological, and statistical features in the spatial, frequency, or time-frequency domains. Traditional methods use denoising and fiducial point extraction through direct or transform processes, while recent techniques employ mathematical computations and neural networks for faster processing. The accuracy of the extracted features significantly impacts the analysis performance, with the QRS complex being the most predominant feature.

Preprocessing is essential in electrocardiogram (ECG) signal analysis to reduce interference and determine signal features [76]. Preprocessing aims to minimize noise and artifacts in the recorded ECG signals to prepare them for further analysis. Bandpass filters are commonly used for this purpose and effectively reduce noise sources like muscular noise, movement-related artifacts, power-line interference, baseline wandering, and high/low-frequency noise signals [77], [78], [79], [80], [81], [82], [83], [84], [85]. Low-pass filters (LPF) eliminate high-frequency components of the signals, while high-pass filters (HPF) eliminate low-frequency components [86], [87]. Notch filters eliminate DC offsets in signals [79], [86], [88], [89]. Median filters remove special effects and arbitrary or baseline wander noise [85], [90], [91], [92], [93]. Other techniques, such as adaptive noise cancellation and leaky-based normalization, have also been proposed for noise reduction [94], [95], [96].

Feature engineering (FE) is crucial for ECG signal analysis and consists of extracting different temporal, morphological, and statistical features from the periodic ECG signal pattern [97]. The accuracy of the extracted features impacts the analysis performance; These features can be acquired in the spatial, frequency, or time-frequency domains [98]. Conventional signal processing techniques and machine learning models have been introduced to find ECG features such as the R-R interval, QRS complex, and others [99]. Traditional FE methods involve denoising the ECG signal and extracting fiducial points through direct or transformation methods like wavelet transform (WT) and discrete wavelet transform (DWT). However, current limitations in terms of processing time and computational constraints have resulted in the development of faster techniques using mathematical computations and neural networks [100]. These techniques rely heavily on accurately identifying features, with the QRS complex being the most predominant.

2) PROCESSING METHOD OF sEMG SIGNAL

Effective signal processing of sEMG signals is crucial for accurately assessing muscle fatigue in the sports domain. The preprocessing and feature extraction of sEMG signals are vital in obtaining accurate results. Recently, a multitude of techniques and features have been utilized to monitor changes in muscle activation and state over time, providing crucial information for sports training and rehabilitation.

Raw sEMG data often contain power line interference and motion artifacts. Therefore, preprocessing techniques such as detrending, filtering, normalization, and windowing mitigate these issues [101], [102], [103]. For example, detrending removes trends (both linear and nonlinear slow shifts of the signal from zero level) on EMG. Detrending is typically performed as an initial step to reduce artifacts and improve the quality of the sEMG signal for further processing and analysis. It is essential for obtaining accurate measurements of muscle activation patterns and identifying changes in muscle function during physical exertion. Other methods used for preprocessing include Independent Component Analysis (ICA) and empirical mode decomposition (EMD) [104], Ensemble Empirical Mode Decomposition (EEMD) with Hilbert Transform (HT) [105], and Discrete Wavelet Transform (DWT) [106]. In estimating muscle activity onsets, methods such as visual and automated methods [107], sample entropy (SampEn) analysis [108], and sequential Gaussian mixture model (GMM) have been proposed [109]. Regarding feature extraction, four main types of features are extracted from sEMG signals time-domain, frequency-domain, time-frequency domain, and nonlinear parameters [110], [111], [112]. Time-domain features include root mean square (RMS), integrated EMG (iEMG), zero-crossing rate (ZCR), waveform length (WL), the variance of electromyography (VAR), and mean absolute value (MAV) [113], [114], [115], [116], [117]. The RMS and iEMG values increase over time as muscle fatigue sets in, indicating changes in muscle activation intensity and human motion state [105], [118], [119], [120]. In the frequency domain, mean frequency (MF) and median frequency (MDF) represent the frequency of measured muscle CV and provide information about muscle fatigue, with MDF being more sensitive to muscle activity [121], [122], [123]. The time-frequency distribution of sEMG signals is also analyzed to provide comprehensive information about physiological muscle changes during exercise.

3) PROCESSING METHOD OF GSR SIGNAL

Efficient signal processing of GSR signals is essential for accurately assessing emotions and stress across various applications. Preprocessing and feature extraction of GSR signals are critical in achieving precise results. A multitude of techniques and features have been employed in recent times to monitor changes in emotional and stress states, providing valuable information for emotion recognition, stress detection, and human-robot interaction.

Over the past few years, numerous academic investigations have been conducted, delving into the intricacies of GSR signal processing. Gautam introduced the Empirical Iterative Algorithm (EIA), an innovative data-driven method for GSR signal preprocessing that improved performance and computational efficiency. The EIA outperformed traditional moving average filters, achieving a 51% enhancement in signal quality and retaining relevant low-frequency information while being 136 times faster than Empirical Mode Decomposition (EMD) [124]. Liu presented a novel human emotion recognition method combining automatically selected GSR signal features and Support Vector Machines (SVM). The proposed approach demonstrated improved recognition accuracy, exceeding 66.67%, by employing a covariance-based feature selection process and optimized SVM input [125]. Atefeh Goshvarpour investigated the effectiveness of the Matching Pursuit (MP) algorithm in emotion recognition, utilizing ECG and GSR data. The study successfully demonstrated an accurate emotion recognition system by achieving a 100% recognition rate using Principal Component Analysis (PCA) and wavelet dictionaries [126]. Dong-Hyun Kang proposed a real-time emotion classification approach utilizing photoplethysmogram (PPG) and GSR signals, a 1D convolutional neural network autoencoder model, and a lightweight model developed via knowledge distillation. The proposed models demonstrated improved accuracy and computation time, enabling fast and real-time emotion classification in limited hardware environments for human-robot interaction [127]. Seyed Amir Hossein Aqajari proposed an open-source GSR analysis tool that leveraged deep learning and statistical algorithms to extract features for stress detection. The tool demonstrated a 92% accuracy in detecting stress using 10-fold cross-validation and features extracted from the GSR signals [128].

D. AI METHOD FOR PROCESSING BIOELECTRIC SIGNALS

The rapid advancement and integration of artificial intelligence (AI) into bioelectric signal processing, particularly in

TABLE 1. AI approaches in bioelectric signal processing across diverse applications.

Author	Application	Metrics Measured	AI Methods
Emma Farago et al. [129]	Wearable Smart Devices	ECG and EMG	Autoregressive, Markov Chain, Recurrent Neural Network Models
Ali Raza et al. [130]	Digital Healthcare	ECG	Transformer-based Autoencoders, Support Vector Data Description, Federated Learning
Ali Raza et al. [131]	ECG-based Healthcare	ECG	Deep Convolutional Neural Networks (CNN), Explainable Artificial Intelligence (XAI), Federated Learning
Bruce Hopenfeld et al. [132]	Sports Activities	ECG	Temporal Pattern Search(TEPS), Methodology to Mitigate Motion Artifacts
Duan Na et al. [133]	Accurate Recognition of Action Modes	EMG	Convolutional Neural Networks (CNN)
Chengyu Liu et al.[134]	Wearable ECG SmartVest System	ECG	Machine Learning (SVM)
Alejandro Castillo-Atoche et al.[135]	Sports Activities Monitoring	ECG	Convolutional Neural Network (CNN)
Xiao Sun et al[136].	Sentiment Classification	GSR	Convolutional Neural Network, Long Short-Term Memory, Self-Attention Mechanism
Shuvodeep Saha et al[137].	Cognitive State Change Classification	GSR, PPG	General Linear Chirplet Transform, Random Forest, Decision Tree, k-Nearest Neighbours

sports-related contexts, have unveiled a host of transformative developments. AI has significantly refined our ability to evaluate muscle activation, fatigue, and overall athletic performance by bolstering the efficiency and accuracy of preprocessing and feature extraction from sport-related bioelectric signals such as electrocardiograms (ECGs) and sEMG. Consequently, this has placed AI at the crux of applications spanning sports training, rehabilitation, and injury prevention, providing a robust foundation for more tailored and potent interventions.

A summary of key research contributions in the field of AI-enhanced bioelectric signal processing in sports is presented in Table 1:

In the field of motion artifact data processing, Emma Farago et al. delved into the application of three distinct AI-based methods: autoregressive models, Markov chain models, and recurrent neural network (RNN) models [129], Autoregressive models employ a linear combination of past observations to predict future values, offering simplicity and computational efficiency. Markov chain models, on the other hand, rely on the principle of 'memorylessness,' where the future state depends solely on the current state, making them suitable for systems with short-term dependencies. However, it was the RNN models that stood out for their ability to capture long-term dependencies in the data, thereby proving to be the most effective in generating diverse motion artifact data that closely emulated experimental data properties. While RNN models have shown superior performance, they are not without limitations. For instance, they are computationally more intensive and may require larger datasets for training. In scenarios where computational resources or data availability are constrained, autoregressive or Markov chain models may offer a more practical alternative. Emerging innovations in the field of artificial intelligence, including the advent of optimized recurrent neural network architectures and the application of transfer learning techniques, offer promising avenues for refining and augmenting the existing methods used in motion artifact data generation.

In response to the limitations of existing simulation techniques, Farago's team introduced and compared three AI-based methods for generating motion artifact data—autoregressive, Markov chain, and recurrent neural network models. Their work substantiated the recurrent neural network model as the most effective in generating diverse motion artifact data that closely emulated experimental data properties, thus enhancing the reliability of bioelectric signal quality analysis in sports applications. In a parallel vein, Ali Raza et al. from ENSAIT's GEMTEX Laboratory presented AnoFed, a pioneering federated learning framework that incorporated transformer-based Autoencoders and Support Vector Data Description [130]. This framework was developed to address the challenges of efficient and privacy-minded anomaly detection in bioelectric signals during sports activities. Notably, AnoFed leverages transformer-based Autoencoders for feature extraction and Support Vector Data Description for anomaly detection, offering a comprehensive solution for ECG analysis in sports settings. The framework has shown promise for broader applications, including other types of bioelectric signals and healthcare scenarios outside of sports. This integration facilitated efficient, privacy-minded anomaly detection in bioelectric signals during sports activities. When applied to ECG analysis, the approach exhibited exceptional performance and computational efficiency, effectively tackling data privacy issues inherent to healthcare applications. In addition, Raza's team proposed an innovative federated learning framework that harmonized explainable artificial intelligence (XAI) and deep convolutional neural networks (CNN) for ECG-based arrhythmia classification during sports, offering promising applicability across various healthcare and sports scenarios [131]. Furthermore, Bruce Hopenfeld et al. introduced a novel methodology that employs autocorrelation and TEPS for the extraction of persistent rhythms in the motion artifact record of the NSTDB. Their work has significant implications for enhancing the accuracy and reliability of

ECG analysis in sports performance evaluation, especially in noisy environments [132], [138], [139]. Focusing on the unique challenges of ECG data, they introduced the highly constrained temporal pattern search for multi-channel heartbeat detection during sports activities and proposed an innovative methodology to mitigate motion artifacts in waist-based ECGs. Their work has contributed to enhancing the accuracy and reliability of ECG analysis in sports performance evaluation.

In a similar endeavor, Duan et al. adopted convolutional neural networks for efficient feature extraction and action classification in sEMG signals during sports activities [133]. Their approach of treating sEMG signal spectrograms as images demonstrated the efficacy of deep convolutional networks in gesture motion recognition during sports, underlining the promising potential of AI methods in sEMG signal processing for athletic performance assessment. On another front, Chengyu Liu et al. devised an innovative IoT-based wearable 12-lead ECG SmartVest system for real-time, continuous cardiovascular disease monitoring [134]. By confronting the real-time signal quality assessment and lightweight QRS detection challenges, their novel methodology combining multiple signal quality indices and machine learning techniques improved the efficiency and reliability of ECG recordings, opening up new possibilities for broad population monitoring. Moreover, Alejandro Castillo-Atoche et al. developed an integrated energy-aware technique and a CNN for a cardiac arrhythmia detection system wearable during sports training [135]. Their introduction of an ultra-low-power microcontroller programmed with a dynamic power management strategy, coupled with a photovoltaic energy harvesting circuit, resulted in a significant extension of battery life. With an arrhythmia detection precision of 98.6%, their proposed system exemplifies the potential of AI in effectively monitoring athletes' conditions.

Innovations in AI-driven bioelectric signal processing have revolutionized sports-related applications, providing enhanced efficiency, accuracy, and privacy in muscle activation, fatigue and performance assessment. The adoption of advanced methods including autoregressive, Markov chain, and recurrent neural networks, as well as federated learning and convolutional neural networks, has enabled breakthroughs in mitigating motion artifact contamination, ECG analysis, sEMG signal processing, and real-time monitoring. These advancements underscore the vital role of AI in sports training, rehabilitation, injury prevention, and healthcare scenarios, and pave the way for further research and development in this domain.

IV. OVERVIEW OF CURRENT SPORTS MONITORING COMMERCIAL INTELLIGENT GARMENT SYSTEM

With adding fitness and health monitoring demand, the request for intelligent garment systems has recently seen significant growth. These systems use advanced cloth detectors and wearable technology to cover biometric data such as heart rate, respiration rate, and physical exertion. The data collected can be fluently transferred to a mobile operation, furnishing real-time feedback to athletes on their health and fitness. This section will present an overview of a selection of presently available intelligent garment systems that have commercial viability.

Xiaomi Mijia Cardiogram T-shirt is an industry-leading intelligent garment system designed to enhance athletic performance with monitoring systems [140]. One of its primary functions is the capability to conduct electrocardiogram (ECG) monitoring, which involves the assessment of the electrical exertion of the heart. This capability is accomplished by the incorporation of technical sensors within the fabric of the t-shirt. The ECG data attained from these detectors offer discerning information about the heart rate and other parameters, enabling the monitoring of physical exertion and detecting any possible heart-related issues. Likewise, this ECG data can be transferred to a mobile operation, furnishing athletes with immediate feedback and enabling them to make well-informed opinions regarding their exercise routines. This system distinguishes itself by focusing on cardiac health, making it particularly useful for athletes concerned with cardiovascular performance.

Athos Shirt is an exemplar in intelligent garments designed to enhance athletic performance [141]. This shirt is equipped with muscle-tracking detectors that can cover the activation of muscle groups during exercise. The data collected by the detectors is transferred to a mobile operation, so the athletes can receive real-time feedback on their performance and identify areas for enhancement. The Athos Shirts are designed for comfort and are made from feather-light, porous materials, equipped with sweat-wicking technology to keep the wearer cool and dry during intensive exercises. Unlike the Xiaomi Mijia, the Athos Shirt specializes in muscle activity, offering a unique set of data valuable for strength training and muscle development.

Tymewear Smart Shirt is a novel intelligent garment system that optimizes athletic performance with monitoring systems [142]. It can measure breathing rate, which reflects the respiratory exertion of the runner. This system is unique in its ability to measure respiratory metrics, offering athletes insights into their aerobic capacity and stamina. The shirt has technical sensors embedded in the fabric that collect breathing data. This data reveals the runner's metabolic thresholds, training load, and VO2 max. Runners can use these parameters to adjust their training intensity, duration, and frequency according to their fitness goals and needs. The shirt also transfers the breathing data to a mobile application, which gives runners immediate feedback and helps them make informed decisions about their exercise routines. A visual representation of the TymeWear Smart Shirt is provided in Figure 12.

Moreover, the shirt measures running power, force production, ground contact time, and cadence from sensors embedded in the fabric. These parameters help runners analyze their biomechanics and gait patterns and improve their running efficiency, performance, and injury prevention.

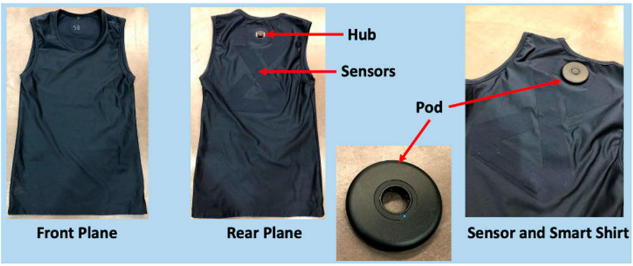

FIGURE 12. External layout of tyme wear smart shirt and pod [143].

Aaron et al. conducted two graded exercise test (GXT) trials to verify the reliability of the TymeWear Smart Shirt [143].

FIGURE 13. OM signal bra [144].

OM Signal Bra (FIGURE 13) is an intelligent garment technology designed explicitly for women. OM Signal Bra incorporates advanced cloth detectors into a comfortable and protective sports bra and can track biometric data, including heart rate, respiration rate, and physical exertion situations. The data collected by the OM Signal Bra can be fluently transferred to a mobile operation, so users are informed about their health and fitness progress in real-time. The OM Signal Bra is designed with comfort and functionality and is made from high-quality, sweat-wicking material.

FIGURE 14. Hexoskin smart shirt [146].

Another product utilizing intelligent garment technology is the Hexoskin Smart [145]. As shown in FIGURE 14, this shirt has advanced cloth detectors knitted into the fabric that can cover various biometric data, including ECG, blood pressure, activity level, skin temperature, etc [146]. The data collected can be fluently transferred to a mobile operation, allowing users to cover their health and fitness progress in real-time. The Hexoskin Smart Shirt is designed to be

TABLE 2. Details of the representative commercial intelligent garment system.

Commercial Products	Biometric data	Washability	Machine Wash	Availability / Price
Xiaomi Mijia Cardiogram T-shirt[140]	ECG	Yes	No	€35.43
Athos shirt[141]	sEMG	Yes	Not recommended	$298
Tymewear[142]	VO_2 Max & Heart Rate	Yes	Yes	$35/ Month
OM Signal Bra[144]	ECG	Yes	Yes	$150
Hexoskin Smart Shirt[145]	ECG	Yes	Yes	$499
Whoop Strap[147]	ECG	Yes	Yes	$264/Year
Nadi X Yoga Pants[148]	sEMG	Yes	Yes	$65

durable and accessible, with the capability to be washed and worn like a regular garment. Hexoskin Smart Shirt takes a more holistic approach by incorporating a range of biometric data, including ECG, blood pressure, activity level, and skin temperature. This makes it a versatile choice for athletes looking for comprehensive health monitoring.

In addition to these commercial intelligent garment systems, several other analogous products are also available. While this overview highlights some of the key commercial IGS available, it's worth noting that the wearable technology spectrum in sports is broad and continually expanding. These include Whoop Strap [147] and Nadi X Yoga Pants [148]. These products use advanced wearable technology to cover biometric data and give real-time feedback via a mobile app. They're designed to be comfortable and discreet, allowing individuals to cover their health and fitness without demanding a separate wearable device. Details of the representative commercial intelligent garment systems are shown in Table 2.

While the table highlights some of the paramount commercial IGS available in the market, it's worth noting that the wearable technology spectrum in sports is broad and continually expanding. Beyond the field of Intelligent Garment Systems, the athletic domain has embraced a slew of other wearable devices. Activity trackers such as Fitbit and Garmin have gained immense traction for their role in optimizing athletes' daily physical activities. Intelligent shoes, with Under Armour's HOVR series as a notable example, have revolutionized footwear by embedding sensors that monitor crucial parameters like pace and stride length. Additionally, innovative sportswear, like Sensoria's heart rate monitoring sports bra, has bridged the gap between apparel and technology. Even minimalist devices, such as the Oura Ring, pack a punch by providing insights into metrics like body temperature and heart rate, aiding athletes in understanding recovery patterns. As the convergence between technology and sportswear deepens, athletes and trainers are better equipped than ever to harness data for performance enhancement.

V. CHALLENGES AND FUTURE DIRECTIONS

Intelligent Garment Systems (IGS) for bioelectric monitoring during long-term sports face several challenges regarding real-time monitoring and connection problems between IGS and sensors. One of the main challenges is the complexity of accurately capturing and monitoring the bioelectric signals during sports activities, particularly when the athletes are engaged in highly dynamic movements. To mitigate this, advanced sensor calibration techniques and noise-filtering algorithms can be employed to improve the accuracy of bioelectric signals. These movements may cause significant fluctuations and noise in the bioelectric signals, which can impact the accuracy of the monitoring results. Another significant challenge is ensuring the reliability and stability of the connection between IGS and sensors during long-term sports. Emerging technologies like low-energy Bluetooth and Zigbee protocols can offer more stable and energy-efficient connections. This requires the development of robust and flexible connections that can withstand the repeated and intense physical movements involved in sports activities while also ensuring a stable and uninterrupted data transfer between the sensors and IGS. In addition, maintaining the durability of fabric-based electrodes after washing remains a significant challenge [149], [150]. Coating technologies using hydrophobic materials could potentially extend the lifespan of these electrodes. Besides, the stability and accuracy of wireless data transmission systems between IGS and terminals, such as textile-based NFC communication devices [151] in long-lasting sports monitoring, is also a challenge that cannot be ignored. The use of error-correction codes can enhance the reliability of data transmission. Moreover, developing a highly reliable power source for IGS is also essential to ensure continuous and uninterrupted monitoring during long-term sports. Innovations in energy harvesting from body movements or thermal energy could offer sustainable power solutions. Furthermore, there are no widely recognized industry standards for e-textiles and IGS, such as test procedures for E-textiles [152] and intelligent garment systems, resulting in commercial wearable products that are more gimmicky than valuable, preventing consumers from getting the wearable products they need.

However, there is currently an important work ongoing aiming at the definition of standards for e-textiles by IPC (https://www.ipc.org). IPC standards recognize that textile-based electrical and electronic assemblies (E-Textile Wearables) are subject to classifications by intended end-item use. Three general end-product classes have been established to reflect differences in manufacturability, complexity, functional performance requirements, and verification (inspection/test/laundering) frequency. It should be recognized that there may be overlaps of products between classes.

Class 1 General E-Textile Wearables

Includes products suitable for application categories where the major requirement is a function of the completed assembly.

Class 2 Dedicated Purpose E-Textile Wearables

Includes products where continued performance and extended life is required, and for which uninterrupted service is desired, but not critical. Typically, the end-use environment would not cause failures.

Class 3 High Performance/Harsh Environment E-Textile Wearables

Includes products where extended-lifetime, high reliability, and performance or performance-on-demand are critical, equipment downtime cannot be tolerated, end-use environment may be uncommonly harsh, and the equipment must function when required, such as life support or other critical systems.

This standard also recognizes Class 2 and Class 3 products that may be designed to be disposable after one- or short-time use. Requirements specific to these product use cases are identified in this standard.

Test methods encompassing various damages such as mechanical (flexing, stretching, bending, torsion, abrasion), exposure (chemical, microbes, sweat, salt water, temperature, washing, etc.) are defined to help the designers and manufacturing companies to determine the e-textile system class and to make them more reliable and ready for the market.

Moreover, an emerging area of interest that warrants further exploration is the optimization of the size, weight, flexibility, and battery life of commercially available IGS systems. These parameters are critical for the practical application and commercial viability of IGS but are often overlooked in existing literature. Future research could focus on developing lightweight and flexible systems with extended battery life to enhance user comfort and experience.

In terms of future research directions, there is a need to advance further the technologies and algorithms for bioelectric signal processing and analysis to increase the accuracy and reliability of bioelectric monitoring during sports activities. Machine learning algorithms, particularly neural networks, could be integrated for real-time data analysis, offering more nuanced insights into athletes' performance. Additionally, developing new and innovative materials and connection technologies is required to enhance the stability and reliability of the connections between IGS and sensors. The use of nanomaterials and conductive polymers could offer more robust and flexible connections. Another research direction is how to use the big data of human bioelectrical signals in long-last sports as a data source to train models for sports performance prediction. Such models allow professional athletes and technicians to obtain not only a simple description of performance in sports in real time but also to predict performance trends and prevent possible future injuries. Also, due to the characteristics of long-lasting sports monitoring, intelligent garment systems require higher specifications of power supply configuration, energy harvesting devices, high-density portable power supply, etc. Exploring these areas could potentially become the main focus of future research. Furthermore, integrating artificial intelligence and machine learning technologies into IGS could provide valuable insights into the complex bioelectric signals generated during sports activities and support more accurate and effective monitoring and analysis of athletic performance. Nevertheless, some associations and standardization organizations, such as IPC (www.ipc.org), IEC (www.iec.ch), CEN (www.cen.eu), AATCC (www.aatcc.org), etc., are committed to developing industry standards on E-textile wearable devices, which will enhance the development of IGS for long-term monitoring of sports.

VI. DISCUSSIONS

Drawing upon the meticulous examination of the literature, as well as the observational analysis of both laboratory and commercially-oriented products, the present discussion seeks to highlight the key discrepancies between laboratory-based IGS specifically engineered for bioelectric monitoring during sports activities and their market-driven IGS counterparts. By emphasizing the interplay of business-driven decision-making and market assessment perspectives, this study identifies three critical factors that account for the incongruity between laboratory research and market products.

First, the reliability and stability of laboratory-based IGS often pose challenges, potentially falling short of meeting the stringent safety requirements of the market. As underscored in Section V, accurately capturing and monitoring bioelectric signals amid highly dynamic movements constitutes a significant obstacle, with the potential to compromise monitoring outcomes. To address this, future research could explore adaptive algorithms that can filter out motion artifacts, thereby enhancing the reliability of bioelectric signal capture during dynamic activities. Ensuring the reliability and stability of the connection between IGS and sensors during extended sports activities is another paramount concern. This could be mitigated by employing fault-tolerant communication protocols that can re-establish connections swiftly, ensuring minimal data loss. Consequently, these limitations hinder laboratory-based IGS from satisfying the rigorous market demands regarding safety and stability.

Market-oriented IGS products often prioritize essential functionalities to strike a balance between performance and cost. However, this focus can lead to a misalignment with the extensive capabilities inherent in laboratory-engineered systems, some of which may not directly address the specific needs of the consumer base. This divergence contributes to the existing gap between academic research and market-oriented products. To bridge this gap, involving end-users in the design phase can align the IGS features more closely with market demands.

Moreover, the transition of these advanced technologies from academic settings to the commercial sector is often impeded by a lack of specialized expertise within commercial R&D department. This deficiency further widens the disconnect between academic advancements and their practical applications, leading to a protracted integration of innovative technologies into market-ready IGS products. To mitigate these challenges, fostering interdisciplinary collaborations between academic researchers and industry professionals could facilitate a more seamless transition from research to market, thereby narrowing the existing gap.

Lastly, the research and development departments within the market often lack personnel possessing the requisite professional background and research capabilities to expedite the transition of novel technologies into marketable IGS products. This gap could be bridged by fostering collaborations between academic researchers and industry professionals, facilitating a more seamless transition from the lab to the market. This shortcoming leads to a protracted integration of innovative technologies into commercially-oriented IGS, leaving ample room for improvement in technical aspects.

Considering these factors, the gap between laboratory-based Intelligent Garment Systems (IGS) and market-oriented products emerges from the reliability and stability issues encountered by laboratory IGS, the misalignment of features with market demands, and the absence of skilled professionals capable of bridging the gap between research and market product development. By implementing these suggested approaches, there is potential for a more seamless translation of laboratory IGS research into viable and valuable market products.

VII. CONCLUSION

The increasing popularity of wearable monitoring technology in sports has driven the development of intelligent garment systems. In addition to the primary bioelectric sensors elaborated upon in this review, it is imperative to acknowledge the burgeoning role of alternative wearable sensors in the realm of comprehensive sports monitoring. These encompass temperature sensors for thermoregulatory assessment, pressure sensors for nuanced gait analysis, and optical sensors for the quantification of blood oxygen saturation levels. While not traditionally incorporated into Intelligent Garment Systems (IGS), the integration of these auxiliary sensors could furnish a more holistic methodology for athlete monitoring, thereby augmenting the system's utility and broadening its applicative scope. Despite advancements in this field, specific challenges persist, particularly regarding the reliability of these systems in extended athletic activities. The stability of the intelligent garment system is influenced by several factors, including the composition of electrodes, the connection between sensors and the clothing system, as well as the subsequent processing of collected signals. To address these issues, academic and commercial sectors continually improve their products to meet higher requirements. In the field of sports and healthcare, the future of Intelligent Garment Systems (IGS) is anticipated to be significantly influenced by the integration of advanced biomechanical sensors and machine learning algorithms. These advancements are poised to enhance real-time data analytics, thereby facilitating more nuanced and individualized health monitoring and performance optimization strategies.

As Intelligent Garment Systems (IGS) continue to mature, ethical considerations and privacy safeguards surrounding the handling of sensitive bioelectrical data are becoming increasingly salient. It is thus incumbent upon future research endeavors to prioritize the formulation of robust encryption algorithms and user verification mechanisms to ensure the confidentiality and integrity of data pertaining to athletes and healthcare recipients.

Additionally, the sustainability of power sources for IGS is a pivotal concern for facilitating continuous, long-term monitoring. Investigative efforts could be directed towards the exploration of energy-harvesting modalities, including but not limited to thermoelectric and piezoelectric mechanisms, as a means to proffer enduring and eco-friendly energy solutions, thereby amplifying the system's operational longevity.

Future advancements in IGS are expected to focus on the integration of AI-based predictive analytics for early detection of health risks and the development of more energy-efficient components to extend battery life. This review offers a focused technical examination of intelligent garment systems geared towards sustained monitoring in sports activities. It aims to contribute to the existing body of knowledge by discussing the interplay of advanced materials and artificial intelligence techniques. The work is intended as a useful point of reference for both scholars and professionals in the field.

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