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TOPICAL REVIEW

Exoskeleton Recognition of Human Movement Intent Based on Surface Electromyographic Signals: Review

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ABSTRACT The lower limb exoskeleton technology is designed to facilitate the movement of human lower limbs. Significant progress has been made in this technology, which has important implications for rehabilitation patients and individuals who are eager to enhance their mobility. Electromyogram (EMG) signals, which encompass the complexity of human physiology, are integrated into lower limb exoskeletons due to their deep connection to movement and predictability before movement begins, and this integration is expected to enable intelligent control and improved human-computer interaction. This review explores a pattern based on EMG signals for identifying human motor intent in lower limb exoskeletons. Firstly, the development of lower limb exoskeleton and the existing lower limb exoskeleton products are systematically described. Combined with the intelligent control system of wearable device, the main methods and research progress of recognizing the motion intention of lower limb exoskeleton by surface EMG are discussed. It shows that the use of surface EMG can effectively improve the human-machine interaction of lower limb exoskeleton. Together, the study provides insight into the challenges that are hindering the commercialization of the market and provides a perspective on the future development of EMG signals.

INDEX TERMS Lower limb exoskeleton, human–machine interaction, movement intent recognition, electromyographic signals, feature classification.

I. INTRODUCTION

According to data from the World Health Organization (WHO), as of 2021, approximately 1.3 billion individuals globally have suffered from severe disabilities, representing about one-sixth of the global population [1]. In China, the disabled population has reached 85 million by 2022, accounting for 6.34% of the entire population. Furthermore, data collected by global medical institutions, including the WHO, have indicated that limb disabilities not only impose challenges in daily life but also increase other disease risks. Observations revealed profound psychological impacts on patients, including heightened levels of self-esteem, anxiety, and depression. Consequently, disability issues have gained increasing international attention.

From the 1960s onward, exoskeleton technology has transitioned from theoretical reports to practical applications, evolving from military contexts to augmenting human mobility within the industrial and medical domains. In the medical field, rehabilitation exercises offer a pathway for disabled patients to enhance their quality of life. However, the ratio of certified rehabilitation professionals to patients is notably disproportionate. Frequently, a single rehabilitation specialist should oversee multiple patients concurrently, compromising both the safety of rehabilitation exercises and the overall efficacy of treatment. Some patients encounter difficulties in receiving specialized care from qualified healthcare practitioners. Scholars have suggested that advanced exoskeleton

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devices can provide consistent functional support, augmenting both the rehabilitation experience and the quality of life for patients and alleviating pressures on healthcare providers. Consequently, the advancement of exoskeleton technology has become a global focus in the field of medication. Recently, electromyographic signals (EMG) have emerged as a pivotal research area, facilitating the identification and anticipation of human movement intentions. These signals hold promise for enhancing the safety, reliability, and intelligence of lower limb exoskeleton systems, accelerating their integration into clinical practices. The rapid development of wearable lower limb exoskeletons in both the national and international scale can substantially optimize rehabilitation outcomes for individuals with lower limb functional deficits [2].

Despite notable advancements in EMG signal research in recent years, several challenges have inhibited the development and application of EMG signals within lower limb exoskeletons. Three primary challenges encompass enhancing the accuracy of signal acquisition in lower limb exoskeletons, ensuring the collection of accurate and stable EMG signals in suboptimal conditions, and achieving accurate identification of human movement intentions via EMG signals. These complexities are further affected by factors including the spatial configuration of the data acquisition apparatus and extraneous environmental variables. Given the progressively aging worldwide population and the sustained high prevalence of individuals with disabilities, the significance of wearable lower limb exoskeleton technology has amplified for improving medical efficiency. Therefore, this study explored the contemporary advancements and challenges in promoting the human-machine interaction of EMG signals, indicating their capacity to augment the intelligence of lower limb exoskeletons and mitigate specific issues within the domain.

This study reviewed contemporary research focused on recognizing and predicting movement intent within lower limb exoskeletons through the analysis of EMG signals. Moreover, this study addressed facets encompassing the acquisition, preprocessing, feature classification, and identification of human movement intention via EMG signals. The elucidations presented aimed to guide researchers, healthcare practitioners, and industry experts engaged in leveraging EMG signals within the context of lower limb exoskeletons.

II. INTRODUCTION OF THE LOWER LIMB EXOSKELETON

Wearable exoskeletons are systematically classified into two primary categories: upper limb exoskeletons and lower limb exoskeletons based on their application domains. These devices facilitate the execution of diverse postures and movements by supporting various anatomical joints. Specifically, upper limb exoskeletons target joints consist of the shoulder, elbow, wrist, fingers, and torso, whereas their lower limb joints involve the hip, knee, and ankle articulations. Within the developmental trajectory of wearable exoskeleton development, researchers have suggested that the upper limbs engender more diverse postures and tasks and inherently exhibit greater versatility in daily functional activities than the lower limbs. Therefore, studies on upper limb exoskeletons are considered more representative. Currently, the research on upper limb exoskeletons has achieved more maturity. However, the introduction of EMG signals has emerged as a pivotal frontier in exoskeletal research. Owing to the intricacies and multifaceted nature of EMG signals within the lower limb domain, especially within non-optimal environments, associated research challenges are more representative, which makes EMG signals in lower limb exoskeletons more research-intensive.

The development of lower limb exoskeletons for military applications commenced in the previous century. Nevertheless, owing to limitations such as rudimentary equipment and insufficient infrastructure at that period, there have been numerous technological obstacles across multiple interdisciplinary domains, including mechanical structure, information sensing process, and automated control. Approximately by 1970, the first wearable exoskeleton apparatus, known as Hardiman [3], [4], was unveiled. This apparatus, constructed in phases, encompassed both upper and lower body components, resulting in improved arm mobility. However, the device was cumbersome, inconvenient to wear, and restricted body movements beyond the upper limbs.

As the 21st century commenced, marked by significant advancements across diverse disciplines, wearable exoskeletons have garnered interests among researchers. The development of wearable exoskeleton technology initiated its first phase, driven by projects such as the U.S. Defense Advanced Research Projects Agency's project titled "Human Performance Augmentation Exoskeleton Systems." Lower limb exoskeletons can be categorized into two distinct types based on their developmental objectives: enhancement and assistance. Enhancement-focused exoskeletons are designed to amplify human motor capabilities, as evidenced by innovations such as the BLEEX exoskeleton crafted at the University of California, Berkeley [5], and the XOS exoskeleton pioneered by the U.S.-based Raytheon Company [6]. These apparatuses aim to promote the combat efficacy of individual soldiers to mitigate physical exertion and provide supplementary power. Conversely, assistance-centric exoskeletons are devised to facilitate routine human movements, predominantly deployed within medical and industrial sectors, exemplified by the MIT-Exoskeleton introduced by the Massachusetts Institute of Technology [7]. This apparatus augments specific ambulatory functions for the users. Such investigative endeavors have indicated the profound potential of exoskeletal devices in the global medical landscape, highlighting the enhanced stability of power-assisted exoskeleton walking methodologies compared to conventional manually assisted techniques. Figure 1 shows several examples of lower limb exoskeleton.

In the vicinity of 2010, exoskeleton technology entered the second phase characterized by pronounced and consistent advancements, witnessing multiple countries producing

FIGURE 1. Lower extremity exoskeleton display.

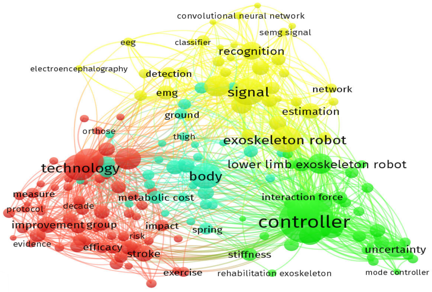

FIGURE 2. Exoskeleton thesis keywords correlation.

their distinctive lower limb exoskeleton apparatuses, predominantly tailored for military, medical, and industrial contexts. Leading contributors to this technology include the United States, Japan, and Germany, while countries including China, France, Israel, New Zealand, Singapore, and South Korea have been diligently advancing in parallel trajectories. Noteworthy innovations in the realm of lower limb exoskeletons comprise the HAL exoskeleton [8], the ReWalk exoskeleton [9], the NTULEE exoskeleton [10], the Aload-L wearable exoskeleton [11], and the ExoMotus M4 exoskeleton [12].

Subsequent studies by Dupont et al. [2] and Long and Xiuze [13] emphasized the main focus of exoskeleton research, such as human-machine interaction control algorithms, mechanical structure design, functional quantification, and human movement intent detection. In 2019, Shi et al. [14] outlined three key technologies for investigating lower limb exoskeletons: refining human-machine interaction, exploring rigid-soft hybrid designs, and integrating personalized gait algorithms with multimodal data fusion.

In light of these orientations, an examination of literature using ''lower limb exoskeleton'' as the principal keyword within the Web of Science database from 2019 to 2023 revealed over 1700 related publications. A discernible surge in publications is evident after 2021, a trend likely attributable to the repercussions of the COVID-19 pandemic between 2019 and 2021, as elucidated in subsequent discussions. Figure 2 illustrates a comprehensive overview of the thematic relevance, where the size of keyword spheres corresponds proportionally to the frequency of appearance across all publications, with larger spheres indicating higher frequency. The predominant areas of focus within exoskeleton research include controllers (green), signal processing (yellow), mechanical design (red), and human intent (blue). Remarkably, commencing from 2019, a consistent augmentation in evaluative research on lower limb exoskeletons [15], [16], [17] has been observed, encompassing investigations centered both on the exoskeleton apparatus itself and empirical assessments involving patients, professionals, and other cohorts. Collectively, these patterns align with the prognostications articulated by scholars in earlier discussions. Within the corpus of examined literature, an excess of 900 publications is intrinsically linked to EMG signals, underscoring the academic community's pronounced engagement with this domain. The exploration of EMG signals is predominantly associated with human-machine interaction and advanced signal processing, mirroring pivotal trajectories within contemporary EMG signal scholarship.

Traditional human-machine interaction traditionally exhibits two primary modalities. The first includes the initiating movement of the human body, subsequently propelling mechanical device assistance to facilitate motion. This mitigates energy expenditure or maintain static postures. Conversely, the second modality involves users directing mechanical movements, followed by their corresponding displacement. Both methods demonstrate suboptimal interactional performance and constrained flexibility. With the advancement of intelligent technologies, human-machine interaction within lower limb exoskeletons have markedly diverged from these conventional approaches.

In advanced lower limb exoskeleton designs, various sensors embedded within the lower-level controller collect data about both the user's physiological state and environment.

This involves identifying the user's physical status and contextual surroundings, facilitating harmonized biomechanical assistance, augmenting the user experience, and providing a more seamless interaction. Subsequently, the middle-level controller transmits information to the overarching upper-level controller. Based on the decisions executed by this upper echelon controller, the intended movement trajectories are delineated within the path planning framework of the lower limb exoskeleton. Serving as the cognitive nexus akin to the neural center of the exoskeleton, the upper-level controller adeptly recognizes the user's movement intentions to obtain a sequence of algorithmic decisions. In addition to individual requirements, the quantitative evaluation of lower limb exoskeleton devices lacks a unified industry standard, owing to disparate research standards across countries. As a result, the evaluation of these devices predominantly relies on subjective feedback from wearers and supplementary assessments by external instruments, such as EMG signal sensors, respiratory apparatus, and cardiac monitoring systems, to measure the physiological responses of users. Such a paradigm causes the absence of objective metrics in evaluations, indicating the substantial strides yet to be made for lower limb exoskeleton devices to attain market readiness.

The evolution of middle-level mechanical architectures in exoskeletal design has transitioned from an initial emphasis on rigid materials to an increasingly prevalent integration of flexible or hybrid materials, encapsulating advancements in driving methods, structural flexibility, and material transformation. Regarding driving methods, beyond conventional hydraulic, pneumatic, and motor-driven mechanical systems, contemporary developments have introduced cost-effective and lightweight alternatives, such as the twisted rope drive [18] and twisted tube drive [19] integrated into lower limb exoskeleton devices. Studies have suggested that the international exploration of these methodologies commenced around 2017, with domestic Chinese initiatives gaining by 2020. The two driving methods significantly improve the viability of convenient and lightweight exoskeletons. Both approaches utilize the restoring force of ropes or flexible tubes to operate the lower limb exoskeleton. Nevertheless, a limitation arises as the self-recovery force of the selected rope or tube can reach its threshold more readily than a mechanical structure. Continuous operation under tension may result in relaxation, contributing to the initial driving performance. Furthermore, the twisted rope drive may experience frequent rope breakages, leading to entanglement and potential complications. The concept of flexible design, pioneered by the Wyss Institute with the first-generation Soft Exosuit [20] for the lower limbs, introduced the concept of anchor points which was strategically positioned in areas of the human body with greater rigidity to facilitate force application. Through flexible material design, force transmission paths were created, which redirected the actuator's force to these anchor points for flexible binding. However, this design revealed increased human fatigue in subsequent testing. In recent years, there has been significant attention towards hybrid flexible-rigid materials, which combine the characteristics of flexible and rigid materials similar to the interplay of human muscles and bones. The series elastic structure from Harbin Institute of Technology [21] has notably enhanced joint flexibility and control by facilitating smoother operation between the motor and the load. Addressing comfort, Alanz's team [22] introduced a multi-joint soft exosuit focusing on body wear and tear. The objective of the material flexibility was to ensure the comfortability, which can differentiate it from the rigid sensation of directly wearing machinery and render the wearing of lower limb exoskeletons similar to that of common attire. Recently, mass production has received significant investment in the development of such clothing. The integration of EMG signals is discussed in the following section.

Within the domain of human-machine interaction, the primary function of the upper-level controller is to identify the intent of the user's movement. Given that individual signals often exhibit limitations in accuracy and stability, simultaneous capture of both physical and biological signals is required. Subsequently, the upper-level control algorithm integrates these signals to determine the user's movement intent, which may be specific offline actions or continuous recognition of joint angle variations. In laboratory scenarios, the focus is typically initiated with offline action recognition, subsequently progressing to the continuous recognition of joint angles. However, the inherent discrete nature of information classification imposes certain constraints, encompassing limitations on intricate movements, movement variability, definitive classification outcomes, inability to identify unfamiliar actions, and vulnerability to external environmental factors.

Human lower limb behavior primarily encompasses straightforward actions encountered in daily activities, such as walking, stair navigation, incline and decline ambulation, squatting, standing, rotational movements, dynamic turns, and backward steps. The control classification of lower limb exoskeletons is aptly tailored for feature categorization. Based on offline classification, continuous recognition of movement intent has been refined, notably mitigating inherent limitations. As advancements in lower limb exoskeleton technology progress, EMG signals increasingly meet researchers' requirements for enhancing intelligent system control. Given this context, contemporary EMG signal research predominantly emphasizes the subsequent facets:

1. Bottom-level collection devices: Portability is essential for wearable EMG collection devices integrated with lower limb exoskeletons. Because of the presence of dense hair on human lower limbs, current experiments mandate hair removal from the collection site, followed by alcohol wiping to eradicate sebum and sweat. Such rigorous prerequisites pose challenges for real-world applications, indicating the need for advancements in the design of collection devices.

2. Bottom-level signal preprocessing: Given that muscles account for a substantial spatial proportion of the human lower limbs (76%) [23], EMG signal collection faces challenges such as interference from muscle group crosstalk, other bioelectrical signal interference, external instrument disruptions, and magnetic field signal interference. Hence, meticulous preprocessing of EMG signals is imperative, encompassing techniques such as amplification, filtering, pre-emphasis, windowing, framing, endpoint detection, and denoising.

3. Upper-level feature classification: EMG signals are nonlinear, non-stationary one-dimensional time series. Traditional feature extraction encompasses time-domain, frequency-domain, time-frequency domain, and nonlinear features. Although conventional time and frequency domain features effectively identify human movement intent, classification algorithms tailored for lower limb exoskeletons demand high computational efficiency, minimal complexity, optimal real-time capabilities, and account for variables, including individual differences and muscle fatigue effects. Currently, high-accuracy classification techniques frequently exhibit either high complexity or limited generalizability, failing to comprehensively address individual variations and fatigue influences, warranting refinement.

4. Upper-level recognition of human movement intent: After the training of action classification models with offline EMG signal features, there is a need for the online recognition of continuous joint movements or discerning movement intent for novel users. Although the existing models exhibit high accuracy within specific contexts, their performance in unfamiliar settings is often compromised by unforeseen variables. Techniques such as transfer learning have been employed to accelerate the adaptation of lower limb exoskeletons to new users, while their actual efficacy remains constrained, posing challenges in achieving the desired performance levels.

The current intelligence capabilities of lower limb exoskeletons are limited, and the incorporation of EMG signals offers solutions to certain challenges. However, issues regarding their utilization persist. The subsequent discussions elucidate the characteristics of EMG signals and their integration within intelligent control systems, as shown in Figure 3.

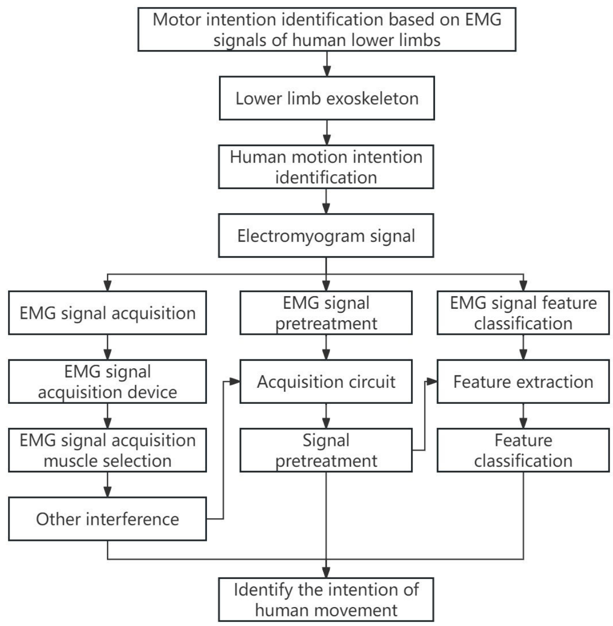

FIGURE 3. Flow chart of EMG application.

III. INTRODUCTION OF THE ELECTROMYOGRAPHY

Since 1791, Italian anatomist Luigi Galvani first conceptualized bioelectricity by studying action potentials in frog muscle contractions. However, owing to equipment constraints, obtaining standardized bioelectric signals was challenging, fueling debates among researchers. In the 19th century, advancements, such as Julius Bernstein's improvements in ammeter technology, facilitated the measurement of nerve conduction velocities in frogs (25–30 m/s), paving the way for broader acceptance of bioelectricity. Over the past three decades, relentless technological progress, enhanced signal acquisition tools, and refined processing methods have led to the development of compact, energy-efficient devices capable of precise EMG signal measurement [24]. With an increasingly comprehensive comprehension of EMG signals, in 2001, Canadian researcher Dan [25] highlighted their rich movement information potential, suggesting diverse applications, including muscle activity detection, human-machine interaction, motion recognition, emotion detection, and forecasting human motion intent.

Human muscles mainly consist of skeletal and smooth muscle types, with skeletal muscles being rich in muscle proteins that can form muscle fibers and responsible for most body movements. Action potentials, pivotal to physiological processes, are predominantly generated from ion movement, specifically sodium, calcium, and potassium ions, across cell membranes [26]. Ion dynamics during muscle contraction and relaxation contributes to a bioelectric potential, and the collective activity of electrode units produces an EMG signal. Therefore, the primary origin of the EMG signal is the bioelectric activity within skeletal muscle fibers [27], [28], [29]. Represented as a nonlinear, nonstationary one-dimensional time series, the EMG signal encapsulates the physiological nuances of human movement, as shown in Figure 4(self-drawing).

The main characteristics of electromyographic (EMG) signals include the following.

(1) Limitation: The amplitude of EMG signals typically ranges from 0 to 10 mV, exhibiting a wide frequency range that generally does not exceed 1000 Hz, and is characterized as a one-dimensional time-action potential sequence.

(2) Low-frequency nature: In the medical domain, neurotransmitter activity is predominantly encapsulated within the frequency range of 20 Hz to 500 Hz [30]. Similarly, EMG signals are primarily within the frequency range of

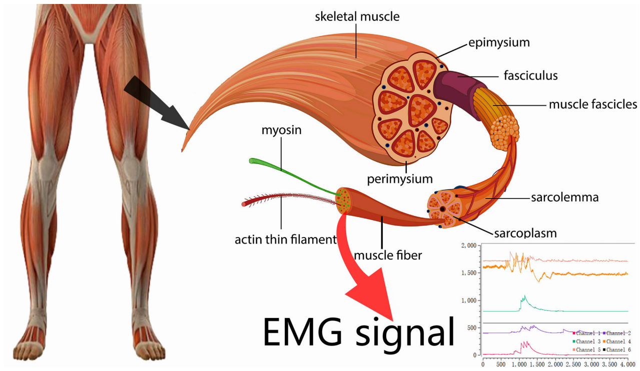

FIGURE 4. EMG signal schematic.

0–500 Hz, with main energy observed between 20–150 Hz. According to Nyquist's sampling theorem, the minimum sampling frequency for EMG signals is 1000 Hz or higher. However, practical experiments can capture signal samples within the 20–150 Hz range, with a selected sampling frequency of 500 Hz and above.

(3) Anticipation of limb movement: EMG signals typically precede limb movements at an approximate interval of 30–150 ms. This anticipatory capability facilitates synchronous movement between the lower limb exoskeleton and the user, after the mechanical perception of human movement intent.

(4) High impedance: The surface resistance of the human body exhibits variability, primarily contingent on the skin humidity levels, resulting in fluctuating resistance values. The peak impedance values can increase to approximately 450 kΩ [31].

In summary, EMG signals contain comprehensive data pertaining to human movement, exhibiting characteristics such as low amplitude, low-frequency, anticipatory nature, and high impedance. Scholars have suggested that these EMG signal attributes render them instrumental in recognizing and predicting human movement intent within lower limb exoskeleton applications.

Lower limb exoskeletons employ sensors to capture both physical and biological signals. Through direct measurements of specific limb segments and the subsequent extraction of pertinent features, these signals facilitate the development of models that correlate with user gait characteristics. The pivotal joints targeted for assistance in lower limb exoskeletons include the hip, knee, and ankle joints. The hip joint consists of three degrees of freedom: flexion/extension,abduction/adduction, and external/internal rotation [32]. The knee joint is characterized by a singular degree of freedom: flexion/extension [33]. The ankle joint has three degrees of freedom: dorsiflexion/plantarflexion, inversion/eversion, and pronation/supination [32]. Overall, the human lower limb exhibited seven degrees of freedom, as shown in Table 1.

Lower limb exoskeletons integrate sensors categorized into mechanical and biological variants [34]. Mechanical sensors, primarily consisting of inertial components, such as gyroscopes, foot pressure sensors, and joint angle sensors, facilitate the detection of human motion. When coupled with encoders, these sensors compute the dynamics of human joint movements. Despite their longstanding developmental history and mature applications, mechanical sensors may exhibit perceptible delays, potentially compromising real-time interaction for users attuned to bodily responsiveness. Biological sensors include EMG, EEG for brain waves [35], and EOG for eye movements [36]. Specifically, EMG and EEG sensors detect neurotransmitters released from the human physical movements, rendering them suitable for predicting human movement intentions. The integration of EMG signals is particularly favored among researchers aiming to enhance exoskeleton synchronization with human kinetics, thus mitigating latency and errors. While EEG signals are the source of EMG signals, they present challenges, including the high information content, decoding complexities, and greater distance from the lower limb exoskeleton. Consequently, EMG serves as the primary biological signal in lower limb exoskeletons, adeptly delivering on-demand assistance.

TABLE 1. Lower limb joints and degrees of freedom.

Articulation	Degree of Freedom	Total Degrees of Freedom
Hip Joint	Flexion/Extension, Abduction/Adduction, External Rotation/Internal Rotation	3
Knee Joint	Flexion/Extension	1
Ankle Joint	Flexion/Extension, Abduction/Adduction, External Rotation/Internal Rotation	3

Cyberdyne Inc., a pioneering Japanese company, emerged as an early adopter of EMG signals, unveiling the HAL (Hybrid Assistive Leg) series of exoskeletons post-2010 [8]. By interpreting user EMG signals, these devices adeptly capture real-time motion intent and deliver tailored assistance and support. Their efficacy has been demonstrated by successful market deployment of mass-produced variants. Concurrently, researchers such as Hugh [37] from MIT engineered BIOM series prosthetics, which harnessed EMG signals from amputees' residual limbs to recognize motion intent and facilitate ankle joint assistance. Similarly, the TUPLEE exoskeleton from the Berlin Institute of Technology [38], [39] integrated EMG sensors into its shell to capture signals from six muscle groups. This system delineated the correlation between EMG signals and joint torque during motion, subsequently estimating the joint torque to provide assistance. Despite these advancements, broader EMG signal applications in lower limb exoskeletons remain nascent due to challenges encompassing accuracy constraints, instability, elevated costs, and algorithmic intricacies under suboptimal conditions.

Based on a comprehensive review of the pertinent literature and subsequent analysis of keywords associated with EMG signal research, as depicted in Figure 5, recent research predominantly focus on three thematic domains: signal acqui-

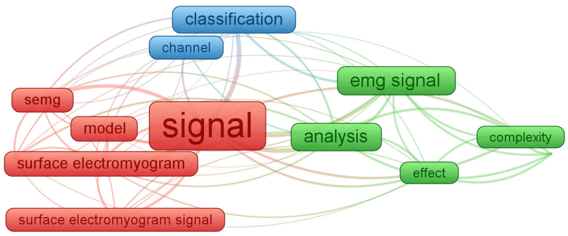

FIGURE 5. Correlation of EMG signal keywords in the thesis.

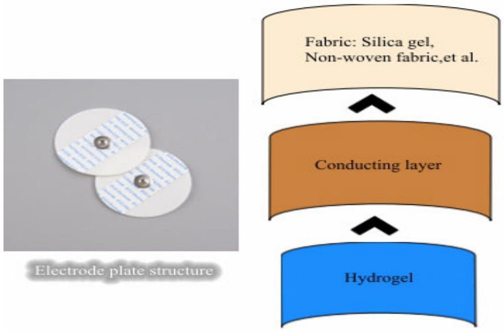

FIGURE 6. Simplified structure of electrode patch.

sition (red), signal analysis (green), and signal classification (blue)

A. EMG SIGNAL ACQUISITION

The acquisition of EMG signals primarily employs two methodologies: surface electromyography (sEMG) and intramuscular electromyography (iEMG) [40]. Although iEMG signals mitigate the challenges associated with sEMG, such as electrode displacement, detachment, and susceptibility to surface factors such as sweat, thereby offering enhanced accuracy and a superior signal-to-noise ratio, they inherently entail invasiveness, posing potential participant risks. Moreover, certain expansive movements may induce participant discomfort, thereby augmenting the operational costs. Consequently, sEMG signals, characterized by their noninvasive nature, have garnered broader research and applications. Subsequent references to EMG signals in this discourse specifically denote the sEMG signals.

In conventional sEMG signal studies, electrode patches can be predominantly divided into two categories: dry and wet, as shown in Figure 6. The primary distinction depends on the presence or absence of an intervening electrolyte gel layer between the electrode and the skin during application. Within living organisms, currents ares primarily ion-conductive, whereas daily life predominantly involves electron-conductive currents. Electrode patches function to transition from ion conductivity to current conductivity. Wet electrode sensors, infused with an electrolyte gel, enhance signal conduction between the skin and electrode and minimize motion artifacts. In addition, dry electrode sensors offer enhanced comfort. Currently, neither type demonstrates a pronounced superiority in experimental settings [41], [42]. Researchers should select based on specific requirements, considering parameters such as the testing environment and measurement precision.

1) EMG SIGNAL ACQUISITION DEVICE

In laboratory settings, the integration of lower limb exoskeletons with sEMG signals primarily utilizes standalone sEMG devices designed for motion analysis, rehabilitation, and biomechanical research. This workflow is similar to that of intelligent control systems: initial signal capture via electrode patches, transmission to the EMG sensor, and subsequent processing through specialized data acquisition and analysis tools to interpret human movement intentions. Advancements in sEMG device technologies have outpaced domestic progress, limiting the availability of locally produced sEMG acquisition tools. Domestic variants often demonstrate compromised accuracy and acquisition capabilities relative to their international counterparts, rendering the market predominantly reliant on foreign manufactured products.

Delsys, based in the U.S. [43], provides the Trigno Research System, tailored for synchronized recording of EMG and Inertial Measurement Unit (IMU) data in research environments. This system facilitates wireless data streaming for up to 32 channels of surface electromyography. Italy's OT Bioelettronica [44] offers Quattrocento, a 400-channel EMG amplifier adept at concurrently capturing surface EMG, intramuscular EMG, and EEG signals. After amplification, filtration, and digital conversion, the data were relayed to a PC via a USB2/Ethernet interface. This device further identifies muscle anatomical features, deciphers the muscle neural drive, and quantifies the spatial distribution of muscle activity. Although the majority of devices in the domestic market are agents of foreign equipment, selected domestic EMG products have shown notable efficacy. A noteworthy entrant is the wireless EMG device RunE-DS R0016 by Shenzhen Runyitaiyi Technology Co., Ltd. [45], distinguished by its low noise and exceptional common mode rejection ratio, achieving an internationally advanced in both software analysis and hardware collection. Although comprehensive EMG signal acquisition devices can be pivotal for theoretical studies centered on exoskeleton-aided EMG signal identification and human movement intention prediction, most of them often prove prohibitively expensive and bulky for direct integration with lower limb exoskeletons. Certain product screenshots are presented in Figure 7.

In recent years, both domestic and international scholars have further developed sEMG sensors tailored for integration within lower limb exoskeletons. These studies have mainly focused on the enhancement of the sEMG signal acquisition materials, electrode geometries, dimensions, and configurations. Fang et al. [46] innovatively utilized a porous polypropylene film to engineer piezoelectric devices, achieving an average motion classification accuracy exceeding 90% when coupled with specific algorithms. Moreover, Colyer et al. [47] pioneered the embedding of textile-based

(a) Trigno Research System[43]

(b)RunE-DS R0016[45]

FIGURE 7. **EMG acquisition equipment.**

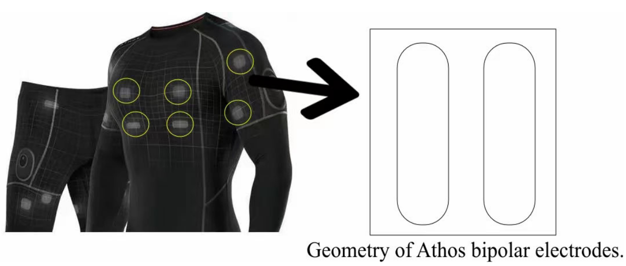

FIGURE 8. **Athos tracksuit [49].**

electrodes into clothing, creating electromyographic shorts to quantify muscle activity across the quadriceps, hamstring, and gluteal regions. This method provided a streamlined and effective avenue for sEMG signal acquisition in non-ideal settings, enhancing the possibility of extra-laboratory sEMG signal measurements outside the laboratory. Furthermore, this innovative approach had substantial potential for replacing conventional methods, particularly for lower limb exoskeleton application, with considerable resources invested in the development in recent years.

Introduced in 2017, the Athos sports suit [48], [49] resembles conventional tight sportswear, as depicted in Figure 8, incorporating washable dual electrode patches that enhanced sEMG signal acquisition convenience. The Myosuit, an agile lower limb assistance attire crafted by the Swiss Federal Institute of Technology in Zurich [50], [51], synergizes sEMG signals with force sensors to determine the user's lower limb movement status, offering supportive aid to the hips and knees during standing. Inspired by these innovations, Huang Pingao from the University of the Chinese Academy of Sciences [52] proposed a nanometer-thin gold-based sensor to monitor muscle deformations. Upon muscle deformation, the associated nanomaterial experiences deformation, facilitating precise detection of the muscle's deformation characteristics. Overall, the utilization of wearable textile fabrics for EMG signal collection is becoming mainstream trend. In 2023, Vidhya et al. [53] overviewed the progress of wearable conductive textile electrodes, detailing their efficacy in collecting bioelectric signals including EMG and electrocardiography (ECG). Their comprehensive analysis encompassed material attributes, manufacturing methodologies, signal enhancement techniques, and device integration. They emphasized the benefits of dry electrodes, which can directly contact with the skin surface for extended periods. They categorized dry electrodes into metal, polymer, textile, and capacitive variants. Additionally, they elucidated the advantages and disadvantages of diverse conductive coatings on textile electrodes and highlighted the challenges and prospective advancements in textile electrode technology.

Research on surface electromyography (sEMG) signals for lower limb exoskeletons has primarily been led by domestic institutions, such as the Harbin Institute of Technology [54], [55] and the University of Electronic Science and Technology [56], [57]. Currently, the integration of EMG signals in lower limb exoskeleton development remains experimental. While countries such as the United States, Germany, Japan, Switzerland, and Singapore have made notable advancement in sEMG signal collection for lower limb applications, domestic endeavors are in their infancy, necessitating comprehensive research on sEMG signal acquisition devices.

2) EMG SIGNAL ACQUISITION MUSCLE SELECTION

Human limb movement is attributed to the coordinated action of the skeletal system, muscular tissues, and joints. Skeletal movement commences with muscular traction, coupled with joint rotation. EMG signals predominantly extract sEMG signals from muscular activities, facilitating the determination of joint angular trajectories, and subsequently enabling the recognition and prediction of human motor intentions. Current investigations have suggested that the muscular components of the human lower limbs constitute a substantial fraction (approximately 76%) [23]. This muscular ensemble is hierarchically classified into distinct groups: hip muscles, thigh muscles, calf muscles, and foot muscles. Muscle density is inherently heterogeneous and affected by factors, including height, weight, activity level, and environmental conditions. When collecting EMG signals, the selection of the optimal muscle area for each individual poses challenges, necessitating the consideration of muscle density, deformability, and inherent inter-individual variations. Conventional electrode patch techniques typically target muscle groups for signal collection, offering a generalized muscle position range for sEMG signal acquisition. This approach hinders precise uniformity in muscle positioning. In the context of lower limb exoskeletons integrated with sEMG signals, the necessity to reposition the signal collection muscle area for each user affects their adaptation curve. Despite this experimental constraint, sEMG signal acquisition for lower limb exoskeletons

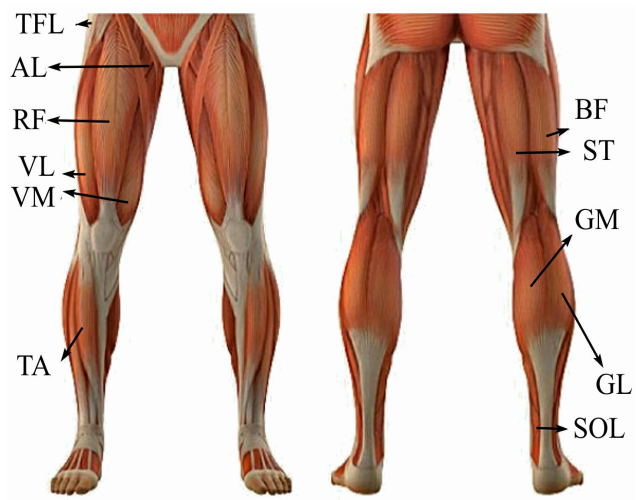

FIGURE 9. Human lower limb muscles.

TABLE 2. sEMG signal acquisition muscle.

Number	Name	Effect	Priority
1	Vastus Medialis, VM	Hip Joint, Knee Joint Flexion/Extension	2
2	Vastus Lateralis, VL		1
3	Biceps Femoris, BF	Hip Joint, Knee Joint Flexion/Extension	1
4	Semitendinosus, ST	Hip Joint Extension	1
5	Adductor Longus, AL	Hip Joint Internal Rotation/External Rotation	2
6	Tnsor Fasciae Latae, TFL	Hip Joint Flexion	2
7	Rectus Femoris, RF	Hip Joint Flexion, Knee Joint Extension	2
8	Tibialis Anterior, TA	Ankle Joint Internal Rotation/External Rotation	1
9	Gastrocnemius Medialis, GM	Ankle Joint Flexion/Extension	2
10	Gastrocnemius Gateralis, GL	Knee Joint Flexion/Extension	2
11	Soleus, SOL	Foot Elevation/Depression	2

typically targets approximately 11 specific muscle positions, as depicted in Figure 9.

Based on experiments by both domestic and international researchers, the optimal prediction of human movement intentions using sEMG signals for fundamental lower limb actions can be achieved by categorizing lower limb muscles into four groups. In most tests, typical human movements include regular walking, stair ascent and descent, uphill and downhill ambulation, squatting, standing, stationary rotation, dynamic turning, and backward stepping. The identified muscles crucial for this purpose include the lateral vastus, biceps femoris, tibialis anterior, and semitendinosus (Table 2). Currently, most studies on muscle selection refer to the following data [55], [58], [59], [60].

To collect data on nonclassical movements, the selection of multiple muscle groups should rely on the muscles involved in different movements, and these muscle groups should be combined and adjusted accordingly. The muscles should not be too close to each other to avoid crosstalk between sEMG signals, which could affect the accuracy of the collected signals. Although some researchers have increased the number of channels to improve accuracy, outstanding results have not yet been achieved [61], [62], [63], [64]. Other studies have compared the interference in different directions or distances, such as along the muscle fiber direction. These studies have primarily demonstrated that capturing precise sEMG signals is easier when the electrodes are parallel to the direction of the muscle fibers, and a larger contact area between the electrode and the muscle results in higher accuracy [65], [66], [67], [68].

3) OTHER INTERFERENCE

When attaching sEMG electrodes to the surface of the human body, various potential problems should be considered, including electrode displacement, the presence of other bioelectric signals, and interference caused by external magnetic fields.

The electrode displacement is a common phenomenon. Traditional methods often involve the attachment of three electrode patches in proximity: one as a reference, devoid of muscle activity, and the remaining two as test electrodes. Such displacement primarily alters the muscle position before and after application, potentially skewing feature distributions and compromising sEMG signal accuracy. Although current technologies can yield accurate sEMG signals using a single electrode patch, this might compromise signal reliability. To address this accuracy issue, a prevalent strategy involves integrating sEMG signals with complementary sensors, such as inertial sensors, to improve the robustness of the model against electrode displacement interference [69], [70]. Stango et al. [71] explored the spatial correlation of sEMG signals across various positions and assessed electrode interference using high-density sEMG sensors, defining a spatial distribution function for the results.

For additional bioelectric signals and magnetic field interference, advancements are currently realized via signal processing during the preprocessing phase of sEMG signals. Modifications tailored to individual variances and muscle fatigue are frequently performed using machine learning and deep learning algorithms. Further insights into interference within non-optimal environments can be obtained from the discourse presented in the study by Ziyu et al. [72].

Given the limited reference cases in China, there is a pressing need to systematically optimize and investigate the conditions in non-ideal environments, where additional potential interference factors may emerge.

In summary, there are few methods for obtaining accurate EMG signals from lower limb exoskeleton products, and the cost-effectiveness of implementing complete EMG signal equipment directly is limited. The utilization of electrode patches requires preparatory efforts, including hair removal and alcohol wiping, with potential long-term issues, such as electrode displacement and body sweat interference. In addition, the choice of muscle groups should be aligned with the specific movements. Current research has focused on three main directions: (1) optimizing EMG signal collection devices for integration into lower limb exoskeletons, exploring alternative collection methods, such as designing textile shorts with embedded electrode patches, developing EMG sportswear, and implementing nanogold technology; (2) determining muscle group selection tailored for distinct movements to mitigate interference factors such as muscle crosstalk; and (3) addressing detachment concerns arising from prolonged use, including data supplementation through the integration of alternative sensors.

B. EMG SIGNAL PRETREATMENT

Drawing on the characteristics of sEMG signals, noise interference from other bioelectric signals or magnetic fields can manifest during the acquisition process. These interferences predominantly consist of the following three categories [73].

(1) Environmental Noise: Electromagnetic radiation noise stemming from extraneous sources, including video, audio, and signal transmissions, arises upon the integration of collection equipment.

(2) Human Body Noise: Bioelectric noise within the human body environment, such as EEG and ECG signals.

(3) Signal Inherent Noise: EMG signals are characterized as stochastic noise, exhibiting subtlety, instability, and vulnerability to interference.

To enhance the signal-to-noise ratio, interventions are required in both hardware and software domains. Given the attenuated characteristics of sEMG signals, amplification and noise mitigation are required. The design of amplification circuits should prioritize the following three aspects.

(1) High Gain: The amplitude of the sEMG signals generally ranges within 10 mV. However, an optimal output signal amplitude is approximately 1 V, mandating the utilization of a high-gain operational amplifier (op-amp).

(2) High Common-Mode Rejection Ratio (CMRR): CMRR is a critical parameter for circuits dedicated to physiological signal acquisition, with the recommended threshold typically exceeding 60 dB [74].

(3) High Impedance: Dynamic acquisition of sEMG signals can result in impedance variations resulting from electrode displacement and deformation. Therefore, a high input impedance is required.

Currently, a prominent method for processing sEMG signals involves the application of wavelet transform. The fast wavelet transform algorithm was introduced by Stephane in 1988 [75]. Given its multiscale nature, wavelet transform is aptly suited for handling nonstationary signals such as sEMG signals. This transform proficiently separates signals from noise, facilitating the extraction of effective sEMG signals, retaining relevant sEMG signals, and mitigating noise interference. Wavelet transform denoising techniques include modulus maxima denoising, correlation denoising, and threshold denoising. Threshold denoising is predominantly employed for sEMG signals. Common methodologies for threshold selection consist of fixed threshold estimation, extremum threshold estimation, unbiased likelihood estimation, and heuristic estimation [76], [77].

Furthermore, most researchers have employed digital filters, such as Butterworth filters [55], Kalman filters, Chebyshev filters, and Causer filters, to augment denoising efficacy and achieve excellent denoising results. Another prevalent technique for denoising bioelectric signals is Empirical Mode Decomposition (EMD). This method decomposes the signal into a sequence of intrinsic mode functions, thereby accomplishing denoising via a selection process. Through the reconstruction of intrinsic functions, noise in sEMG is effectively altered, and filters such as low-pass, band-pass, and high-pass filters can be tailored by manipulating parameter configurations [78], [79]. Enhanced algorithms that amalgamate empirical mode decomposition have also been developed [80]. Within the field of international medical research, the least-mean-square filter has been a prevalent option for sEMG signals. This filter utilizes the sinusoidal amplitude and least-squares technique to reduce interference [81]. Such methodologies are pivotal for optimizing the processing of other bioelectric signals. For instance, to address interference from electrocardiographic signals, Krzyztof et al. [82] introduced a novel algorithm based on raw measurements for muscle activity assessment. Their findings indicated that the proposed electromyographic signal processing technique effectively mitigated electrocardiographic interference without compromising diagnostic integrity.

Considering the nonstationary nature of sEMG signals, segmentation is often necessary. Although manual segmentation proves to be both time-consuming and labor-intensive, the implementation of endpoint detection algorithms can improve the efficiency. Therefore, the topic of sEMG signal endpoint detection remains a focal point in current sEMG signal research [83], [84], [85]. For instance, Bengacemi et al. [86] introduced an adaptive linear energy detector designed to ascertain the onset of a signal by analyzing its fluctuations.

In conjunction with the aforementioned approaches, Negro et al. [87] conducted a comparative analysis of four distinct preprocessing techniques aimed at detecting the common input of motor neuron pools: raw surface electromyograms, corrected surface electromyograms, activity indices, and high-order activity indices. The findings indicated that with a relatively low cut-off frequency of the high-pass filter, the raw surface electromyogram exhibited the highest consistency, followed by the high-order activity index. Nevertheless, in practical scenarios where the cut-off frequency of the high-pass filter tended to be high, the detection of the original sEMG signal became challenging. Additionally, the computational cost of the high-order activity index was comparatively substantial.

TABLE 3. sEMG signal feature analysis.

Name	Function
Time-domain features	Used to describe the basic statistical characteristics and amplitude details of a signal, contributing to the determination of the overall properties of the signal.
Frequency-domain features	Employed to describe characteristics across various frequency components, aiding in the analysis of the signal's spectral distribution.
Time-frequency domain features	Capable of capturing the time-varying characteristics of a signal, proving invaluable in discerning human movement intentions.
Nonlinear features	Encompassing intricate attributes, typically addressed using deep learning and machine learning algorithms to enhance the accuracy of motion recognition.

In summary, for the enhancement of collected signals, it is imperative not only to optimize the collection apparatus, but also to apply specific operations to the signals to guarantee the extraction of pure EMG signals. Although signal processing methodologies are well established, conventional approaches often yield only moderate efficacy. Hence, the development of tailored techniques for EMG signals is essential, considering the challenges posed by interference in sEMG signal acquisition under non-ideal conditions and the intrinsic characteristics of EMG signals.

C. EMG SIGNAL FEATURE CLASSIFICATION

Feature extraction algorithms are designed to extract valuable information from sEMG signals and eliminate redundancy. Currently, the predominant feature analyses for sEMG encompass linear methodologies, namely time-domain analysis, frequency-domain analysis, time-frequency analysis, and nonlinear analysis. The primary objectives of the analyses are presented in Table 3.

Within the realm of sEMG analysis, time-domain and frequency-domain methodologies were established by Phinyomark et al. from Thailand in 2012 [88]. They introduced 37 distinct time-domain and frequency-domain features to investigate the sEMG properties. Their findings indicated that the majority of time-domain features were redundant. Consequently, for optimal selection, emphasis should be placed on select 3–6 feature sets tailored to specific research needs. A comprehensive comparison of time-frequency domain features remains elusive. However, given the intrinsic characteristics of sEMG, analyses within the time-frequency domain can notably enhance the temporal aspect of sEMG. Commonly used methods in this domain include the Short-time Fourier Transform (STFT), Choi-Williams distribution, Wigner-Ville distribution, and Wavelet Transform (WT). Notable time-frequency domain features include spectrograms, approximate entropy, and instantaneous frequency.

Conventional time-domain, frequency-domain, and time-frequency domain features have demonstrated commendable accuracy in recognizing human movements under ideal conditions. In contrast, in real-world nonideal settings, challenges emerge from the impact of individual variations and muscle fatigue on movement recognition precision. Consequently, contemporary research predominantly emphasizes the utilization of deep learning and machine learning algorithms for extracting nonlinear features from sEMG signals, with the objective of enhancing the movement recognition accuracy.

To address individual variations, two primary calibration methodologies have been employed. The first entails referencing specific real-world application scenarios to augment the accuracy in particular environments. For instance, Wei et al. [89] employed Support Vector Machines (SVM) for gait phase recognition based on EMG signals from 10 children with spastic cerebral palsy. Their findings indicated that the SVM's utilization of the average absolute value and zero-crossing feature set of EMG signals in children surpassed other feature sets in recognition accuracy. The second methodology involves devising a training framework or employing transfer learning to mitigate individual disparities. Guo et al. from Shanghai Jiao Tong University [90] formulated an encompassing training structure to address such differences, achieving an impressive accuracy rate of 85% for new participants. Techniques such as domain adaptation and transfer learning further serve to diminish individual discrepancies and bolster generalization accuracy for distinct test subjects. For instance, Chattopadhyay et al. [91] adopted domain adaptation methodologies rooted in low-dimensional space-conserved data, thereby enhancing user similarity and increasing generalization accuracy. Similarly, Ozcan et al. [92] integrated transfer-learning algorithms with the AlexNet model, yielding congruent outcomes across datasets. Additionally, Zhang et al. [93] introduced a bifurcated transfer learning framework that utilized the weak inter-user correlations of sEMG signals in the initial layer to formulate pseudo-labels for novel user data while emphasizing the robust consistency of an individual's actions in the subsequent layer for action recognition.

Muscle fatigue, induced by sustained or atypical muscular exertion, can decrease muscular functionality [94]. Investigating the ramifications of muscle fatigue on sEMG signals constitutes a pivotal research avenue. Although prior investigations have predominantly endeavored to circumvent the influence of muscle fatigue in experimental setups, its inevitability in real-world contexts, especially in the prolonged utilization of sEMG-integrated lower limb exoskeletons, mandates its comprehensive examination. Cifrek et al. from Croatia [95] elucidated that muscle fatigue precipitates a decline in the conduction velocity of sEMG signals. Several methodologies have been delineated to counteract the effects of muscle fatigue, encompassing signal compensation strategies under fatigued conditions and the formulation of muscle fatigue categorization algorithms. For instance, Park et al. [96] in 1993 suggested compensating sEMG signal drift induced by muscle fatigue by converting the power spectrum of fatigued EMG signals to the non-fatigued conditions. Conventional fatigue assessment models have proven inappropriate for classifying sEMG signal fatigue [97]. Consequently, the development of dedicated muscle fatigue classification algorithms tailored to sEMG signals remains imperative. Feng et al. [98] employed deep learning methodologies to devise an F_GRU model for identifying muscle fatigue status. Their findings demonstrated that the F_GRU model surpassed alternative machine learning algorithms in time efficiency, memory utilization, and achieved an impressive accuracy of 98%. A team from the Harbin Institute of Technology, led by Jianfei [99], deployed a muscle fatigue adaptation algorithm to ensure rapid adaptability by generating data encapsulating muscular fatigue scenarios. Edward et al. [100] analyzed sEMG recordings from a cohort of 50 individuals, analyzing muscular electrical activity via spectral correlation, and discerned that escalating fatigue levels corresponded with a marked reduction in both sample entropy and approximate entropy. This underscores the efficacy of spectral correlation techniques in delineating the varying degrees of muscle fatigue. Furthermore, Moniri et al. [101] combined shallow models with deep convolutional neural networks to predict five prevalent sEMG signal attributes, furnishing a holistic model for precise athletic activity predictions. Pravin et al. [102] employed random forest, support vector machine, and logistic regression methodologies with six statistical features extrapolated from filtered signals, confirming the proficiency of machine learning methods in identifying muscle fatigue manifestations within sEMG data. Overall, research on understanding muscle fatigue can be pivotal for refining the fidelity of sEMG signal interpretations in pragmatic contexts.

Classifiers designed for the classification of sEMG signals are primarily tailored to accommodate the intrinsic nonlinear characteristics inherent in such signals. In addition to the previously discussed feature extraction and classification methodologies pertinent to individual variances and muscle fatigue, other nonlinear features should be considered. Table 4 lists the prevalent machine-learning algorithms frequently employed in the realm of EMG signal analysis.

In recent years, as machine learning and deep learning have continuously advanced, researchers have proposed novel algorithms for the feature classification of sEMG signals, validating their performance through experiments. AL-Quraishi et al. [109] from Malaysia conducted research demonstrating a close relationship between the accuracy of pattern recognition techniques and the feature extraction of sEMG signals. Their experiments on ankle joint movement classification achieved an accuracy of 96.20% $\pm$ 4.1. Ao et al. [110] utilized the Hill model to establish a muscle-driven Hill-type neuromusculoskeletal model (HNM) and collected EMG data from eight experimental subjects. They successfully estimated the torque of the ankle joint. Mature results in the upper limbs can guide the development of the lower limbs. For instance, in upper limb exoskeletons, Rajapriya et al. [111] proposed an invariant high-order statistical feature set-frequency domain feature set, which can identify gestures with an accuracy of over 90% in different positions. Conversely, the applicability of this approach in lower limb exoskeleton usage environments remains under investigation. Waris et al. [112] compared five classification techniques, LDA, ANN, SVM, KNN, and TREE, —for hand movements, with ANN demonstrating the best performance, followed by LDA. This provided a reference for the classification of sEMG signals in lower limbs. Furthermore,

TABLE 4. sEMG signal feature classification algorithm.

No	Algorithm Name	Full Name	Self-Advantages	sEMG Advantages
1	ANN [103]	Artificial Neural Network	Strong adaptability of structure	Strong effects in different postures
2	RNN [104]	Recurrent Neural Network	Proficient in dynamic analysis	Handles temporal aspects
3	QDA [103]	Quadratic Discriminant Analysis	Strong ability to handle high-dimensional data	Enhances classification performance
4	SVM	Support Vector Machine	Widely applicable	Simple, accurate, and high confidence
5	KNN [105]	K-Nearest Neighbors	Simple and effective	Strong analysis of small samples
6	EL [106]	Ensemble Learning	Combines outputs of multiple classifiers	Enhances classification performance
7	GA	Genetic Algorithm	Optimizes parameter selection	Enhances classification performance
8	ELM	Extreme Learning Machine	Fast processing speed	Exceptional processing speed
9	RF	Random Forest	Strong ability to handle high-dimensional data	High classification accuracy
10	TREE	Decision Tree	Strong interpretability	Interpretable classification model
11	LDA	Linear Discriminant Analysis	Traditional and classic approach	Low complexity
12	DTL [106]	Decision Tree Learning	Improves classification performance	Enhances classification performance
13	FL [75]	Fuzzy Logic	Suitable for fuzzy classification	Strong performance in specific scenarios
14	GAN [107]	Generative Adversarial Network	Rich experimental data	Reduces individual differences
15	WM-CNN [108]	Wavelet Moment-Convolutional Neural Network	Strong data fusion capabilities	Enhances classification

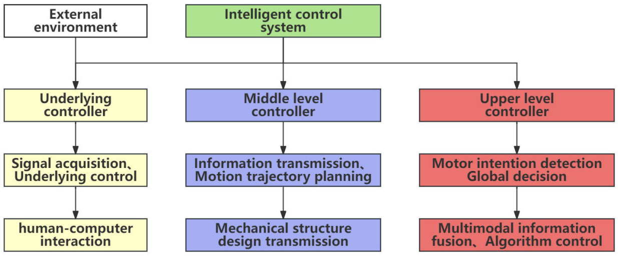

FIGURE 10. **Intelligent control system.**

some researchers have attempted to combine fuzzy learning algorithms, genetic algorithms, and particle swarm optimization algorithms with feature extraction algorithms [113] to seek universal human characteristics. This integration enable exoskeletons to be widely applied in daily life. These evolving classifier methods are crucial for improving the accuracy and practicality of the EMG signal processing. Table 5 summarizes some of the experimental classification accuracies since 2019, which can serve as a reference.

IV. IDENTIFICATION OF HUMAN MOTION INTENTION BASED ON EMG SIGNALS

Tucker et al. [121] classified the exoskeleton control system into three distinct layers from the perspective of a lower limb exoskeleton control system. These layers encompass:

(1) Bottom-Level Control: This layer collects environmental states and human motion data for monitoring and control purposes.

(2) Middle-Level Control: The middle-level controller is responsible for processing the provided information and translating the motion intent into path planning.

(3) Top-Level Control: The top-level controller is designed to recognize and predict the human motion intent.

These three system layers correspond directly to the integration of human-machine interaction, mechanical structure design and transmission, and the amalgamation of multimodal information with algorithmic control, as shown in Figure 10.

The bottom-level controller serves as a pivotal connection of human-machine interactions. It facilitates acquiring human-body information and concurrently directing the machine to execute relevant actions. Given the pronounced nonlinearity and time-variant attributes inherent in human-machine interactions, a singular behavior often emerges from the cumulative responses of numerous components. Conversely, a single component can correspond to multiple behaviors. In such contexts, beyond fulfilling the foundational prerequisites, the apparatus must exhibit resilience. This indicates the necessity for sensors capable of self-adjustment, particularly in instances of unforeseen events, such as collisions or inadvertent user tremors. Such resilience ensures accurate data acquisition, even under challenging conditions. This parallels the adaptive mechanisms observed in human physiology. Within the domain of bottom-level controllers, sensors are expected to exhibit enhanced adaptability and robustness. Typically, machine learning or deep learning methods are employed to perform linear approximations, addressing the intricate nonlinearities intrinsic to human-machine dynamics. Notably, experimental instances in EMG signal processing encompass the segmentation of the exoskeleton's inertia matrix into discernible and uncertain parts, promoting the exoskeleton's self-calibration [122]. In addition, strategies to rectify the EMG signal collection have been devised to optimize the EMG signal acquisition of the exoskeleton [123]. Innovations such as leveraging microelectrodes aim to augment the environmental perception of bottom-level controllers [124]. Moreover, slider controllers have been integrated to mitigate anomalous spasms and involuntary tremors in users, ensuring the sustained calibration functionality of the apparatus [125], [126].

Within the domain of EMG signal processing for lower limb exoskeletons, the conveyance of mid-level EMG signals through electrode patches predominantly includes both wired and wireless modalities. Conventional electrode patches adopt wired transmission methodologies, primarily to optimize costs. Such an approach imposes minimal ramifications on the ultimate fabrication of lower limb exoskeletons, as it necessitates subsequent encapsulation procedures. Wireless transmission integrates technologies, such as Bluetooth and WiFi modules, to facilitate data transfer. Considering potential scenarios characterized by suboptimal network connectivity or constraints on wireless dissemination, the selection of the transmission modality should be judiciously aligned with specific exigencies.

Within the framework of the upper-level controller, techniques for decoding human movement intentions from EMG signals are predominantly divided into model-based and non-model-based methodologies [127]. Model-based strategies necessitate the formulation of a model that delineates the interrelation between the human neuromuscular system and musculoskeletal framework to derive joint torque during movement. Although adept at establishing a robust linkage between EMG signals and joint torque, this approach requires intricate parameter calibration and the precise discernment of physiological parameters. Such prerequisites render its implementation generally intricate and impede subsequent advancements.

Within non-model-based methodologies, machine learning and deep learning algorithms have been employed to establish the relationship between EMG signals and kinematics. The initial techniques encompassed offline action pattern recognition predicted on discerned features within discrete motion classifications. These features underwent labeling and categorization with a predominant voting mechanism adjudicating prospective actions based on the recognized features. Subsequently, thresholds corresponding to specific feature values of EMG signals were set, transforming them into simple direct drivers for action initiation and cessation. Although initial laboratory experiments

TABLE 5. Experimental comparison of EMG.

Year	Muscle selection	signal acquisition	movement	Feature extraction	Classifier	Average classification accuracy (corresponding classifier)
2019 [114]	VL, BF GM, TA	Increase the number of muscle channels from one to four (Accuracy is the accuracy of a single channel) Elliptical bandpass filter	Lift your toes, lift your heels, move your toes to the right, move your toes to the left, lean on your heels, lean on your toes	4 time domain features	SVM (1 channel) SVM (2 channel) SVM (3 channel) SVM (4 channel)	84.0% 79.0% 80.0% 74.0%
2019 [115]	VL, BF RF, ST	Sampling frequency 2048Hz Batwolf of the fourth order	Sit/stand	6 time domain features 5 frequency domain features 4 time-frequency domain features	LDA NB KNN SVM	71.6% 75.1% 87.9% 92.2%
2020 [116]	GM,VL ST	Sampling frequency 2000Hz	Walking, crossing obstacles, standing, going up and down stairs	8 time domain features 2 frequency domain features 1 time-frequency domain feature	MKRVM RF BPNN GK-LDA WNN	87.2% 89.9% 78.2% 91.2% 79.8%
2021 [117]	VL, BF GM, GL TA	Sampling frequency 2000Hz Batwolf of the fourth order Batwolf of the second order	Walk, up and down stairs, up and down hills	3 time domain features 2 frequency domain features	BP	95.16%
2021 [118]	BF, VM RF, ST	Sampling frequency 1000Hz Wavelet Denoising Oversampling	Walk with legs bent up and legs sitting straight	11 time domain features	ID3 CART Bagging GB RF ET SVM MLPNN	76.2% 75.6% 89.2% 87.5% 90.7% 93.1% 81.4% 85.5%
2021 [119]	TA, GM	Sampling frequency 2000Hz Batwolf of the fourth order TKEO	Dorsal foot drive, sole foot drive, valgus, inverted foot	3 time domain features 2 time-frequency domain features	NB DT SVM ANN	84.0% 76.1% 91.3% 94.5%
2022 [120]	RF, VM VL, BF SL, GM GL, TA	Sampling frequency 1000Hz Batwolf of the fourth order Batwolf of the third order Discrete wavelet transform	Walk, run, go up and down stairs, stand to sit, sit to stand, jump	9 time domain features 6 frequency domain features	ConvLSTM KRR RFR SVR BP	92.4% 91.7% 90.6% 91.7% 90.8%

achieved commendable accuracy by leveraging time-domain and frequency-domain features, their applicability remained circumscribed to predetermined actions and contexts. Recent algorithmic innovations have facilitated the categorization of the nonlinear and nonstationary attributes of EMG signals, encompassing multi-degree-of-freedom movements of the lower limb [128], [129]. Scholars have explored real-time decoding of continuous joint angles via machine learning applied to EMG signals, comparing linear regression with other regressors, and providing insights for regressor formulation. Finally, algorithmic recognition requires on-site validation based on pragmatic environments and non-ideal variables, as diverse contexts may require different algorithms. Consequently, the fidelity of the procured EMG signals, efficacy of feature extraction, and accuracy of feature categorization markedly modulate the precision of machine-driven discernment of human movement intentions. Addressing transitional discrepancies, managing confounding factors, and reducing systemic errors are challenging. Therefore, the assessment of EMG signals tailored for lower limb exoskeleton applications has emerged as an important research domain.

In summary, algorithms designed for the high-accuracy extraction and classification of EMG signals exhibit intricacies and have certain response times. Conversely, algorithms with low accuracy suffer from the nuanced differentiation of human movement intentions. The quest for a genuinely precise and efficient EMG signal feature extraction algorithm remains unfulfilled, presenting a challenge in the field. Existing algorithms, when considering factors including individual differences, muscle fatigue, and movement patterns, frequently necessitate intricate algorithms for EMG signal feature extraction. However, in the context of lower limb exoskeletons, there is a pressing need to simplify algorithms to enhance the response speed. Specifically, an algorithm tailored for EMG signals is essential, whereas existing experimental data are insufficient for comprehensive machine learning model training. Currently, reliance primarily relies on transfer learning and data augmentation techniques [130] to accelerate training for new users or, alternatively, on generative adversarial networks for virtual data generation. However, only utilizing transfer learning relies on a large amount of classified data and may hinder further enhancement. Concurrently, maximizing the application of valid electromyographic features from limited datasets as inputs for deep neural networks is paramount for optimizing data exploitation.

In 2023, the ATLAS 2030 [131] version of exoskeleton developed by Armada for children, which can work for 2.5 hours, has achieved relatively good human-computer interaction control. The experiment assisted a child with cerebral palsy for 10 times of rehabilitation treatment assistance, and achieved good therapeutic effect. It is believed that reasonable use of EMG man-machine interactive control will further enhance the possibility of lower limb exoskeleton development.

V. CONCLUSION AND FUTURE OUTLOOK

This review elucidated the advancements and challenges intrinsic to the evolution of lower limb exoskeletons, encompassing the domains of EMG signal acquisition, preprocessing, and the extraction and classification of EMG signals tailored for discerning and prognosticating human motion intentions. Detailed examinations were conducted to explore sources of interference in EMG signals, encompassing aspects such as electrode displacement, biological artifacts, and other extraneous interferences. Concurrently, methodological approaches, including filtering, windowing, and endpoint detection, was analyzed for their efficacy in mitigating these interferences. Collectively, these methodologies provided the foundational framework for precise acquisition and subsequent analysis of EMG signals.

This review subsequently investigated methodologies for feature extraction and classification of EMG signals. Feature extraction in lower limb exoskeletons encompasses time-domain, frequency-domain, time-frequency-domain, and nonlinear features, with classifiers employing feature selection and machine learning techniques for categorization. Current intelligent lower limb exoskeletons exhibit limited human-machine interaction, inadequate sophistication in control systems, and predominant preliminary research across academic and industrial sectors. EMG signals have demonstrated potential in augmenting human-machine interaction, especially with advancements such as multi-data fusion that enhances single-sensor data accuracy and stability. The evolution of textile EMG suits and deep-learning algorithms has propelled market-driven advancements in EMG-based exoskeletons. Collectively, these advancements pave the way for enhanced human-machine interaction and elevated exoskeleton intelligence, as the integration of EMG signals is strengthened across diverse industries.

In 2023, two seminal advancements within the realm of information technology are anticipated to significantly bolster the progression of intelligence in lower limb exoskeletons:

(1) The introduction and enhancement of OPENAI's CHATGPT-4. Certain researchers are directing their efforts towards harnessing AI technology for voice command capabilities in exoskeletons. Concurrently, investigations are underway to incorporate CHATGPT-4 into exoskeleton robotics to minimize the training period for new users. By employing a pipeline model for exoskeleton trajectory planning, this method markedly augments the potential for human-machine interaction.

(2) The introduction of the APPLE's first AR glasses, Vision Pro. This innovation combines reality and virtuality. When coupled with bioinformation such as EMG signals, it holds the potential to enhance sophisticated control systems. In a seminal study conducted in 2012, J. GanceCitz et al. conducted research to maneuver exoskeletons via brain-computer interfaces, adopting VR technology, and integrated electromechanical control methodologies with EEG signals.

Novel advancements in EMG signal development, complemented by the emergence of two pivotal technologies in recent years, inspire consideration for their integration into the pragmatic utilization of EMG signals within lower limb exoskeletons. This encompasses enhancements in the efficacy, processing, and convenience of the EMG signal acquisition. Future consideration may involve the direct integration of CHATGPT-4 training methodologies or the combination of AR glasses with EMG signal assessment to mitigate redundancies in data collection, thereby streamlining tasks. Successfully navigating these challenges is anticipated to contribute to notable progress and innovations in utilizing EMG signals for lower limb exoskeleton applications.

REFERENCES

[1] *Global Report on Health Equity for Persons With Disabilities*, World Health Org., Geneva, Switzerland, 2022.

[2] P. E. Dupont, B. J. Nelson, M. Goldfarb, B. Hannaford, A. Menciassi, M. K. O'Malley, N. Simaan, P. Valdastri, and G.-Z. Yang, "A decade retrospective of medical robotics research from 2010 to 2020," *Sci. Robot.*, vol. 6, no. 60, Nov. 2021, Art. no. eabi8017.

[3] B. R. Fick and J. B. Makinson, "Hardiman I prototype for machine augmentation of human strength and endurance," 1971.

[4] General Electric Co., "Hardiman I prototype project, special interim study," Gen. Electr. Rep. S-68-1060, Schenectady, NY, USA, 1968.

[5] R. Bogue, "Exoskeletons and robotic prosthetics: A review of recent developments," *Ind. Robot, Int. J.*, vol. 36, no. 5, pp. 421–427, Aug. 2009.

[6] E. Guizzo and H. Goldstein, "The rise of the body bots [robotic exoskeletons," *IEEE Spectr.*, vol. 42, no. 10, pp. 50–56, Oct. 2005.

[7] C. Walsh, K. Pasch, and H. Herr, "An autonomous, underactuated exoskeleton for load-carrying augmentation," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, Beijing, China, Oct. 2006, pp. 09–15.

[8] H. Kawamoto and Y. Sankai, "Power assist system HAL-3 for gait disorder person," in *Proc. Int. Conf. Comput. Handicapped Persons*, 2002, pp. 6–9.

[9] G. Zeilig, H. Weingarden, M. Zwecker, I. Dudkiewicz, A. Bloch, and A. Esquenazi, "Safety and tolerance of the ReWalk^{TM} exoskeleton suit for ambulation by people with complete spinal cord injury: A pilot study," *J. Spinal Cord Med.*, vol. 35, no. 2, pp. 96–101, Mar. 2012.

[10] K. H. Low, X. Liu, and H. Yu, "Design and implementation of NTU wearable exoskeleton as an enhancement and assistive device," *Appl. Bionics Biomech.*, vol. 3, no. 3, pp. 209–225, Jan. 2006.

[11] SEEPPO. (2023). *Aload-L Device Piggyback Exoskeleton*. [Online]. Available: https://www.shipengexo.com/productinfo2.html#p2

[12] Fourier Intelligence. (2022). *Fourier Intelligent Lower Limb Rehabilitation Robot Was Selected Into the 'Second Batch of Shanghai Innovative Products Recommended Catalogue in 2022'*. [Online]. Available: https://fftai.cn/zixun/zixun_bk.php?id=630

[13] C. Long and X. Xiuze, "A survey of intelligent control of upper limb rehabilitation exoskeleton," *Robot*, vol. 44, no. 6, pp. 750–768, 2022.

[14] D. Shi, W. Zhang, W. Zhang, and X. Ding, "A review on lower limb rehabilitation exoskeleton robots," *Chin. J. Mech. Eng.*, vol. 32, no. 1, p. 74, Dec. 2019.

[15] D. Pinto-Fernandez, D. Torricelli, M. d. C. Sanchez-Villamanan, F. Aller, K. Mombaur, R. Conti, N. Vitiello, J. C. Moreno, and J. L. Pons, "Performance evaluation of lower limb exoskeletons: A systematic review," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 7, pp. 1573–1583, Jul. 2020.

[16] M. F. Hamza, R. A. R. Ghazilla, B. B. Muhammad, and H. J. Yap, "Balance and stability issues in lower extremity exoskeletons: A systematic review," *Biocybern. Biomed. Eng.*, vol. 40, no. 4, pp. 1666–1679, Oct. 2020.

[17] C. McGibbon, A. Sexton, P. Gryfe, T. Dutta, A. Jayaraman, S. Deems-Dluhy, A. Novak, E. Fabara, C. Adans-Dester, and P. Bonato, "Effect of using of a lower-extremity exoskeleton on disability of people with multiple sclerosis," *Disab. Rehabil., Assistive Technol.*, vol. 18, no. 5, pp. 475–482, Jul. 2023.

[18] J. Lei, *Control Principle and Design of Exoskeleton Robot*. Beijing, China: Tsinghua Univ. Press, 2022.

[19] Y. Li, T. Ren, Y. Chen, J. Zhou, Y. Hu, Z. Wang, W. Sun, and C. Xiong, "Untethered multimode fluidic actuation: A new approach to soft and compliant robotics," *Soft Robot.*, vol. 8, no. 1, pp. 71–84, Feb. 2021.

[20] M. Wehner, B. Quinlivan, P. M. Aubin, E. Martinez-Villalpando, M. Baumann, L. Stirling, K. Holt, R. Wood, and C. Walsh, "A lightweight soft exosuit for gait assistance," in *Proc. IEEE Int. Conf. Robot. Autom.*, Karlsruhe, Germany, May 2013, pp. 3362–3369.

[21] C. Chaofeng, "Design and interactive control strategy of wearable lower limb exoskeleton system," Harbin Inst. Technol., Harbin, China, Tech. Rep., 2020.

[22] A. T. Asbeck, K. Schmidt, I. Galiana, D. Wagner, and C. J. Walsh, "Multi-joint soft exosuit for gait assistance," in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, Seattle, WA, USA, May 2015, pp. 6197–6204.

[23] H. Menno and C. Thomas. *Should You Train Large Muscles Differently Than Small Muscles?* Accessed: Nov. 30, 2023. [Online]. Available: https://mennohenselmans.com/optimal-training-large-small-muscles/

[24] S. Patel, H. Park, P. Bonato, L. Chan, and M. Rodgers, "A review of wearable sensors and systems with application in rehabilitation," *J. NeuroEng. Rehabil.*, vol. 9, no. 1, p. 21, Dec. 2012.

[25] D. Stashuk, "EMG signal decomposition: How can it be accomplished and used?" *J. Electromyogr. Kinesiol.*, vol. 11, no. 3, pp. 151–173, Jun. 2001.

[26] E. Michael and J. E. Hall, *Guyton and Hall Textbook of Medical Physiology*, 1st ed. Amsterdam, The Netherlands: Elsevier, 2020.

[27] J. Ryu, B.-H. Lee, and D.-H. Kim, "SEMG signal-based lower limb human motion detection using a top and slope feature extraction algorithm," *IEEE Signal Process. Lett.*, vol. 24, no. 7, pp. 929–932, Jul. 2017.

[28] Y. Lee and T.-W. Lee, "Organic synapses for neuromorphic electronics: From brain-inspired computing to sensorimotor nervetronics," *Accounts Chem. Res.*, vol. 52, no. 4, pp. 964–974, Apr. 2019.

[29] K. Minassian, U. S. Hofstoetter, F. Dzeladini, P. A. Guertin, and A. Ijspeert, "The human central pattern generator for locomotion: Does it exist and contribute to walking?" *Neuroscientist*, vol. 23, no. 6, pp. 649–663, Dec. 2017.

[30] C. J. De Luca, "Surface electromyography: Detection and recording," DelSys Incorporated, Tech. Rep., 2002, pp. 1–10.

[31] K. Veer and T. Sharma, "A novel feature extraction for robust EMG pattern recognition," *J. Med. Eng. Technol.*, vol. 40, pp. 149–154, Jul. 2016.

[32] J. E. Muscolino, *Kinesiology: The Skeletal System and Muscle Function*, 3rd ed. Philadelphia, PA, USA: Mosby, 2016.

[33] D. A. Neumann, *Kinesiology of the Musculoskeletal System Foundations for Rehabilitation*, 3rd ed. Philadelphia, PA, USA: Mosby, 2016.

[34] J. C. Nickel, L. R. Iwasaki, Y. M. Gonzalez, L. M. Gallo, and H. Yao, "Mechanobehavior and ontogenesis of the temporomandibular joint," *J. Dental Res.*, vol. 97, no. 11, pp. 1185–1192, Oct. 2018.

[35] S. Jacob, M. Alagirisamy, V. G. Menon, B. M. Kumar, N. Z. Jhanjhi, V. Ponnusamy, P. G. Shynu, and V. Balasubramanian, "An adaptive and flexible brain energized full body exoskeleton with IoT edge for assisting the paralyzed patients," *IEEE Access*, vol. 8, pp. 100721–100731, 2020.

[36] Y. Nam, B. Koo, A. Cichocki, and S. Choi, "GOM-face: GKP, EOG, and EMG-based multimodal interface with application to humanoid robot control," *IEEE Trans. Biomed. Eng.*, vol. 61, no. 2, pp. 453–462, Feb. 2014.

[37] A. M. Grabowski and S. D'Andrea, "Effects of a powered ankle-foot prosthesis on kinetic loading of the unaffected leg during level-ground walking," *J. NeuroEng. Rehabil.*, vol. 10, no. 1, p. 49, 2013.

[38] C. Fleischer and G. Hommel, "A human-exoskeleton interface utilizing electromyography," *IEEE Trans. Robot.*, vol. 24, no. 4, pp. 872–882, Aug. 2008.

[39] C. Fleischer, C. Reinicke, and G. Hommel, "Predicting the intended motion with EMG signals for an exoskeleton orthosis controller," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, Edmonton, AB, Canada, Apr. 2005.

[40] S. Salminger, A. Sturma, C. Hofer, M. Evangelista, M. Perrin, K. D. Bergmeister, A. D. Roche, T. Hasenoehrl, H. Dietl, D. Farina, and O. C. Aszmann, "Long-term implant of intramuscular sensors and nerve transfers for wireless control of robotic arms in above-elbow amputees," *Sci. Robot.*, vol. 4, no. 32, Jul. 2019, Art. no. eaaw6306.

[41] P. Laferriere, E. D. Lemaire, and A. D. C. Chan, "Surface electromyographic signals using dry electrodes," *IEEE Trans. Instrum. Meas.*, vol. 60, no. 10, pp. 3259–3268, Oct. 2011.

[42] J. W. Y. Kam, S. Griffin, A. Shen, S. Patel, H. Hinrichs, H.-J. Heinze, L. Y. Deouell, and R. T. Knight, "Systematic comparison between a wireless EEG system with dry electrodes and a wired EEG system with wet electrodes," *NeuroImage*, vol. 184, pp. 119–129, Jan. 2019.

[43] DELSYS. *Trigno Research System*. Accessed: Nov. 30, 2023. [Online]. Available: https://delsys.com/trigno-emg/

[44] Otbioelettronica. *Quattrocento*. Accessed: Nov. 30, 2023. [Online]. Available: https://otbioelettronica.it/negozio/

[45] R. T. Yi. (Nov. 2, 2023). *What You Don't Know About Muscle Science: Surface Electromyography Acquisition and Scientific Application 2022*. sEMG Res. Inst. [Online]. Available: https://www.sohu.com/a/556727765_121367846

[46] P. Fang, X. Ma, X. Li, X. Qiu, R. Gerhard, X. Zhang, and G. Li, "Fabrication, structure characterization, and performance testing of piezoelectret-film sensors for recording body motion," *IEEE Sensors J.*, vol. 18, no. 1, pp. 401–412, Jan. 2018.

[47] S. L. Colyer and P. M. McGuigan, "Textile electrodes embedded in clothing: A practical alternative to traditional surface electromyography when assessing muscle excitation during functional movements," *J. Sports Sci. Med.*, vol. 17, pp. 101–109, Dec. 2018.

[48] S. Desmarais and M. Giess, "Athos wearable technology: A comparison study," Senior thesis, Univ. South Carolina, Columbia, SC, USA, 2017.

[49] S. K. Lynn, C. M. Watkins, M. A. Wong, K. Balfany, and D. F. Feeney, "Validity and reliability of surface electromyography measurements from a wearable athlete performance system," *J. Sports Sci. Med.*, vol. 17, pp. 205–215, Jun. 2018.

[50] K. Schmidt, J. E. Duarte, M. Grimmer, A. Sancho-Puchades, H. Wei, C. S. Easthope, and R. Riener, "The myosuit: Bi-articular anti-gravity exosuit that reduces hip extensor activity in sitting transfers," *Frontiers Neurorobot.*, vol. 11, p. 57, Oct. 2017.

[51] V. Bartenbach, K. Schmidt, M. Naef, D. Wyss, and R. Riener, "Concept of a soft exosuit for the support of leg function in rehabilitation," in *Proc. IEEE Int. Conf. Rehabil. Robot. (ICORR)*, Singapore, Aug. 2015, pp. 125–130.

[52] H. Pingao, "Research on the key technology of sensing and recognizing motion intention of intelligent lower limb prosthesis," Shenzhen Inst. Adv. Technol., Shenzhen, China, Tech. Rep., 2020.

[53] C. M. Vidhya, Y. Maithani, and J. P. Singh, "Recent advances and challenges in textile electrodes for wearable biopotential signal monitoring: A comprehensive review," *Biosensors*, vol. 13, no. 7, p. 679, Jun. 2023.

[54] Y. Chunzhi, G. Hao, and D. Zhen, "Research progress of lower-limb exoskeleton and joint kinematics calculation," *CAAI Trans. Intell. Syst.*, vol. 13, pp. 878–888, Feb. 2018.

[55] G. Hao, "Research on perception and prediction of human lower limb motion intention based on EMG," Harbin Inst. Technol., Harbin, China, Tech. Rep., 2020.

[56] K. Tong, "Human motion intention recognition based on surface myography," Univ. Electron. Sci. Technol. China, Chengdu, China, Tech. Rep., 2022.

[57] X. Xiang, "Study on acquisition and processing of surface EMG signal based on flexible electrode," Univ. Electron. Sci. Technol. China, Chengdu, China, Tech. Rep., 2018.

[58] L. J. Hargrove, K. Englehart, and B. Hudgins, "A comparison of surface and intramuscular myoelectric signal classification," *IEEE Trans. Biomed. Eng.*, vol. 54, no. 5, pp. 847–853, May 2007.

[59] T. A. Trappe, N. A. Burd, E. S. Louis, G. A. Lee, and S. W. Trappe, "Influence of concurrent exercise or nutrition countermeasures on thigh and calf muscle size and function during 60 days of bed rest in women," *Acta Physiologica*, vol. 191, no. 2, pp. 147–159, Oct. 2007.

[60] M. B. Lanza, L. T. Lacerda, H. C. Martins-Costa, R. C. Diniz, M. H. Chagas, and F. V. Lima, "Normalization of the electromyography amplitude during a multiple-set resistance training protocol: Reliability and differences between approaches," *J. Electromyogr. Kinesiol.*, vol. 68, Feb. 2023, Art. no. 102724.

[61] G. Purushothaman and R. Vikas, "Identification of a feature selection based pattern recognition scheme for finger movement recognition from multichannel EMG signals," *Australas. Phys. Eng. Sci. Med.*, vol. 41, no. 2, pp. 549–559, Jun. 2018.

[62] N. Li, L. Zhou, W. Li, Y. Liu, J. Wang, and P. He, "Protective effects of ginsenosides Rg1 and Rb1 on an Alzheimer's disease mouse model: A metabolomics study," *J. Chromatography B*, vol. 985, pp. 54–61, Mar. 2015.

[63] J. D. Miller, M. S. Beazer, and M. E. Hahn, "Myoelectric walking mode classification for transtibial amputees," *IEEE Trans. Biomed. Eng.*, vol. 60, no. 10, pp. 2745–2750, Oct. 2013.

[64] E. Ceseracciu, M. Reggiani, Z. Sawacha, M. Sartori, F. Spolaor, C. Cobelli, and E. Pagello, "SVM classification of locomotion modes using surface electromyography for applications in rehabilitation robotics," in *Proc. 19th Int. Symp. Robot Human Interact. Commun.*, Viareggio, Italy, Sep. 2010, pp. 165–170.

[65] A. J. Young, L. J. Hargrove, and T. A. Kuiken, "The effects of electrode size and orientation on the sensitivity of myoelectric pattern recognition systems to electrode shift," *IEEE Trans. Biomed. Eng.*, vol. 58, no. 9, pp. 2537–2544, Sep. 2011.

[66] J. He, X. Sheng, X. Zhu, and N. Jiang, "Electrode density affects the robustness of myoelectric pattern recognition system with and without electrode shift," *IEEE J. Biomed. Health Informat.*, vol. 23, no. 1, pp. 156–163, Jan. 2019.

[67] J. He and X. Zhu, "Combining improved gray-level co-occurrence matrix with high density grid for myoelectric control robustness to electrode shift," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 25, no. 9, pp. 1539–1548, Sep. 2017.

[68] J. Feng, Y. Xunfeng, and Y. Chunzhi, "A review of the research and application of calculating joint torque by electromyography signals," *CAAI Trans. Intell. Syst.*, vol. 15, no. 2, pp. 193–203, 2020.

[69] A. Fougner, E. Scheme, A. D. C. Chan, K. Englehart, and Ø. Stavdahl, "A multi-modal approach for hand motion classification using surface EMG and accelerometers," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Aug. 2011, pp. 4247–4250.

[70] N. M. López, F. di Sciascio, C. M. Soria, and M. E. Valentinuzzi, "Robust EMG sensing system based on data fusion for myoelectric control of a robotic arm," *Biomed. Eng. OnLine*, vol. 8, no. 1, p. 5, 2009.

[71] A. Stango, F. Negro, and D. Farina, "Spatial correlation of high density EMG signals provides features robust to electrode number and shift in pattern recognition for myocontrol," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 23, no. 2, pp. 189–198, Mar. 2015.

[72] L. Zi-You, Z. Xin-Gang, Z. Bi, D. Qi-Chuan, Z. Dao-Hui, and H. Jian-Da, "Review of sEMG-based motion intent recognition methods in non-ideal conditions," *Acta Autom. Sinica*, vol. 47, no. 5, pp. 955–969, 2021.

[73] G. Yang and N. Li, "Design of the human surface electromyogra signal acquisition system and signal analysis," in *Proc. 7th Asia Int. Symp. Mechatronics*, vol. 589, B. Duan, K. Umeda, and W. Hwang, Eds. Singapore: Springer, 2020, pp. 915–926.

[74] E. J. Perreault, I. W. Hunter, and R. E. Kearney, "Quantitative analysis of four EMG amplifiers," *J. Biomed. Eng.*, vol. 15, no. 5, pp. 413–419, Sep. 1993.

[75] S. J. Lehmler, M. Saif-Ur-Rehman, T. Glasmachers, and I. Iossifidis, "Deep transfer-learning for patient specific model re-calibration: Application to sEMG-classification," *J. Neural Eng.*, vol. 9, no. 5, pp. 1–12, 2022.

[76] X. Zheng, W. Chen, and B. Cui, "Multi-gradient surface electromyography (SEMG) movement feature recognition based on wavelet packet analysis and support vector machine (SVM)," in *Proc. 5th Int. Conf. Bioinf. Biomed. Eng.*, Wuhan, China, May 2011, pp. 1–4.

[77] G. L. Chen, G. X. Wang, and G. Q. Liu, "EMG signal de-noising based on wavelet packet μ rhythm threshold method," *Appl. Mech. Mater.*, vol. 394, pp. 560–565, Sep. 2013.

[78] A. O. Andrade, S. Nasuto, P. Kyberd, C. M. Sweeney-Reed, and F. R. Van Kanijn, "EMG signal filtering based on empirical mode decomposition," *Biomed. Signal Process. Control*, vol. 1, no. 1, pp. 44–55, Jan. 2006.

[79] K.-M. Chang, "Arrhythmia ECG noise reduction by ensemble empirical mode decomposition," *Sensors*, vol. 10, no. 6, pp. 6063–6080, Jun. 2010.

[80] Q. Wu, C. Xi, L. Ding, C. Wei, H. Ren, R. Law, H. Dong, and X. L. Li, "Classification of EMG signals by BFA-optimized GSVCM for diagnosis of fatigue status," *IEEE Trans. Autom. Sci. Eng.*, vol. 14, no. 2, pp. 915–930, Apr. 2017.

[81] T. K. C. Piotr, L. Grzegorz, and K. Marcin, "The use of sinusoidal magnitude averaging with the least squares method to reduce interference and to implement control algorithms," *Prz. Elektrotech.*, vol. 92, pp. 141–145, Jan. 2016.

[82] K. Strzecha, M. Krakós, B. Więcek, P. Chudzik, K. Tatar, G. Lisowski, V. Mosorov, and D. Sankowski, "Processing of EMG signals with high impact of power line and cardiac interferences," *Appl. Sci.*, vol. 11, no. 10, p. 4625, May 2021.

[83] M. Wang, X. Wang, C. Peng, S. Zhang, Z. Fan, and Z. Liu, "Research on EMG segmentation algorithm and walking analysis based on signal envelope and integral electrical signal," *Photonic Netw. Commun.*, vol. 37, no. 2, pp. 195–203, Apr. 2019.

[84] L. Shi, Z. Liu, and Q. Wang, "A novel method of sEMG signal segmentation," in *Proc. IEEE 9th Int. Conf. Mobile Ad-Hoc Sensor Netw.*, Dalian, China, Dec. 2013, pp. 515–520.

[85] L. Lin, W. Jianhui, and D. Liang, "An improved method for sEMG segmentation," in *Proc. 24th Chin. Control Decis. Conf. (CCDC)*, Taiyuan, China, May 2012, pp. 1308–1311.

[86] H. Bengacemi, A. Mesloub, A. Ouldali, and K. Abed-Meraim, "Adaptive linear energy detector based on onset and offset electromyography activity detection," in *Proc. 6th Int. Conf. Syst. Control (ICSC)*, Batna, Algeria, May 2017, pp. 409–413.

[87] R. Istenic, F. Negro, A. Holobar, D. Zazula, and D. Farina, "Surface EMG pre-processing techniques for the detection of common input to motor neuron populations," in *Proc. 6th Int. Conf. Biomed. Eng. Informat.*, Hangzhou, China, Dec. 2013, pp. 256–259.

[88] A. Phinyomark, P. Phukpattaranont, and C. Limsakul, "Feature reduction and selection for EMG signal classification," *Expert Syst. Appl.*, vol. 39, no. 8, pp. 7420–7431, Jun. 2012.

[89] P.-N. Wei, R. Xie, R. Tang, C. Li, J. Kim, and M. Wu, "SEMG based gait phase recognition for children with spastic cerebral palsy," *Ann. Biomed. Eng.*, vol. 47, no. 1, pp. 223–230, Jan. 2019.

[90] W. Guo, X. Sheng, J. Liu, L. Hua, D. Zhang, and X. Zhu, "Towards zero training for myoelectric control based on a wearable wireless sEMG armband," in *Proc. IEEE Int. Conf. Adv. Intell. Mechatronics (AIM)*, Jul. 2015, pp. 196–201.

[91] R. Chattopadhyay, N. C. Krishnan, and S. Panchanathan, "Topology preserving domain adaptation for addressing subject based variability in SEMG signal," in *Proc. AAAI Spring Symp. Ser.*, 2011.

[92] T. Ozcan and A. Basturk, "Transfer learning-based convolutional neural networks with heuristic optimization for hand gesture recognition," *Neural Comput. Appl.*, vol. 31, no. 12, pp. 8955–8970, Dec. 2019.

[93] Y. Zhang, Y. Chen, H. Yu, X. Yang, and W. Lu, "Dual layer transfer learning for sEMG-based user-independent gesture recognition," *Pers. Ubiquitous Comput.*, vol. 26, no. 3, pp. 575–586, Jun. 2022.

[94] R. M. Enoka and J. Duchateau, "Muscle fatigue: What, why and how it influences muscle function," *J. Physiol.*, vol. 586, no. 1, pp. 11–23, Jan. 2008.

[95] M. Cifrek, V. Medved, S. Tonković, and S. Ostojić, "Surface EMG based muscle fatigue evaluation in biomechanics," *Clin. Biomechanics*, vol. 24, no. 4, pp. 327–340, May 2009.

[96] E. Park and S. G. Meek, "Fatigue compensation of the electromyographic signal for prosthetic control and force estimation," *IEEE Trans. Biomed. Eng.*, vol. 40, no. 10, pp. 1019–1023, Jul. 1993.

[97] S. Chand, A. McDaid, and Y. Lu, "Dynamic muscle fatigue assessment using s-EMG technology towards human–centric human–robot collaboration," *J. Manuf. Syst.*, vol. 68, pp. 508–522, Jun. 2023.

[98] Z. Feng, Y. Wang, and L. Liu, "Muscle fatigue detection method based on feature extraction and deep learning," in *Proc. 7th Int. Conf. Intell. Comput. Signal Process. (ICSP)*, Xi'an, China, Apr. 2022, pp. 97–100.

[99] Z. Jianfei, "Muscle fatigue adaptation of EMG gait phase recognition algorithm," Harbin Inst. Technol., Harbin, China, Tech. Rep., 2022.

[100] S. E. Jero and S. Ramakrishnan, "Order frequency spectral correlation based cyclo-nonstationary analysis of surface EMG signals in biceps brachii muscles," in *Proc. 41st Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Jul. 2019, pp. 7165–7168.

[101] A. Moniri, D. Terracina, J. Rodriguez-Manzano, P. H. Strutton, and P. Georgiou, ''Real-time forecasting of sEMG features for trunk muscle fatigue using machine learning,'' *IEEE Trans. Biomed. Eng.*, vol. 68, no. 2, pp. 718–727, Feb. 2021.
[102] D. V. Pravin, A. J. Ragavkumar, S. Abinesh, and G. Kavitha, ''Extraction, processing and analysis of surface electromyogram signal and detection of muscle fatigue using machine learning methods,'' in *Proc. Int. Conf. Bio Signals, Images, Instrum. (ICBSII)*, Chennai, India, Mar. 2023, pp. 16–17.
[103] N. Miljković and M. S. Isaković, ''Effect of the sEMG electrode (re)placement and feature set size on the hand movement recognition,'' *Biomed. Signal Process. Control*, vol. 64, Feb. 2021, Art. no. 102292.
[104] R. B. Azhiri, M. Esmaeili, and M. Nourani, ''Real-time EMG signal classification via recurrent neural networks,'' in *Proc. IEEE Int. Conf. Bioinf. Biomed. (BIBM)*, Houston, TX, USA, Dec. 2021, pp. 2628–2635.
[105] G. Guo, H. Wang, D. Bell, Y. Bi, and K. Greer, ''KNN model-based approach in classification,'' in *On The Move To Meaningful Internet Systems 2003: CoopIS, DOA, and ODBASE*, R. Meersman, Z. Tari, and D. C. Schmidt, Eds. Berlin, Germany: Springer, 2003, pp. 986–996.
[106] R. E. Schapire, ''The boosting approach to machine learning: An overview,'' in *Nonlinear Estimation and Classification*, vol. 171, D. D. Denison, M. H. Hansen, C. C. Holmes, B. Mallick, and B. Yu, Eds. New York, NY, USA: Springer, 2003, pp. 149–171.
[107] W. Sun, J.-W. Lin, S.-F. Su, N. Wang, and M. J. Er, ''Reduced adaptive fuzzy decoupling control for lower limb exoskeleton,'' *IEEE Trans. Cybern.*, vol. 51, no. 3, pp. 1099–1109, Mar. 2021.
[108] Z. Qing, Y. Liu, J. He, C. Hao, S. Teng, S. Zhang, and D. Fan, ''Wavelet-based multi-branch convolutional neural network for cross-individual ALS disease identification with EMG signal,'' in *Proc. IEEE Int. Conf. Bioinf. Biomed. (BIBM)*, Houston, TX, USA, Dec. 2021, pp. 1481–1484.
[109] M. S. Al-Quraishi, A. J. Ishak, S. A. Ahmad, and M. K. Hasan, ''Impact of feature extraction techniques on classification accuracy for EMG based ankle joint movements,'' in *Proc. 10th Asian Control Conf. (ASCC)*, Kota Kinabalu, Sabah, May 2015, pp. 1–5.
[110] D. Ao, R. Song, and J. Gao, ''Movement performance of human–robot cooperation control based on EMG-driven hill-type and proportional models for an ankle power-assist exoskeleton robot,'' *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 25, no. 8, pp. 1125–1134, Aug. 2017.
[111] R. Rajapriya, K. Rajeswari, and S. J. Thiruvengadam, ''Deep learning and machine learning techniques to improve hand movement classification in myoelectric control system,'' *Biocybern. Biomed. Eng.*, vol. 41, no. 2, pp. 554–571, Apr. 2021.
[112] A. Waris, I. K. Niazi, M. Jamil, K. Englehart, W. Jensen, and E. N. Kamavuako, ''Multiday evaluation of techniques for EMG-based classification of hand motions,'' *IEEE J. Biomed. Health Informat.*, vol. 23, no. 4, pp. 1526–1534, Jul. 2019.
[113] Y. Hua, J. Fan, G. Liu, X. Zhang, M. Lai, M. Li, T. Zheng, G. Zhang, J. Zhao, and Y. Zhu, ''A novel weight-bearing lower limb exoskeleton based on motion intention prediction and locomotion state identification,'' *IEEE Access*, vol. 7, pp. 37620–37638, 2019.
[114] D. Toledo-Pérez, M. Martínez-Prado, R. Gómez-Loenzo, W. Paredes-García, and J. Rodríguez-Reséndiz, ''A study of movement classification of the lower limb based on up to 4-EMG channels,'' *Electronics*, vol. 8, no. 3, p. 259, Feb. 2019.
[115] I. S. Dhindsa, R. Agarwal, and H. S. Ryait, ''Performance evaluation of various classifiers for predicting knee angle from electromyography signals,'' *Expert Syst.*, vol. 36, no. 3, p. e12381, Jun. 2019.
[116] P. Qin and X. Shi, ''Evaluation of feature extraction and classification for lower limb motion based on sEMG signal,'' *Entropy*, vol. 22, no. 8, p. 852, Jul. 2020.
[117] J. Wang, Y. Dai, T. Kang, and X. Si, ''Research on gait recognition based on lower limb EMG signal,'' in *Proc. IEEE Int. Conf. Mechatronics Autom. (ICMA)*, Takamatsu, Japan, Aug. 2021, pp. 212–217.
[118] A. Vijayvargiya, C. Prakash, R. Kumar, S. Bansal, and J. M. R. S. Tavares, ''Human knee abnormality detection from imbalanced sEMG data,'' *Biomed. Signal Process. Control*, vol. 66, Apr. 2021, Art. no. 102406.
[119] C. Zhou, L. Yang, H. Liao, B. Liang, and X. Ye, ''Ankle foot motion recognition based on wireless wearable sEMG and acceleration sensors for smart AFO,'' *Sens. Actuators A, Phys.*, vol. 331, Nov. 2021, Art. no. 113025.
[120] Y. Lu, H. Wang, B. Zhou, C. Wei, and S. Xu, ''Continuous and simultaneous estimation of lower limb multi-joint angles from sEMG signals based on stacked convolutional and LSTM models,'' *Expert Syst. Appl.*, vol. 203, Oct. 2022, Art. no. 117340.
[121] M. R. Tucker, J. Olivier, A. Pagel, H. Bleuler, M. Bouri, O. Lambercy, J. D. R. Millán, R. Riener, H. Vallery, and R. Gassert, ''Control strategies for active lower extremity prosthetics and orthotics: A review,'' *J. NeuroEng. Rehabil.*, vol. 12, no. 1, p. 1, 2015.
[122] Y. Zhao, C. Liang, Z. Gu, Y. Zheng, and Q. Wu, ''A new design scheme for intelligent upper limb rehabilitation training robot,'' *Int. J. Environ. Res. Public Health*, vol. 17, no. 8, p. 2948, Apr. 2020.
[123] J. Navallas, A. Eciolaza, C. Mariscal, A. Malanda, and J. Rodrágues-Falces, ''EMG probability density function: A new way to look at EMG signal filling from single motor unit potential to full interference pattern,'' *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 31, pp. 1188–1198, 2023.
[124] W. Yingying, ''Research on information acquisition and feedback methods for reconstruction of motor sensory function in amputees,'' Univ. Chin. Acad. Sci., Shenzhen, China, Tech. Rep., 2022.
[125] S. J. Gambhire, D. R. Kishore, P. S. Londhe, and S. N. Pawar, ''Review of sliding mode based control techniques for control system applications,'' *Int. J. Dyn. Control*, vol. 9, no. 1, pp. 363–378, Mar. 2021.
[126] H. K. Kristensen, J. Præstegaard, and C. Ytterberg, ''Discourses in stroke rehabilitation as they present themselves in current physiotherapy and occupational therapy,'' *Disability Rehabil.*, vol. 39, no. 3, pp. 223–235, Jan. 2017.
[127] Y. Chunzhi, ''Research on the key technology of human motion intention perception for lower limb exoskeleton robot,'' Harbin Inst. Technol., Harbin, China, Tech. Rep., 2022.
[128] J. A. Brantley, T. P. Luu, S. Nakagome, and J. L. Contreras-Vidal, ''Prediction of lower-limb joint kinematics from surface EMG during overground locomotion,'' in *Proc. IEEE Int. Conf. Syst., Man, Cybern. (SMC)*, Banff, AB, Canada, Oct. 2017, pp. 1705–1709.
[129] A. W. Shehata, E. J. Scheme, and J. W. Sensinger, ''Evaluating internal model strength and performance of myoelectric prosthesis control strategies,'' *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 26, no. 5, pp. 1046–1055, May 2018.
[130] W. Yang, D. Yang, J. Li, Y. Liu, and H. Liu, ''EMG dataset augmentation approaches for improving the multi-DOF wrist movement regression accuracy and robustness,'' in *Proc. IEEE Int. Conf. Robot. Biomimetics (ROBIO)*, Kuala Lumpur, Malaysia, Dec. 2018, pp. 1268–1273.
[131] C. Cumplido-Trasmonte, J. Ramos-Rojas, E. Delgado-Castillejo, E. Garcés-Castellote, G. Puyuelo-Quintana, M. A. Destarac-Eguizabal, E. Barquín-Santos, A. Plaza-Flores, M. Hernández-Melero, A. Gutiérrez-Ayala, M. Martínez-Moreno, and E. García-Armada, ''Effects of ATLAS 2030 gait exoskeleton on strength and range of motion in children with spinal muscular atrophy II: A case series,'' *J. NeuroEng. Rehabil.*, vol. 19, no. 1, p. 75, Dec. 2022.

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