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Review

Electromyography Monitoring Systems in Rehabilitation: A Review of Clinical Applications, Wearable Devices and Signal Acquisition Methodologies

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Abstract: Recently, there has been an evolution toward a science-supported medicine, which uses replicable results from comprehensive studies to assist clinical decision-making. Reliable techniques are required to improve the consistency and replicability of studies assessing the effectiveness of clinical guidelines, mostly in muscular and therapeutic healthcare. In scientific research, surface electromyography (sEMG) is prevalent but underutilized as a valuable tool for physical medicine and rehabilitation. Other electrophysiological signals (e.g., from electrocardiogram (ECG), electroencephalogram (EEG), and needle EMG) are regularly monitored by medical specialists; nevertheless, the sEMG technique has not yet been effectively implemented in practical medical settings. However, sEMG has considerable clinical promise in evaluating muscle condition and operation; nevertheless, precise data extraction requires the definition of the procedures for tracking and interpreting sEMG and understanding the fundamental biophysics. This review is centered around the application of sEMG in rehabilitation and health monitoring systems, evaluating their technical specifications, including wearability. At first, this study examines methods and systems for tele-rehabilitation applications (i.e., neuromuscular, post-stroke, and sports) based on detecting EMG signals. Then, the fundamentals of EMG signal processing techniques and architectures commonly used to acquire and elaborate EMG signals are discussed. Afterward, a comprehensive and updated survey of wearable devices for sEMG detection, both reported in the scientific literature and on the market, is provided, mainly applied in rehabilitation training and physiological tracking. Discussions and comparisons about the examined solutions are presented to emphasize how rehabilitation professionals can reap the aid of neurobiological detection systems and identify perspectives in this field. These analyses contribute to identifying the key requirements of the next generation of wearable or portable sEMG devices employed in the healthcare field.

Keywords: electromyography; EMG instrumentation; tele-rehabilitation; signal processing

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1. Introduction

Electromyography (EMG) is a neuro-muscular assessment method that involves detecting, monitoring, and evaluating biopotentials produced by motor units inside a muscular tissue during voluntary or involuntary actions. Two approaches may be identified based on the receiving sensor typology: intramuscular and superficial electromyography (sEMG) [1,2]. This enables the effective study of particular muscle activation, and has thus found several uses in medical investigations such as orthopedics, surgical procedures, nervous system studies, and gait and postural assessment [3–7]. EMG is also applied in risk prevention and ergonomic designs [8–11]. Sport-specific EMGs may provide a convenient point-of-care diagnostic test and a tool to improve sports performance [12]. Athletes use EMG to avoid muscular damage during performance evaluations [13]. sEMG can be utilized to develop muscle fatigue measurements in pre- and post-surgery monitoring and rehabilitation [14]. In recent years, EMG has grown in prominence for physical rehabilitation [15]; it also provides quantitative information on the muscle's myoelectric output and is widely used in neurorehabilitation research [16–18].

Surface electromyography allows recording of entire muscular biopotential signals from several muscle groups, evaluating the functional condition of a muscular area rather than simply a single motor unit [19]. The surface approach uses the characteristic of large-scale electrical conductivity, which eliminates the influence of electrode proximity from the signal source on its form and character [20]. This approach enables the use of non-invasive electrodes, removing the pain and risk of monitoring. Surface electromyography detects and monitors the biopotentials generated when a neurological or electrochemical stimulus triggers muscle fibers. The responses include data on muscle activation, tone, and exhaustion, as well as recruitment and synchronization patterns [17,21–23]. EMG permits a more reliable interpretation of electrical events in the innervated muscles thanks to many years of study and continuous improvement of EMG signal recording technologies in detection and processing [24,25]. Simultaneously, a rapid technical growth of sEMG equipment has been observed, enabling more and more new chances to use this technology in various domains of medicine, predominantly in rehabilitation. For instance, identifying frames from sEMG data uses Gradient Boosted Regression Tree ensembles to predict wrist and finger kinematics, or novel algorithms to identify low-level hand movement by categorizing a single channel sEMG signal [26–30]. The rising use of sEMG in rehabilitation and physiotherapy, in the research field and clinical setting, suggests the need to present its applications, particularly in physiotherapy, where sEMG is commonly employed as a diagnostic and treatment tool [31–33].

Our review aims to provide an informative evaluation of the clinical applications of sEMG in rehabilitation and therapy by looking at the most current clinical applications of sEMG in rehabilitation and physiotherapy during the last decade. This paper comprises experimental studies and gives a summary of the treatment techniques employed and the findings and conclusions of the research listed. At first, an overview of methods and systems to acquire EMG signals suitable for tele-rehabilitation applications are discussed; then, the characteristics of EMG signals are introduced, along with the most common techniques and instruments to detect and process them. Afterward, an overview of EMG portable and wearable devices presented in the scientific literature is reported, and several commercial EMG wearable devices are reviewed. For both device categories, we focused on compact, unobtrusive, and wireless devices allowing simple and accurate detection of EMG signals and the derived parameters, such as amplitude and spectral parameters, time delay, correlation dimension, sample entropy, as well as RQA (Recurrence Quantification Analysis) parameters. The hardware and firmware of the described wearable devices were examined to reveal their strengths and limitations. Comparisons are provided in each section in order to outline the requirements of the next generation of EMG detection systems. The main strength of the presented paper is represented by the extensive reviews of the scientific literature, but above all, of commercial devices that are not analyzed in other similar scientific works. Comparative analyses are a strength of the presented work, enabling the reader to understand future perspectives of EMG sensors.

The main contributions of the presented review work are:

- A complete overview of methods and systems to acquire and analyze EMG signals for tele-rehabilitation applications. In detail, the discussion considers the main applications involving the EMG signals, such as neuromuscular rehabilitation, post-stroke rehabilitation, and sports rehabilitation.

- A detailed discussion about the signal processing techniques for EMG signals, as well as fundamentals about the structure and characteristics of the EMG signals, are provided, along with details on the architectures of EMG acquisition systems.
- A comprehensive and updated scientific literature survey about portable and wearable systems to monitor EMG signals applied to rehabilitation purposes. Comparative analyses are provided for determining the desirable features for the next generation of wearable EMG detectors.
- An up-to-date review of commercial wearable EMG detectors used for rehabilitation applications, and reporting comparative analysis to bring out their main requirements.

The remainder of the article is arranged as follows. Section 2 presents an overview of the main methodologies and systems to detect EMG signals applied to tele-rehabilitation applications. Section 3 discusses the main characteristics and processing techniques for EMG signals. Section 4 reports a survey of EMG portable and wearable devices. Finally, Section 5 reviews commercially available EMG sensors, as well as related comparative analyses are presented.

2. EMG Methods and Systems Applied to Tele-Rehabilitation Applications

The past decade has seen an emergence of advanced tele-medicine applications utilizing devices and computer technology [34]. As a relatively new and rapidly expanding field, tele-rehabilitation remains one of the most important applications. The benefit of tele-rehabilitation is that it reduces the cost both for healthcare organizations and patients compared to conventional inpatient rehabilitation or a face-to-face approach. Patients living in remote places can also benefit from tele-rehabilitation, which enables them to receive therapy remotely. Tele-rehabilitation has primarily been applied to physiotherapy [35]. It often takes the form of tele-monitoring, essentially efficient monitoring of physiological parameters in patients with chronic diseases, such as cardiovascular disease and oxygen levels [36]. Tele-rehabilitation enhanced treatment program versatility and eliminated the requirement for patients to go to sessions personally [37–39]. Additionally, patients with disabilities have reported physical and functional improvements [40–42].

Therapist-patient relationships developed through tele-rehabilitation were as good as those formed through in-person sessions [38,43]. Physiotherapy combined with telerehabilitation is an effective treatment option for musculoskeletal problems and physical illnesses. Furthermore, it helps healthcare professionals create a personalized physical training program for physical rehabilitation, improving patients' posture and mobility [44]. The examination and monitoring of neuromuscular problems are required in the rehabilitation sector to establish treatment aimed at developing and strengthening proper motor and sensory contractions. By acquiring these EMG signals, processing, and interpreting them, a powerful rehab tool for patients with severe impairments is obtained. Amplitude, timing, morphology, and spectral features of muscle activation can be expressed in various ways.

Numerous studies have been conducted internationally in the context of the COVID-19 epidemic to investigate the usage and feasibility of tele-rehabilitation, with differing data [41,45–47]. Persons with respiratory problems, for instance, embraced the online provisions and had better therapeutic results [45]. Similarly, despite some technical hurdles, persons saw tele-rehabilitation as practical and accepted it. Those persons noted disparities in service quality and favored traditional in-person therapy over tele-rehabilitation treatment [46]. Another study, on the contrary hand, discovered no statistically significant changes in patient satisfaction among patients who received in-person physical therapy compared to a patient who received remote physical therapy [47].

The possible clinical uses of sEMG sensors in rehabilitation medicine are described in the following sections, with an emphasis on (i) neuromuscular rehabilitation, (ii) stroke rehabilitation, and (iii) athletic rehabilitation.

2.1. EMG Applied to Neuromuscular Rehabilitation

An efficient rehabilitation process can restore some motor functions of damaged limbs in neurorehabilitation medicine and is an important aspect of clinical research [48]. Physicians need to assess their patients' physical and physiological health to determine if the exercise has an influence and, ultimately, to modify their follow-up rehabilitation program. The ability to identify impairments in the physician's clinical evaluation is aided by functional changes based on muscle activation data. With the ability to measure the muscle activation by EMG signals, electrodiagnostic medicine has become increasingly relevant and useful in neurorehabilitation, especially over the past four decades [49,50]. In [19], sEMG techniques are proposed to be utilized in neurorehabilitation. Firstly, the authors examine the use of EMG in neurological rehabilitation for assessing and treating muscle spasticity. This is due to EMG's capability to evaluate the changes caused by these abnormalities. The authors discuss a limited number of clinical applications. Manca et al. have conducted another study concerning surface electromyography utilization in neurorehabilitation [51]. In their study, they collected information regarding:

(i) sEMG's present applications and therapeutic effects;
(ii) professionals mainly concerned with sEMG;
(iii) academic aspects;
(iv) potential impediments and explanations for its seeming limited utilization in neurorehabilitation.

Different researchers in this field have proposed and discussed different aspects of sEMG use in neurorehabilitation, including the most recently developed applications, the educational, methodological, and technical characteristics, the possibilities of translation into clinical practice, and the possible benefits for patients and clinicians of this technique.

Neuro-rehabilitation employs surface EMG signals for (i) tracking neuro-muscular diseases, (ii) the avoidance of risks and disorders associated with the workplace, and (iii) observation and assessment of neuro-muscular state and healing progress in acutely ill patients. Valuable information regarding muscular activation patterns during motion and effort can assist clinicians in evaluating and providing a clinical assessment of both disability and functional changes [52–54]. Moreover, EMG and EEG (electro-encephalography) signals can be acquired through biosignal amplifiers to enhance the functionality of devices and systems used in brain-computer interface (BCI) applications. EEG and EMG can be used to predict the patient's imminent movements. It is not unusual to combine EEG and EMG in BCI applications to either predict as many movements as possible or to improve the prediction accuracy [55].

2.2. EMG Applied to Post-Stroke Rehabilitation

Among adults worldwide, stroke is a major cause of chronic disabilities [56]. Many stroke survivors suffer from hemiplegia, which hinders their ability to walk. Therefore, the rehabilitation of stroke patients is important to regain their motor coordination, muscle strength, and motor control [57]. From this point of view, exercises that enhance muscle activity and neuromuscular control are considered effective in motor rehabilitation [58]. EMG-based methods can help detect residual electro-muscular activity and, thus, assist in controlling exoskeletons, during the post-stroke period, for patients who can't generate enough torque for their joints [59]. Controlled neuromuscular electrical stimulation (NMES) in conjunction with electromyography has produced the best results for patients with stroke in clinical trials [60]. Accordingly, a systematic review was proposed by Monte-Silva et al. [61] about how EMG-NMES improves upper limb recovery following stroke. Another important study is provided by Hameed et al. [62]. The researchers show how assistive robotic devices can help patients with hand impairments perform everyday tasks and regain their ability to use their hands. In particular, they demonstrate that sEMG can control hand robotic devices, such as gloves and exoskeletons, for hand function recovery and enhancement.

Additionally, the researchers in [63] examined the possibility of EMG signals to detect the intention of hand or wrist extension movements, consequently triggering robot-assisted training. They present a comparison between detecting movement intention by an EMG sensor and a BCI using EEG sensorimotor rhythms. They concluded that therapy based on EMG devices has a legitimate and feasible approach to initiating robot-assisted training with a simpler interface and smaller dimensions than EEG-BCI systems.

2.3. EMG Applied to Sports Rehabilitation

Surface EMG is useful for assessing the status of skeletal muscles, which is important for muscular rehabilitation and physical exercises. Sport and rehabilitation scientists are increasingly using surface EMG as a research tool. The EMG is beneficial in the rehabilitation of athletes because it can be used to diagnose muscle impairment, detect incorrect muscle activation patterns, and evaluate treatment outcomes [12,64–66]. A better understanding of how to perform their tasks safely helps them avoid damage, since athletes need the proper usage of muscles and rapid detection of abnormal muscle patterns. sEMG's dynamic study of muscles is extremely useful in sports, notably for injury prevention [67–69]. For example, the measurement of the sEMG signal might develop the enactment of the exercise by assessing muscle activity and/or fatigue [70,71]. Fatigue analysis in the triceps brachii is an essential use of EMG in athletic rehabilitation. Based on sEMG, Hussain et al. [72] present an intriguing review of fatigue analysis in the human triceps brachii. Other contributions include post-operative rehabilitation when it is required for patients who have undergone rotator cuff surgery [73,74], and the study of particular muscle tissue interactions with external stimulation such as deoxygenation and exercise [12,75]. Trainers, coaches, and athletes can better understand the day-to-day need of athletes using wearable biosensors [76–78]. In [79], the author employed smart wearable sensing electronics and IoT technologies to create a sports rehabilitative tracking system. Sensors in this system collect and monitor biopotential signals, mobility orientation, skin temperature, and other vital signs. The experimental results reveal that the system can accurately monitor physiological parameter variations while providing immediate input and analysis. Additionally, the physiological data collected may be examined to assist clinicians in developing successful rehabilitation training regimens that provide extra features of the wearable system for EMG capture and processing to measure athlete performance. A proposed sEMG method has been tested by the authors in [80] regarding the capability to precisely and reliably determine muscle-firing waveforms during the isokinetic assessment of knee joint extensors and flexors.

3. EMG Signal Processing: General Considerations

The human physical activities produced by muscles, such as continuously pumping blood from the heart, are commanded and controlled by the brain. This gives rise to three primary bioelectrical signals: EMG, ECG (Electrocardiogram), and EEG. Detection, processing, and interpretation of these vital signs have been well documented in the literature [81–86] (Figure 1).

During limb motion, related skeletal muscles are neurologically stimulated and produce contraction, thereby generating action potentials that are picked up to form EMG signals [70,85]. As a result, EMG measurement has become an effective and widely used procedure in rehabilitation and management, as well as in monitoring physical activity and evaluating of muscle diseases. A well-designed electromyograph is used to capture high-quality EMG signals, and it is critical to ensure proper signal processing and EMG feature extraction [87].

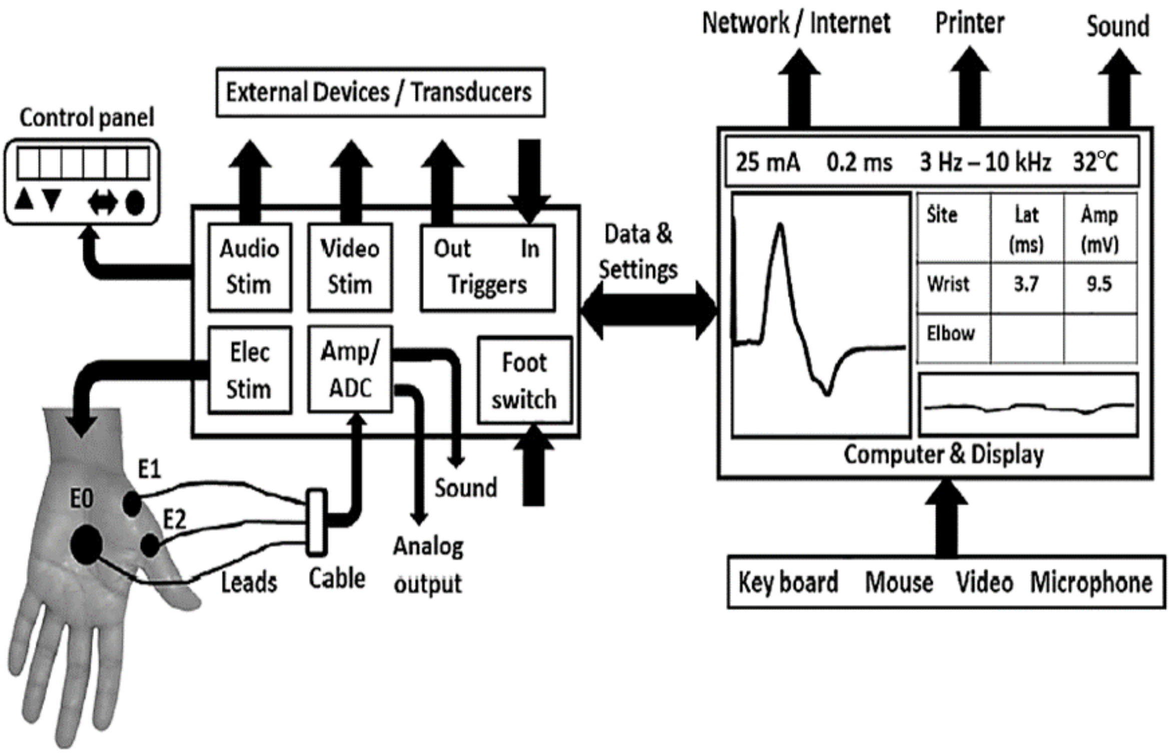

Figure 1. Schematic of generalized biopotential measurement (main components) [87] (Reproduced with permission from [87], Elsevier, 2020).

3.1. EMG Signal Characteristics

EMG is an electrodiagnostic medical technique for evaluating and recording the muscular electrical signal produced by skeletal muscle movements [88]. The EMG signal represents neuromuscular activity by measuring electrical currents produced in muscles during contraction [89]. As a result, an EMG provides valuable information on muscle health and the function of motor neurons that carry electrical impulses to muscle fibers and allow them to contract. EMG signals have a frequency range of 20 to approximately 2000 Hz and an amplitude of roughly 50 µV to 20 mV [90]. The biomechanics of human skeletal muscles or activity levels may be monitored and studied using the features analysis of EMG signals, which can provide body muscular activity information such as fitness, weariness, and stamina level, as well as a gesture. Muscle functioning during different levels of physical activities may provide important information about disability and functional changes [91]. EMG is employed in rehabilitative medicine, human-machine interface design, biomedical research, and various other applications, such as prostheses, as shown in Figure 2 [92,93].

EMG is used for physiological investigations, neurological disease monitoring, therapy planning, intervention evaluation, and control of prostheses and robotics [94]. Surface or internal electrodes are the two types of electrodes used in electromyography. Surface electrodes are used to track a muscle's overall activity, whereas nerve electrodes are used to disclose the electrical activity of a neuron. EMG signals show the status of limb muscle activity, representing skeletal muscle movement and nervous system control information, and are extremely valuable in stroke rehabilitation programs [91]. EMG signals may be used to identify and distinguish various limb movements, assisting in identifying and researching limb motions and their features [52]. Particularly, sEMG offers a non-invasive and thorough measurement of muscle activity that might be useful in movement analysis applications that need frequent evaluations or information on the activation patterns of various muscles [95]. Surface EMG, for example, might be a useful technique for quantifying progress and evaluating treatment results in sports, rehabilitation, and clinical assessment [96]. Surface EMG is typically done on bigger, superficial muscles that are easily accessible. The surface EMG approach captures data on the amount of excitation from a broad region, which may comprise several distinct motor unit populations. Despite its widespread application and ease of implementation, surface EMG has disadvantages. For example, recording selectively from extremely deep muscles is not viable. In addition, cross-talk, an error source resulting from the vast pick-up region of the electrodes, may result in the recording of erroneous signals from deep muscles. Cross-talk must be handled carefully when analyzing an EMG signal, and can produce erroneous results. Techniques to limit cross-talk include strategically positioning electrodes on the surface, employing electrodes of the appropriate size, and maintaining a safe spacing between them. Because electrodes close to the innervation zone or tendon region may generate significant signal amplitude variation, it is essential to position them in the proper locations on the surface. During contractions, the movement of the muscle beneath the skin and the electrodes may also significantly impact the surface EMG signal [97,98]. Ag-AgCl electrodes are usually employed sEMG, including a conductive gel to reduce the impedance between the skin and electrode surface [87].

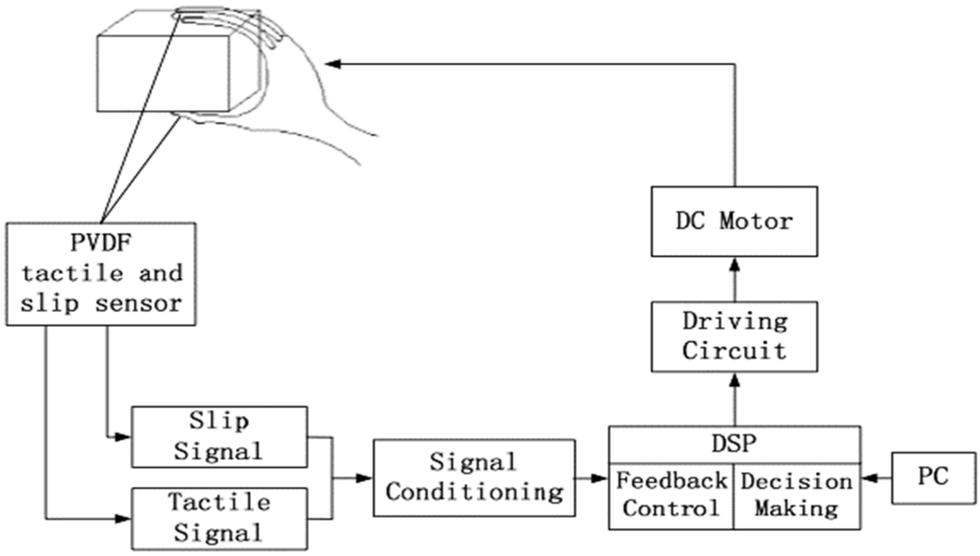

Figure 2. Schematic of the prosthetic hand control system presented in [93] (Reproduced with permission from [93], IEEE, 2012).

Internal EMG electrodes are rarely utilized due to their invasive nature. This technique is generally applied to evaluate deep muscles and those with a narrow cross-section. Unlike the implantation of surface electrodes, the insertion of electrodes requires particular knowledge and time. Thus, a professional operator (e.g., a neurologist, physiatrist, or physiotherapist) must place the electrode and monitor the muscle's activity. Intramuscular EMG is superior to surface EMG because it can detect a specific muscle's EMG signals under static and dynamic conditions with low interference. Two types of electrodes are common in internal EMG: a monopolar needle, constituted by a tip that acts as single electrodes, and the concentric needle, constituted by an inner core (active electrodes) inside an outer cannula as a reference electrode. In some circumstances, intramuscular EMG can be considered unneeded or excessively intrusive. The signal acquired from each electrode provides a very local representation of the muscle's activity. Since skeletal muscle inner structures vary, different locations must be considered to obtain a reliable analysis. Surface electromyographic signals are less spatially selective than intramuscular recordings due to the tissues' low-pass filtering impact on the sources (muscle fibers) and recording electrodes [99,100].

3.2. EMG Instrumentation

Similar to every biopotential signal, sEMG signals are nondeterministic, noisy, and complex; they also have small amplitudes and a frequency range. As a result, their acquisition is complicated. Noise from the electronic acquisition equipment, skin-electrode interface, and power lines all contribute to background noise. Therefore, a well-designed system is needed to enhance the acquisition and analysis of EMG signals. Such acquisition systems comprise electrodes, pre-processing stages (preamplifiers and filters), amplifiers, analog-to-digital conversions, power supply sections, and wireless transmission modules [101] (Figure 3).

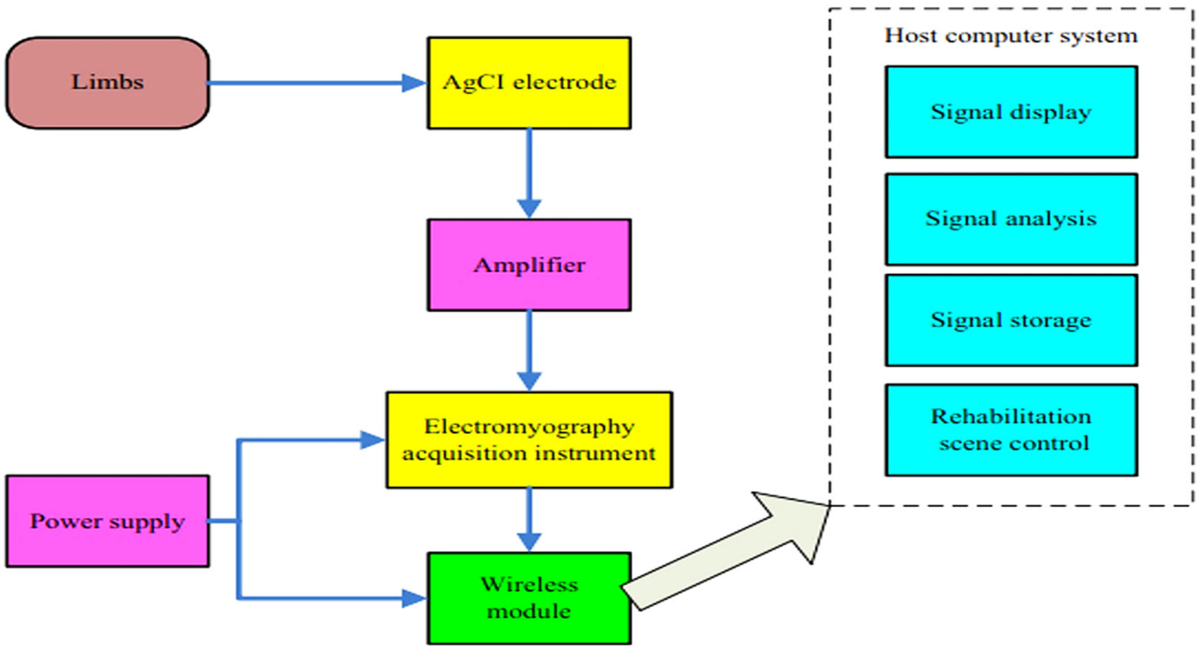

Figure 3. Flowchart of electromyography acquisition system [101] (Reproduced with permission from [101], Springer Nature, 2019).

The amplification stage aims to increase the level of the differential signal between the electrodes while rejecting unwanted common noise. Then, the resulting signal is filtered and digitized with an analog-to-digital converter (ADC) for further analysis. In addition, the signal acquisition can occur in two different ways: the monopolar mode measures the differential voltage between an active electrode and an electrode-secluded marker located outside of a phasing region, whereas the bipolar mode measures the differential voltage between two electrodes. Furthermore, the system's wireless transmission module allows data to be collected, analyzed, displayed, and stored via an external PC. Furthermore, this module is essential to achieving a portable form of rehabilitation training.

The acquired EMG signal carries a wide range of desired and undesired information based on the surroundings, physiological, and instrumentation noise conditions. In particular, a pre-processing module composed of a low-pass and high-pass filter is necessary to remove the baseline and main frequency components from the EMG signal [102], and 50/60 Hz rejection, implemented with a notch filter, removes the harmonic noise generated by the power lines. The low-frequency cutoff of high-pass filters must be precisely defined because it is considered the main reason for the initial loss of amplitude in signals that change slowly, waveform misrepresentation, reducing the time to peak value, and originating artifacts [87]. A low-pass filter and high-frequency cutoff must also be o chosen to avoid reducing the amplitude and rise time of the informative component. After conditioning and processing steps, the EMG signal should be sent to a suitable data acquisition system to acquire, analyze, and/or store data. A digital value is assigned to the amplitude of the signal at predefined time points by a converter that discretizes the signal time and amplitude. This procedure is required to perform further signal analysis for clinical diagnosis and research purposes.

In general, the EMG acquisition stage should meet the following substantial specifications [103]:

- Accuracy: many electronic elements, such as differential amplifiers, ADC converters, and others, are subject to intrinsic noise. The target is to minimize the noise in each element so that accuracy may be achieved.
- Sensitivity: pertains to the analog to digital resolution and, therefore, the total resolution of the device. This helps the medical staff control readings.
- CMRR: which stands for Common-Mode Rejection Ratio, and indicates the ability of a differential amplifier to reject signals common to both inputs. A high CMRR is essential in preventing 50–60 Hz power line interference.
- Input impedance: its compatibility is important in the selection of differential amplifiers and applications relative to the skin type and electrode interface.
- Input range: this specification applies to circuitry and the analog to digital converter, defining the range of EMG signal that can be amplified without saturating the amplifier. To acquire the complete signal, a greater input range is desired, but this necessitates an increase in signal resolution.
- SNR: signal-to-noise ratio measures the power of the desired signal relative to background noise.

4. EMG Portable Devices for Rehabilitation

Rehabilitation involves assessments and specialized training, but healthcare centers' limited resources often make this process challenging. For this reason, wearable technology represents a valid and important solution for objectively assessing and monitoring patients inside and outside of clinical environments. Using this technology, more detailed information about the impairment can be determined, allowing rehabilitation therapies to be identified [104]. The portability, low cost, and unobtrusiveness of wearable devices make this technology highly effective in tracking movements to improve neurologic or musculoskeletal care. As an added benefit, these sensors allow the evaluation of motor behavior, which is useful in compensatory motor recovery mechanisms, remote monitoring, and tele-rehabilitation [105–107].

Electrical biosignals can gauge the health and fitness conditions of the human body. In real-time e-health monitoring systems, biosignals such as ECG, EMG, and EEG are captured and analyzed to extract relevant and useful information for observation, diagnosis, and treatment [108].

As shown in Figure 4, these systems are generally configured as follows. The EEG, ECG, and EMG signals are extracted using electrodes placed on the subject and are acquired and processed by sensor devices connected to proper monitoring equipment. These systems generally have problems with slow data acquisition and transmission speeds, poor energy consumption, and cumbersome form factors that restrict their versatility.

Wearable devices monitor activity through two main processes: (i) acquiring, pre-processing, and managing data, and (ii) analyzing, classifying, and transmitting the data. Amplification and filtering are examples of signal pre-processing, while signal analysis comprises methods such as pooling or extracting crucial features used as a classifier test dataset (Figure 5) [54,109].

Smart sensors are often used in wearable devices to detect and monitor a collection of physiological characteristics to maintain a constant watch for the sake of diagnosis, treatment, and regulation [110]. The aging population's requirement for healthcare administration requires wearable medicinal products to collect individual health data promptly. During muscle exercises, electrical signal fluctuations create ECG and EMG, which are significant and widely used measures in healthcare management and rehabilitation regimens.

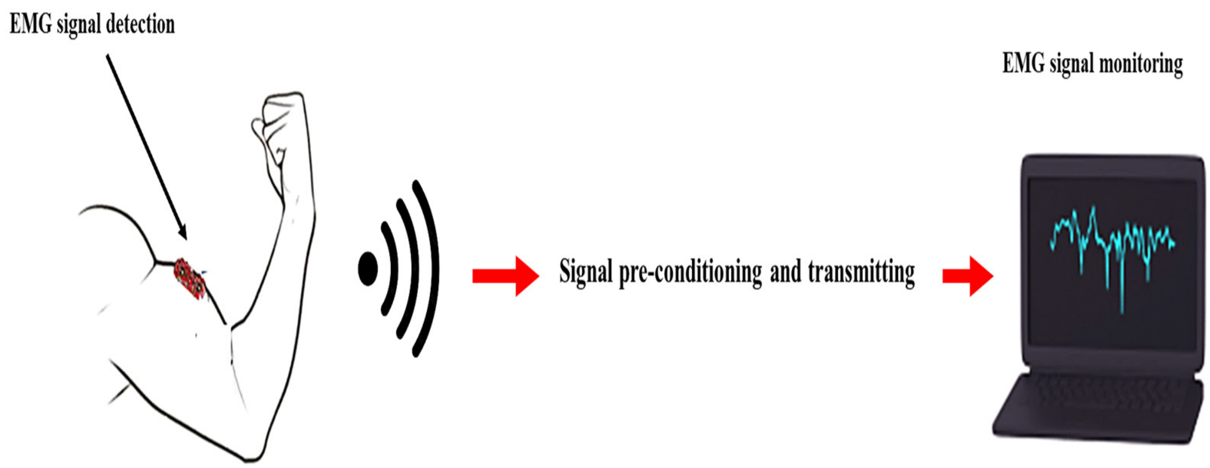

Figure 4. EMG monitoring system structure.

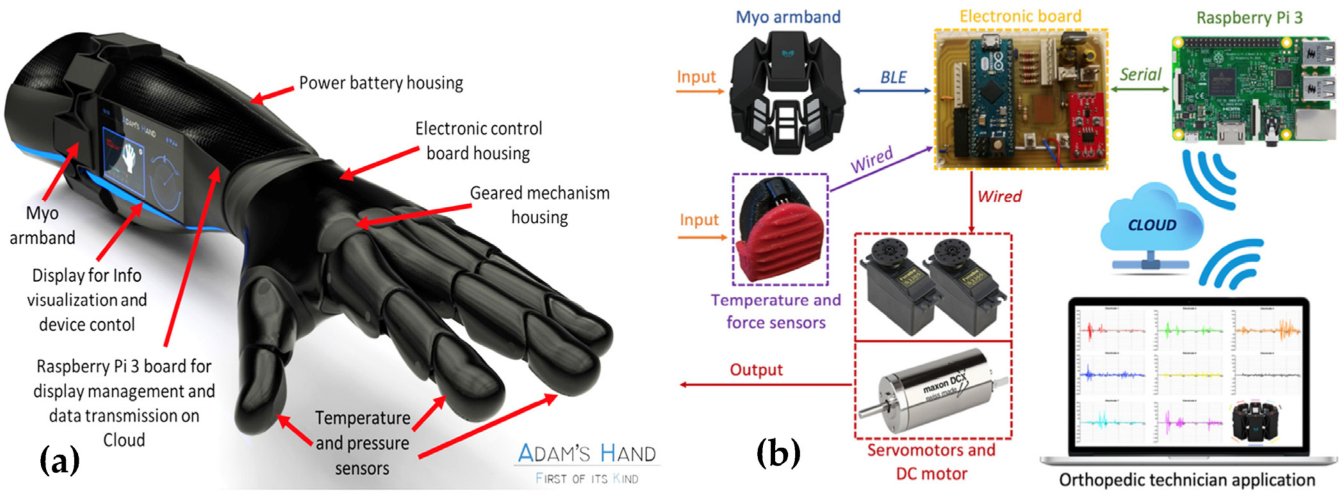

Figure 5. Transradial prosthesis based on the Myo wireless myoelectric armband proposed in [54]: (**a**) Adam's Hand prosthesis with its main embedded mechanical and electronical modules; (**b**) functional scheme of the employed electronic modules and related web application (Web-source: https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/iet-smt.2018.5108, every aspect related to the human subjects' involvement has been taken into consideration by the authors in [54]) (Reproduced with permission from [54], John Wiley and Sons, 2019).

Zhao et al. presented a wearable device for upper limb rehabilitation [110], i.e., a robotic glove for assistance training that acquires EMG and ECG signals. In detail, these signals were acquired, pre-processed, digitalized, and transmitted through a Bluetooth Low-Energy (BLE) module to a remote receiver. Furthermore, a software platform for data processing was created by combining several instructions to show the captured electrophysiological data and reveal interest patterns. The EMG and ECG sensors, respectively, detect hand movements and changes related to these movements in a subject's physiological condition. The findings demonstrate that monitoring ECG and EMG signals can help the patient enhance upper limb improvement based on the treatment settings and needs of the users. In this work, wet electrodes were employed for detecting EMG, which can induce a change of contact impedance with the skin due to gel drying [111].

In [112], the authors present a wireless device to acquire and monitor physiological signals (i.e., ECG, EMG, PPG, and body acceleration). The system consists primarily of a portable device, a graphical user interface (GUI), and a software application for presenting the data on a computer or intelligent device. This system has eight measurement channels, a powerful microcontroller unit, a lithium battery, Bluetooth 3.0 data transfer, and a 2 GB integrated flash memory. The results suggest that the developed device can help clinicians and scientists collect required physiological signals, exploiting its ability to acquire real-time data.

Similarly, in [113], the authors present a real-time and remote-control IoT system based on EMG and inertial signals. Using the Myo-band on an arm, a user may remotely manage domestic utilities (lights, room heaters, air-conditioners, ventilators, etc.) through eight gestures (Figure 6). The IoT system comprises four parts: sensing devices, gateway, cloud servers, and smart devices. The Myo armband collects EMG signals and motion-related inertial data, forwarding them via Bluetooth toward the gateway (Intel UPS-GWS01), which filters and extracts information from data and sends them to the cloud server. For managing electrical appliances and establishing a wireless connection to the home gateway, ESP8266 was employed. The tests demonstrated that the proposed system could achieve high accuracies, such as 100% for basic gestures and 90% for challenging ones.

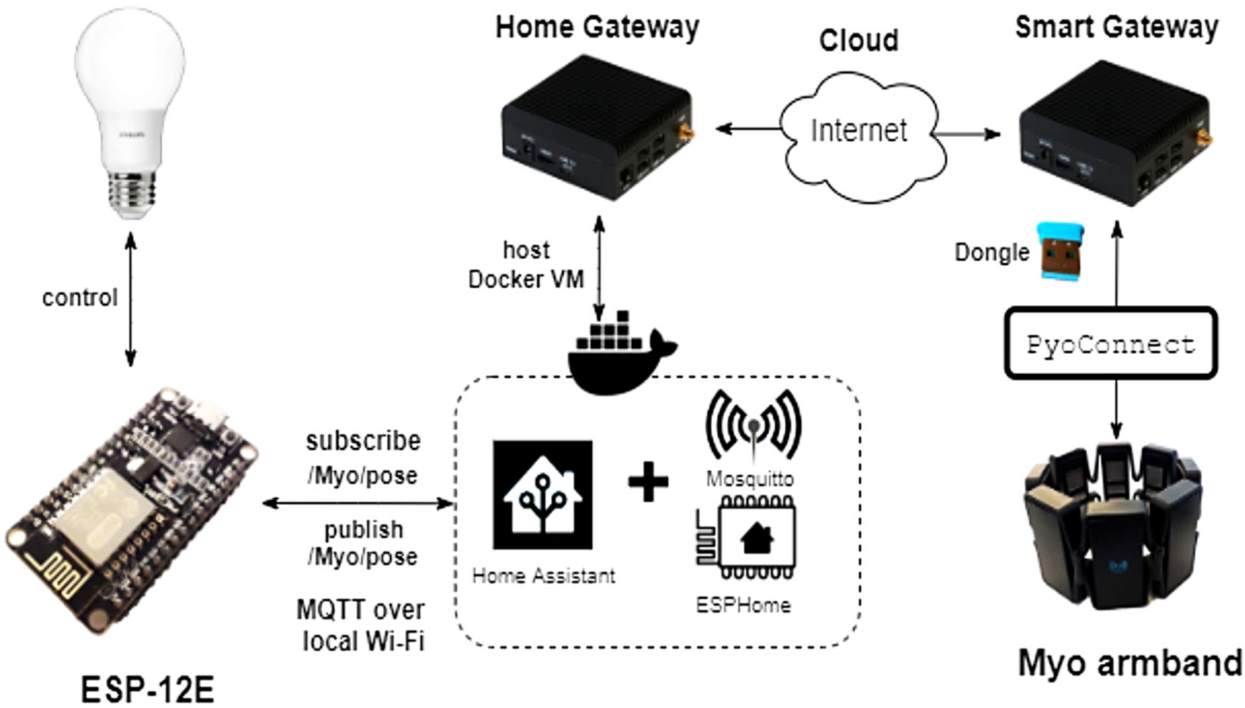

Figure 6. Architecture of the EMG-based control system proposed in [113] (Reproduced with permission from [113], IEEE, 2021).

System latency linked to the internet network load could be a problem, heavily influencing the performance of the developed system.

Park et al. present an energy-efficient integrated circuit using a 128-channel Δ-modulated $\Delta\Sigma$ analog front-end (Δ-$\Delta\Sigma$ AFE) for 1024-channel neural recording microsystems [114]. Platform components include eight multi-shank neural probes connected to individual AFEs (analog front-ends) based on a modular architecture using 128 channels (Figure 7). A spectrum equalization scheme was implemented to reduce the amount of area and energy consumed, taking advantage of the inherent spectral properties of neural signals (the bulk of the energy is found in the low frequencies). Δ-$\Delta\Sigma$ AFEs were designed to obtain the following features: the single-channel AFEs consume 3.05 W at 0.5 and 1.0 V from an area of 0.05 mm^2 with a 63.8-dB signal-to-noise-and-distortion ratio and a 3.02 noise efficiency factor.

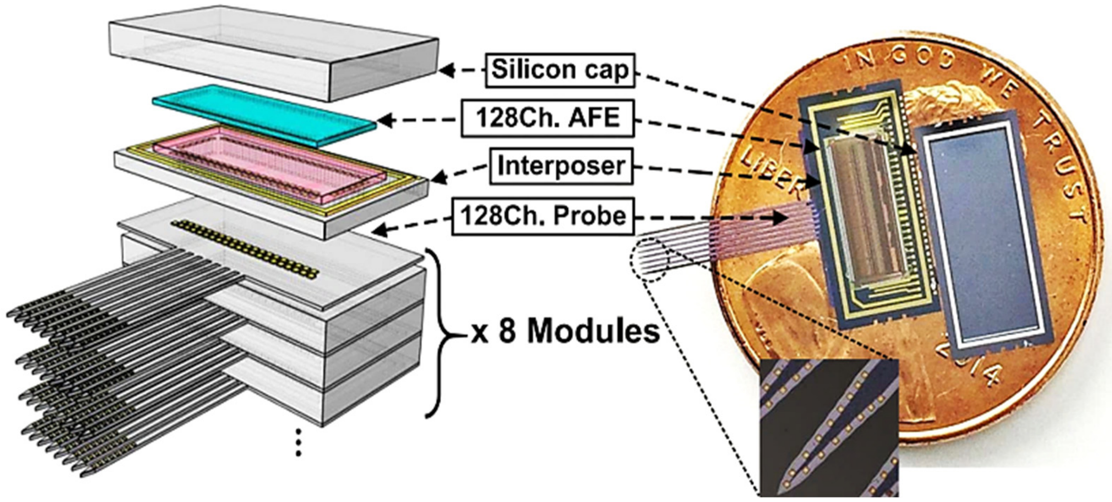

Figure 7. Proposed IC in [114]: Conceptual diagram of a 1024-channel parallel-recording platform assembled with the proposed 128-channel AFEs, interposers, silicon caps, and 128-channel multi-shank probes, and a photograph of the fabricated module on the top of a U.S. penny (Reproduced with permission from [114], IEEE, 2018).

In [115], a multi-channel data acquisition system is described to record bio-electrical signals, including EMG. An eight-module front-end acquisition system is coupled with a synchronization module that ensures reliable synchronization between all acquired signals. A separate universal serial bus data link connects each front-end acquisition module to the computer. Using an external clock, it synchronizes with other modules, providing the microcontrollers with a time base. It is possible to analyze movements in real-time with a synchronization error lower than 10 µs. Additionally, each AFE relies on the highly integrated ADS1299 chip, containing analog filters and an eight-channel ADC for digitalizing bipolar signals simultaneously. As a result, the proposed system can record up to 64 bipolar channels in real-time. In the end, raw data are analyzed and saved on a personal or single-board computer. However, the device presented in [115] does not have a wireless transceiver on board the acquisition board, and therefore requires a wired connection with the processing section (PC or Raspberry Pi board), limiting the use of the device in the acquisition of EMG signals in daily activities.

Tran et al. introduced their most recent contribution in [116]. The author developed a four-channel neural recording AFE integrated circuit (IC) featured by high power efficiency and low-noise. A low-noise amplifier (LNA), a programmable gain amplifier (PGA), and buffers made up each front-end channel. A 4-to-1 multiplexer (MUX) and an ADC accompany the four-channel AFE were used to acquire the four channels sequentially. The system had a programmable gain ranging from 45 to 63 dB and a 10 kHz operative band. The characterization demonstrated that the developed four-channel neural recording AFE produced 3.16 μV_{RMS} input-referred noise, a 2.04 noise efficiency factor, a 4.16 power-efficiency factor, and a 2.82 µW power consumption for each channel, considering a 1 V supply voltage. D.J. Piccinini et al. reported a versatile and wearable device for collecting and wirelessly transmitting biological signals [117]. This system relies on ane ADS1294 Medical AFE and CC3200 MCU (microcontroller unit, manufactured by Texas Instruments), customized for various signals such as ECG and EMG. The resulting solution is lightweight and powered by two Li-ion batteries. The test results showed that the developed device is very promising in terms of size, physical reduction, wireless transmission resilience, and data collecting and processing dependability. The device relies on an SoC (C3200, manufactured by Texas Instruments) with an embedded WiFi transceiver to transmit data to a host device where the data is processed. This limits the use of the device in areas where a WiFi hotspot is required.

Sarker et al. presented another application in [118], i.e., a compact wearable device for acquiring biosignals. Real-time data wireless transmission and minimal energy usage are its distinguishing features. The device is set up to record ECG and EMG signals over eight channels with a 24-bit resolution per channel and 500 SPS (samples per second) sampling rate. The system was presented as an example of prospective integration in an IoT-based system (Figure 8).

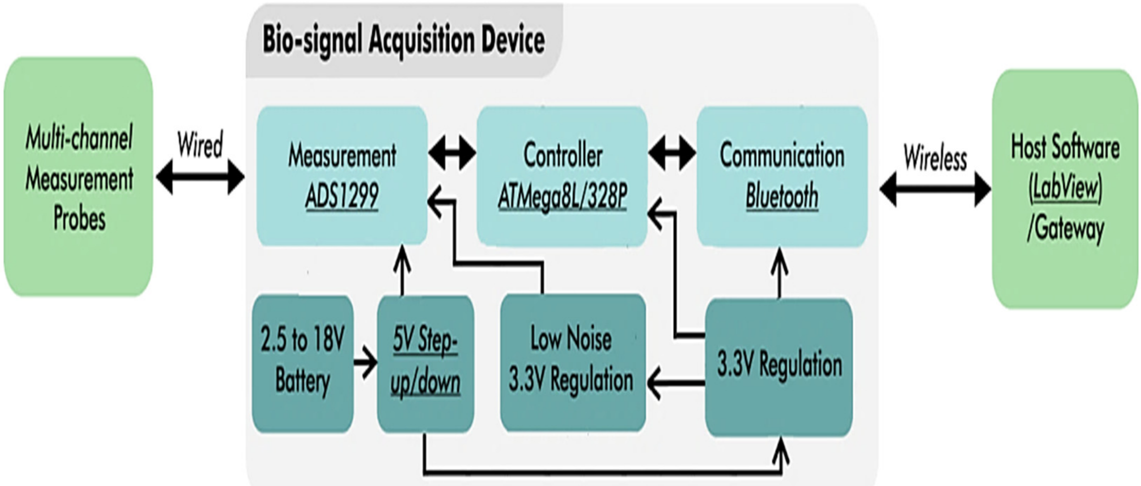

Figure 8. Device architecture proposed in [118] (Reproduced with permission from [118], IEEE, 2017).

The size of the presented device could be further reduced to enable integration into wearable devices, and the firmware further optimized to ensure better energy efficiency, extending its autonomy.

Mazzetta et al. presented a stand-alone wearable sEMG device for real-time monitoring of muscle activation [119]. This device can detect muscle activation potentials and, owing to an integrated low-power microprocessor, can perform entire real-time data processing. The system is designed for low power consumption, compactness, and energy independence, allowing it to collect patients' vital diagnostic data sets daily. Furthermore, the results of testing the system show that it had a specificity and sensitivity of over 87 percent and 82 percent in detecting correct activity time, respectively, with the added benefit of being wireless and comfortable to wear.

Another contribution in [120] describes 3D-printed smart glasses with bone vibration sensors and electrodes for electromyography (EMG) installed at the frame (Figure 9). To measure the EMG, a Bitalino EMG sensor was employed, using flexible fabric electrodes. A 64 µm PET monofilament was woven in the warp and weft directions to create the electrodes. To record Temporalis muscle activations, two stripes were applied to the right temple's ear bend and temple end of the eyeglasses frame. EMG signals were acquired at 1 kHz and high-pass filtered at 10 Hz to eliminate baseline drift. The test results demonstrated that the developed smart glasses obtained a high SNR (15–20 dB) appropriate to identify chew activities. The main problem of the solution presented in [120] was maintaining contact between the electrodes and the user's skin, especially with the user in motion, a potential source of artifacts on the acquired signals.

For the capture of bioelectric signals in portable systems, compact and low-noise (AFEs) are becoming crucial. A low-power, multi-modal AFE for wearable health monitoring sensors is presented by Kim et al. [121]. It is based on CMOS (Complementary Metal Oxide Semiconductor) technology, revolutionary system architecture, and large-scale IC design approaches. Three sensors to measure bio-potential (i.e., ECG, EEG, and EMG), photoplethysmography (PPG), and bioelectrical impedance analyzer (BIA) are incorporated for reducing size and power consumption. The findings revealed that high-quality AFE enables users to easily self-monitor various clinically important physiological indicators. As suggested by the authors, several functional blocks could be shared among the bio-signal and BIA AFEs, such as anti-aliasing filters and ADCs, further reducing the used area.

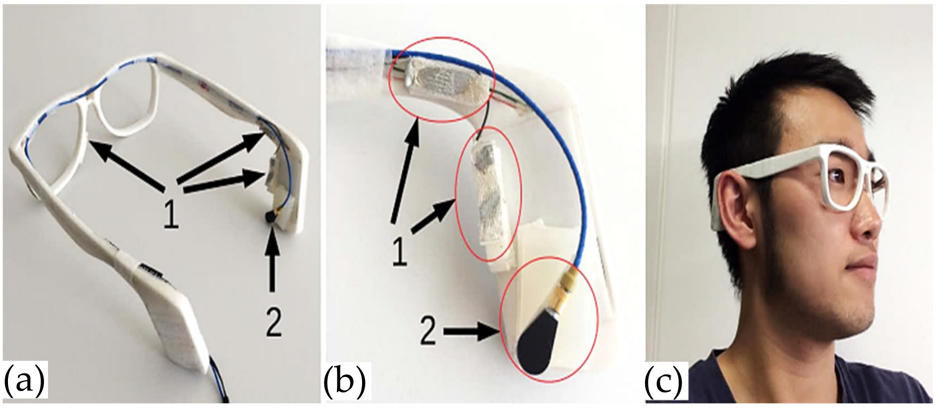

Figure 9. Prototype of the 3D-printed smart glasses, presented in [120] (**a**) with integrated bone vibration sensor and EMG electrodes applied on the right temple (**b**). Smart eyeglasses worn by a user (**c**) (Web-source: https://dl.acm.org/doi/10.1145/2971763.2971799, every aspect related to the human sub-jects' involvement has been taken into consideration by the authors in [120]) (Image courtsey by the authors, R. Zhang and O. Amft [120]).

In [122], the authors present a novel AFE featured by three properties: input impedance's dependency on voltage, bandpass amplification, and stray capacitance lowering utilizing capacitively coupled electrocardiogram (cECG) and capacitively coupled electromyogram (cEMG). The AFE characterization demonstrated that it could achieve a good balance of sensitivity and stability in capacitive biopotential measurements (CBMs). As a result, it is a more flexible solution than the traditional voltage followers employed in CBMs (Figure 10).

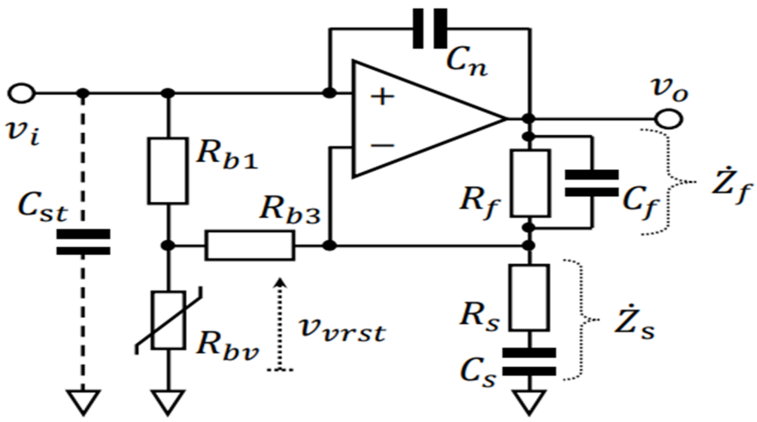

Figure 10. Proposed AFE (BNArf) [122] (Reproduced with permission from [122], MDPI, 2020).

Non-invasive EMG and accelerometer signals have been obtained using a wearable wireless device introduced by Biagetti et al. [123] to monitor human activity during sports and physical activities, as well as in healthcare applications. This system employs several tiny, lightweight wireless sensing nodes to collect, analyze, and transmit motion-related body signals (medical and accelerometer). These were sent to one or more base stations over an ad hoc 2.4 GHz radio connection. A user interface was also created for accessing, recording, and interpreting data from a remotely controlled personal computer linked to the base stations via USB (Universal Serial Bus). Data recorded from many participants were utilized to develop and test an automated classifier to determine the performed exercise for evaluating the system's capacity to identify the user's activity. On four activities conducted by three participants, the automated classifier obtained a maximum accuracy of 85.7 percent using data collected from acceleration and sEMG signals.

Following the earlier designed application, Biagetti et al. [124] reported a wireless sensing unit for the real-time capture of bioelectrical signals such as EMG and ECG. This instrument was designed to provide a continuous stream of data suited for individual activity recognition, motion tracking, and technology-assisted support for people with mobility or intellectual impairment (Figure 11). Up to three separate electrophysiologic channels, each of which has 24 bits of resolution and a sampling rate of up to 3.2 kHz, could be achieved using six electrodes. Furthermore, a BLE wireless connection was utilized to contact a wide range of consumer equipment. In particular, this work looked into the data rate restraints specified by these devices suggesting a technique achieving maximum available bandwidth and the transmission dependability.

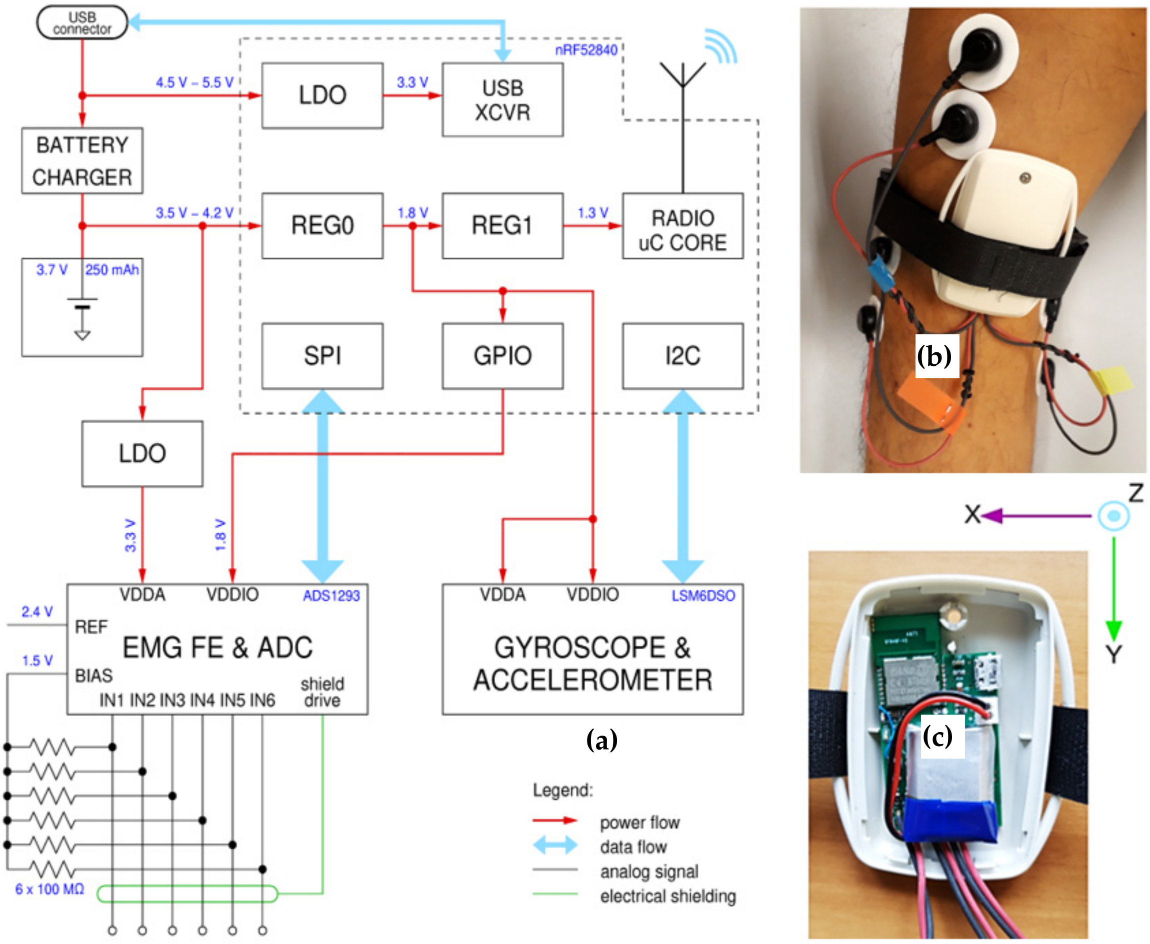

Figure 11. Sensor node architecture with different power supply subsystems highlighted and employed for reducing the power requirements and the data interfaces. When the general-purpose input/output (GPIO) line is active, the ADS1293 collects the analog signals and transfers them to the SoC via a serial peripheral interface (SPI). Using inter-integrated circuit (I2C) communication, the LSM6DSO inertial measurement unit (IMU) provides data from it to the MCU [124] (**a**). The electrodes and electronic section are positioned on the top part of the right forearm, connected to the biceps brachii, triceps brachii, and deltoideus medium (highlighted in yellow, orange, and blue markers, respectively) (**b**). The image on the right below, which depicts the enclosure internal with the battery atop the circuit board, clearly illustrates the mechanical axis' alignment (**c**). When the device is put on, axes are positioned such that the Y is parallel to the arm and oriented downward at resting, the X is parallel to the sagittal plane and faces forward, and the Z axis is parallel to the coronal plane and faces the arm. (Web-source: https://www.mdpi.com/2079-9292/9/6/934, every aspect related to the human subjects' involvement has been taken into consideration by the authors in [124]) (Reproduced with permission from [124], MDPI, 2020).

The device's design and electrode configuration can be further optimized to make it more discreet and compact. In addition, some processing (filtering) sections may be integrated into the device's firmware, limiting post-processing.

Xian Li and Ye Sun offer a wirelessly non-skin contact button-like wearable system for long-term tracking of several bioelectric signals (ECG, EMG, and EEG) [125]. For non-contact sensing, this system relies on the analog front-ultra-high end's input impedance. The system is powered by a 150 mAh rechargeable Li-ion battery and comes in a 24.0 g 3D printed compact box with dimensions of 39 mm $\times$ 32 mm $\times$ 17 mm. A power control circuit is incorporated to offer a dual power supply to feed the operational amplifiers. Several movement patterns with various fabric types were used to assess the system's effectiveness, and the experimental results suggested that long-term bioelectric tracking is possible without disrupting everyday tasks.

D. Velumani et al. proposed an IoT-based tool for diagnosing bruxism, detected by measuring the activity of the masticatory muscles using sEMG [126]. This project's primary objective was to gather biosignals using an EMG sensor by placing surface electrodes over the cheeks and measuring muscle activity to identify signs of bruxism and its performance, as well as other metrics such as pulse rate. An ESP32 is the core of the developed wearable device to which EMG and HR sensors are interfaced. The patient is warned when the RMS (Root Mean Square) of the EMG signal overcomes the threshold value by sending an alert message to an IoT cloud platform, where the information is wirelessly saved and used for telediagnosis at any time. In our opinion, the main problem of the proposed solution is the stability of the contact between the EMG electrode and the patient's cheek, which could deteriorate due to the user's movements during sleep, inducing artifacts on the acquired signal.

The authors of [127] proposed a handheld device for EMG and other biopotential signal recording sections to assist in diagnosing and progressing many illnesses. The signal processing section removes baseline fluctuation (0.1–0.5 Hz) and (50/60 Hz) interfering components, and the processor generates control signals to set the AFE in two modalities: low noise–large CMRR and average noise–moderate CMRR modes. A signal filtering section was developed to pass the interest frequency band and reject the unwanted components. A Successive Approximation Register (SAR) DAC-digital to analog converter receives the control signals from the section above. The resulting biosignal elaborating section has a total size of 33.005 μm^2 and power usage of 0.382 mW, thanks to Spartan-3E FPGA (Field Programmable Gate Array) and 0.18 μm CMOS TSMC technology.

Lee et al. describe a new wireless ExG sensing tag with different channels for electrophysiological data acquisition (PSA) for collecting biopotential data [128]. In addition, a combined microprocessor system-on-chip (SoC) and a BLE transceiver was integrated for instant detection and wireless communication. The developed system includes an AFE, a PGA- programmable gain amplifier, a reconfigurable $\sum$-Δ ADC, and a 32-bit RISC processor. High-performance computing is used in FFT (Fast Fourier Analysis) and entropy coding processors with direct memory access (DMA) to decrease dynamic power. This device is designed to be energy efficient, and continuous recording of ExG signals in medical diagnostic instruments may be accomplished in as little as 12 h using a 200 mAH battery.

An ECG and EMG recorder featuring versatile architecture is presented in [129] that supports wired and wireless body sensor networks. Various options can be configured regarding hardware parameters, signal processing, and recording (Figure 12). The proposed architecture is arranged into three primary levels: data acquisition, processing, and transmission. A programmed analog front-end ADAS1000 with five single-ended gain lines with variable gain has been built. A 24-bit resolution ADC with a customizable data rate of up to 128 kHz has also been developed. A 24-bit resolution analog-to-digital converter with a customizable data rate of up to 128 kHz has also been developed.

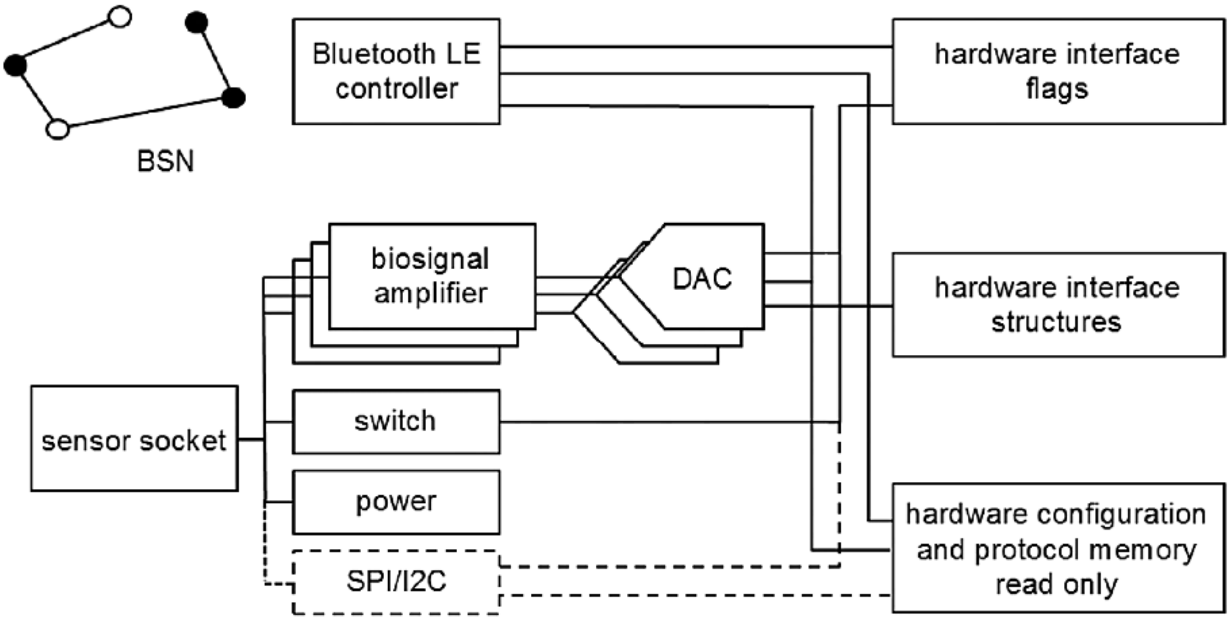

Figure 12. Flow diagram of the data acquisition layer proposed in [129] (Reproduced with permission from [129], Elsevier, 2016).

The suggested system might be improved by automatically adjusting the remote recorder's software by the server by the reported diagnostic quality, allowing some firmware blocks to be tailored according to the target device.

In [130], researchers describe an interference-oriented biosensor front-end integrated into an ASIC (Application Specific Integrated Circuit) for wireless body sensor nodes and implanted biomedical instruments. The ASIC is made in a 0.18-micron CMOS processing and can be reconfigured to handle various bioelectrical signals, with high-pass and low-pass critical frequencies of 0.5–300 Hz and 150 Hz–10 kHz, accordingly. For the swapping 10-bit SAR ADC, an antialiasing filter is also provided. The AFE has a programmable gain ranging from 38 to 72 dB. A power control unit supplies the entire device with power, various voltage, and bias current levels. The AFE and ADC dissipate 5.74 μW and 306 nW, respectively, and the device has 2.98 μV_{RMS} input-referred noise, a 2.6 noise efficiency factor, and a 9.46 power efficiency factor. The AFE covers an area of 0.0228 mm^2.

A musculoskeletal rehabilitation evaluation (MSEva) system is proposed in [131] to assess neuromuscular activities using EMG signals, able to recognize five rehabilitative exercises from EMG data. MSEva collects signal characteristics with the Wavelet Transform (WT) and then trains its models with the Long Short-Term Memory (LSTM). The system employs an LSTM model to detect if the EMG response to rehabilitative procedures is normal. In terms of accuracy, MSEva reaches an average of 94.37%, which is significant for directing neuromuscular rehabilitation.

Table 1 summarizes the main features and strengths of scientific works on electromyography wearable monitoring systems published in peer-reviewed journals in the last six years.

Table 1. Summarizing table of wearable monitoring systems reviewed in the manuscript (sorted by publication year).

Reference	Year	Number of Channels	Signal Acquisition	Sampling Frequency	Wireless Connection	Technical Features and Strengths
S. Zhao et al. [110]	2020	2 channels	STM32L15 (MCU) + Precision instrumentation amplifiers + BMD 101 (16-bit ADC)	N.A. [a]	BLE	• A wearable smart monitoring system for upper limb rehabilitation based on acquiring and processing the ECG e EMG signals. • Wireless data transmission to a remote processing device to reduce wearable device requirements. • Integrated software platform based on multi-thread technology for detecting fatigue (ECG) and training progress (EMG) using an adaptative strategy.
S. H. Liu et al. [112]	2019	8 channels	MSP430 MCU (12-bit ADC)	100 Hz	Bluetooth 3.0 (BTM-204B)	• Portable and wireless acquisition system to record physiological signals (ECG, EEG, EOG, GSR, and PPG). • Real-time monitoring of the multiple biosignals through proper smartphone and PC applications
M. Nguyen et al. [113]	2021	8 channels	Myo Armband	200 Hz	Bluetooth	• Real-time and remote household utilities. • Edge computing exploiting a local smart gateway. • Processing supported by inertial data
S.-Y. Park et al. [114]	2018	128 channels	128-channel Custom AFE (10.9-bit Δ-ΔΣ ADC)	800 kHz	No	• Energy and area-efficient 128-channel AFE, including a modular Δ-modulated ∑Δ acquisition system. • 1024-channel for high-density detection of brain activity. • Implementation of spectrum equalization scheme to exploit the spectral features of neural signals. • Low power consumption (3.05 µW/channel @ 1 V supply) and area (0.05 mm^2). • High SNRD (63.8 dB) and low NEF (3.02) for noise suppression.
L. Tran et al. [116]	2021	4 channels	4-channel Neural recording AFE IC (10-bit SAR ADC)	1–10 kHz	No	• Amplification that can be adjusted from 45 dB to 63 dB. • Low input referred noise (3.16 V_{RMS}) inside the 10 kHz bandwidth. • Low NEF (2.04) and high PEF (power efficiency factor) (4.16) • Low power consumption (2.82 W/channel).

Table 1. *Cont.*

Reference	Year	Number of Channels	Signal Acquisition	Sampling Frequency	Wireless Connection	Technical Features and Strengths
D. J. Piccinini et al. [117]	2016	N.A. [a]	CC3200 MCU + ADS1294 AFE (24-bit $\Delta\Sigma$)	32 kHz	WiFi (CC3200)	• Wireless wearable acquisition system for detecting biosignals (EMG, ECG, movement, body temperature). • Discreet and reliable in data acquisition, processing, and transmission.
V.K. Sarker et al. [118]	2017	8 channels	ATmega328p + ADS1299 AFE (24-bit ADC)	250–1000 Hz	Bluetooth 2.0 (HC-05)	• Lightweight and wearable monitoring system gathering multiple bio-signals (ECG and EMG). • High resolution (24 bit) and sample rate (500 samples per second). • Extended energy autonomy (13.6 h with a 1700 mAh).
I. Mazzetta et al. [119]	2018	Differential 1 channel	Bio2Bit	$\geq$4 kHz	Bluetooth 4.0	• Wearable sEMG system for real-time detection of muscle activity. • Fully embedded system for the real-time elaboration of sEMG signals. • Wearable, compact, and ubiquitous. • Low power consumption (26 mW). • High specificity and sensitivity in detecting the activation times (87% and 82%, respectively).
R. Zhang et al. [120]	2016	1 channel	Bitalino EMG	1 kHz	No	• Compact and low-power wearable and wireless system for continuously monitoring EMG signals and bone vibration. • Fabric-based flexible electrodes applied on the temple ear bend and temple end. • High SNR on EMG acquisition (15–20 dB).
I. Kim et al. [121]	2016	N.A. [a]	Cyclone IV FPGA + Custom AFE (10-bit SAR ADC)	1.10 MHz	No	• Low power and multi-modal AFE for monitoring PPG, BIA, and biopotential. • Small covered area (2.5 mm $\times$ 2.5 mm) and power consumption (0.4 mW @ 1.2 V supply voltage).

Table 1. *Cont.*

Reference	Year	Number of Channels	Signal Acquisition	Sampling Frequency	Wireless Connection	Technical Features and Strengths
H. Nakamura et al. [122]	2020	N.A. [a]	Custom AFE to capacitive biopotential measurements (CBMs) (16-bit ADC)	1 kHz	No	• Novel AFE architecture featured by: voltage-dependent input impedance, band amplification, and stray capacitance reduction. • Suitable for capacitive biopotential measurements (CBM). • Improved SNR
G. Biagetti et al. [123]	2018	1 channel	sEMG sensing nodes (12-bit ADC)	2 kHz	2.4 GHz radio link	• Wearable sensor node to detect and wirelessly transmit signals related to body motions (sEMG and inertial). • Discreet and cost-effective • Custom software platform for gathering and processing the acquired data to recognize human activity.
G. Biagetti et al. [124]	2020	3 channels	nRF52840 MCU + ADS1293 AFE (24-bit ADC)	3.2 kHz	BLE	• Wearable sensor for continuous monitoring of the bioelectrical (EMG and ECG) and inertial signals for activity detection. • High resolution (24-bit) and sampling rate (3.2 kHz). • Reliable wireless data transmission (BLE) toward a host device (smartphone or tablet), which acts as an aggregator.
X. Li et al. [125]	2017	N.A. [a]	ATmega328p (10-bit ADC)	N.A. [a]	2.4 GHz radio link (nRF24L01)	• Wearable wireless sensor for real-time and long-term monitoring of biosignals (EMG, EEG, and EEG), using multi-layer cloth electrodes without direct contact with the skin. • Compact (39 mm × 32 mm × 17 mm) and lightweight (24 g).
D. Velumani et al. [126]	2022	1 channel	ESP32 (12-bit SAR ADC)	N.A. [a]	WiFi (ESP32)	• IoT wearable system for diagnosing bruxism. • A cloud platform supports the device operation storing event when the RMS value of the EMG signal overcomes a threshold.

Table 1. *Cont.*

Reference	Year	Number of Channels	Signal Acquisition	Sampling Frequency	Wireless Connection	Technical Features and Strengths
B. Senapati et al. [127]	2017	N.A. [a]	Spartan-3E FPGA + Custom AFE (16-bit SAR ADC)	N.A. [a]	No	• Biopotential processor for acquiring ECG, EEG, EMG, and EOG signals. • High resolution and capability of rejecting baseline wander and powerline interference (50/60 Hz). • Two operative modalities: low noise-High CMRR and average noise and average CMRR modes. • 33,005 μm^2 total area and 0.38 mW power consumption.
S.C. Lee et al. [128]	2016	8 channels	Open RISC 1200 MCU (12-bit ADC) + Custom AFE	N.A. [a]	Bluetooth 4.0	• Wireless ExG sensor tag for acquiring multiple physiological signals. • Low battery consumption (12-h recording time)
Augustyniak et al. [129]	2016	Single-ended 5 channels	PXA-270 CPU + ADAS1000 (24-bit ADC)	500 Hz	WiFi	• Multi-purpose BSN architecture (wired and wireless) to detect physiological signals (e.g., ECG, EMG). • Fully reconfigurable from the point of view of hardware configuration, data elaboration, and software management.
H. Bhamra et al. [130]	2017	N.A. [a]	ASIC 9.1-bit SAR ADC	4 kHz	No	• Integrated AFE for wearable and implantable devices, reconfigurable to acquire different biosignals. • Amplification gain from 38 dB to 72 dB. • Low noise (2.98 μV_{RMS} input-referred noise, 2.6 NEF, and 9.46 PEF). • Low power consumption (5.74 μW for the AFE, 306 nW for the ADC).

[a] N.A.: Not Available.

5. Commercial Wearable Devices

Wearable medical systems are designed to collect and process medical information regularly, rapidly diagnosing abnormal indicators and enhancing illness monitoring and management [132]. Wearable modified electromyography systems are commonly accessible in the market and are developed and manufactured to meet various requirements. The following sections present an overview of commercial biosignal sensing devices for vital signs in this context. These devices were chosen because they are the most used devices in diagnosis and have comparable qualities that may be measured [133].

Biometrics Ltd. (Newport, UK) provides a variety of monitoring devices to acquire analog or digital data from various sensor typologies; different device categories are available, namely mobile, handheld, and lab versions. The proposed wearable devices enable a complete range of motion without needing cables [134]. Biometrics Ltd. provides non-invasive wireless electromyography sensors and surface EMG amplifiers (Figure 13). They are available in 2-, 4-, 8-, and 16-channeled variants for acquiring EMG signals with non-invasive, compact, and light detectors, enabling secure and effective myoelectric measurements at a distance of up to 30 m from the medical staff who analyze the data. The major characteristics of these detectors are operating bandwidth ranging from 10 Hz to 250 Hz up to 5 kHz, and sensitivity ranging from +/60 mV to +/6000 mV for full-scale peak-to-peak readings [135]. Wearable devices are constituted by both sensors and instrumentation systems for stationary and non-stationary measurements in a medical environment, an academic institute, or any distant point such as an office, work, or house.

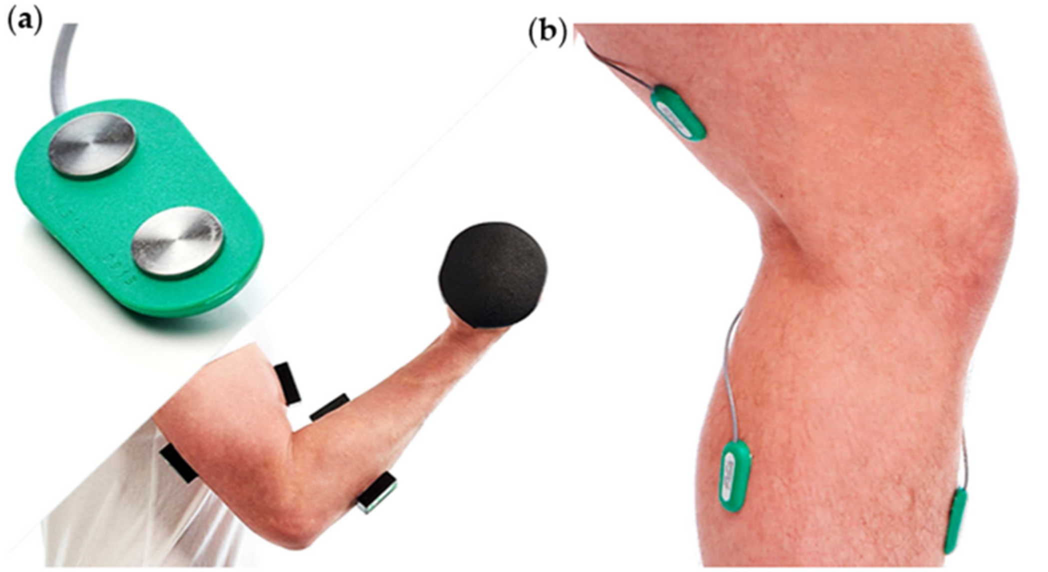

Figure 13. Biometrics Ltd. EMG sensors and systems are used extensively in the fields of ergonomics, sports science, and medical research, where measurements are commonly taken for a wide range of applications. The surface EMG sensor LE230 can be positioned in different body positions, such as arms (**a**) and legs (**b**) (Web-source: https://www.biometricsltd.com/surface-emg-sensor.htm arms (**a**), https://www.medicalexpo.com/prod/biometrics/product-123702-880665.html legs (**b**), every aspect related to the human subjects' involvement has been taken into consideration by Biometrics Ltd.) (Image courtsey by Biometrics Ltd., Newport, UK).

Several sensors are available from Shimmer Co. (Dublin, Ireland) for measuring various parameters [136–138], including configurable digital front-ends for EMG data acquisition and evaluation [137] (Figure 14a). They manufacture surface transducers to monitor muscle activity. By a shared referenced electrode, the wireless EMG system offers multiple information channels. Besides EMG, ECG signals can be acquired, but the two measurements cannot be made simultaneously. A 450 mAh rechargeable Li-ion battery powers the Shimmer3 EMG unit, which includes an MSP430 microprocessor, a Bluetooth transceiver (RN-42), and an in-built 8 GB micro-SD card. Since the Shimmer 3 EMG sensor has a centralized acquisition and processing unit to which the EMG probes must be connected (Figure 14a), it can be uncomfortable and hinder the movements due to the presence of cables.

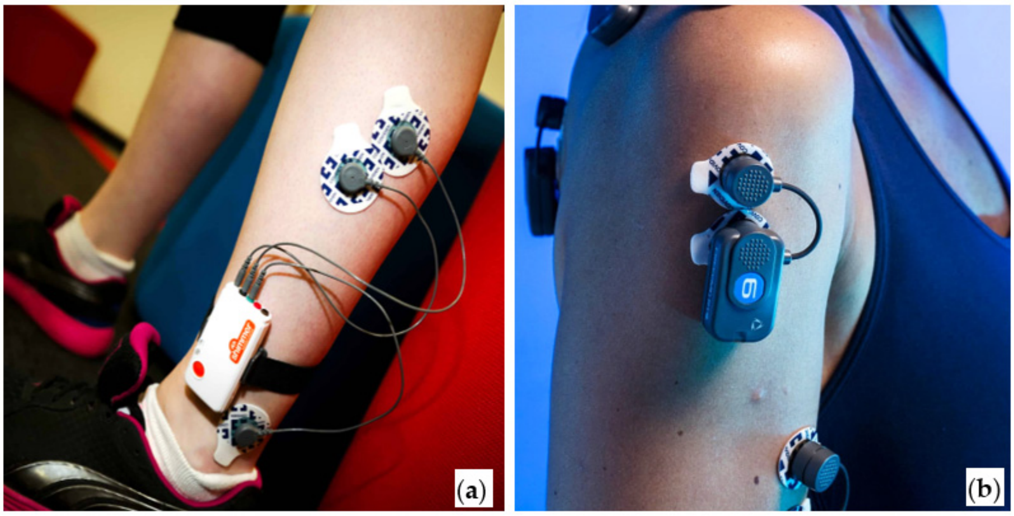

Figure 14. Applications of the Shimmer3 EMG (**a**) and FreeEMG (**b**) sensors on the legs and shoulder for monitoring body movements (Web-source: https://www.biometricsltd.com/surface-emg-sensor.htm (**a**), https://www.medicalexpo.com/prod/biometrics/product-123702-880665.html (**b**), every aspect related to the human subjects' involvement has been taken into consideration by Shimmer Co. (Dublin, Ireland) and BTS S.p.A. (Garbagnate Milanese, MI Italy), respectively) (Image courtsey by Shimmer Co. (Dublin, Ireland) and BTS S.p.A. (Garbagnate Milanese, MI Italy), respectively).

Both previous wearable devices (Biometrics and Shimmer 3) were employed in [139] for validating proposed EMG sensors. The experimental results demonstrated that both commercial devices obtained a good SNR (≈20 dB). In contrast, the EMG sensor solution reached an SNR in the range of 11 and 18 dB according to the method used for SNR calculation. Biometric EMG sensors were involved in a scientific study to analyze the influence of related muscular co-activities (i.e., vastus lateralis and gastrocnemius) with knee flexor-extensor actions associated with the onset of Osteoarthritis (OA) [140]. The outcome focused on the postural efficacy of muscular activities in the stability problems of knee joint motions and demonstrates that the voltage amplitudes of EMG signals changed significantly with advancing age.

BioSemi Instrumentation Co. (Amsterdam, The Netherlands) offers the ActiveTwo bioelectric detection device for scientific purposes [141]. This system integrates up to a 256-channel DC amplifier, 24-bit ADC per channel, and active electrodes, which are thinner and lighter than previous models, with significantly improved low-frequency noise and input impedance specifications. Notably, the Active Two system offers up to 256 + 8 electrodes + 7 sensor channels in a single ultra-compact box, a battery-powered front-end with fiber optic data transfer, reliable readings without skin treatment, and improved digital resolution with a 31 nV LSB (Least Significant Bit) value, and a user-configurable sampling rate of 2, 4, 8, 16 kHz/channel. The system provides the user with a graphical LabVIEW application for controlling the different sensor parameters, making it suitable for detecting different biosignals, such as EEG, ECG, and EMG. The ActiveTwo EMG sensor is impractical for EMG monitoring during daily life, as the acquisition and processing unit is bulky and requires a large flat cable to connect the electrodes. In addition, the device has no transceiver for wirelessly transmitting the acquired data.

In [142], an ActiveTwo EMG sensor acquired and analyzed tiny intestine bioelectrical signals through flexible PCB electrode arrays, enabling up to 256 simultaneous recordings. The Falling-Edge Variable-Threshold technique was used to automate data processing, resulting in 92% sensitivity and a 94% positive predictive value. The automatic production of animations and isochronal maps allowed for the visualization of slow wave propagation patterns.

The FreeEMG (manufactured by BTS S.p.A., Garbagnate Milanese, MI Italy) is a portable electromyography system that analyzes musculoskeletal activity in real-time [143] (Figure 14b). It is a surface EMG monitoring device with 4G technology that ensures data reliability, lightness, and comfort, thanks to the absence of wires and the smaller probes. Orthopedic and neurologic problems, pharmacological therapies, the progression of motor impairments, retraining and follow-up, and sports performance adaptation are all common uses for FreeEMG. This sensor was employed in [144] to explore the dynamic asymmetries of healthy individuals' lower limbs during gait adaptation on a split-belt treadmill. Ankle, knee, and hip joints, joint rotations, muscle lengthening, and SEMG were concurrently monitored, along with the produced sagittal power and work. According to the SENIAM (surface EMG for non-invasive assessment of muscles) recommendations, four sEMG probes were placed bilaterally on the bellies of the Tibialis Anterior, Gastrocnemius Lateralis (GaLat), Vastus Medialis, and Semi-Membranosus. The obtained results confirm that, on solid ground, the problematic leg "escapes" from load while walking with a limp, whereas in split gait, the quicker leg "escapes" from being pulled behind, the slower limb.

PLUX Wireless Biosignals Co. (Lisbon, Portugal) has created biosignal collection and monitoring solutions that incorporate wearable body sensors such as EMG and ECG, as well as wireless connection and software applications [145]. BITalino and Biosignalplux are two of these systems. The BITalino (r)evolution kit is a versatile board that includes all parts pre-connected and available to use outside the arrangement, as well as Bluetooth connectivity [146]. Its non-invasive EMG electrodes are created specifically for it. The bipolar design is perfect for limiting the noise on collected data, whereas the unfiltered output makes it suitable for both human-computer interface and biological applications.

Biosignalsplux is a wireless toolbox for collecting and analyzing high-resolution biosignal data [147]. It comes with a variety of wired and wearable sensors. For gathering muscular information, the Biosignalsplux EMG sensor is a high-performance bipolar sensor with minimal noise. The bipolar architecture of this sensor is suitable for acquiring low-noise data meant to detect muscle activity. The raw data generated is medical-grade, allowing it to be used for sophisticated medical biomechanics and athletics studies. The main features of this system are the usage of bipolar differential detection, availability of pre-processed analog output, high SNR, and medical-grade unfiltered output data; it is also tiny and simple to use. The muscleBAND is a portable single-channel EMG instrument for continuous muscle monitoring. It is a single-channel EMG sensor with a triaxial accelerometer and magnetometer for gathering muscle activity and motion data and a dual Bluetooth module. The integrated battery adequately feeds the device, ensuring long-term data streaming and allowing data collection with up to 16-bit resolution at up to 1000 Hz sampling rate.

The main limitation of Trigno Avanti sensors is the need to use a proprietary wireless station (Trigno Wireless System) for receiving data from the sensors using a proprietary RF protocol, which could be a problem when collecting data from different typologies of sensors. The BiosignalsPlux® device was utilized to track the shoulder muscle contraction pattern during five ADLs (activities of daily living) with various motor patterns [148]. The major goal of this article is to demonstrate the use of BiosignalsPlux® sensors to characterize the shoulder muscles' pattern of contraction while performing ADLs in healthy people. The results indicate that the pattern of shoulder muscle contraction varies depending on whether an ADL is aimed at the midline or the opposite side, and that various ADLs directed at the midline exhibit diverse behaviors.

Delsys Inc. (Natick, MA, USA) offers wearable EMG-based body motion tracking systems for scientific, medical, and teaching applications [149]. These technologies include scientific, handheld, light solutions, EMG electrodes, mobile platforms, and device integration software. Trigno Avanti Sensor is the most commonly used EMG detector since it effectively detects muscle movement signals. It has patented technology, increased radiation efficiency, wireless design, adjustable EMG frequency choices, and integrated signal analyzing, and it is intended to operate with all Trigno units. It also enables bipolar EMG measurement within a very tiny size and weight. Trigno Research+ is an effective-performance system that makes EMG signal sensing reliable and simple while providing a comprehensive range of physiologic and musculoskeletal detection capabilities to facilitate complex studies and produce the best qualitative data. Trigno's proprietary RF protocol ensures sensor coordination and data transfer from Trigno sensing devices to a Trigno base station.

In [150], Z. Hu et al. analyzed badminton single-leg landing following an overhead shot, and demonstrated that a deficiency of biomechanical indicators of the knee indicates the risk of anterior cruciate ligament (ACL). Kinematic data were gathered through 13 infrared cameras with a 120 Hz sampling rate. EMG data were collected using the Trigno Avanti sensor, placed on the quadriceps femoris (rectus femoris), medial hamstrings (semitendinosus), lateral hamstrings (biceps femoris), medial gastrocnemius, and lateral gastrocnemius; the sampling frequency was 1200 Hz. The results suggest that during the single-leg landing in badminton, lower extremity muscle activity and knee kinematics and kinetics are correlated; thus, lower extremity muscle activity should be taken into account to create rehabilitation or injury prevention programs.

Table 2 compares the commercial EMG sensing devices previously discussed from the point of view of the additional detected signals, the number of EMG channels, dimension, weight, sampling frequency, electrode typology, availability of wireless connectivity, and suggested applications. In this way, different devices can be compared to highlight their potentialities and limitations.

From the presented analysis, it can be deduced that the ActiveTwo EMG monitoring device is the most complete and flexible solution for acquiring biopotential signals, including EMG signals, given its wide range of acquisition channels (280 channels) and high resolution (24-bit). Nevertheless, because this system is wired, it is not suitable for monitoring EMG signals when the user is moving. Likewise, the FreeEMG system represents an optimal solution in terms of compactness, discretion, and ease of use, given its small dimensions (27 mm $\times$ 37 mm $\times$ 15 mm), weight (14 g), and availability of wireless connection (WiFi), enabling its employment in every user condition. Furthermore, it guarantees good resolution (16-bit) and sampling rate (2 kHz) in detecting the EMG signals.

Table 2. Comparison between the commercial devices previously discussed from the perspectives of additional acquired signal, number of channels, dimension, weight, sampling frequency, electrode typology, availability of wireless connectivity, and suggested application.

Device	Other Detected Signals	N° of EMG Channels	Dimension/ Weight	Sampling Frequency [Hz]	Electrode Typology	Wireless Connectivity	Suggested Applications
Biometrics wireless sensors [134]	Joint angle (electro-goniometers-optionally)	2, 4, 8, 16	N.A. [a]	500, 1000, 2000	Disposable sEMG electrodes with 4 mm snap	Yes (WiFi)	• Symmetry studies during gait • Timing data in biomechanics • Sport performance monitoring • Neuro Rehabilitation
Shimmer3 EMG units [137]	ECG	2	65 mm × 32 mm × 12 mm/31 g	125–8000	Patented disposable EMG electrodes	Yes (Bluetooth)	• Gait, muscle, and posture disturbances analysis
ActiveTwo EMG unit [141]	EEG, ECG	280	N.A. [a]	200, 400, 8000, 16,000	Special silver-plated electrode-tip	No	• General bio-potential measurements for research applications
FreeEMG sensors [143]	Joint angle (electrogoniometers-optionally)	1	27 mm × 37 mm × 15 mm/14 g	≤4000	Standard with a clip connection	Yes (WiFi)	• Functional evaluation of gait analysis • Sport biomechanics. • Injury prevention and return to play. • Cognitive and mobility rehabilitation.
Trigo Wireless EMG sensors [149]	Inertial data	4, 8, 16	N.A. [a]	2000	Silver electrodes	Yes (WiFi and BLE)	• Sport science • Rehabilitation sciences • Robotics • Kinesiology. • Speech pathology. • Gaming-rehabilitation • Motor control

[a] Not Available.

6. Discussion

Using and interpreting EMG signals in rehabilitative clinical follow-up is a valuable tool in identifying and monitoring muscles' healthy and unhealthy electrophysiological conditions. A significant amount of research has been conducted on surface electromyography. EMG signals provide measurable information about a muscle's biopotential signal. However, research outcomes and actual medical applications are conflicting regarding using sEMG. Several factors are responsible for this, including shortage of time and knowledge due, for example, to sensor locations and device configuration, medically unrelated sEMG device characteristics, primarily due to sEMG's restricted spatial resolution, and insufficient education and assertiveness in sEMG implementing technology. The obvious issues are technological in nature and include data analyzing and processing algorithms that do not immediately provide clinically useful data. Another difficulty is that certain equipment is difficult to operate.

Furthermore, the equipment's cost and the timed process to perform a study and acquire medically crucial results have detrimental effects. Concerning wearable applications, the main required features for a wearable sensor are minimal power consumption, portability, and reliability. Furthermore, portable equipment must be small and comfortable enough to be worn. Additionally, they must be equipped with a storage device and radio transmission to continuously monitor human activity in every condition. Numerous commercialized sensors are now flexible enough to meet these criteria, providing tailored solutions based on unique demands. Because of their tiny size and wearability, these sensors are more useful in patient control in hospital settings and tele-medicine scenarios.

The main issue that wearable EMG sensors may confront is that each time a muscle is utilized, the electrodes shift slightly about the underlying musculature. Electrode movement occurs during user activity due to stresses and limb positioning. A change in the limb's EMG characteristic (recording) as a result of such an electrode relocation can make analyzing the motions more difficult.

It is common practice to record an individual's EMG signal from their limb position when they are in a stationary position (sitting); however, in a real-world scenario, users must employ the device in various positions (walking, climbing stairs). On the other hand, the accuracy of EMG categorization is affected by subtle changes in limb posture. The same limb assists different muscular contraction forces throughout daily tasks. Therefore, the discrepancy in myoelectric signal pattern classification happens because muscle contraction force varies even when the same limb is targeted. Furthermore, the change in gravitational force caused by different leg postures causes the displacement of target muscles. EMG signal pattern variation is a result of these factors. Modern commercial sensors are limited mostly by their high cost and the system's complexity employed by a single subject, and they are not always simple to utilize. Frequently, these commercial sensors have complicated designs primarily centered on advanced technology with minimal emphasis on pleasant sensor-subject contact. An additional issue is that such devices are built using laboratory measurements, prototypes, and patient simulators, neglecting the factors and performing well in simulation but exhibiting flaws in real-world situations. Because the most recent sensor technology must fulfill the demands of physicians and patients, experimental models are now more vital in overcoming these restrictions. State-of-the-art EMG sensors should detect prospective diagnostic and therapeutic needs by highlighting relevant bioelectrical signals associated with certain muscular activities and pursuing the creation of solutions based on innovative detection systems. These new solutions must be able to track muscular activities from convenient places by employing innovative communication techniques. The equipment must also be constructed with these limits and needs in mind. In the near future, the sEMG technique will aid in collecting myoelectrical signals at home, proactive clinical procedures, and improving remote treatment and rehabilitation programs. As a result, the next stages will focus on creating smaller and cost-effective devices that a broad population will utilize.

Even once these studies are done, it may be a while before the discussed wearable systems or treatments are ready for commercialization. Developers of devices are concerned because they must spend a lot of money to bring their products to the market. It may not pay off to be the first to market with cutting-edge technology if the new product's window of opportunity for big profits is small. Bringing new technology into hospitals is a complex process that requires buy-in from both doctors and upper administration.

Despite efforts by some of the world's leading academic institutions to hasten innovation and the introduction of new goods to the market, progress is slowed by a lack of cooperation and exchange of ideas between the medical and engineering communities. A sustainable medical device business has emerged in developing nations, partly due to the reverse engineering of current items, to compensate for the scarcity of affordable devices.

The medical device R&D process and the subsequent commercialization of these products are extremely high-risk endeavors. It takes a long time and a lot of money to take an idea from the drawing board to actual use in the clinic. Early research is typically conducted in universities, whereas the rest of the process, including testing and manufacturing, is handled by private industry. Procedures typically take a long time and a lot of money to complete. Despite extensive ex vivo and in vivo testing, there is always a potential that a new product will fail, leading to major medical problems for the individual and financial devastation for the producer. Even if they face different health problems, the wealthiest countries still struggle with healthcare distribution and access. In theory, everyone in need should have access to transplantation and other life-support equipment such as dialysis and circulatory assist devices, but in practice, access is severely limited around the world. This exemplifies moral quandaries that are relevant to other costly implantable technologies as well.

The merger of medical and technical expertise may result in more rapid and targeted development and, as a result, more investment resources may be available. Early research and development can take place through consortia that include academics, industry, and government agencies, which can reduce investor reluctance to take risks. It is possible that streamlining clinical testing and taking a more consistent approach to the health technology assessment process will hasten the process of introducing cost-effective devices into the market and spreading their use. Alterations to existing patent rules and the application of those laws could lead to lower prices and greater levels of competition. Although decreased pricing would threaten the current business model that device firms use, increasing sales might be able to repay them financially by forming an open worldwide market. There is a high likelihood that the pricing of medical gadgets, which can be extravagant at times, cannot be maintained in the world's wealthy or low-to-middle-income regions. Many potentially life-saving medical technologies have the potential to become mass-produced items at prices that are affordable. When dealing with medical technology, such advancement would make it simpler for the medical industry to stay true to the fundamental ethical values that guide it.

7. Conclusions

Electromyography is a clinical test to evaluate the condition of the muscular and nerve cells that drive them (motor neurons). EMG results can identify difficulties with nerve-to-muscle signal transmission, muscle dysfunction, or both. This article deals with the most generally utilized electrophysiological monitoring devices in the field of rehabilitation. It focuses on sEMG monitoring as one of the key platforms for assisting doctors, injured patients, and general people in rehabilitation. At first, an overview of the main EMG methodologies and systems applied to tele-medicine applications is introduced. Then, the characteristics of the EMG signals are discussed, along with the common approaches for conditioning and processing them. Afterward, a survey of EMG portable and wearable devices is reported in detail, many references from the literature being included in this study to demonstrate the relevance of EMG signal capture, processing, and tracking to muscular activity management. Many commercially applied EMG detectors are reviewed and compared to determine the most common characteristics of such sensors in EMG recording. The main requirements are low dimension and size, reduced power consumption, and the availability of wirelessly data transfer to ensure actual usage in rehabilitation.

To make the EMG-based motor intention prediction more practically applicable, significant attention should be paid to many joints while they are engaged in complex motion circumstances. In addition, as opposed to rehabilitation, more general applications may require the operators' left and right arms to move, and these movements may frequently have different trajectories.

Hence, figuring out how to use EMG signals to anticipate the movement intention of one arm while the other arm is simultaneously in motion, and how to predict the movement intents of both arms simultaneously, are useful in practice, hinting at a new research avenue.

Several approaches have been developed to integrate the EMG and the intelligence of robots to increase the overall performance of collaboration systems. These methods are seen from the point of view of shared control. To make up for the shortcomings of the EMG signals, systems that use shared control might be utilized. The concept of shared control was developed as a solution to address several issues, including the potential for hazardous circumstances and accidents, the imprecision of human control, and the exhaustion that can result from maintaining continuous control over a device. As a result of the limitations inherent to human control, an intelligent controller and a human controller may have some level of influence over the equipment being controlled. As a result, advanced approaches and procedures for shared control can also considerably improve EMG-based human-robot collaboration systems.

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