Use of Advanced Materials and Artificial Intelligence in Electromyography Signal Detection and Interpretation

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1. Introduction

Electromyography (EMG) is the superposition of motor unit action potentials (MUAPs) in muscle fibers. Their main role is to be the link between the person’s musculoskeletal and neurological systems. Hence, EMG signals have been used in health care to detect neurodegenerative diseases that affect motor functions such as Parkinson’s and stroke. Additionally, EMG signals have been used to track the rehabilitation progress of patients who have suffered injuries or diseases. Recent advances in biomedical technology also allow new application areas for EMG, such as a control signal to exoskeleton systems for assisting patients to complete tasks that cannot be performed due to the impairment of the musculoskeletal system.

For EMG signals, there are two main attributes that are desired: high signal-to-noise ratio (SNR) and good repeatability, both of which are challenging to obtain. The amplitude and frequency characteristics of EMG signals are susceptible to various internal and external factors. Generally speaking, it is hard to control the number of detected muscle fibers, location and distance of fibers relative to electrodes, and impedance between electrodes and fibers. Externally, the changes in electrode impedance, shifts in the position of the electrode, and artifacts cause instability in EMG signals.

Electromyography (EMG) is an integral part of many biomedical and healthcare applications. It has been used as a metric for tracking rehabilitation progress and identifying diseases that affect muscle activation patterns. Although it is widely used in many disciplines, conventional EMG recording and interpretation techniques lack in providing precise signal detection and robust classification accuracy. In recent years, thanks to advances in both material science and artificial intelligence, EMG detection techniques are improving at a rapid pace. Materials that allow for enhanced biocompatibility have improved the quality of data recorded by electrodes. The use of machine learning algorithms has paved new ways to understand complex EMG signals, triggering diverse, novel, and improved application scenarios within the healthcare framework. To help readers establish a clear picture of the two most important components in EMG technology, i.e., electrodes and algorithms, while catching up with the latest research outcomes, this review article is composed. The article starts by introducing conventional EMG electrode materials and architectures, then explains how state-of-the-art works have improved electrode utilization. Subsequently, EMG signal conditioning and interpretation algorithms are investigated. Finally, current challenges in the research domain and authors’ perspectives are discussed.

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Thanks to recent development in materials science, advanced EMG electrodes can offer merits such as high flexibility and skin irritation-free, yielding improved EMG signal quality. For instance, due to the conformal contact with the skin, many thin-film sEMG electrodes with thickness below the critical value of 25 μm can reach high SNR.[3] Thin-film technology-based intramuscular electromyography (iEMG) electrodes can record reliable signals for a prolonged period of time.[4] In addition, smart algorithms based on machine learning methods enhance interpretation accuracy even more. Apart from the improvement of traditional machine learning methods such as linear discriminant analysis (LDA),[5] support vector machine (SVM),[6,7] and deep-learning-based methods which can better decode information in EMG signals compared to hand-crafted features have been broadly proposed.[8,9] The advancements in material science and artificial intelligence have laid a solid foundation for the further promotion of EMG-related technologies.

The EMG technology development has been proceeding rapidly, resulting in fruitful research outcomes and a demonstration of how important EMG is in a wide range of fields, which can be seen in Figure 1. To offer readers a comprehensive understanding of EMG technology from fundamentals to the state of the art, we have composed this article. Our main focus in this article is to demonstrate how the advancements in both material science and machine learning have impacted the EMG signal quality and allowed for more in-depth analysis of the signals by uncovering existing signal patterns. First, we explain the physiology mechanism of EMG signal, and introduce the classical sEMG and iEMG electrodes, together with the discussion of their merits and drawbacks. Second, advanced materials-based electrodes

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Figure 1. Summary of commonly used EMG electrodes and their applications in different fields. Reproduced with permission. From the top center-right picture, in the clockwise order: sEMG used in adolescent idiopathic scoliosis monitoring.[10] Copyright 2010, BMC. sEMG exerted on upper-limb amputation reorganization.[11] Copyright 2013, Elsevier. sEMG utilizing in the diagnosis of preterm labor.[12] Copyright 2012 Facts, Views & Vision. sEMG used in buccal mass diagnosis.[13] Copyright 2021, Kaunas University of Technology. Use of uterine electromyography to diagnose term and preterm labor.[14] Copyright 2010, Wiley-Blackwell. sEMG for upper limb assistance during lifting tasks.[15] Copyright 2007, Elsevier. sEMG helping lower limb prosthesis control during gait.[16] Copyright 2012, BMC. sEMG combined with HD for improving identification of task and force in SCI patients.[17] Copyright 2016, BMC. sEMG used in therapy of autogenic training of spinal myoclonus.[18] Copyright 2007, BMC. sEMG cooperated with EGG for the motor rehabilitation of stroke patients.[19] Copyright 2017, IEEE. sEMG assistance in Wheelchair Propulsion.[20] Copyright 2009, SAGE. sEMG-controlled prosthetic hand with sensory system.[21] Copyright 2017, Elsevier. iEMG used in the control of robotic arms in above-elbow amputees.[22] Copyright 2019, AAAS. A needle electromyography exam robotic simulator.[23] Copyright 2016, SAGE. iEMG used in upper-limb power-assist exoskeleton.[24] Copyright 2014, MDPI. iEMG assistance in congenital insensitivity to pain and erythromelalgia.[25] Copyright 2013, BMJ. Intramuscular electrophysiological assessment of the deltoid muscle.[26] Copyright 2011, Bentham. iEMG assistance in adolescent idiopathic scoliosis surgery.[27] Copyright 2011, KSS. iEMG utilization in target specific spinal cord tracts and segments.[28] Copyright 2019, Springer. iEMG enhancing deep learning movement intent decoders training.[29] Copyright 2019, IEEE. iEMG diagnosis in ALS pathogenesis.[30] Copyright 2019, frontiers. Technical application of iEMG during maximum voluntary isometric contractions.[31] Copyright 2017, Elsevier. Intraoperative EMG neuromonitoring sacroiliac joint.[32] Copyright 2014, Hindawi.
are thoroughly reviewed from the aspects of materials, fabrication methods, and unique advantages compared to the conventional ones. Third, the procedure of EMG signal processing is summarized, with an emphasis on the AI interpretation algorithms. Finally, after illustrating applications, challenges and perspectives are drawn.

2. Mechanism of EMG Signal

The average human muscle contains around 20-50 motor units, which consist of muscle cells and motor neurons. During the activation process, the density of internal and external ions (especially $K^+$, $Na^+$, and $Cl^-$ ions) in muscle cells changes, resulting in the fluctuations of MUAPs of cell membranes. The activation cycle of a muscle cell has three sequential steps: resting potential, depolarization, and repolarization. They are explained in Figure 2.

**Resting Potential:** Before stimulation (receiving neurotransmitter), the distribution of ions on both sides of the cell membrane is maintained by ion pumps. $K^+$ ions density in the membrane is higher than its outside counterpart, while $Na^+$ and $Cl^-$ ions are in a reverse manner. The typical potential difference across the cell membrane is within the range of 80–90 mV.

**Depolarization:** During activation, neurotransmitters released from the nerve ending of the cell break the balance of ions density, indicating that $Na^+$ ions flow in while $K^+$ ions flow out, and giving rise to a change of potential difference around 100 mV.

**Repolarization:** After depolarization, the ion pumps make the muscle cell immediately restore to the original state (resting potential) by adversely exchanging ions, and the potential difference will recover to the resting potential. The muscle cell is now prepared for the next activation cycle.

In the activation process, the muscle cells along the nerve conduction direction are stimulated in sequence, generating the overlapped MUAPs, which create EMG signals (10 to 450 Hz), as conceptually explained in Figure 2. By looking at the different characteristics of the EMG signal, different aspects of the corresponding muscle can be learned.

According to the detection position, the EMG signal can be classified into two categories: iEMG and surface EMG (sEMG). The former is detected by implanted needles or wires and enjoys the benefits of high selectivity (as it can analyze the signal from a single motor unit and even a single muscle fiber), deep muscles detection (such as the genioglossus). Therefore, they are widely utilized in neuromuscular evaluations of clinical treatments. However, this technique is highly invasive, with risks of harming the patients and affecting local detection property. Also, the implementation of iEMG is limited to certified professionals and is conducted under strict supervision, both of which limit its overall accessibility. In contrast, sEMG can provide a noninvasive detection method with electrodes placed on the skin. This method is much more accepted by both patients and researchers, hence it is also used by professionals in nonmedical fields such as kinesiology and ergonomics. However, the sEMG signal is of low amplitude.

![Figure 2. Mechanism of the activation cycle of muscle fibers, and schematics of both intramuscular electromyography (iEMG) and surface EMG (sEMG) electrodes.](image-url)
(0.01 to 10 mV)\textsuperscript{37} and positional sensitivity, hence is susceptible to ambient electromagnetic interference (EMI), boundary condition (also known as skin–electrode interface noise), and incorrect placement, resulting in the lack of robustness and signal quality. In the following section, the design of electrodes for reading EMG signals will be elaborated from the aspects of material, geometry and topology.

3. Electrodes

3.1. Key Properties for EMG Electrode Materials Selection

In this section, four key assessment criteria for all materials used to construct the electrodes are put forward and discussed in the following. Specific requirements for different electrode components and corresponding material selections will be discussed in the following section.

3.1.1. Electrical Properties

The electrochemical impedance of the electrode (especially at 1 kHz) has a critical impact on the quality of recorded EMG signals.\textsuperscript{38} Several studies have stated that lower electrode impedance can improve the signal quality by reducing the white noise power.\textsuperscript{139} However, there is a tradeoff: researchers have to face between larger electrodes with smaller impedance and smaller electrodes which are less invasive and higher spatial resolution but suffer from higher impedance that causes a reduction in signal quality. The common solution to this dilemma is to increase the electrochemical active surface area (ECSA) of electrodes by surface modification with nanostructures, nanomaterials, or electrically conducting polymers. For example, Young-Tae Kwon et al. use a nanostructured self-assembled monolayer (SAM) of 3-mercaptopropyl to enhance the adhesion of copper and achieve printed, skin-conformal Cu electrodes with a very low skin-electrode impedance (<50 kΩ).\textsuperscript{40} Jeong Hun Kim et al. proposed nanocomposite materials (CNT/PDMS) electrodes to improve the electrical conductivity of polymer composites.\textsuperscript{41}

3.1.2. Mechanical Properties

Materials with high Young’s modulus can be easily inserted into tissue, but a considerable portion of electrode failures have been attributed to the mismatch between rigid electrodes and soft muscle tissue (Young’s modulus between 10 to 100 kPa).\textsuperscript{42,43} Electrodes with high Young’s modulus may induce an inflammatory and rejection response.\textsuperscript{44} In addition, the rejection effect induced by the thick fibrous wall will break the electrical coupling between muscle cells and electrodes, ultimately causing signals to deteriorate and implantation failure. Larger Young’s modulus mismatches will also cause the electrodes to move away from the target muscle during muscle contractions, resulting in unreliable signal recording from certain muscle cells. For example, silicon is extensively used as an electrode substrate due to its good electrical property. However, the rigidity of silicon-based intramuscular electrodes brings problems during in vivo implantations. One way to address this issue is to choose substrate materials with a balanced combination of electrical and mechanical properties such as parylene. Cinzia Metallo et al. fabricate flexible parylene-based microelectrode arrays, which provide conformal convergence between electrodes and muscles thus higher SNR and less suffer to subjects.\textsuperscript{45}

Moreover, tissue deformation and extrusion can also bring mechanical damage to implanted electrodes such as delamination or cracks which give rise to recording failure. A narrower Young’s modulus mismatch gap can achieve better performance of accuracy recording by minimizing the current shunting to the less electrical resistive extracellular fluids due to conformal contact between electrodes and tissues.\textsuperscript{46} Therefore, flexibility and low stiffness materials are desired.

3.1.3. Chemical Stability

The chemical stability is an important indicator for implanted electrodes. High chemical stability indicates that the properties of the electrodes will not strongly alter after long-term use. During practical use, four aspects will challenge the chemical stability. First, before the electrodes are inserted into the human body, sterilization procedures are applied to the electrodes.\textsuperscript{47} Among them, high temperatures during autoclaving (120–135 °C) and dry heating (160–190 °C) will accelerate the corrosion and oxidation process of the materials, particularly for easily oxidized materials such as silver. Second, after the electrodes are inserted percutaneously, the ion-rich chemical environment that is created by the internal moisture of the tissue will impose a higher stability requirement on the electrodes. Third, when the inflammation happens, reactive oxidative species (ROS) are released, which will react with the implants. Fourth, in the encapsulation of the collagen capsule, proteins and cells will adhere to the electrodes and obstruct the ion dissipations,\textsuperscript{48} reacting with the electrodes.

3.1.4. Biocompatibility

Biocompatibility indicates the materials should be nontoxic and generate the most appropriate response in a specific situation, i.e., inducing the least immune response and foreign body reactions. F. Williams et al. proposed that the degree of biocompatibility depends on the mechanical and chemical properties and morphological characteristics.\textsuperscript{49} To evaluate this comprehensive indicator, the International Standards Organization (ISO) has published a variety of protocols. The recommended evaluation methods are explained by Silver Frederick et al.\textsuperscript{50} The gel of conventional gelled electrodes, usually with low air and water permission, may irritate the skin of subjects which shows bad biocompatibility during long-term use. To counter this, nanocomposite materials blending elastic polymers and nanomaterials such as CNT/PDMS can be effectively used for continuous biopotential recording.\textsuperscript{4,44}

3.2. iEMG Electrodes

3.2.1. Needle Electrodes

Needle electrodes are widely applied to clinical procedures in disease pathology and neuromuscular evaluation. Due to the
difference between structure and signals acquisition mode, it can be categorized into the following typical types, as shown in Figure 3.

Monopolar Needle Electrode: The monopolar needle electrode (MNE) was first proposed by Jasper et al. in 1949. This prototype consists of a Teflon-coated stainless steel electrode except for a bare tip with 0.5 mm length and 0.56–0.80 mm² recording area. As for the monopolar electrode, it needs an extra surface reference electrode to be the second input of the differential amplifier and commonly has twice the recording surface area compared to the concentric needle electrode (CNE) with similar diameters. The typical materials that are used for core electrodes can be chosen from a variety of metals such as stainless steel, gold, tungsten, platinum-iridium alloy, cobalt-chromium-nickel-molybdenum alloy, and pure iridium metal. To make a proper choice of the utilized materials, different properties should be taken into consideration.

Outside the inner metal is an insulated thin film commonly deposited by Parylene-C, Teflon, nylon, and polyimide. This outside shelter is used to decrease capacitance and keep currents from shunting. Among them, Teflon and nylon were proposed as early solutions to act as insulation films. Compared to other materials, polyimide can provide better performance of heat resistance and chemical stability.

CNE: CNE contains an insulated wire(s) fixed firmly in a cannula and has a metallic part of the outside cannula to serve as a reference electrode. The application of concentric needle electrodes to detect intramuscular EMG signals was first introduced by Adrian et al. Conventional CNE only has one wire inside the cannula. The tip of the inner insulated wire is bare as the detection surface (usually 0.07 mm²) and potential differences are picked between the surface (active electrode) and reference electrode. To improve selectivity and obtain recordings from small muscles like ocular muscles, concentric bipolar electrodes and so-called facial concentric electrodes are developed and often used in motor unit studies.

Single Fiber Electrode: With the emergence of the need for applications such as jitter recording which require rather a high selectivity by recording electrical signals from only one muscle fiber, single fiber electrodes (SFEs) have been proposed. Though the single-fiber analysis is performed by G. Sarrigiannis et al. with the use of miniaturized CNE, it is difficult to ensure accuracy when potential spikes appear nearly simultaneously. The single recording surface area of SFE can reach as low as 0.002 mm² while even the concentric facial electrodes can only reach surfaces areas of ≈0.015 mm².

Macro Needle Electrode: Macro needle electrodes have been proposed by E Stålberg et al. in 1979 to record the electrical activity of a whole motor unit in contrast to the local information measured by conventional intramuscular electrodes. This electrode is in practice a modified SFE but with a fixed length of the uninsulated cannula. The recording is obtained from two channels: one is the action potential recorded by the wire in the cannula from just one muscle fiber and the other one is the potential difference between the cannula and an extra reference electrode. It expands the uptake area and can be applied to analyze muscular jitter and fiber density and perform a greater degree of pathology for diseases such as polio.

The aforementioned iEMG electrodes are summarized in Table 1, together with their relative merits and drawbacks. Needle electrodes offer merits of high selectivity and are convenient to reposition after insertion. However, it brings...
discomfort to subjects during insertion; and the relative displacement between the needle and tissue during muscle movements challenges the accurate interpretation of the recording signals. Both the two drawbacks give rise to the popularization of wire electrodes which is explained in the following.

### 3.2.2. Wire Electrodes

The development of wire electrodes has been brought about by the implementation of percutaneous electrode methods. Like monopolar electrodes and CNE electrodes, the wire electrodes also have an inner conductor and outer insulation. The inner part is made up of non-oxidizing insulated wires with small diameters and could be made from metals such as stainless steel\textsuperscript{[57]} and nickel–chromium alloy.\textsuperscript{[58]} For inserting the wire needle into the desired muscle location, a hypodermic needle is used. The wire electrode is originally confined in the hypodermic needle. During operation, the hypodermic needle first brings the wire electrode to the target position and then is removed and disposed of, leaving the wire electrode in the human body. Wire electrodes are less invasive and painful than needle electrodes whose cannula retains in the muscles during measurements. Since the first wire electrode presented in 1962, fruitful results have been reported. Up to date, the wire electrodes can be divided into three categories, as shown in Table 2.

- **Bipolar Wire Electrode:** The most prevailing wire electrode fabrication method was introduced by V. Basmajian et al. in 1962.\textsuperscript{[59]} Two nylon-coated Karma alloy wires are placed in a hypodermic needle and bent at the tip. The hooked ends of wires enable them to be fixed in the muscle but can also become straight with the mild force exerted on the electrodes when pulling out. Additionally, adhesive tapes can be applied to the conjunctions to protect electrodes from an incidental tug. However, the barb structure limits their capacity for further position adjustment in muscles after insertion.

- **Quadriﬁlar Wire Electrodes:** Quadriﬁlar (QF) wire electrodes were developed by J. De Luca in 1972.\textsuperscript{[60]} Its square-like four wires construction (as shown in Table 2) enhances selectivity since it provides choices of four monopolar electrodes and six bipolar electrodes. The initial structure of QF wire electrodes was similar to concentric needle electrodes, easily inserted but prone to drift during muscle movements. Later on, Ahmed et

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### Table 2. Summary of the commonly used wire electrodes.

| Electrode       | Advantage                                                                 | Disadvantage                                                                 |
|-----------------|---------------------------------------------------------------------------|------------------------------------------------------------------------------|
| Bipolar         | Less painful                                                              | Cannot adjust position after removal of the needle                           |
|                 | Allow strong contractions without discomfort                              | Problematic repositioning                                                    |
|                 | More stable than needle electrodes                                         |                                                                              |
| Quadriﬁlar     | Provide choices of four monopolar electrodes and six bipolar electrodes    | More discomfort                                                              |
|                 | to enhance selectivity                                                    | Unstandardized manufacturing method                                          |
|                 | Stable recording of single motor unit signals up to maximal muscle         | Lack of selectivity for single muscle fiber                                  |
|                 | contractions                                                               |                                                                              |

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al provided a new protocol for QF wire electrode construction to retain its advantages as a wire electrode and apply it in laryngeal muscles to research focal dystonia. Instead of fixing wires in the needle with epoxy cement, they use surgical-quality adhesive to secure the arrangement.

**Branched Electrode:** Branched electrodes that consist of two parallel wires with fixed relative distance and three leading-off areas (as depicted in Table 2) have also been developed for single motor unit analysis.\[61\] The signals recorded by the wire with two uninsulated areas are averaged and subtracted from the signal from the second wire. With subcutaneous branched electrodes, an analysis of a single motor unit with strong contractions can be conducted.

3.2.3. Microtechnology-Based Electrodes

The major limitation of needle and wire electrodes is the inconvenience to record concurrent activity from different locations inside muscles. The conventional solution of placing multiple wires into the cannula of the same needle is still limited to a small uptake area. More recently, some thin-film electrodes fabricated by microtechnology have been developed to achieve multi-channeled and more chronic recordings.\[62-64\] Thin-film electrodes normally consist of polyimide, which acts as substrate and insulator, and the detection sites are made of metal (usually Platinum or Au). The prototype of the multichannel thin-film electrode to record intramuscular electromyographic developed by D. Farina et al. in 2007 is polyimide-based with eight platinum–platinum chloride recording sites.\[65\] Subsequently, versatile thin-film electrodes even with more channels have been proposed. For example, A. Benvenuto et al. use microfabricated thin-film technology to arrange eight active sites on one electrode for nerve recordings.\[64\] Silvia Muceli et al. also designed a thin-film electrode with 12 active sites for both recording and stimulating purposes.\[62\] For the conduction layer, both Au and microrough platinum are applied. Apart from electrodes, the whole structure composes of a hypodermic needle with a guiding filament that is hooked to a cannula.

3.3. sEMG Electrodes

3.3.1. Types and Materials of Surface Electrodes

Two types of surface electrodes are commonly used to convey sEMG signals from the skin surface to further processing systems: 1) Gelled electrodes and 2) dry electrodes, as shown in Figure 4.

**Gelled Electrodes:** Gelled electrodes consist of an electrolytic gel between the skin and electrode, which can provide low skin-electrode impedance and stability during muscle movements. The quality of the electrical signal recordings largely depends on the electrode-skin impedance. Stable impedance over time and consistent spatial impedance of different sites are essential because the differential amplification, which processes the electrical signals can only cancel common signal components. As the impedance becomes different with time and electrodes’ sites change, the output signals become unreliable. Moreover, stable and low impedance can minimize noises such as power line interference thus resulting in a high SNR.\[66\]

Unfortunately, there are a few downsides to the benefits provided by gelled electrodes. The gel is usually low water and air permissible.\[67\] During long-term use, the gel also may dry out, which causes impedance variation. Moreover, gelled electrodes need inconvenient skin preparation during practical use. To address these issues, great effort has been made to develop dry electrodes.

**Dry Electrodes:** Without the electrolytic gel, dry electrodes contact directly with the skin and can be applied in line/array electrodes whose size or geometry do not allow gel. Furthermore, dry electrodes require fewer skin preparations and could be more suitable for long-term detections compared to gelled electrodes.

The main disadvantage of dry electrodes is that the contact is not conformed to the skin have air pockets at the interaction point. The absence of gel results in high skin-electrode impedance and susceptibility to motion artifacts. To decrease the detriment of high impedance, a dry electrode is commonly integrated with a pre-amplifier.

Various materials can be used in surface electrodes such as silver–silver chloride (Ag–AgCl), silver chloride (AgCl), silver (Ag), and gold (Au). For line/array electrodes, Ag and Au are commonly used.\[68\] Among them, electrodes made of pre-gelled Ag–AgCl are the most widely used and show excellent electrical properties. The AgCl layer allows more fluent currents to pass across the electrode-gel junction, unlike gold or gold-plated electrodes, whose impedance shows capacitance property and is susceptible to frequency. The impedance of the Ag–AgCl electrode has electrical resistance property thus little affected by the frequency changes. Besides, Ag–AgCl electrodes can also provide relatively high SNR and are commercially accessible.

In addition to the traditional electrode materials mentioned earlier, electrodes made of other advanced materials have also been reported in recent years. To overcome the disadvantages of typical wet electrodes made of Ag/AgCl, various electrodes made from advanced materials and fabrication methods have

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**Figure 4.** a) Gelled electrode. b) Dry electrode.
been manufactured. Metal thin-film electrodes have high conductivity property while increasing the breakage strain and decreasing the modulus of traditional bulk metals. Metallic nanomaterials-based electrodes also show excellent electrical conductivity and SNR. M. Namkoong et al.\cite{69} fabricated nanocomposite electrodes for robust EMG recordings. In terms of the architecture of the electrodes, PEDOT:PSS is coated on both sides of the silver nanomesh layer. Higher SNR and lower skin-electrode interface impedance have been validated in their research. Their fabrication process is shown in Figure 5a. Kanhao Zhu et al.\cite{70} designed ECC – PDMS electrodes to achieve high SNR and sufficiently low skin-electrode impedance. Carbon material electrodes also play a promising role in the development of EMG electrodes due to their excellent characteristics such as high electrical conductivity and flexibility. Ha-Chul Jung et al.\cite{4} introduced a carbon nanotube (CNT)/polydimethylsiloxane (PDMS) composite-based dry electrode, which is long-term wearable and reliable while conventional gel-type Ag/AgCl electrode may irritate the skin and decrease signal quality due to gel interface. Chen-Yang Huang et al.\cite{71} produced nanofiber carbon electrodes that were prepared by electrospinning with low impedance, high water-contact angle, reliable electrical signal, and high durability. Apart from the improvement in materials, some novel fabrication methods have also been proposed. Zhuo Li et al.\cite{72} reported a scalable fabrication method that can produce a large number of on-skin electrodes called reduced graphene oxide (rGO) electrodes. P. Jastrzebska-Perfect et al.\cite{73} coated mixed-conducting polymer particles on Au-based layers to acquire EMG signals. Different sizes of mixed-conducting particles and the physical process steps to create conducting polymer particles are shown in Figure 5b. Higher spatial resolution and equivalent SNR compared to traditional gel-based electrodes have been achieved.

3.3.2. Shape and Size

There are a wide variety of shapes and sizes when it comes to sEMG electrodes, with no clear standards established. Some common factors to consider are: 1. Though different shapes
of electrodes may affect frequency characteristics of signals (i.e., specific shapes may cause dips in frequency spectrum), more theoretical and predictable results need many further types of research. With respect to skin impedance and noise, different shapes of electrodes show similar performances with similar surface area, conventionally, round-shaped electrodes are widely used.

sEMG electrodes can be divided into unit and array-based structures. The size of the former determines the scale of the detection area, in array structures, each electrode is normally at mm² level; a smaller size would contribute to higher EMG image resolution, while may result in complex readout circuitry. Both the two structures are discussed in the following.

Electrodes with different sizes are suitable for different muscle sites. For example, Ag/AgCl electrodes with 0.5 cm diameter detection area and 1.5 cm, diameter housing area are commonly used in limbs and trunks to obtain representative EMG signals of large muscles, while smaller electrodes with 0.25 cm diameter detection area and 1 or 0.5 cm diameter housing area are usually used in facial sites. A single surface electrode can be viewed as a series of point electrodes distributed densely with the detection surface. It averages the action potentials under its surface. As the area becomes larger, the low-pass filter effect of electrodes becomes more distinct, and higher frequency components of signals are attenuated or removed. Though more global signals can be obtained, electrodes with greater sizes imply an increasing smoothing effect, higher error of power, and lower selectivity. Thus, in this circumstance, small electrodes (diameter < 5 mm) are preferred to improve signal quality.

Apart from this, small electrodes (diameter = 2 mm) can be arranged in multipolar configurations to acquire more features of muscles.

3.3.3. Configurations

Monopolar Configuration: Monopolar configuration uses only a single electrode to record the MUAPs nearby the regions of interest with respect to a reference electrode. Though this configuration is simple to implement, as shown in Figure 6, it is not preferred in sEMG because the recorded signals are prone to couple into noise such as crosstalk and power frequency interference due to a lack of procedure to filter out common mode noise.

Bipolar Configuration: Bipolar measurements use two electrodes aligned with the muscle fiber extension direction to detect and amplify the action potentials difference on the same motor unit; both electrodes are relative to a reference electrode, as shown in Figure 7. According to the differential amplifier

![Figure 6. Monopolar signal acquisition configuration.](image)

![Figure 7. Bipolar signal acquisition configuration.](image)
structure, the common-mode noise (e.g., ambient noise and power-line noise) can be significantly eliminated and detect a signal with high SNR. However, the amplitude and frequency content of the detected sEMG signal is sensitive to bipolar electrode alignment error.\[\text{79}\] Besides, to maintain the sEMG amplitude, two electrodes of large size (usually 8–10 mm diameter) are required to record one sEMG signal,\[\text{80}\] resulting in a low spatial resolution. Moreover, bipolar configurations reduce the detection depth and attenuate the signals from deep muscles.\[\text{77}\]

**Distributed Configuration:** Distributed electrode configuration is an sEMG acquisition method, where many electrodes are placed together. Depending on the electrode’s distribution, distributed electrodes can be divided into two types: electrode arrays and electrode matrices. In 1979, Lynn initially extended three surface electrodes in one direction to form a line electrodes configuration for sEMG detection.\[\text{81}\] After 1980, electrodes matrix became widely used for diagnostic purposes, measuring muscle fiber conduction velocity,\[\text{82}\] telerobotics,\[\text{83,84}\] and hand gestures recognition.\[\text{85}\] The selectivity of distributed electrodes can be further improved by the spatial filter process, which means the transmitted signal is the weighted summation of electrodes in different spatial sites. Typical configurations are shown in Figure 8. The percentages of discriminated MUAPs of these spatial filters are all higher than bipolar configuration (single differential filter).\[\text{86,87}\]

In more recent years, high-density sEMG maps have also been confirmed to be useful in EMG analysis,\[\text{70,81,84}\] as shown in Figure 9. This measurement method is characterized by higher resolution and an enhanced capability to distinguish action potentials from different motor units and abundant information, compared to single monopolar or bipolar electrodes. Benefit from the high electrode density (equally 32, 64, or more electrodes on the same muscle or a muscle group), it can acquire the spatial–temporal motion characteristics within a certain muscle area, even the locations of innervation zones, helping researchers analyze the muscle activation mechanism. Apart from this, distributed electrodes can obtain superior quantities of signal,\[\text{88}\] providing redundant information for denoising algorithms like correlation analysis and adaptive filtering to improve the SNR, eliminating the influence of transient ambient changes and lack of robustness.

### 4. EMG Signal Processing Algorithms

To interpret the EMG signal, algorithms based on machine learning or deep learning techniques have been utilized. In this section, the two essential parts of EMG signal processing, i.e., preprocessing and interpretation, are discussed. The complete processing flowchart is shown in Figure 10. Raw EMG data is collected from subjects by surface or needle electrodes (the example in Figure 10 is from a dataset created by M. Ozdemir et al.\[\text{89}\]). To remove the DC offset and low-frequency noise, a high-pass filter (cutoff frequency at 2 Hz\[\text{90}\]) can be applied in the first pre-processing step. Then, windowing the period in the time-domain which we are interested in to exclude the confusion impact from other periods.\[\text{91}\] In this example, the chosen window is hamming window and it works well in decreasing spectrum leakage. A 50 Hz notch filter is then adopted to eliminate the interference from power frequency. Last, rectifying could be optionally carried out for classification algorithms for obtaining better results.

#### 4.1. Preprocessing

Before EMG data is transmitted to algorithm-based classifiers, there are two steps to guarantee the precision and utility of the recoded signals. The prior process is called pre-processing, which can mainly be divided into three subparts: signal windowing or signal segmentation, signal filtering or denoising, and

![Figure 8](image_url1)

**Figure 8.** a) Bipolar (single differential filter). b) Branched (double differential filter). c) Laplacian double differential filter. d) Laplacian 2D double differential filter. e) Laplacian inverse rectangle filter.

![Figure 9](image_url2)

**Figure 9.** Example of HD-electromyography (EMG) from the right arm, electrodes configuration, and maps.
signal rectification. The windowing (or segmentation) helps to extract features and lower the dimension of the data, improving classification accuracy. Filtering could help denoising or remove several interferences. Rectification’s role is still controversial but many experiments regard it indispensable.[92]

4.1.1. Windowing

The EMG signal windowing method has two main parts: overlapping windows and adjacent windows. Through segmentation, the classifier’s accuracy can be enhanced, especially during the acquisition of new data.[93] Overlapping windows increase the possibility of successful feature extraction and minimize missing information.[94] A new window will overlap with a previous one, and the overlapping area ratio between the two could be 25% or 50%.[95] This method also produces a reasonably dense and continuous decision-making data stream in accordance with hardware capacity.[96] The maximum overlapping window length is restricted to no more than 300 ms.[97] M. Kunapipat et al. developed a method to consider hand gestures and the greatest prediction accuracy was reached when the overlapping size is half of the time length.[95] Similarly, C. Tepe et al. employed a 100 ms 50% overlapping window to preprocess EMG signals to control prosthesis and achieved a 95.8% classification accuracy for 5 fingers and 1 rest gesture.[98] Adjacent windows are mostly used in the determination of the stationarity of EMG signals.[99] Different from the overlap window method, the window will begin where the last one ends. J. Chen et al. used 150 sampling points sliding windows to preprocess EMG signal data and the accuracy for gesture recognition was over 98%.100] Z. Taghizadeh et al. used adjacent segments of window size 128 ms to overcome the non-stationarity of EMG signals and the classification accuracy improved to 98.12%.[100]

4.1.2. Filtering

EMG data that is collected from a subject is bound to be contaminated by a variety of sources such as the surroundings and the electrodes themselves. Several noise types, including the baseline wave (BW) or drift, Gaussian white noise (GWN), power line interference (PLI), and artifact noise are the most mentioned ones.[101] The commonly used filters can be divided into two categories: hardware filters and software filters, the latter called digital filters as well. Nowadays, the signals recorded from EMG electrodes can be converted to digital signals by analog-to-digital converter (ADC), which can be swiftly processed by PCs, hence digital filters are more widely employed. For instance, C. Li et al. used a 50 Hz comb filter to eliminate power frequency interference.[102] J. R. Torres-Castillo et al. use a rejects-band filter (notch filter) to remove power line interference and a third-order Butterworth filter to attenuate the baseline oscillations caused by the subject’s involuntary motion.[103] H. ElMohandes et al. used the Kalman filter to decode kinesthetic signals.[104] K. Strzecha et al. used an
infinite impulse response (IIR) filter to eliminate frequency drift, power line, and ECG noise, which highly resemble EMG signals.\[99\] Furthermore, wavelet or model decomposition basing algorithms are equally employed in signal filtering for they can adapt to various signals. Wavelet transform could efficiently remove spectral overlapping noise but the main limitation lies in non-data-driven principles and the parameters’ choice will largely affect filtering results.\[100\] Empirical mode decomposition (EMD).\[100\] Ensemble EMD was put to solve the shortage of bad performances in complicated spatial and temporal structures noises eliminating.\[106\] S. Ma et al. used a variable mode decomposition (VMD)-based filter to denoise PLI, BW, and GWN, achieving a relatively low RMSE with the same SNR.\[101\] M. Mortezaee et al. use singular spectrum analysis to eliminate ECG interference, whose method needs no parameters and is model-free, which can be applied to decompose slowly time-varying signals.\[107\]

4.1.3. Rectification

The MUAP as the source of EMG data fundamentally influences the quality of the data. MUAP’s role in one contraction is similar to a high-pass filter of the neural drive, which will damage the low-frequency components. To offset this effect, EMG rectification was introduced.\[108\] For instance, in C. J. Dakin’s et al. work, EMG rectification is an essential step to extract signal envelope modulation.\[109\] There are several methods to rectify EMG signals, including the most-used full-wave and half-wave rectification. The full-wave method polarizes signals to a positive value with their energy being conserved while the half-wave method directly ignores signals below the baseline value. For this reason of energy conservation, full-wave rectification is recommended.\[110\] T. Roland et al. proposed a square rectification method, whose output data was the square value of input signal data.\[111\] N. J. Ward et al. work demonstrated that rectified EMG signals can better predict motor unit (MU)’s synchronization for the frequency components in low-intensity movement and rectified signals have a smaller residual partial correlation in the beta-frequency band for the bidirectional load process.\[112\] However, due to its repression of high-frequency components, EMG rectification is not suitable in certain conditions. Amplitude cancellation will distort the frequency spectrum.\[108\] And rectification of EMG is not a linear process that introduces unwanted central frequency filters which make the power spectrum distort.\[113,114\] Y. Ruiz-González et al. found that rectified EMG signals descend the significance level of the lower beta-frequency band and distort the coherence estimation in high-frequency portions, which contributes to a seriously bad impact on corticomuscular coherence (CMC) and intermuscular coherence (IMC) estimation.\[115\]

4.2. Features

Feature extraction can infer the hidden information of the EMG signal, and study the characteristics and behavior of the signal. Features in sEMG signals can be classified into four categories: time domain (TD), frequency domain (FD), time–frequency domain (TFD), and spatial domain (SD).

4.2.1. TD

The TD characteristics of the EMG signal are indicators based on statistical methods, and the EMG signal is regarded as a function of time. This is an intuitive expression of the EMG signal. Due to the relatively low computational complexity, many early-stage studies have focused on TD features. Bhattacharya et al.\[116\] extracted EMG signals from hand movements including autorregressive (AR), root mean square (RMS), zero crossing (ZC), slope sign change (SSC), waveform length (WL), and mean absolute value (MAV). LDA, K nearest neighbor (KNN), etc., are used to classify these TD features. The classification accuracy of the 6-feature mixed multi-feature set is the highest, which is 83.33%. Phinyomark et al.\[117,118\] studied 11 common temporal characteristics of 8 types of hand movements, including MAV, WL, variance (VAR), Willison amplitude (WAMP), ZC, SSC, RMS, logarithmic detector (LD), myoelectric histogram (HIST9), 9th-order autoregressive coefficient (AR9) and 9th-order cepstral coefficient (CC9). These features are used to study the effect of sampling rate on classification performance.

4.2.2. FD

The FD characteristic of the EMG signal represents the TD signal that has been transformed into an FD through Fourier transformation and other methods, and then analyzes the signal’s spectral characteristics or power spectrum characteristics. The advantage of the frequency domain feature is that it is relatively stable and less susceptible to noise, and it is easier to extract stable features. Power spectral density (PSD) is the main analysis method in the frequency domain. It directly shows the level of muscle activation. Too et al.\[119\] compared the discrimination ability of TD features and frequency domain features on EMG signals for hand movement recognition. In this study, the LDA classifier was employed, and the classification accuracy of FD features was the highest, which was 91.34%. FD features such as mean frequency (MNF), median frequency (MDF), and frequency ratio (FR) require more calculation time but have obvious advantages in classification accuracy under experimental conditions.

4.2.3. TFD

The traditional Fourier transform can only describe the frequency characteristics of the signal but hardly provide the frequency information of the signal in any TD. The combination of time and frequency characteristics absorbs the advantages of both sides. Therefore, time-frequency analysis methods represented by short-time Fourier transform (STFT), Wigner–Ville transform, Choi–Williams distribution, and wavelet transform (WT) have attracted the attention of researchers. Shanmuganathan et al.\[119\] collected the EMG signal of the forearm, used wavelet packet transform (WPT) for feature extraction after preprocessing, and used the R-CNN classifier for classification. This scheme is used to realize gesture recognition, with an
The accuracy rate of 96.48%. Among them, WPT is an improvement over WT. The signal analysis is more detailed, and the resolution of high-frequency signals is better than that of WT.

4.2.4. Spatial Domain

EMG signal measurement can not only extract time and spectral information but also extract spatial information. SD features can provide the relationship between EMG signal and spatial position, which has considerable advantages in muscle control. Stango et al.\cite{120} proposed an EMG signal classification method based on SD features for muscle control, which improved the robustness and reliability of the pattern recognition system. In this article, the experimental variogram, which describes the spatial correlation between observations, is used as the classification feature, and the average classification accuracy is 95%.

A brief review of the common features and pattern recognition techniques applied in relevant studies is shown below in Table 3.

### Table 3. Review of the common features and pattern recognition techniques.

| Reference | Feature extraction | Classifier                  | Accuracy    |
|-----------|--------------------|-----------------------------|-------------|
| [116]     | AR, RMS, ZC, SSC, WL, MAV | Ensemble, KNN, QDA, LDA     | Up to 83.33% |
| [117]     | MAV, WL, VAR, WAMP, ZC, SSC, RMS, LD, HIST9, AR9, CC9 | SVM, LDA | Up to about 94% |
| [118]     | FD features such as MNF, MDF, FR, TD features | LDA | The accuracy of FD feature classification is up to 91.34% |
| [121]     | Spectrum analysis and PSD method to extract FD features, TD features | Attribute selected classifier | The overall accuracy rate is 93.8% |
| [119]     | WPT                | R-CNN                       | 96.48%      |

4.3. Classification

Among the classification methods of EMG signals, traditional machine learning algorithms such as LDA, KNN, hidden Markov model (HMM), fuzzy logic (FL), and SVM are very commonly used. With the development of deep learning related technologies, deep learning related algorithms are also very commonly used in EMG signal classification in different scenarios. These algorithms are explained in Table 4.

### Table 4. Summary of the algorithm features and application.

| Classifier | Advantages | Disadvantages | Application |
|------------|------------|---------------|-------------|
| LDA        | Low complexity of computation Simple implementation | Incapable of handling the linear inseparable problem | Diagnosis of amyotrophic lateral sclerosis.\cite{122} Prosthetic control\cite{123} |
| KNN        | Nonparametric nature Suitable for multiple classification problems | May lack resolution when the sample is unbalanced Large amount of calculation | diagnose gastrointestinal diseases\cite{124} |
| HMM        | Strong spatiotemporal sequence modeling ability | The application range is limited due to the space–time characteristics of the algorithm | Game-based training method for prosthetic control\cite{125} Parkinsonian rest tremor detection\cite{126} |
| FL         | Have advantages in biomedical signal processing | Sometimes lack of accuracy | Omnidirectional Wheelchair control\cite{127} Elbow rehabilitation Robot control and remote therapy\cite{128} |
| SVM        | The optimal kernel function can obtain high accuracy Able to project the indivisible linear data to a linearly separable set in high-dimensional space Perform well even with low sampling rate Many improved versions | Unsuitable for large quantities of samples Require large system memory and processing time | Differentiating essential tremors from dominant Parkinson’s disease\cite{129} Diagnosis accuracy for neuromuscular disorders\cite{130,131} |
| ANN        | Can describe nonlinear class boundaries among different categories Resistant to noise | Long training period High complexity of computation | Diagnose bruxism\cite{132} forearm Physiotherapy\cite{133} |
| RNN        | It can view data as sequences Time information can be modeled | Problem of long-term dependence High computational cost | Motorized wheelchair control\cite{134} Myolectric prostheses control\cite{135} |
| CNN        | Image-based Can extract more potential features | Optimization function is easy to fall into a local optimal solution Easy gradient disappears High computational cost | Myoelectric hand control or neuro-prosthesis control\cite{136,137} |
4.3.1. LDA

LDA is a supervised dimensionality reduction method, similar to principal component analysis (PCA), which is to project data in different dimensional spaces to achieve the purpose of dimensionality reduction. Both have been used for classifying EMG data for a wide range of applications. However, LDA and PCA do have some fundamental differences from each other. First of all, PCA is unsupervised, while LDA is supervised. When using the PCA model, category labels are not used, while LDA uses the information provided by the data category labels when performing data dimensionality reduction. Secondly, the goal of PCA dimensional reduction is to project the largest variance of the low-dimensional space data, to preserve the information of the data to the greatest extent. The basic idea of LDA is to project the data in the high-dimensional space into the optimal discriminant vector space to achieve the effect of extracting classification information and compressing the dimension of feature space. Therefore, PCA lacks the ability to distinguish, while LDA can achieve good classification results while reducing dimensionality in many cases. Zhang et al.\cite{138} compared different feature extraction methods, such as LDA for raw EMG, LDA for features, PCA and LDA for raw EMG, and PCA and LDA for features. The results show that extracting features from EMG signals can improve classification accuracy, and using PCA to reduce dimensionality is also conducive to classification. For hand movement classification, the highest classification success rate is 99.8%. Negi et al.\cite{139} drew a scatter plot of the time-domain features of the EMG signal and used PCA and uncorrelated linear discriminant analysis (ULDA) feature reduction techniques for classification. The results prove that the linear discriminant classifier can achieve very good classification accuracy.

The ULDA algorithm is a fast statistically uncorrelated LDA algorithm. Different from the general LDA algorithm, the projection vector set obtained by the ULDA algorithm is conjugate orthogonal to each other, and the features obtained by the ULDA algorithm are statistically irrelevant, which improves the computational efficiency of the LDA algorithm. Phinyomark et al.\cite{139} obtained EMG signals from forearm muscle channels and hand movements, extracted feature sets from EMG signals based on TD and time scale domain, and used them as the input of the classifier, used ULDA for dimensionality reduction, used LDA as a classifier for performance evaluation. In more cases, the LDA algorithm combined with other methods can combine the advantages of different algorithms to achieve better accuracy and stability of the classifier. Zhang et al.\cite{140} proposed an unsupervised adaptive linear discriminant analysis (ALDA) classifier. The adaptive strategy includes periodic replacement of training datasets and adjustment of parameters based on probability weighting. By using the adaptive strategy, the parameters of ALDA are always calculated from the latest training data set, so the method has a higher classification accuracy of EMG signal than LDA under stable conditions or with added noise. Joshi et al.\cite{141} used Bayesian information criterion (BIC), some standard feature extraction methods and LDA classification algorithms, and use lower limb EMG signal data to separate different stages of gait. Experiments show that this method is very effective for real-time EMG prosthesis control. The QDA classification algorithm is a more general version of the LDA algorithm, which divides different classes through a secondary plane, and has a non-linear classification capability. Pancholi et al.\cite{142} extracted TFD features from arm muscles, used LDA and QDA algorithms for classification, and achieved good classification results.

4.3.2. KNN

KNN is a nonparametric statistical classifier that predicts the category of the test sample based on the training sample closest to the test sample and classifies it as the category with the highest category probability. When KNN is used as a classifier for EMG signals, the classification is simple and easy to implement, and it is very suitable for multi-classification problems. Murugappan\cite{143} used KNN for human emotion classification based on EMG signals. After removing noise and external interference, the EMG signal is decomposed into four different frequency ranges using discrete wavelet transform (DWT). KNN is used to map the statistical features extracted from different frequency bands into five different emotions. In the classification of the five main emotions, the highest classification accuracy rate is 100%. Kim et al.\cite{144} compared a variety of algorithms to classify the direction of wrist movement. After statistical analysis, the performance of the KNN algorithm was found to have statistical advantages. In recent years, the KNN algorithm has been widely used in the field of disease rehabilitation. Arteaga et al.\cite{145} proposed a preliminary method of robot-assisted hand movement therapy for stroke rehabilitation. They obtained sEMG signals from the flexors and extensors of the forearm. The time and frequency characteristics were used as input to the machine learning algorithm to recognize six gestures. KNN has better performance for gesture classification. Tuncer et al.\cite{146} proposed a new iterative feature extraction method based on three-value mode and discrete wavelet (TP-DWT). Using the proposed feature extraction network based on TP-DWT, a surface EMG signal recognition method is proposed and used for artificial hand control. The KNN classifier is selected and a classification accuracy of 99.14% is achieved. In addition, KNN is sometimes combined with other algorithms. Kim et al.\cite{147} combined the KNN classifier and Bayes classifier for gesture recognition and achieved a recognition accuracy of 94%. These two classification methods are based on the decision tree structure, combining the two in decision level fusion, and input common statistical features such as variance and TD, and FD features into the combined classifier to achieve real-time classification and ensure high recognition accuracy.

4.3.3. HMM

HMM is a classic machine learning model. This method is based on the Markov chain and has advantages over other algorithms in its modeling capabilities for spatiotemporal sequences. HMM can capture the relationship between continuous metrics, which means that the current decision is biased toward the previous decision, which helps eliminate some false misclassifications, and has a wide range of applications in the field of continuous EMG signal classification. Chan et al.\cite{148} used HMM to process four-channel EMG signals for the recognition of six limb
movements. This method does not need to segment the EMG signal, and achieves a classification accuracy of 94.63%. In this scheme, HMM has low computational complexity and low computational overhead. Rossi et al.\cite{149} used the combined classifier of SVM and HMM, which not only used the excellent time-independent classification ability of SVM but also used HMM’s ability to capture time series information. This combined method is used for gesture classification, and the classification accuracy is improved by 12% compared with only using SVM.

4.3.4. FL

FL is an algorithm with advantages in the classification of biomedical signals. The characteristic of FL is that there is no strict boundary of membership, and the attribution of the class is measured by the degree of membership. FL has unique advantages for biomedical signals that cannot always be completely repeated or even contradictory. Moreover, the FL system is not easily sensitive to overtraining, which is also conducive to the correct classification of EMG signals. Ajiboye et al.\cite{150} proposed an FL method for prosthesis control. This method uses basic features to construct membership functions and uses fuzzy c-means (FCMs) data clustering to automatically construct inference rules bases. The overall classification accuracy rate is above 94%. Chan et al.\cite{151} proposed an FL-based EMG signal classification method for prosthesis control. This method inputs the time segmentation feature into the system for clustering and then uses the clustering results to initialize the fuzzy system parameters and perform the fuzzy system training. This method obtains classification results similar to ANN, and compared to ANN, FL has some potential advantages.

4.3.5. SVM

SVM is a commonly used machine learning technique in the classification of EMG signals. SVM distinguishes different categories by finding a hyperplane in high-dimensional space. The classification accuracy of SVM mainly depends on the selection of kernel function and parameters. Under the effective parameter optimization method, SVM can obtain high classification performance. Paul et al.\cite{152} conducted a comparative analysis on linear SVM and KNN classifiers. This article selects seven commonly used TD features. Experimental results show that linear SVM has higher accuracy than KNN for EMG signals in the TD. Bellingeagi et al.\cite{153} used different classifiers to classify the sEMG data of patients with trans-radial amputation. The comparative analysis among NLR, MLP, and SVM showed that the classification performance and the number of classification parameters, SVM reached the highest values. SVM effectively combines with other methods by flexibly setting kernel parameters to improve classification accuracy. Particle swarm optimization (PSO) is a swarm intelligence optimization algorithm, derived from the study of bird swarm foraging behavior. Subasi et al.\cite{154} mixed particle swarm optimization (PSO) and SVM, and set the nuclear parameters reasonably in the SVM training process to improve the accuracy of EMG signal classification and used to classify into normal, neurogenic, or myopathic. Gokgoz et al.\cite{155} significantly improved the accuracy of EMG signal classification by using multiscale principal component analysis (MSPCA) denoising method and rearranging the kernel parameters of SVM for the diagnosis of neuromuscular diseases. In recent years, the application of surface EMG sensors in wearable devices such as armbands has received more and more attention as the integration of human machine interfaces (HMIs) input sources. Tavakoli et al.\cite{156} installed two EMG channels on the flexor and extensor muscles of the forearm and used SVM as a classifier to classify gestures, achieving high accuracy, simple, fast, and accurate gesture recognition. Demir et al.\cite{157} preprocessed the sEMG signal through a short-time Fourier transform, and used a time-frequency image (TFI) as the input of the pretrained convolutional neural network model for deep feature extraction, and used SVM for classification. The classifier achieves 99.04% classification accuracy of physical behavior.

4.3.6. Deep Learning

The concept of “deep learning” originated in 2006. Hinton et al.\cite{158} derived a greedy algorithm for the fast training of deep belief networks. The deep learning method can automatically learn features of different abstraction levels from a large number of input samples, thereby avoiding the complicated and tedious manual extraction and optimization of signal features, and realizing end-to-end MG gesture recognition. In recent years, with the rapid development of deep learning technology, EMG recognition methods based on deep learning have been widely used. Morbidoni et al.\cite{159} used an artificial neural network (ANN)-based method to classify gait events (correct standing and swinging phases) for use in overcoming the constraints of a controlled environment under more natural walking conditions. Convolutional neural network (CNN) is currently the most popular EMG pattern recognition deep learning method. Its input is image-based, and the hidden layer is usually composed of a convolutional layer and a pooling layer. Samanta et al.\cite{160} performed cross wavelet transform on the electromyogram signals of health, myopathy, and amyotrophic lateral sclerosis disorders, and used CNN for the depth feature extraction of the cross wavelet spectrum images of the electromyogram signals, and the extracted depth The features are fed back to multiple benchmark machine learning classifiers for the recognition of EMG signals, which can achieve the highest average classification accuracy of 100%. This method can be used for the real-time detection of neuromuscular diseases and reflects the powerful feature learning ability of CNN. CNN-based classifiers are also widely used in human-machine interaction (HMI) applications. Zhai et al.\cite{161} proposed a CNN-based self-calibration classifier, which uses a short-delay dimensionality reduction sEMG spectrogram as input to perform hand movement classification for upper limb neuroprosthetic control. By combining the CNN classifier with a simple tag updating mechanism, the classifier provides the effective self-calibration capability. Compared with SVM, the CNN-based system always shows higher absolute performance and more effective training. Zia et al.\cite{162} used the original EMG signal as a direct input and used CNN for motion pattern recognition, which significantly improved the performance of upper limb prosthetic EMG control, and the
classification performance of CNN was better than LDA and stacked sparse autoencoders with raw samples (SSAE-r). In terms of improving the performance of classifiers, CNN has considerable potential to speed up classification performance and reduce hardware costs. Asif et al.\cite{Asif2022} used CNN to decode gestures from surface EMG data to study the influence of hyperparameters on gestures. The results showed that a reasonable learning rate and other hyperparameter settings will significantly improve the recognition ability and performance of the classifier, making it based on deep learning.

Deep learning methods have the potential to become a more robust alternative to traditional machine learning algorithms. Fajardo et al.\cite{Fajardo2020} proposed an EMG signal classification method combining manual features based on time-spectrum discrete analysis and deep features extracted by CNN for gesture recognition, reducing the time required for training the system. Recurrent neural network (RNN) is also a commonly used classification algorithm. It can process sequence information by dynamically changing its internal state. It is often used to model the time information in the sequence. However, because RNN cannot solve the problem of long-term dependence, the long and short-term memory (LSTM) network of the forget gate is proposed. Jabbari et al.\cite{Jabbari2022} used an LSTM-based neural network to classify the grip posture in multiple categories. Four different feature sets are extracted from the original signal and input into LSTM for classification, which is used for upper limb prosthesis control. Compared with CNN and other structures, it pays attention to the time dependence of muscle contraction.

The deep belief network (DBN) is a network organized in a deep structure. The network uses a greedy algorithm to train layer by layer, which solves the difficult problem of multilayer neural network training and has stronger modeling capabilities. Chen et al.\cite{Chen2022} established a DBN composed of a restricted Boltzmann machine (RBM), by extracting the time series of the surface EMG signal intensity of the lower limbs, using the DBN for low-dimensional coding, and extracting the optimal features for analysis. This method improves the motion stability between man and machine. In addition to the commonly used deep learning algorithms, some new methods of EMG signal classification have begun to appear. A spike neural network (SNN) is a network composed of spike neurons, usually modeled by a phenomenological model (such as a spike response model). Donati et al.\cite{Donati2022} proposed a neuromorphic implementation of SNN, which can be deployed locally on the sensor side to locally extract the spatiotemporal information of the EMG signal and classify gestures with extremely low power consumption. This method has significant advantages over traditional methods that need to process large amounts of data.

5. Application

As previously described, multiple classification methods had been proposed to identify the intrinsic information behind various features of EMG signals, some of which combined EMG with other signals to satisfy more diverse needs and to compensate for EMG signals’ shortcomings, as shown in Figure 11. These advancing tools pave the way for the practical application of EMG. Currently, there are widely used technologies of hand or gait pattern recognition, which showed a promising role in artificial intelligence (AI), HMI, virtual reality (VR), and remote

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**Figure 11.** Summary of commonly used EMG-based signals integration with application schemes respectively. Reproduced with permission: gait parameters detection\cite{Dijkmans2020}, Copyright 2020, MDPI. Construct musculoskeletal model\cite{Dijkmans2020}, Copyright 2020, Springer Nature. Human activity recognition\cite{Dijkmans2020}, Copyright 2020, Springer Nature. Prosthesis control\cite{Dijkmans2020}, Copyright 2020, Springer Nature. Human–computer interface\cite{Dijkmans2020}, Copyright 2022, Springer Nature. Emotion detection\cite{Dijkmans2020}, Copyright 2021, Springer Nature. Rehabilitation assistance\cite{Dijkmans2020}, Copyright 2022, Springer Nature. Disease analysis\cite{Dijkmans2020}, Copyright 2016, Springer Nature.
intelligent manipulation. Furthermore, these increasingly prosperous EMG technologies enhance medical and clinical practices, which can be mainly divided into diagnosis and rehabilitation applications. The existing information beneath the time and frequency domain features of EMG now is widely used to diagnose neuropathy, myopathy, or other diseases related. Meanwhile, the assistive, prosthetic, and other rehabilitation facilities focus more on EMG-based control methods, largely facilitating the rehabilitation process and improving user's experiences.

5.1. sEMG Application

5.1.1. Disease Analysis

X. Zhang et al.\textsuperscript{[122]} present a noninvasive surface EMG method for supporting the diagnosis of amyotrophic lateral sclerosis (ALS). Using a flexible surface electrode array (TMS International BV, The Netherlands), which was placed at the the-nar and first dorsal interosseous (FDI) muscles while the reference electrode was located near the elbow, the EMG signals were preprocessed by linear discriminant analysis (LDA) classifier, achieving a diagnostic performance of 90% sensitivity and 100% specificity for diagnosing ALS subjects.

E. Suh et al.\textsuperscript{[175]} determined and evaluated a biomarker that could predict the disease of patients with chronic obstructive pulmonary disease (COPD) potential development during their period of hospitalization, which was acquired by neural respiratory drive extracted from sEMG signals. Placing surface electrodes (Blue Sensor Q, Ambu, St Ives, UK) in the second intercostal spaces, immediately lateral to the sternum, they processed the data via t-tests or Wilcoxon signed-rank tests, logistic regression, receiver-operator characteristic (ROC), Kaplan–Meier plots and log-rank tests, finally achieving relatively high accuracy in readmission in 14 and 28 days.

M. U. Khan et al.\textsuperscript{[124]} proposed a method to diagnose gastrointestinal diseases through patients' sEMG signals. They adopted BIOPAC Systems Model MP36 Data Acquisition Unit and placed the disposable gel surface electrodes on the near area of the umbilicus. The recording signals were preprocessed by empirical model decomposition and then were transmitted to a series of machine learning classifiers including Quadratic SVM, Fine KNN, RUS Boosted Trees, and Cubic SVM, among which the highest one achieved 100% accuracy for differentiating diarrhea, constipation, and normal gastrointestinal situations.

I. Conradsen et al.\textsuperscript{[176,177]} developed a generic algorithm based on sEMG to automatically detect tonic-clonic epileptic seizures. The 9 mm silver/silver chloride electrodes were placed on subject's deltoid and anterior tibial muscles on both sides in a monopolar setting. Through DWT and wavelet packet transformation (WPT), their algorithm was validated by a fourfold cross-validation method, achieving a sensitivity of 100% with a mean detection latency of 13.7 s.

T. Sommezocak et al.\textsuperscript{[112]} propose an analytic approach based on EMG signal to diagnose bruxism. The electrode was an Ag/AgCl bipolar electrode of 15 mm diameter and was positioned on the skin surface over the masseter muscle of the subjects at 1 cm intervals.

Autoregression (AR) and DWT were applied to extract features and ANN was used to classify, this approach achieved an accuracy of 100% for differentiating people with bruxism from normal ones.

A. Sarcher et al.\textsuperscript{[178]} proposed a semiautomatic method for assisting in precisely diagnosing unilateral spastic cerebral palsy, based on EMG signals. They chose to use self-adhesive pairs of disposable bipolar Ag/AgCl surface EMG electrodes (recording diameter 10 mm), which were placed on the pronator teres (PT) and pronator quadratus (PQ) muscles. The recorded signals were pre-processed and then submitted to three EMG experts for analyzing intra-rater reliability. Krippendorff’s alpha reliability estimate with 95% confidence intervals was employed to validate the results, showing a 96% positive predictive accuracy while 91% for a negative one.

N. Ghassemi et al.\textsuperscript{[129]} proposed an analysis method for differentiating patients with essential tremor from dominant Parkinson’s disease with the combination of accelerometer and EMG. EMG signals were collected for bipolar surface Ag/AgCl electrodes attached to the subject’s extensor and flexor muscles of the left and right forearm, which were pre-processed by DWT and PCA. The classification algorithm was SVM, and the overall accuracy was 83% to discriminate ET patients from PD ones.

Y. Hu et al.\textsuperscript{[179]} presented a dynamic sEMG topographic prognosis tool for patients’ intensive nonsurgical rehabilitation with chronic lower back pain (LBP). They evaluated patients’ three posture responses to the rehabilitation program. The 1.5 cm in diameter electrodes (UT611; Uni-T LTD, Shenzhen, China) were distributed as a 3 by 7 array in the lumbar region from the spinal level. They used relative area, relative width, and relative height of root-mean-square difference (RMSD) to assess, and the result showed a 74.7% accuracy for extension posture while 73.2% for flexion posture.

Several applications of sEMG in disease analysis have been shown in Table 5.

5.1.2. Rehabilitation

C. Loconsole et al.\textsuperscript{[181]} proposed an sEMG-based method for online torque prediction and robot joint control to support patients’ movement during therapy. They used foam pre-gelled Ag/AgCl electrodes, which had a conductive diameter of 16 mm, placed on five different muscles, pectoralis major (PM), deltoideus anterior (DA), deltoideus posterior (DP), biceps brachii (BB), and triceps brachii (TB), with a 20 mm distance between each bipolar derivation, to record signals. Employing time delay neural network (TDNN) to control and root mean square error (RMSE) to verify. The results showed the RMSE for the shoulder was 2.17 Nm while for the elbow was 1.19 Nm.

H. Converse et al.\textsuperscript{[133]} developed an EMG-biofeedback-based video game device for the utility in forearm physiotherapy with a surface electrode (Covidien, Mansfield, MA) on subject’s arms and grounding electrodes on their elbow. ANN was employed to control this system, which has 200 input nodes, 102 hidden nodes, and 6 output nodes, reaching an accuracy of 92% for detecting six-class detection problems and 96% for two-class one.
A. Radmand et al.\cite{123} proposed a method to improve prosthetic control schemes by characterizing the effect of limb position on EMG features. Using wireless surface electrodes, which were equally spaced placed around the dominant forearm, to acquire EMG signals and Trigno Wireless System (Delsys Inc., USA) to process primarily, the data was classified by LDA, which was trained by hybrid approach, increasing the accuracy of position form merely 70\% to 89\% for control prosthetic positions.

C. Prahm et al.\cite{184} developed an sEMG-based rehabilitation method of video game-based training for controlling myoelectric prosthesis, which placed the active surface EMG electrodes (Ottobock Healthcare GmbH 13E200) on the top of prominent flexor and extensor muscles of the wrist on the subject’s non-dominant side. Nonparametric tests and Shapiro–Wilk tests were employed to assess and the result showed that participants significantly improved their electrode separation and fine muscle control.

D. Leonardis et al.\cite{185} presented an sEMG-driven hand grasping rehabilitation exoskeleton for post-stroke patients. They used pre-gelled Ag/AgCl foam electrodes with a 24 mm diameter width, which were positioned at a distance of 20 mm for each bipolar derivation at the subject’s wrist. Employing an NN algorithm to analyze the outcomes, the device showed reliable accuracy and stability (the mean absolute error is 20 \pm 7\%) to control the grasping pressure.

Several applications of sEMG in rehabilitation have been shown in Table 6.

### 5.2. iEMG Application: Disease Analysis

S. Jose et al.\cite{186} developed an automated technique for diagnosing neuromuscular disorders, a standard concentric needle electrode, which has a 0.07 mm² leading-off area was placed at three levels of insertion (deep, medium, and low) in the brachial biceps muscles in five places. Preliminarily processed by DWT and using maximum likelihood estimation (ML-estimation) to extract features, the ML-perceptron neural network (PNN) was used to classify. The average classification accuracy reached 86.5\% for classifying healthy, myopathy, and neuropathy subjects with an 83.33\% specificity, 91.66\% sensitivity for myopathy, and 83.33\% for neuropathy.

A. Subasi et al.\cite{130} developed a classifier to improve diagnosis accuracy for neuromuscular disorders. The raw signal data was acquired from concentric needle electrodes with a leading-off area of 0.07 mm², placed at the biceps brachii muscle. Using particle swarm optimization (PSO)-SVM classifier, the result illustrated the total accuracy was 97.41\% for three categories: normal, myopathic neurogenic, which improved from 96.75\% in the basic SVM classifier. In another research,\cite{131} they employed DWT to extract signal features and evolutionarily GA integrated SVM algorithm to classify. The specificity was 93.75\%, with 98.25\% sensitivity for myopathy and 99\% for neuropathy. The overall accuracy was 97\%.\cite{39}

V. K. Mishra et al.\cite{187} used EMG signals to differentiate normal, ALS, and myopathy. Using a standard concentric needle

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### Table 5. Applications of sEMG in disease analysis.

| Application                        | Electrodes                          | Algorithm               | Result                      | Advantages                                                                                     | Disadvantages                                                                 |
|-----------------------------------|-------------------------------------|-------------------------|-----------------------------|-------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------|
| Detect neuromyopathy disorders\cite{172,176,177} | 9 mm silver/silver chloride electrodes | DWT                     | False detection rate of one in 12 days | Higher sensitivity and specificity Relatively simple processing                                | Low cost and less time-consuming                                                |
| Diagnose disease\cite{124,129,132,180} | Surface electrode array, Gel surface electrodes, Ag/AgCl bipolar electrode | LDA                     | 83\%–100\% accuracy        | High compatibility with residual limbs Highly specific sensitivity Easy electrode application | High sensitivity and specificity                                                |
| Prognose disease\cite{181,182}      | Surface electrode array              | Wilcoxon signed-rank tests | \(\approx 74.7\%\) accuracy | Trade-off between repeatability and separability Long stimulation time                        |                                                                              |

### Table 6. Applications of sEMG in rehabilitation.

| Application                        | Electrodes                          | Algorithm          | Result                           | Advantages                                                                                     | Disadvantages                                                                 |
|-----------------------------------|-------------------------------------|--------------------|----------------------------------|-------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------|
| Prosthesis control and assistance\cite{123,183,185} | pre-gelled Ag/AgCl electrodes       | TDNN               | RMSE 1.19–2.17 Nm               | More effective                                                                                | High compatibility with residual limbs                                      |
| Rehabilitation training and physiotherapy\cite{131,184} | Surface electrode, Active surface electrodes | ANN                | 89\%–92\% accuracy             | Highly specific sensitivity Easy electrode application                                         |                                                                              |
|                                   |                                     | LDA                |                                 | High compatibility with residual limbs Highly specific sensitivity Easy electrode application |                                                                              |
|                                   |                                     | Nonparametric tests | Shapiro-Wilk tests              | Trade-off between repeatability and separability Long stimulation time                         |                                                                              |
6. EMG-centered multisensory applications

Studies that use a multisensory approach utilizing various physical and physiological sensors with EMG sensors have been reported. A summary of broadly used EMG-centered multisensory-based technologies and their applications is demonstrated in Figure 11.

6.1. EMG Fusion with Physical Sensors

Physical sensors usually perceive information that characterizes in vitro, such as the locomotion status, force, and moment. Various types of physical sensors have been combined with EMG for versatile applications. Not only limited to use in the healthcare field like monitoring diseases and rehabilitation progress, these multisensory EMG systems also provide a promising platform for human activity recognition (HAR) and prosthetic hand control, etc. The following part will explain different EMG-centered fusion strategies with physical sensors and the state-of-the-art studies involved.

6.1.1. Inertial Sensors

Inertial sensors, which consist of accelerometers, gyroscopes, and magnetometers, are one of the most popular devices to be combined with EMG sensors. They provide intuitive information regarding the motion in three dimensions and compensate for the limited information provided by EMG which mainly consists of how the motion is represented in the body but not the spatial information related to the movement. Combining these two techniques strongly benefit HAR applications. For example, S. Bangaru et al.[189] proposed a wearable armband sensor that consists of a nine-axes inertial measurement unit (IMU) and eight EMG sensors. It can achieve complex recognition of construction-related activities through an ANN-based method. Different body parts and their motions can be recognized with an overall accuracy of 93.29%. The prosthetic hand control can be regarded as a derivative application of HAR. In ref. [190], A. Krasoulis et al. proposed a classification-based prosthetic control strategy that comprises EMG-IMU sensors. Both able-bodied and amputee participants can use this strategy to control the commercial prostheses (Ossur robo-limb) and complete specified tasks. The median completion rates and time duration of the able-bodied/amputee participants are 95%/85% and 37.43 s/44.28 s, respectively. They concluded that the classification accuracy of prosthetic control can be improved by combining EMG with inertial sensors, compared to employing merely a single type of sensor. M. Chu et al.[191] used flexible EMG sensors and IMU to control five degrees of freedom (DOFs) robotic arm. The recognition accuracy of different muscle modes has reached 98.66%.

In the healthcare field, the combination of IMU and EMG can provide auxiliary information for disease diagnosis and even rehabilitation assistance. T. Dorszewski et al.[192] used EMG and IMU sensors to find out several indicators of ataxia-type disease. M. Lyu et al.[193] developed a user-friendly home-use rehabilitation system for post-stroke patients, which combined an EMG-controlled exoskeleton with a visuomotor game. Subjects donned Myo armbands on their knee joint which was close to the rectus femoris, and it was employed to record EMG and IMU signals. A one-way analysis of variance was used to assess several metrics and the results showed the time lag caused by this exoskeleton was 110 ms with no significant difference between left and right legs. After the game, experimental results show that patients gained higher muscle activation levels.

6.1.2. Force and Moment Sensors

Apart from the 3D motion information obtained by inertial sensors, force and moment are also essential physical properties during the movement process. To detect these analytical dynamic quantities, pressure sensors like force sensing resistors (FSR), textile-based capacitive pressure sensors, and strain gauged transducers are usually utilized. The joint use of EMG and analytical...
dynamic sensors stimulates improvement in fields like real-time control, gait parameters measurement, and fall detection.

In the earlier studies, the EMG-based control strategy could only classify a limited number of discrete motions. For example, N. Carbonaro et al.\textsuperscript{[194]} used EMG and force myography (FMG) sensors to interpret the grip attention of subjects. The result of the SVM classifier controls whether or not the prosthesis hand will be activated. At present, 3D continuous and smooth motion control still remains a challenge, but significant progress has been made after merging force information from muscles. C. Xie et al.\textsuperscript{[195]} built an arm-hand rehabilitation robot system consisting of EMG sensors and a force sensors system. It can assist people with reach-and-grasp tasks. To control this assistive device, they designed an EMG-based admittance controller which can generate smoother trajectory control compared to strategy without force sensors.

Apart from the interactive force mentioned earlier, ground reaction force (GRF) is also a widely used parameter combined with EMG, especially in gait parameters detection and lower limbs rehabilitation. S. Gao et al.\textsuperscript{[167]} constructed an automatic terrain classification system with only two EMG sensors and two GRF sensors. After training the SVM learning model and verifying the high correlation between 21 extracted features and terrain changes, a satisfactory accuracy of 96.8% was obtained. Three categories of terrain and the muscles of interest are demonstrated in Figure 12. E. Kellis et al.\textsuperscript{[196]} explored the knee joint biomechanics in soccer kicks by recording GRF and EMG activity data. They found that the knee joint of the supporting leg may suffer from significant loads while kicking an angled approaching soccer. To provide more compliant lower limb rehabilitation assistance, it is critical to validate comprehensive human biomechanical gait models. L. Moreira et al.\textsuperscript{[197]} proposed a high-quality GRF and EMG dataset of lower limbs during speed-controlled walking. To obtain the data, they placed EMG sensors on subjects who walk on the force platforms. Their contributions make it possible to adjust the assistance level as the gait speed changes.

### 6.1.3. Visual Motion Capture Systems

Visual motion capture is another technique used to accurately measure the motion of moving objects in 3D space. It is based on the principles of computer graphics and captures the motion of moving objects (trackers) through several devices arranged in space. The motion capture system commonly isn’t combined with EMG alone, but also with inertial, force, and moment sensors discussed above.

Visual motion capture systems provide a noncontact and precise method to obtain spatial information about human’s bodies to establish a frame of reference for biomechanical analysis of human movements. R. Hubaut et al.\textsuperscript{[198]} equipped subjects with EMG, IMU, and reflective markers to analyze musculoskeletal disorder risks of work. EMG methodology was used to estimate the fatigue status of muscles, while IMU and the motion capture systems were applied to compute the orientation of several body segments. The good agreement between the multisensory systems and the gold standard was validated. D. Panariello et al.\textsuperscript{[199]} proposed a biomechanical analysis system of the upper body which consists of motion capture, EMG sensors, and force platforms. The analysis results it provides can help to design assistive devices for workers and prevent them from work-related musculoskeletal disorders (WMSD). The overall methodology involved is demonstrated in Figure 13. Several examples of EMG fusion with physical sensors have been shown in Table 8.

### 6.2. EMG Fusion with Physiological Sensors

Compared with physical sensors, several physiological signals could also provide necessary complements for EMG signals, such as electrooculogram (EOG), electrocardiogram (ECG), electroencephalogram (EEG), electrodermal activity (EDA), and galvanic skin response (GSR)\textsuperscript{[200].} From different perspectives, these signals represent diverse information about human behaviors, which enables researchers to explore more features, executing more sophisticated operations if combined with machine learning or deep learning algorithms.\textsuperscript{[201]} For example, EMG with ECG could help in detecting muscle fatigue and stress\textsuperscript{[202,203]} while EMG with near-infrared spectroscopy (NIRS) could monitor muscle activity in real time during neuromotor control and rehabilitation exercise.\textsuperscript{[204,205]} Physiological signals’ complement has enhanced the precision of classification and robustness.\textsuperscript{[200,206]} In the following part, we will discuss the fusion of EMG and physiological sensors from the aspects of applications.

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**Figure 12.** An overview of the EMG-GRF combination system which can identify the three different terrains. Reproduced with permission.\textsuperscript{[167]} Copyright 2020, MDPI.
Figure 13. Flow chart of the biomechanical analysis to reduce the risks of work-related musculoskeletal disorders. Reproduced with permission.[199] Copyright 2022, Springer Nature.

Table 8. Examples of EMG fusion with physical sensors.

| Ref. | Sensor types | Features | Algorithm          | Application | Performance                        |
|------|--------------|----------|--------------------|-------------|------------------------------------|
| [189] | EMG + IMU    | 38 features (32 EMG, 3 Acc, and 3 Gyro) | ANN         | Classify fifteen scaffold builder activities | Overall testing accuracy of 93.29% |
| [190] | EMG + IMU    | 7 EMG and 9 IMU features          | RDA         | Control commercial prosthesis      | Completion rates of 95% and 85%  |
| [191] | EMG + IMU    | 14 statistical features           | SVM         | Control commercial prosthesis      | Accuracy of 98.66%                |
| [192] | EMG + IMU    | 3 EMG features and steadiness of IMU data | Statistical method | Monitor disease progression        | Provide auxiliary diagnosis       |
| [193] | EMG + IMU    | RMS, MVE                           | Kalman filter, PID control | Rehabilitation assist             | Patients get higher scores in games after training |
| [194] | EMG + IMU + FSR | Not given | an adaptive peak detector algorithm | Control prosthesis hand           | Accuracy above 90%                |
| [195] | EMG + Force sensor + Motion capture system | MVC, RMSE, force zero-crossing rates (FZCR) | PID control, 3rd-order MIMO system | Arm-hand rehabilitation           | Smoother trajectory control (lower RMS jerk and FZCR) |
| [167] | EMG + GRF    | 9 GRF features and 12 EMG features | SVM         | Terrain classification            | Accuracy of 96.8%                 |
| [196] | EMG + GRF + Motion capture system | Mean, standard deviation | Not given | Identify knee biomechanics in soccer kicks | Need further research to identify injury mechanisms in soccer |
| [199] | EMG + Force platforms + Motion capture system | RMS | Digital human model | Analyze musculoskeletal disorder risks | Help to design the assistive devices |
| [198] | EMG + IMU + Motion capture system | Not given | Linear regression | Analyze musculoskeletal disorder risks | Good agreement with the gold standard |
6.2.1. Applications in Physiological State Monitoring

The fusion of EMG and other kinds of physiological sensors measures human biological signals from diverse aspects. It can profile a comprehensive biological model and is of great significance for the detection of physiological states such as disease, stress, and emotion.

Muscle fatigue has a strong relationship with some musculoskeletal diseases and some studies have used this relationship to predict the occurrence of musculoskeletal diseases. S. Pourmohammadi et al. [203] combined EMG with ECG signals to detect subject’s muscle fatigue, to determine whether the muscle was in stress or rest stages. They used the SX230 surface electrode and Skintact F-55 electrode to collect EMG and ECG signals. Three feature selection algorithms: mutual information, sequential forward floating search, and random subset feature selection were employed to create a subset of EMG and ECG features from two feature sets of EMG and ECG, respectively. Each feature subset could be explained as a feature vector for SVM classification. The accuracy of two-level stress detection reached 100% with three-level 97.6% and four-level 96.2%. Mental fatigue also influences human safety. R. Fu et al. [207] developed an HMM for monitoring driver’s fatigue condition simultaneously. A portable Biofeedback 2000 x-pert system with three physiological sensors was used in recording EMG, EEG, and respiration signals. The features chosen were the power spectrum of EEG, RMS of EMG, and mean frequency power of respiration signals. They optimized the weight of each feature by maximizing the area under the ROC curve (AUC), which helped determine the driver’s fatigue situation by HMM. Results illustrated that fusion features largely enhanced the separability. The highest one reached 96%.

The detection of emotion status by using multisensory EMG systems has shown great potential in understanding human beings in an intuitive way. F. Alqahtani et al. [208] used bio-signals sensors (EMG, EEG, ECG) to detect participants’ affective state during the English language test. The systems could predict the difficulty level of each question and whether the participant’s answer is right or not. T. Althobaiti et al. [209] combined EMG with EEG and ECG to examine human’s emotional response in the case of human–horse interaction. Compared with the self-assessment of emotional status, the valence and arousal classification performances were 90.35% and 70.18% in accuracy. The proposed methodology paves a new way to quantify the interaction during animal-assisted therapy.

Apart from the internal status of human beings, spatial status can also be recognized. M. Al-Quraishi et al. [210] utilized the fused EMG and EEG signals to recognize the movement of the lower limb. In this study, EEG and EMG signals were recorded simultaneously through an NVX52 (MKS cooperation Inc, Russia) system and the features chosen were the same, both of which were RMS, MAV, WL, and fourth-order autoregressive model (AR). A discriminant correlation analysis (DCA) method was applied to reduce the correlation between the two signals so that helped features fuse. Four machine learning methods LDA, KNN, NB, RF, and DT, were employed to classify. Among which the highest recognition accuracy was 96.64 ± 4.48% from the LDA method, largely improved from 89.99 ± 7.94% using EEG signal alone.

6.2.2. Applications in Rehabilitation

M. Nowak et al. [211] developed a protocol to control the prosthesis, combining EMG with FMG (force myography). They used a data acquisition device, consisting of an ADC and two bracelets with sEMG and FMG sensors to collect these two signals from subjects. The experimental setup is depicted in Figure 14. Features extracted were determined by the method of random Fourier features (RFFs) and were processed by Ridge regression, which is similar to the SVM algorithm. The highest success rate among the 12 subjects was 75%, with the significance level being 98% under the one-way analysis of variance.

W. Guo et al. [212] designed a method of controlling upper limb prosthesis through hybrid EMG and NIR signals. Four hybrid sensors were placed on subject’s four muscles to collect EMG and NIR signals. They chose MAV, zero crossings, slope sign changes, and WL as EMG signal’s features and MAV, WL, and NIRV (the variance of the NIRS signal) as NIR’s features. Employing LDA and SVM, the offline classification accuracy

![Figure 14](image-url)
was 87.7% (enhance by 14.9% compared with EMG-only) and the online average selection and completion time were less than the EMG-only condition, as well as online classification accuracy (90% versus 83%).

N. Krausz et al.\textsuperscript{[213]} developed a method of controlling arm prosthesis based on the combination of EMG and gaze detection. The EMG signal was collected from 14 upper limb muscles using a DTS Noraxon system and the gaze detection was finished by a pair of glasses equipped with eye cameras. For features, they selected waveform length, root mean square, and mean of each signal as EMG’s features. After the regression, EMG’s features were fused with the eyes’ gaze information. The mean squared error (MSE) provided the accuracy of the Kalman Filter-based position estimation, which determined the final position of prosthesis. Results showed that fusion signals yielded less position control RMSE (6.85 ± 2.4 cm) compared with single EMG control (7.8 ± 2.9 cm).

6.2.3. Application in Disease Diagnosis

The utilization of physiological sensors fusion strategy in disease diagnosis is also reported. J. Ma et al.\textsuperscript{[214]} used EMG fused with MUS signals to elucidate fasciculation distributions’ features in amyotrophic lateral sclerosis (ALS). A conventional sonographic scanner was utilized to record MUS signals while needle electrodes were placed in 205 muscles to collect EMG signals. They chose AUC as the feature of MUS and EMG, testing the differences between two or more mean values by Mann–Whitney U-test or Kruskal–Wallis test and testing the linear relationship by Spearman correlation analysis. After using EMG, the percentage of muscles with fasciculation activity rose from 21.6% to 55.9%, which means EMG provided auxiliary information to make the diagnosis of ALS earlier and easier. Several examples of EMG fusion with physiological sensors have been shown in Table 9.

### 6.3. EMG Fusion with Both Physical and Physiological Sensors

Recent developments in artificial intelligence and data processing capabilities have made possible the combination of more than two modes, which can have a significant impact in certain scenarios. In the following subsections, we will discuss the applications of the EMG-based multimodal systems.

#### 6.3.1. Applications in Healthcare Monitoring

With the advantage of measuring comprehensive biological signals, EMG-based multimodal systems offer various combinations for the detection of human states such as health, activity, and emotion.

Medical monitoring devices have been transformed from bulky devices that require patients to visit the hospital for measurements to portable and wearable multisensory systems. W. Xia et al.\textsuperscript{[217]} proposed a wearable ECG-enhanced multi-sensor solution, which plays a crucial role in the prevention of cardiovascular diseases. This scheme detects and fuses IMU and EMG data to

### Table 9. Examples of EMG fusion with physiological sensors.

| Ref. | Sensor types | Features | Algorithm | Application | Performance |
|------|--------------|----------|-----------|-------------|-------------|
| [203] | EMG, ECG | MI, SFFS, RSFS (both EMG and ECG) | SVM | Muscles fatigue detection | Accuracy<br>Two-level: 100%<br>Three-level: 97.6%<br>Four-level: 96.2% |
| [207] | EMG, EEG | PS, RMS (both EMG and ECG), MFP of respiration | HMM | Driver’s fatigue monitoring | Classification separability: 96% |
| [209] | EMG, EEG and ECG | 2 ECG features and 6 EMG features | KNN, DT, LSVM, SVM-RBF, LDA | Emotion examination | Classification accuracy:<br>Valence: 90.33%<br>Arousal: 70.18% |
| [210] | EMG, EEG | RMS, MAV, WL, and AR | LDA, KNN, NB, RF, and DT | Limb movement recognition | Recognition accuracy:<br>LDA: 96.64% |
| [211] | EMG, FMG | Determined by random Fourier features | Ridge regression | Prosthesis control | Success rate: 75% |
| [214] | EMG, MUS | AUC | Mann–Whitney U-test or Kruskal–Wallis test | Elucidate fasciculation distributions’ features | Percentage of muscles with fasciculation activity: 55.9% |
| [212] | EMG, NIR | 4 EMG features and 3 NIR features | LDA, SVM | Prosthesis control | Classification accuracy:<br>Offline: 87.7%<br>Online: 90% |
| [213] | EMG, eyes’ gaze | WL, RMS, mean | Regression, Kalman filtering | Prosthesis control | RMSE: 6.85 ± 2.4 cm |
| [215] | EMG, ECG | 5 EMG features and 8 ECG features | SVM, RF | Muscles fatigue detection | Accuracy of 85% |
| [216] | EMG, ECG, EOG | Determined by Tsallis entropy | EBT | Sleep scoring model | Classification accuracy:<br>Three-class: 91.8%<br>Five-class: 86.6% |
determine the effectiveness of ECG signal, and realizes the heart rate monitoring function in different body states accurately, conveniently, and quickly. G. Biagetti et al.\textsuperscript{[218]} proposed a wireless sensor device that collects bioelectrical signals such as EMG and ECG and combines IMU to provide comprehensive data flow, so as to realize low-power detection of patients’ daily activities, improve the quality of life of patients, and caregivers and reduce medical costs.

As for human activity recognition, H. Verma et al.\textsuperscript{[219]} used five kinds of biomedical sensors, ECG, EMG, RESP (ventilation), FSR, and accelerometer (ACC), to collect the raw data of human activities. The TD characteristics such as mean, variance, standard deviation, skewness, and kurtosis were extracted. This characteristic information is used to train and test classifiers to identify human activity. Among tested classifiers, including KNN, SVM using Gaussian kernel, and SVM using linear kernel, KNN has the highest classification accuracy which reaches 99.86%.

Emotional status has a great impact on the health and performance of a human. J. Perdiz et al.\textsuperscript{[220]} based on EMG and combined with EOG and IMU, proposed an emotion detection system that combines facial expression detection and saccade detection to detect sadness, happiness, anger, and other emotions. N. Jia et al.\textsuperscript{[221]} proposed a proof-of-concept device that captures data from ECG, EMG, EDA, and IMU sensors to assess a physician’s pressure state during surgery. The pressure state of the doctor during the operation is critical to the impact of surgical performance and patient safety, and the device can objectively assess the pressure state of the doctor and the impact of the operation.

6.3.2. Applications in Traffic Safety

Safety is of the utmost importance while driving a car. The measurement of driver’s biological data is of great help to improve the safety of autonomous vehicles and the ability of vehicles to avoid emergencies. A. Seckin et al.\textsuperscript{[222]} designed a driver data collection and marking system using EEG, EMG, and IMU in a comprehensive way and extracted features for training to improve the vehicle’s ability to identify dangerous situations in autonomous driving. The data are classified by the KNN algorithm after PCA dimensionality reduction. The accuracy of classification is 92.2%. S. Said et al.\textsuperscript{[223]} developed an advanced system that collects EMG, ECG, electrodermal activity (EDA), ACC, and other biological signal data through wearable biosensor bracelets to detect the emergency situation when the driver loses his ability and control the vehicle to avoid danger. In the simulated driving scenario, the success rate is 77%.

6.3.3. Applications in Rehabilitation and Prosthesis Control

Physical rehabilitation therapy is often necessary for a full recovery after certain surgeries and illnesses and using multimodal measurement systems allows for a more accurate monitoring of the progress. J. Monge et al.\textsuperscript{[224]} proposed an intelligent physical rehabilitation system that combined augmented reality with EMG, ECG, and IMU sensors to improve the patient’s participation in the rehabilitation process, as well as remote health status assessment and assisted rehabilitation. J. Gallego et al.\textsuperscript{[225]} proposed a multimodal HMI to drive neural prosthesis for tremor management. Tremor is one of the most common movement disorders, and this method is based on EEG, EMG, and IMU data to obtain accurate information about tremors and provide rapid compensatory actions. For amputees, having easily controlled and robust prosthetics can greatly improve the quality of their life. But single EMG control method limits the fluid motion and dynamic functionality of the prosthesis. To address this issue, H. Martin et al.\textsuperscript{[226]} proposed a new architecture for value motion control based on multiclass signals. The proposed system combines human vision with EMG and IMU to achieve semi-autonomous, simultaneous, and multijoint operation of the prosthesis. The overview of their system architecture is shown in Figure 15.

7. Challenge

7.1. Instability of EMG Signals

The outputted EMG signals suffer from instability issues (especially for sEMG technology), indicating that the reproducibility of EMG signals becomes a problem. In many cases, even the same subject could generate EMG signals with different amplitudes, bringing great challenges in disease analysis and intention/motion interpretation.

The instability property of EMG signals accounts for the following reasons:

For sEMG systems, changing skin-electrode impedance, motion artifacts, and cross-talk from adjacent muscles are the three major sources that contribute to the instability issue. Many factors can change the skin-electrode impedance. For example, air pockets between the skin and dry electrodes indicate bad contact between them which results in varying impedance with different muscle contractions or motions. The electrolytic gel drying out during the data collection process also leads to a variation of impedance. In motion artifacts, the mismatch between muscle fibers and electrode pads will influence the signal characters. For instance, the electrode–skin contact movements, cable motion, and stress applied to the skin below the electrode can all generate motion artifacts. As for crosstalk, it means the recorded signals are generated by one or more neighboring muscles rather than merely from the desired one. Although the action potentials from muscles close to the electrodes can dominate the recorded signals, signals from more distant sources may confront crosstalk.

As to iEMG sensors, the electrode positions are difficult to be maintained in different experiments, due to the small detection areas, implying the challenge in reproducibility. Furthermore, the mechanical properties of intramuscular electrodes render them prone to either break during strong muscle contractions or move to compliance with soft tissues. Lastly, foreign body rejection and inflammation will slowly but continuously erode the iEMG electrode, resulting in unstable signal quality and eventually failure of functionality. Due to the instability of EMG signals, interpretation methods mainly rely on pattern recognition-related machine learning methods, rather than mathematical modeling.
7.2. Real-Time Interpretation with High Accuracy

EMG signal is broadly used for user’s intention interpretation in controlling exoskeleton and teleoperation. However, concurrently achieving high interpretation accuracy and less control delay hasn’t been obtained yet. First, higher interpretation accuracy normally requires longer EMG signal recording time, which results in unwanted delay in real-time control systems. Second, to minimize the disturbance of recorded EMG signals such as varied skin-electrode impedance, motion artifacts, and ambient noises, the implementation of high-density electrode arrays is required to obtain topographical maps of muscle electrical activity, which significantly increase the number of signal channels. However, it is noted that a larger number of EMG channels need a more complex preprocessing circuit, dimensional reduction process, and smarter feature selection (such as deep learning). Thus requiring higher computation power and undesired longer computational time.

8. Outlook

8.1. Creating Neuro System Map for Disease

In neurological diseases, the impairment level of the neural system is challenging and yet to be studied in detail. Traditionally, empirical methods, such as analysis of a patient’s motion status by observations, inquiry into the patient’s symptoms, and muscle biopsies have been broadly utilized. In recent years, CT, EMG, and EEG-based techniques have increasingly been to be employed in investigating neural system impairment in hospitals. The systems that are used for these measurements are often bulky, requiring patients to visit. However, it is not convenient for neuromuscular patients to visit medical institutions frequently. In addition, the periodical measurements lack in providing information about the real-time development of the patient’s neurological condition. In contrast, wearable EMG monitoring systems built with advanced materials support long-term usage requirements without disturbing users’ daily activities. Smart algorithms have the potential to interpret and reconstruct patients’ neural system changes by being fed with real-time and historical EMG data, indicating the possibility for medical staff to better understand patients’ status and develop more effective treatments.

8.2. Play as a Control Signal for Robotics

Intelligent humanoids are believed to be highly merged into our society in foreseeable future. One of the current challenges for humanoids is to fully mimic the movement patterns of human beings. After several decades of research, the architectural problems have largely been resolved. However, the control signal for the body is still yet to be established. Although some machine learning methods have been demonstrated to be feasible in allowing humanoids to perform tasks in a diverse complex environment, the black-box issue and transferability of machine learning algorithms hinder the applications in a wider stage. With the thoughtful study of the relationship between EMG signals and the musculoskeletal system, the control methodologies of humanoids would be beneficial. Pioneer research outputs illustrate the feasibility to develop humanoid robot hands which can mimic the adaptability and dexterity of the human hand with the EMG control strategy, encouraging more scientists and engineers to devote themselves to the field of bionic neural control.

Figure 15. Overview of the prosthesis control system architecture. Reproduced with permission. Copyright 2021, Western Libraries.
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Conflict of Interest

The authors declare no conflict of interest.

Keywords

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