From Brain to Movement: Wearables-Based Motion Intention Prediction Across the Human Nervous System

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Abstract. Fueled by the recent proliferation of energy-efficient and energy-autonomous or self-powered nanotechnology-based wearable smart systems, human motion intention prediction (MIP) plays a critical role in a wide range of applications, such as rehabilitation and assistive robotics, to enable more natural, biologically inspired, and seamless integrated motion assistance task execution, including for elders and physically impaired patients. With the increasing complexity of human-machine interactions and the need for personalized assistance, there is a growing demand for real-time and accurate MIP systems. This review aims to provide a comprehensive understanding of the interdisciplinary field of MIP, under the logic of its physiological foundations, by discussing state-of-the-art sensing technologies, including brain-computer interfaces (BCI), electromyography (EMG), and motion sensors, alongside the relevant data processing techniques and decoding algorithms.

We emphasize the importance of fostering collaboration among scholars from different domains to capture the intricate dependencies between the set of stimuli and responses of the central nervous system and the activation of the complex set of muscles and joints that produce human motion. By offering insights into the recent advancements and future prospects of the field, this review seeks to stimulate further research and innovation in the rapidly evolving area of human motion intention prediction, for a future where technologies understand and respond to complex human intentions patterns, anticipating their needs.

Keywords: Motion Intention Prediction (MIP); Wearable Sensors; Brain-Computer Interface (BCI); Electromyography (EMG); Explainable AI; Multimodal Motion Analysis.

1 Introduction

Human motion intention prediction (MIP) has become an indispensable tool in various domains, including healthcare [1], rehabilitation [2], and robotics [3], among others. The study of MIP can be traced back to the pioneering works by Wolpaw *et al.* in the field of brain-computer interfaces (BCI), which made use of innovative techniques to achieve critical milestones in motion prediction [4]. Since then, a plethora of MIP technologies has emerged, contributing significantly to advancements in diverse applications, such as prosthetic control [5] and exoskeleton-assisted movement [6].

In today's fast-paced world, driven by rapid technological advancements in the field of portable and wearable self-powered sensor systems [7, 8], and ultra-low power electronics energy efficient systems [9], the increasing complexity of human-machine interactions and the growing need for personalized assistance in various fields have further elevated the demands for real-time and accurate MIP. Traditional MIP methods fail to meet these growing requirements. Consequently, the MIP field has integrated state-of-the-art materials, such as flexible and stretchable sensors [10, 11, 12], and deep learning algorithms [13, 14, 15] to push the boundaries of prediction accuracy and real-time performance as illustrated in Figure 1.

However, the interdisciplinary nature of MIP has created barriers for scholars from

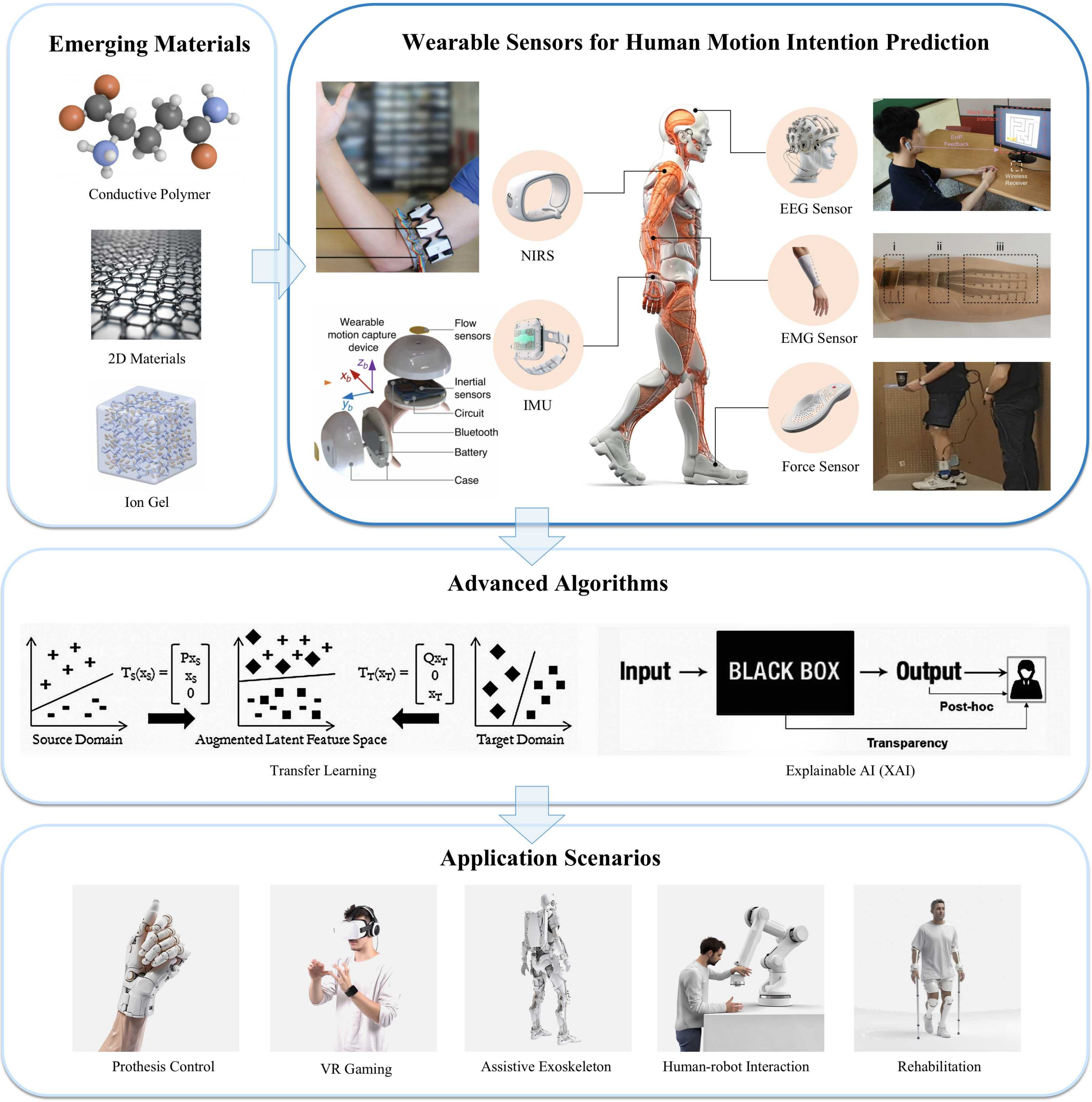

Figure 1: Overview of the human motion intention prediction. Illustration of Ion Gel is reproduced from [16]; Illustration of Transfer Learning is reproduced from [18]; Illustration of Explainable AI reproduced from [19]. Photos of wearable sensors are reproduced from [54, 125, 79, 112, 123] respectively. NIRS represents Near Infrared Spectroscopy.

different domains to fully comprehend the potential and importance of each other's work in MIP applications. This gap becomes more apparent when state-of-the-art methods are introduced. To address this issue, we have written this review, which starts with the physiological foundations of MIP and proceeds discussing the latest sensing methodologies, including BCI, EMG, and motion sensors, as well as the most recent data processing and decoding algorithms. Our aim is to foster collaboration, provide comprehensive insights, and stimulate further progress in this rapidly evolving field.

The organization of this paper is as follows: Section 2 provides an overview of the physiological mechanisms of motion intention. Sections 3, 4, and 5 discuss brain-computer interfaces (BCI), electromyography (EMG), and motion sensors, respectively, in the generation, transmission, and execution processes of human motion prediction, while emphasizing key publications and state-of-the-art methods. Section 6 delves into multimodal approaches, and Section 7 discusses the limitations and future prospects of the field.

2 The Physiology Mechanisms of Motion Intention

The generation, transmission, and execution of motion intention is a complex, coordinated process involving multiple physiological systems in the human body. This process can be studied and understood by obtaining signals derived from the central and peripheral nervous system, from muscle activity, and from inertial measurements. These data sets provide the basis for detecting and classifying the human motion patterns in real-time using wearable sensor technologies, such as Brain-Computer Interface (BCI), Electromyography (EMG), Inertial Measurement Units (IMU) and force sensors, in order to achieve efficient motion intention prediction models.

The process of voluntary movement begins in the prefrontal and parietal areas, where the intention to move is generated [20, 21]. This intention is then transmitted to the primary motor cortex, which is responsible for planning and executing actions. The primary motor cortex receives input from other areas of the brain, such as the somatosensory cortex, which provides information about the position and movement of the body's limbs and joints. This information, combined with the intention to move, generates signals that coordinate the activity of motor neurons [22].

During the generation of the intention to move, multiple functional areas of the brain coordinate their physiological activities, resulting in neural electrical signals [23]. In addition, due to neurovascular coupling, the concentration of brain hemoglobin changes [24]. These physiological signals can be detected and analyzed through various BCI systems, enabling the detection of the intention to move at the level of the central nervous system. BCI technology can be divided into invasive and non-invasive detection methods, with this article focusing on non-invasive methods such as Electroencephalogram (EEG) and near-infrared spectroscopy (NIRS) for the application of wearable technology in predicting motion intention.

The corticospinal pathway connects the brain and spinal cord, transmitting signals related to the intention to move within the central nervous system (CNS). In the spinal cord, motor neurons are activated and release neurotransmitters (such as acetylcholine) after receiving signals from the central nervous system. These neurotransmitters transmit movement information to muscles through neuromuscular connections, inducing the production and propagation of action potentials on the muscle fiber membrane [25]. These signals cause muscle contraction and relaxation, resulting in the desired movement.

The action potential on the muscle fiber membrane can be collected and recorded on the skin surface through electrodes, and it contains features of the motion patterns transferred from the CNS to the peripheral nervous system (PNS). The sum of the electromyographic signals triggered by the activation pulses of motor neurons that dominate the nerves is the electromyographic signal, which can reflect the intention to move at the level of the PNS [5]. Thus, EMG technology can be used to predict motion intention during the transmission of signals at the muscle fiber membrane.

Moreover, detecting kinematic and kinetic parameters related to movement in real-time is another possible method for predicting motion intention. For a specific intention to move, the way of executing the movement is relatively well-known. Systems based on IMU, pressure sensors, and many other motion sensors record time series of parameters such as force, acceleration, and angular velocity, and extract features to establish prediction models. By analyzing the human body's movement status and trajectory using these sensors, researchers can achieve motion intention prediction, offering a comprehensive understanding of the entire process from motion intention generation to execution [26]. Nevertheless, the accuracy and processing time required to analyse the motion data and fit into prediction model parameters mean that the MIP task cannot be executed in real time without introducing a lag between the time when the IMU data are acquired by the sensors and the time when an action associated with the MIP data would actually take place.

3 BCI in the Intention Generation Process

3.1 Overview of BCI methods

The extraction and decoding of neural signals from the brain have long been acknowledged as a promising approach for predicting motion intentions, since the brain serves as the origin of these signals, which can be detected earlier than by other methods. Brain-Computer Interface (BCI) technology facilitates the direct extraction and decoding of these neural signals, enabling real-time prediction of motion intentions. In recent years, there has been increasing interest in employing BCIs to predict human motion intention, with the aim of creating systems that assist individuals with motor impairments or enable the control of external devices using thought alone [27, 28, 29]. It is worth noting that in the BCI domain, motion intention prediction is often called motor imagery (MI) [30]. Therefore, in this section, MI is used to represent MIP. This emerging area of BCI research necessitates a thorough understanding of both the fundamental neural mechanisms of movement intention and the technical challenges involved in developing reliable and accurate prediction algorithms. In this section, we will examine the signal acquisition, characterization, and processing methods of wearable non-invasive technology that can be used for motion intention prediction, including Electroencephalography (EEG) and Near-Infrared Spectroscopy (NIRS). While Magnetoencephalography (MEG) and Functional Magnetic Resonance Imaging (fMRI) are also prevalent brain-computer interface devices, they are not suitable for use in motion intention prediction scenarios. fMRI requires a large magnet to generate a magnetic field for detection, rendering it unsuitable for wearables and inappropriate for such applications. Although MEG has the potential to be wearable, it is vulnerable to motion artefacts and interference from external magnetic fields, and is prohibitively expensive to implement [31, 32].

NIRS is a non-invasive, wearable brain imaging technique that measures changes in oxygenated and deoxygenated hemoglobin levels in the brain. Although NIRS has several advantages, such as being portable, lightweight, and less susceptible to artefacts compared to EEG, it has a significant limitation: low temporal resolution. Compared to high resolution (in the order of msec) of methods such as EEG and EMG, the lower temporal resolution of NIRS (in the order of 1 sec) makes this method less effective, when used alone, for motion intention prediction (MIP) tasks [33]. However, due to the unique information modality provided by NIRS, it is often combined with other methods such as EEG and EMG to construct multimodal systems for predicting motion intention, which is further discussed in section 6 (Multimodal Approaches). The combination of these methods can overcome the limitations of individual techniques, leading to improved prediction accuracy and robustness [34].

EEG is a widely-used non-invasive method for monitoring brain activity across various fields. EEG signals originate from synchronized synaptic activity among populations of cortical neurons during the physiological process of motion intention generation. These signals are produced by synchronous electrical pulses from postsynaptic neurons in the cortex. To record these signals, electrode arrays are normally placed on the scalp. Typically, the electrodes are connected to wires or cables that convey the electrical signal to an amplifier before being analyzed by the processor.

3.2 Evolution of EEG Devices

Non-invasive EEG has evolved over time, with different types of electrodes and sensors being developed to improve signal acquisition and user experience [35, 36, 37, 38]:

- **Wet Electrodes:** As the earliest method for EEG signal acquisition, wet electrodes require a conductive gel or paste to establish a good electrical connection between the electrode and the scalp. These electrodes of the first generation are being replaced by subsequent advancements in EEG technology offering better performance and convenience, e.g. in terms of user comfort.

- **Active Electrodes:** In response to the need for reduced signal interference and noise, active electrodes were developed. These incorporate built-in amplifiers to improve the signal-to-noise ratio by amplifying the EEG signals directly at the electrode site before transmission to the data acquisition system.

- **Dry Electrodes:** To provide a more convenient and user-friendly alternative to wet electrodes, dry electrodes were introduced, which are based on conformable conductive or non-conductive electrode structures, made of metallic, metal oxides, carbon-based or conductive polymer-based materials. Thanks to their high active surface area and combined ionic and electronic conductivity, dry electrodes are capable of achieving low impedance with skin, hence high signal-to-noise ratio, comparable to wet electrodes, removing the need for electrolyte gels and reducing skin preparation and setup time [39].

- **Flexible Sensors:** As material science advanced and interest in wearable devices grew, flexible sensors emerged. Designed to conform to the shape of the scalp, they offer better contact and comfort compared to traditional rigid electrodes and facilitate integration into wearable devices for long-term EEG monitoring and daily use.

- **High-Density EEG Systems:** With the increasing demand for higher spatial resolution in brain dynamics research and accurate localization of brain activity, high-density EEG systems were developed. These systems utilize a larger number of closely spaced electrodes to provide a more detailed map of brain activity, although they are more challenging to set up and maintain due to the increased number of electrodes.

3.3 EEG Signal Processing and Classification

After the raw signals are retrieved by the devices, algorithms play a crucial role in transforming the raw data into meaningful information for real-time communication and control. These algorithms can be broadly classified into four categories: preprocessing, feature extraction, feature selection, and classification [40, 41, 42, 43].

- **Preprocessing:** The preprocessing stage aims at reducing noise, artefacts, and irrelevant information from the raw signals. Common techniques used for EEG preprocessing include band-pass filtering to focus on specific frequency bands (e.g., delta, theta, alpha, beta, gamma) and artefact removal (Independent Component Analysis (ICA), Principal Component Analysis (PCA)) to mitigate the artefact interference.

- **Feature extraction:** Feature extraction techniques are employed to transform the preprocessed signals into feature vectors, which can be used to identify different mental states or cognitive tasks. For EEG signals, common methods include time-domain (Hjorth parameters, Autoregressive (AR) coefficients), frequency-domain (spectral power, coherence), and time-frequency domain (wavelet transform, Hilbert-Huang transform) features.

- **Feature selection:** Feature selection methods help in identifying the most relevant features for the task at hand, leading to improved classification performance and reduced computational complexity. Common feature selection techniques include filter methods (correlation, mutual information), wrapper methods (forward, backward, recursive feature elimination), and embedded methods (LASSO, Ridge Regression).

- **Classification:** At the end of the decision system, the selected features are fed into a classification algorithm, which determines the motion intention from the user. Popular classifiers for BCI systems include classical machine learning models (linear discriminant analysis (LDA), support vector machines (SVM), and artificial neural networks (ANN)) and deep learning models (convolutional neural networks (CNN), long short-term memory (LSTM), and transformer).

3.4 Latest Breakthroughs in EEG-based MIP

Although several review articles in recent years have summarized some important work in the field of MI-based BCIs, or specifically EEG [41, 44, 45], there is still need for further analysis, which is investigated in this review. This is mainly due to the rapid development of nanotechnology and the emergence of new machine learning methods, which facilitates the development of devices with better performance and user acceptance, as well as algorithms with better mobility and transparency.

The future of wearable sensors depends on achieving miniaturization, self-powered, and enhanced comfort while maintaining decent precision [46, 47, 48]. These key attributes are set to promote widespread adoption and transform a wide array of applications across diverse domains. This vision holds true for EEG sensors as well, and significant efforts are made by researchers in this respect.

- **Graphene-based electrodes:** Graphene-based electrodes are an attractive option due to their high conductivity, flexibility, and biocompatibility. Their ability to conform to the scalp improves user comfort and long-term monitoring, while providing

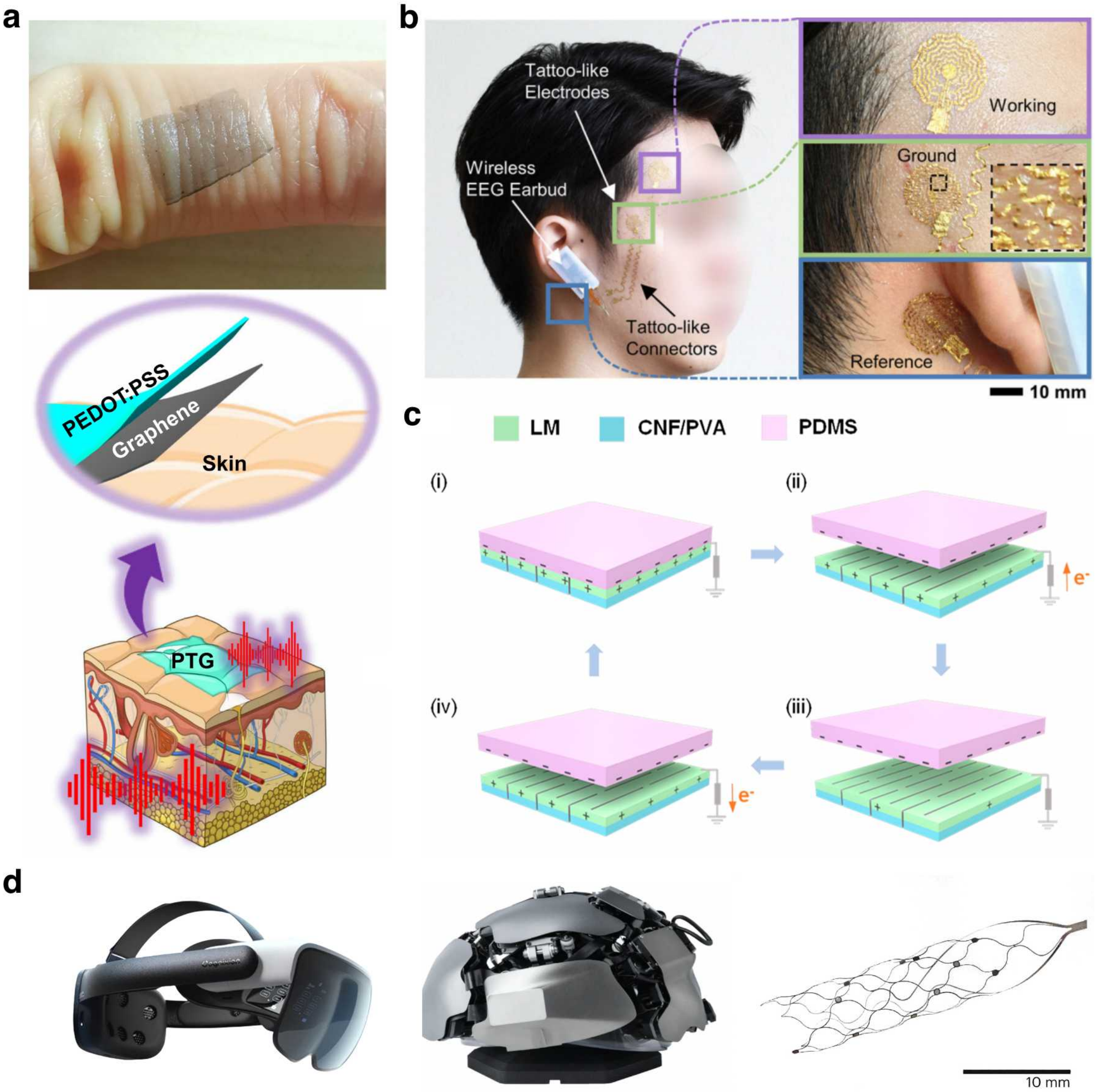

Figure 2: Latest breakthroughs in EEG devices. (a) Dry electrodes of PEDOT:PSS transferred CVD graphene film [49]. (b) Miniaturized wearable EEG devices composed of tattoo-like electronics and a wireless EEG earbud device [54]. (c) A kirigami-structured LM paper based self-powered E-skin [57]. (d) EEG equipment from the industry (Left: Cognixion ONE headset; Middle: Kernel Flow headset; Right: stentrode from Synchron) [56].

a better signal-to-noise ratio. For example, Zhao *et al.* proposed a graphene-based ultra-thin dry epidermal electrode in 2021, which showcased low sheet resistance ($\sim$24Ω/sq), high signal-to-noise ratio (23±0.7dB), high transparency, and mechano-electrical stability (Figure 2(a)) [49]. Islam *et al.* demonstrated the potential of fully printed, highly conductive, flexible, and machine-washable e-textiles for EEG signal recording in 2022 [50]. Graphene electronic tattoos (GETs) are another advanced method to enable long-term wear and minimal discomfort in EEG monitoring. In 2022, towards the lack of sweat permeability and the variability in tattoo performance, Kireev *et al.* introduced GETs 2.0 with the addition of graphene nanoscrolls (GNS) or multilayer (2L and 3L) graphene structures, which exhibit 3.5-fold decreased sheet resistance, 2.5-fold lower skin impedance, and 5-fold reduced standard deviations of these values [51].

As a nanomaterial, a number of studies have been conducted in relation to the biocompatibility of graphene-based materials in their different forms, shape and size, for use as biomedical material, providing a framework for the design of graphene-based electrodes by minimizing any adverse effects related to the exposure and potential cytotoxicity for long-term use [52]. Commercial applications of graphene-based materials are currently being developed for both wearable and implantable devices, such as wound healing and skin biosensors, i.e. in direct contact with skin and blood vessels, by companies such as Grapheal, or short-term implantable devices for electrophysiology and neural recording, from companies such as InBrain, upon receiving positive assessment from regulatory bodies through clinical trials. As such, while graphene-based electrodes hold the potential of representing a valid alternative to other wet and dry electrode materials, their adoption is subject to the necessary regulatory approval in specific use case applications.

- **Miniaturized wearable EEG platforms:** The development of miniaturized wearable EEG platforms has aimed to make EEG systems more portable and user-friendly.

Designed to operate in real-world environments, these platforms have the potential to expand the applications of EEG-based MI systems. A pioneering work in this field was the wearable in-ear EEG sensor described in [53], which validated the feasibility of observing Auditory Steady State Response (ASSR) and Steady State Visually Evoked Potential (SSVEP) in single-channel EEG recorded from inside the ear canal. More recently, Shin *et al.* developed a wireless earbud-like EEG measurement device which utilized tattoo-like electrodes and connectors for continuous recording of high-quality EEG signals (shown in Figure 2(b)) [54]. Indeed, continuous and unobtrusive monitoring from ear-EEG would enable the development of user-friendly and discreet BCI. The setup time for standard scalp EEG recordings is often lengthy due to the placement of multiple electrodes on the subject's head. As a result, scalp EEG recordings are typically conducted in a hospital setting. Due to their proximity to the brain, the ears offer a unique alternative location for a lightweight, portable, and user-friendly wearable device designed to continuously monitor ear-EEG without requiring the presence of a clinician. To ensure accurate and high signal-to-noise ratio readings it is crucial to minimize interference and artefacts derived from everyday activities which result in jaw, head or full body movements, such as talking, chewing, or walking. A solution to this problem is discussed in section 6 (Multimodal Approaches), and reported in [55] based on multi-modal ear-EEG assisted by accelerometer and microphone signals to capture and remove artefacts. Concurrently, companies like Neurable, NextSense, and InteraXon have been working on innovative products such as EEG-integrated Bluetooth headphones, earbuds with EEG sensors, and headbands designed for EEG monitoring above the frontal lobes (example shown in Figure 2(d)) [56].

- **Self-powered EEG sensors:** With growing demand for wearable EEG sensors, researchers are focusing on self-powered solutions to extend operational time and reduce dependence on external power sources. By harvesting energy from the surrounding environment or from the user's body, self-powered EEG sensors can provide uninterrupted and sustainable brain monitoring. One interesting example is the kirigami-structured liquid metal paper (KLP) developed by Li *et al.* in 2022, which can acquire high-quality electrophysiological signals such as EEG, ECG, and EMG (as shown in Figure 2(c)) [57]. When combined with a triboelectric nanogenerator (TENG), this multifunctional E-skin can also function as a self-powered solution for various applications, including healthcare monitoring, intelligent control, smart robots, virtual reality, and on-skin personal electronics.

Alongside device-level innovations, significant strides have been made in developing advanced algorithms that can effectively process and interpret EEG data for MI applications. These algorithms play a crucial role in enhancing the accuracy, robustness, and practicality of EEG-based MI systems.

- **Deep learning-based methods:** Deep learning techniques have revolutionized EEG-based MI due to their end-to-end nature, eliminating the need for manual feature extraction. However, traditional CNNs used in deep learning-based EEG methods have limitations in perceiving global dependencies, making them unsuitable for common EEG paradigms. Researchers have attempted to address this issue, with Song *et al.* proposing an attention mechanism-based EEG decoding method in 2021 that achieved state-of-the-art multi-classification performance with fewer parameters [58]. More recently, in 2023, Hu *et al.* developed a cross-space convolutional neural network (CS-CNN) that effectively fused information from measuring and source spaces, preserving subject-specific information and achieving a 1.98% accuracy improvement and a 5.15% standard deviation reduction on the BCI competition IV-2a dataset (a prevailing benchmark dataset for MI task) [59].

- **Transfer learning method:** Transfer learning (TL) approaches are being explored to tackle inter-subject and inter-session variability in EEG signals by leveraging

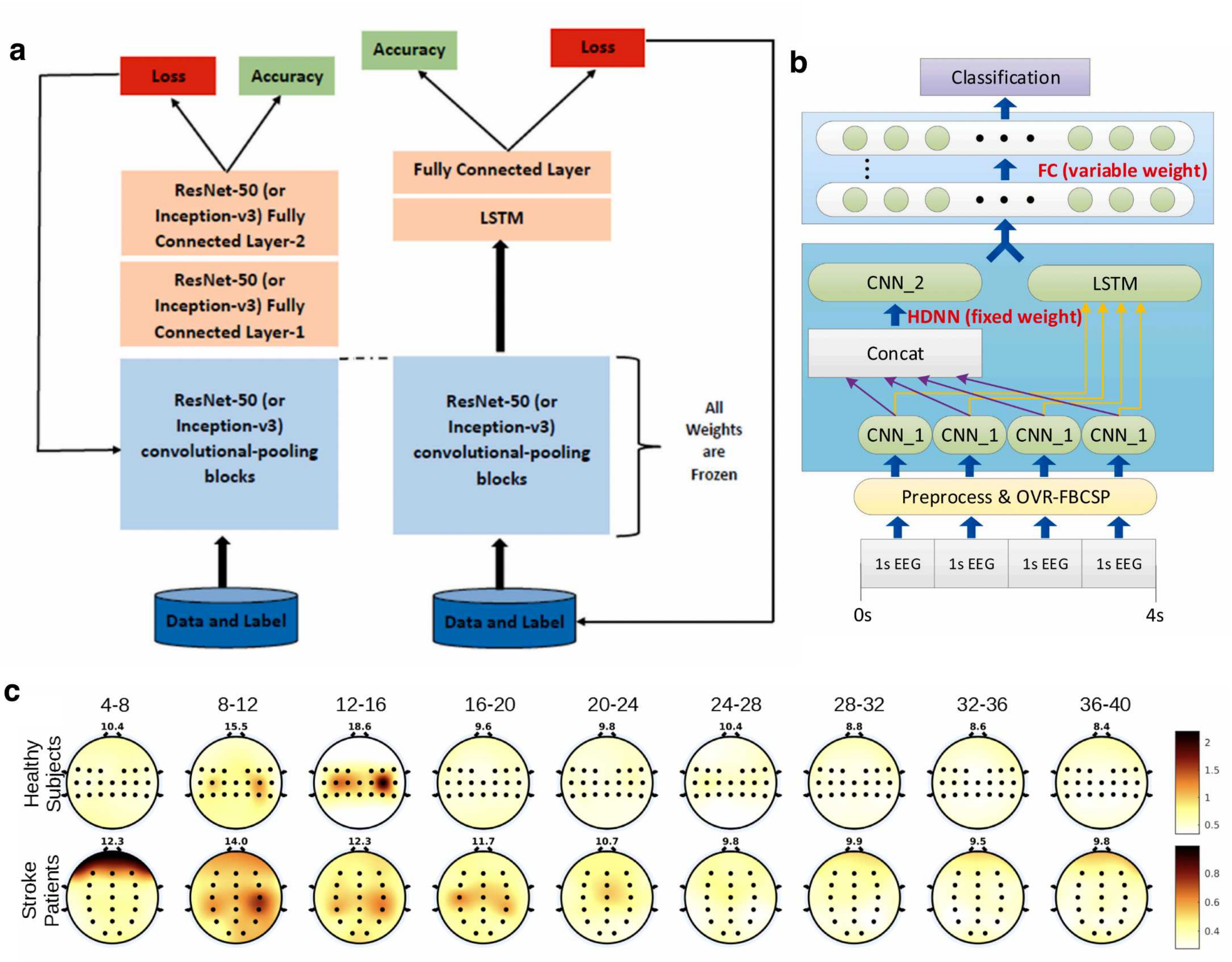

Figure 3: Latest breakthroughs in algorithms for EEG-based MIP systems. (a) The transfer learning-based CNN and LSTM hybrid deep learning model [61]. (b) The architecture of the end-to-end HDNN-TL [60]. (c) XAI is used to analyze healthy subjects and stroke patients [63].

pre-trained models and adapting them to new subjects or sessions. This reduces the need for extensive subject-specific training data. In 2021, Zhang *et al.* proposed a "brain-ID" framework based on the hybrid deep neural network with transfer learning (HDNN-TL) to deal with individual differences of 4-class MI task, which obtained 0.8 kappa value on BCI competition IV dataset 2a (Figure 3(b)) [60]. In 2022, Khademi *et al.* presented a hybrid TL model combining a pre-trained CNN with LSTM, achieving the best accuracy of 92% and kappa value of 0.88 on dataset IV-2a (shown in Figure 3(a)) [61]. Additionally, Roy introduced an efficient TL-based multi-scale feature fused CNN (MSFFCNN) that year, capturing distinguishable EEG features across multiple frequency bands for multi-class MI classification. On dataset IV-2a, the model achieved an average accuracy of 94.06% and the kappa value of 0.88 [62]. TL methods continue to attract researchers aiming to optimize their performance in EEG-based MI systems.

- **Explainable AI (XAI):** With the increasing complexity of MI systems, it is crucial to understand the decision-making process of underlying algorithms to ensure trust and interpretability. Researchers are now focusing on developing XAI methods that offer insights into the mechanisms driving MI predictions, thus enhancing user confidence in these systems. Some early efforts include Mane *et al.*'s 2021 proposal of a Filter-Bank Convolutional Network (FBCNet) for MI classification, which employed explainable AI techniques to analyze the differences in discriminative EEG features between healthy subjects and stroke patients (Figure 3(c)) [63]. While not directly applying XAI to the EEG-MI task, Huang *et al.* discussed the importance of XAI for MI in 2022, emphasizing the need to unravel the ”black box” of deep neural networks during the training phase [64].

3.5 Advantages and Limitations of EEG

EEG offers the benefit of high temporal resolution, rendering it well-suited for examining rapid fluctuations in neural activity linked to cognitive processes and sensory experiences, as the earliest stage of motion intention development and pattern generation in the brain. Nevertheless, EEG has also some drawbacks, such as limited spatial resolution, susceptibility to noise and artefacts, and challenges in pinpointing the precise source of brain activity [65]. Despite these constraints, EEG remains a valuable instrument for investigating brain function and in a broad spectrum of applications across diverse fields.

4 EMG in the Motion Intention Transmission Process

Action potentials are an inevitable product of the neural system controlling the final outcome of muscle movements. Electromyography (EMG) serves as a valuable tool for monitoring neuromuscular signals, providing fine-grained information on motion intention. The generation of these signals, occurring 30-150 milliseconds before the onset of motion, enables the possibility of high-bandwidth, low-latency action intention prediction [66]. EMG techniques can be broadly categorized into intramuscular EMG and surface EMG (sEMG). Intramuscular EMG, which is based on needle or wire electrodes, constitutes an invasive method for recording neuromuscular signals. It allows for the monitoring of action potentials from individual muscle fibers and is considered the gold standard in clinical diagnose. Conversely, sEMG employs electrodes placed on the skin to monitor the overall bioelectric signals of muscle groups within a specific region. Although sEMG sacrifices specificity, its non-invasive nature has led to widespread adoption in clinical diagnostics, gesture recognition, and prosthetic control. In comparison to BCI, sEMG measuring protocols exhibit greater diversity, depending on the application and hardware configuration, yet the fidelity of sEMG is more severely affected by motion artefact. In recent years, there has been a growing interest in transitioning sEMG from a medical tool to a high-bandwidth human-machine interface, which has stimulated a plethora of research at the device and algorithmic levels. In this section, we will review the latest developments in signal acquisition, characterization, and processing methods of sEMG technology towards MIP application.

4.1 Evolution of EMG Devices

In order to achieve high signal stability and an optimal signal-to-noise ratio (SNR) while maintaining user comfort, a variety of electrodes and sensors have been developed. These include wet electrodes, dry electrodes, and flexible sensors, which share similar classifications and structures as previously discussed in the electroencephalography (EEG) section. High-density (HD) EMG systems are also one of the recent hotspots in hardware development. Unlike traditional electrode configurations (monopolar, bipolar, and array structures), HD-EMG performs dense multi-channel acquisition on the surface of muscles, which can improve the spatial resolution of signals and provide more detailed information on muscle activity, including the distribution of electric potentials inside the muscle, the activation area, and the direction of muscle fibers [67, 68]. However, there are still technology challenges such as complex equipment and difficult signal processing, which require further research.

4.2 EMG Signal Processing and Classification

Suitable signal processing methods are needed to improve the SNR for subsequent signal analysis, which plays an important role in improving the accuracy of predicting motion intention. These algorithms can be roughly divided into four categories in a similar way to BCI systems: pre-processing, feature extraction, feature selection, and classification/regression [69, 70]. It is worth noting that regression algorithms are widely used in EMG systems and have different functions than classification algorithms.

- **Preprocessing:** The raw EMG signal collected by electrodes is a non-stationary microelectronic signal that contains various types of interference, including electrocardiographic interference and interference introduced by the acquisition system [71]. EMG signal preprocessing generally includes baseline correction, noise reduction through amplification, filtering, and modulation of the signal envelope. The difficulty of completely removing the ECG component interference is high, and many studies focus on applying integrated algorithms, such as Niegowski *et al.*'s unsupervised learning method based on wavelets [72].

- **Feature extraction and selection:** For EMG signals, features are divided into three categories: time-domain (mean absolute value (MAV), root mean square (RMS), waveform length (WL), etc.), frequency-domain (autoregressive coefficients (AR), power spectrum (PS), mean frequency (MNF)), and time-frequency domain (wavelet transform, short-time Fourier transform (STFT)) features. Some research suggests that using frequency-domain and time-frequency domain features may lead to higher efficiency but lower accuracy compared to time-domain features [73]. However, further research is needed to validate this viewpoint. Selecting optimal feature combinations and extracting features with appropriate time windows are also research focuses.

- **Classification or regression:** The algorithms for analyzing motion intentions based on the EMG system can be divided into discrete methods and continuous methods. Discrete methods classify specific motion intentions (such as gesture classification) through classification algorithms, while continuous methods establish linear or non-linear relationships between EMG signal features (input) and motion parameters (such as torque and joint angles) through regression methods. Discrete methods are implemented through machine learning and deep learning algorithms, while continuous methods include model-based methods (based on kinematics, dynamics, or skeletal muscle models) and model-free methods (directly establishing input-output relationships through machine learning and neural networks). Compared to discrete intention prediction, continuous motion intention prediction is more valuable for the stable control of assistive mechanical systems (such as prostheses, exoskeletons, etc.). In continuous intention prediction, model-based methods require prior knowledge about the human body's limbs and involve complex parameter identification, which limits their application [74]. Model-free methods have become a hot research direction in recent years, but ”black-box” model issues remain, which limit interpretability.

4.3 Latest breakthroughs in EMG-related MIP

In recent years, significant advancements have been made in the field of sEMG-based MIPs and related signal processing algorithms [75]. Additionally, progress has been observed in classification algorithms [74] and systems aimed at predicting movement intentions [73, 76, 77]. Here, we review some of the most relevant research and state-of-the-art work in this field, and summarize the latest developments.

4.3.1 Device advances

Due to the susceptibility of sEMG to motion artefacts and the growing demand for continuous, all-day monitoring, sEMG electrodes with conformable form factors such as textiles and tattoo-like structures have been developed in combination with flexible interface materials in order to balance between high fidelity and user comfort. Specifically, Lee *et al.* developed a multi-channel sEMG knit band sensor for use in myoelectric prostheses [78]. The sensor is made by knitting silver-plated conductive yarn with moisture-wicking technical yarn, allowing for the recording of eight-channel sEMG signals simultaneously (shown in Figure 4(a)). The knitted sensor offers advantages such as flexibility, wearability, breathability, washability, high conductivity, and no skin side effects. Experimental results demonstrated that the knitted sensor outperformed disposable electrodes in terms of signal-to-noise ratio and motion classification accuracy. Most recently, Jiang *et al.* developed a universal interface for electronic skin devices that allows for robust and highly stretchable connections between soft, rigid, and encapsulation modules (demonstrated in Figure 4(b)) [79]. A 21-channel sEMG device assembled with this interface outperformed its commercial counterparts in terms of signal quality and resistance to mechanical interferences. When exposed to pressure or strain, the device maintained clear signals and high signal-to-noise ratios, while control devices experienced signal weakening and noise. Moreover, the EMG device was able to map various gestures and perform well underwater and on sweaty skin. Furthermore, Lee *et al.* developed a highly accurate gesture recogni-

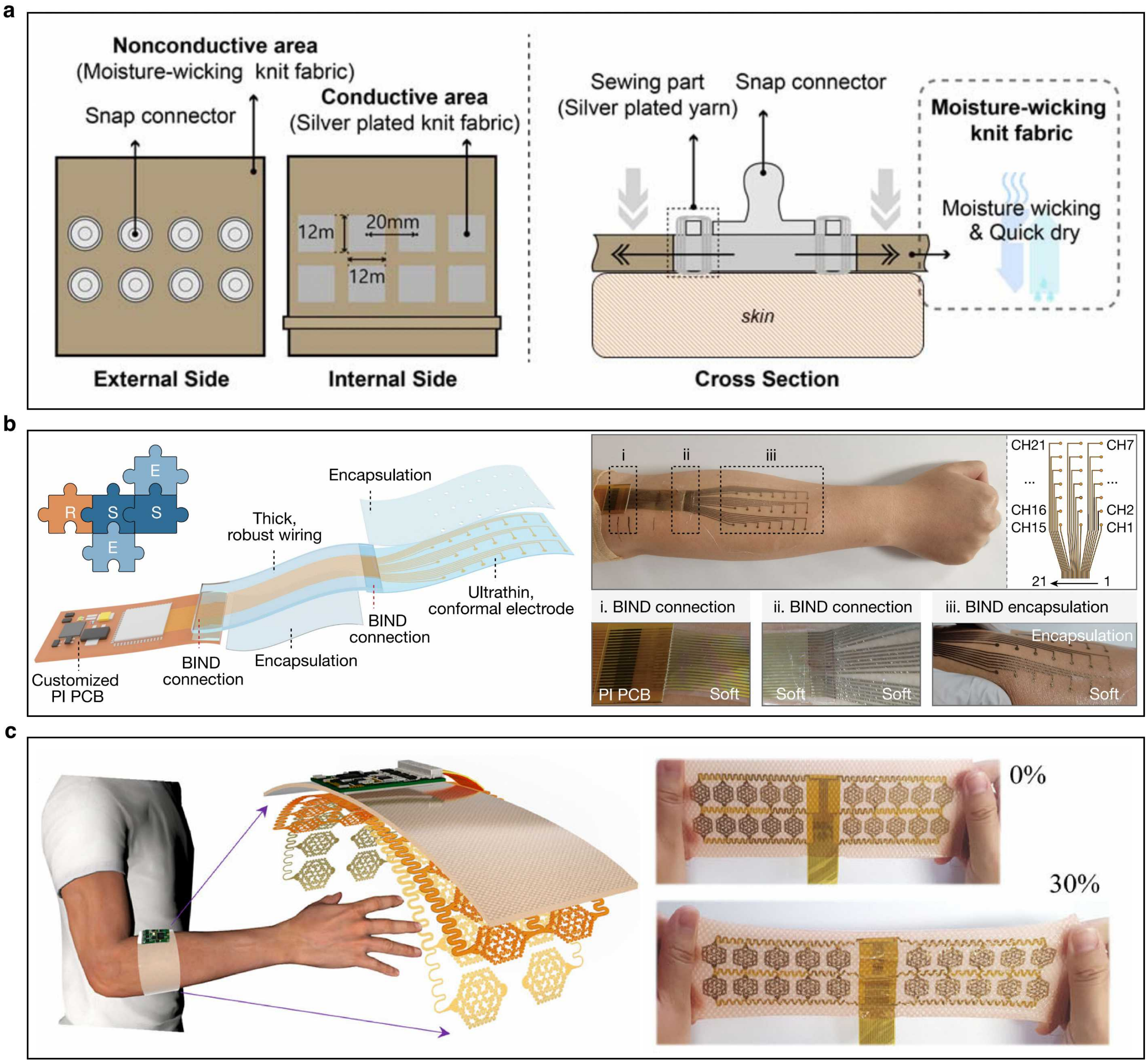

Figure 4: Latest breakthroughs in EMG devices which can be used to establish MIP systems. (a) The multi-channel knit band sensor [78]. (b) The 21-channel on-skin EMG electrode array assembled using plugand-play BIND connections [79]. (c) The stretchable array sEMG sensor with GNN for static and dynamic gestures recognition system [80].

tion system using an array of stretchable sEMG electrodes and a self-attention-based graph neural network (shown in Figure 4(c)). Designed to spatially cover skeletal muscles, the system can distinguish 18 gestures with 97% accuracy. A sticky patchwork of holes on the sensor array provides skin-like attributes, maintaining stable EMG signals and 95% recognition accuracy even after 72 hours of testing and 10 reuses. This approach has significant potential for improving gesture recognition in applications such as rehabilitation, gaming, and human-computer interaction [80].

The construction of low-power and low-latency wearable sEMG systems is challenging due to the large amount of data generated by motor neurons during muscle activity. Neuromorphic devices are promising for small-scale, real-time, and low-power embedded systems for sEMG signal processing. Donati *et al.* integrated a neuromorphic processor with a spiking neural network (SNN) to locally process and classify hand gestures in real-time, with minimal power consumption [81]. The SNN implemented on the chip effectively separated gesture samples into distinct classes, achieving a classification rate of 74% with only 0.05 mW power consumption, showing the potential as an end-to-end solution in clinical diagnosis and rehabilitation research.

4.3.2 Algorithm advances

Advancements in signal processing algorithms, classification, and regression have opened up new possibilities for motion prediction applications. The following are some major advancements in this field.

- **Advancements in preprocessing and feature extraction methods**

  Filtering methods: Filtering is crucial for decoding neural information, especially for amputee users. Jarrah *et al.* [82] proposed a method based on Wiener Filtering (WF), which improved the quality of the EMG signal for amputee users. Compared to median filtering and Hampel filtering, WF improved the accuracy of a single

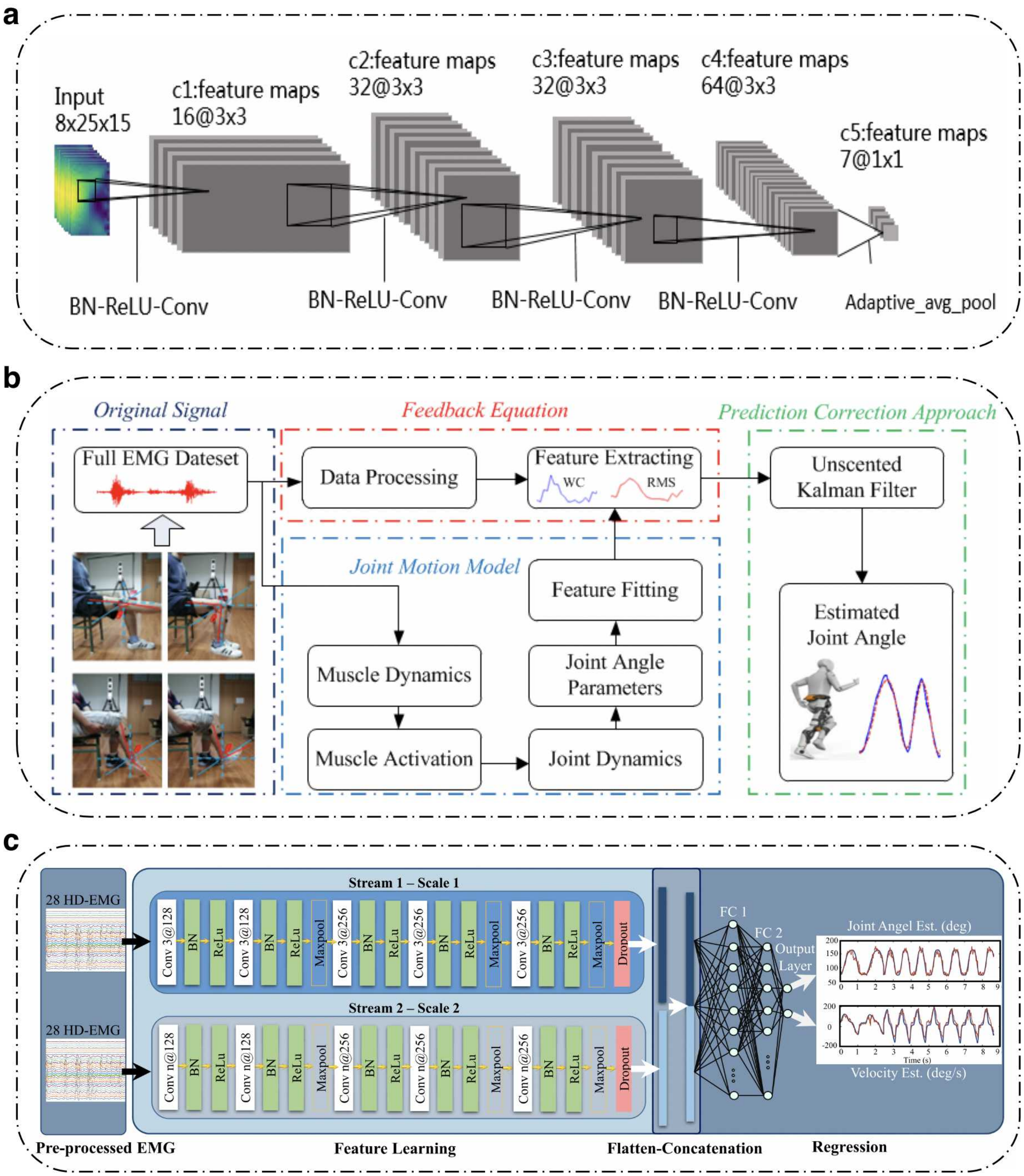

Figure 5: Latest breakthroughs in algorithms of EMG-related MIP. (a) EMGNet: Architecture contains four convolutional layers and a max pooling layer without using the full connection layer as the final output [91]. (b) An overview of Hill-based muscle model (HMM) combined with the forward dynamics for sEMG-based MIP [98]. (c) An overview of proposed TS-CNN method [101].

movement category by 18.64%, which may have a positive impact on prosthetic control schemes.

Feature selection: In supervised learning studies, traditional feature selection methods have a high time cost in feature selections with the increase of the number of features. A few methods, such as Extreme Random Trees (ERT) [83], have been applied to feature selection, which combines the results of multiple decorrelated decision trees to promote efficient feature selection and improve classification performance. Energy kernel methods have also been applied to feature screening [84], with low time costs (only 3.7% of the cost of discrete box counting), which can better meet real-time requirements.

Window selection: The window segmentation strategies need to balance the impact on response speed, classification performance, and subsequent control functions [85]. Previous research has analyzed that shortening the window length increases classification error [86], but few studies have considered the trade-off of the above comprehensive performance. Asogbon *et al.* [87] systematically studied the relationship between various dynamic factors (window parameters, signal conditioning, and feature sets) based on linear discriminant analysis (LDA) and the decoding performance of the EMG system for movement intent. They found that at the optimal window parameters of 250 ms/100 ms, multiple features have high robustness to additive noise and can always achieve a minimum decoding error of less than 10%, while the selection of the number of features has a clear trade-off between accuracy and computation time.

- **Discrete Motion Intention**

Elastic Pipeline Method: By applying the elastic classification pipeline method, the overall classification performance can be improved by merging the prediction results of multiple classification models, and the robustness and flexibility of the model can be increased without discarding samples. In [88], the elastic classification pipeline method of extreme learning machine (ELM) was used to classify an EMG database containing 17 hand gestures without sample discarding. This method was compared with the baseline ELM and sample discarding (DISC) methods in all databases, and the average accuracy was improved by about 10%.

Deep Learning Method: In the application of deep learning methods in the MIP field, new neural network application ideas and network structures are generated, which eliminate the dependence on manual feature extraction, and extract richer features for more accurate classification [89, 90]. In these studies, the surface electromyography signals of each channel were subjected to short-time Fourier transform or wavelet transform to form image signals, which were classified by CNN. Ideas such as transfer learning have also been applied in EMG-based MIP. Traditional neural network models have a large number of parameters and high training costs. New neural network structures based on the characteristics of EMG classification tasks, such as EMGNet (shown in Figure 5(a)) [91], which consists of four convolutional layers and a compact and parameter-limited max-pooling layer, not only reduce the complexity of the model but also improve classification accuracy.

Dynamic Models: The dynamic model recognizes the inherent temporal structure of the activation patterns of surface electromyography signals by capturing the time dependence of the signals and achieves early prediction of movement intentions during the movement initiation process. The dynamic Bayesian network model hidden Markov model (HMM) is a typical algorithm that has been widely used in gesture recognition [92]. Chen *et al.* [93] designed a hierarchical machine learning method, which includes two dynamic Bayesian networks (modeled by Gaussian mixture model-hidden Markov model), respectively modeling the surface electromyography signal activities in idle and movement initiation states. This method allows the possibility of the upcoming movement type to be calculated at any time point before the start of the movement. Compared with the traditional HMM, the accuracy is improved to 93.83%.

- **Continuous motion intention**

Optimized Model-based approaches: Optimized Musculoskeletal Model: Model-based methods have strong interpretability and no black-box problem, but the setting of physiological parameters has a significant impact on the prediction performance, resulting in unavoidable errors. A series of works [94, 95, 96] have established a musculoskeletal model for predicting continuous movements of the upper limb wrist and elbow, but problems with numerical stiffness and overestimation of physiological parameters exist. Zhao *et al.* [97] proposed a musculoskeletal model to estimate the continuous motion of the wrist joint and designed a genetic algorithm to optimize physiological parameters, addressing the aforementioned issues. In single flexion-extension, continuous cycle, and random motion experiments, the root-mean-square errors were 10.08°, 10.33°, 13.22°, and 17.59°, respectively.

Optimized Physiological Muscle Model: The Hill-based muscle model is a physiological muscle model for estimating continuous joint motion and involves many complex physiological parameters. The process of recursive joint angle calculation can affect prediction accuracy. Xi *et al.* [98] proposed a state-space model that integrates HMM and forward dynamics of the joint (as shown in Figure 5(b)) to simultaneously and continuously estimate multi-joint motion, eliminating the accumulation error of joint angle estimation.

New Model-free approaches: ML-based continuous motion regression methods include shallow neural networks and deep neural networks [73]. In addition, we discuss here a dynamic model method based on Evolution and Autoregressive Models.

Shallow Neural Network: The ANN structure is simple and computationally efficient, and research in this area has focused on improving algorithm accuracy and control application performance. For example, Kim *at al.* [99] used a shallow neural network to estimate the torque of two axes (tibial and fibular axes) with five electromyography signals as inputs, for efficient rehabilitation and precise control of an ankle exoskeleton robot. The algorithm errors were 0.37 Nm, 0.5% of the required torque (tibial), and 0.57 Nm, 1.5% (fibular). More studies of ANN methods (before 2019) can be found in [73].

Deep Neural Network: Deep learning methods can achieve more complex continuous prediction tasks, such as decoding multiple degrees of freedom information simultaneously. Compared with using traditional methods to establish independent models for each degree of freedom, these methods have better robustness and adaptability. Yang *et al.* [100] proposed a novel convolutional neural network (CNN) structure based on the features of raw electromyography signals, which can effectively decode the complex three-degree-of-freedom wrist motion directly from raw electromyography signals and determine the partial relationship between the raw electromyography signals and the force involved in multi-degree-of-freedom motion. Hajian *et al.* [101] proposed a new method using two CNN streams (called TS-CNN, shown in Figure 5(c)), which for the first time accurately predicts joint angles and velocities from EMG signals and achieves regression performance (R2 values) of 0.81±0.06 for joint angle estimation and 0.78±0.05 for velocity estimation under quasi-dynamic (controlled force or velocity) and dynamic (uncontrolled force and velocity) experimental conditions. Feleke *et al.* [102] used a regression fuzzy neural network (RFNN) to achieve the direct prediction of the three-dimensional position of the hand under complex trajectories from EMG for the first time. It achieves an effect of average CC (Correlation Coefficient) = 0.85 and NRMSE (Normalized Root Mean Square Error) = 0.105 within 250 ms.

Evolution and Autoregressive Models: Analyzing unspecified human kinematics and human motion intent is a major challenge in the field of MIP. Zeng *et al.* [84] used Evolutionary GP models to predict electromyography (EMG) motion intention for the first time, using an evolutionary nonlinear autoregressive with exogenous inputs (NARX) framework based on Gaussian processes. The structure and parameters of the framework are adaptively adjusted according to the input data, achieving accurate prediction of muscle force and joint angle under time-varying motion patterns, with a normalized mean square error (NMSE) of 0.9994 and 0.9993.

4.4 Advantages and Limitations of EMG

Surface electromyography (sEMG) is a non-invasive technique with high temporal and spatial resolution, making it ideal for studying muscle activity and movement control due to its high sensitivity, good repeatability, and real-time performance. However, sEMG also has some limitations, such as being affected by factors such as electrode placement, muscle morphology, and skin condition, difficulty in distinguishing between activities of different muscles, and the need for signal preprocessing to extract useful information [103, 104]. Despite these limitations, sEMG remains a powerful tool for evaluating muscle function and disease, monitoring human motion and posture, and designing rehabilitation plans. It has wide applications in the fields of rehabilitation medicine, exercise physiology, and robotics.

5 Motion Sensors in the Motion Intention Execution Process

Unlike MIP methods based on BCI and EMG, using motion sensors at the site of the executed movement results in a delay in obtaining signals after the movement has occurred. Nevertheless, by analyzing completed and ongoing movements, it is still possible to predict future motion intentions. By using motion sensors, patterns and trends in the movement data can be identified, allowing for the extrapolation of these patterns to make predictions about what the intended motion will be in the future. As the most frequently employed motion sensors for MIP, IMUs, pressure sensors, and strain sensors can be placed at joints, soles of the feet, lower back, and other locations to capture information on acceleration, force, and deformation during movement execution. These sensors offer a comprehensive understanding of human motion, enabling accurate prediction of motion intentions and promoting seamless human-machine interaction [105, 106].

5.1 Classical Motion Sensors Used for MIP

- **Inertial Measurement Units (IMUs):** They typically consist of accelerometers, gyroscopes, and magnetometers, providing accurate measurements of linear acceleration, angular velocity, and orientation. The advent of micro-electromechanical systems (MEMS) technology has enabled the development of smaller, lower-cost, and more power-efficient IMUs, facilitating their integration into wearable devices and MIP applications [105].

- **Pressure Sensors:** Pressure sensors play a crucial role in capturing force-related information for MIP. Piezoresistive pressure sensors, one of the most common types, change their electrical resistance when subjected to pressure. Capacitive, piezoelectric, and optical pressure sensors have also been employed in various MIP applications, offering different levels of sensitivity, accuracy, and robustness [107].

- **Strain Sensors:** Strain sensors measure deformation, elongation, or compression resulting from applied forces. These sensors, including resistive, capacitive, and optical strain sensors, have been widely used in MIP applications to capture muscle activity, joint angles, and other biomechanical parameters [108].

5.2 Motion Sensor Signal Processing and Classification

The processing and classification of motion sensor signals follow similar stages as in BCI and EMG systems, including preprocessing, feature extraction, feature selection, and classification [109, 110, 111]. Here, we provide a concise summary while emphasizing the methods specific to motion sensors:

- **Preprocessing:** Motion sensor preprocessing shares techniques with BCI and EMG systems, such as filtering (low-pass, high-pass, band-pass) and normalization. For motion sensors, additional preprocessing steps like sensor fusion (e.g., combining accelerometer, gyroscope, and magnetometer data) and orientation estimation (e.g., using Kalman filters or Madgwick algorithms) may be employed.

- **Feature extraction:** Many feature extraction methods for motion sensors are analogous to those in EMG systems, including time-domain, frequency-domain, and time-frequency domain features. Some motion sensor-specific features include orientation and angular velocity derived from IMUs and force distribution patterns from pressure sensors.

- **Feature selection:** Similar feature selection methods are applied across BCI, EMG, and motion sensor systems, including filter methods, wrapper methods, and embedded methods. For motion sensors, the most relevant features may vary depending on the type of sensor (IMU, pressure, or strain) and the application.

- **Classification:** Motion sensor systems employ classifiers that are common in both BCI and EMG systems, such as LDA, SVM, ANN, CNN, LSTM, and transformer.

In some cases, motion sensors may use regression algorithms to establish a continuous relationship between sensor features and motion parameters (e.g., torque, joint angle), which is particularly useful for controlling mechanical systems like prosthetics and exoskeletons.

5.3 Latest Breakthroughs in Motion Sensors-related MIP

5.3.1 Device advances

Researchers in the field of motion sensors often prefer to use human motion recognition as a demonstration experiment. Therefore, here, we also include novel motion sensors designed for human motion recognition within the scope of our discussion. Since the main difference between motion recognition and prediction tasks lies in the application of data (recognition tasks use cross-sectional data, while prediction tasks use time series data) and the device and algorithm backbones are essentially consistent, these sensors can be applied to human motion prediction. Similarly, the corresponding algorithms can be used in MIP with minor adaptations.

Over the past decade, despite numerous companies like InvenSense, STMicroelectronics, and Sensortec continuously exploring methods to reduce noise and power consumption in IMUs, the basic principles of operation for IMUs remained unchanged. An innovative approach emerged in 2020 by Liu *et al.*, which introduced a wearable motion capture device that combines micro tri-axis flow sensors with micro tri-axis inertial sensors for accurate and drift-free limb motion capture, even during strenuous activities and prolonged exercises. The researchers also established a neural network model for intra-limb coordination in human walking and running, enabling the simplification of capture devices and cost reduction [112]. Although their work did not involve predicting motion but merely capturing it, the IMU device they designed with integral-free velocity detection in their study holds significant implications for the application of MIP.

Flexible sensors are currently the most versatile and prevailing devices used for mon-

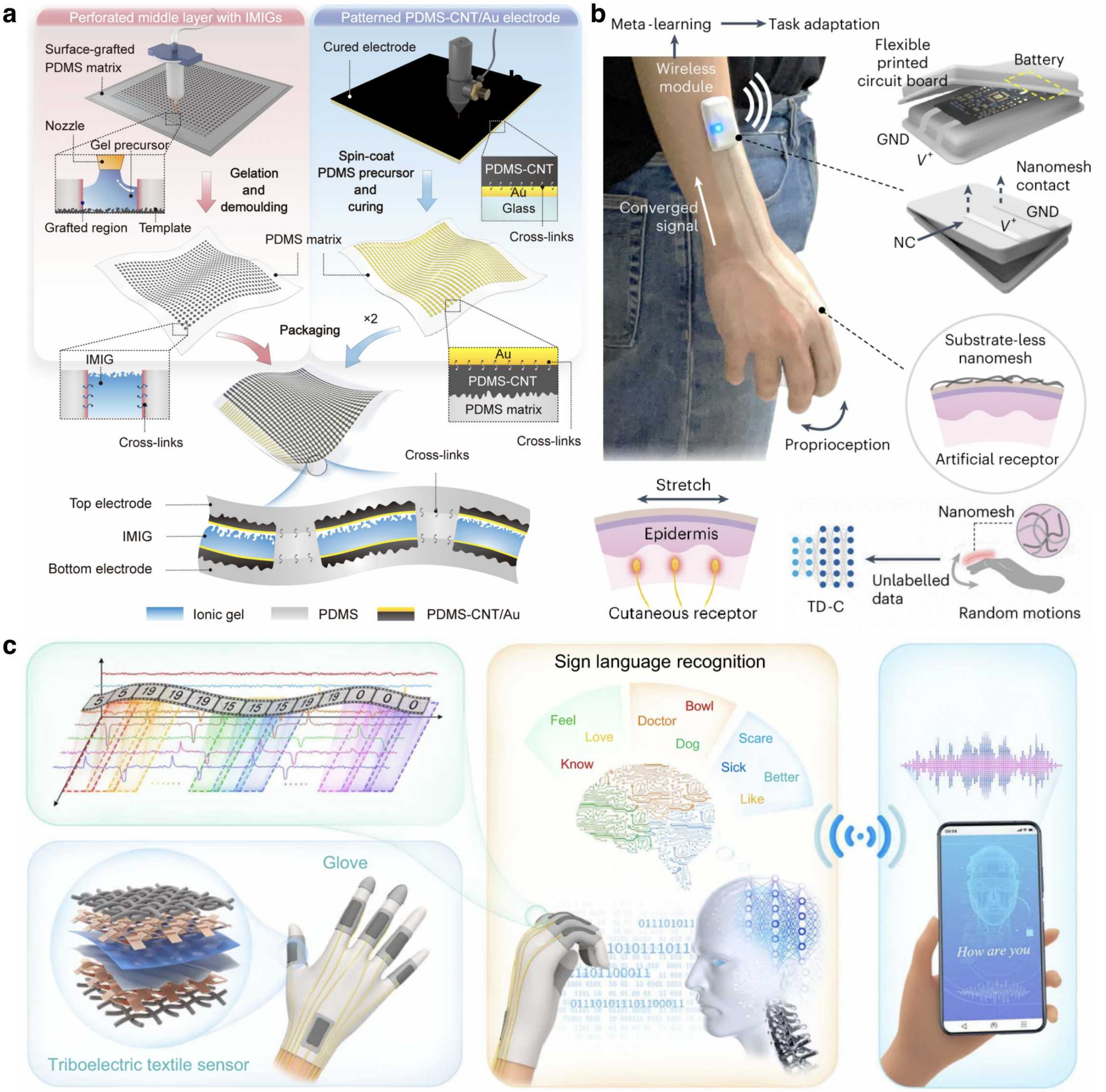

Figure 6: Latest breakthroughs in motion sensor which can be used to establish MIP systems. (a) Fabrication of the iontronic pressure sensor [114]. (b) A wireless artificial sensory intelligence system that consists of printed, biocompatible nanomesh cutaneous receptors [116]. (c) Schematics of the sign language recognition and communication system based on the TENG glove [117].

itoring or predicting human body movements suitable for large-area wearable devices, with high comfort and flexibility, while the wearer is in motion. For flexible pressure sensors, the main factor that hinders further development in the task of analyzing human motion is the difficulty in maintaining their performance, accuracy, and reliability over a long period of time under mechanical deformation and mechanical pressure. Towards this issue, Su *et al.* presented a design for a highly stretchable and highly sensitive pressure sensor that can provide unaltered sensing performance under stretching in 2021. Via the synergistic creations of an ionic capacitive sensing mechanism and a mechanically hierarchical microstructure, the sensor exhibits 98% strain insensitivity up to 50% strain and a low pressure detection limit of 0.2 Pa [113]. More recently, in 2023, Shi *et al.* made a skin-like iontronic pressure sensor for use in robot haptics. They used a microstructured ionic gel embedded in an elastomeric matrix and cross-linked laterally to enhance the interfacial robustness while maintaining sensitivity (as shown in Figure 6(a)). This design suppressed cross-talk between the sensing elements and improved the mechanical stability of the sensor [114].

Similar issue to pressure sensors also occur in strain sensors: that is, maintaining good performance while ensuring the best possible fit during stretching. This is because both types of sensors would need to maintain close and continuous contact between the user and the device in order to provide accurate data. Fruitful attempts have been made to overcome the issue in recent years. In 2021, Tang *et al.* designed a stretchable and conformal electronic tattoo with multilayered integration for skin health and movement sensing. The tattoo amplifies strain sensor output by three times with a crease amplification effect, is easy to transfer and has a simple fabrication process. The three-layered tattoo was developed with 1 heater and 15 strain sensors for temperature adjustment, movement monitoring, and robot remote control [115]. Then in 2023, Kim *et al.* developed a substrate-free nanomesh receptor for hand movements. The biocompatible nanomesh, which can be directly printed on a person's hand, translates electrical resistance changes from skin stretches into proprioception (as shown in Figure 6(b)). It can measure finger movements from multiple joints simultaneously and has a low computational cost. The nanomesh receptor provides a simple and efficient solution for tracking human hand movements [116].

In addition to classical methods such as IMU and force sensors for analyzing movements, a new approach has emerged in the motion analysis domain in recent years: triboelectric nanogenerator (TENG) sensors. TENG-based wearable sensors have been increasingly employed for healthcare monitoring owing to simple fabrication, wide material choice, and expeditious dynamic response. For instance, in 2021, Wen *et al.* proposed a sign language recognition system using gloves with triboelectric sensors, a deep learning block, and virtual reality interface. It recognizes 50 words and 20 sentences with 86.67% accuracy for new sentences. Results are translated into text and audio for communication between signers and non-signers. The gloves were made by coating a conductive textile with Ecoflex and attaching a wrinkled nitrile layer, then sewing the triboelectric sensors onto the gloves (as shown in Figure 6(c)) [117]. Furthermore, in 2023, Liu *et al.* proposed a methodology for improving the triboelectricity of marine polysaccharides by incorporating charged phyllosilicate nanosheets. A flexible, flame-retardant, and eco-friendly triboelectric sensor was developed using a composite paper made from alginate fibers and vermiculite nanosheets. This triboelectric sensor monitored slight motion signals from various joints of the human body and achieved a machine-learning model accuracy of 96.2% for human motion identification and 99.8% for prediction. The methodology offers a promising strategy for improving triboelectricity and implementing self-powered, intelligent platforms for emerging applications [118].

5.3.2 Algorithm advances

As previously mentioned, motion recognition and motion prediction share a similar underlying goal in algorithms: they both aim to extract the most relevant features from the signals of motion sensors and utilize them. The difference is that motion recognition focuses on the current motion, while motion prediction uses these features to predict future

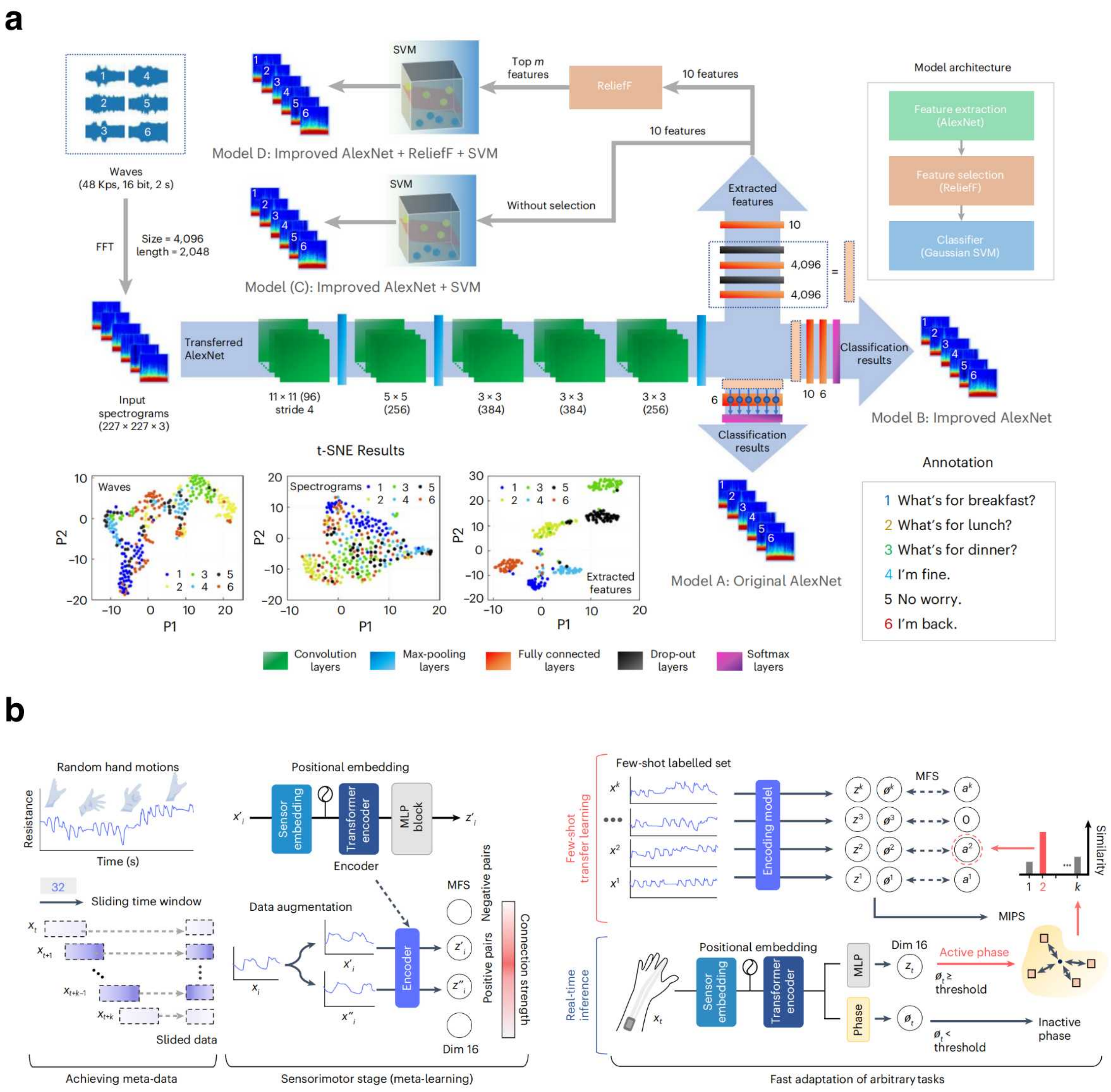

Figure 7: Latest breakthroughs algorithms which can be used to establish motion sensor-based MIP systems. (a) Structure of an integrated model transferred to a laryngectomy patient [120]. (b) Sensor signal processing and unsupervised TD-C learning for learning the MFS [116].

motion. Therefore, motion recognition-related algorithms are also included in this review.

One of the most interesting algorithmic problems to explore in the field of using motion sensors to recognize and predict movements is the difficulty in finding a universal approach, or quickly establishing and converging a model from scratch when there is no universal method. This is mainly due to the variety of motion sensor types and the flexibility in their placement on users, which results in a lack of a universal baseline dataset for researchers to conduct incremental studies.

In 2023, Straczkiewicz *et al.* presented a ”one-size-fits-most” walking recognition method for smartphones, smartwatches, and wearable accelerometers. Leveraging tri-axial accelerometer data, the method focuses on walking's inherent features, offering a more accurate approach than traditional ”activity counts.” Validated against 20 public datasets, the method shows promise in studying human behavior through personal digital devices [119]. The pre-train and fine-tune architecture of transfer learning is a strong alternative option in the absence of a general method. By pre-training on easily accessible datasets, the model can learn a certain ability to capture modality information, greatly accelerating the convergence speed in the training of actual tasks. For instance, Yang *et al.* used the Fast Fourier Transform (FFT) to convert strain sensor signals that respond to subtle throat movements into two-dimensional images. They pre-trained the model using the large-scale ImageNet dataset and performed fine-tuning on CNN architectures such as ResNet-50. Eventually, they achieved a good speech recognition accuracy of 99.05%, and the fine-tuned model was also able to achieve 91% zero-shot accuracy in a laryngectomy patient after undergoing optimization of the network structure (shown in Figure 7(a)) [120]. In addition, Kim *et al.* proposed a transfer learning method, Time-Dependent Contrastive Learning (TD-C) (shown in Figure 7(b)), which creates a generalizable latent feature space (MFS) for human finger motions by employing contrastive learning with temporal features. The model effectively extracts motion information from unlabelled random hand motions and adapts to new users and tasks using few-shot learning. TD-C overcomes domain shift issues by incorporating time-wise correlation, data augmentation, and a metric-based inference mechanism, offering a promising solution for recognizing hand gestures across different users and daily tasks [116].

5.4 Advantages and Limitations of Motion Sensors

One of the significant advantages of using motion sensors in MIP systems lies in their non-invasive nature. Unlike BCI and EMG techniques, which may require skin contact or even invasive procedures, motion sensors can be placed on the body or embedded in wearable devices without causing discomfort and reducing the risk of skin irritation after prolonged use by the user. Motion sensors, like IMUs, pressure sensors, and strain sensors, provide comprehensive information about human motion. For instance, IMUs, which combine accelerometers and gyroscopes, can measure linear acceleration, angular velocity, and orientation in various human motion planes such as the sagittal, coronal (frontal), and transverse planes. Pressure sensors can capture absolute position information (i.e. height) as well as force-related information, and strain sensors can measure deformation, tensile, or compressive strain resulting from applied forces. This diversity of information allows for a more holistic understanding of motion intention, potentially leading to more accurate prediction and better user experience [109].

Despite these advantages, the use of motion sensors in MIP systems also has several limitations. First, the information obtained from motion sensors inherently has a delay, as it only becomes available after the movement has started. This limits the system's ability to predict motion intentions in real-time and may result in a less smooth user experience compared to methods that can predict motion intention prior to movement initiation, like BCI and EMG. Besides, the quality of motion sensor data can be affected by various factors, including sensor placement, calibration, and environmental conditions. For example, sensor placement on the body must be precise and consistent to ensure accurate data collection. Calibration is necessary to account for individual differences and sensor drift over time. Environmental conditions, like temperature or magnetic fields, can also influence the

Table 1: Comparison of Advantages and Disadvantages of Different Modalities of MIP Methods

Neural System Process	Modality	Advantage	Disadvantage
Generation Process	EEG	High temporal resolution	Susceptible to noise and artefacts; Low spatial resolution
	NIRS	Resilience to artefacts	Low temporal resolution
Transmission Process	EMG	Direct measurement of muscle activity	Vulnerable to muscle fatigue
Execution Process	IMU	Provide portable information on the user's motion and orientation	Affected by drift and external disturbances and not sensitive to subtle movements
	Pressure Sensor	Detect force distribution changes	Limited in detecting non-contact motions and gestures, and has limited scope
	Strain Sensor	Measure changes in shape and deformation	

sensor readings, requiring additional compensation mechanisms to ensure data accuracy [124].

6 Multimodal Approaches

As shown in Table 1, different modalities of signals related to motion intention have their own advantages and disadvantages in use. Therefore, for some more complex applications such as prosthetic control and exoskeleton assistance, researchers often use a fusion of multiple modalities of information to complement the advantages of different modalities. Here, we review the latest multimodal MIP methods and summarize state-of-the-art MIP research based on various modalities (including both single and multimodal approaches) in Table 2.

In 2020, Nsugbe *et al.* explored the potential of fusing wearable EMG and NIR sensors to classify eight hand gesture motions in 12 able-bodied participants, aiming to

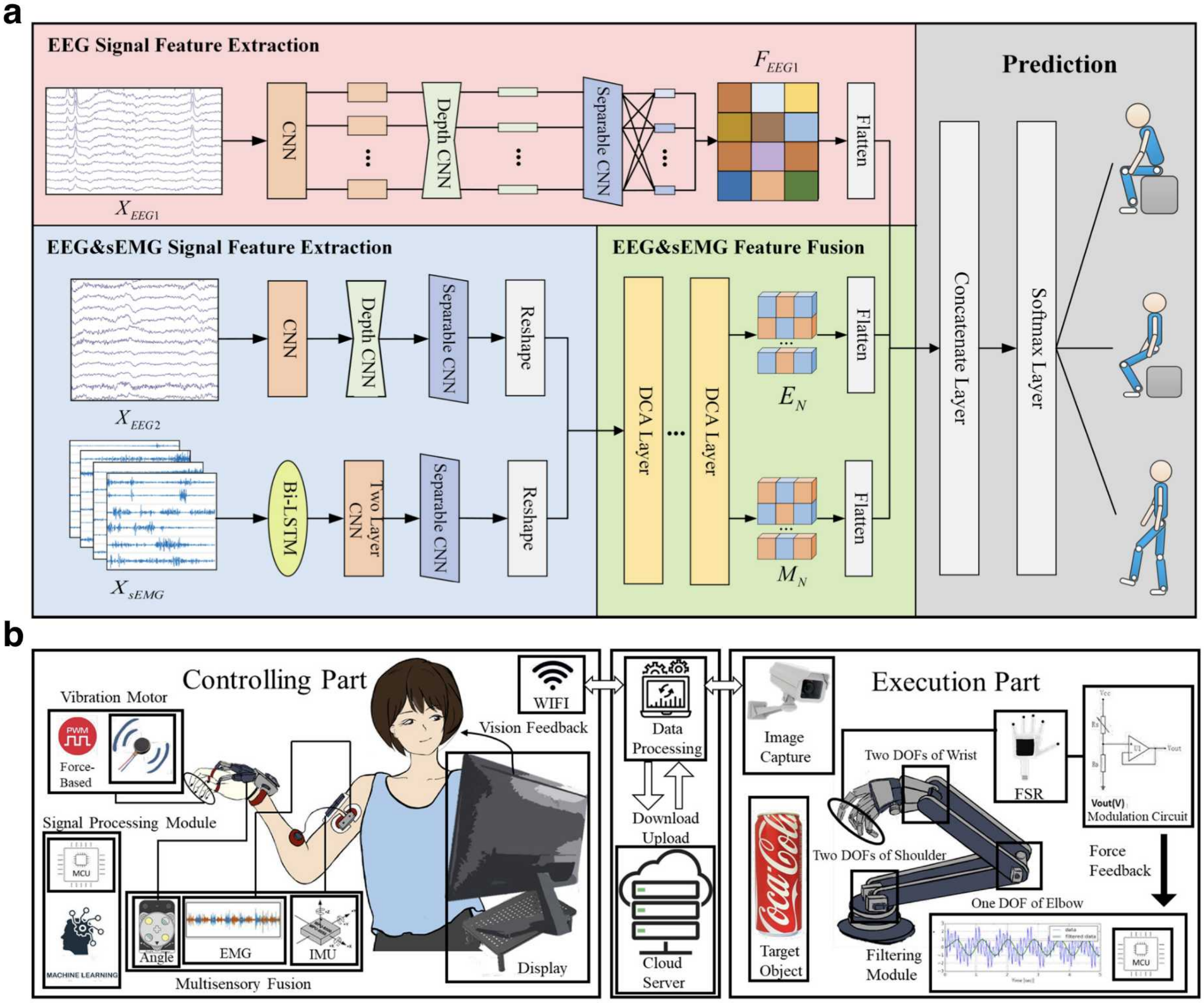

Figure 8: Latest breakthroughs in multimodal MIP systems. (a) Structure of the DMEFNet for lower limb movement prediction [125]. (b) The teleoperation system combining IMU and EMG [129].

overcome the limitations associated with myoelectric prosthesis limbs. The classification accuracy of different sensing configurations (EMG-only, NIR-only, and EMG-NIR) is investigated using a multi-layer perceptron neural network, linear discriminant analysis, and quadratic discriminant analysis. The results suggest that it could be possible to develop transhumeral prosthesis using affordable, ergonomic, and wearable EMG and NIR sensing without requiring invasive neuromuscular sensors or added hardware complexity [125]. Similarly, in 2022, Shi *et al.* presented a Dense Co-attention Mechanism-based Multimodal Enhance Fusion Network (DMEFNet) for lower limb movement prediction in hemiplegia patients (Figure 8(a)). By deeply fusing EEG and sEMG signals, the DMEFNet achieved high accuracy in both within-subject and cross-subject scenarios (82.96% and 88.44%), addressing the unreliability of sEMG single modal human-robot interfaces [126]. The fusion of EMG and BCI methods is not uncommon, primarily because combining these techniques can enhance the reliability and accuracy of MIP, leading to improved control and user experience. For instance, such fusion can mitigate the effects of inherent noise in individual modalities and leverage complementary information from both EMG and BCI signals. Moreover, IMUs, which directly reflect human joint movement and can be used to construct human motion skeleton models, are often combined with other methods [127, 128, 129, 130]. For instance, in 2020, Seeley *et al.* presented a promising approach to measuring vGRF during running using instrumented shoes with piezoresponsive sensors and accelerometers. The results demonstrated relatively low percent errors for vGRF impulse, active peak vGRF, and ground contact time, while higher errors were observed for vGRF load rates [128]. Furthermore, in 2022, Chu *et al.* presented a closed-loop teleoperation system integrating multisensory fusion, visual, and haptic feedback within an IoT framework to address physical and mental fatigue in teleoperating robots (shown in Figure 8(b)). In order to achieve the reading of the operator's motion intention, the authors adopted a method that combines IMU signals with EMG signals. The authors used SVM to analyze the operator's intention and constructed a system using machine vision-based grasping assistance and force feedback gloves. Ultimately, this greatly reduces the user's mental and physical fatigue while assisting in the identification and tracking of different objects [129]. In addition to the above, the multimodality of combining IMU with EEG systems can be exploited to capture and remove artefacts which corrupt the physiological signals. In [55], an in-ear wearable EEG device was combined with IMU, whose signals were used to capture and remove motion artefacts generated by walking. Here the proposed solution combined Noise-Assisted Multivariate Empirical Mode Decomposition (NA-MEMD) [131] with adaptive filters in the adaptive noise cancellation configuration

(ANC). The algorithm relied on the correlation in some specific frequency bands that the artefact was affecting, between the artefactual signal in EEG and the signals captured by the IMU system.

Table 2: State-of-the-Art Works in Motion Intention Prediction

Modality	Application scenarios	Sensor description	Data description	AI Algorithm	Result	Refs
EEG	Autonomous driving and assistant interfaces	Wireless earbud-like EEG device, combined with tattoo-like electrodes and connectors	Continuous recording of EEG signals in multiple tasks	Supervised learning: LSTM	The accuracy of over 80% for detecting the ErrP	[54]
	Decoding MI-EEG signals	N/A	Datasets 2a of BCI Competition IV; Datasets 2b of BCI Competition IV	Spatial-Temporal Tiny Transformer	Accuracy of 90.37%-92.03% on 2a; Accuracy of 84.26% on 2b	[58]
	Decoding MI-EEG signals	N/A	Datasets 2a of BCI Competition IV	Transfer learning-based multi-scale feature fused CNN	Average accuracy of 94.06% and Kappa value of 0.88	[62]
EMG	Hand gesture recognition	Myo armband (200Hz, 8-channel, dry-electrodes)	Collected 7 types of gestures	EMGNet (compact CNN model)	Reduced the complexity of the model and improved the accuracy (98.81%)	[91]
	Human-machine interfacing	Ultra-thin dry epidermal electrode, PEDOT:PSS thin film-transferred CVD-grown graphene (PTG)	The volunteer slept, exercised, and recovered to calm	N/A	Precisely control the robotic hand by facial muscle expression	[49]
	Estimate wrist joint motion	Delsys Trigno TM system(2000Hz)	EMG Data collected by electrodes placed over five wrist muscles over right forearm, trajectory data captured through the motion capture system	Musculoskeletal model	The RMSE were 10.08°, 10.33°, 13.22°, and 17.59° in the single flexion-extension, continuous-cycle, and random-motion trials	[97]
Triboelectric	Healthcare	Triboelectric sensor based on all-natural composite paper from alginate fibers and vermiculite nanosheets	Eight types of body motion	PCA + linear regression	99.8% accuracy in predicting the joint bending angle	[118]
IMU	Fall detection	Waist-worn commercial safety IMU	Steps of construction workers performing various tasks throughout the indoor and outdoor workplaces	Supervised learning: BiLSTM	The average Unweighted Average Recall (UAR) of 87.5%	[121]
	Powered intelligent prostheses control	One IMU (MTw Awinda, Xsens)	Shank and foot angular positions from seven able-bodied subjects	Temporal convolution-based online foot angle trajectory prediction network	Predictions with high accuracy (R2=0.94, =0.98, and NRMSE=5%)	[122]
Pressure sensor	Predict Freezing of gait (FOG) in advanced stage Parkinson's disease (PD)	FScan pressure sensing insoles (Tekscan, Boston, MA)	Walking data collected from 11 male participant under the eligibility criteria	Supervised learning: LSTM	82.1% (SD 6.2%) mean sensitivity and 89.5% (SD 3.6%) mean specificity	[123]
EEG, EMG	Human-exoskeleton interface	EMG: myoMUSCLE (1500 Hz); EEG: waveguard (1000 Hz)	10 healthy subjects completed three lower limb movements under incompletely asynchronous paradigm	Dense co-attention mechanism-based Multimodal Enhance fusion Network	The highest accuracy of 88.44% in lower limb movement prediction	[126]
IMU, EMG	Teleoperation robotic arm's motion control	IMU: MPU6050; EMG: MyoWare	20 participants grabbed the items on the messy plateau	SVM	The robot arm can successfully grip objects according to teleoperation	[129]

7 Challenge and Outlook

7.1 Challenge and Limitations

The fields of wearable sensors and artificial intelligence have both experienced rapid progress in recent years and showcased tremendous potential in MIP applications. Nonetheless, the integration of these advancements to yield precise, comfortable, and real-time predictions of human motion intention across various scenarios remains a formidable challenge, necessitating progress in the different technology areas and application domains. Here, we discuss the primary unresolved questions in this field and pinpoint research areas that hold the potential to deliver viable solutions.

7.1.1 Devices fabrication

Long-term monitoring presents a significant challenge in the context of MIP device development, as it necessitates the creation of responsive materials with enhanced efficiency and stability to address current limitations. Furthermore, MIP devices must withstand complex and fluctuating conditions during extended use when users keep moving, which differ from controlled laboratory settings. These conditions place unique demands on all device components, including substrates, sensing elements, power supply modules, and encapsulation materials. For instance, ensuring that the substrates maintain their flexibility and stretchability under extreme temperatures or dry conditions remains a difficult task [132].

Biocompatibility is another critical concern in sensor fabrication for MIP applications due to unwanted side effects such as skin allergy or discomfort caused by the materials used for ensuring deep contact of the device with skin. This adds on top of the risk of infection or other adverse reactions due to long-term direct contact between the wearable device and the user's skin. To address this issue, researchers can explore natural materials such as cotton, wool, silk, hemp, linen, and chitin, which have been used for millennia in clothing production. These materials offer flexibility, mechanical robustness, and biocompatibility due to their biological origin. Although natural materials lack certain desirable properties like conductivity and optical attributes, they can be modified or combined with other materials during the fabrication process to acquire these properties. Furthermore, researchers can investigate synthetic polymers and hydrogels, which offer versatility, biocompatibility, and unique properties for wearables [133]. However, careful consideration of potential hazards is crucial, particularly when using synthetic polymers that may not be skin-safe for long-term direct exposure [134]. Developing a new generation of green polymer chemistry and soft functional materials can help improve sustainability and biocompatibility, paving the way for a broader range of MIP applications.

7.1.2 Algorithm development

The significant variation in physical attributes such as height, body shape, skin impedance, and other individual characteristics pose an actual challenge in the development of effective MIP algorithm. Although various transfer learning-based algorithms have been developed to tackle this issue, they often rely on pre-training with publicly available datasets, which may not accurately capture the target task's features. An alternative solution is multimodal contrastive self-supervised learning, which is derived from the integration of machine vision and natural language processing domain [135]. By automatically matching different modal data with intrinsic relationships, the model can perform self-supervised learning without relying on labeled data, thus overcoming the limitations of pre-training with task-specific datasets that lack labeling information.

As previously discussed, Explainable AI (XAI) represents an emerging direction in MIP systems. However, when dealing with human-related data, XAI encounters a critical issue: bias. Bias in XAI can arise from various aspects, including model development and datasets. In such situations, explanations lack performance guarantees. In fact, the performance of explanations is seldom assessed, and when evaluations do occur, they primarily rely on heuristic measures rather than explicitly scoring the explanation from a human perspective [136]. This poses a challenge because explanations only serve as approximations of the model's decision-making process, and as such, they do not fully encapsulate the underlying model's behavior.

7.1.3 Ethical issues

Addressing challenges and developing effective solutions in the ethical domain of MIP technologies is vital to ensure their successful adoption and societal integration. Safety, privacy and security concerns arise from the need to ensure safety of the wearer using the technology and making sure sensitive motion intention data is kept private and is only accessible by authorized persons. The safety aspects of medical devices are covered by international standards presenting basic safety and essential performance in the IEC 60601 family of standards as collateral and particular standards and appropriate measures have to be adopted via detailed risk assessment and risk management procedures as presented in ISO 14971. This requires analyzing all potential single fault conditions and ensuring there is no possibility of causing harm to the wearer nor compromising the essential performance of the medical device. Such guarantees of safety and performance can only be satisfied by using redundancy in the system design to ensure potential errors due to single fault conditions can be eliminated in the use of the medical device.

Another important issue regarding safety is the growing use of Artificial Intelligence in medical equipment; such methods are heuristic in nature and the decision making can not be fully understand in all situations and hence can be seen as ”black-box” approaches which can be seen as presenting hazards in real-world scenarios. Allowing the AI system to self-learning also can offer regulatory certification concerns and if it can be included into current medical equipment. The international community is currently investigating how such ”black-box AI methods can be safely introduced into medical devices and the normal risk-benefit to the patient assessment seems to offer the best approach.

The privacy and security issues cover physical security as well as cybersecurity concerns and both need to be addressed. Preventing physical access via mechanical locks and physical keys can accommodated. Cybersecurity Hardware concerns can be addressed by implementing advanced encryption methods like homomorphic encryption and secure multi-party computation which offer access to authorized persons. These techniques offer robust data protection while allowing for secure data processing and analysis, without the need for decryption [137] .

Accessibility and affordability are also significant challenges, particularly as they pertain to the equitable distribution of MIP technologies across diverse socioeconomic backgrounds [138]. To tackle this issue, researchers can promote open-source hardware and software solutions, as well as investigate low-cost materials and fabrication methods, to make these advanced technologies available to a broader range of users.

User autonomy and control are critical ethical aspects that must be considered, as individuals should retain control over their data and devices. Researchers can focus on designing user-centric MIP systems that emphasize informed consent, customizable settings, and transparency in data usage. Additionally, the adoption of privacy-preserving techniques, such as federated learning, can strike a balance between algorithmic improvements and minimal data sharing, thereby empowering users to maintain control.

7.2 Future Outlook

In recent years, researchers have made significant strides in human motion intention prediction (MIP), harnessing advancements in nanotechnology-enabled wearable smart systems, energy harvesting and storage, sensors, artificial intelligence, and material sciences. Moving forward, the focus of the field should be on the seamless integration of these cutting-edge technologies to deliver accurate, real-time, and comfortable predictions of human motion intention across diverse scenarios.

In the short term, the field can concentrate on the development of highly sensitive and biocompatible sensors, advanced algorithms for efficient data processing, and improved multimodal approaches that combine various sensing modalities for enhanced prediction performance. These innovations will enable more effective human-machine interactions, benefiting applications such as rehabilitation, healthcare, and assistive robotics.

Looking ahead, the long-term goal is to create MIP systems that exhibit the adaptability and perception of natural systems, capable of understanding and responding to complex human emotions and intentions. This will pave the way for a future where MIP technologies are tightly integrated with society, including in-home assistive robots that can discern and react to subtle gestures, collaborative robots working in harmony with humans, and autonomous exploratory robots that can safely navigate the unpredictability of real-world environments. By fostering collaboration and innovation in this rapidly evolving field, researchers can play a pivotal role in shaping a more connected and interactive future between humans and machines.

Data Availability

No new data were generated in this study.

Acknowledgments

The authors CT and LGO acknowledge funding from Endoenergy Ltd. E.O. was supported by UKRI Centre for Doctoral Training in AI for Healthcare grant number EP/S023283/1.

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