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«BRAIN – COMPUTER» INTERFACE (BCI). PT I: CLASSICAL TECHNOLOGY

Tyatyushkina Olga Yu.[1], Ulyanov Sergey V.[2]

[1]*PhD in Engineering sciences, associate professor;*
Dubna State University;
19 Universitetskaya Str., Dubna, Moscow region, 141980, Russia;
e-mail: tyatyushkina@mail.ru.

[2]*Grand PhD in Physical and Mathematical Sciences, professor;*
Dubna State University;
19 Universitetskaya Str., Dubna, Moscow region, 141980, Russia;
Chief Researcher;
Joint Institute for Nuclear Research;
6 Joliot-Curie Str., Dubna, Moscow region, 141980, Russia;
e-mail: ulyanovsv46_46@mail.ru.

In traditional BCI techniques, different types of signal acquisition may be used, depending on the application. In this paper we have chosen to treat a complex EEG-EMG-based solution for the control of an artificial arm because only the results offered by motor imaginary solution are not satisfying excepting the fact that electroencephalogram signals present a lower amplitude in comparison with the EMG signals because of limited number of mental commands that can be accessed at the same time through the BCI interface and which must be combined with physical commands, such as facial gestures that can also be recognized and mapped to predefined sequences of keystrokes. This makes it impossible to generate sequences that involve complex movements on a group of servomotors in real time being necessary to record the motion intention generated by each group of muscles to replicate the movement of the human arm. This makes it impossible to generate sequences that involve complex movements on a group of servomotors in real time being necessary to record the motion intention generated by each group of muscles to replicate the movement of the human arm. The EEG solution is also useful in limitation of human error produced by mental workload due to the capacity of recognizing the mental states that produced by the drowsiness state signalized by the increase of blink rate.

Keywords: Electroencephalography, Magnetoencephalography, BCI, brain - computer interface.

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«МОЗГ – КОМПЬЮТЕР» ИНТЕРФЕЙС (МКИ). ЧАСТЬ I: КЛАССИЧЕСКАЯ ТЕХНОЛОГИЯ

Тятюшкина Ольга Юрьевна[1], Ульянов Сергей Викторович[2]

[1]*Кандидат технических наук, доцент;*
Государственный университет «Дубна»;
Россия, 141980, Московская обл., г. Дубна, ул. Университетская, д. 19;
e-mail: tyatyushkina@mail.ru.

[2]*Доктор физико-математических наук, профессор;*
Государственный университет «Дубна»;
Россия, 141980, Московская обл., г. Дубна, ул. Университетская, д. 19;
Главный научный сотрудник;
Объединенный институт ядерных исследований;
Россия, 141980, Московская обл., г. Дубна, ул. Жолио-Кюри, д. 6;
e-mail: ulyanovsv46_46@mail.ru.

В традиционных методах МКИ могут использоваться различные типы сбора сигналов, в зависимости от приложения. В этой статье для рассмотрения выбрали решение на основе ЭЭГ-ЭМГ для управления искусственной роботизированной рукой, поскольку результаты, предлагаемые только моторным воображаемым решением, не удовлетворяют потребностям практики, за исключением того факта, что сигналы электроэнцефалограммы имеют меньшую амплитуду по сравнению с сигналами ЭМГ из-за ограниченного числа ментальных команд к которым можно получить доступ одновременно через интерфейс МКИ. Ментальные команды должны сочетаться с физическими командами, такими как жесты лица, которые также могут быть распознаны и сопоставлены с предопределенными последовательностями нажатий клавиш. Это делает невозможным создание последовательностей, включающих сложные движения группы серводвигателей в режиме реального времени, что необходимо для записи намерения движения, генерируемого каждой группой мышц, чтобы воспроизвести движение руки человека. Решение ЭЭГ также полезно для снижения человеческих ошибок, вызванных умственной нагрузкой, благодаря способности распознавать психические состояния, вызванные состоянием сонливости, сигнализируемым увеличением частоты моргания.

Ключевые слова: электроэнцефалография, магнитоэнцефалография, МКИ, мозг - компьютерный интерфейс.

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1. Definitions and models of bio-neuro-signals

In the following, we briefly describe four types of brain signals, their properties, and the suitable machine interfaces [1-15].

Electroencephalography (EEG) signals. EEG is the most employed method to detect electrical activity of the brain by use of small electrodes attached to the scalp. These signals are recorded by a machine for tracing both normal brain function and diagnosing pathological conditions (e.g., epilepsy). In stimulus (e.g., visual cue) induced EEG, there is positive deflection of voltage with a latency (delay between stimulus and response) of roughly 250–500 ms, which is called event related potentials (ERP). Examples of such ERP is the so-called P300 formed at time 300 ms, which is related to decision making. Indeed, cognitive impairment is often correlated with modifications in the P300. It is considered an endogenous potential, as its occurrence links not to a stimulus' physical attributes, but a person's reaction to it. More specifically, the P300 is thought to reflect processes involved in stimulus evaluation or categorization. The presence, magnitude, topography, and timing of this signal are often used as metrics of cognitive function in decision-making processes and hence used in BCIs. The P300 has several desirable qualities for pattern recognition. First, the waveform is consistently detectable and is elicited in response to precise stimuli. The P300 waveform can also be evoked in nearly all subjects with little variation in measurement techniques, which help simplify interface designs and permit greater usability. The speed at which an interface can operate depends on how detectable the signal is despite "noise." One negative characteristic of the P300 is that the waveform's amplitude requires averaging multiple recordings to isolate the signal. This and other post-recording processing steps determine the overall speed of a BCI interface.

Magnetoencephalography (MEG) *signals.* MEG is a functional neuroimaging technique monitoring brain activity via magnetic fields of electrical currents in the brain, using SQUIDs (superconducting quantum interference devices), which are very sensitive magnetometers operated in a cryogenic environment. Another type of magnetometer is spin exchange relaxation-free (SERF) magnetometer, which can increase portability of MEG scanners, while it features sensitivity equivalent to that of SQUIDs. A typical SERF magnetometer is relatively small and does not require bulky cooling system to operate. It has been demonstrated that MEG could work with a type of SERF, i.e., chip-scale atomic magnetometer (CSAM), where its development can be used efficiently for BCI. Basically, MEG may provide signals with higher spatiotemporal resolution than EEG, and therefore useful for an increased BCI communication speed.

Electrocorticography (ECoG) *signals*. ECoG uses electrodes placed directly on the surface of the brain to record electrical activity from the cerebral cortex, i.e., an invasive technology that involves removing a part of the skull to expose the brain surface to enable the implant of an electrode grid on the surface of the brain, i.e., called craniotomy, which is a surgical procedure performed either under general anesthesia or under local anesthesia if patient interaction is required for functional cortical mapping. The spatial and temporal resolution of the resulting signal is higher and the signal to noise ratio (SNR) superior to those of EEG due to the closer proximity to neural activity. Thus, ECoG is a promising recording technique for use in BCI, especially for decoding imagined speech or music, in which users simply imagine words, sentences, or music that the BCI can directly interpret.

Functional near-infrared spectroscopy (fNIRS) *signals*. fNIRS is a non-invasive optical imaging technique that measures changes in hemoglobin (Hb) concentrations in the brain by means of the characteristic absorption spectra of Hb in the near-infrared (NIR) range. fNIRS tomography makes use of the fact that light penetrates up to several centimeters into biological tissue, i.e., a safe technique that is minimally invasive and which relies on small, relatively inexpensive easy-to handle technology, and provides relatively low spatial resolution. The penetration range of light in tissue limits the size of the target tissue volume. fNIRS can be used in BCI for the restoration of movement capability for people with motor disabilities. fNIRS cannot afford high error rates for safety purposes, and must be fast enough to provide real-time control. Several fNIRS-BCI studies have tried to improve classification accuracies and information transfer rates.

2. Hybrid brain–computer interfaces (BCIs) models

Brain–computer interfaces (BCIs) allow disabled people to establish a new communication channel between the human brain and a machine. This communication is based on the analysis of electrophysiological brain signals recorded by the electroencephalogram (EEG). Although BCI technology has shown impressive progress in the last few years, it cannot be compared to non-BCI control channels in terms of performance and interaction speed. Therefore, the development of practical BCIs for disabled people should allow them to use *all* their remaining functionalities as control possibilities and to use the *currently best* available ones. Especially since the physical and mental conditions of a patient (e.g. early stage of amyotrophic lateral sclerosis) are changing over the day, various control strategies could be applied, e.g. sometimes muscular activity would be available (most likely in the morning when they are not exhausted), whereas at other times maybe only brain signals can be voluntarily controlled.

Such a combination and parallel usage of at least one BCI and at least one additional communication (e.g. another physiological signal or special assistive input devices such as joysticks, switches) is called a *hybrid BCI* [1-3]. Generally, these control channels can operate different parts of the assistive device or all of them could be combined to allow users to smoothly switch from one control channel to the other, depending on their preference and performance. We can assume that such a hybrid BCI will improve the quality of life of a patient. The following examples of hybrid BCIs can already be found in the literature: based on multiple brain signals, such as the combination of a motor imagery (MI)-based BCI with a steady-state visual evoked potential (SSVEP)-based BCI or the combination of an MI BCI with error potential (ErrP) detection and correction of false mental commands, or the combination of a SSVEP BCI with a heart rate controlled on/off switch.

The EEG was acquired monopolarly over the motor cortex with 16 electrodes (see Fig. 1).

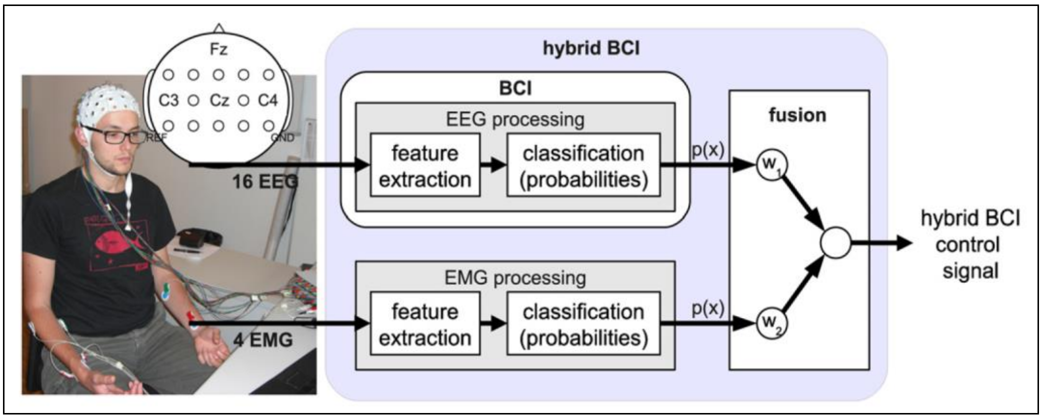
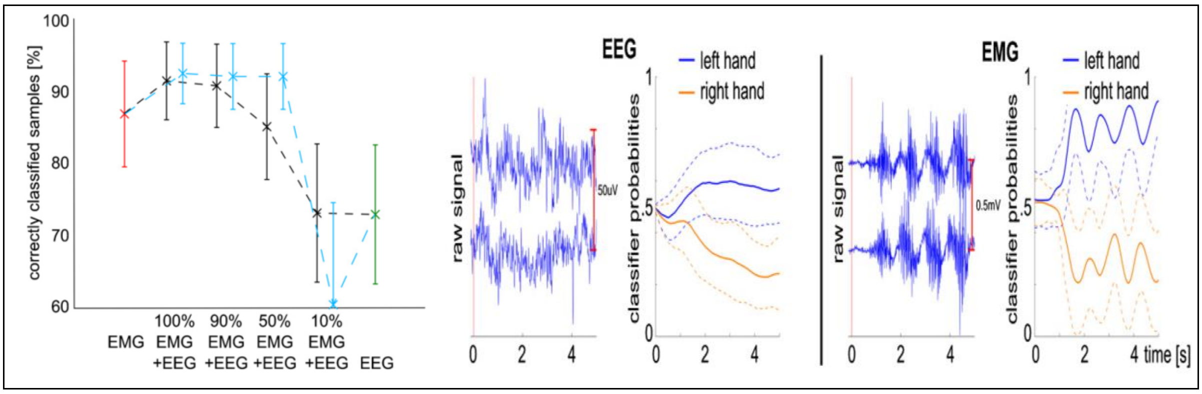


Fig. 1. The photograph shows a subject wearing the cap with 16 EEG electrodes over the motor cortex and 4 EMG channels at the flexor and extensor of the left and right forearm [The diagram explains the processing and fusion principle of muscular and brain activities in a hybrid BCI]

From the Laplacian filtered EEG, the power spectral density (PSD) was estimated in the band 4–48 Hz with 2 Hz resolution over the last second. The EMG was acquired bipolarly over the flexor and extensor of the left and right forearm (see Fig. 1).

The BCI can be controlled either by a single modality (EEG or EMG) or by the fused activity of both. In total we have compared six different conditions in Fig. 2(a): two single modalities and four fused activities with increasing levels of muscular fatigue (i.e. 0%, 10%, 50%, 90% attenuation of EMG amplitude).



(a) *(b)*

Fig. 2. (a) Mean ± the standard deviation (SD) of correctly classified samples over the whole task period (0–5 s) for the six conditions. [The leftmost (red) and rightmost (green) conditions correspond to the single modalities, EMG and EEG, respectively. The four conditions in the middle correspond to the fusion of EEG and EMG with different levels of remaining amplitude (i.e. 0%, 10%, 50%, 90% attenuation). For each of these conditions two performances provided according to the fusion modality: simple fusion (left side in black) and Bayesian fusion (right side in blue)]; (b) Examples of raw signals and averaged classifier outputs (integrated probabilities; mean in solid lines ± SD in dotted lines) of EEG (left) and EMG (right). The cue appeared at 0 s

The average performance of all subjects for the EEG activity alone was 73% and for EMG activity alone was 87%. In the first fusion approach (equally weighted sources) the fused activity achieved an increase to 91%. Remarkably, thanks to the fusion of EEG and EMG, increasing muscular fatigue (from 10% to 50% to 90% attenuation) led to a moderate and graceful degradation of performance: 90%, 85% and 73% accuracy, respectively. It is worth noting that in the case of fusion with only 10% of EMG amplitude (90% attenuation), the performance is the same as for EEG alone despite the fact that the fusion weights are the same over all conditions.

The second fusion technique based on the Bayesian approach achieved similar results but with smaller the standard deviation (SD) (see Fig.2). Interestingly the Bayesian fusion performance is very stable over the first three fatigue conditions. Especially in the 50% EMG condition, a tremendous increase could be achieved compared to the other fusion technique (statistically significant from 85.1% to 92.0%). In contrast, in the last condition (90% EMG attenuation) the Bayesian approach failed and had a result of 60.4%, which is worse than EEG alone. The reason is that the confusion matrices of the Bayesian fusion have been calculated using a non-fatigued subject and the method assumes that the sources do not change over time. However, a strong level of EMG fatigue leads to almost a removal of this source, thus causing the significant performance decrease.

The experiment demonstrates the benefits of a hybrid BCI. Multimodal fusion of muscular and brain activity yielded better and more stable performance compared to the single conditions. Furthermore, the increasing muscular fatigue led only to a moderate and graceful degradation of performance compared to the non-fatigued case. Therefore, such a system allows the user a very reliable hybrid BCI control, even though she/he is getting more and more exhausted or fatigued during the day.

Comparing the behavior of the two fusion techniques, it is obvious that the Bayesian fusion achieved a constant performance over a wide range of muscular fatigue, compared to the steadily decreasing performance in the case of the simple fusion. However, the Bayesian approach yielded the worst performance in case of 10% EMG, even lower than the EEG alone condition. This behavior can be explained by the dominance dependence of the Bayesian fusion approach on the EMG classifier output. For fatigue levels of 50% and lower the output of the classifier was still reliable and therefore the Bayesian approach achieved better results. However, in the conditions in which the quality of the EMG input signals dropped below a certain threshold the results were worse. The reason is the strong violation of the assumption that the input patterns are stationary over time, necessary to compute the Bayesian confusion matrices. This problem could be overcome by adapting the way contribution of the different modalities. Let us chosen a static approach (computed once and kept constant over time). Instead it should dynamically update these coefficients based on the reliability of the input channels, or the confidence/certainty the system has on its outputs.

Surprisingly [1], the fused activity resulted in a 6% improvement in classification compared with the EMG alone condition. One may expect that EMG classification leads to a perfect classification of 100%. The reason for the ‘non-perfect’ classification of the single EMG condition is based on the fact that the movements were repetitively executed and that the number of correctly classified samples over the whole task time is used as a performance measure. A glance at the raw signals and the extracted classifier outputs exemplifies the behavior (see Fig.2(b)). The EEG classifier had a smooth but stable improvement over the trial time compared to the fast and strong but fluctuating response of the EMG classifier, which also had a large variation over time. The EMG fluctuation over time can be explained by the repetitive execution of the hand movements during the task time. Sometimes the subject executes the movements and sometimes pauses them.

Thereby the EMG power drops below the detection threshold and therefore is counted as not detected. On the other side, repetitive movements are commonly used in BCI research, since they lead to more discriminative and stable EEG patterns. Generally speaking, besides muscular fatigue a mental fatigue could also appear. This would influence the reliability of the EEG signal in a similar way as the simulated muscular fatigue influenced the performances of the EMG channel.

Such a reliability could be estimated from supervision signals such as cognitive mental states in the case of EEG (e.g. fatigue, error potentials) and physiological parameters (e.g. median frequency of the myoelectric signal power spectrum in the case of muscular fatigue). Another possibility is to analyses the performance of the individual classifiers in achieving the task (e.g. stability over time, influence of noise, etc) and thereby adapt the fusion weights.

Electroencephalography (EEG) and functional near infrared spectroscopy (fNIRS) endow brain – computer interfaces (BCIs) with their essential and indispensable attributes of non-invasiveness, low cost, and portability. EEG- and fNIRS-based BCIs have enabled paralyzed patients to communicate and control external devices with their own brain functions. Unfortunately, classification accuracy in these modalities diminishes as the number of BCI commands increases. As a mean of overcoming the problem of the reduction of classification accuracy upon an increase in the number of control commands, the concept of hybrid brain–computer interface (hBCI) was introduced. The hBCI pursues the following three main objectives: (i) enhanced BCI classification accuracy, (ii) increased number of brain commands for control application, and (iii) shortened brain-command detection time. These benefits provide hBCI a clear advantage over any single brain signal acquisition modality. The hBCI is meant to combine either (i) more than two modalities (of which at least one is a brain signal acquisition device) or (ii) more than two brain activities with a single modality, for example, the combination of P300 and steady-state visual evoked potential (SSVEP) with EEG.

An hybrid BCI (hBCI) system is similar to a simple BCI but that it needs additionally to fulfill the following four criteria: (i) the activity should be directly acquired from the brain; (ii) at least one of multiple brain signal acquisition modalities should be employed in acquiring such activity, which can be in electrical potential, magnetic field, or hemodynamic change form; (iii) the signals must be processed in real time/ online to establish communication between the brain and a computer for generation of control commands; and (iv) feedback describing the outcomes of the brain activity for communication and control must be provided.

Six aspects (hardware, signal processing, brain activity, feature extraction, classification, and feedback) need to be considered in developing an hBCI: (i) the hardware should consist of at least one brain signal acquisition modality; (ii) the hybrid system should detect and process different physiological signals simultaneously; (iii) the paradigm should be able to acquire multiple brain activities simultaneously using multiple modalities; (iv) a number of features for classification should be acquired in real time/online for both accuracy enhancement and additional control-command generation; (v) the classified output should have a potential for interfacing with external devices (e.g., wheelchairs and robots); and (vi) it should also provide feedback to the user for rehabilitation and control purposes.

Figure 3 provides an example of an hBCI scheme.

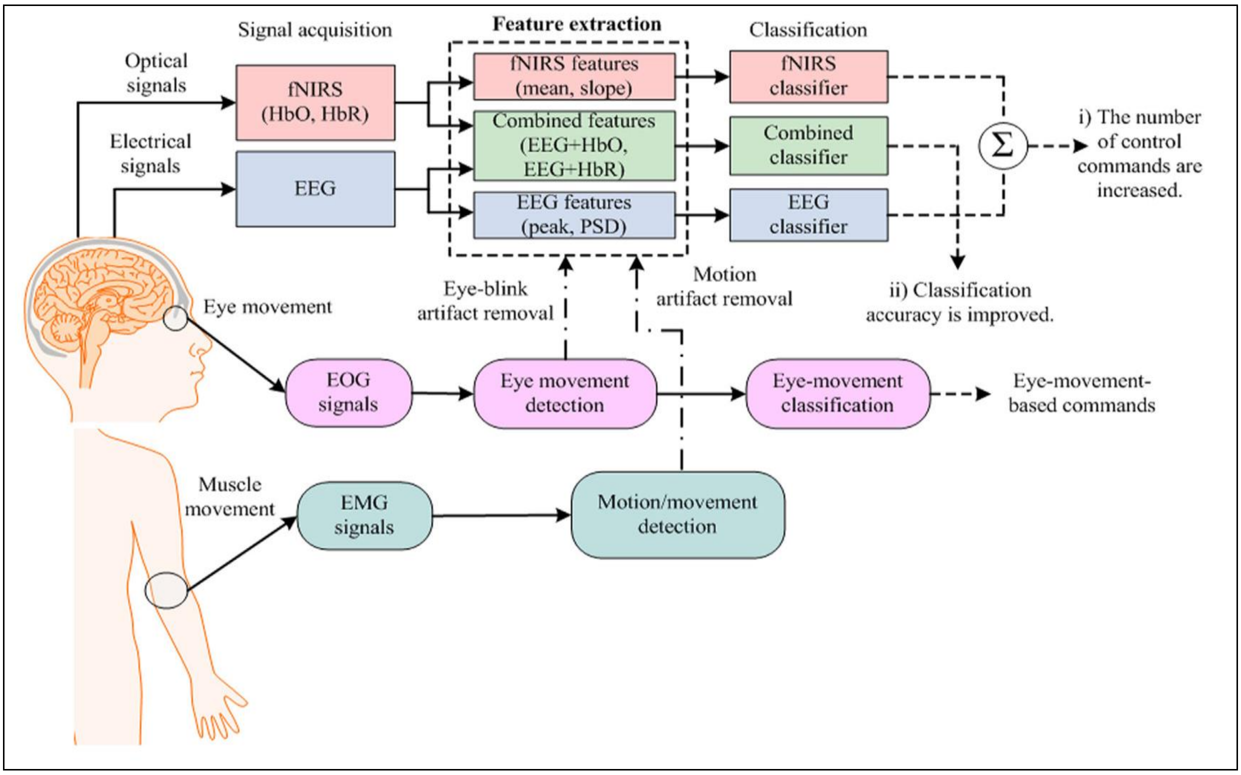


Fig. 3. Purposes of hybrid brain–computer interface: (i) increase the number of control commands by combining electroencephalography (EEG) with functional near infrared spectroscopy (fNIRS) [further electrooculography (EOG)] and (ii) improve the classification accuracy by removing motion artifacts

It indicates the following two things: (i) multiple activities are required for hBCI and (ii) a combination of brain and non-brain signal acquisition modalities is overviewed.

After detection, the activities are processed simultaneously for feature extraction and classification; then, the classified results are used as feedback for the user's rehabilitation and control applications. Hybrid brain–computer interface hardware can be configured in the following two ways: (i) combination of a brain signal acquisition modality with a non-brain signal acquisition modality and (ii) combination of a brain signal acquisition modality with another brain signal acquisition modality. Brain and non-brain signal acquisition modalities are combined either to remove motion artifacts or to increase the number of commands in a BCI system. Two brain signal acquisition modalities are combined and positioned over the same brain region in order to enhance the classification accuracy, or, they are positioned in different regions to increase the number of control commands.

Electromyography signals are generated and detected as a result of muscular movement. These act as an artifact in EEG signals, resulting in the false detection of brain signals. The purpose behind a hybrid EEG–EMG-based hBCI is to combine EEG and EMG signals in hBCI. This incorporation of EMG signals is user specific and depends on the activity or task performed by that user. The applications of hybrid approaches vary from a simple game control application for an able-bodied person through to a prosthetic arm control application for an amputee.

Figure 4 shows a typical strategy used for incorporating EEG and EMG signals into an hBCI system.

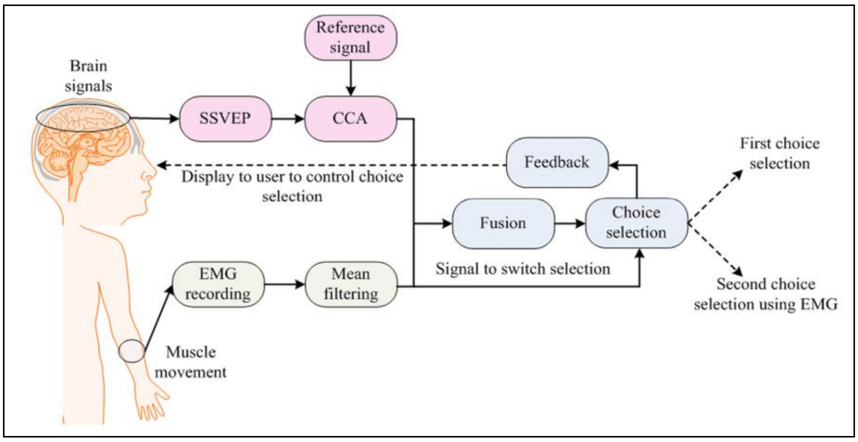


Fig. 4. Electroencephalography–electromyography (EMG)-based brain–computer interface: one choice is selected using steady-state visual evoked potential (SSVEP) and muscle movement is used to change the selected option

The steady-state visual evoked potential (SSVEP) signals are detected mostly in the occipital brain region. They are generated by gazing at a stimulus, which causes an increase in neural activity in the brain. VEPs are elicited by sudden visual stimuli, the repetition of which leads to a stable voltage oscillation pattern in EEG that is known as SSVEP. The stimulus used for these signals is light flickering at different frequencies (sometimes in the "checker board" pattern with changing colors). Using SSVEP signals, multiple reactive commands can be generated. The drawback of this activity is the need for the continuous focus on flashing light, which might not be possible or an ineffective approach for some patients. The signal detection time for these signals has been reduced to less than 1 s using spatio-temporal features with a reduced number of channels.

The applications of EEG–EMG-based hBCI are found in the control area of assistive devices. In the early work using EEG with EOG and EMG, the EMG signals were used to categorize different "locked-in" patient types. In their study, six types were defined, the first three of which were categorized using EMG as follows:

- Patients capable of movement (e.g., eye movement and finger movement);
- Patients incapable of movement but showing some detectable EMG activity due to partial muscle movements;
- Fully locked-in patients with no muscular activity detectable by EMG signals.

Figure 5 shows the recent trend in EEG- and fNIRS-based hBCIs.

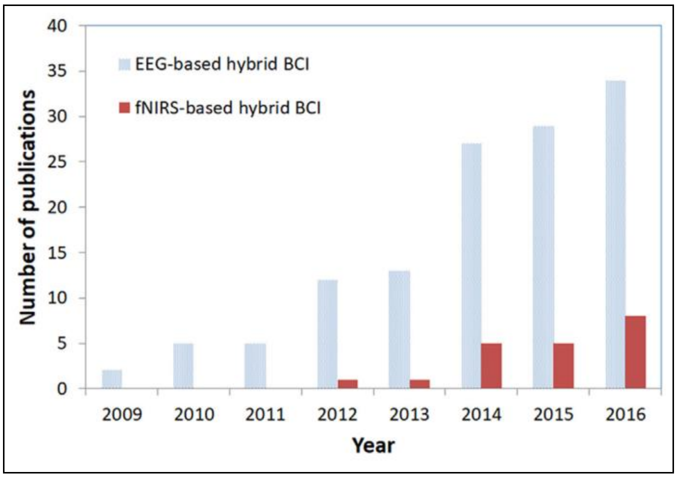


Fig. 5. Trend in electroencephalography (EEG)/functional near infrared spectroscopy (fNIRS)-based hybrid brain–computer interface (BCI) [2]

The remaining three types of patients were categorized using EOG and EEG signals. For EEG–EMG-based BCI, a neuro-electric interface was developed for real-time control applications.

Most hybridization strate-gies that have been introduced are applicable to EEG-based BCI; yet, further improvement of fNIRS-based BCI systems is needed.

The major hBCI emphasis is the EEG–EOG-based hBCI. Most of these studies have combined, or are combining, two modalities for eye movement artifact removal and additional BCI commands.

EEG–EMG-based hBCIs have limited applications and are used only in muscular-artifact removal from brain data for enhanced classification accuracy. Meanwhile, only very limited research has been done on EEG–fNIRS-based BCI applications. Moreover, the works done have focused mostly on an improvement of classification accuracy, with very little attention having been paid to the issue of command-number increase.

Another important aspect that requires a focus with respect to hBCI is the selection of active control commands. The reactive commands can be increased by changing the flickering stimuli for BCI. In fact, using reactive tasks, more than 50 commands can be achieved. A BCI using active commands is more desirable than one based on reactive commands. After, at most, three or four active commands, the accuracy severely drops, making it difficult to control an external device with a further increased number of commands. The current need is such strategies that can be used to achieve active control of BCI systems without impacting negatively on accuracy. In this regard, the hBCI can play an important role. Future research in this area will provide a solution to the problems related to the increase in the number of active commands.

3. EEG–EMG dataset

Electromyography (EMG) is a method to record the electric manifestation of skeletal muscular activity. The information is captured using electrodes. The torque applied to the skeletal system joints due to muscle contraction leads to movement in the body. Muscles are composed of fibers that are innervated alpha motor neurons, which receive efferent neural drive descending from the central nervous system. A motor unit is made of motor neuron and all the muscle fibres which the neuron innervates. Each motor neuron controls a varying number of muscle fibers depending on different muscle types. This number is called the *innveration* ratio. Motor neuron depolarization propagates as a wave through axons from the spinal cord to muscle fibres to activate a motor unit. The propagating depolarization of the neuronal membrane can be recorded by electrodes placed in the vicinity of the membrane, and such activity is called a motor neuron action potential (MUAP). When the MUAP reaches the neuromuscular junction (NMJ), special neurotransmitters are released from the axon to the muscle fibre membrane, which depolarizes the muscle fibers. And such fibre depolarization would, in turn, propagate from the NMJ, along with the fibre, toward the two tendons, to which the fibres are attached. This propagating depolarization can also be detected by electrodes place in its vicinity and is called muscle fibre action potential.

The collective muscle fibre actional potentials from the same motor unit often appear to be a single action potential because all fibres within the unit would be activated simultaneously. And this ‘collective’ action potential is often called the motor unit action potential. One motor unit action potential is often referred to as a ‘firing’ of a motor unit. The frequency of motor unit ‘firing’, or the firing rate ranges from 4-6 Hz (firings per second) to approximately 30-40 Hz. The above is a brief description of the electric process of muscular activation.

A mechanical process of muscular activation occurs simultaneously with this electric process. Upon the membrane depolarization, muscle fibres would shorten, resulting in mechanical contraction. The amount of contractile tension generated by the fibres differs among different types of muscle fibres. Furthermore, the overall contractile tension generated by a muscular contraction further depends on factors, such as how many motor units being activated. The motor unit action potential, being an electromagnetic signal, can be detected at the skin surface, usually by Ag/Ag-Cl electrodes with conducting gel. The gel helps to reduce impedance between the skin and electrode. For long-duration applications, a gel electrode system is not preferred; instead, dry electrodes made of a material such as stainless steel or conductive ceramics are used. Dry electrodes often have higher noise levels due to higher electrode-skin impedance.

In addition to the above described non-invasive measurement of EMG, also known as surface EMG (sEMG), EMG can also be measured by invasive electrodes, such as needles or fine wires that are transcutaneously inserted into the muscle under investigation. This latter method is called intramuscular EMG. Although intramuscular EMG collects muscle activity of individual muscle fibers, sEMG is more frequently used in disciplines outside neurophysiology, where these invasive methods are not practical due to problems such as electrode insertion, infection, and subject compliance. The sEMG signal contains two types of information, Time-Domain, and Frequency-Domain, which depend upon intensity and duration of muscle contraction, electrode-amplifier configuration, skin-electrode contact quality, and placement of electrode with respect to muscle.

There are multiple sources of noise while acquiring EMG data, such as relative displacement between the recording electrode and the muscles under investigation, the movement of the electrode with respect to the skin, electromagnetic interferences due to power line, etc. This noise degrades the performance of the system and needed to be rectified before any processing.

Multiple methods can be used to rectify these problems, such as filtering techniques like bandpass and stop, high and low pass filters. Noise such as power line noise and motion artifact can be largely removed with these techniques.

The dynamic development of electronics, mechanical engineering, and biomedical engineering has opened up new possibilities in the field of prosthetics and smart devices. Thanks to modern equipment, rehabilitation is faster, more-advanced surgery is possible, and recovery after accidents is more efficient. The observation of such bioelectric signals as EEGs, ECGs, and EMGs is often the basis for finding a particular disease or deciding on further treatment(s) for the patient. Research related to biomedical engineering and processing bioelectric signals is still ongoing. There are more and more devices controlled by human-machine interfaces. To improve such systems, more-accurate measurement systems, more-complex control algorithms, and more-precise positioning systems are needed. The topic of discussion in the following article will be the analysis of EMG signals, which is the process of forming electrical potentials on human skin during muscle tension (specifically, surface EMG [sEMG]). This signal is mainly used for testing motor dysfunction among people. The aim of the study is to present the problem of measuring and filtering an EMG signal. Through the use of digital filtering and the appropriate signal processing, relevant information carried by the signal should be obtained. The experiment will provide the results on whether an EMG signal is suitable for use in systems controlled by muscle tension (for example, an intelligent prosthetic hand or exoskeleton).

We briefly overview the human skeletomuscular physiology that gives rise to sEMG signals followed by a review of developments in sEMG acquisition hardware. Special attention is paid towards the fidelity of these devices as well as form factor, as recent advances have pushed the limits of user comfort and high-bandwidth acquisition. We explore work quantifying the information content of natural human gestures and then review the various signal processing and machine learning methods developed to extract information in sEMG signals. Finally, we discuss the future outlook in this field, highlighting the key gaps in current methods to enable seamless natural interactions between humans and machines.

4. Myoelectric Physiology of The Human Body

When the brain instructs the body to move, it sends an electrical impulse signal down the spinal cord and through an intricate network of peripheral nerves to the targeted muscle. This neuronal signal is transduced into a muscular contraction by numerous neurons known as motor units, each consisting of a motor neuron (anterior horn cell), its axon, and all the individual muscle fibers it innervates (Fig. 6).

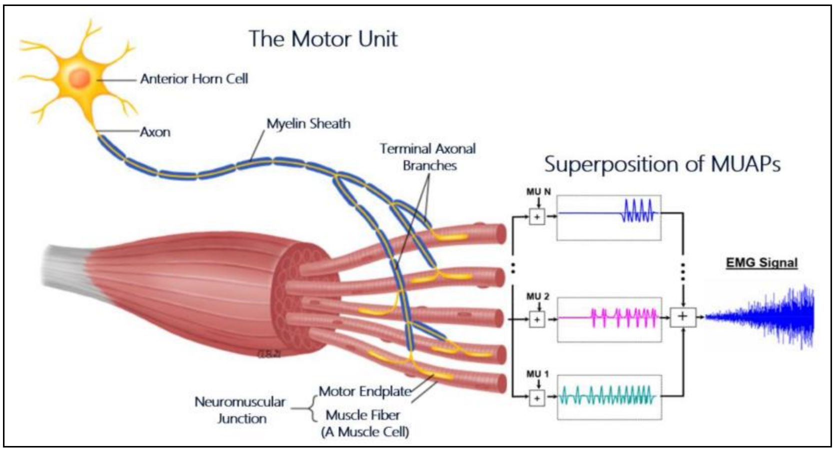


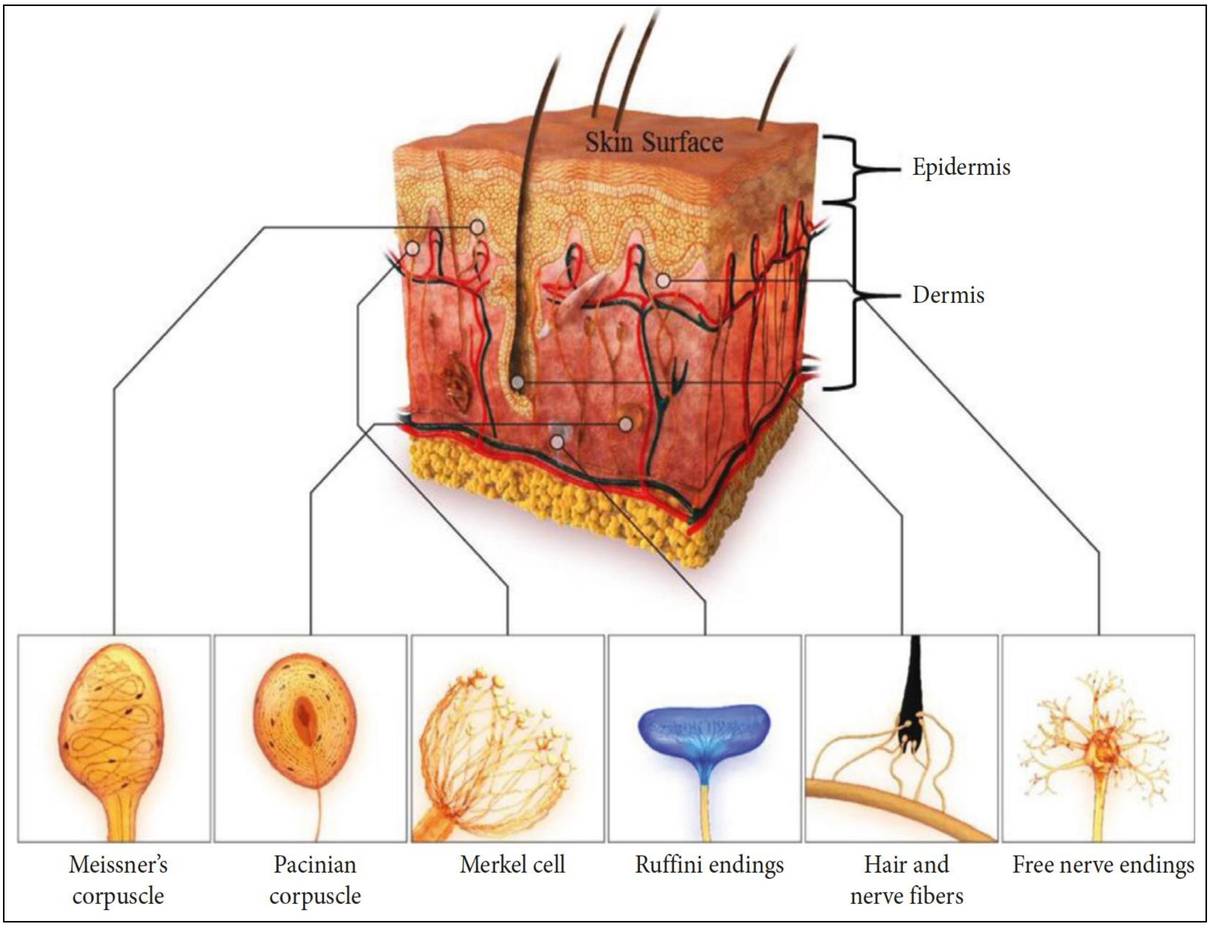
Fig. 6. A single motor unit and the muscle fibers it innervates [When an anterior horn cell is activated, all muscle fibers depolarizes synchronously to generate a motor unit action potential (MUAP). Action potentials measurable by electrodes from all motor units superimpose to form the EMG signal]

The fast development of electronic skin offers the feasibility to address the demanded features. The pioneering work in this area is more focusing on soft robots, health engineering, human/robot fingertips, and human-robot interfaces on human body. Apart from the above focuses, some significant efforts also have been devoted to developing electronic skin for large-area and rigid cobot body (i.e., robot skin). To well blend into human living environments, future skin-covered cobots are coupled robotic systems composed of rigid, flexible, and soft component. Cobots will inherently provide the rigid part to ensure necessary force, power, and responsiveness of actuation, while robot skin will offer the soft part for the requirements of demanded features.

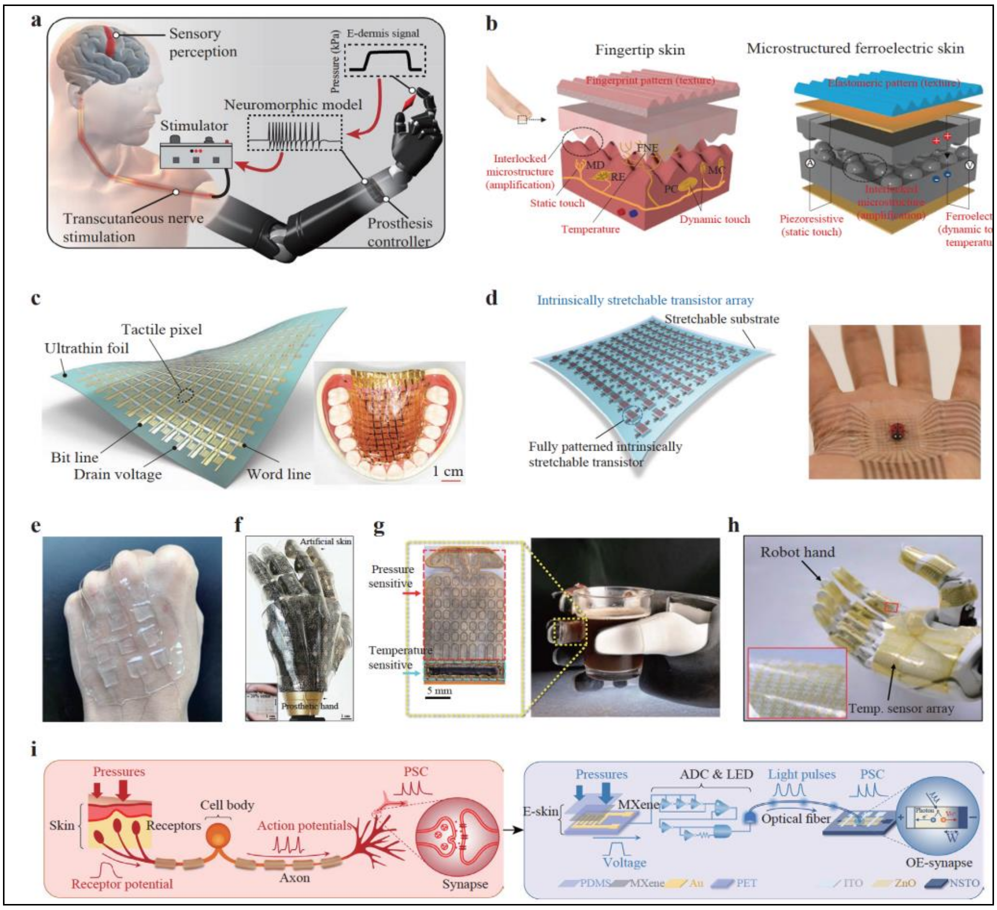
Individually, mechanoreceptor appear as jelly-like materials located under the human skin. Lexically, they can be said to be a network of receptors and processing centers combining to form the haptic sensory system. The latter is responsible for the perception of the information acquired from surroundings, flashing it to the central nervous system (CNS) as signals. After analyzing and processing the signals, the body then gives feedback in the form of a physical response

The human sense-of-touch involves different sensory subsystems that can be classified according different factors. One of the most common classification methods is by the source of neural inputs which may be cutaneous, kinesthetic, or haptic. The cutaneous subsystem is associated with the skin and involves physical contact with stimuli. This subsystem performs the spatiotemporal perception of external stimuli via receptors such as thermoreceptors for temperature and thermal inputs and nociceptors, which respond to pain and damage. The mechanoreceptors, which are the focus of this review, play vital roles in providing the CNS with information about mechanical effects, such as vibration and contact pressure. The kinesthetic subsystem acquires sensory information received through mechanoreceptors located in the muscles, joints, and tendons of the human body system.

Thus, kinesthetic information enables the CNS to know about the position and movement of the body and limb segments in both cases, static and dynamic. The haptic sense is combining sensory stimulations of both the cutaneous and kinesthetic subsystems, in purpose to perform and stimuli body activities efficiently. Human skin is an active sensory system which protects our bodies from injury, dehydration, radiation, and toxic substances in the external environment by tactile sensation of stimuli. The skin consists of complex layers of specialized receptors [10], such as the epidermis, dermis, and hypodermis (Fig. 7).


Skin Surface
Epidermis
Dermis
Meissner's corpuscle
Pacinian corpuscle
Merkel cell
Ruffini endings
Hair and nerve fibers
Free nerve endings

(A)


a
Sensory perception
E-dermis signal
Pressure (kPa)
Neuromorphic model
Stimulator
Transcutaneous nerve stimulation
Prosthesis controller
b
Fingertip skin
Microstructured ferroelectric skin
Fingerprint pattern (texture)
Elastomeric pattern (texture)
Interlocked microstructure (amplification)
Static touch
Temperature
Dynamic touch
Piezoresistive (static touch)
c
Tactile pixel
Ultrathin foil
Bit line
Drain voltage
Word line
1 cm
d
Intrinsically stretchable transistor array
Stretchable substrate
Fully patterned intrinsically stretchable transistor
e
f
Artificial skin
Prosthetic hand
g
Pressure sensitive
Temperature sensitive
5 mm
h
Robot hand
Temp. sensor array
i
Pressures
PSC
Skin
Cell body
Receptors
Action potentials
Receptor potential
Axon
Synapse
E-skin
MXene
ADC & LED
Light pulses
Optical fiber
Voltage
OE-synapse
PDMS
MXene
Au
PET
ITO
ZnO
NSTO

(B)

Fig. 7. (A) Description of sensory touch receptors in glabrous human skin; (B) Skin-integrated electronics for tactile sense.

[(a) Prosthesis with e-skin that perceives touch and pain; (b) Fingertip skin-inspired e-skin; structure and functions of human fingertips (left); artificial multimodal e-skin (right); (c) Illustration of ultra-lightweight large-area tactile flexible electronics; (d) Intrinsically stretchable transistor array for e-skin. The array enables accurate sensing of the position of a synthetic ladybug with six conductive legs; (e) Image of a triboelectric nanogenerator-based e-skin attached on a curvy hand; (f) Photograph of an artificial skin with stretchable silicon nanoribbon electronics covering the entire surface area of a prosthetic hand; (g) Photograph of a prosthetic hand with a multi-modal sensor on the finger grasping a cup of hot coffee; (h) Prosthetic hand wearing a temperature sensor array; (i) Schematic diagram of the biological and bio-inspired optoelectronic spiking afferent nerve systems] [11]

The external layer of the epidermis is responsible for regulating body temperature and consists of impervious protective surfaces. The dermis layer, which is located under the epidermis, transmits nerve information from thermal, mechanical, and chemical stimuli. The third layer is hypodermis which, depending on the study, may or may not be considered a part of human skin. This part of the external layer consists of connective and subcutaneous tissues that separate the dermis from the muscle and bone.

The skin-like wearable sensors can be highly attached to the human skin or the surface of clothing with high comfort and acceptability. It has good application potential in health monitoring of elderly patients and assisting elderly patients in their daily life. Recent advances in health monitoring devices and intelligent assistive devices based on skin sensors can be seen in Fig. 8.

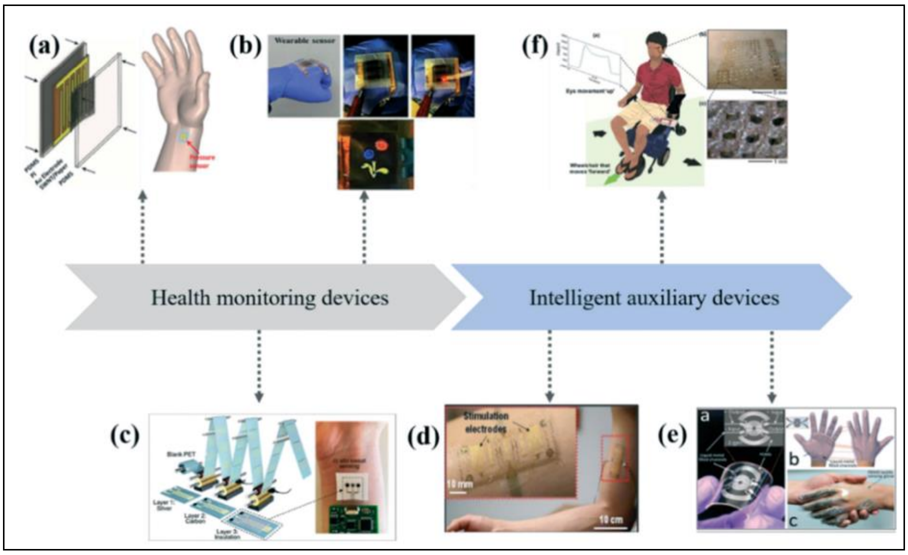


Fig. 8. Recent advances in health monitoring devices and intelligent assistive devices based on skin sensors [12]

[(a) A flexible, wearable, and flexible skin-like pressure sensor, which could monitor important physiological signals in real time; (b) A wearable tactile sensor that responds instantly to external stimuli; (c) A wearable sensor based on the roll-to-roll (R2R) gravure printed electrodes for real-time, in situ perspiration monitoring during exercise; (d) An irritable, skin-like wearable sensor can induce muscle contractions by increasing electrical levels to aid in the recovery of paralyzed limbs; (e) A smart prosthesis based on skin-like sensors can be used by patients to receive tactile sensations as they grab, grab, squeeze, shake or touch; (f) A soft, conformal bioelectronics for a wireless human-wheelchair interface]

According to different sensing mechanisms, a variety of skin-like wearable sensors, including electrochemical, bioimpedance, photoelectric and other wear-able sensors and the research progress on the health monitoring and the development of smart assistive devices in recent years developed [5-9]. Several studies have been carried out on different applications of human-machine interaction such as manipulation, grasping, position recognition, and pressure evaluation. Another important direction of in the development human-machine interaction devices is methods based on deep learning. Recently, the deep learning technique was used to realize an extremely simple macro-scale electronic skin without macro-, nano-, and micro-patterns. The deep learning network (DNN) architecture that has been used is shown in Fig. 9.

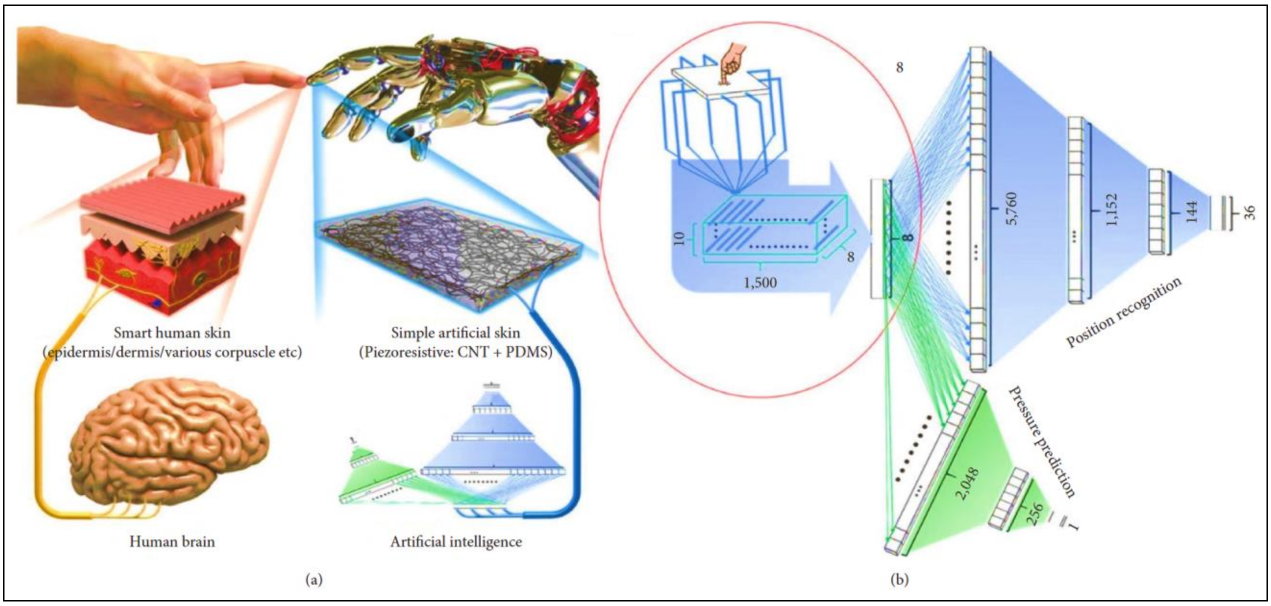


Fig. 9. The schematic illustration of basic concept for e-skin and DNN architecture for reliable sensing. (a) A schematic elucidating the comparison between the human skin and the proposed e-skin; (b) The DNN architecture for tactile sensing [10].

The reported deep learning-based method enables the use of a sample of bulky sheet (40 × 40 mm^2) piezoresistive MWCNT-PDMS to play a role in the smart sensory devices (e.g., e-skin). The results show that the proposed e-skin based on deep learning obtained a 97.22% level of test ac-curacy for position recognition and had a reliable pressure estimation with a 3.12% RMSE and therefore approximated the capability of human skin. Furthermore, DNN-based e-skin showed high performance in pressure sensitivity and high spatial resolution (0.78 ± 0.44 mm) for position recognition. The great potential of this revolutionary concept could open a new era for many fields, not only for e-skin application but also high-end applications such flexible keyboard, sign language interpreting, touch panels, and diagnosis motility.

4.1. EEG–EMG dataset

Electromyography (EMG) is a method to record the electric manifestation of skeletal muscular activity. The information is captured using electrodes. The torque applied to the skeletal system joints due to muscle contraction leads to movement in the body. Muscles are composed of fibers that are innervated alpha motor neurons, which receive efferent neural drive descending from the central nervous system. A motor unit is made of motor neuron and all the muscle fibres which the neuron innervates. Each motor neuron controls a varying number of muscle fibers depending on different muscle types. This number is called the *innveration* ratio. Motor neuron depolarization propagates as a wave through axons from the spinal cord to muscle fibres to activate a motor unit. The propagating depolarization of the neuronal membrane can be recorded by electrodes placed in the vicinity of the membrane, and such activity is called a motor neuron action potential (MUAP). When the MUAP reaches the neuromuscular junction (NMJ), special neurotransmitters are released from the axon to the muscle fibre membrane, which depolarizes the muscle fibers. And such fibre depolarization would, in turn, propagate from the NMJ, along with the fibre, toward the two tendons, to which the fibres are attached. This propagating depolarization can also be detected by electrodes place in its vicinity and is called muscle fibre action potential.

The collective muscle fibre actional potentials from the same motor unit often appear to be a single action potential because all fibres within the unit would be activated simultaneously. And this ‘collective’ action potential is often called the motor unit action potential. One motor unit action potential is often referred to as a ‘firing’ of a motor unit. The frequency of motor unit ‘firing’, or the firing rate ranges from 4-6 Hz (firings per second) to approximately 30-40 Hz. The above is a brief description of the electric process of muscular activation.

A mechanical process of muscular activation occurs simultaneously with this electric process. Upon the membrane depolarization, muscle fibres would shorten, resulting in mechanical contraction. The amount of contractile tension generated by the fibres differs among different types of muscle fibres. Furthermore, the overall contractile tension generated by a muscular contraction further depends on factors, such as how many motor units being activated. The motor unit action potential, being an electromagnetic signal, can be detected at the skin surface, usually by Ag/Ag-Cl electrodes with conducting gel. The gel helps to reduce impedance between the skin and electrode. For long-duration applications, a gel electrode system is not preferred; instead, dry electrodes made of a material such as stainless steel or conductive ceramics are used. Dry electrodes often have higher noise levels due to higher electrode-skin impedance.

In addition to the above described non-invasive measurement of EMG, also known as surface EMG (sEMG), EMG can also be measured by invasive electrodes, such as needles or fine wires that are transcutaneously inserted into the muscle under investigation. This latter method is called intramuscular EMG. Although intramuscular EMG collectes muscle activity of individual muscle fibers, sEMG is more frequently used in disciplines outside neurophysiology, where these invasive methods are not practical due to problems such as electrode insertion, infection, and subject compliance. The sEMG signal contains two types of information, Time-Domain, and Frequency-Domain, which depend upon intensity and duration of muscle contraction, electrode-amplifier configuration, skin-electrode contact quality, and placement of electrode with respect to muscle.

There are multiple sources of noise while acquiring EMG data, such as relative displacement between the recording electrode and the muscles under investigation, the movement of the electrode with respect to the skin, electromagnetic interferences due to power line, etc. This noise degrades the performance of the system and needed to be rectified before any processing.

Multiple methods can be used to rectify these problems, such as filtering techniques like bandpass and stop, high and low pass filters. Noise such as power line noise and motion artifact can be largely removed with these techniques.

4.2. EMG based Pattern Recognition

Pattern recognition involves extracting knowledge and statistical information from the data to develop classification or regression capacity. It is a multi-stage process. The significant limitation of pattern recognition in EMG signals is low classification capacity due to high noise in the acquired data. Pattern recognition is the process of identifying characteristics of known data that can be utilized to perform classification or regression to unseen data. Often EMG applications follow a series of steps for classification, which involves filtering and pre-processing, feature extraction and reduction, model training, followed by real-time or offline classification.

A sub-category of the bionic HMI is one that utilizes EMG, which is the recording of the electrical activity of muscle recruitment. Compare to EEG, which is the recording of cortical neuron’s electric activities and is usually in the range of microvolts, EMG is usually in millivolts, requires less sophisticated amplification instrumentation, and is less susceptible to various noise and artifacts. Several HMI applications rely on EMG, for instance, full-body exoskeleton to increase user strength, gesture recognition, motionless gestures, and myoelectric control. Furthermore, EMG-based HMI in gaming is also used in rehabilitation and for user engagement and participation. Previous studies used EMG to measure engagement in the Levee Patroller game training, in myo-gaming, or EMG controlled game to test improvement in prosthesis control. This work was implemented using the WAY-EEG-GAL dataset, which is an open and free available EEG–EMG dataset.

5. Electromyography methods

Electrical activities of the skeletal muscles can be recorded by surface electrodes or needle electrodes. Needle electrodes are the clinical gold-standard method to evaluate individual motor units within a muscle. This approach, albeit invasive, provides detailed composition of the EMG signals and is advantageous for diagnosing medical conditions such as neuromuscular dystrophy or polymyositis. EMG measurement through surface electrodes, on the other hand, lack the measurement specificity but are popularly embraced for being non-invasive. The detection of EMG signals through adhesive electrodes on the skin surface have been clinically beneficial in kinesiology studies of gait analysis and rehabilitation of prosthetic patients, as well as human-machine interface applications such as the control of robots and drones

Upon arrival of the electrical impulse from the brain, the motor units quickly depolarize the cell membrane space of their respective axon terminals, leading to a propagating action potential wave that travels across the muscle fibers. Since an activation impulse from the brain can recruit multiple motor units, all the resultant motor unit action potentials (MUAPs) become superposed as their electrical signals radiate though the muscle. The resultant electrical signal can be sensed on the skin by the surface electrodes, giving the characteristics EMG signal.

The state-of-the-art methods used in the recognition of recurring patterns in EMG data streams. Pattern recognition usually has three stages: 1) Signal pre-processing: reduction of the influence of external noise sources and SNR improvement; 2) Feature extraction: determination of the gesture pattern predictors; 3) Classification.

Rather than reading the electric potential on the motor nerves, an EMG electrode reads the electric potential generated in the muscle fibers when they contract. An EMG electrode usually consists of a pair of poles aligned along the muscle fiber direction. There are also sensors with monopoles which measure the potential in respect to other reference electrodes. Monopoles have the advantage of allowing more flexible setups, since any two poles can be connected to obtain a reading. Bipolar electrodes are limited to specific electrode widths. The distance between each electrode pole and their diameter also have a significant influence on the EMG signal.

The provenance of signals measured with sEMG electrodes is the potentials generated by muscle cells when excited by motor nerves, rather than the electric potentials within the nerves themselves. However, there is a strong correlation between these two potentials. The EMG potential reading is also correlated with the activation level of muscles and the force they generate. However, this relationship is nonlinear and difficult to model. sEMG signals have inherently low SNR, which means that they are very susceptible o environmental noise. The first study describes methods to decrease the captured noise, signal artifacts and interferences in EMG recordings, as well as signal processing techniques for noise suppression (e.g. band-pass filtering, adaptive noise cancellation filters and filters based on the wavelet transform). sEMG electric potentials are acquired with electrodes placed on the surface of the skin just above the target muscle, which is a non-invasive technique.

A graphical representation of the forearm muscles is presented in Fig. 10.

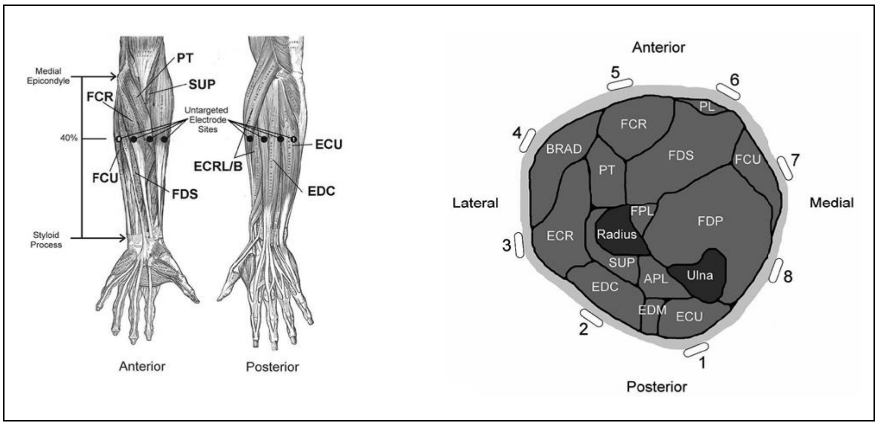


Fig. 10. Longitudinal and transverse representations of the forearm muscles [3]

Universal protocols for EMG measurements are hard to define due to the diversity of applications and hardware configurations. However, general guidelines can be observed and have been predominantly documented in academic textbooks with minor cross-reference variations. It is generally accepted that prior to filtering and processing the superposed MUAPs, sEMG sensors should produce a raw signal ideally on a low-noise baseline, as seen in the example of Fig. 11(a) where three biceps brachii contractions were executed with a rest interval in between. The general analog process of EMG signal conditioning is illustrated by the flow chart in Fig. 11(c).

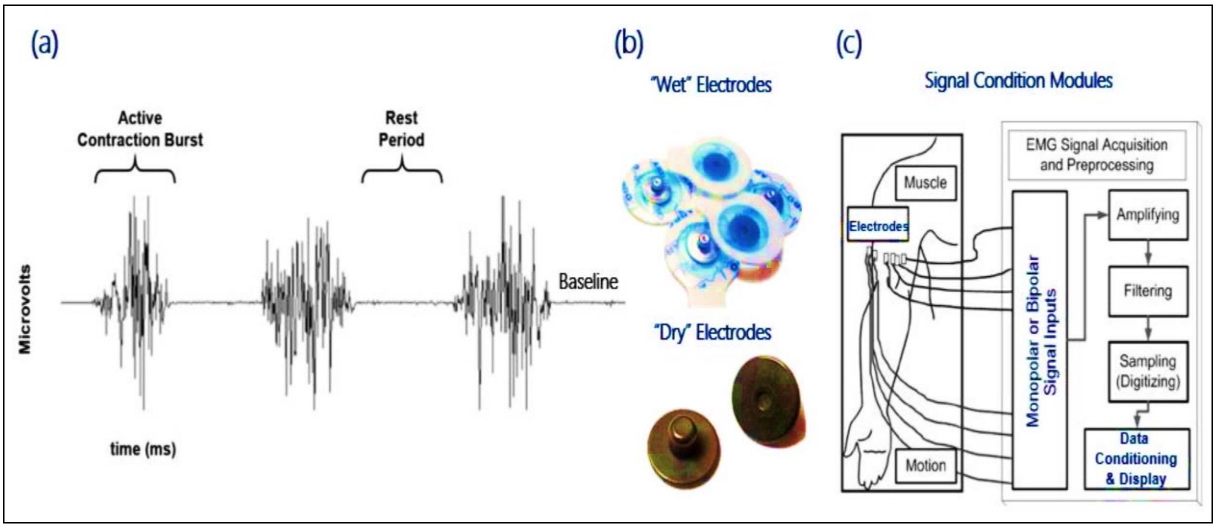


Fig. 11. a) An example of raw EMG signal recording of 3 contractions bursts of the Biceps Brachii; b) Two types of electrodes commonly used, wet and dry; c) Signal conditioning modules that amplify, filter, sample and display EMG for analysis [4]

Bipolar electrodes coupled with a differential amplifier is the most commonly employed measurement arrangement [4]. With this technique, a pair of differential electrodes are placed along the length of muscle fiber, and a third reference electrode on an electrically neutral site. In contrast, monopolar recording consists of a single recording electrode and a reference electrode. Bipolar arrangement is typically more advantageous since it offers common-mode electrical noise rejection and therefore higher SNR. The un-amplified EMG signal amplitudes measured on the skin are only a few microvolts to millivolts, therefore the signal is always amplified by a factor of at least 500 to 1000 to match input voltage ranges of commercially available analog-to-digital converters (ADCs). Input impedance of the amplifier is typically in the range of 1 – 10 Megaohms. The frequency range of the EMG signal is a frequently adjusted parameter, typically performed by an analog bandpass filter to capture either the full range or selective region of the signal spectrum. sEMG signals typically have a frequency content ranging between 10 – 500 Hz, with dominant frequency power from 20 – 150 Hz depending on the skeletal muscle being measured.

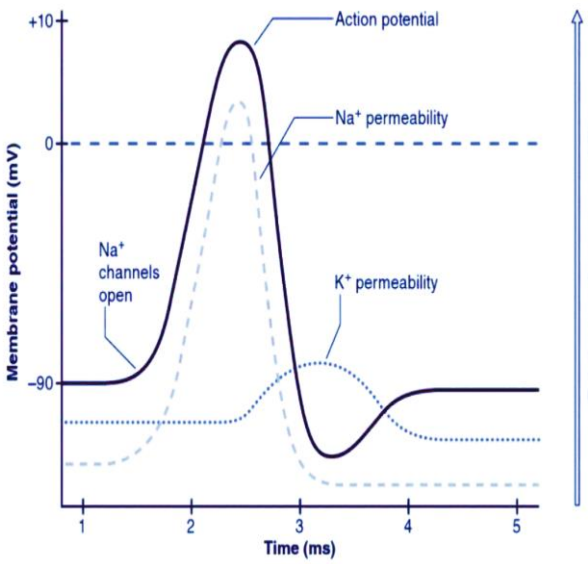
Before the EMG signal can be analyzed on a computer, it must be converted from an analog voltage to a digital format. This conversion process is typically performed through a 12-bit ADC with a dynamic range capable of capturing the full signal from noise floor to peak EMG amplitude. The ADC sampling rate must be sufficiently high to capture the full bandwidth of EMG frequencies, which according to the Nyquist Sampling Theorem is double the highest desirable frequency component. Literature reports vary widely on the selection of sampling frequency depending on the application, but typically range from 200 Hz to 2 kHz and beyond.

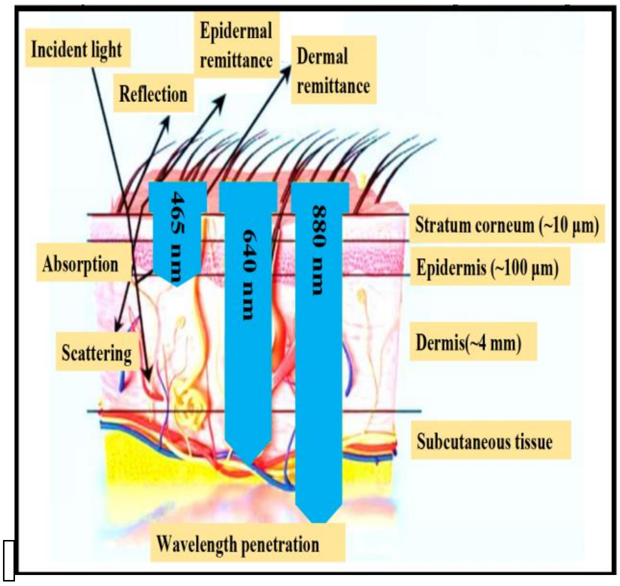
Averaged baseline noise level is a good assessment of overall EMG signal quality and should not exceed 3-5 microvolts in a high-fidelity system. To obtain a high signal-to-noise (SNR) ratio, sufficient electrical contact with the skin must be achieved. “Wet” adhesive electrodes incorporating silver and silver-chloride (Ag/AgCl) metal is commonly recognized as the gold-standard (Fig. 11(b)). Dry electrodes made of non-liquid based conductive materials such as stainless steel have been explored for enhanced user comfort that is free from adhesives and gel residues. However, they are prone to interfacial slippage, which causes unpredictable changes to electrode position and contact resistance, increasing noise and it is the main challenge to universal adoption.

Electromyography (EMG) is a valuable technique for studying human movement, evaluating mechanisms involving neuromuscular physiology, and diagnosing neuromuscular disorders. However, there are many potential pitfalls in the use of EMG as a tool. The question that a researcher is asking may not be amenable to solution using EMG techniques. Furthermore, the interpretation of the EMG signal requires a thorough knowledge of the origin of the signal. The waveform of an EMG signal is frequently evaluated as an electrical signal; this is why its characteristics can be analyzed using conventional signal processing techniques. The source of an EMG signal is a single muscle fiber or group of fibers. The anatomical features of an individual fiber and physiology of the whole muscle action potential formation are key to understanding how to record, analyze, and interpret the EMG signal.

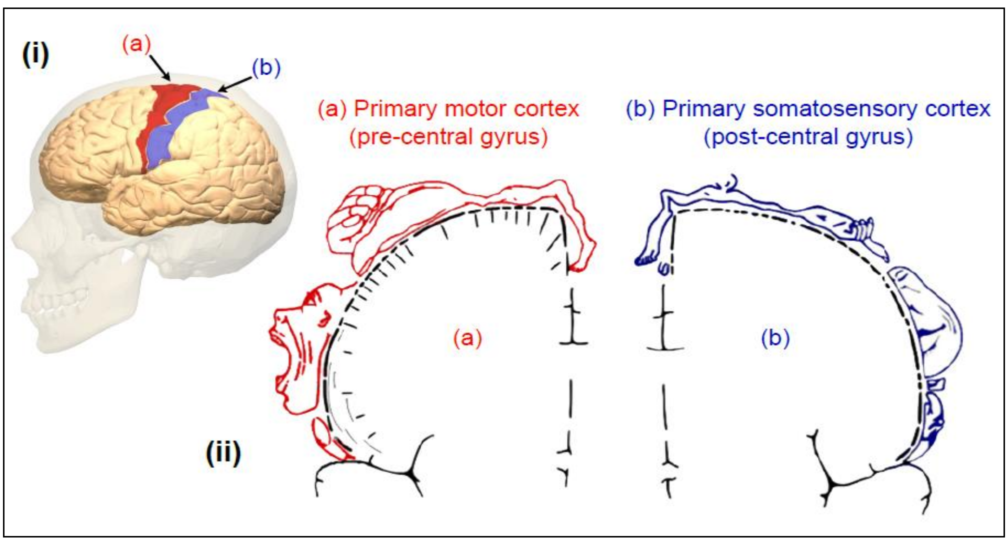
While at rest, there is a potential gradient across the membrane of the muscle fiber. Inside the cell, there is the potential of about –90 mV with respect to the exterior of the cell. The potential difference is produced with different concentrations of sodium cations (Na+), potassium cations (K+), chlorine anions (Cl^-), and other anions near the membrane. During the state of rest, the concentration of Na+ ions is relatively high on the outside of the cell membrane and relatively lower inside. On the other hand, the concentration of K^+ ions is relatively low on the outside and higher inside the muscle fiber. Muscle fibers are excitable tissues. When the fiber is depolarized by a potential of about 10 mV or greater, the membrane potential reacts specifically and in a predictable manner to produce a response that is called the muscle fiber action potential or simply action potential.

The action potential is generated through a neuromuscular joint and spreads along the muscle fiber in both directions relative to this joint. In the first phase of the action potential, the permeability of sodium cations grows and move into the cell, eventually reversing the polarity of the cell so that it temporarily reaches a positive potential – about +10 mV. When the migration of Na+ increases, then the membrane permeability for K^+ is changed. They emerge on the outside, which eventually results in the potential return to the resting state. Described process of generation of action potential has been presented [6] in Fig. 12.





(a) *(b)*



(c)

Fig. 12. (a) The time course of muscle fiber action potential is mediated be changes in membrane permeability to Na+ and K^+ ions; (b) At different sites in the skin layers, incident light displays reflection, absorption, and scattering effects; (c) - (i) the lateral surface of the human cerebral cortex with the (a) precentral (i.e., the primary motor cortex) and (b) post-central (i.e., primary somatosensory cortex) regions highlighted in red and blue; and (ii) splices of these regions overlaid with representations from Penfield's Homunculus

A motor unit is described as a combination of a single motoneuron and all of the muscle fibers innervating by this motoneuron. All fibers that the motoneuron innervates are activated at the same time as when action potential appears on the motoneuron.

The total activity of the muscle fibers of the same motor unit results in generation of motor unit action potential (MUAP). The signal amplitude of a motor unit is the super-position of all action potentials generated by the muscle fibers. This process is shown in Fig. 13.

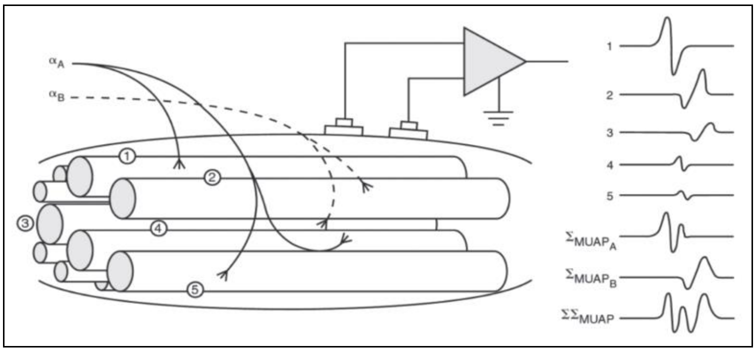


Fig. 13. The surface electromyogram as a composition of signals form all motor unit action potentials

Bearing in mind that many individual muscle fibers are innervated by the same motoneuron in any motor unit, each of these fibers generate a discharge almost simultaneously.

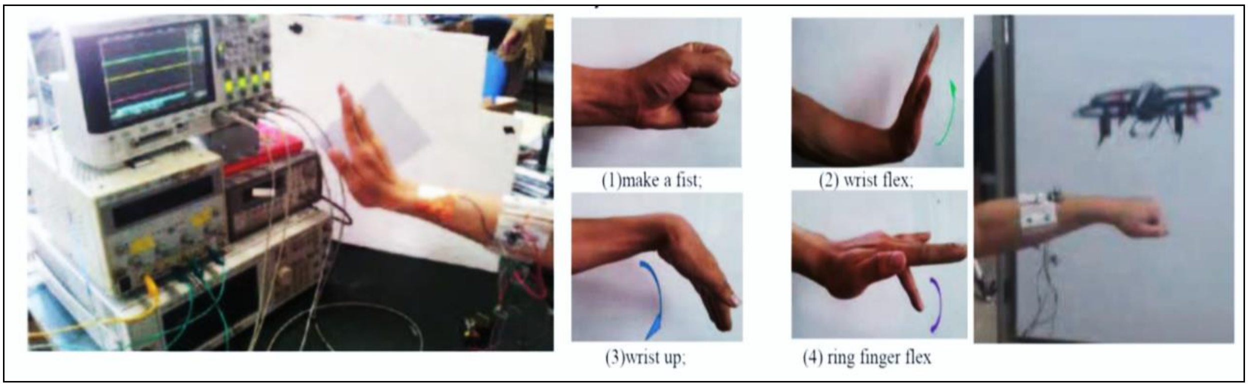
6. Surface electromyography HMI

Surface electromyography (sEMG) is a non-invasive method of measuring neuromuscular potentials generated when the brain instructs the body to perform both fine and coarse locomotion. This technique has seen extensive investigation over the last two decades, with significant advances in both the hardware and signal processing methods used to collect and analyze sEMG signals. While early work focused mainly on medical applications, there has been growing interest in utilizing sEMG as a sensing modality to enable next-generation, high-bandwidth, and natural human-machine interfaces.

Since the dawn of the 1st industrial revolution, we have sought effective modes of interaction with machines to help improve our efficiency and productivity. Early interaction with machines was dominated by simple mechanical actuators such as levers, ropes, and knobs which required significant human physicality. The advent of the Computer Age fundamentally transformed the way humans and machines interact, with the emphasis on physical interaction shifting to digital interaction. Blunt physical instruments were replaced by keyboard-controlled command line interfaces, mouse-navigated graphical user interfaces (GUI), and simple touch-based interfaces. Today, GUIs are ubiquitous in almost every sector of society, enabling flexibility of control parameters and input streams, while providing security and privacy features.

The increasing complexity and flexibility of mechanized systems, however, has led to a corresponding increase in the complexity of these HMIs, leading to a strain on the cognitive workload of human workers. Exacerbating this, we are now entering into the 4th industrial revolution, where the fusion of artificial intelligence (AI), robotics, Internet of Things (IoT), 3D printing, and other technologies are giving rise to a new age of cyber-physical connectivity, blurring the boundaries between digital, biological and the physical worlds. This explosion of linked devices and systems constantly increases the number of communication channels between humans and machines, challenging mental capacities and requiring the development of ever more sophisticated HMI technology. In an attempt to increase the bandwidth of HMI without placing increasing burden on humans to learn artificial controls, there has been a move towards creating a more natural form of interactions with machines, known as a Natural User Interface (NUI).

NUIs sense the user's body movements, voice inputs, and potentially even thoughts to create an experience where even a novice instantly feels like they have expert control. Physically, NUIs rely on unobtrusive sensors embedded either on a person or in their immediate environment. Inertial measurement units (IMU) embedded in a wristband or glove, for example, have been demonstrated to track hand gestures via motion of the fingers and hand. Video cameras are another common physical sensor employed, with real-time video analytics techniques demonstrated that can interpret physical movements and body language. IMUs and video analytics, however, are unable to fully capture the rich fine-grained and subtle motion of the human musculoskeletal system. Early use of sEMG required a simple hardware assembly: a few pairs of wet electrodes, a signal conditioner and an analog-to-digital converter (Fig. 14(a)).

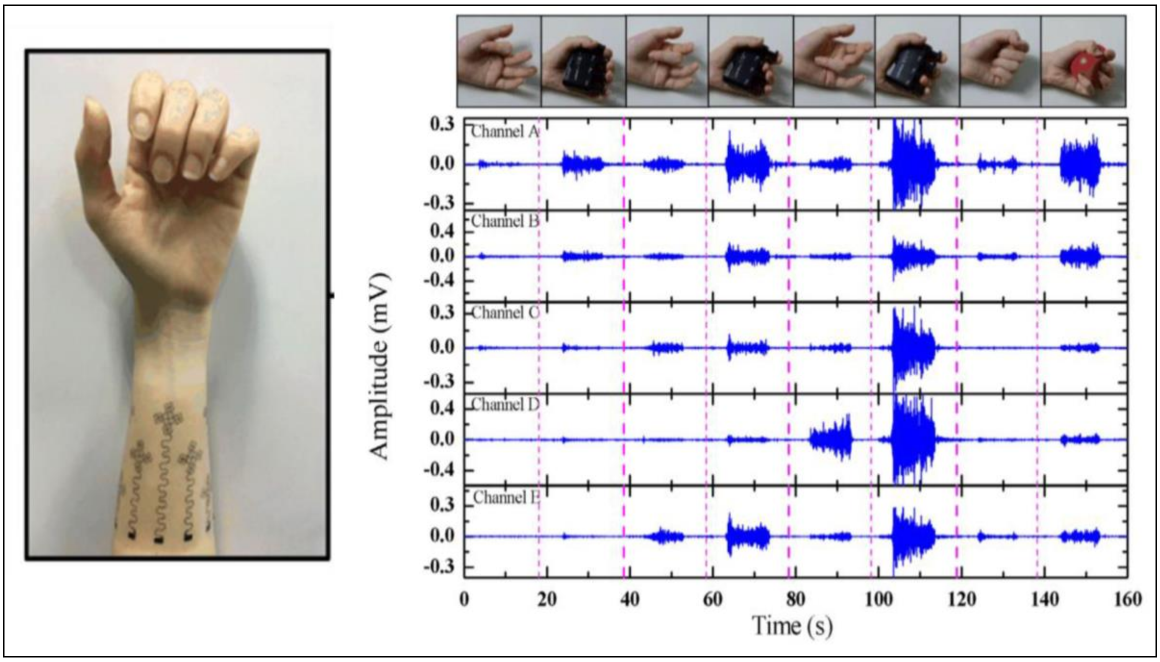


(a) *(b)*

Fig. 14. a) Typical sEMG benchtop hardware setup to obtain gesture differentiating signals. (b) Control of aerial drone with 4 hand gestures enabled by sEMG benchtop system

Early demonstrations often focused on simple hand gesture detection, such as binary "on" or "off" commands to interact with remote-controlled toys. For example, it was showed one pair of wet electrodes placed on the forearm anterior muscles to be sufficient in moving a toy car in the forward and backward direction. In a similar fashion, used five pairs of wet electrodes and benchtop electronics to control an aerial drone in four directions with four coarse but unique hand gestures (fist, wrist flex, wrist up, and ring finger flex) (Fig.14(b)). More complex hand and finger gestures detection have been widely demonstrated, while exploring different forearm electrode placements for optimal recognition accuracy.

Surface electrodes of sEMG systems can take up large sensing area on the body, and the requirement for a gel or water-based interface further presents challenge to miniaturization. Even with dry electrodes, insufficient contact and skin impedances across different individuals under different conditions can result in varying degrees of noise levels. Tattoo-based electrodes have been shown as a promising candidate to overcome these challenges. As the electrode size decreases, greater degree of contact can be achieved with the skin without exerting external pressure through Van der Waals forces to secure them in place. Furthermore, a smaller footprint allows more sensing electrodes to be included for highly refined measurement of biopotentials from minor muscle fibers. One of the earliest works in this area was performed by Lapatki et al. in 2004, in which they constructed a thin, 2D multielectrode grid on a highly flexible polyimide material. After adding silver-chloride coated copper as the electrodes on the grid, the resultant patch is only 470-micron thick and sits on a double-sided adhesive that allows easy attachment to the skin. sEMG measurement was conducted by the group to show differentiable muscle activities on the face. Using a nonconductive and stretchable laminate (e.g. polydimethylsiloxane) as the base material, conducting metal such as copper or gold are either transferred or sputtered onto the laminate to serve as the electrodes and wiring traces. Additional laminate and etching process finalize the sandwich construct to expose only the electrodes to the skin (Fig. 15(a)).

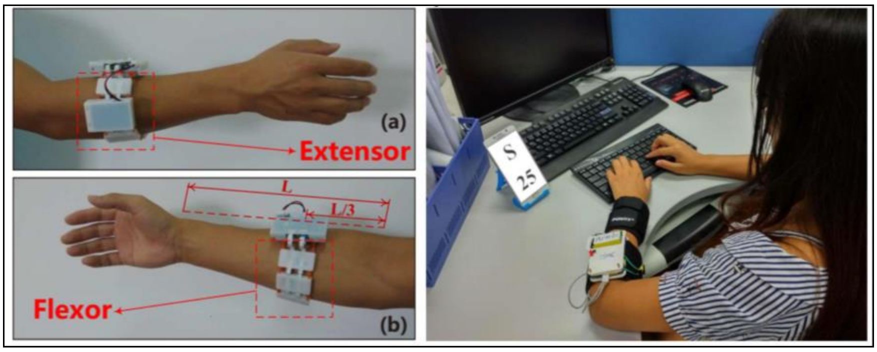


(a) *(b)*

Fig. 15. a) Stretchable micron thick sEMG patches attached onto the forearm to record myoelectric activities as shown in b) during various grasping force exertions. Channel A – E are 5 separate EMG recording channels showing EMG signals with dashed pink line separating intervals

Both research groups have demonstrated excellent sEMG signal quality and the ability to discriminate hand gestures with high accuracy (Fig. 15(b)).

Ultimately, the success of sEMG as a ubiquitous NUI is limited by the simplicity, compactness, and comfortability of its physical form. To that end, there has been a significant amount of work reducing the size and complexity of these systems to facilitate end-user applications. An elastic armband is the most common form factor for its ease of on-and-off boarding, greater sensing coverage with circumferential measurement, and firm placement during hand motions. In addition to snug fit, a stand-alone, portable sEMG armband requires four main functional blocks: signal conditioning, signal processing, power supply, and data transmission. To date, there have been numerous research prototypes and commercialized versions of this type of device, such as those shown in Fig. 16.



(a) *(b)*

Fig. 16. a) Forearm EMG armband capable of wireless gesture detection via onboard electronics; b) ArmIn armband employing sEMG sensor for keystroke detection

In an interesting study, the stiffness command to a robot was derived in real-time from the measurement of 8 EMG channels from an operator's arm, Fig. 17.

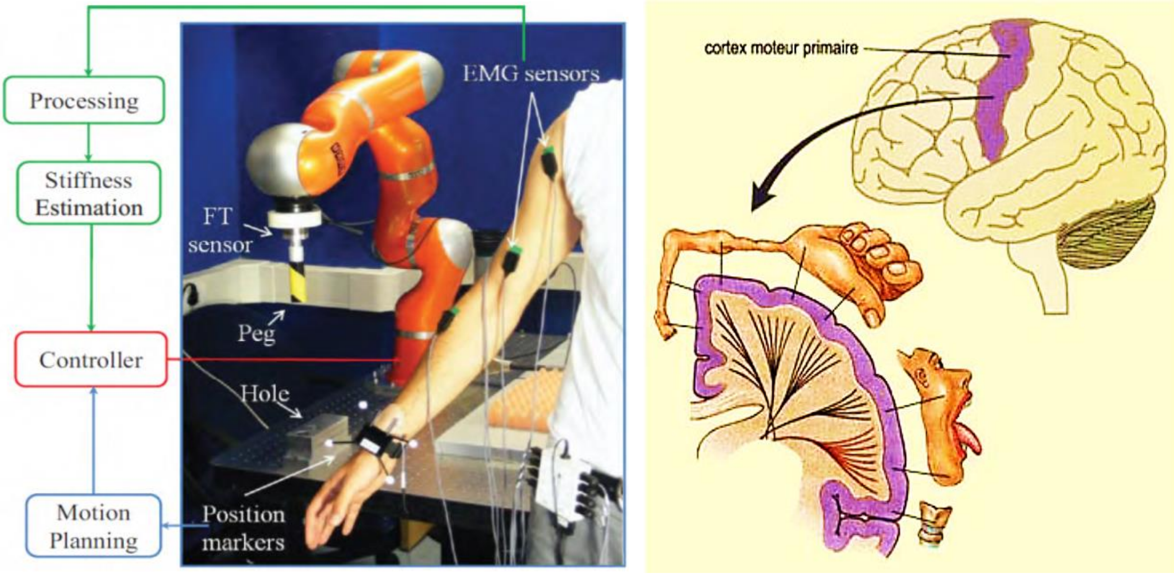


Fig. 17. Diagram of a data acquisition system used to estimate the joint stiffness to be replicated by a robot during a tele-operation session

Most research systems focus on recognizing individual gestures one at a time. After preprocessing, the traditional pipeline for gesture recognition via sEMG extracts a number of pre-chosen *"features"* which characterize the gesture in a much more compact way than the original signal, while still retaining the information necessary for gesture recognition. In parallel, a *gesture detection* method is typically used to determine when the continuous signal contains a gesture. When a gesture is recognized, a *classification* method is used to determine which of the set of gestures it is. A typical system architecture is presented in Fig. 18.

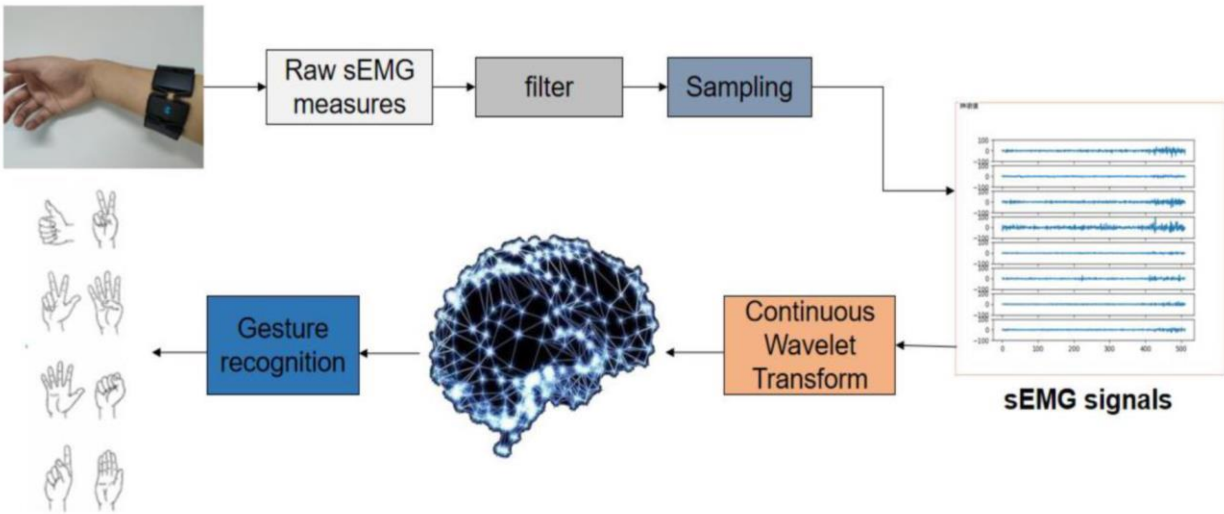


Fig. 18. One typical gesture recognition system architecture [6]
[sEMG signals are collected, the frequency range of interest is selected via filtering or other preprocessing, and the signals are then digitally sampled. Features of interest (in this case Continuous Wavelet Transform coefficients) are calculated from the signals, and then a classifier (in this case a neural network) is applied to these features, outputting the probabilities of various gestures]

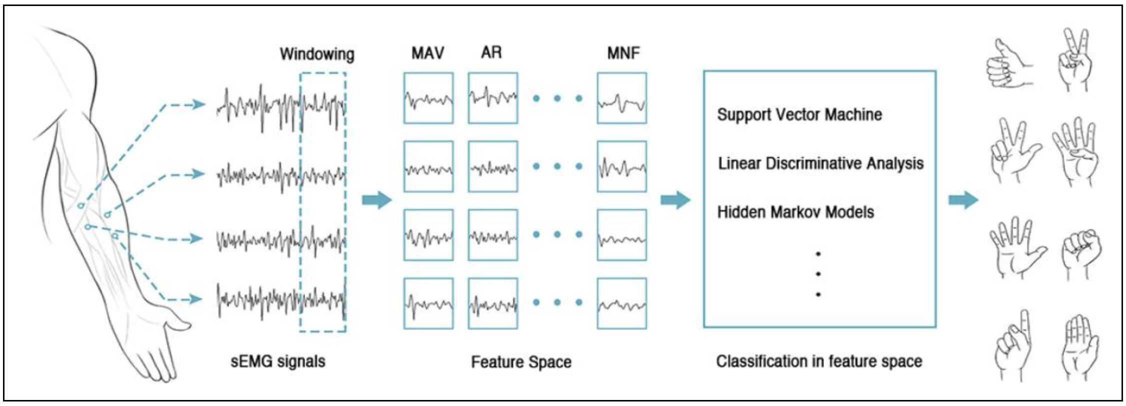
It is important to note that sEMG signals vary widely from person to person, and can significantly differ even between the same user on different days. When a system is evaluated on a user who was not part of the training data, this is the "interuser" accuracy. When a system is evaluated on a known user who was part of the training data, but the device has been removed and re-placed on the user, this is the "intersession" accuracy. When some of the gesture repetitions from a user and session are used for training a system, and the system is evaluated on other repetitions from this user and session, this is the "intrasession" accuracy. The intrasession accuracy, intersession accuracy, and interuser accuracy form a hierarchy of increasing difficulty.

When comparing accuracy numbers from different authors on the same dataset, it is important to keep in mind which accuracy is being reported. One approach to achieving higher interuser accuracy is to “pre-train” the system on a large training set from multiple users, then to fine-tune the system on a limited training set from an individual user.

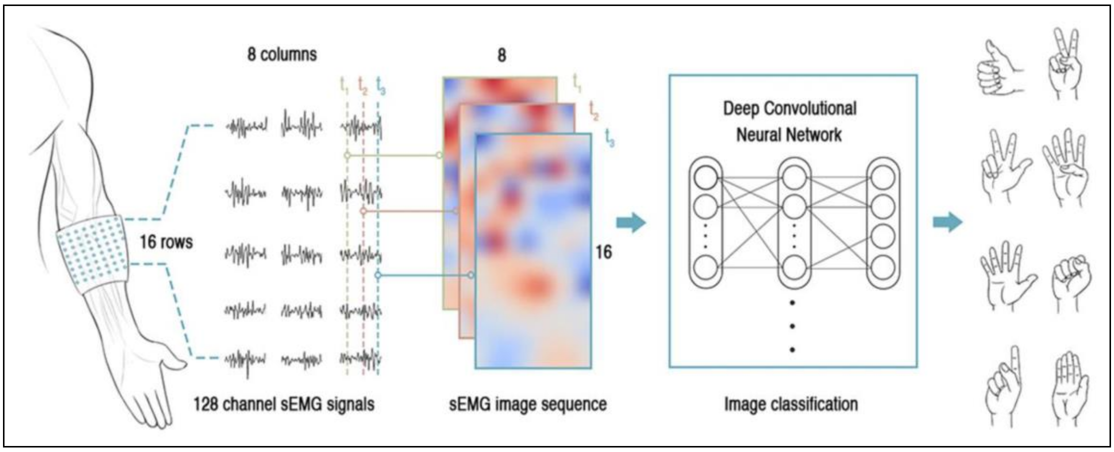
In the case of EMG signals, there are several forms of structure available. EMG signals contain one-time dimension, and one or two spatial dimensions (depending whether the electrodes are arranged linearly or in a grid). In the spatial dimension(s), networks commonly use *convolutional* layers, which learn features that are applied in a sliding-window fashion across the one or two spatial dimensions. In the time dimension, researchers have worked with *recurrent* layers, which learn features that read an input sequentially, “remembering” some of the values it has seen. The most popular type of recurrent layer is the “Long Short-Term Memory” (LSTM) layer, which explicitly models the process of learning which values to “forget” [6]. Researchers have also used convolutional layers to analyze time series data. Due to the physical mechanisms that generate sEMG signals, they are highly stochastic and historically it was generally accepted that the instantaneous value of an EMG signal was of little use.

For example, existing gesture recognition methods using sEMG are largely based on a conventional pattern recognition algorithms (such as support vector machine, hidden Markov model, etc.) on sEMG feature space, i.e., the sequence of myoelectric signals of each channel often need to be transformed into a set of descriptive and discriminatory features extracted using a window of EMG data (or segment).

Figure 19(a) shows a classical framework of gesture recognition using windowed sEMG.



(a)



(b)

Fig. 19. (a) Schematic illustration of gesture recognition by windowing sEMG signals. MAV: mean absolute value. AR: auto-regressive coefficients. MNF: mean frequency; (b) The architecture of the deep learning network. Electrodes are placed in a square grid pattern, and the instantaneous sEMG signal amplitudes are then processed using networks originally designed for image processing applications [6, 7]

The optimal window length represents a compromise between classification error and controller delay in the field of assistive technology, physical rehabilitation and human computer interactions. However, on HD-sEMG signals, which have two spatial dimensions, the spatial patterns in an instantaneous reading have been analyzed successfully with high accuracy via convolutional networks, using techniques from image recognition (see Fig. 19(b)).

A similar architecture has also been used for analyzing sparse sEMG signals through an entire time window, using a 2-dimensional convolution that looks for patterns over both the time and space axes. One recent paper makes the natural extension to a 3-dimensional convolution over an HD-sEMG signal evolving through time. When LSTMs are used for time analysis, they are typically combined with convolutions, also in the time dimension. Most research uses convolutional layers for feature extraction, with LSTM layers being used to build the classifier, but there is limited evidence that the other order may work equivalently well. A similar architecture has also been used for analyzing sparse sEMG signals through an entire time window, using a 2-dimensional convolution that looks for patterns over both the time and space axes.

As sEMG hardware and classification systems continue to provide higher accuracy at lower latencies, the overarching systems that map the outcome of these gestures to actions still needs to be fully investigated. To date, most systems use individual gestures with one-to-one control mappings, such as up/down/left/right to control a drone and are not truly a natural way to interact with a machine. Natural gesturing can take many forms and can have a diverse number of meanings depending on situational context. Incorporating context into an sEMG system and developing a system that can understand the language of natural human gesture is still a very open and exciting research area, and may be the ultimate hurdle to overcome before sEMG systems can be ubiquitously deployed as natural human-machine interfaces.

7. EMG based Pattern Recognition

Pattern recognition involves extracting knowledge and statistical information from the data to develop classification or regression capacity. It is a multi-stage process. The significant limitation of pattern recognition in EMG signals is low classification capacity due to high noise in the acquired data. Pattern recognition is the process of identifying characteristics of known data that can be utilized to perform classification or regression to unseen data. Often EMG applications follow a series of steps for classification, which involves filtering and pre-processing, feature extraction and reduction, model training, followed by real-time or off-line classification.

A sub-category of the bionic HMI is one that utilizes EMG, which is the recording of the electrical activity of muscle recruitment. Compare to EEG, which is the recording of cortical neuron's electric activities and is usually in the range of microvolts, EMG is usually in millivolts, requires less sophisticated amplification instrumentation, and is less susceptible to various noise and artifacts. Several HMI applications rely on EMG, for instance, full-body exoskeleton to increase user strength, gesture recognition, motionless gestures, and myoelectric control. Furthermore, EMG-based HMI in gaming is also used in rehabilitation and for user engagement and participation. Previous studies used EMG to measure engagement in the Levee Patroller game training, in myo-gaming, or EMG controlled game to test improvement in prosthesis control. This work was implemented using the WAY-EEG-GAL dataset, which is an open and free available EEG–EMG dataset.

The dataset consists of EEG and EMG recordings, as well as 3D hand and object position measurements. Twelve healthy right-handed subjects (8 females and 4 males, aged 19–35 years) were recorded using 32 EEG channels located at Fp1, Fp2, F7, F3, Fz, F4, F8, FC5, FC1, FC2, FC6, T7, C3, Cz, C4, T8, TP9, CP5, CP1, CP2, CP6, TP10, P7, P3, Pz, P4, P8, PO9, O1, Oz, O2, PO10 according to the 10–20 international EEG placement system. Reference and ground electrodes were connected to FCz and AFz locations, respectively. In addition, five EMG channels from the following muscles: 1. Anterior Deltoid (AD), 2. Brachioradialis (B), 3. Flexor Figitorum (FD), 4. Common Extensor Digitorum (CED), and 5. First Dorsal Interosseous (FDI). EEG signals were recorded with the ActiCap device at a sampling rate of 500 Hz. On the other hand, EMG signals were recorded using five sensors at a sampling frequency of 4 kHz.

Figure 20 shows the experimental setup for the dataset acquisition.

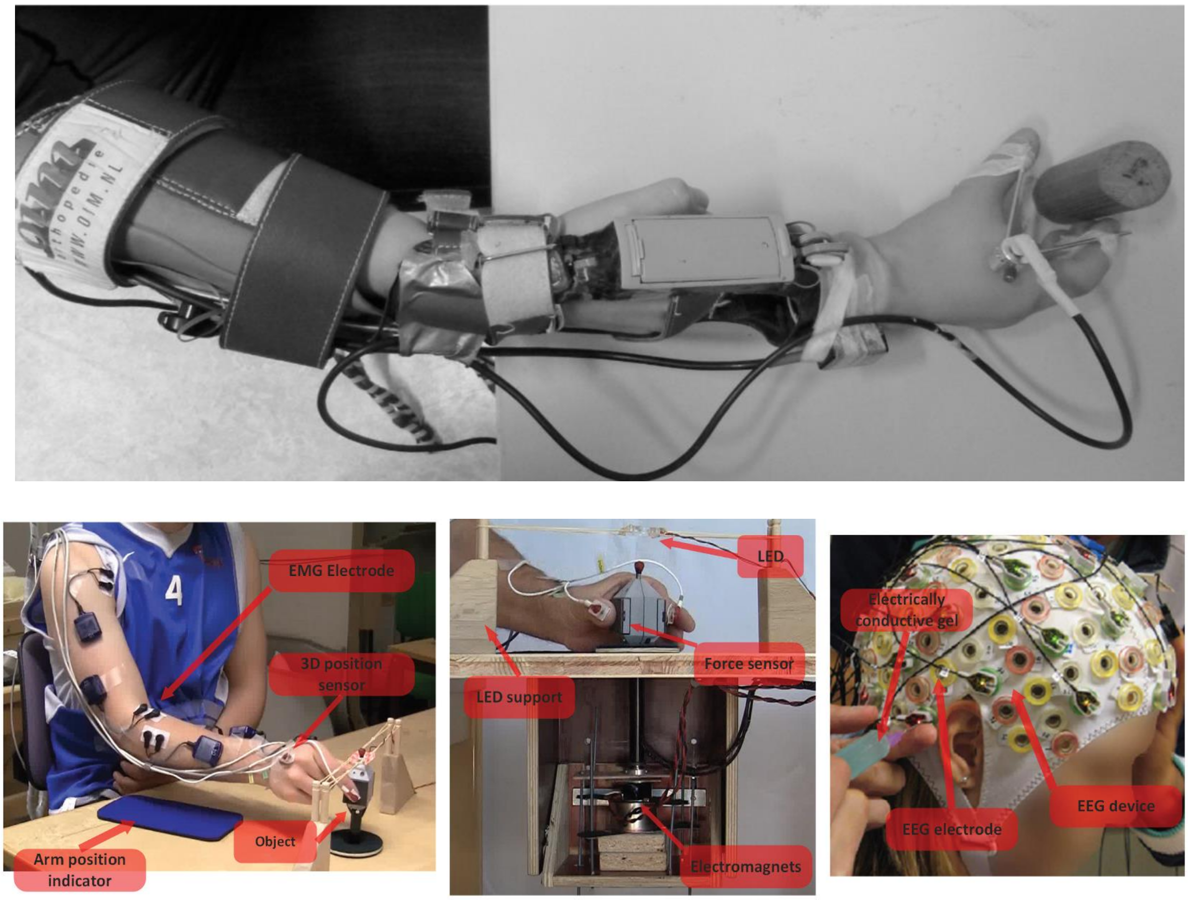


Fig. 20. Experimental setup for data acquisition. A EMG based controller for a video game (up); A myoelectric hand connected to participant's hand with an open cast [7]

Remark. Tactile HMI requires physical touch to something by users, which is considered as input to the system. Mouse and keyboards are examples of tactile HMI. The most popular technology of tactile HMI is touch screens, which we used in our mobile, tablet, and laptops. Recently, a pressure-based toggling mechanism of buttons is used in mobile devices instead of the button's physical press. One application in medical practice is haptic feedback based surgical procedures.

In the protocol, initially, there is a rest period of 2 seconds before starting the movement where subjects maintain the right upper limb leaning on a table, next, the subject receives a visual indication from a LED to start performing a reaching movement of the right hand toward an object. Then, the user grasps it with the index and thumb fingers; afterward lifts it and holds the object steadily within a circle that is about 5 cm from the table for 2 seconds until the LED turned off, and subsequently replacing the object and returns the upper limb to the position indicator, as shown in Fig. 1. Ten series of approximately 32 trials were recorded, for a total of 328 trials per participant in which the weight of the object (0:165, 0:330, 0:660 kg), the contact surface (sandpaper, chamois, silk), or both was changed.

This study used 3 EEG channels (C_3, C_z, and C_4) and five EMG channels for calculating cortico-muscular connectivity, following the international 10–20 system of EEG electrode placement and muscle location for EMG, as presented in Fig. 21.

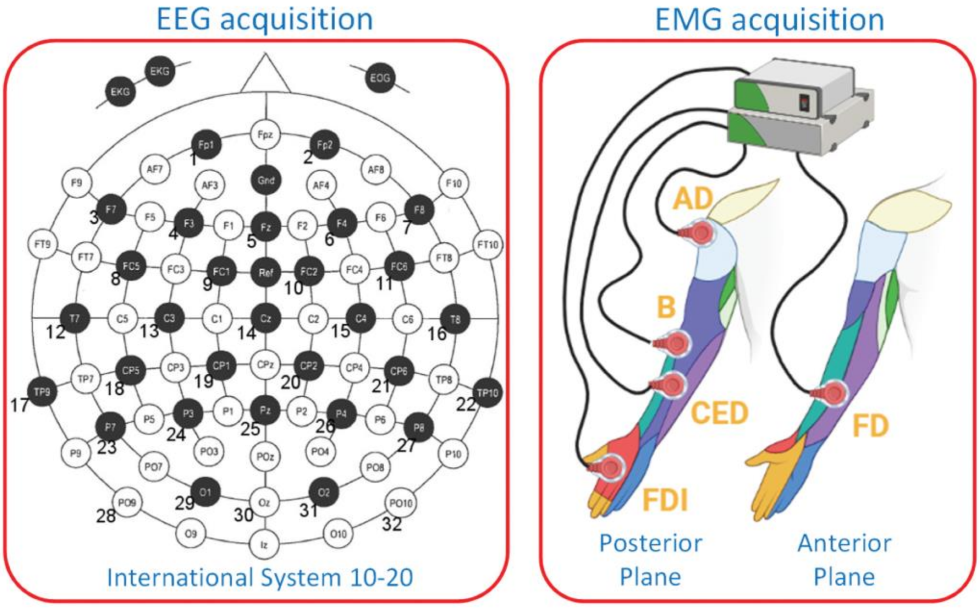


Fig. 21. EEG electrodes layout following the international 10–20 system used in the original WAY-EEG-GAL dataset and EMG electrode placement following the locations of five upper limb muscles [8]

Data from two different weights were used when the subject manipulated the object (0:165 and 0:660 kg) where the contact surface was kept constant with sandpaper. Five series of weights were used where each series included 22 trials, for a total of 110 trials per participant. Finally, data were taken for each trial until the subject performed the task of replacing the object.

After dataset integrity validation the methodology for EEG–EMG coherence analysis presented in Fig.22 was implemented.

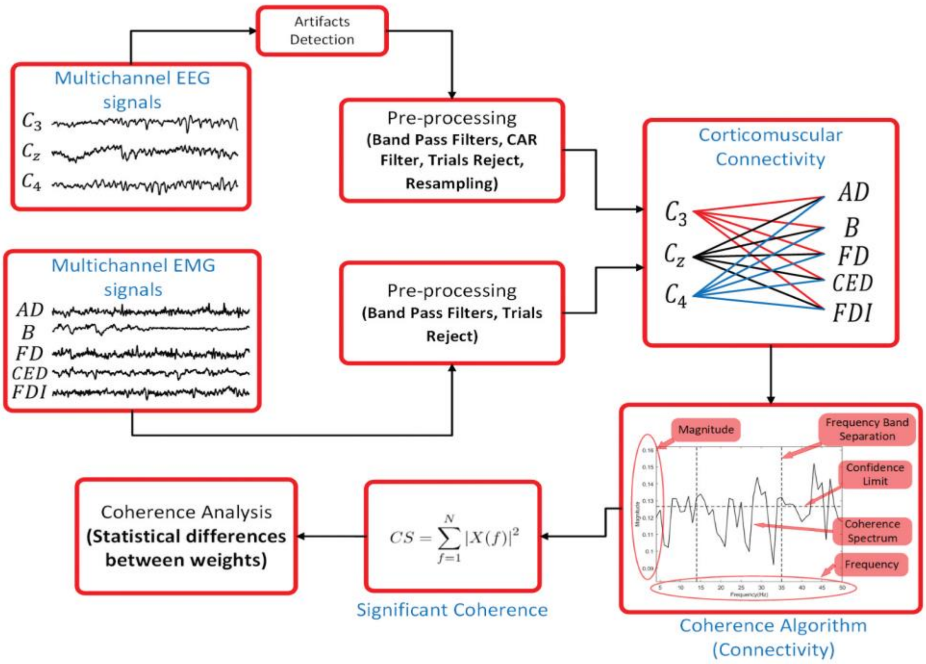


Fig. 22. Block diagram of the implemented methodology in this study to estimate cortico-muscular connectivity between EEG and EMG signals during the movement of reach-grasp-lift-hold and replace an object

First, the study is delimited using two weights and selecting subjects. After, artifacts are detected in the EEG signal, and channels are selected. Next, the signals are pre-processed using filters. After, the EEG and EMG signals are segmented by using a Hanning window of 1 second overlapped to 25% for calculating the coherence, which is represented using significant coherence values.

Connectivity analysis between EEG and EMG signals was calculated using the coherence algorithm, a measure of connection or correlation between two signals in the frequency domain that determines the strength of correlation in the range of 0–1 [6].

Coherence was implemented to evaluate the connectivity between the electrical activity of the brain and muscles when performing an object manipulation movement. To calculate coherence, the frequency components of EEG and EMG signals in the range 6 - 50 Hz were extracted by calculating the auto-spectrum and cross-spectrum using MATLAB (Version R2020b, MathWorks Inc). EEG and EMG signals were segmented by a 1 second Hanning window with 25% overlap at a frequency resolution of 2 Hz between 6 and 50 Hz for each trial and subject.

Combinations between channels were obtained by relating the 3 EEG channels (C_3, C_4, C_z) with each EMG channel (5 Channels), which generate a total of 15 combinations between channels, as shown in Fig.22.

Data were taken for each trial until the subject performed the task of replacing the object. First, obtained results of the data integrity validation were presented. Next, coherence between EEG and EMG signals was shown in frequency bands and upper-limb muscles involved and finally, the study is presented to demonstrate which muscles are mostly in communication with the hemispheres of the motor cortex.

Figure 23 presents the head maps for each analyzed weight using all trials and subjects spanning the frequency range 8 - 30 Hz from 2 - 8 seconds.

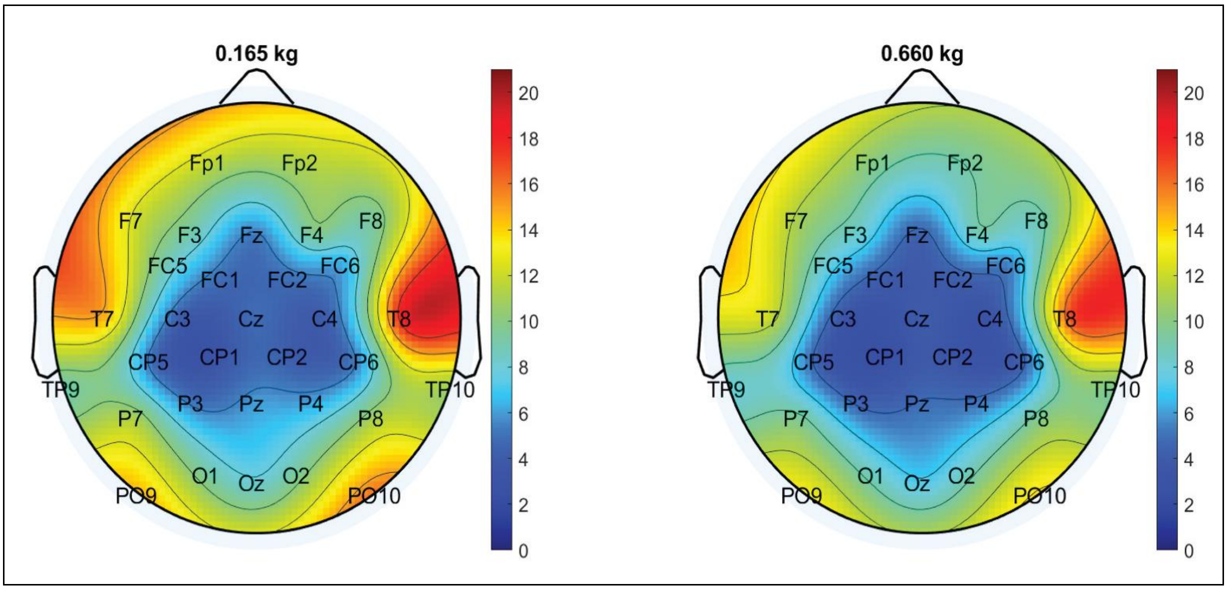


Fig. 23. Power Spectral Density (PSD) for all EEG channels (32 channels) for both weights using all trials and subjects analyzed. PSD magnitude extends in the range (0 - 20) of magnitude expressed in the head map for the execution movement (2 - 8 seconds) in the 8 - 30 Hz frequency band [8]

According to the Fig.20, the movement was distributed in all cortical cortex by the power decrease presented in the head map, where this effect could be presented by the movement complexity. Finally, the EEG channels chosen for the coherence analysis were C_3; C_4 and C_z due to the main location in the cortical-motor cortex.

Significant differences in the movement of manipulation of an object with two different weights were found by quantifying the connectivity of EEG and EMG signals. Specifically, significant differences were found of; a) coherence of C_3 with Anterior Deltoid and Brachioradial muscles; b) coherence of C_z with Brachioradial muscle; c) coherence of $C4$ with Flexor Digitorum and Brachioradial muscles. Furthermore, the greatest coherence was found in the β band for the 3 EEG channels, which is in agreement with the results of previous studies. Those studies reported that subjects showed a peak in the coherence spectra between 15 – 30 Hz bandwidth during a hold task involving stable force production where the coherence between signals may be affected by the performance in the development of motor tasks.

EMG-EEG coherence is higher in the beta frequency band were demonstrated, individualized differences in coherence have been found according to each muscle involved during the reaching and grasping movement, showing that the brachioradialis muscle is the most involved in the connectivity due to the significant differences found in the EEG channels. Additionally, it has been demonstrated how the EMG-EEG coherence could change depending on the force exerted to grasp an object of different weight, and it has been determined which muscles are mostly in communication with each side of the cerebral hemispheres.

Coherence is significantly higher at a weight of $0{:}165$ kg than at a weight of $0{:}660$ kg for the α band in the C_3, C_z and in α and β for the C_4 channel. In addition, these differences are found in the C_3-AD, C_3-B, C_z-B, Cz-CED, C_4-B and C_4-FD channel combinations. These results are of great importance in rehabilitation engineering applications because cortico-muscular connectivity can be used as a descriptor to improve the classification rates, usability, and control of prostheses based on BCI systems. In this case, the application of prostheses for weightlifting identification.

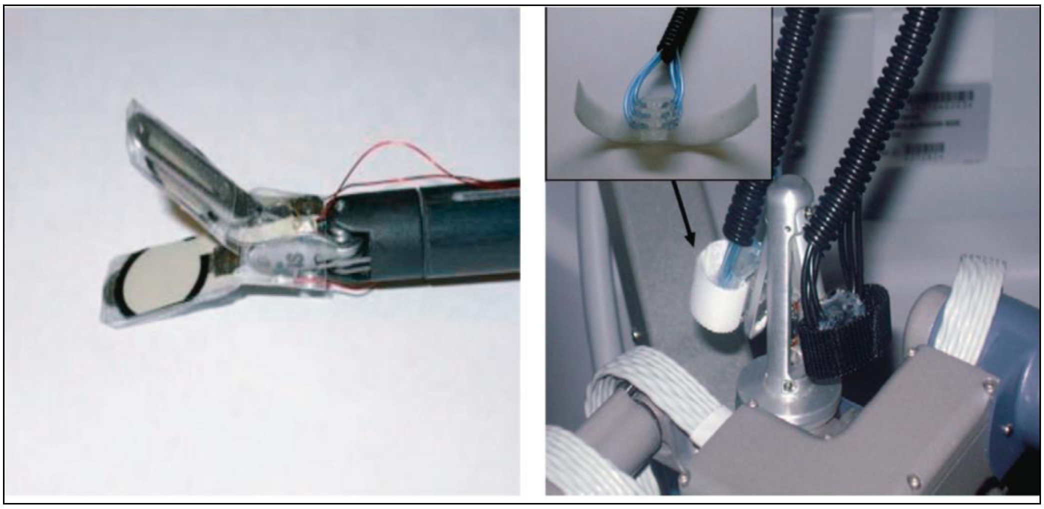
As future studies proposed to evaluate other methods such as Granger Causality to establish connectivity and delay times between EEG and EMG information when performing other types of movements involved in activities of daily living. As well as using corticomuscular connectivity as a rehabilitation method for people with disabilities, for implementing computational methods based on connectivity to improve identification rates using techniques such as filter banks.

8. Example: Hybrid EEG-EMG based brain computer interface (BCI) system for on-line robotic arm control

Bio-signal based BCI systems are widely being used in healthcare systems and hence proven to be an effective tool in rehabilitation engineering to assist disabled people in improving their quality of life. Handicapped people with above hand amputee have been targeted and hence non-invasive EEG and EMG biosensors are used to design wireless hybrid BCI system. The hybrid system is able to control real-time movement of robotic arm via combined effect of brain waves (attention and meditation mind states) and wrist muscles movements of healthy arm as command signal. The system operates the robotic arm within 3 degree of freedom (DOF) motion which corresponds to movement of shoulder (internal and external rotation), elbow (flexion and extension) and wrist (Gripper open and close) joint. It has been experimentally tested on 4 subjects with upper limb amputee (having one healthy arm) after training period of one day. On receiving the input signals from EEG and EMG sensors, subjects have successfully controlled the movements of the robotic arm with accuracy of 70% to 90%. In order to validate the obtained results, a potentiometer has been fixed on robotic arm and angular motion of shoulder and elbow joint is recorded (actual motion) and compared with results of the BCI system (required motion). The comparison shows high resemblance between actual and required motion which reflects the reliability of the system. In addition, apart from robotic prototype, its 2D modelled is also designed on visual studio. The presented preliminary experimental results show that the motorized prosthetic prototype movement due to mind and muscle control is in accordance with the 2D modelled virtual arm permitting to improve its real-time adoption for rehabilitation.

The BCI system aims to control the movement of targeted body area in the similar fashion as the normal body moves in response to the bio signals acquired from muscles and brain. The implemented BCI system uses patient's bio potentials (EEG and EMG signals) in simultaneous manner to control the movement of robotic arm.

The first tactile feedback system reported for MIS is found in da Vinci surgical robots. The system contains an end-effector, which comprises piezoresistive force sensor and pneumatic balloon both used for creating tactile feelings, and it is driven with a semiautomated control system during robotic surgery. The tactile feedback in the system was evaluated by 16 novices and 4 experts peg transfer tasks. During the experiments, the force of effectors was measured from three blocks, but only the middle set provided tactile feedback. Control system of the da Vinci surgical robot was equipped with digital signal processor which enables the system to process the voltage signal and accordingly, based on signal conditioning electronics, determined the inflation level corresponding to the input voltage as well as for the generated an output signal to affect the inflation. The signal was relayed to the pneumatic balloons mounted at the master control to provide the thumb and index finger with feedback, as shown in Fig. 24.

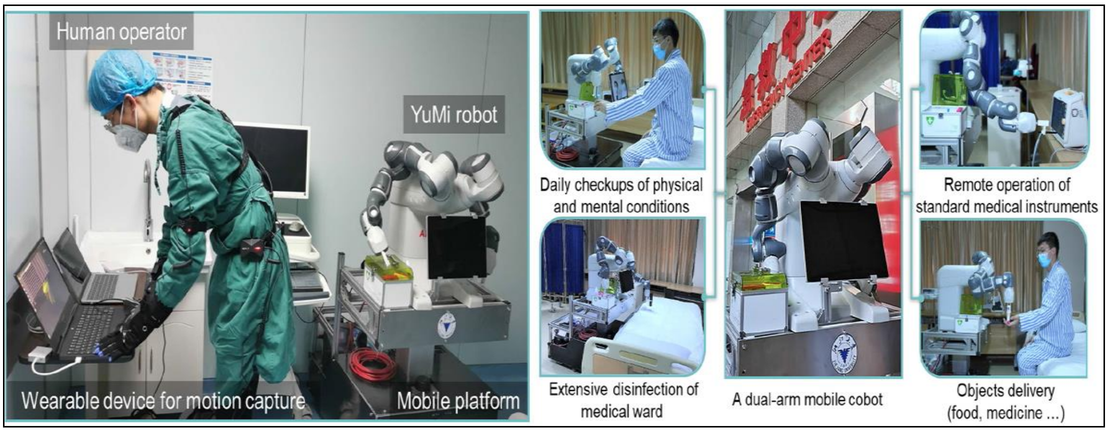


(a) (b)

Fig. 24. (a) Modified FlexiForce sensor mounted on the top and bottom jaws of the Cadiere grasper for the da Vinci System. (b) The balloon tactile displays were mounted directly onto the da Vinci master control for thumb and index finger [10]

This system was the first complete tactile system known to be applied to commercial robotic surgical system; it is used to evaluate the direct tactile feedback in robotic surgery. Additionally, it has been adopted for various applications including prosthetics rehabilitation, surgical training, and robotic manipulation.

The current features of cobots, such as flexible mechanical design, varying price, and safety features, are still lagging behind in the effectiveness of deployment for human care, where the requirements of cobots are stringent. For instance, during the field investigation of the cobot at a COVID-19 specific hospital in Fig. 24, there are many issues limiting the real implementation of cobots: 1) High-performance wireless communications; 2) Temperature and haptics sensing at the robot fingers and body parts; 3) Perception of patient's responses and affective state; 4) Usability and accuracy of the remote operation; 5) Robot self-disinfection; and 6) Self-learning for new tasks. For example, a cobot has been experimentally used to verify the potential application useful to combat the coronavirus disease outbreak during the COVID-19 pandemic. As demonstrated in Fig.25 (a), in this field investigation, a cobot was installed on a mobile platform in an isolation ward and wirelessly controlled by a human operator through a wearable device in a remote-control center. Simple tasks that the telecobot can complete were validated, as shown in Fig. 25 (b), including the daily checkups of physical and mental conditions, remote operation of standard medical instruments, extensive disinfection of medical ward, and objects delivery for care recipients.



(a) (b)

Fig. 25. The ongoing field tests of a dual-arm mobile cobot for patient-care applications at the Emergency Department of the First Affiliated Hospital of Zhejiang University, Hangzhou, China: (a) The teleoperation system consists of a mobile platform, a dual-arm cobot (YuMi, IRB14000), and a wearable motion capture device including a pair of data gloves to capture the finger motions for the teleoperation of grippers; (b) By leveraging the motion capture device, motion data collected from the upper limb of the healthcare worker

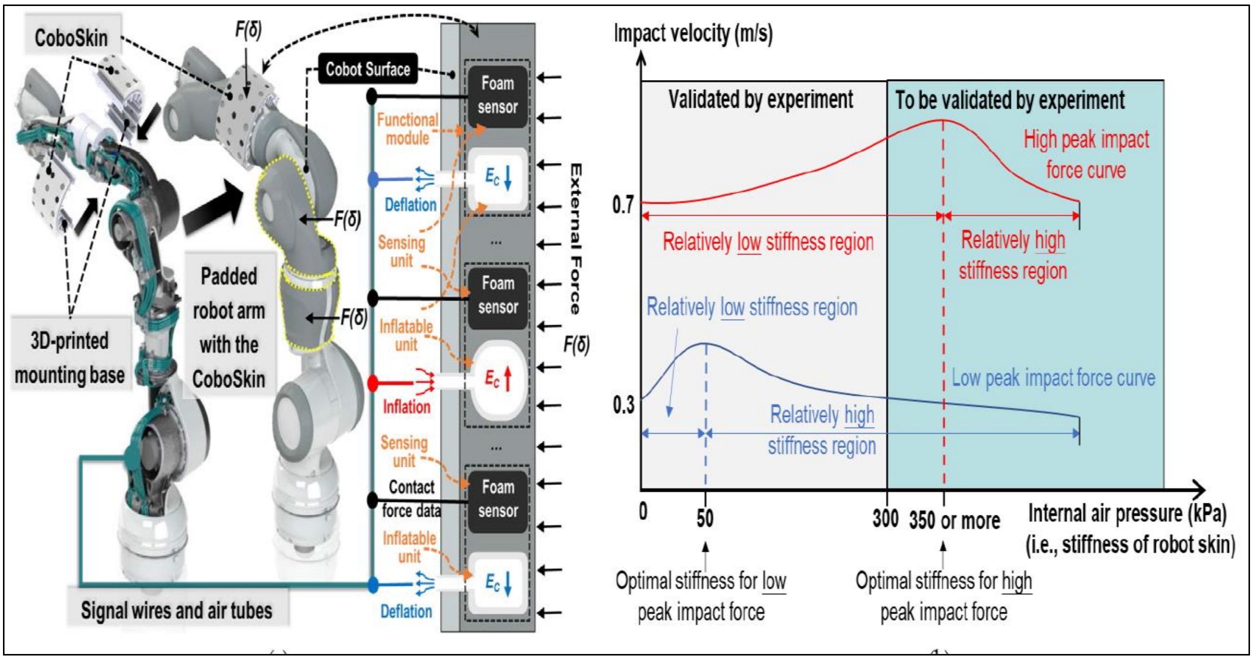
can be obtained, processed, and used to wirelessly control the robot arm remotely for delivering healthcare services [Ethical approval has been granted to the research team for the related research, which covers the human-subject related aspects and test of devices in hospital environment, where ethical principles are fully followed]

Another urgent need is regulations on functional safety, privacy, and ethical issues because the existing ones are originated from traditional robot applications, and ward-care is not well addressed.

Endowing robot skin with the stiffness-tuning capability by coupling sensors and actuators is an emerging research topic. By integrating inflatable actuators and force sensing units, proposed a soft robot skin with variable stiffness for safer HRC was proposed.

As shown in Fig. 26, the skin can alter its stiffness without affecting the initial impedance of sensing units and the robotic motion of host robots.

Thanks to the capability of stiffness modulation, their skin is capable of not only reducing the peak collision force but also extending the sensitivity of sensing units. They further generalized the design of the skin to an off-the-shelf cobot body. The stiffness-tuning capabilities of the above robot skin are actuated by the pneumatic power source and cannot cover the entire cobot body. The sensing function is also supplely narrowed down to contact force with limited spatial resolution. They are inherently limited by the original application-orientated codesign of sensing and actuation. Stiffness tuning has gained much attention with the development of soft robots and continuum robots, resulting in a diverse range of methods to achieve it.



(a) *(b)*

Fig. 26. Robot skin with the ability of stiffness tuning. (a) Illustration of the working principle of safety improvement by altering the stiffness of robot skin according to the predicted impact velocity or the limited peak impact force E_c is the elastic modulus of covering materials; (b) When the limited peak impact force is below 30 newtons, or the impact velocity is below 0.3 meters per second, the optimal stiffness is obtained by altering internal air pressure below 50 kilopascals [16]

Therefore, the application scenarios of cobots are extending from traditional manufacturing to the services sector. Cobots have the potential to deliver human care services in the future while equipping with demanded features, including safe collaboration, immersive teleoperation, and affective interaction. Robot skin tightly coupled with multimodal sensing and self-contained actuation may play an important role in addressing these features by improving cobot safety, giving intuitive feedback, providing natural interfaces. As a potential enabler, robot skin is expected to be capable of proximity sensing, pressure sensing, temperature sensing, sensory feedback, and stiffness tuning, which are required for directly powering fundamentals of sensing and actuation desired in demanded features.

Apart from the application in common robots, tactile sensor systems also have great potential application value in micro/nanorobots for a variety of deep-sea exploration and biomedical applications. In virtual and augmented reality field, tactile sensors are also widely used. For example, a tactile sensor system used for real-time detection of eyeball vergence in virtual reality can treat the astigmatism of eyes at home.

Using a skin-integrated wireless haptic interface, people can touch far-away relatives (Fig. 27A). Those with disabled upper limbs can regain the sense of touch with the help of a flexible sensor system (Fig. 27B). People who play fighting games may feel the virtual pain from the game (Fig.27C). In addition, a soft virtual reality glove integrating a pneumatic actuator with a piezoelectric tactile sensor can transmit the real stimulus to the users from virtual reality (Fig. 27D).

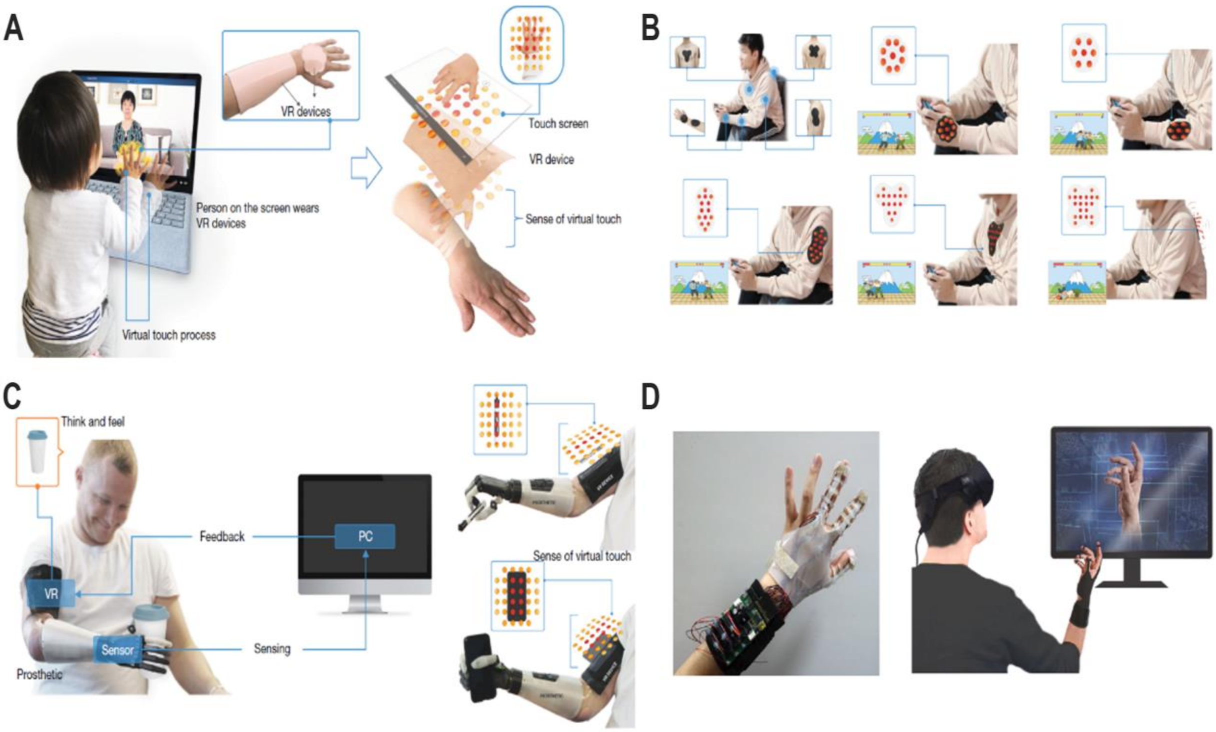


Fig. 27. Applications in virtual and augmented reality of tactile sensing systems [12].
[(A) The child touches grandmother on the screen and the grandmother wearing the VR devices on arm can feel the touch; (B) The man with disabled upper limbs has the sense of virtual touch with the help of the sensor system. (C) The man playing fighting games feels the virtual pain from the game; (D) The actual appearance of the virtual reality glove, and the man wearing the virtual reality glove can feel the real stimulus from the virtual reality]

The setup does not require the human operator to be in the same room as the patient. Therefore, it enables remote diagnostic procedures over a network.

9. Solution based on EEG-EMG

Telerobotics is a form of teleoperation in which a human operator behaves as a supervisor, intermittently communicating to a computer information about goals, assumptions, suggestions and orders suitable to a limited task, getting back information about raw sensory data, performances and difficulties and meanwhile the subordinate telerobot executes the task based on information received from the human operator and its own intelligence and artificial sensing. Robot development has always started from the model of the human body or from a part of it. That's why robotic arms know how to reproduce the movement of a human arm. This leads to the idea that, if the right sensors are used, a robotic arm can be controlled by the movements of a human arm (Fig. 28).

Because the brain is the one who sends the motion control signals, we used 2 types of sensors to “read” the signals that are given by the brain. One type of sensors are EEGs that can read the brainwave signals of a particular intent of motion and can reproduce it in actions based on pre-set mental commands.

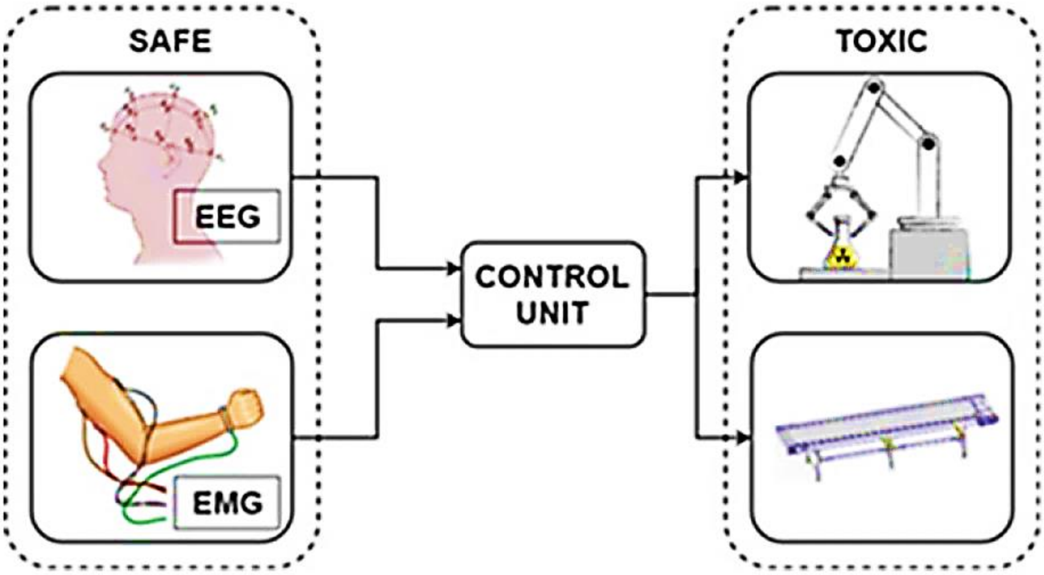


Fig. 28. Proposed solution block diagram for EEG-EMG control system [17]

During the training of the mental command, it is necessary that the user maintains a high level of attention and focus over the mental action that it is supposed to learn because these two key factors correspond to chemical reactions over the brain that give a high level of beta brainwave on the frontal cortex that is responsible, among many others, for conscious thoughts and imaginary actions formation presented in Fig. 28 as a result, from a real time recording session according to impose mental action, together with Emotiv BCI headset EEG signals quality at scalp level (Fig. 29).

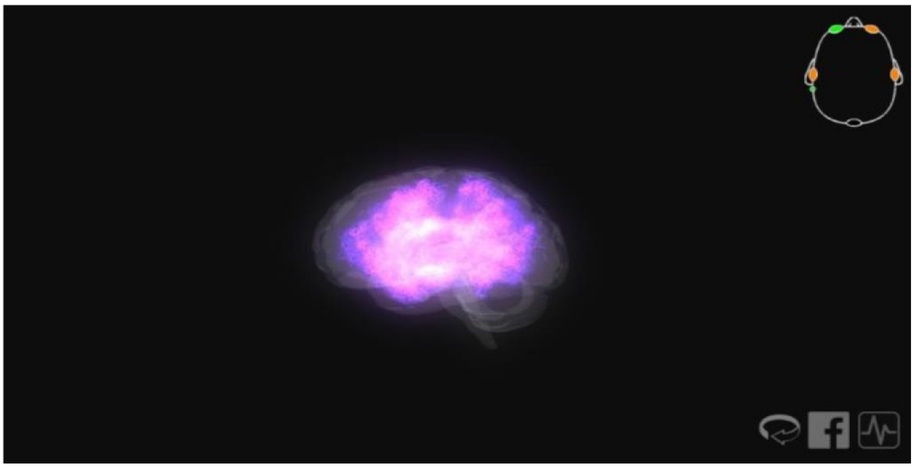
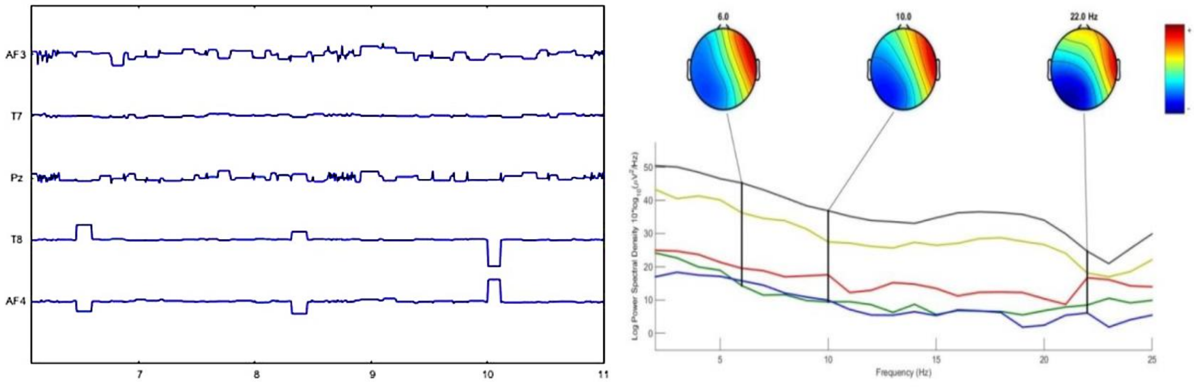


Fig. 29. 3D Brain Visualizer Emotiv Interface of beta brainwave activation for impose Lift mental action

In order to create a neural network based on an EEG solution, it is not enough just to train it, which requires, among other things, mapping each mental action to a predefined sequence of keystrokes to link the imagined movement to a robotic arm action. EEGLAB provides a programming environment that allows user to store, access, measure and manipulate the single-trial and/or averaged EEG data and display it hierarchized according to the number of EEG communication channels provided by BCI equipment.Based on its functionality it can be represented (Fig. 30) the EEG signals distributions for each one of the five EEG channels provided by Emotiv Insight BCI headset corresponding to impose Lift mental action.



(a) *(b)*

Fig. 30. (a) EEGLAB EEG Signals Plot for impose Lift mental action; (b) EEGLAB Spectral Analysis for Lift mental task

It is also able to provide a spectral analysis for every data channel using a trace of color for every particular area of the brain according to the power at a frequency between 6Hz and 22Hz, as can see in figure 6 with parieto-temporal cortex predominance.

Another type of sensors is EMG [8] used in combination with EEG sensors solution, principally due to the fact that it is too difficult to create a complex group of movements over a several servomotors in case of artificial arm brain control because of the limited mental commands that can be use at a time and also due to the absence of the movement intention that it is given by brain over a particular group of muscles of the human arm. For this reason, the role of EMG sensors is to read the electrical signal sent by the brain to each muscle group to make a movement. With this type of command for the robotic arm, a remote control can be made when the robotic arm is in a dangerous environment and must perform certain movements that do not follow a particular pattern and have to make certain movements. In this case, the human operator places sensors on him and is positioned in a safe area where he can observe the movement area of the robotic arm. The robotic arm is tied to the control unit and does exactly the same movements as the human operator. Signals purchased through the Arduino prototyping system are used as input data for the neural network that had an initial training period.

During the training period, sets of values acquired from the EMG (Fig. 31) and EEG (Fig.30) sensors were used as inputs in neural network together with signals taken from the IMU sensor to determine the position of the arm and are used as outputs of the network.

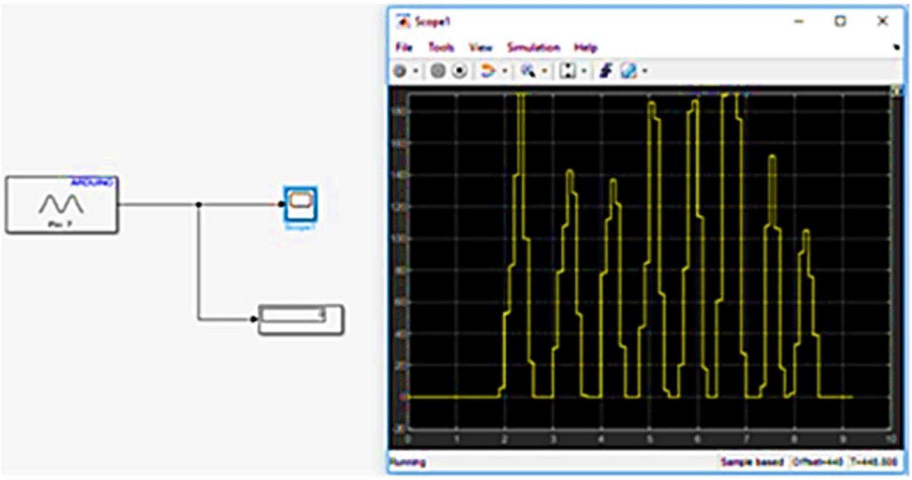


Fig. 31. EMG signal aquisition

Following the training of the network, the two types of EMG and EEG signals are used as inputs into the neural network (Fig. 32), and depending on them, the position of the robotic arm is determined.

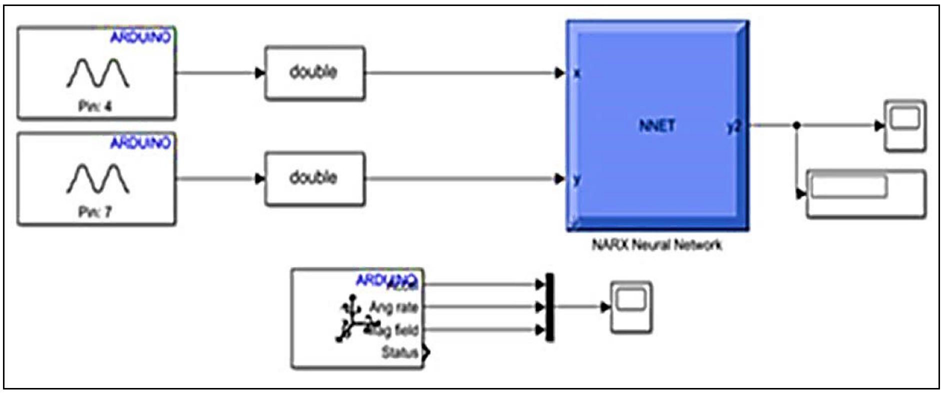


Fig. 32. Neural network based on EEG-EMG solution

IMU type signals are still displayed to see if the value displayed on the network output is roughly equal to the value still displayed by the IMU sensor.

Another example of smart sensing involves using the human brain as the source of signals in [18-28] demonstrated.

Conclusions

The EEG-EMG-based solution enables the user to manipulate a large number of substances with high potential hazard only by using his own brain signals through a neural network and in a way that gives him the capacity to view the whole process from a safe distance. In this paper we have chosen to treat a complex EEG-EMG-based solution for the control of an artificial arm because only the results offered by motor imaginary solution are not satisfying excepting the fact that electroencephalogram signals present a lower amplitude in comparison with the EMG signals because of limited number of mental commands that can be accessed at the same time through the BCI interface and which must be combined with physical commands, such as facial gestures that can also be recognized and mapped to predefined sequences of keystrokes. This makes it impossible to generate sequences that involve complex movements on a group of servomotors in real time being necessary to record the motion intention generated by each group of muscles to replicate the movement of the human arm. The EEG solution is also useful in limitation of human error produced by mental workload due to the capacity of recognizing the mental states that produced by the drowsiness state signalized by the increase of blink rate. Also, the EMG solution together with IMU sensors offers the advantage of constantly knowing the position of the robotic arm making it predictable to be used in precision operations that imply the synchronizing movements with the human operator.

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