Brain-Machine Interface: Review of Current State and Clinical Applications

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Abstract

Brain-machine interface (BMI) is a novel device that allows the translation of brain activity like action potentials in the neurons into commands and data that can be processed by machines and used. In the hope of helping neuromuscular patients with their severe disabilities, research has rapidly increased on BMIs in the past decade and a half. BMIs have been demonstrated to control robotic limbs, wheelchairs, computer cursors, and even allowed patients that are unable to talk to synthesize speech through them. In this review article, BMIs will be reviewed from its definition to the different types, invasive or noninvasive

I. Introduction

Brain-Machine Interfaces (BMIs) are novel devices that allow the translation of brain activity in terms of electric activity on the cortical surface of the brain, allowing the user to communicate with machines without moving peripheral nerves and muscles [1]. These devices provide a novel method of communication and control for humans in general with the outside world like the ability to control external devices such as personal computers to play video games, robotic arms and wheelchairs [2] [3] [4]. BMIs also show strong promise for critical neuromuscular disorders such as amyotrophic lateral sclerosis (ALS), Parkinson's disease, multiple sclerosis, etc. as it allows the usage of different neural pathways.

BMIs are typically characterized into dependent and independent BMIs. Dependent BMIs don't use the brain's normal output pathways to carry the message, but rather depends on the activity of the brain to detect a certain action. For example, in a visual experiment, instead of trying to track eye movement to activate a certain machine, dependent BMIs can detect the visual evoked potential (VEP) caused by said eye movement [5]. On the other hand, an independent BMI does not depend in anyway on the normal brain pathways, but rather depend on the intent of a user to do an action instead of actually doing it [5]. Like in the same example, an independent BMI would detect the intention to move your eyes and not the actual activity of the peripheral nerves and muscles to move the eye [6]. Because of this difference, independent BMIs have proven to have a lot more potential in clinical applications.

Any BMIs, regardless of its purpose and application, goes through four main processes as shown in figure 1: signal acquisition, feature extraction, translation algorithm, and device output [42]. These four main processes allow the main translation of the brain signals to device output. This review will go through these four main processes by focusing on Brain-Machine Interface's characterization, the different brain signals, explanation of the four processes, and decoders.

II. Noninvasive and Invasive BMIs

BMIs are also divided into two types: non-invasive and invasive. Non-invasive BMIs depend

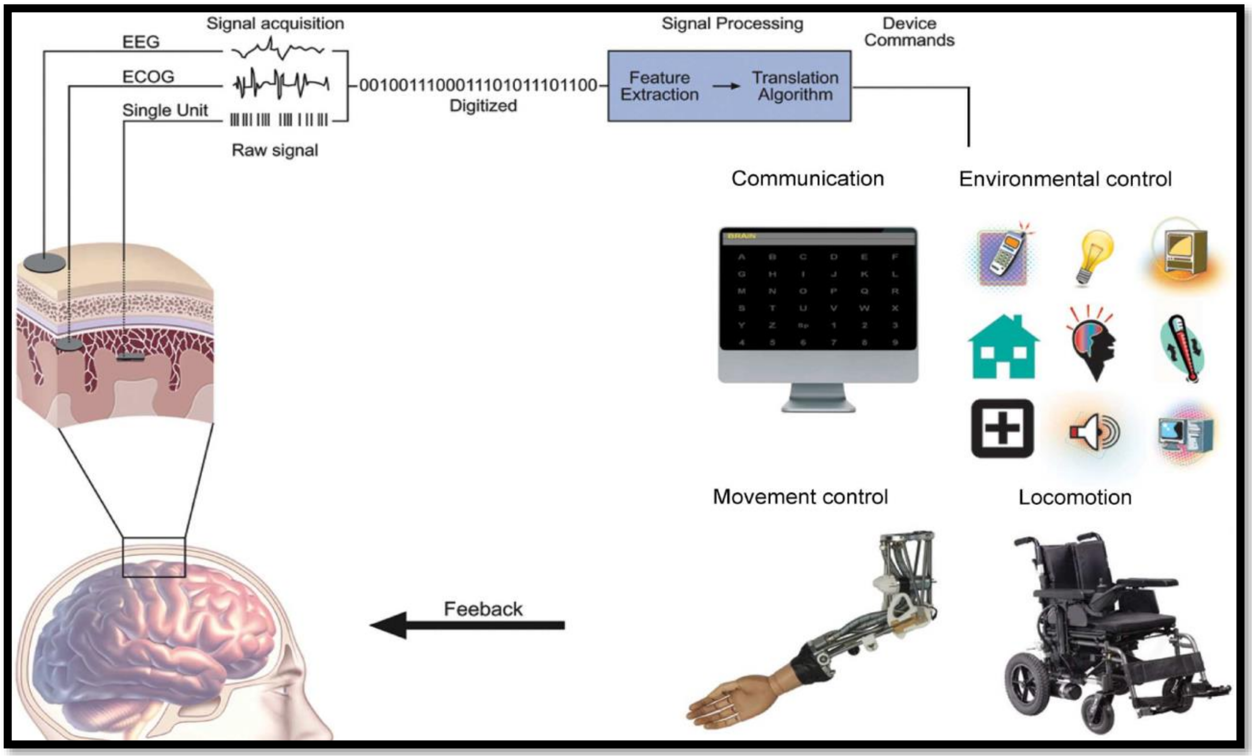

Figure 1 [42]: The components of the BMI operation, which includes signal acquisition, feature extraction, feature translation and device output. This figure further shows the potential clinical applications of these BMIs.

on electroencephalography (EEG) to detect electrical activity in the brain [10]. As neurons communicate through electric pulses in postsynaptic potentials, and thousands of neurons are firing per second, this activity is detectable through the use of small metal electrodes that are pasted on patients' scalp [7] [8] [9]. As the detected changes in voltage due to the many neurons' firing is very small, the electric pulse is usually amplified and then printed as a sequence of voltage changes over a certain brain area [9]. The area over which the electrodes are placed depends on the purpose of the EEG as for example, if examining the reaction to visual stimuli, electrodes are placed over the occipital cortex [7] [9].

Invasive BMIs require surgical implantation of electrodes in the brain, which means they require opening the scalp and skull and penetrating the brain tissue [10]. They are not preferred over non-invasive BMIs due to the possible risks like infection, especially if the implant is not entirely contained within the brain. Invasive BMIs are classified into five main types: local field potentials, single-unit activity, multi-unit activity, electrocorticography (ECoG) and calcium channel permeability [10].

Local field potential (LFP) is the transient electrical signals, which are formed from the combination of large neuronal populations, in the order of tens of thousands [11]. While singe-unit invasive BMI detects the activity of single neuron's action potentials, the multi-unit invasive BMIs detect the activity of multiple neurons at the same time. For instance, a single-unit BMI would only decode specific neuronal activity in an area like motor commands in M1 or cognitive signals in PP [12]. These methods usually employ extracellular methods to record and discriminate postsynaptic potentials generated by the hundreds of cortical neurons [12].

Furthermore, the fourth type electrocorticography is sometimes considered a semi-invasive method because it requires surgical procedure to remove a part of the skull, but it doesn't penetrate any brain tissue. ECoGs are basically EEGs attached to the surface of the brain itself, where a grid of electrodes detects the activity of the brain [13] [14] [15]. ECoGs could be epidural or subdural, where the difference is that the latter's dura mater is left open. This allows for better accuracy and detection as shown in [16]. They are advantageous over normal EEG-BMIs because they have better spatial and temporal resolution [17]. Still, its performance and accuracy can't still rival with invasive BMIs [16] [17]. Lastly, the calcium channel invasive BMIs (CaBMI) were developed in [18], where ten mice were genetically modified to express a calcium indicator gCaMP6f in L2/3 of both primary motor M1 and somatosensory (S1) cortices. Two-photon calcium imaging were used to record activity in the small field of view [18].

III. Brain Signals Detectable by Noninvasive BMIs

Non-invasive BMIs detect seven types of signals: slow cortical potentials (SCP), sensorimotor rhythms, P300 event-related potential, steady-state visual evoked potentials, error-related negative evoked potentials, blood oxygenation level and cerebral oxygenation changes.

i. Slow Cortical Potentials (SCP)

Slow cortical potentials are the occurrence of cortical polarization, which can be easily recorded using direct amplifiers from any location on the scalp [5]. They usually occur over 0.5-10.0 seconds. Voltage changes across the scalp can be either positive or negative; while BMIs detect negative SCPs during movement causing cortical activation, they detect positive SCPs which are caused by reduced cortical activation [19] [20]. In Birbaumer studies, it was shown that it is possible to control SCPs and even control the movement of a cursor on a computer screen [21]. In [22], a thought translation device (TTD), a non-invasive BMI, has been developed, where it was able to deliver basic communication with late-stage ALS patients in [23].

ii. Mu and beta rhythms

Mu and beta rhythms from somatosensory cortex sinusoidal frequencies in ranges 8-13 Hz that are detected by BMIs at the somatosensory and motor cortical regions [10]. These rhythms decrease in amplitude as movement of the body increases. Sensorimotor rhythms of Fp1, Fp2, F3, Fz, F4, T7, T8, C3, Cz, C4, Cp3, Cp4, P3, Pz, P4 and Oz were recorded using 16 EEG channels in [24] to control cursor movement in a computer screen, which achieved more than 50% accuracy (p-value lower than 0.001).

iii. P300 event-related potential

When the somatosensory cortex gets activated through significant auditory, visual, or any stimuli, it typically evokes the non-invasive BMI over the parietal cortex at about 300 milliseconds [25]. Thus, it was named P300 event-related potential as it only evokes at 300 ms when any event occurs causing a particularly significant stimuli to the patient [5]. The signal of the potential increases in amplitude when the patient maintains greater attention to that specific stimuli [10]. Using P300 event-related potentials in [26], a paradigm has been introduced that have been used as a BMI spelling application in [27], [28], and [29].

iv. Steady-state visual evoked potential (SSVEP)

Steady-state visual evoked potentials are signals evoked from the occipital cortex during the occurrence of periodic presentation of visual stimuli of 6 hertz [10]. A survey showed that SSVEP can be utilized by presenting a rendered visual stimulus (RVS) to the user through alternating graphical patterns on computer screens [31]. Even more, [30] developed a novel independent SSVEP-BMI based on covert attention that helped locked-in syndrome patients. However, SSVEP BMIs are limited as they depend on attentional capacity and vision, which is mostly compromised in patients with more severe neurological diseases [5].

v. Error-related negative evoked potentials (ERNP)

ERNPs occur 200-250 miliseconds after "the detection of an erroneous response in a continuous stimulus-response sequence [10]." For instance, when a patient is subjected to continuous visual stimuli and then has to pick out a certain stimuli of the bunch, a P300 event-related potential is evoked if the target stimuli is found. However, if any stimuli occur other than the target, then the error-related negative evoked potential occurs [32].

vi. Blood Oxygenation Level

This type of BMI doesn't depend on EEGs but instead of functional MRIs. Blood oxygen level-dependent fMRI detects the metabolic activity in the brain, which represent the changes in neural activity [10] [33] [34] [35]. BOLD was used in the past in patients with neuropsychiatric disorders in which a novel brain self-regulation technique that crosslinked psychological and neurobiological approaches through utilizing the neurofeedback of the fMRI [37]. The results were rather promising as the patients' Hamilton Rating Scale for Depression improved significantly in [37].

Real-time control of robotic arm was demonstrated to be possible using real-time functional MRI that detected the blood oxygenation level dependent signals from the regional cortical activations in the primary motor area M1 [36]. This allowed the movement of the robotic arm only through the subjects' thought processes.

vii. Cerebral oxygenation changes

Near Infrared spectroscopy (NIRS) is an spectroscopic technique that measures light absorbance to calculate oxy-HB and deoxy-HB, which provides insight of brain activity [37]. NIRS is characterized with high temporal resolution and spatial resolution. NIRS has enabled non-invasive measurement of the cerebral oxygenation changes through BMI in patients [40]. As EEG-BMI have not succeeded with complete locked-in state patients [41], metabolic brain-machine interfaces based on near-infrared spectroscopy has provided a novel method to allow the slightest communication for these patients.

IV. Signal Acquisition

Signal acquisition is basically the measurement of the neurophysiologic state of the brain, where the BMI is tracking the aforementioned signals in the brain [42]. These signals will reflect the person's intent to do a certain action, which is used to drive the brain-machine interfaces [1]. These signals will be acquired in various techniques, which include, but aren't limited to, electrodes on the scalp recording EEG, electrodes beneath the skull and over the cortical surface of the brain recording electrocorticography, and, lastly, LFPs and neuronal action potentials recorded by invasive BMIs – microelectrodes - within the brain tissue [1]. After that, these signals are amplified and then digitized to move into signal processing [42].

V. Feature Extraction

The first step of signal processing is feature extraction, which is the extraction of main changes in signals that are encoding the intent of the user [42]. To have the highest efficiency and effectiveness, the extracted features should be highly coherent with the user's actual intent. The digitized signals from the signal acquisition step are passed through certain procedures like spatial filtering, voltage amplitude measurements, spectral analysis, or single-neuron separation [1]. For example, the firing of a specific cortical neuron or the rhythmic synaptic activation in sensorimotor cortex, producing a mu rhythm. The location, size and function of this cortical area generating the evoked potential is essential to know how it should be recorded and how users will adapt to control its amplitude [1]. To analyze the neuronal signals, time domain or frequency domain analyses is utilized with respect to time or how much a certain signal is present among a given frequency band respectively [43]. Both the time domain, such as evoked potential amplitudes or neuronal firing rates, and frequency domain, such as mu or beta-rhythm amplitudes, are used to analyze the signal features in BMIs [1] [44] [45]. Even more, a study has shown that both these domain and frequency-domain signal features, improving performance and accuracy [46]. Furthermore, BMI could use other pathways like autoregressive parameters, which correlate with the user's intent but don't necessarily represent what is actually happening in the brain [1]. Finally, the signal is sent into the next step: translation algorithm

VI. Decoding of brain signals

After the BMIs extract the features of the signal, either invasive or non-invasive, computational algorithms are employed to translate these neuronal activities for direct communication with the brain [17]. These algorithms, often called decoders, use statistical and machine-learned techniques to translate these signals. Decoders are especially utilized in BMIs that have multiple input and outputs, which are provided by neural recording channels [17]. This algorithm might use linear methods like statistical analyses or nonlinear methods like neural networks [47]. Through this algorithm, the signal features are changed into commands that could be understood [1].

When a new user first uses the BMI, the algorithm attempts to adapt to the user's static features, adjusting to the user's feature signal like mu-rhythm, P300 event-related potentials and single cortical neuron's firing rate [1]. However, being subjected to different times of day, hormonal levels, recent events, fatigue, illness, and other factors causes short-term variations in the signals detected from BMIs. Therefore, another level of adaption is always employed that reduce those instant variations. To further increase adaption of the algorithm, effective interaction between the BMI and the user's brain is accommodated by engaging the adaptive capacities of the brain. As you train the brain by achieving the expected results of BMI operation, the brain will adapt over time and modify the output signal due to its plasticity, improving the operation of the BMI. Usually, this has been done by rewarding the user by any means after successful use to help increase plasticity's chance to favor strengthening the signal.

VII. Device Output

After signal acquisition, feature extraction and going through decoding algorithms, the signal is then passed through its final phase, which is the translation of that signal into an action. This action could be the selection of words through a computer screen [48], move the cursor on a computer screen as tested in [49], [50] and [51], neuroprosthetic control of wheelchairs [52] [53] and robotic limbs [54] [55] [56].

VIII. Conclusion

Full recovery for patients with motor progressive diseases, as of right now, is not possible, as diseases like amyotrophic lateral sclerosis (ALS), Parkinson's disease, multiple sclerosis still don't have viable treatments that can stop the progression of them [57] [58] [59]. Patients with severe trauma caused by stroke, cerebral palsy, or injury to the spinal cord or brain also have little to no full motor recovery [60] [61]. Thus, researchers have been attempting to develop ways to improve these patients' quality of life as most of these neurological conditions are permeant.

Brain-machine interfaces hold great promise for being that solution for these disabling neurological disorders, from helping completely locked-in patients achieve control of computer cursors, wheelchairs, robotic arms [54] [55] [56], and even speech synthesizers [62]. Although most of these ideas are still early for clinical application, most of them hold promise but are still just lacking due to the limited number of electrodes – no more than 256 electrodes - that can be used in invasive BMIs. However, this is all changing soon as Neuralink, a project started by Elon Musk, is proposing a scalable high-bandwith novel BMI system, that has as many as 3072 electrodes per array. In this ground-breaking project, they have also built a neurosurgical robot capable of inserting 192 electrodes per minute into patients' brains [63]. This new BMI system will also house on-board amplification and digitization system in less than 27 x 18.5 x 2 mm^3 [63]. This approach to BMIs has allowed an unprecedented packaging density and scalability and also in a small footprint that is clinically relevant [63].

IX. References

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