Brain Controlled Robots: A Survey
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Abstract
A few decades back, the notion of controlling a robot with the mind would have seemed ludicrous and almost fictional, though with extensive research in the field of bio-mechatronics the idea today has become a reality. Brain controlled exoskeletons, prosthetics and wheelchairs have progressed from machines in sci-fi to nearly commercialized products. Brain controlled robots are based on Brain Computer Interface (BCI). This paper is delves into the technical aspects involved in BCIs and also provides an overview of some state-of-the-art BCIs.

Keywords- Electroencephalogram (EEG), Magnetoencephalography (MEG), Brain Computer Interface (BCI), Motor Imagery (MI), brain controlled robots, Human Machine Interaction (HMI)

I. INTRODUCTION

In the recent years the development of brain controlled systems have revolutionized the way we humans interact with robots. Jacques Vidal’s work in 1973 illustrated the potential of the human mind to control robots [1]. Brain Controlled Interface (BCI) permits humans to directly communicate with machines (robots) without any movements, physical or neurological. Brain Robot Interface (BRI) has emerged from the field of BCI and is now gaining the attention of several researchers [2], [3]. Since it’s emergence, BCIs have found their application in various sectors. In military BCIs can be used to remotely control robots using the especially developed/captured signals from the cortex of the brain [2]. In the healthcare sector such systems are being used for assistance and rehabilitation of the disabled subjects. These BCI systems, in particular are used to control prosthetic devices that can help patients suffering from ALS (Amyotrophic Lateral Sclerosis) and Locked-in Syndrome (LS) to retrieve their motor functions [3].

II. BCI WORKING

Every activity we perform results in a pulse in the brain. These pulses when recorded can be used for understanding a person’s intent. BCIs record these brain pulses and process them in such a manner so that it can be understood by a robot/controller. The robot then performs certain tasks depending upon the signals received. Thus signal processing is an integral part of a BCI system, as it extracts useful data from these recorded signals.

A. Brain Signal Acquisition

There are two ways in which brain signals can be recorded: a) Invasive and b) Non-Invasive.

Invasive method: This method requires surgery to implant micro-electrodes directly inside the cortex. In this method highly localized single unit spike activity of the brain signal can be recorded with high degree of fidelity.

Non-Invasive method: In this method macro-electrodes are places on the scalp of the head to record various signals like EEG, and MEG [6]. These signals monitor the macroscopic responses of various cortical areas evoked by external stimuli [35].

Invasive measurements have better resolution but require incision [25]. As there is always some risk involved in surgery, non-invasive methods are mostly preferred for patients with disabilities and for basic research.

As mentioned earlier there are several techniques to non-invasively record neural signals. Some of them are discussed below.

Electromyography (EMG)
The muscular cells of the skeletal muscle produce electric potentials when electrically or neurologically activated. These potentials are detected with EMG.

Magnetoencephalography (MEG)

Brain activities produce electrical signals. The magnetic fields of these signals can be recorded by MEG, which can be analyzed and then be used in BCIs. Sensitive magnetometers are used to detect these magnetic fields and predict subject’s intent.

Electroencephalogram (EEG)

EEGs record the electrical fields produced by the brain during neural activity. It does so by measuring the voltage fluctuations of the electrodes that are placed on the scalp of the head [11].
These signals are then amplified and transmitted to the BCIs for further processing.

B. Why use Electroencephalogram (EEG)?
Out of the above-mentioned techniques, EEGs are widely used in modern BCI systems due to their many advantages.

Advantages of EEG:
EEG signals have high temporal resolution hence accurate measurements can be recorded with respect to time [5].

EEG devices are low cost and portable hence preferred over others like MEGs that require bulky equipment along with magnetically shielded rooms making it an inconvenient process [5].

Disadvantages of EEG:
EEG signals have poor spatial resolution; hence images recorded are highly pixelated and not clear. The spatial resolution of a single electrode is in the order of a centimeter of a cortex, which contains thousands of neurons. Strong electric fields picked up by nearby electrodes [6] also affect the signal and make the pinpointing of the exact source of the activity difficult.

Voltages measured through EEGs are extremely small (in μV to nV range) making them vulnerable to external interferences [7].

Even with these drawbacks EEGs are still a preferred choice in research as they are cheap, safe [25] and have decent accuracy [15].

The domain of EEG based BCI is broad and they find various applications, from controlling a cursor on the screen [4] to moving a full-fledged humanoid robot [8].

C. EEG BCI Methods

BCIs are categorized into 4 types based on the EEG brain activity patterns they work with: 1) P300 [42] 2) Slow Cortical Systems [46] 3) SSVEPs [7], [15] 4) ERD/ERS [43].

1) P300
P300 signal is one of the typical patterns captured from EEG at the central cortex region of the brain. It has a positive potential component (shows positive deflection) that occurs at an interval of about 300ms after stimulus [10]. This stimulus may be visual, auditory or somatosensory. Researches have shown that P300 is a robust way to control Brain-controlled robots [10]. A number of P300 based BCIs have been mentioned in the literature [8], [10], [27], [20], [21].

2) Slow Cortical Systems
Slow Cortical Systems detect brain waves like slow cortical potentials or neural oscillations (alpha, beta, gamma rhythms). These waves are generated due to changes in the membrane potentials that usually last from 300ms to several seconds. These rhythms are also known to be affected by attention levels hence require training of the subject [11].

3) SSVEP (Steady-State Visual Evoked Potentials)
Studies have suggested increased neural activity elicited by gazing stimuli [12]. These stimuli result in stable voltage oscillation patterns in EEG that are called SSVEP [13]. SSVEP contain the same primary and some harmonics of the fundamental frequency of light that evokes the stimuli [13]. A number of researchers have used SSVEP in their experiment [7], [15], [44].

4) ERD/ERD
During certain mental tasks like Motor Imagery (MI), mental arithmetic, the synchronized patterns of the mu rhythms are desynchronized [14]. These changes when recorded and analyzed reflect the subject’s intentions and are hence used in BCIs.

Out of the above-mentioned methods, P300 and SSVEP BCIs are called exogenous (or synchronous), as they are based on external stimuli whereas ERD/ERS BCIs are independent of external stimulation and hence called endogenous(or asynchronous) BCIs [15]. Since endogenous BCIs do not require any external stimulus, they seem to be a more appropriate choice for brain-controlled robots, as the subject needs to only focus their attention on driving the robot rather than focusing on external stimuli.

There have been several asynchronous BCIs mentioned in the literature though studies have shown that they have some drawbacks.

Drawbacks of Asynchronous BCI systems
Asynchronous BCIs require extensive training of the subject and the time duration may run into weeks. Such a system is very inconvenient for people with disabilities [16].

Its performance varies broadly from person to person, as its accuracy depends majorly on the attention levels of the subject.

The rate of information transfer is comparatively lower than synchronous types and hence speed performance is an issue [16].
On the contrary, synchronous BCIs have lower training periods and comparatively have a better performance in terms of transfer rates and accuracy [see Fig. 3].

![Fig. 2 Comparison of P300, SSVEP and ERD/ERS with respect to time and information transfer rates [13].](image)

Table I lists various publications with the type of BCI EEG system used.

<table>
<thead>
<tr>
<th>Publication</th>
<th>BCI type</th>
<th>Control</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rebsamen et al[17]</td>
<td>P300</td>
<td>Wheelchair with emergency halt</td>
</tr>
<tr>
<td>Andrew McDaid[7]</td>
<td>SSVEP</td>
<td>Lower Limb</td>
</tr>
<tr>
<td>Narendra[18]</td>
<td>MI</td>
<td>Humanoid Robot</td>
</tr>
<tr>
<td>Guneysu[44]</td>
<td>SSVEP</td>
<td>Robot Arm</td>
</tr>
</tbody>
</table>

A hybrid model, which uses more than one of the BCI models have also been used in some researches. Allison et al. [19] used a hybrid MI and SSVEP BCI model and got a high classification accuracy of 81.0% compared to SSVEP (76.9%) or MI (74.8%) alone. Another group of researchers combined MI and P300 and used it for target selection [20]. They achieved a high accuracy rate of about 94% in their experiments. Furthermore they used this hybrid paradigm to control a wheelchair [21]. Lin et al. [22] used both MI and Selective Sensation [48] (another example of ERD/ERS) and results showed an accuracy of 90%.

D. Signal Acquisition

Signal Acquisition involves the process of collecting the EEG signals from the brain through BCIs. This is done by placing electrodes on the scalp of the head.

1) Electrodes

Electrodes are an important component of BCI devices as they create a pathway between the brain and the BCI itself. Quality of the electrodes can go a long way in decreasing the Signal to noise Ratio (SNR). Discussion on signal noise has been done in the next section. 

Electrodes are usually classified into wet or dry types depending upon the presence of electrolytic gel between the skin and the electrode [23].

Ag/AgCl, an example of wet-type electrode, is widely used in a number of modern day BCIs. This is because they have a low contact impedance, good stability and are affordable.

Besides wet electrodes, there is also a mention of dry electrodes in the literature. Lee et al. [15] designed a BCI gaming interface using IMEC dry electrodes. Results showed that they are more comfortable and convenient for the user to wear, as the process of placing wet electrodes is cumbersome. Dry electrodes are usually not used as they have high contact impedances.

![Fig.3 Wet Ag/AgCl electrode used in McDaid’s experiment [7].](image)

2) Placement of electrodes

Another important aspect of EEG signal acquisition is placement of electrodes on the scalp. The International 10-20 system is used globally as a standard method. “10” - “20” refers that the electrodes are placed at a distance of 10% or 20% of the total front-back or left-right length of the skull. Depending on the EEG Signal used, the positions of the electrodes differ. For P300 BCIs, the signals are recorded in the inferior frontal, central, and parietal regions; for SSVEP BCIs, electrodes are placed in the occipital region [24].

Various devices used for signal acquisition in BCIs have been listed in Table II.

<table>
<thead>
<tr>
<th>Publication</th>
<th>Electrode Type</th>
<th>EEG hardware</th>
</tr>
</thead>
<tbody>
<tr>
<td>Keun-Tae Kim[40]</td>
<td>Wet(Ag/Ag Cl)</td>
<td>BrainAmp</td>
</tr>
<tr>
<td>Hyun Seok Kim[41]</td>
<td>Wet-type</td>
<td>PhysioNet</td>
</tr>
<tr>
<td>Lee[15]</td>
<td>Dry-type</td>
<td>IMEC headset V1</td>
</tr>
</tbody>
</table>
After choosing the suitable type of brain signal and then acquiring the signal, the next step is Signal Processing.

E. Signal Processing

Signal processing includes signal filtering, feature extraction and classification. These steps may differ depending on the BCI component used (P300 or MI or SSVEP) e.g. Feature extraction for the P300 uses unsupervised tempo-spatial filter based on Principal Component Analysis (PCS) whereas MI uses supervised spatial filter like Common Spatial Feature (CSP) [25].

Signal processing is essential as it attenuates the artefacts and noises present in the acquired signal, crucial for enhancing the relevant information [26].

Below the three major components of signal processing have been discussed.

1) Signal Filtering

Signal Filtering involves removal of artefacts and noises from the EEG signal. This step is also called signal pre-processing.

Common Sources of artefacts in EEG signals-
- External electromagnetic fields like power-line noise that interfere with the neural signals.
- Changes in the impedances of the electrodes due to changing skin resistance caused by sweating, reduced electrode pressure, etc.
- EEG equipment interferences caused by moving cables, electrode drifts [11].
- Muscular Activities. e.g. Eye blinks, eye movements and heart beats.

Artefacts caused by muscular activity is a major cause of concern as these sometimes mislead researchers by mimicking the actual EEG based control e.g. the subject can affect the EEG output by merely moving an arm or moving their eyes.

Thus this step is an important part of signal processing. Band pass and Notch filters are commonly used filters in BCIs [27], [43], [41], [42].

Table III lists the type of filters used in several BCIs.

<table>
<thead>
<tr>
<th>Publication</th>
<th>Filter type</th>
<th>Frequency suppressed</th>
<th>Sample Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dilok Puanhvun [27]</td>
<td>Notch Filter</td>
<td>50Hz</td>
<td>200Hz</td>
</tr>
<tr>
<td></td>
<td>Band Pass filter</td>
<td>0.5-35Hz</td>
<td></td>
</tr>
<tr>
<td>Seok Kim[41]</td>
<td>Band Pass filter</td>
<td>6-30Hz</td>
<td>-</td>
</tr>
<tr>
<td>Lin Yao[22]</td>
<td>Analog Bandwidth Filter</td>
<td>0.5-70Hz</td>
<td>250Hz</td>
</tr>
<tr>
<td>Pablo Lana[43]</td>
<td>Band Pass filter</td>
<td>0.1-100Hz</td>
<td>600Hz</td>
</tr>
</tbody>
</table>
large number of parameters to tune, which is difficult if the relationships are poorly understood as in the case of EEG. They produce nonlinear decision boundaries. Furthermore, they are generative, which enables them to perform more efficient rejection of uncertain samples than discriminative classifiers. However, these classifiers are not as widespread as linear classifiers [34] e.g. Artificial Neural Network (ANN).

In recent years, Artificial Neural Network (a non-linear classifier which uses radial based function network to categorize signals) has also been implemented in a number of research experiments. Khare et al. [51] used WPT along with ANN to move a brain controlled wheelchair in various directions i.e. forward, backward, right, left and stop. Their experiment achieved a remarkable 100% accuracy.

Dasgupta et al. [35] used an SVM classifier to control an iRobot to move in various directions. Tweaked matching classifier algorithm helped improve accuracy results by almost 4%.

F. Shared Control
As the name suggests, shared control intelligently switches the control of the device between the subject and the controller. This is intended to overcome problems such as dangerous situations and accidents, inaccuracy of human control, as well as fatigue during a continuous control over a device, due to the lack of human control capacities [37].

Geng et al. [38] proposed a shared control system to develop brain-controlled mobile robots, where the user controls the turning left and right by imagining moving his/her left and right hands, and the navigation system controls going forward at different timing switched by the user via imagining moving his/her feet.

Satti et al. [39] used another kind of approach to develop a robotic system, where the user controls the robot by the BCI based on motor imagery, whereas the intelligent controller is only triggered in the situations of obstacle avoidance and corridor following in an automatic way. This research especially caught attention of the people as it provided an automatic switching control between the user and the controller hence more useful for disabled people.

Once the signal is processed, the data is then transferred to the robot or a microprocessor to get a desired task. The robot may be a prosthetic arm, a wheelchair or even a full-fledged humanoid.

III. RECENT BRAIN CONTROLLED ROBOTS

A. For rehabilitation purposes, a team of researchers at the University of North Florida have used a visual matrix (Fig. 9) to control a robotic arm. The matrix had flashing symbols that evoked brain signals which were recorded through BCI and then mapped into control commands for three dimensional motion of the robotic arm [45]. P300 signals were captured and processed by the BCI2000 software. This was a fully autonomous system and aimed at providing a long-term solution to disabled people.

B. At the 4th Annual IEEE conference on cyber technology in automation, control and intelligent systems, 2014, a team of researches presented a humanoid robot (HRP-2) controlled via a BCI using SSVEP [53]. A live feedback from the robot embedded camera is displayed on a Head Mounted Display (HMD) that is attached to the subject’s head. This acts as a source of stimuli for the user. The robot moves towards the subject and poses finally such that it can interact with the subject. The researchers used a new navigation algorithm known as visual SLAM feedback mechanism. SLAM helped in creating real time maps in order to detect objects while walking. Results showed that the robot got confused and there was a significant reduction in the BCI performance as the robot came close to the subject. Thus proving difficulty in designing an accurate BCI-controlled manual navigation system.

C. Low-level control in semi-autonomous rehabilitation robotic system via a Brain-Computer Interface [54]
Thorsten Lüth et al. demonstrated how a robotic arm attached to the FRIEND II can be controlled by a user in case something goes wrong during the execution of high level tasks like “grab the bottle” or “pour the beverage”. It follows the principle of semi-autonomous technique. During the task execution, the sensors (camera, artificial skin, etc.) of the system may sometimes fail to provide enough precise position information. After the user completes this task the system then proceeds with the completion of other tasks as planned. The control architecture MASSIVE was used with the FRIEND II robot. MASSIVE has a unique feature of extracting information from various input devices (speech, BCI, mouse, etc.). The processing structure is shown in figure 21 below.

The methodology is illustrated in Figure below.

![Fig. 8 Khepera robot framework](image)

**IV. CHALLENGES**

A. **BCI Illiteracy**

In a number of experiments conducted by researchers it was found that the performance of the BCIs varied vastly between different subjects[9]. According to a latest survey it was found that BCI control does not work for about 15%-30% of the test subjects[47]. This is called ‘BCI Illiteracy’ and is currently one of the biggest challenges of BCI research. In order to overcome this problem, a group of researchers from Berlin Institute of Technology, Germany [47] used a “supervised adaptation” method and came up with good results. Eleven subjects took part in the study. Subjects were divided into three categories: (I) a classifier could be successfully trained for such subjects and who performed feedback with good accuracy; (II) a classifier could be successfully trained, but feedback did not work well for these subjects; (III) no classifier with acceptable accuracy could be trained. Six subjects belonged to Cat. I, two further subjects belonged to Cat. II and three subjects to Cat. III. 100 test runs were performed and the results were plotted. Using their machine learning techniques researches managed to achieve increased performances with proceeding test runs. The figure below shows improved results in all three categories with the implementation of the adaption paradigm.

![Fig. 9 Feedback accuracy [%] comparison](image)

B. **Subjects**

Another major problem faced by researchers is using BCI systems with “locked in” patients (patients whose inherent ability to transfer information is extremely limited). Studies suggest that good performance of a BCI system for healthy population may not necessarily mean a good performance with disabled people. Another problem is the large variation in

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*Fig. 7 Processing structure of the BCI*
the training period between subjects. Ortner [50] in his experiment showed how the performance dropped for the disabled subjects. Accuracy of these systems is also affected by the state of mind of the subjects. Poor attention levels due to illness or fatigue are known to reduce the accuracy levels [5].

Aging is another factor that hampers the efficiency of BCIs. It is often observed in older subjects that an insulation of plaque on the receptors of the neurons that subdues signal quality. Some neurons damaged due to accident or aging also loose their acumen and have difficulty in resetting after a lapse.

C. Environment

In most of these research experiments the test conditions and environment were under controlled settings with highly specific tasks, like moving a robot from point A to point B. Implementation of such systems in the real world is still not possible as there are several more parameters that the BCI systems yet cannot handle.

V. CONCLUSION

This nascent field of bio-mechatronics is unexplored. We still have a long to way. Current BCI systems are not fully reliable and the rate of accuracy is also a concern. More research should be done in identifying new modes of brain signals that give a more detailed insight on the state of our mind. “Hybrid" BCIs are also a growing research topic. Most BCIs still rely only on a single type (P300 or ERD or SSVEP) of brain signal to identify our intentions. Though as mentioned, there is a problem of ‘BCI illiteracy’ associated with these systems. Hybrid systems somewhat overcome this issue and broaden the user coverage. With continued research and development, BCI systems can bridge the gap between technology and people with disabilities. Not just in the healthcare sector, BCIs can also be used in military, entertainment, agriculture, and education. The goal is to make the interaction of humans with robots flawless and that can only be possible once our BCI systems can work in real world environment with high accuracy over any given condition/task or subject. Some researchers also question the prospect of BCIs as it sometimes appears to be a weaker proposition for realistic implementation. More research is needed in making BCI systems more efficient, robust and economical. This paper hopes to assist researchers with identifying current trends in BCIs and also overcoming the challenges and issues currently present.

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REFERENCES


