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SURVEY OF BRAIN COMPUTER INTERFACE SYSTEMS

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Abstract— The Brain Computer Interface (BCI), called also often a Mind Machine Interface (MMI), or in other cases called a Brain Machine Interface (BMI), is a direct communication link or a communication pathway between the human brain and an external device. In case of the BCI system, user's communication channels do not rely on peripheral nerves and muscles.

Brain computer interface (BCI) systems offer communication and control capabilities to people with severe disabilities. BCI's use electroencephalographic (EEG) signals recorded from scalp to control computer cursor movement, select letters or icons on the screen, etc.; but there exist other invasive methods too to record the brain's activity.

One example of BCI application is the EEG-based brain-controlled mobile robots, that can serve as powerful aids for severely disabled people, especially people with "locked in" syndrome in their daily life, to help them move voluntarily and communicate with the external world.

Keywords — BCI general description, BCI survey, brain-computer interface (BCI), brain-controlled mobile robot, EEG

I. INTRODUCTION

A. WHAT is a BCI?

THE Brain Computer Interface (BCI), called also often a Mind Machine Interface (MMI), or in other cases called a Brain Machine Interface (BMI), is a direct communication link or a communication pathway between the human brain and an external electronic or electro-mechanic device. A BCI is a communication and control system that does not depend on the brain's standard neuromuscular channels or its normal output channels. The user's intent is conveyed by brain signals instead of by peripheral nerves and muscles - it means the realization of these brain signals do not depend on the body's neuromuscular activity. With other words, BCIs translate brain activity into command and control signals.

A BCI establishes a real time interaction between the user – at one side, and the outside world – on the other side. The user receives feedback reflecting the result of the BCI's operation, through his/her eyes and that feedback can affect the user's next intent and its expression in brain signals.

Current BCI's use electroencephalographic (EEG) activity recorded from the scalp which records brain activity signals from cortex to control computer cursor movement, select letters or icons on the screen, but there are other invasive methods too to record the brain's activity.

BCI operation depends on the interaction between two adaptive controllers: the first is the user, who encodes his or her commands in the electrophysiological input provided to the BCI, and the second is the BCI, which recognizes the commands contained in the input signal and expresses them in device control. Current BCI's have maximum information transfer rates of 5–25 b/min [1].

B. Early History

Electrical signals produced by brain activity were first recorded from the cortical surface of animals by Richard Caton in 1875 and from the human scalp by Hans Berger in 1929. In this almost 85 years since Berger's report, electroencephalography has been used the most for clinical diagnosis and/or for exploring brain function. Scientists have speculated that the EEG might provide the brain with another means of transferring messages and commands to the external world. EEG and other methods suggested the possibility of non-muscular communication and control, which is achievable through a brain–computer interface (BCI) [1].

C. Recent interest and activity in BCI

This recent interest and activity around BCI is focused on the next four factors. The first is the increased appreciation of needs and abilities of people, who are severely affected by paralysis or by the "locked-in" syndrome motor disorders, such as cerebral palsy, spinal cord injury, brain stem stroke, amyotrophic lateral sclerosis (ALS), etc. Even people who are totally "locked-in" to their bodies, unable to communicate, can lead their lives, if they can be provided with even the most minimal means of communication and control.

The second factor is the highly increased understanding of the nature and biology. This new knowledge and technology are guiding and supporting BCI research and development.

The third factor contains the technical part, more exactly the availability of powerful and low cost computer hardware. This allows complex real time analyses of brain activity, which is essential for BCI operation.

The fourth factor is recognition of the remarkable adaptive capacities of the human central nervous system (CNS), both in normal life and in response to damage or disease. This capacity recognition has generated great excitement and interest between the scientists and there is the possibility of engaging these adaptive capacities to establish new kind of interactions between brain tissue and computer-based devices. The new interaction possibilities probably will augment the brain's normal neuromuscular interactions with the world [1].

The percentage of BCI articles based on invasive methods decreased from 43% to 25% between 2007 and 2011, although the absolute number did not change significantly. These trends mean that new investigators in BCI research tend to select EEG as the most important neural signal recording modality. This trend is because EEG studies can be conducted relatively easily compared to invasive studies, which are facing ethical issues [2].

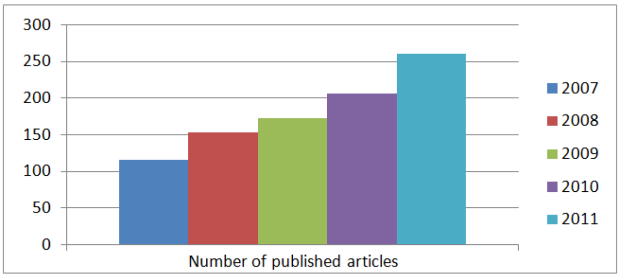

Fig. 1. The number of published brain–computer interface (BCI) articles for each year from 2007 to 2011 [2]

As it can be seen, in the 2007 and 2011 period the EEG-based BCI papers introducing new paradigms and practical applications have more than doubled.

Fig. 2. The numbers of EEG-based brain–computer interface (BCI) applications developed in BCI articles introduced from 2007 to 2011 [2], [5]

The BCI applications that were classified as "others" increased considerably in 2010 and 2011, indicating that BCI technology has increasingly been applied to new application fields; these included a mobile phone application, a real-time drowsiness detection system, a brain-controlled smart home system, etc. [2].

II. BCI SYSTEM BASIC PRINCIPLE

A. General description

A BCI uses brain signals to control a device or to adjust the communication between user and a device [1]. Figure 1 shows the basic design and operation mode/concept of BCI.

During embryonic development and after that throughout later life, the CNS (Central Nervous System) neurons and synapses continually change to acquire new behaviors and to maintain the already acquired ones. Such CNS plasticity underlies acquisition of standard skills such as locomotion and speech and more specialized skills as well, and it responds to and is guided by the results achieved [1].

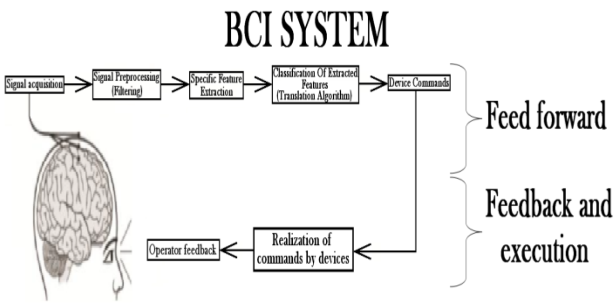

Fig. 3. The BCI System – basic concept

The BCI translates this features recorded from the scalp or from the cortex into commands that will operate a device in realtime, such as word processing program, wheelchair driving, mobile phone application, drowsiness detection, etc.

The BCI depends on the cooperation of two adaptive controllers: the user, who generates brain signals; and the BCI system, that translates these signals in commands. That is why BCI use is like a skill that both user and system must acquire and maintain in time. The adaptation of user-to-system and system-to-user is the fundamental principle of BCI operation.

Generally, the electrodes are placed according to the standard of 10–20 international system, which means that electrodes are located on the scalp at 10% and 20% of a measured distance from reference sites including nasion, inion, left, and right preauricular [2], [3].

There are a lot of techniques and methodologies to record brain signals for BCI. They can be divided in two categories:

1) noninvasive record methods;

2) invasive record methods.

The noninvasive recording methods include: recording of electrical or magnetic fields (like electroencephalography [EEG], magnetoencephalography [MEG]), functional magnetic resonance imaging [fMRI] [7], positron emission tomography [PET], infrared [IR] imaging, near-infrared spectroscopy [NIRS], fetal magnetoencephalography [fMEG], single photon emission computed tomography [SPECT] [2].

Other BCI researchers have used invasive record methods: electrocorticography [ECoG] or microelectrode arrays [MEAs] [2].

B. EEG-based BCIs

Until today three different kinds of EEG-based BCIs have been tested on humans. The difference is in the particular EEG features that conveys the user's intentions.

A P300-based BCI: It uses the P300 component of the event related brain potential, which appears in the EEG about 300ms after presentation of a salient or attended stimulus [1], [8].

The P300 BCI system in use was described by Donchin's group as flashing letters or other symbols in rapid succession. The letter or symbol that the user wants to select produces a P300 potential - detecting it, the BCI system can determine the user's choice of specific letter or symbol. Subjects using this BCI method are able to operate a simple word processing program that helps them to write words at a rate of a few letters or even few short words per minute.

The P300 can be used together with other methods, like in [13], where a combined brain–computer interface was used; it was based both on P300 potentials and motion-onset visual evoked potentials.

Other example is in [14], where the main objective of this study was to implement and evaluate a BCI based on P300; this speller used directional cues of auditory stimuli - presented over headphones. The interstimulus interval (ISI) was reduced successively to determine the optimal combination of speed and accuracy of it. In the study were quantified the differences in subjective workload between auditory and visual P300 spelling applications [14]. In their conclusions the results of the online study suggested that the proposed paradigm offered a possibility of communication for most healthy users. It's significance was that it showed that the described auditory BCI can serve as a communication channel for completely paralyzed patients too.

In case of brain-controlled mobile robots, we can divide them in two categories according to their operational modes. The first category is called "direct control by the BCI" - it means that the BCI translates EEG signals directly into motion commands to control the robots. No robot intelligence is needed and their cost and computational complexity is low. In addition, users can be in charge of their movements as much as possible.

The second types of brain-controlled robots are those with "shared control", where a user and an intelligent controller share the control over the robot or wheelchair. Its disadvantage is that the cost and computational complexity are high because it has to use an array of expensive sensors [9].

Another typical example is the robotic wheelchair, where a desired location is selected from a list of predefined locations using a P300 BCI, and then the autonomous system will drive the wheelchair to the desired location, in a known environment, but the user is able to stop the wheelchair at any time [9].

Even if many researchers have developed various brain controlled mobile robots, to the best of our knowledge, none of the existing brain-controlled mobile robots is brought out of a controlled laboratory environment [4].

Signal Acquisition: EEG signals can be collected with electrodes placed on the scalps surface. The most widely used electrodes are silver/silver chloride (Ag/AgCl) because their low cost, low contact impedance, and relatively good stability. Using Ag/AgCl electrodes requires removing outer skin layer and filling gel between electrodes and scalp (that is why this kind of electrodes are called "wet" electrodes). These operations take long time and are uncomfortable to users. Some researchers have been exploring "dry" electrodes, which do not need to use gel and skin cleaning. The main disadvantage of existing dry electrodes is that the acquired EEG signals are worse than those acquired with conventional electrodes due to the increase of contact impedance [4].

Common BCI techniques and inputs include [11]:

1) motor imagery;
2) event related potentials;
3) steady state evoked potentials.

C. Signal processing

The acquired signals are first preprocessed in order to remove artifacts such as power line noise, electrocardiogram (ECG), electrooculogram (EOG), electromyogram (EMG), etc. and any body movement. Features are then extracted from the preprocessed signals. Finally, the classifier translates these extracted features into commands that subjects desire to output [4].

A BCI records brain signals and processes this signals to produce device commands. This signal processing has two stages: The first stage is feature extraction, (calculation of the values of specific features of the signals). The feature extraction stage must focus on features that encode the user's intent, and extract those features as accurately as possible. The second stage is the translation algorithm: features are translated into device commands.

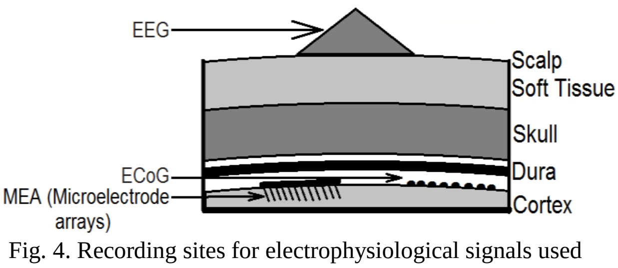

Fig. 4. Recording sites for electrophysiological signals used by BCI systems [3], page 31

Evaluation Metrics

It can be classified in two major categories:

1) "Task metrics" - which focuses on the question "How well specified tasks can be performed with the brain-controlled robots?". The widely used and easiest task metric is "task success", but there are "task completion time" or "mission time" and "BCI accuracy".

2) *"Ergonomic metrics"* - representing the state of the user rather than his/her performance. Workload is a commonly used ergonomic metric, measuring user mental effort when using brain-controlled robot systems.

Two other ergonomic metrics include "learnability", representing the ease of learning to use the robot, and "level of confidence" experienced by the participants [4].

The cost factor should also be considered in evaluating the robot systems.

Evaluating and comparing performance of a variety of brain controlled mobile robots has a critical role in facilitating the research and development of brain-controlled mobile robots. However, standardized performance evaluation method has not yet been established.

Almost all of the existing brain-controlled mobile robots used healthy participants to evaluate their systems with several exceptions.

III. APPLICATIONS

In the beginning BCI technology was developed as a communication device for the "locked-in" users, but the range of research has increased to include non-medical applications too; today even first commercial products are available for home users. As a result, new disciplines enter the BCI community, and new researches are introduced.

Nowadays improving the BCI system's usability by increasing accuracy and improving the information transfer rate (ITR) is priority in BCI research. The most important are the used calibration methods and are paramount for reaching high online accuracy, ITR, clean EEG, well-differentiated target and non-target brain activity; all this lends to train a robust classifier, which is necessary for efficient use of the BCI system [11].

It is important to mention that a good performance of a BCI system for healthy participants does not necessarily mean good performance for the disabled population.

A. Device control

One of the most important desire in developing BCI's was to give users, who lost full control of their limbs, access to devices and communication with the other people. Users can already benefit from BCI devices, like mentioned above, even if it has limited speed, accuracy and efficiency yet. For healthy users a BCI nowadays cannot act as a competitive source of control signals due to its limitation in bandwidth and accuracy compared to the standard muscular control. Healthy users could also benefit from either additional control channels or hands-free control offered by BCI [6].

Assistive robots can provide support for disabled people in daily and professional life, thus creating a growing demand for them [10]. Some other special interfaces like sip-and-puff systems, single switches, and eye-tracking systems have been proposed.

However, these interfaces do not work for some severely disabled people with illnesses such as the amyotrophic lateral sclerosis (ALS), multiple sclerosis (MS), or strokes. As a result, even autonomous robots are not yet able to transport severely disabled users to desired locations.

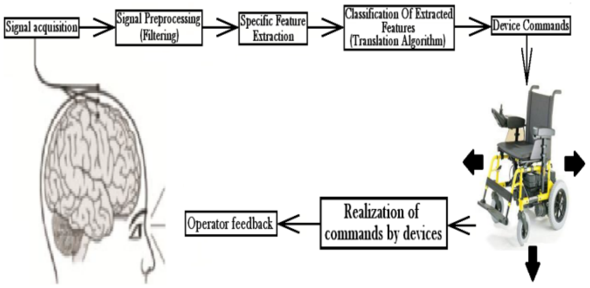

Fig. 5. BCI used in Device Control

B. Communication

People with amyotrophic lateral sclerosis (ALS), multiple sclerosis (MS), or stroke need to communicate their needing to the external world. They are able today to do this, using BCI systems. Some examples of communication are controlling a cursor on the screen, selecting letters from a virtual keyboard, browsing internet, etc.

A communication example is the example of the event-related potential (ERP)-based brain-computer interfacing (BCI), which is an effective basic communication method; but collecting all the calibration data for the experiment, and the classifier trainings - all this detracts from the amount of time allocated for real online communication. If the calibration time can be reduced, there will remain more time for additional online use, potentially lower fatigue, and even improved performance [11].

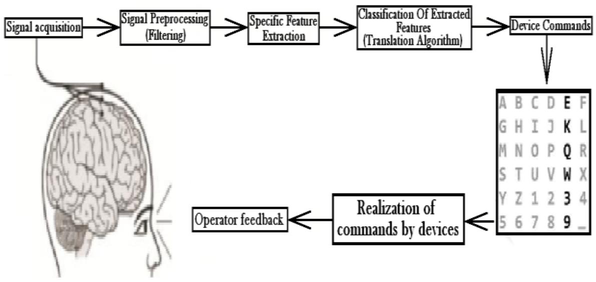

Fig. 6. BCI used in Communication

C. User state monitoring

User-machine interfaces in the future will need to understand user's current state and user's intentions or commands. These future implementations will require systems to gather and interpret information on mental states such as emotions, attention, workload stress, and even mistakes [1].

D. Evaluation

Evaluation applications can be used online and offline. Neuro marketing and neuroergonomics are only two evaluation examples. Neuroergonomics is linked to Human Computer Interaction: it evaluates how well a technology matches human capabilities and limitations [1].

E. Training and education

A lot of aspects of training are related to the brain and its plasticity. Measuring this plasticity and the afferent changes in the brain can help to improve training methods in general. Indicators like learning state and rate of progress are useful for automated training systems and virtual instructors. Currently, this application area is in a theoretical phase with limited experimental evidence [1].

F. Gaming and entertainment

The entertainment industry is very often the front runner in introducing new concepts - among others in human-computer interaction for consumers. In the last few years new games have been developed that are exclusively for use with an EEG headset by companies like Neurosky, Emotiv, Uncle Milton, MindGames, Mattel, Microsoft, Hitachi, Sega Toys, IBM, etc. [1].

The first application of non-medical BCIs were in the field of gaming/entertainment, where the first stand-alone games came out to the market in 2009 and even a broadening to console games may follow soon [1].

There have hardly been any attempts to design BCI games where BCI is considered to be one of multiple possible input modalities (together with keyboard, speech, gestures, etc.) that can be used to control the game. One reason may be that research still follows the paradigms of the traditional, medically oriented, BCI approaches.

There were just a few attempts to design BCI games, where BCI is considered to be one of multiple possible input modalities (side-by-side with keyboard, mouse, speech, gestures, etc.) that can be used to control the game [12].

These gaming programs/applications are not that different from medical or military BCI applications [12]. Medical applications aim to provide patients with communication and movement possibilities and skills – these applications have seen many research efforts and have a lot of attention. But, in fact, anybody is “handicapped”, because everybody will meet situations where it is desirable to have more skills, limbs, and communication means than are usable / available when people are using the usual verbal and nonverbal interaction modalities [12]. In fact, everybody will meet situations, where people would benefit from extra communication or movement modalities (extra skills, limbs, and communication). This sentence is particularly true in games, sports and entertainment.

G. Safety and security

EEG alone or combined EEG could realize the support of the detection of abnormal behavior and suspicious objects. An observer or multiple observers are watching CCTV and using EEG with eye movements together might help to identify potential targets that otherwise may not be noticed consciously [1].

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