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BRAIN-COMPUTER INTERFACES IN ROBOTICS

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Abstract: The review describes the main principles as well as advantages and disadvantages of the modern brain-computer interfaces applied in robotic devices. The invasive and non-invasive devices based on the origin of a signal, invasiveness and location of probes are discussed in the paper. The description of some electrical (EMG, EEG, etc.) and chemical (fMRI, fNIRS, etc.) methods to detect neural activation are concerned. Spatial resolution of electrical neural interfaces is rather low, therefore one of their main disadvantage is the difficulty in detecting the exact region of activation. The main disadvantage of chemical neural interfaces is long reaction time. Unfortunately, none of the non-invasive methods today allows inventing an effective neural interface for interactive control of robotic devices. Modern invasive methods are rather harmful; therefore, they are unacceptable in studies with humans for ethical reasons. In this respect, the most promising is the use of the combined brain-computer non-invasive interfaces, combining sensors of both electrical and chemical activity of the nervous system. In combined neural interfaces the disadvantages of one method are compensated by the advantages of another one. The main area of practical use of neural interfaces in robotics in the foreseeable future will be devices for the rehabilitation of persons with disabilities. The use of neurointerfaces for other robotic devices will have only scientific significance until the advent of new safe invasive neurointerfaces, since non-invasive neurointerfaces do not have significant advantages over traditional control systems for healthy people.

Keywords: Brain Computer Interface (BCI), robot, neurotechnology, control system, cyborg.

I. INTRODUCTION

Interfaces used in brain-computer interaction are specifically designed to exchange information between the brain and nervous system and an electronic device in a real-time mode. Currently, they are increasingly applied in robotics. However, only cases with special BCI applications are considered in the majority of published scientific papers within this area.

Since cognitive activities of humans are accompanied by the activation of corresponding neuron assemblies, the operation principle of most modern neural interfaces is based on applying brain mapping to detect neural correlates of cognitive processes. It is known that cognitive activity is carried out through the exchange of brain neuron electrical impulses. At the same time, the electrical activity of neurons can also arise due to the chemical processes occurring in them. Successful identification of brain activation in the area of interest allows interpreting it as a mental command to perform a particular action. By stimulating the corresponding neuron ensembles, it is also possible to implement neurofeedback.

Aim: In the present paper our aims are to review the applications of BCI in robotics, and to identify the most promising ways of their development nowadays.

II. Classification of Modern Brain-Computer Interfaces in Robotics

Despite the fact that neurotechnologies have started developing rapidly only recently there is a great diversity in existing brain-computer interfaces [1-4]. The most important parameters of neural interfaces' classification for robotic devices are invasiveness (invasive and non-invasive), location of probes (in central or peripheral nervous system), and the origin of a signal (electrical or chemical) (Fig. 1).

Invasive neural interfaces are based on the technique when probes are implanted inside nervous system with a help of surgery. Such interfaces detect the neuronal activity rather successfully. When an invasive neural interface is applied, an operator can usually give immediate mental commands to the control system to perform the required actions. Nowadays only invasive interfaces allow getting a feedback, sending information to the brain directly. Among pitfalls are the high probabilities of the harm to humans' health. Moreover, such interfaces are easily accreted with connective tissue after a while, neurons that transfer the signal die, and it leads to the necessity of repeated surgery. Therefore, the use of invasive neural interfaces among healthy people is unacceptable for ethical reasons. On contrary non-invasive neural interfaces are installed on skin surface and do not cause harm to humans. However, their sensitivity is worse than that of invasive interfaces.

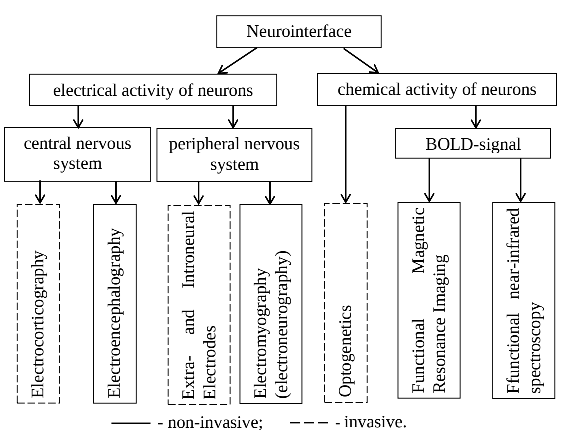

Figure 1. Classification of the mostly used brain-computer interfaces in robotics by location of the probes and the origin of a signal

According to the origin of a signal they can be divided into neural interfaces that are based on the analysis of electrical or chemical activity of the neurons. The oldest and the most common ones are neural interfaces based on the analysis of neural oscillations, or brainwaves that can be regarded as repetitive patterns of neural activity in the central nervous system. The most important advantage of these neural interfaces is temporal resolution. However, their spatial resolution is rather low; therefore one of the main disadvantages in electrical neural interfaces is the difficulty in detecting the exact region of activation [1, 2, 3]. Based on the electrodes' disposition within neural interfaces, they can be divided into two subgroups: central system interfaces and peripheral nerve interfaces.

The neural interfaces based on the analysis of the peripheral nervous system electrical activity include electromyography (EMG) sensors and extraneural electrodes. Non-invasive EMG sensors are located on the skin at any point of the body, except for the upper part of the skull. Normally they capture electrical impulses from muscles, but they can also detect much weaker electrical signals from the peripheral nervous system (in this case, the method is called electroneurography). EMG sensors are widely used nowadays to control bionic limb prostheses using residual stump muscles because the signals perceived by them mainly reflect information are about motor activity [5-9]. Currently, there is a large number of industrially manufactured designs of bionic limb prostheses controlled by EMG sensors. The feedback in such prosthetic control systems can be implemented, for example, by providing electrical impulses provision to the skin around the stump.

Electromyography is the most successful example of neural interface use in robotics. However, its possibilities are rather limited, for example, rehabilitation of the paralyzed people, and sometimes impractical – for example, manipulator control.

The main advantage of invasive extra- and intra-neural electrodes [8, 10, 11] is the possibility of more effective feedback implementation within bionic prostheses. The difference between extra and intra-neural electrodes is that the former ones are attached to the nerve from the outside, and the latter ones are inserted into it. Due to the above-discussed disadvantages of all invasive neural interfaces, interfaces based on extra- and introneural electrodes are not applied widely in robotic devices. However, there is a successful experience of applying these invasive neural interfaces in creating "Cyborg Insects" [11, 12] to control the behavior of beetles, dragonflies, butterflies, etc. The main principle is that electrical impulses are supplied into the nervous system of an insect via extra- or intraneural electrodes, and the movements are defined by remote control or some program. Cyborg insects are a very promising alternative to mechanical mobile microrobots in agriculture, military affairs and other fields, but all these neurotechnologies are still on the experimental, but not prototype level.

Neural interfaces based on central nervous system electrical activity analysis include electroencephalography- and electrocorticography- based BCI. During electroencephalography (EEG), electrodes are mounted on the skin of the upper part of the skull and record electrical signals from cortical and subcortical regions of the brain. The electrodes positions on the head are usually identified in accordance with international system "10-20" (Fig. 2).

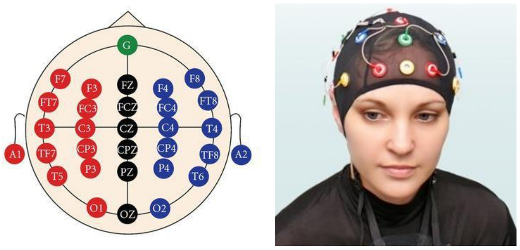

Figure 2: EEG electrode installation system

EEG is one of the oldest methods in brain research [13]. The attempts to apply EEG for BCI have had a long history. However, regarding applications in robotics, they are in most cases unsuccessful. Since electrical impulses propagate at the speed of light and are significantly distorted when passing through the skin and bones of the skull, it is almost impossible to detect the activity of individual neuron ensembles using EEG sensors. In this regard, integral brain electrical activity, or various electrical rhythms are analyzed in EEG-based neural interfaces. In this case a complex set of easily recognized mental signals, such as predetermined alternation of relax-concentrate commands, but not thoughts to fulfill any action are used as commands to the control system.

Most frequently EEG was used to control bionic prosthetic limbs and exoskeletons in order to rehabilitate disabled people [1, 2, 3, 8, 14]. EEG-based neural interfaces were also applied to control manipulators [15], mobile robots [16] and wheelchairs [17], multicopter [18], etc. Various methods were used to recognize control commands, including artificial neural networks [19, 20]. However, the error of control command recognition in EEG-based interfaces usually exceeds 50%. In this regard, EEG-based neural interfaces have been practically applied only when a large percentage of control system errors is uncritical: in the neural communication devices, for example the NeuroChat hardware and software for text typing for paralyzed people and in numerous games and simulators.

Electrocorticography - an invasive neurointerface, installed in the cerebral cortex - demonstrates high efficiency [8, 10]. Electrocorticography makes it possible to register the activity of individual neuron ensembles accurately. There are successful experiments on manipulator control using electrocorticographic interfaces. These experiments were conducted on monkeys [21, 22]. In the conducted studies, a monkey was able to bring the pieces of food to its mouth using the manipulator controlled by an electrode mounted in its cerebral cortex. Similar studies have been conducted in humans [23]. During the experiments patients learned to control a cursor on a computer screens and a robotic arm to bring a cup of coffee to their mouths. However, electrocorticographic interfaces have aforementioned disadvantages of invasive neural interfaces. In this respect nowadays they are used only in experiments with animals and rarely to rehabilitate completely paralyzed disabled people.

Neural interfaces based on nervous system chemical activity, allow determining the concentration change of certain substances that can affect the activity of neurons. Their main advantage is the ability to detect the activity of individual neuron ensembles even during non-invasive interface application. The main disadvantage of such neural interfaces is long reaction time [1, 2, 3].

Most modern non-invasive neural interfaces based on the analysis of nervous system chemical activity apply the BOLD (blood-oxygenation-level-dependent) principle: activated neurons absorb several times more oxygen than inactive areas of the brain. The BOLD principle is based on hemoglobin concentration (oxygenated and deoxygenated) detection in some brain parts that bring oxygen to neurons. Nowadays the most powerful non-invasive neurointerface based on BOLD-principle is functional magnetic resonance imaging (fMRI) [24, 25]. The principle of fMRI is based on electromagnetic response of atomic nuclei measuring in a strong magnetic field. fMRI allows to make volumetric maps of neuron activity with the resolution of up to 1 mm throughout the whole brain volume. fMRI-based neural interfaces are successfully used to control android robots [26] and manipulators [27]. However, fMRI requires the patient staying mostly motionless in the scanner during measurements. Besides, fMRI equipment is very cumbersome, energy-intensive and expensive. Thus, nowadays the use of fMRI as a neural interface for robotic devices is not rational. Usually fMRI is used additionally to set up other neural interfaces in the laboratory [28].

Another neural interface based on the BOLD-principle is functional near infrared spectroscopy (fNIRS), that doesn’t have fMRI disadvantages [29, 30, 31]. fNIRS uses near infrared radiation to measure the optical absorption spectrum of hemoglobin. fNIRS scheme is presented by fig. 3.

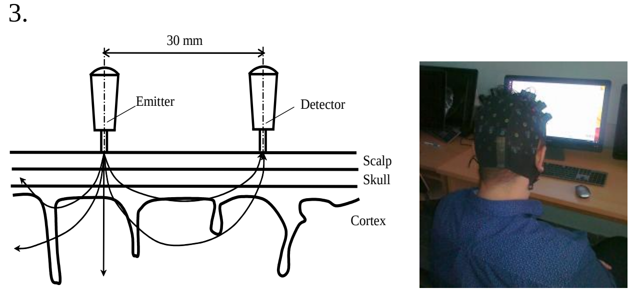

Figure 3: fNIRS scheme

The main advantages of fNIRS in comparison with fMRI include portability, relatively low cost of equipment and the absence of serious restrictions to the operator's physical activity. The greatest disadvantages of fNIRS are its spatial resolution (not more than 3 cm deep), as well as the time delay of 3-5 seconds during the identification of brain activity areas associated with the inertia of blood inflow and outflow processes. There is a relatively successful experience of fNIRS use to control bionic limb prostheses [32, 33], android robots [34, 35], wheelchairs [17], etc.

The methods of optogenetics are referred to the invasive neural interfaces based on nervous system chemical activity management [30, 36]. The main principle of these methods is to make nerve cell sensitive to electromagnetic radiation of a certain range using genetic engineering. In order to make neurons sensitive to visible light, they are injected with corresponding sensitive proteins, such as rhodopsin. The beams of thin optical fibers are fed to provide light radiation to the necessary groups of neurons. This method is more selective and less traumatic as compared with the activation of neurons by electric current using invasive electrodes. In order to detect the activation of neurons, they introduce electrodes-sensors along with optometers. The thermogenetics method [37] is the type of optogenetics, in which neurons are made sensitive to infrared radiation. Due to the low level of knowledge and potential danger, the methods of optogenetics are currently applied only in animal experiments. From the point of view of robotics, such methods can be interesting so far only as the means of inventing a cyborg animal. Greater selectivity will allow the use of optogenetics to control highly developed mammals, such as laboratory mice and rats, in comparison with other invasive neural interfaces [38].

III. Discussion

The review allows us to conclude that spatial resolution of electrical neural interfaces is rather low; therefore one of their main disadvantages is the difficulty in detecting the exact region of activation. The main disadvantage of chemical neural interfaces is long reaction time. Unfortunately, none of the non-invasive methods today allows inventing an effective neural interface for interactive control of robotic devices. Modern invasive methods are rather harmful; therefore, they are unacceptable in studies with humans for ethical reasons. Thus, due to significant shortcomings, none of the existing neural interfaces can currently individually be successfully used to control robotic devices.

The most promising is the use of combined non-invasive neural interfaces in robotics, for example, based on the combination of EEG and fNIRS. Regarding these neural interfaces, the disadvantages of one method are compensated for by the advantages of another. There are successful examples of such combined neural interface implementation to control bionic prostheses [39], quadrocopters [40] and other robotic devices [41].

IV. CONCLUSION

We can draw the following conclusions from the study:

1. During the review, the neural interfaces of robotic devices were classified for the first time according to the principle of operation and location. It is established that despite the wide variety of existing neural interfaces, their use for controlling robots causes considerable difficulties.
2. Experiments with animals remain the main area of invasive neural interfaces application now and in the nearest future. The wide use of invasive neural interfaces applied to humans, for rehabilitation of disabled people, for example, will be possible only when fundamentally new, harmless neural interfaces appear.
3. Combined non-invasive neural interfaces, in particular the neural interfaces based on the combination of EEG and fNIRS, will be applied widely for bionic prostheses, exoskeletons and other robotic devices intended for the rehabilitation of disabled people.
4. Robot-based games and the simulators with neural interfaces based on EMG, EEG and fNIRS will be used more and more often.
5. The use of neural interfaces for other robotic devices will be of scientific importance only until new safe invasive neural interface development, since non-invasive neural interfaces do not have significant advantages over traditional control systems for healthy people.

Abbreviations:
BCI - Brain Computer Interface;
BOLD - Blood-oxygenation-level-dependent;
EEG – electroencephalography;
EMG – electromyography;
fMRI - Functional magnetic resonance imaging;
fNIRS - Functional near infrared spectroscopy.

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