Brain-Machine Interface - A 21st Century Dynamic Technology: Anticipatory Brain Potentials and Robot Control

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Brain-Machine Interface is a technology that allows people to control devices using only the bioelectrical signals from the brain. The challenge has been around since 1973, and the first experimental proof of the feasibility of the technology was given in 1988. However, the real worldwide interest was shown in the 21st century. Currently, there are research laboratories and companies around the world offering research and products in the area. The technology allows recognizing various states of the human brain through brain signal processing. The applications so far included movement of the cursor, hands-free typewriter, wheelchair (robot) movement, and robot arm (prosthesis) movement, among others. Here, an investigation is reported, in which Brain-Machine Interface is used based on anticipatory brain potentials. The device controlled is a robotic arm.

Key words: Brain potentials taxonomy, Brain-robot interface, Anticipatory potentials, Controlling robotic arm

1 INTRODUCTION

The term Brain-Machine Interface refers to the use of brain signals to control external devices with signals produced by the brain alone. External devices could be home appliances such as a TV set, a wheelchair, arm prosthesis, or a robot, among other possibilities. The term comes from the term Brain-Computer Interface which was used by Vidal [Vidal 1977]. His laboratory at University of California at Los Angeles (UCLA) was named Brain-Computer Interface Laboratory. Although the terms Brain-Computer Interface and Brain-Machine Interface are often used as synonyms, in this paper it is understood that Brain-Machine Interface (BMI) refers to applications beyond standard computer peripherals. Another term, Brain-Robot Interface (BRI) is used for brain control of special physical devices, namely robots. Therefore, in this paper it is understood that the relations between the above research areas is BCI $\supset$ BMI $\supset$ BRI, meaning that BCI includes BMI, which in turn includes BRI. For example, moving a screen cursor is not considered a BMI, and turning on/off a TV set is not considered a BRI.

Brain-Computer Interface becomes appealing not only for research but for industry as well. Besides small companies, big companies have also strategies and investments in this area (Honda is an example). Governments and funding agencies are involved, a good example being the European Union FP7 ICT program. This program encourages research institutions and market oriented companies to collaborate in producing products for the market.

Let us mention some of the milestones in Brain-Computer Interface research. EEG was first introduced by Berger [1929]. Possibility of controlling devices using EEG was mentioned by Vidal [1973], and he also demonstrated [Vidal 1977] the possibility of screen symbol movement using brain signals The EEG alpha rhythm was proposed to be used by Osaka [1984]. The first BMI, control of a physical mobile robot using EEG signals took place in Macedonia [Bozinovski et al 1988]. In 1988, the concept of mental prosthesis was introduced and event related potentials were used to write text on a computer screen [Farwell and Donchin. 1988]. The last decade of the 20th century gave theoretical advances [Keirn and Aunon 1990], as well as experimental results, such as screen cursor movement [Wolpaw et al 1991]. The importance of digital signal processing in BCI was emphasized by McFarland et al [1997]. Alpha rhythm was again used as a mind switch [Craig et al, 1997]. An invasive approach, recording signals inside the brain rather than on the scalp, was introduced in the late 1990s [Chapin et al, 1988]. The development taking place in the 21st century will be addressed below in the text.

Following is a description of a taxonomy of brain potentials, which considers the anticipatory brain potentials as a subclass of event related potentials. Then, after describing the CNV (Contingent Negative Variation) potentials, the experimental paradigm is described, which includes feedback, and which is called the CNV flip-flop paradigm. The device that will be controlled is a robotic arm. Behavior-based robot control architecture is used with behavior design for solving the well known Towers of Hanoi problem. Results of the experimental investigations are presented, with a defined anticipation-based BRI, i.e., more specifically, an expectation-based BRI.

2 TAXONOMY OF BRAIN POTENTIALS

In the 1970s, the understanding of the variety of brain potentials was depicted by a taxonomy that included background EEG and Event Related Potentials (ERP), which were also called Evoked Responses. The distinction among ERPs was described in [Vidal 1977]. According to that taxonomy, there are four types of ERPs:

Sensory ERPs. Elicited by human sensors for light, audio, etc, as well as direct electrical stimulation. Such ERPs appear at short latencies, between 50ms and 100 ms.

Motor ERPs. Voluntary motor movements, which may be found actually preceding a behavioral event. Examples are limb movement, eye movement, and phonation.

Long Latency Potentials. Responses in latencies between 250ms and 450ms. Usually related to cognitive processing related to the event. Most prominent is the P300 (positive potential at 300ms) potential.

Artifacts. Appear because of movement of muscles, eye movements (EOG), heartbeat (ECG) and other potentials of non-neural origin. They are usually considered noise in a brain potentials investigation.

A more recent taxonomy proposed in 1992 by Bozinovska [Bozinovska et al 1992] introduced a difference between Evoked Potentials (EP) and Event Related Potentials (ERP). It also introduced anticipatory potentials (AnP) and Expectancy Potentials (ExP). Figure 1 shows this taxonomy. Event Related Potentials are divided into pre-event and post-event. Pre-event potentials and named Anticipatory Potentials (AnP) while post-event potentials are the Evoked Potentials (EP).

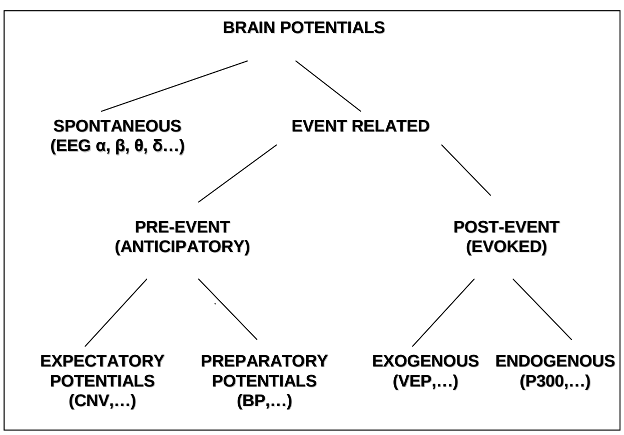

Figure 1. A taxonomy of brain potentials

Anticipatory Brain Potentials (AnP) are divided into Preparatory Potentials (PrP) and show preparation for a willing action (an example is the Bereitschaftspotential – BP) [Kornhuber and Deecke, 1965], and Expectatory Potentials (ExP) that show expectation for an event (an example is the Contingent Negative Variation – CNV) [Walter et al, 1964].

This paper focuses on the CNV potential. Figure 2 shows the morphology of a CNV potential, following the convention that the negative shift is shown as directing upwards. The signal shown was obtained in the investigations where sound (beep) stimuli were used.

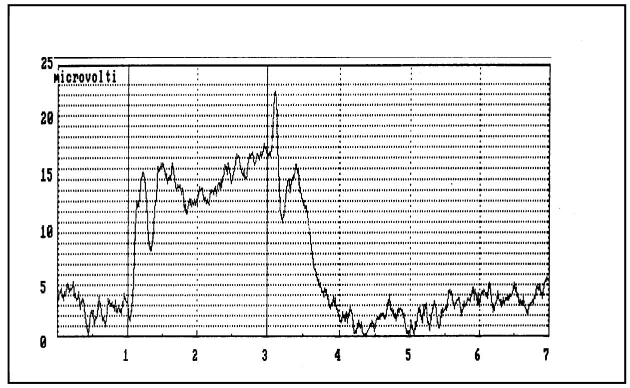

Figure 2. Morphology of a CNV potential

3 THE CNV FLIP-FLOP PARADIGM

CNV appears in the so-called CNV paradigm, introduced by a research team led by Walter [Walter et al, 1964]. In this experimental paradigm, the EEG is measured in a standard reaction-time paradigm, in which the subject is presented with two stimuli: S1, which is short in duration and serves as a signal, that a next, S2, will follow, which is longer and needs to be interrupted by the user (usually by pressing a button). The user is instructed to press the button (i.e. stop S2) as quickly as possible. After averaging over several trials, a specific shape forms between S1 and S2, which is the CNV potential. Several modifications of the original CNV paradigm have been proposed, and the CNV potential itself has been extensively studied [Tecce and Cattacach, 1993]. An example of a CNV paradigm modification is the probability-driven appearance of S2 [Bozinovska et al, 1985].

The modification of the original CNV paradigm used in this work is named CNV flip-flop paradigm and is obtained by adding a feedback loop to the paradigm. The feedback is introduced by monitoring the appearance and disappearance of the CNV potential and using that information to switch the imperative stimulus S2 off and on. The recognition of a CNV appearance would result in the lack of a need for the subject to react, which would eventually lead to a decline of his/her expectancy, and thus a decay of the CNV potential. The computer would recognize this and consequently switch on the S2 stimulus again, which would in turn force the subject to expect and react again, thus redeveloping his/her CNV potential, and so on. The experiment would go on as long as there were trials available. While the subject's reaction is usually measured by him/her pressing a button, it has been shown that the CNV flip-flop paradigm does not necessarily need a press button part [Božinovski et al 2007]. The CNV is generated by an expectancy process in the brain which can be monitored, and this means that the paradigm truly bypasses the need for motor organs. In 2005, it was realized that the anticipatory potentials could be utilized in the brain-computer interface research. [Božinovski 2005, Božinovski et al 2006, Božinovski et al 2007]. Other groups have joined the research in anticipation driven brain computer interface [Garipelli et al 2008] and anticipatory potentials related to the theory of anticipatory systems [Kadim 2007].

4 BRAIN-ROBOT INTERFACE

The original brain-robot interface paradigm [Bozinovski 1988] includes an EEG signal acquisition, a software system for the recognition of the desired signal (including feature extraction), and an interface towards a controlled device. The research in expectation based brain-robot interface presented in this work includes the experimenter and points out the CNV oriented signal processing (Figure 3).

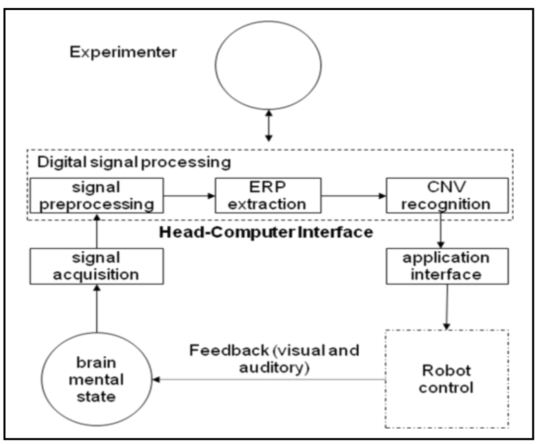

Figure 3. An expectation based brain-robot interface

As Figure 3 shows, the brain-machine interface used contains a brain signals acquisition unit, a signal processing part, and an application interface, in this case a robot interface.

5 BIOSIGNAL PROCESSING PART

The biosignal preprocessing part of the BMI software filters the artefacts (such as EOG and electric current noise) from the recorded EEG. The feature extraction part extracts the Event Related Potential (ERP). The problem to be solved is the time-varying nature of the ERP. Since the paradigm requires that the obtained signal will form towards and decay from its CNV shape, a classical averaging technique is not suitable. Therefore, an adaptive filter was used [Božinovski 2005]. Another signal processing module is the CNV recognition part, which should recognize that the obtained ERP has a shape of a CNV. Since the expected CNV is a ramp-like signal, the pattern recognition software looks for parameters of that ramp. The parameters that are computed are the slope of the regression angle and amplitude of the ERP at the vicinity of S2. The ERP baseline is computed from the values of the ERP signal from the beginning of the trial until the appearance of the S1 stimulus.

In normal subjects, the CNV flop-flop paradigm generates oscillations of the CNV amplitude. The CNV flip-flop curve was used as a triggering process for a sequence of robot behaviors in the Brain-Robot Interface research.

6 ROBOT CONTROL ARCHITECTURE

A robot control architecture is used that contains predefined behaviors. Behavior-based robotics [Arkin 1998] is currently widely used approach in robot control. The architecture consists of a set of preprogrammed behaviors, a triggering system for a particular behavior, and a behavior selection system. In BRI paradigms, the triggering mechanism is the brain signal recognition. The behavior based BRI architecture used here is shown in Figure 4.

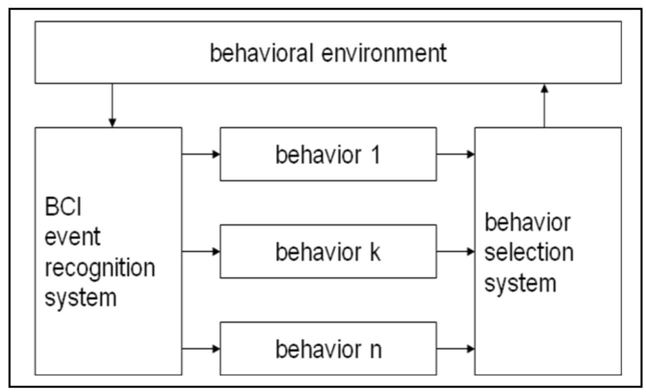

Figure 4. The BRI approach using behavior based robot control architecture

As can be seen from Figure 4, behaviors are triggered by a BCI event recognition system. An example of the set of behaviors can be a set of two hardwired behaviors {FOLLOW_LINE, STOP}, which was used in [Bozinovski et al 1988]. The robot had a default behavior of following a black line drawn on the floor. When a behavior triggering system recognized an increased intensity of an alpha rhythm, the STOP behavior was executed. If the alpha rhythm intensity decreased, the default behavior was resumed.

In this research, a robotic arm solving the Towers of Hanoi problem was considered, which had already been used [Božinovski 2005]. The sketch is given in Figure 5. Given a set of disks with different diameters, a *tower* is defined as a disk stack in which a smaller disk is always above a larger one. Three spots are given – A, B, and C. If the initial tower is in the spot A, the task is to move it to the spot C, using a "buffer" tower in the spot B. Note that at each step of the task the concept of a tower is preserved, i.e. a smaller disk is always above a larger one.

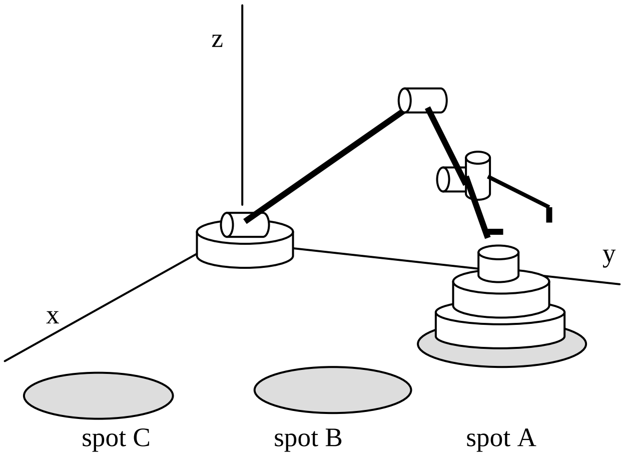

Figure 5. The Towers of Hanoi problem for a robotic arm

The Towers of Hanoi is a well known problem in theory of algorithms and artificial intelligence, and it is known that, to move a tower of d disks, 2^d-1 movements of the individual disks are required. It is also pointed out that the state space of this problem has a fractal structure [Bozinovski 1994]. The sequence of behaviors to be preprogrammed for a two disk stack is (AtoB, AtoC, BtoC). If the height of a particular disk in the stack is denoted, the sequence can be represented as (A2toB1, A1toC1, B1toC2). Once the problem is decomposed into a sequence of robot behaviors, a brain process is needed, that will generate a control sequence for executing the behaviors. Indeed, the CNV flip-flop paradigm generates such a sequence.

7 MATERIALS AND METHODS

The equipment used consists of a 4-channel biopotential amplifier, a PC Windows based computer, and a 6-degrees-of-freedom robotic arm. The CNV flip-flop paradigm part recognizes series of appearances and disappearances of the CNV potential, and triggers the behavior execution part, which moves the robotic arm towards the completion of the Towers of Hanoi task. The robot interface consists of a USBtoCOM cable connecting a robot controlled by a servo controller. Each robot behavior is interfaced with the triggering signal that comes from the CNV flip-flop paradigm. The subject is connected to the biopotential amplifier with EEG electrodes placed on Cz and mastoid, while the forehead is the ground. A photo of the experimental setup is shown in Figure 6.

8 SOFTWARE

Custom software was developed for the experimental research, written in C#. The signal processing part is described above. The robot control software counts the events of CNV appearance and disappearance. The initial state of noCNV triggers no robot movement. The first CNV appearance is named CNV1 and triggers the Behavior1. The CNV disappearance is named CNV2 and triggers Behavior2. The events are denoted by CNVk where if k is an odd number it is a CNV appearance while an even k means CNV disappearance. Figure 7 shows the graphical user interface which the experimenter observes during each trial.

Figure 6. Experimental setup: subject, electrodes, robotic arm, biopotential amplifier, two disk Tower of Hanoi, and computer.

The screen shows six channels out of which the first four are acquisition channels and the last two are mathematically computed channels. The first channel is the EEG acquisition channel, the second is the EMG acquisition from the arm pressing the button, the third is the EOG signal channel, and the fourth is the press-button recognition channel. The sixth channel is the event related potential extracted so far. If an appearance or disappearance of CNV is recognized on that channel, the signal is given to the robot to move and that is recorded on the fifth channel.

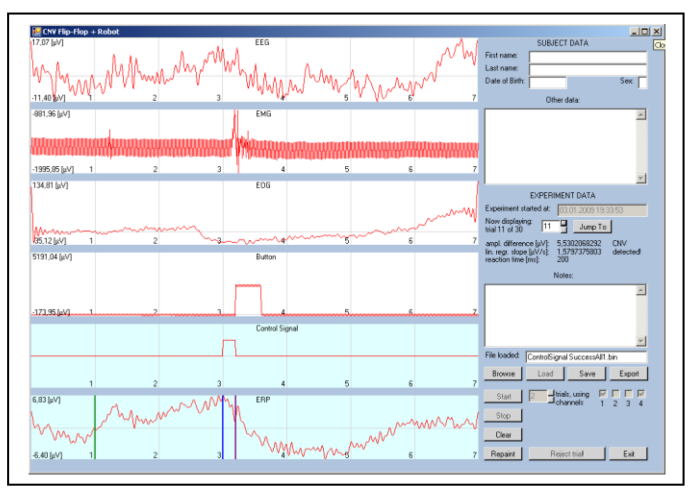

Figure 7. An experimental trial with CNV control of behavior-based robotics

The rightmost part of the screen is used for control of the exeperiment, including subject data and the name of the file where the experiment is stored.

9 EXPERIMENTAL INVESTIGATION: RESULTS

The experimental investigation described here is just a proof-of-concept series of experiments. Four experiments were performed on one subject different than the experimenter/programmer. A two-disk Tower of Hanoi requires three behaviors to complete the task, which means that the subject needs to produce a CNV1-CNV2-CNV3 sequence in the CNV flip-flop paradigm to complete the task. Each experiment contains 30 trials. Table 1 summarizes the experiments.

Table 1. Proof-of-concept series of experiments

	Experiment			
	1	2	3	4
Event → Behavior	Trial number			
CNV1 → Behavior1	16	12	11	6
CNV2 → Behavior2	22	23	12	19
CNV3 → Behavior3	26	29	22	22
CNV4			29	26
CNV5				30

Each entry in Table 1 is the trial number in which the event occurred. For example, in the first experiment, the first appearance of CNV was in trial 16, the disappearance was in trial 22, and the second CNV appearance was in trial 26. As can be seen from Table 1, in each experiment, within 30 trials the two-disk Tower of Hanoi task was executed successfully using a BRI. Table 1 also suggests that a learning process is taking place, in which the subject in each new experiment tends to develop its first CNV potential earlier, and also tends to increase the number of appearances and disappearances of a CNV potential.

10 BRAIN-MACHINE INTERFACE AS A 21 CENTURY DYNAMIC TECHNOLOGY

The 21st century shows advancement and maturity in the field of BMI. Various types of brain signals are used. Besides the above described research of using anticipatory brain potentials, other types of brain signals used are the frequency bands of spontaneous EEG signals. Evoked potentials such as visual evoked potentials and potentials due to imaginary movements are also used.

Here, some of the achievements in the field in the 21st century will be mentioned. The concept of imaginary voluntary movement-related potentials (IMMRP) was proposed by Mason and Birch [2000]. The evoked potential P300 was used in a BCI paradigm by Donchin et al [2000]. Anticipatory potentials in a BCI paradigm were introduced by Božinovski [2005].

Research in invasive BMIs continued on animals controlling robotic arms [Lebedev et al 2005]. Invasive motor neuroprosthesis research continues in humans, with the aim to either restore movement in the case of subject paralysis or assist with computers or robot arms. Brain implants were used in case of tetraplegic patients [Hochberg et al 2006].

A new approach was introduced with transfected neural cells. Cells are introduced in a somatosensory cortex of a mouse which moves freely. Decision of where to move is influenced by a light signal, which affects the transfected cells [Huber et al 2008].

Partially invasive Brain Computer Interface was introduced. Instead of implanting electrodes inside the brain, electrodes are implanted above the brain but below the skull. The term Electrocorticography (ECoG) is used for such measurements.

Noninvasive technologies mostly rely on electric signals from the skull; this technique is known as electroencephalography (EEG). Other technologies are also used, such as Near Infrared Sensing (NIRS), functional Magnetic Resonance Imaging (fMRI) and magnetoencephalography (MEG). New technologies enabled decoding visual images from inside the brain [Muyawaki et al 2008].

A new direction is opened in interfacing cultured neural cells with external devices. Recently, a neural network cultured in a petri dish was used to generate simulated actions of pitch and yaw for a flight simulator [Mazzarenta et al 2007].

Commercially available products, which utilize non-invasive technologies, are already on the market. As examples, the company G.TEC is offering the BCI2000 system, which is used for training purposes in BCI area, and the company Emotiv is selling a video game controller that uses electromagnetic sensors.

11 CONCLUSION

Although brain-machine interface research started in the 1970s, the 21st century is actually the era of this field for science and technology. A brief overview of the state of the art of the technology is presented. In particular, the paper gives description of an anticipation based brain-machine interface. The considered BMI uses the CNV potential and in a feedback loop generates a curve that triggers behaviors needed to solve a benchmark problem in computer science, in this case the Towers of Hanoi.

REFERENCES

W. Amai, J. Fahrenholtz, C. Leger, Hands-Free Operation of a Small Mobile Robot," Autonomous robots 11, pp. 69-76, 2001

R. Arkin, Behavior-Based Robotics, The MIT Press, 1998

H. Berger, Über das Elektrenkephalogramm des Menschen," Arch. Psychiat. Nervenkr. vol 87, pp. 527-570, 1929

R. Brooks. A robust layered control system for a mobile robot. IEEE Journal of Robotics and Automation 2: pp. 14-23, 1986

L. Bozinovska, V. Isgum, B. Barac, Electrophysiological and phenomenological evidence of the expectation process in the reaction time measurements. Yugoslavian Physiologica and Pharmacologica Acta, pp. 21-22, 1985

L. Bozinovska, S. Bozinovski, G. Stojanov, Electroexpectogram: Experimental Design and Algorithms, Proc. IEEE International Biomedical Engineering Days, pp. 58-60, Istanbul, 1992

A. Božinovski, CNV Flip-flop as a Brain-Computer Interface Paradigm, Proc. 7th Conf. of the Croatian Association of Medical Informatics, pp. 149-154, Rijeka, 2005

A. Božinovski, Control Software for the Towers of Hanoi Problem Solving Using Manipulative Robot – A Case Study, Proc. 2nd Balkan Conf. in Informatics, pp. 366-378, Ohrid, 2005

A. Božinovski, L. Božinovska, S. Tonković. A Cognitive Wave From a Human Brain In a Brain-Computer Interface Paradigm. Proc. 10th International Conference on Cognitive and Neural Systems, Boston, p. 102, 2006

A. Božinovski, L. Božinovska, S. Tonković, A CNV Anticipatory Potential Related Brain-Computer Interface, Proc. 11th International Conf. on Cognitive and Neural Systems, p. 43, Boston, 2007

A. Božinovski, S. Tonković, V. Išgum, R. Magjarević, L. Božinovska. Electrophysiology of expectancy process: Processing the CNV potential. Proc. 5th Internat. Conf. Informatics and Information Technology, pp. 129-137, Bitola, 2007

A. Božinovski, L. Božinovska , Anticipatory Brain Potentials in a Brain-Robot Interface Paradigm, Proc. 4th International IEEE EMBS Conf. on Neural Engineering, pp. 451-454, Antalya, 2009

S. Bozinovski, L. Bozinovska, M. Setakov Mobile robot control using alpha wave from the human brain (In Croatian) Proc. Symp. JUREMA, pp. 247-249, Zagreb, 1988

S. Bozinovski, M. Sestakov, L. Bozinovska Using EEG Alpha Rhythm to Control a Mobile Robot, Proc 10th Annual Conf. of the IEEE Engineering in Medicine and Biology Society, Vol 3, pp. 1515-1516, New Orleans, 1988

S. Bozinovski, Mobile Robot Trajectory Control: From Fixed Rails to Direct Bioelectric Control, in O. Kaynak (Ed.) Proc IEEE International Workshop on Intelligent Motion Control, vol 2, pp. 463-467, Istanbul, 1990

S. Bozinovski. The Artificial Intelligence (In Macedonian) Gocmar Press, Skopje, 1994

J. K. Chapin., K. A. Moxon., R. S. Markowitz, M. A. L. Nicolelis., Real-Time Control of a Robot Arm Using Simultaneously Recorded Neurons in the Motor Cortex, Nature Neuroscience., vol. 2, pp. 664–670, 1999

P. J. Cilliers, A. J. W. Van Der Kouwe, A VEP-Based Computer Interface for C2-Quadriplegics, Proc. of the 15th Annual International Conf. of the IEEE, p. 1263, 1993

A. Craig, L. Kirkup, P. McIsaak, A. Searle, The Mind as a Reliable Switch: Challenges of Rapidly Controlling Devices Without Prior Learning, in S. Howard, J. Hammond., G. Lindgaard (eds.) Human Computer Interaction, Chapman and Hall, pp. 4-10, 1997

E. Donchin, K. Spencer, R. Wijesinghe, The Mental Prosthesis: Assessing the Speed of a P300-Based Brain-Computer Interface, IEEE Trans. Rehab. Eng. 8, pp. 174-179, 2000

G. Garipelli, R. Chavarriaga, J. de R. Millan. Recognition of anticipatory behavior from human EEG, Proc 4th Int. Brain-computer interface workshop, Gratz, 2008

L. Hochberg, M. Serruya, G. Friehs, J. Mukand, M. Saleh, A. Caplan, A. Branner, D. Chen, R. Penn, J. Donoghue. Neuronal ensemble control of prosthetic devices by a human with tetraplegia Nature 442(7099), pp. 164-171, 2006

D. Huber, L. Petreanu, N. Ghitani, S. Ranade, .T. Hromadka, Z. Mainen, K. Svoboda, Sparse optical microstimulation in barrel cortex drives learned behavior in freely moving mice. Nature 451(7174), pp. 61-64, 2008.

H. Kadim. Modelling of Anticipatory Behaviour for Self-Control and Adaptability with Applications to Autonomous Systems Proc. IEEE ECSIS Symposium on Bio-inspired, Learning, and Intelligent Systems for Security, pp. 91-94, 2007

H. Kornuber, L. Deecke, Hirnpotentialänderungen bei Willkürbewegungen und passiven Bewegungen des Menschen: Bereitschaftspotential und reaferente Potentiale, Pflügers Arch. 284, pp.1-17, 1965

M. Lebedev, J. Carmena, J. O'Doherty, M. Zachenhouse, C. Henriques, J. Principe, M. Nicolelis, Cortical ensemble adaptation to represent velocity of an artificial actuator controlled by a brain-machine interface. Journal of Neuroscienece 25(19), p. 4681, 2005

S. Mason, G. Birch, A Brain-Controlled Switch for Asynchronous Control Applications, IEEE Trans. Biomedical Engineering 47 (10), pp. 1297-1307, 2000

A. Mazzatenta, M. Giugliano, S. Campidelli, L. Gambazzi, L. Businaro, H. Markram, M. Prato, L. Ballerini, Interfacing Neurons with Carbon Nanotubes: Electrical Signal Transfer and Synaptic Stimulation in Cultured Brain Circuits, Journal of Neuroscience 27 (26), pp. 6931, 2007

Y. Muyawaki, H. Uchida, O. Yamashita, M. Sato, Y. Morito, H. Tanabe, N. Sadato, Y. Kamitani. Decoding the mind's eye: - Visual image reconstruction from human brain activity using a combination of multiscale local image decoders. Neuron 60(5), pp. 915-929, 2008

G. Pfurtsheller, C. Neuper. Motor imagery and direct brain-computer communication. Proc. IEEE, 89, pp. 112-1134, 2001

A. Searle, Electrode performance and signal processing strategies for discrimination of EEG alpha waves: Implementations for environmental control by unconstrained subjects without training. PhD. Thesis, Department of Applied Physics and Technology, Sydney, 2000

E. Sellers, D. Krusienski, T. McFarland, T. Vaughan, J. Wolpaw, A P300 Event-Related Potential Brain-Computer Interface (BCI): The Effects of Matrix Size and Inter-Stimulus Interval on Performance, Biological Psychology 73(3), pp. 242-252, 2006

J. Tecce, L. Cattanach, Contingent Negative Variation (CNV), in E. Niedermeyer and F. Lopes da Silva (eds.) Electroencephalography: Basic Principles, Clinical Applications and Related Fields (3rd ed.) Williams and Wilkins, pp. 887-910, 1993

J. Vidal, Toward Direct Brain-Computer Communication, Annual Review of Biophysics and Bioengineering, pp. 157-180, 1973

G. Walter, R. Cooper, V. Aldridge, W. McCallum, Contingent Negative Variation: An Electric Sign of Sensory-Motor Association and Expectancy in The Human Brain, Nature, 1964

I. Wickelgren, Tapping the Mind, Science vol. 299, pp. 496-499, 2003

J. Wolpaw, D. McFarland, G. Neat, C. Forneris, An EEG-based brain-computer interface for cursor control, Electroencephalography and Clinical Neurophysiology, vol. 78, no. 3, pp. 252-259, March 1991