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Brain–Computer Interface in Europe: the thirtieth anniversary

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ABSTRACT

This paper reviews the development of Brain–Computer Interface research, covering period from 1973 when the term Brain–Computer Interface was introduced, till the last year of the twentieth century, 1999. The focus is on the first two brain–computer interface demonstrations done in Europe, in 1988. This paper written in 2018 marks the thirtieth anniversary of those two events. The first event was control of a computer buzzer using EEG contingent negative potential variation, and the second event was control of a physical object with a mass, a robot, using EEG alpha rhythm amplitude variation. Movement of a physical object with a mass through signals emanating from a human brain was named psychokinesis and before 1988 it was in the realm of science fiction. The paper describes the two events in chronological order, from the basic idea to the engineering realization.

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psychokinesis

Introduction

In 1973 Vidal [1] introduced the term Brain–Computer Interface (BCI), and set a challenge of controlling objects using signals from a human electroencephalogram (EEG). He actually stated two challenges for researches in the EEG area (1) develop methods for EEG control of objects not being part of a human body (2) develop methods for extracting event-related potentials, other than standard averaging method.

The methodology of a BCI is: (1) produce a state in a (human or animal) brain which will be manifested by a particular EEG signal in which a control command is encoded (2) record the EEG signal and transmit it to a computer, (3) analyse the EEG signal and decode the control command, (4) send the decoded signal to a controlled object, such is a visual object, or a sound object, or a physical object with a mass.

EEG is classical modality of obtaining a brain signal, but other ways of recording brain signals (e.g. magnetoencephalogram) are also being developed. Various EEG features are recognized in a brain signal, such as change in an EEG frequency band or appearance of an event-related potential (ERP).

There are two ways of generating EEG-encoded commands to control objects.

(1) External stimulus-driven EEG-encoded command. This method uses a stimulus (e.g. light variation) to generate an EEG response which then is used for object control. Example is a visual stimulus sent to a particular part of computer screen to produce corresponding evoked and/or cognitive

visual potential in the brain. This method usually requires active movement of the eyes in order to move eye gaze to a particular area on the screen.

(2) Intention-driven EEG-encoded command. This method encodes a command in EEG by a human intention (connatively, willingly). Example is willingly increasing amplitudes of the EEG frequency band 8–13 Hz by a relaxation technique, e.g. by closing the eyes.

Essential objective of the BCI software is to find an EEG feature which will be used as *EEG switch*, which will be then used to control an object. Recently other control structures are being explored to be emulated by EEG, such as flip-flops, demultiplexers, and modems [2].

Response to the BCI challenge was relatively slow in the years after 1973. After the Vidal's challenge was stated, the first report on control of an object using EEG was given by Vidal in 1977 [3] who used Visual Evoked Potential (VEP) to control cursor-like appearance on a computer screen. In 1988 three reports appeared on implementing BCI: Farwell and Donchin in 1988 [4] who used P300 potential to control appearance of a letter and writing a text on a computer screen; Bozinovska et al. in 1988 [5–8] who used Contingent Negative Variation (CNV) potential to control a buzzer; and Bozinovski et al. in 1988 [9–12] who used changes in EEG alpha frequency band (contingent alpha variation, $C\alpha V$) to control a movement of a physical object, a robot. It is worthy of mentioning that one of the pioneering results in BCI, controlling a physical object

with a mass (a robot) using EEG signals was originally reported at a conference in Croatia, and published in its proceedings [9].

Out of the four pioneering works mentioned above, two happened in Europe in 1988, and they will be reviewed here. Those are the CNV-based BCI for buzzer control and $C\alpha V$ -based BCI for robot control. The CNV-based BCI was first developed and will be described first. CNV is important also because Vidal in his challenge specially pointed to CNV as a signal to be used in BCI.

After the above-mentioned four pioneering works, following the Vidal's BCI challenge, several others appeared till the end of the twentieth century. This paper in the discussion section will give a brief review of the twentieth-century BCI works.

In the sequel, we will first describe a taxonomy of brain potentials and the place of CNV and $C\alpha V$ in that taxonomy. After that, we will describe the two mentioned 1988 works, the CNV-based BCI for control of a buzzer and $C\alpha V$ -based BCI for control of a robot. Discussion section is about the context in which the result is obtained in 1988 from the prospective of the thirtieth anniversary in 2018.

1. A taxonomy of brain potentials

This work describes two types of EEG signals for control of objects. One is the contingent change of shape of an anticipatory potential (CNV) and the other is contingent change of amplitude of the alpha rhythm ($C\alpha V$). The first taxonomy of brain potentials which included *anticipatory potentials* was presented in 1992 [8].

EEG signals could be divided into spontaneous (ongoing) EEG, and event-related potentials, which are part of an ongoing EEG.

In an ongoing EEG signal, some frequency bands are more prominent than others, manifesting the state the brain is in. One of the bands is the alpha band, around 10 Hz, most often defined as 8–13 Hz frequency band. Part of the brain where this EEG band is dominant on the EEG record manifests a relaxation state of that part of the brain. If recorded from the visual area, this band represents itself as almost a 10 Hz sine wave, and is named alpha rhythm. If alpha band is recorded from the sensorimotor area, it is named mu (μ) rhythm. Mu rhythm has a sharper amplitude shape than the alpha rhythm. Regardless of where the alpha band is measured, the BCI algorithms are the same: They monitor the change of amplitude and/or energy of the frequency band. Other bands such as beta, gamma, delta, and theta are also processed the same way.

Event-related potentials (ERPs) are transient potentials inside an ongoing EEG. They are generated due to some external event, for example, a sound stimulus. They are divided [8] into pre-event and post event.

Post-event (evoked) potentials can be divided [13] into exogenous (reflexive to the outside event, such as visual evoked potential (VEP)) and endogenous (cognitive processing because of the event). Pre-event (*anticipatory*) potentials are divided [8] into expectancy and preparatory. A preparatory potential e.g. readiness or Bereitschaftspotential (BP) [14] appears in preparation of an motor action. An expectancy potential, e.g. CNV [15], appears in expectation of an event. The fact that CNV represents learned expectation, relates it to the cognitive processes of adaptation and learning.

From engineering standpoint, $C\alpha V$ and CNV require different techniques to be obtained from an ongoing EEG. $C\alpha V$ can be obtained using a band pass filter, CNV can be obtained by a simple averaging filter, or, if CNV changes in time, by a more complex adaptive filter.

2. A BCI using contingent negative variation (CNV) potential to control a computer buzzer

The CNV potential appears in an experimental procedure known as *CNV paradigm*, originally proposed by Walter et al. [15]. It is a well-known procedure (e.g. [16,17]) in which, *in an open loop way*, a slow negative potential shift (the CNV) appears in the inter-stimulus interval of the S1-S2 stimulus pair. The negative *slow potential* shift is interpreted as expectancy wave and is related to learning and memory. In the open-loop design, after stimulus S1, the brain is expecting stimulus S2 and is preparing to produce reaction R on S2. The ERP between S1 and S2 gradually develops to be a recognizable CNV. The CNV paradigm produces a ramp-like potential related to the pair S1-S2 for which CNV is recognizable, but also produces a number of other evoked, cognitive, and preparatory potentials related to S1 and S2.

Our interest in the CNV paradigm started 1981 [18], after previous work on S1-S2 processing structure of a reaction time (RT) paradigm [19,20]. In essence, the classical CNV paradigm is sequence of RT paradigms in which EEG is recorded and averaged between S1 and S2. The first experiments with CNV potential we did in 1985, where we used some modifications in the classical CNV paradigm [21]. In 1986 we got an idea of introducing feedback in the classical CNV paradigm. The realization of the setup and the first results were obtained in 1988 [5] and in the subsequent years [6–8].

Figure 1 shows the BCI setup for controlling a buzzer using CNV potential from a human EEG. It shows the subject, the EEG acquisition, the computer processing EEG, ERP and CNV variables, the interface toward controlled object, the controlled buzzer, and the feedback where subject can hear the result of her/his EEG-encoded command.

As can be seen from Figure 1, the subject generates an EEG which contains a stimulated ERP. The EEG

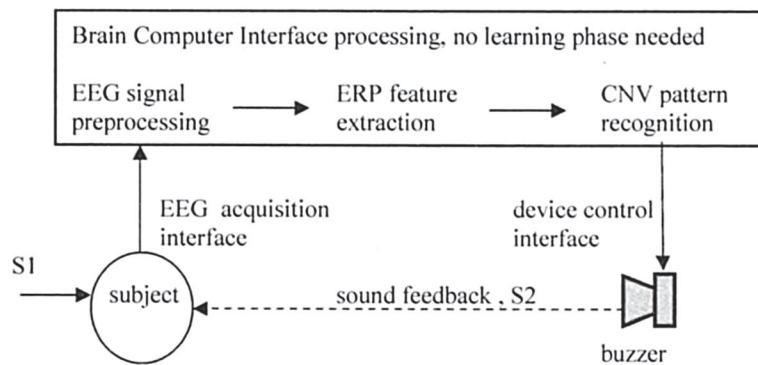


Figure 1. The 1988 CNV-based Brain–Computer Interface system setup for control of a buzzer.

undergoes initial signal processing, after which follows a procedure of feature extraction and then a procedure of CNV pattern recognition. Once the presence or absence of CNV is recognized, the control signal (ENABLE/DISABLE) is sent to the controlled buzzer.

The BCI procedure starts with building CNV potential in the subject by generating S1-S2 pairs of sounds. By classical conditioning, an expectation of S2, $E(S2)$ is being built. After repetitions, which are part of the learning process, the expectation to S2 is formed in the subject's brain, and a CNV is manifested. That event, recognition of a CNV, can be used to control an external device, such as a sound generator, a robot, or something else. In case expectation is not built, the CNV will gradually degrade and disappear. That point, recognition of no-CNV (no expectation) event, can also be used to control an external device, in our 1988 experiment to enable the buzzer.

Standard way of building expectation is using a reaction $R(S2)$ to stop the duration of S2 signal, usually by pressing a button. It is not necessary, a subject develops expectation regardless of a motor reaction [22].

Note that the subject could stop building expectation willingly, by not paying attention to the S2 stimulus. But in that case, there is no adaptive interaction between the subject and BCI, and adaptive interaction is what makes this BCI interesting.

2.1. Assembling lab equipment

After the research idea was developed, a lab equipment was planned and assembled in the Neurophysiology Lab, Institute of Physiology, Medical School of the University Cyril and Methodius in Skopje. A workstation was developed which is shown in Figure 2. The workstation contains racks, desk, and drawers for placing the instrumentation.

As Figure 2 shows, the workstation has a 1988 PC XT computer part (in the desktop rack) and a biopotential amplifier part (in the rack below the desktop). The biopotential amplifier was designed for our research and was built by LME (Laboratorij Mjerne Elektronike) from Zagreb. At that time, they already produced



Figure 2. The research workstation for the CNV-based buzzer control.

a standard paper-based table-looking EEG system. We visited them and we designed a rack-based system, without a paper part. That was the first paperless EEG system they ever built. They named it LME Poly Sub-complet. The front part, shown in Figure 2, contains four amplifiers, two for EEG, one for EOG (electrooculogram) and one for EMG (electromyogram). The outputs of the amplifiers were connected to a Flytech 14-bit analogue-to-digital card (16 analogue inputs, 2 analogue outputs) inside the computer. A digital input/output card (48 channels) with a timer was also used as part of buzzer control. The cards were purchased in Munich, Germany. Below the LME system,

in a drawer, it is shown the printer for documenting the results from the experimental work. Some of those prints are shown in the result section below. Above the computer is an oscilloscope for real-time signal view. As can be seen, it was a very compact design of a BCI research workstation.

On the back of the workstation were inputs to the biopotential amplifiers. The subject's head was connected by Ag/AgCl electrodes then to an electrode box, which was connected the amplifiers by a shielded cable. EEG signal was recorded from Fz, Cz, and mastoid, and EOG signal was recorded simultaneously. An EOG channel was used for artefact observing purposes.

2.2. Dealing with a time-varying ERP

Vidal in his BCI challenge [1] pointed out that techniques other than standard EEG signal averaging should be explored in relation to BCI. So in addition to the response to his "CNV-based BCI" challenge, this 1988 work can be viewed also as response to his "other than averaging" challenge.

The paradigm we designed, the bidirectional adaptive BCI, indeed includes a time-varying ERP, for which averaging is not applicable. So we faced a challenge how to deal with a time-varying ERP which shapes into CNV and then again degrades into an ERP.

For solving that problem, we introduced an adaptive filter with the following learning rule.

$$\text{ERP}(n) = p \text{ERP}(n - 1) + q \text{EEG}(n), \quad (1)$$

$$\text{where } p + q = 1, \quad (2)$$

The parameter p is much bigger than q , for example, either $p = 0.8$ or $p = 0.9$. The idea was to attenuate the new noise in real time, instead of using averaging.

More details on parameter computing and adaptive filter description are given in [8]

2.3. Result: BCI control of a computer buzzer

The flow of the experiment, trial after trial, was recorded on the computer screen. An example is given in Figure 3.

Each box on the screen shown in Figure 3 is an ERP obtained in one trial. The trials are numbered, and here are shown up to the 15th trial, although the experiment continues further building and degrading a CNV and with that controlling the buzzer. The controlled buzzer is the second vertical line inside a box. It is present or absent depending on whether CNV (expectation state of the brain) is absent or present. In this particular experiment, the subject was able to stop the buzzer at the trial 11. The expectation is not formed after that, and CNV is degraded. Example of a CNV obtained in the trial 46 is shown in Figure 4.

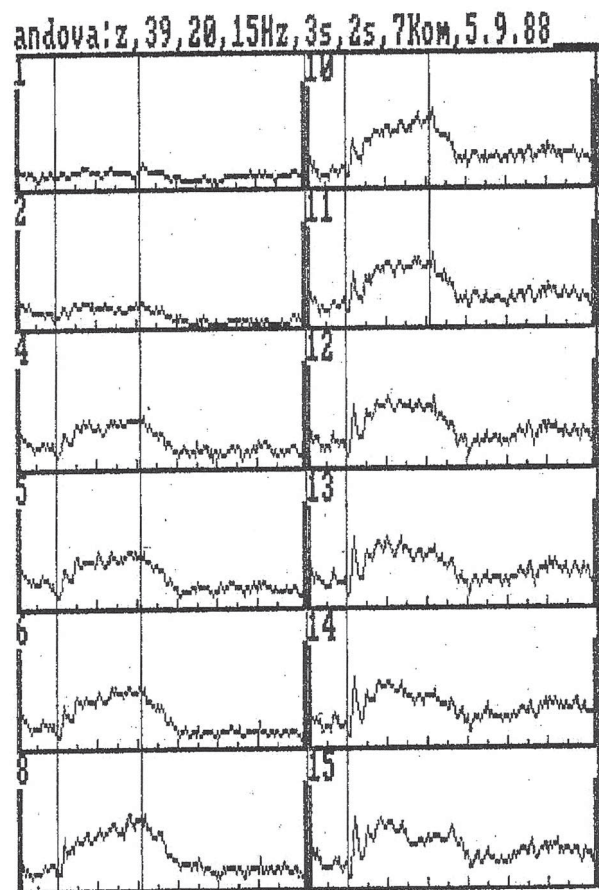


Figure 3. Flow of the experiment shown on computer screen, up to trial 15.

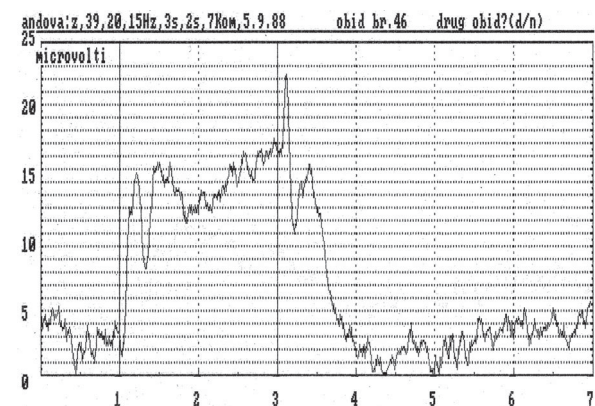


Figure 4. CNV potential obtained September 5, 1988, in a trial of an experiment of CNV-controlled buzzer.

Figure 5 shows a result of a 1988 experiment.

The top graph, S2, (thick line) shows the BCI goal, the control of the S2 buzzer: The buzzer is controlled by the regression angle of the CNV potential, shown in the main graph. If the regression angle is above a threshold (in our experiments $3.6 \mu\text{V/s}$) for three trials, the buzzer is disabled. If it is below the threshold for three times the buzzer is enabled again. In this experiment, in 100 trials the subject was able to disable the enabled buzzer 4 times. A dotted horizontal line is the threshold when the computer decides that the expectancy state is

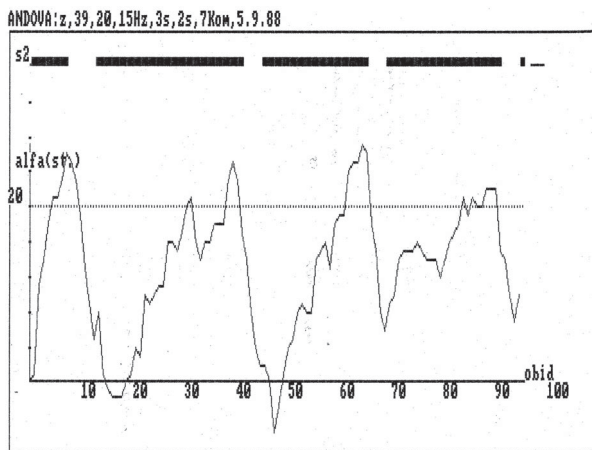


Figure 5. BCI control of the buzzer S2, based on the regression angle of the CNV potential.

above required level or below a predefined level. This graph we call ElectroXpectoGram (EXG) It is a result of adaptive interaction [23] between a human brain and an environment, under the CNV-based BCI.

In such a way, we obtained the bidirectional adaptive BCI, where subject controls an external buzzer using EEG manifestation (the CNV) of its expectancy brain state. The subject adapts to the changing environment which sometimes contains event S2, sometimes not. The environment with S1-S2 will remain as such until the subject decides to change it by focusing on S2 and disabling it. The subject controls the expectancy state by choosing to reach it, after which the BCI disables the external object, the computer buzzer.

3. A BCI using contingent alpha variation (C α V) to control a robot

Here we describe our second EEG control of an object, in this case, a physical object, a robot. The original idea was to find an engineering solution of psychokinesis, the phenomenon of using energy emanating from a human brain to control movement of a physical object. The term “psychokinesis” appeared in science fiction and indeed till 1988 it was in the realm of science fiction. The engineering approach we implemented was to use EEG as representation of an energy emanating from a brain.

We define *EEG-controlled psychokinesis* as the use of EEG signals to control movement of a mechanical object. In this paper, *kinesis* is understood as mechanical movement of an object. It includes movement of objects such as robots, wheelchairs, prostheses, drones etc. However, it does not include movements of objects on a computer screen or a virtual reality screen.

Figure 6 shows the BCI block diagram, which uses change of alpha rhythm amplitude (C α V), as the engineering solution of the 1988 idea of EEG-based

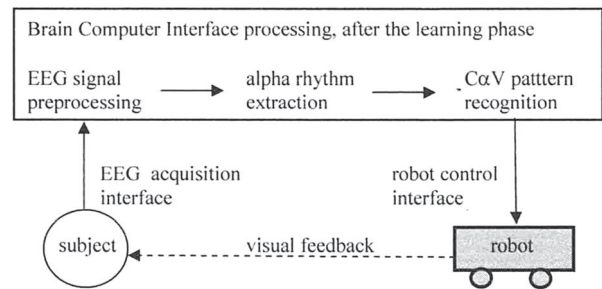


Figure 6. The 1988 C α V-based Brain-Computer Interface system setup for control of a robot.

psychokinesis. The 1988 report [9] is the first report that presented a BCI block diagram.

As can be seen from Figure 6 the experimental setup consists of:

- (1) A human subject willingly encoding commands into EEG signals. Note that there is no separate stimulus as in case of an ERP-based BCI, as is the case in Figure 1. In this case, the subject willingly changes energy (amplitudes) in the EEG alpha band. S/he does that by entering the relaxation state of the brain, for example by closing the eyes and relaxing, or other relaxation technique. The eyes closing is not necessary if the subject is able to relax in a different way.
- (2) An interface toward a computer, which captures EEG signals. In our 1988 case that was the mentioned biopotential amplifier Poly Subcomplet.
- (3) A computer for processing of EEG signals, including learning (calibration) and pattern recognition algorithms based on the processing of the C α V. In 1988 that was a PC/XT computer.
- (4) An interface toward the physical object. If the physical object is a robot, a preprogrammed behaviour can be stored in the robot controller, so an EEG signal can actuate a rather complex behavioural routine if needed in a particular experiment or application.
- (5) A feedback (visual, audio, etc.), ensuring that the subject who controls the robot kinesis, observes results of her/his intentions which were encoded as EEG patterns.

3.1. The robot

In 1984, we purchased at Akihabara market in Tokyo, Japan, a kit for a robot named Movit Line Tracer, a product of Elehobby Company from Japan [24]. That was a robot which had own intelligence to follow an arbitrary black line drawn on the floor. It had only a mechanical on/off switch. Figure 7 shows the robot kit.

We replaced the mechanical switch onboard the robot with the EEG switch, based on amplitude change



Figure 7. The robot kit used for building in EEG-controlled robot, purchased at Akihabara market in Tokyo, Japan, in 1984.

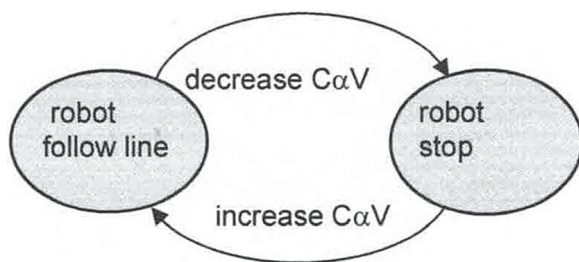


Figure 8. The robot behaviour graph, Moore type automaton, used in design of scenario for demonstration of EEG control of a robot.

of the alpha rhythm. So we had a robot that has intelligence to follow a line, and we have chosen the following challenging task: Choose default the behaviour to be “follow line” and using BCI, execute “stop moving” behaviour at some point of the line. After that execute behaviour “follow line”. using another BCI command. The BCI control of the robot, as a Moore type automaton, is shown in Figure 8.

As can be seen from the behaviour graph, as long as the $C\alpha V$ has increased activity a robot will follow the line. The increased $C\alpha V$ activity can be achieved willingly by the subject, with a relaxation technique, often with eyes closed. To stop the robot willingly, the $C\alpha V$ should have lower amplitudes, and that can be achieved by opening the eyes and focusing on the robot. A task to the subject was to stop the robot at a desired point on the drawn line. The subject will drive the robot with eyes closed and will check the position of the robot with eyes open. With open eyes, while robot is stopped, the subject can assess how far the robot is from the desired stop point.

During 1985–1988, we carried out experiments simulating some episodes of Flexible Manufacturing Systems (FMS) and we designed outfits for our mobile robots to mimic the Autonomous Guided Vehicles (AGVs) in various FMS scenarios. We also designed appearance of the Line Tracer robot to be an AGV like vehicle.



Figure 9. The experimental setup for control of a physical object using EEG signals, 1988.

3.2. The experimental setup

In 1986, we obtained a new lab space in a new building, which was expansion of the Electrical Engineering Department building of the Cyril and Methodius University. Since we already had previous robotics and signal processing equipment at the Mechanical Engineering Department IBM Series/1 Computing Center we moved it to the new lab space. The new lab was named Laboratory for Intelligent Machines, Bioinformation Systems, and Systems Software (LIMBISS). Figure 9 shows a segment of the organization of the new lab, devoted to BCI control of robots.

Central part of the BCI segment of the lab was a two-floor lab infrastructural unit named Robot Polygon. As shown in Figure 9, it is basically a white ping-pong size table where robots move, with added second floor as rack above the table, where computer-robot interfaces are placed. In some experiments, the second-floor rack contained a camera. Because in 1988 there was no wireless control at our disposal, we managed all the connections to the robots to come from above. A control computer (a 1988 PC/XT) placed outside the Robot Polygon (Figure 9), was connected to the robots controller above the surface where the robots moved.

In this setup, a subject (a student) was connected with Ag/AgCl electrodes to the area of his head where alpha rhythm is rather easily controllable, such as occipital area, and Fz as reference electrode and mastoid as ground electrode. We also experimented with sensory-motor area. The signal was filtered and amplified using Poly Subcomplet rack. From the amplifier, the signal was converted to a digital form by a 14 bit AD/DA converter. Additional Digital I/O card containing a hardware timer was used for measuring time. The signal processing was done in real time by a PC/XT computer. The output was sent to the robot controller on the second floor of the Robot Polygon where from the signal was sent to the robot.

3.3. Learning and pattern recognition procedure

The EEG signal processing part presented two engineering problems.

The first problem was stopping a moving robot at a particular point. If the subject wants to stop the robot at a particular point, the EEG signal processing should be very fast. We decided to find a hard real-time algorithm, the one which will execute an action inside the sampling interval of the EEG signal, which in our case was 10 ms (100 Hz sampling rate). We needed a procedure that reads an EEG sample, extracts the EEG features, compares them to template features, and sends command to the robot, all that in less than 10 ms on a 1988 PC/XT computer.

The second problem was variability of the alpha rhythm amplitude across subjects and even for the same subject during a day. In order to adapt to such changes, it was obvious that a learning algorithm was needed to be applied before each experiment of alpha rhythm based robot control.

Since we needed an *algorithm that executes inside a sampling interval*, we could use neither a frequency domain analysis nor time domain averaging of the EEG signal. So we developed a statistical pattern recognition method consisting of two phases:

- (1) a learning (calibration) phase in which the computer learns the statistical features of the EEG of a particular subject, and defines regions in statistical distributions where from it can decide whether the brain is in its relaxation state or not
- (2) a pattern recognition phase in which computer compares the just observed EEG features of that subject and compares those features against the statistical distributions obtained in the learning phase.

We have chosen 10 s of learning procedure in which subject will open and close her/his eyes and generate amplitude change in the alpha rhythm. Since our sampling rate was 100 Hz, we acquired 1000 samples where the template features will be learned from.

The basic idea of the approach for our algorithm building was to observe an onset of a dominant alpha rhythm in an EEG. When a contingent alpha rhythm appears (relaxation state), both the amplitudes and time distance between amplitudes are greater than the ones in an alert state (beta rhythm).

So, our algorithm in the learning phase collected both *changes* of EEG amplitude and *changes* of time intervals between EEG amplitudes. Figure 10 shows the features extracted from an EEG.

As Figure 10 shows, the learning algorithm scans the 1000 EEG samples obtained in the 10-s learning phase, and looks for local extrema, peaks and valleys of the signal, the points of the signal where the gradient changes

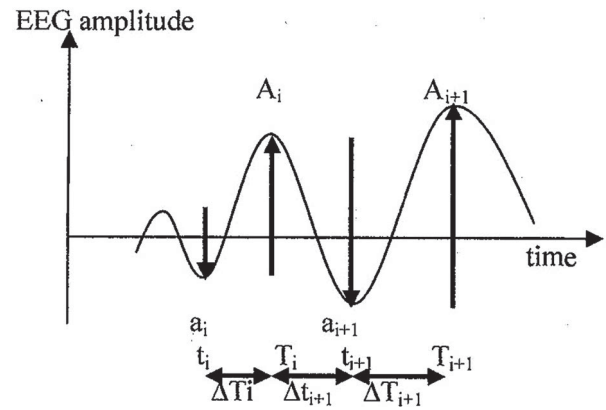


Figure 10. The 1988 BCI algorithm. EEG features are both time differences and amplitude differences for the EEG signal extrema.

the sign. The feature extracted is difference between a local maximum and the previous local minimum of the signal.

In mathematical terms, whenever change of the sign of gradient of the EEG curve is sensed on a point EEG(t), two differences are computed.

One is the time difference between the maxima and minima of the EEG hills. Symbolically $\Delta T_i = T_i - t_i$, is the time difference between the i th maximum and the i th minimum, and $\Delta t_{i+1} = t_{i+1} - T_i$ is the time difference between the $(i+1)$ th minimum and the i th maximum.

The other is the amplitude difference between the maxima and minima, $\Delta A_i = A_i - a_i$ and $\Delta a_{i+1} = a_{i+1} - A_i$. Actually we compute the absolute values of the differences.

After computing the differences, their probability density distributions (pdd) are computed. So for each subject we obtain both the EEG amplitude difference pdd pA and EEG time difference pdd pT. Due to open and closed eyes conditions each of the pdd's has two instances, so we obtained four pdd's, pA(open/alert), pA(closed/relaxed), pT(open/alert) and pT(closed/relaxed). Collecting the distributions in a calibration session calibrates the classifier. With the obtained probability density distributions, and with determined thresholds, the learning process calibrated the classifier for the pattern classification process that comes in the examination (test) phase and the exploitation (real-time BCI) phase.

Figure 11 shows the statistical pattern recognition method used. The basic idea is to find the differences in amplitude of the EEG signal between relaxed state of the brain (eyes closed) and alert state (eyes open).

The exploitation procedure is the real demonstration of the process of control of a robot using EEG signal. The subject's decision when to close or open the eyes is asynchronous to any external event, and is the subject's choice. However, due to limited buffer where the EEG samples are stored, a limited time is given (e.g.

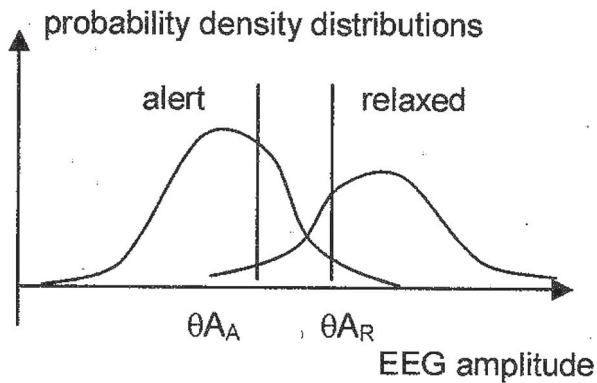


Figure 11. Pattern recognition method used.

14 s) inside which the computer observes the subject's decision.

In the examination and exploitation phase, the subject is given a time, for example, 15 s, in which s/he will close and open the eyes at least once. It is assumed that the stop points on a robot trajectory are at most 15 s apart. The decision process we used was based on confirmation sequence of three samples in a row, meaning that in each sample its amplitude difference and time difference should be greater than the corresponding thresholds θ_A and θ_T . The decision criterion for relaxed state of the brain and to move the robot was

$$\text{if } A(t) > \theta_{A_R} \text{ and } T(t) > \theta_{T_R}$$

for three consecutive times,

then brain state is relaxed and brain behaviour is "follow line".

Here $A(t)$ and $T(t)$ is the current EEG amplitude and time difference, while θ_{A_R} and θ_{T_R} are the corresponding decision thresholds. recognizing relaxation state of the brain, after which the robot is actuated.

Note that this algorithm inherently contains artefact rejection. If high amplitude appears while the brain is in alert state (beta rhythm) it will be ignored by the algorithm, since the frequency condition is not satisfied.

The software was written in Pascal with some inline sections in assembler. The pseudocode was written in pseudo Cobol due to appreciation of Cobol's PERFORM command [25]. The next program block shows the pseudocode of the program [12]

In the experimental setup we used $\text{required_votes} = 3$. That is also an artefact protection feature of the algorithm

3.4. Result: BCI control of a robot

Figure 12 shows the printed computer screen with 1988 graphics, where it can be seen result of the EEG pattern recognition and robot control.

The bottom part of the screen shows an acquired EEG signal in duration of 10–15 s during which a subject generates EEG signal and controls the robot. A line

EKG BASED CONTROL
 PROCEDURE LEARNING:
 Perform 10 sec Acquisition during which the subject has eyes open;
 Compute distributions for the time intervals between two extreme points, and the amplitudes of those points.
 Perform PROCEDURE LEARNING replacing "eyes open" with "eyes closed".
 Compute decision border points for the pairs of distributions for "open" and "closed" case.

PROCEDURE RECOGNITION:
 While the subject opens and closes his eyes in real time do:
 Perform Acquisition until a next extreme point is found, compute its time interval compute its amplitude;
 Compare amplitude and time intervals with the respective "open"/"closed" distributions
 if they fall in "open" region
 vote "open"
 increment open-counter
 reset closed-counter
 if open-counter = required_votes
 then decision = "ALERT/STOP";
 if they fall in "closed" region
 vote "closed"
 increment closed-counter
 reset open-counter
 if closed counter = required_votes
 then decision = "RELAXED/GO";

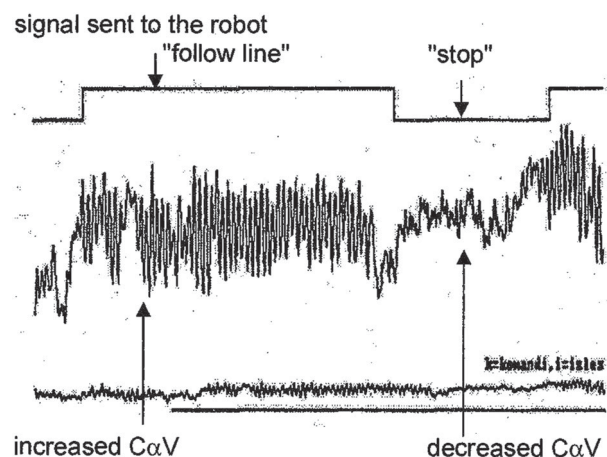


Figure 12. EEG $C\alpha V$, its recognition, and signal sent to the robot, in the 1988 EEG-based control of a robot experiment.

below that EEG signal is the zoom tool of the developed software. The zoomed segment is shown in the middle of the screen. The pattern recognition algorithm draws a rectangle waveform on the upper part of the screen showing segments where relaxation brain state is evident ($C\alpha V$ increased) as well as segments where relaxation is not evident. The rectangle line at the same time shows the signal sent to the robot when to resume behaviour "follow line" and when to stop moving.

Figure 13 shows the demonstration scenario of the BCI for robot control. The robot is the Movit Line Tracer robot, here in its FMS outfit. The Figure also shows the designed black closed line which was followed by the robot.

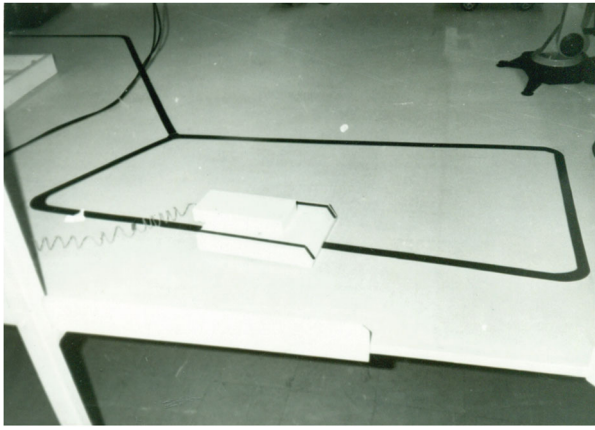


Figure 13. The FMS outfit of the Movit Line Tracer robot, here shown on the Robot Polygon, and the closed line it follows if actuated.

Total six students were engaged in the experiments. Two students of Computer Science major were engaged in the experimental work during 1988, and they successfully carried out the experiments of moving the robot along the closed trajectory and stopping it at a particular place. Four additional students were engaged in experiments of moving the robot for a segment of the trajectory. The average learning time was about 30 min before successful EEG control was achieved.

4. Discussion

In this section we discuss the described 1988 works in the context of other BCI works between 1973 (statement of BCI challenge) and 1999 (end of the twentieth century).

In 1973 the research field of brain–computer communication was established, and the term Brain–Computer Interface was introduced by Vidal [1]. The challenge was stated as control of objects using EEG signals as well as to find ERP extraction methods other than averaging method. Vidal also said that after the EEG control, other signals such as EOG can be used to control objects. Vidal himself presented the first BCI work after his challenge: In 1977, he achieved an EEG control of a visual object on a CRT screen [3]. The visual object in form of a small triangle was moved through a 2D maze. That was the first application of moving a cursor-like object on a computer screen. It was the first BCI which used active, task-related muscle movement in a BCI. Active muscle engagement was used for moving the eyes on the screen where from a stimulus should be received. Once a stimulus is received from a particular part of the screen, a Visual Evoked Potential (VEP) determined direction of the object movement.

Three events happened in 1988 related to BCI. (1) One of them was about writing text (word “BRAIN”) on a computer screen using EEG signals [4]. P300 potential

was used in a responsive setup in which a 6×6 letter matrix was shown and in each trial a row or a column was enlightened. The letter was chosen due to P300 response with a higher amplitude. (2) The other, was about a control of a buzzer (sound object) using CNV potential [5–8] and is reviewed in this paper. It was designed a two-way adaptive BCI in which a computer buzzer was disabled and enabled using CNV appearance and disappearance. It was the first use of a CNV potential in a BCI task. The CNV potential was specially emphasized by Vidal in his challenge [1]. (3) The third 1988 event is also reviewed in this paper. It was the first BCI used to control a physical object with a mass, a robot [9–12].

In 1989 EOG signals were used to control robots [11]. EOG signals were also part of the Vidal’s BCI challenge [1], although the focus was on the EEG signals.

A 1990 BCI research was reported in 2013 [26] about a cursor control using N400 potential.

In 1991 it was shown a BCI control [27] of an up-down 1D movement of a computer screen cursor using alpha rhythm recorded from the sensory-motor area of the brain. First, in 1990, the pattern classification problem was solved, but the object control was done by a human operator [28]. The paper uses the term mu rhythm [29] for the sensory-motor alpha rhythm, originally reported as Rolandic rhythm [30]. The algorithm only considers the alpha band frequency and not specific shape of the Rolandic rhythm. So actually it is an alpha band based EEG control of an object. The signal is recorded around the C3 spot on a human scalp. In this work, the term Brain–Computer Interface (BCI) was used. This work actually revived the term, which after this work was very popular for use for EEG control of objects. Before this work, various terms were used for EEG-based control of objects outside human body. In 1997, this work was extended to movement of cursor in 2D [31].

In 1992 a system was built that allows control of a virtual keyboard and a speech synthesizer using eye movements [32]. The direction of the eye gaze was determined by visual evoked potentials (VEPs) collected from the occipital region of the brain. The direction of the sight corresponds to a part of the screen where particular command is encoded. This system also introduced wireless transmission of amplified EEG signals, from the human head to the A/D converter of the system. New to BCI experiments were implanted electrodes below the scalp but not inside the brain. The BCI here is named Brain Response Interface (BRI), to emphasize that it is a *responding setup* rather than a intentional, self-paced setup.

A report on using flickering light VEP in a BCI was given in 1993 [33]. It was a text typing application designed for quadriplegic patients. The phenomenon of rhythmic response of the EEG when brain is stimulated by a flickering light was originally observed

in [34] following the introduction of EEG and alpha rhythm [35].

In 1993 another paper [36] emphasized the use of sensorimotor rhythm in 1D (left–right) control of a cursor on a computer screen. It focused on C3 and C4 electrode positions of 10–20 electrode placement international standard. That way the advantage of brain hemisphere-difference was utilized in regards to imaginary left–right fingers movement. The contingent attenuation of sensorimotor alpha rhythm amplitude was denoted as event-related desynchronization (ERD), a term which was described in a previous paper as alpha power decrease [37]. ERD was computed in two different ways, one as signal power computation and the other as amplitude envelope computation. It was reported that the amplitude method was more accurate but power method was faster to compute. In 1997 another work along this line [38] studied the alpha and beta band during imagination of left and right-hand movement using visual cues telling the subject what movement to perform. Brain hemisphere difference was studied in relation to increase and decrease of the amplitude of the mentioned bands.

In 1999 a BCI spelling device was built for paralyzed patients [39]. It uses the negativity and positivity of slow cortical potentials (EEG baseline shift). A patient was able to write a short letter using this device.

In 1999 was given the second report on controlling a robot using BCI [40]. An invasive EEG recording (electrodes inside the brain) was applied on an open brain of an animal, a rat. Experiments were carried out showing animal EEG control of a robotic arm.

The reports on BCI work published in the twenty-first century, starting year 2000, are out of the scope of this review. Good review of the work done in twenty-first century in the area of EEG control of objects is given in [41–43].

Regarding continuation of the 1988 works reviewed here we would mention two recent works: (1) the BCI control of two robotic arms for solving the Towers of Hanoi problem using CNV potential [44] and (2) EEG emulation of digital control circuits, such as switch, flip-flop and demultiplexer. [2].

Finally, let us mention that both 1988 papers reviewed here in significant part were related to biomedical engineering activities carried out by the University of Zagreb. The first CNV experiment in the research described here was done 1985 at the Rebro Medical Center and the first EEG control of a robot was reported 1988 at a JUREMA conference in Zagreb.

5. Conclusion

In Europe, after the BCI challenge was stated by Vidal in 1973, the first BCI experiments were carried out in 1988. This paper is written on the thirtieth anniversary of those events. The paper also gives the overview of

the context provided by other experimental BCI works worldwide during the twentieth century. The period covered is 1973–1999. They are works describing actual BCI experiments, where a subject using EEG willingly actuates change of the environment either on a computer screen, or as a controlled sound source, or as a movement of a physical object. There were works which provided conceptual and theoretical background for potential BCI research, and they are not included in this review.

The importance of the two works done in 1988 in Europe can be summarized as this:

One of them is the first work worldwide on a BCI using CNV potential. CNV potential was especially emphasized in the Vidal's 1973 challenge. The second Vidal's challenge of using methods other than averaging to extract an ERP was also addressed by this paper and an adaptive filter was described to extract a time-varying ERP which oscillates between a CNV and a non-specific ERP. This work is also the first to describe a bidirectional BCI, where both the subject and the BCI adapted to each other.

The other one is about the worldwide first BCI to control a physical object. It solved the long-lasting problem of how to make an engineering solution of psychokinesis, i.e. control movement of physical object using energy emanating from a human brain. This work is significant also because of the time distance, 11 years, till the next work on this topic was reported. After the 1988 report on a non-invasive recording from a human brain to control a mobile robot, the next, 1999 report was on an invasive recording inside an animal brain to control a robotic arm.

In regards to other BCI reports in Europe done in the period between the BCI challenge in 1973 and the end of the century in 1999, let us mention that after the first two in 1988 the third one was reported 1993 on controlling in 1D a cursor-like object on a screen, and the fourth one in 1999 reported on use a BCI as a spelling device for handicapped persons. They are commented in this paper.

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No potential conflict of interest was reported by the authors.

References

- [1] Vidal J. Toward direct brain-computer communication. *Annu Rev Biophys Bioeng.* 1973;2:157–180.

- [2] Bozinovski S, Bozinovski A. Mental states, EEG manifestations, and mentally emulated digital circuits for brain-robot interaction. *IEEE Trans Auton Ment Dev.* 2015;7(1):39–51.
- [3] Vidal J. Real-time detection of brain events in EEG. *Proc IEEE.* 1977;65:633–641.
- [4] Farwell L, Donchin E. Talking off the top of your head: a mental prosthesis utilizing event-related brain potentials. *Electroencephalogr Clin Neurophysiol.* 1988;70:510–523.
- [5] Bozinovska L, Sestakov M, Stojanovski G, et al. [Intensity variation of the CNV potential during the biofeedback training guided by a personal computer][abstract]. *Neurologija.* 1988;37(suppl. 2):76. Serbian.
- [6] Bozinovska L, Bozinovski S, Stojanov G, et al. [Introduction of biofeedback in the CNV paradigm]. *Proceedings of the Conference ETAN;* 1989; Novi Sad, Serbian. p. XII.93–98.
- [7] Bozinovska L, Stojanov G, Sestakov M, et al. CNV pattern recognition – a step toward cognitive wave observation. In: Torres L, Masgray E, Lagunas M, editor. *Signal processing: theories and applications. Proceedings of the Fifth European Signal Processing Conference (EUSIPCO 90);* 1990, Barcelona. Amsterdam: Elsevier Science Publishers; 1990. p. 1659–1662.
- [8] Bozinovska L, Bozinovski S, Stojanov G. Electroexpectogram: experimental design and algorithms. *Proceedings of the IEEE International. Biomedical. Engineering Days;* 1992. Istanbul. p. 58–60.
- [9] Bozinovski S, Sestakov M, Bozinovska L. [Control of a mobile robot using alpha rhythm from a human brain]. *Proceedings of the Symposium JUREMA;* Zagreb; 1988. p. 247–249. Croatian.
- [10] Bozinovski S, Sestakov M, Bozinovska L. Using EEG alpha rhythm to control a mobile robot. In: Harris G., Walker C. editors. *Proceedings of 10th Annual Conference of the IEEE Engineering in Medicine and Biology Society, track 17, Biorobotics,* 1988; New Orleans. LA. vol. 10, p. 1515–1516.
- [11] Bozinovski S, Sestakov M, Stojanov G, et al. [Bioelectric control of mobile robots]. *Proceedings of the 6th Yugoslav symposium for applied robotics and flexible automation;* 1989. Novi Sad. p. 237–24. Macedonian.
- [12] Bozinovski S. Mobile robot trajectory control: from fixed rails to direct bioelectric control. In: Kaynak O, editor. *Proceedings of the IEEE International Workshop on Intelligent Motion Control.* Istanbul: IEEE; 1990. vol 2. p. 463–467.
- [13] Sutton S, Braren M, Zubin J, et al. Evoked potential correlates of stimulus uncertainty. *Science.* 1965;150(3700):1187–1188.
- [14] Kornhuber H, Deecke L. Changes in brain potentials in voluntary and passive movement in humans: readiness and reafferent potential. *Pfluegers Archiv für die Gesamte Physiologie der Menschen und Tiere.* 1965;284:1–17. German.
- [15] Walter G, Cooper R, Aldridge V, et al. Contingent negative variation: an electric sign of sensory-motor association and expectancy in the human brain. *Nature.* 1964;203:380–384.
- [16] Tecce J. CNV and physiological process in man. *Physiological Bulletin.* 1972;77:73–108.
- [17] Holscher C. Long-term potentiation: a good model for learning and memory? *Prog Neuro-Psychopharmacology Biol Psychiatry.* 1997;21:47–68.
- [18] Bozinovska L. The CNV paradigm: Electrophysiological evidence of expectation and attention. [Term paper, Course PSYCH330 Physiological Psychology, Instructor Beth Powel, Psychology Department, University of Massachusetts at Amherst]. 1981.
- [19] Bozinovska L. Simultaneous investigation of psychomotor reaction, EMG and EEG evoked potentials, and influence of some physical and psychological factors on the psychomotor reaction [master's thesis]. Institute of Physiology, Medical Department, University Cyril and Methodius; 1980. Macedonian.
- [20] Bozinovska L, Kovacev V, Naumovski R, et al. Simultaneous measurements of reaction time, and electromyographically and visually evoked potential latencies. *Proceedings of the 12th Congress of Yugoslav Physiological Society;* 1982. Sarajevo. p. 11–13.
- [21] Bozinovska L, Isgum V, Barac B. Electrophysiological and phenomenological evidence of the expectation process in the reaction time measurements. *Iugoslavica Physiologica and Pharlacologica Acta.* 1985;21:21–22.
- [22] Bozinovski A, Tonkovic S, Isgum V, et al. Electrophysiology of the expectancy process: Processing the CNV potential. *Proceedings of the 5th International Conference on Informatics and Information Technology;* Bitola; 2007. p. 129–137.
- [23] Bozinovski S. Adaptation and training: a viewpoint. *Automatika.* 1985;3–4:137–144.
- [24] Onosko T. Enter the Movits hightech toys. *Creat Comput.* 1984;10(12):119.
- [25] Walker T. *Fundamentals of Cobol programming: a structured approach.* Boston (MA): Allyn and Bacon; 1976.
- [26] Principe J. The cortical mouse. *IEEE Pulse.* 2013; 4:26–29.
- [27] Wolpaw J, McFarland D, Neat G, et al. An EEG-based brain-computer interface for cursor control. *Electroencephalogr Clin Neurophysiol.* 1991;78:252–259.
- [28] Neat G, McFarland D, Forneris C, et al. EEG-based brain-to-computer communication: system description. *Proc Annu Int Conf IEEE Eng Med Biol Soc.* 1990;12(5):2298–2300.
- [29] Kuhlman W. Functional topography of the human mu rhythm. *Electroencephalogr Clin Neurophysiol.* 1978;44:83–93.
- [30] Gastaut H. Electro corticographic study of the reactivity of rolandic rhythm. *Rev Neurol. (Paris).* 1952;87(2):176–182. French.
- [31] McFarland D, Toddlefkowicz A, Wolpaw J. Design and operation of an EEG-based brain-computer interface with digital signal processing technology. *Behavi Res Meth Instrum Comput.* 1997;29(3):337–345.
- [32] Sutter E. The brain response interface communication through visually induced electrical brain responses. *J Microcomput Appl.* 1992;15:31–45.
- [33] Ciliers P, van der Kouwe A. A web based computer interface for C2 quadriplegics. *Proceedings of the IEEE Annual Conference on Engineering in Medicine and Biology Society;* 1993. p. 1236.
- [34] Adrian E, Matthews B. The Berger rhythm: potential changes from the occipital lobes in man. *Brain.* 1934;57:355–385.
- [35] Berger H. About the electroencephalogram of humans. *Arhiv fur Psychiatrie und Nervenkranken.* 1929;87:527–570. German.
- [36] Pfurtscheller G, Aranibar A. Evaluation of event-related desynchronization (ERD) preceding and following voluntary self-paced movement. *Electroencephalogr Clin Neurophysiol.* 1979;46:138–146.

- [37] Pfurtscheller G, Flotzinger D, Kalcher J. Brain-computer interface – a new communication device for handicapped persons. *J Microcomput Appl.* **1993**;16:293–299.
- [38] Pfurtscheller G, Neuper D, Flotzinger D, et al. EEG based discrimination between imagination of right and left hand movement. *Electroencephalogr Clin Neurophysiol.* **1997**;103:642–651.
- [39] Birbaumer N, Ghanayim N, Hinterberger T, et al. A spelling device for the paralysed. *Nature.* **1999**;398:297–298.
- [40] Chapin J, Moxon K, Markowitz R, et al. Real-time control of a robot arm using simultaneously recorded neurons in the motor cortex. *Nat Neurosci.* **1999**;2:664–670.
- [41] Li W, Jaramillo C, Li Y. A brain computer interface based humanoid robot control system. *Proceedings of the IASTED International Conference on Robotics.* Pittsburgh, PA; 2007. p. 390–396.
- [42] Lebedev M. Augmentation of sensorimotor functions with neural prostheses. *Opera Medica Physiologica.* **2016**;2 (3):211–227.
- [43] Lebedev M, Nicolelis M. Brain-machine interfaces: from basic science to neuroprostheses and neurorehabilitation. *Physiol Rev.* **2017**;97:767–867.
- [44] Bozinovski A, Tonkovic S, Isgum V, et al. Robot control using anticipatory brain potentials. *Automatika.* **2011**;52(1):20–30.