Controlling Robots Using EEG Signals, Since 1988

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Abstract. The paper considers the emergence of the field of controlling robots using EEG signals. It looks back to the first result in the field, achieved in 1988. From a viewpoint of EEG driven control, it was the first result in controlling a physical object using EEG signals. The paper gives details of the development of the research infrastructure which enabled such a result, including description of the lab setup and algorithms. The paper also gives a description of the scientific context in which the result was achieved by giving a short overview of the first ten papers in the field of EEG driven control.

Keywords: psychokinesis, EEG control of physical objects, EEG control of robots**,** biosignal processing, contingent negative variation, contingent alpha rhythm variation, probability density distribution, real-time EEG control.

1 Introduction

Telekinesis and psychokinesis are concepts with meaning of moving objects by utilizing energy emanating from a human brain produced by the brain mental processes. One approach to achieve such an effect is using a computer with two interfaces: one toward the brain for EEG signal processing, and the other toward a physical object for example a robot; with today's technology either interface can be wireless.

This paper is looking back to the first result of using EEG signals to control a movement of a physical object, a mobile robot, which was achieved in 1988 [1][2][3][4]. The next section of the paper gives some introductory knowledge on EEG driven control of robots, then this paper describes the details of the realization, and finally it discusses the scientific context in which the result was obtained, by giving brief overview of the first 10 papers in the area of EEG based control.

2 EEG Driven Control of Robots: Basic Concepts

The background knowledge about controlling robots can be presented by the block diagram [1] shown in Fig. 1. The system usually operates in real-time or near-real time.

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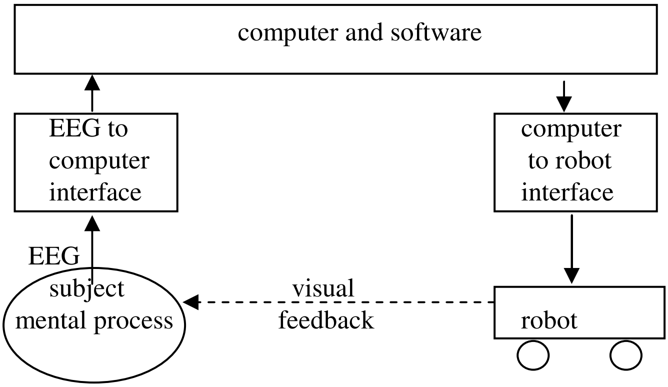

Fig. 1. Conceptual block diagram of EEG driven control of a robot

As Fig.1 shows, a subject generates EEG signals which are amplified and possibly filtered by a EEG amplifier. The generated signal can be result of an intentional mental process, for example, entering willingly a relaxation state can generate higher amplitude of the EEG alpha rhythm. Another way of generating a specific EEG signal is reaction to an event, for example, if a specific pattern is observed on a screen then a brain might react with a P300 potential. Yet another way of generating a EEG signal is before an event, for example, generating CNV signal in expectation of an event. The signal processing software should be able to extract needed features and perform pattern recognition process that would recognize a particular pattern in the EEG signal, for example a CNV shape, or increased amplitude of the alpha rhythm. The pattern classification process often requires a machine learning phase, in which for a given subject the computer learns the template features of a EEG signal pattern, against which, in the exploitation phase, received signal patterns will be compared. Once the pattern recognition process decides that a particular EEG pattern is present, it sends a signal to a robot to perform a predefined behavior. The predefined behavior might be either a simple action such as move or stop, or a rather complex behavior such as wait until some event happens and then turn left. It is often case that a robot executes a default background behavior, such a follow a line on the floor, on which other EEG controlled behaviors are superimposed.

Both single-channel and multi-channel processing might be utilized. Single channel is used if there is a known spot on the scalp where from a particular type of signal can be extracted. Example is alpha rhythm, which can be detected with a single-channel recording from the back of the scalp (occipital, parietal, and temporal area). In some applications at least two-channel recording is needed, for example when brain hemisphere processing difference is utilized, so one channel records from each brain hemisphere. A multi-channel system is often used with ability to give a 2D and 3D spatial distribution of an EEG activity.

3 EEG Potentials

Our interest in EEG patterns recognition started in 1981 and was motivated by the 1964 work of Gray Walter and collaborators [5] describing the CNV (Contingent Negative Variation) potential and the CNV experimental paradigm. We noticed that it is actually a S1-S2-RT paradigm which we knew about since we previously built digital controllers for that paradigm. The CNV potential is related to the processes of expectation and learning. We decided to pursue research on this topic, and the first report was written as a Term paper in 1981 [6]. After some research in the area [7], we introduced [8] a *taxonomy of EEG potentials* in which we distinguished between event related potentials and evoked potentials, and included a new class of potentials, anticipatory potentials containing both the expectation potentials (for example CNV) and preparatory potentials (for example BP Bereitschaftspotenzial [9]

In 1986 we started experimenting with an extension of the classical CNV experimental paradigm by introducing biofeedback in the paradigm [10]. We extended the paradigm beyond CNV appearance, by introducing EEG control of the buzzer that generates the S2 signal. Once CNV is build up, it stops the S2 buzzer, which will cause gradual decay of the CNV signal in the extended paradigm, which in turn will cause the S2 buzzer to be turned on again. In such a way the new experimental paradigm builds an oscillatory expectancy process in the brain. Since the CNV potential in this paradigm changes its shape, an adaptive digital filter was built to extract the variable CNV [8]. In this research we gained experience with adaptive signal processing used later in EEG based robot control. We also built a lab unit devoted to EEG signal processing. Central part was the biopotential amplifier which we obtained from Laboratory of Medical Electronics from Zagreb. It had gain up to 100,000 (10μV/V), adjustable analog filters for band pass filtering, a separate 50Hz filter, long time constant 10s, and input impedance 9MΩ. We requested and obtained a 19” rack system version.

4 Robot Control

The first mobile robot named Adriel-1 we built in 1982 out of a toy car to which we added three tactile sensors and a voltage sensor. The demonstration task was moving in room around a wall and sensing a “door”. The computer used was IBM Series/1 with true multithreading (multitasking) programming language named Event Driven Language (EDL) which utilized explicit commands WAIT and POST for interprocess communication and ENQ (enter queue) and DEQ (depart queue) for resource management. Our first mobile robots were indeed multitasking driven with separate tasks for sensors and motors [11].

In 1984 we purchased from Akihabara market in Tokyo, Japan, a kit for a robot named Elehoby Line Tracer. That was a robot which had own intelligence to follow an arbitrary line drawn on the floor. The external control was a mechanical on/off switch.

5 The Idea of EEG Driven Robot Control

By 1987 we developed a Lab for Intelligent Machines, Bioinformation Systems, and Systems Software in the new annex of the Electrical Engineering Department, University Sts Cyril and Methodius. Inside the lab we built two lab units, one for EEG signal processing (subject chairs, biopotential amplifier rack, and oscilloscope) and one for robotics (polygon rack with several robots and an interface box). The idea came to connect the units and try to control a robot using EEG signals. The subsequent idea that it points toward an engineered solution of the psychokinesis phenomenon looked even more exciting. As result, Fig. 2 shows the lab setup which we built for controlling robots using EEG signals.

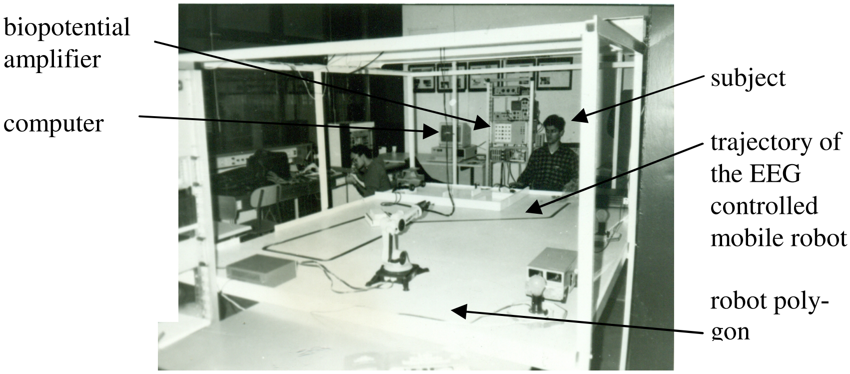

Fig. 2. The lab setup for controlling robots using EEG signals, photo from 1988

Fig. 2 shows the robot polygon we built, containing several mobile and manipulative robots, and a drawn trajectory on the polygon where the Elehoby Line Tracer robot moved. We replaced the mechanical on/off switch of the Elehoby Line Tracer robot with a computer-controlled switch, and connected the same computer with the biopotential amplifier. Fig. 3. shows the drawn trajectory for the robot. The robot was given a "coat" to look as a Flexible Manufacturing System shuttle robot which moves along a closed trajectory.

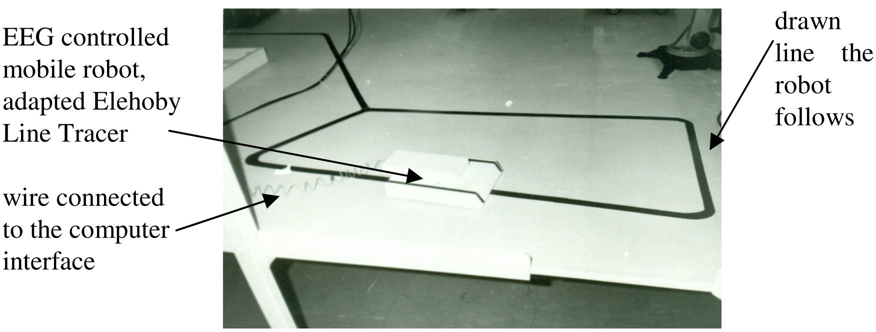

Fig. 3. Robot polygon with trajectory of the EEG controlled mobile robot, 1988

The mental process used for EEG control was relaxation process representing itself by amplitude change of the alpha rhythm, in other words the *contingent alpha rhythm* variation (CαV) of the EEG.

Since we have chosen the alpha rhythm variation, for electrode placement we used spots on the occipital and parietal area, such as O_2 and Pz, where the changes in the frequency band 8-13Hz (alpha rhythm) significantly influence the EEG signal.

The following scenario was introduced: while following a line on the floor, the Elehoby Line Tracer robot will be start to move by alpha rhythm amplitude increase which will be willingly decided by the subject who will close the eyes and relax. Analogously, when the subject decides to open the eyes and consequently reduce alpha rhythm amplitude, the robot will stop at a particular place on the trajectory.

6 The Realization of the Idea

6.1 Robot Control

We already had a robot with own intelligence executing a follow-line behavior. We just needed an EEG switch that will change between robot follow line and robot stop behaviors. Fig. 4. shows the Moore automaton model of the control we used. The events EEGα(+) and EEGα(-) are generated by the subject who willingly increases/decreases the amplitude of the EEG alpha rhythm.

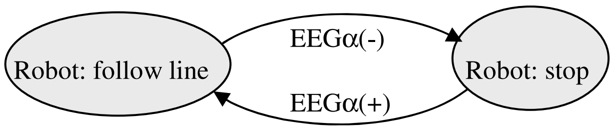

Fig. 4. Line following robot control using EEG switch

6.2 EEG Signal Processing for Robot Control

The 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 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 10ms (100 Hz sampling rate). We needed a procedure that reads an EEG sample, extracts the EEG features, compares them to template feature, 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 processing nor averaging of the EEG signal. So we used analog filtering provided by the biopotential amplifier to extract a frequency band containing the alpha rhythm. Further, we developed an adaptive pattern recognition method consisting of two phases: a learning phase in which the computer learns the EEG features related to increase/decrease of the amplitude of the alpha rhythm, and a pattern recognition phase in which computer compares the just observed features against the template one.

We have chosen 10 seconds 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 from the template features will be learned.

Our algorithm used both *changes* of EEG amplitude and *changes* of time intervals between EEG amplitudes (Fig 5).

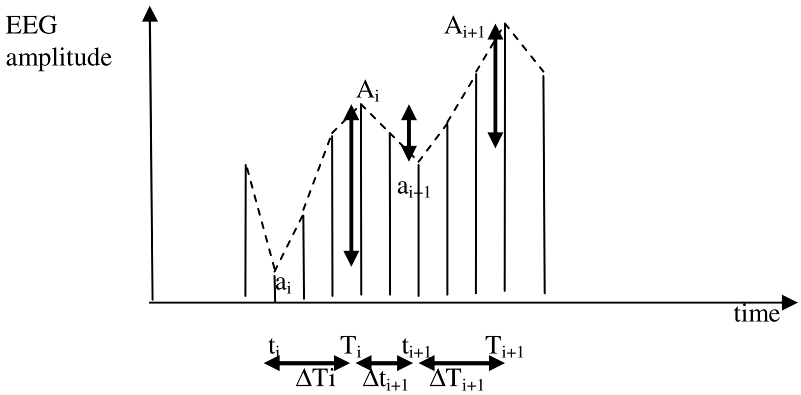

Fig. 5. Obtaining both time difference and amplitude difference for EEG extrema

Those features are fast computable since it needs comparison only with the previous sample to obtain the changes. The learning algorithm scans the EEG samples and looks for local extrema, peaks and valleys of the signal, the points where gradient changes the sign. For each peak, its amplitude is determined relative to the immediate previous valley. Also for each peak the width of the hill is determined as time distance between the previous valley and the peak.

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. For each amplitude extremum, the amplitude difference is computed, $\Delta A_i = A_i - a_i$ and $\Delta a_{i+1} = a_{i+1} - A_i$. Actually we compute the absolute values of the differences.

In the learning process the amplitude differences and time differences are counted and probability density distributions (pdd) are obtained. So for each subject we obtain both the EEG amplitude difference pdd p(A) and EEG time difference pdd p(T). Dute to open and closed eyes each of the pdd's has two instances, so we obtained four pdd's, p(A/open), p(A/closed), p(T/open) and p(T/closed) as shown in Fig. 6. Due to distributions overlap, there are possibilities of false positive and false negative decisions. Decision thresholds should be determined for pair of overlapping distributions, as shown in Fig 6. The decision areas $\Delta T < \theta_{\Delta TO}$ and $\Delta T > \theta_{\Delta TC}$, as well as $\Delta A < \theta_{\Delta AO}$ and $\Delta A > \theta_{\Delta AC}$, are areas where minimum number of false decisions are made.

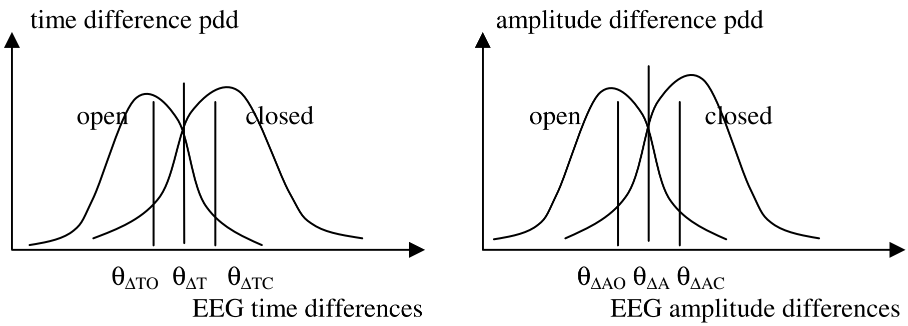

Fig. 6. Probability density distributions for amplitude and time difference

The decision process used *confirmation sequence* of three samples in a row, meaning that in each sample its amplitude difference and time difference should be greater than θΔA and θΔT respectively. So the decision criterion for eyes closed is

if ΔA(t) > θΔAC and ΔT(t) > θΔTC for three consecutive times, then eyes = "closed"

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 phase and the exploitation phase.

Examination procedure tests the learning process. The subject is given a time, for example 15 seconds, in which s/he will close and open the eyes at least once. 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.

7 Results

Example of a computer screen obtained in our 1988 experiments is shown in Fig. 7. The bottom part of the screen shows an acquired filtered EEG signal in duration of 10-15 seconds. A line below the EEG signal is the segment that will be zoomed. 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 process is evident (alpha rhythm amplitude has increased) and segments where it is not present.

The software was written in Pascal with some inline sections in assembler. The pseudocode was written in pseudo Cobol [3][4] due to appreciation of Cobol's PERFORM command. [12].

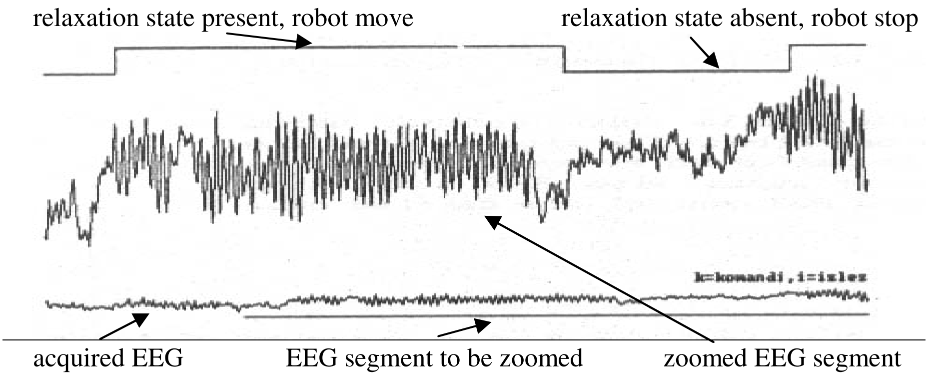

Fig. 7. Example of a asynchronous EEG driven robot control in real time

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

8 Research Context

This paper is written almost quarter century after the 1988 result. It is now clear that at that time nobody else attempted an engineering solution of moving a physical object using EEG signals. However, there were efforts of moving objects on a computer screen, of which we were not aware at that time. The first paper that provided a context to us was the paper [13] which came out after we achieved the result. In this section we give a brief overview of the first 10 papers describing control of objects using EEG signals, both physical and objects on computer screen.

The earliest report of using EEG signals for control of external events was given in 1967 [14], about producing Morse code using EEG alpha rhythm. In 1973 the research field of brain-computer communication was established, and the term

Brain-Computer Interface was introduced by Vidal [15]. The challenge was stated of control of objects using EEG signals. Various EEG signals were mentioned as part of the challenge such as EEG rhythms, evoked potentials, P300 potential, and CNV potential among others; EOG signals were also mentioned. In 1977, EEG control of a graphical object on a computer screen was achieved [16]. In 1988, the first control of a physical object was achieved [1][2]. The same year an important computer screen based application was reported [17] in which P300 potential was used to select a letter shown on the screen and write a text from the selected letters. In 1990 a review was given [3] on various types of controlling mobile robots, including EOG control which happened in 1989. In 1990 it was also a report [13] on using EEG difference in brain hemispheres for EEG based control. A control of a one-dimensional cursor movement on a computer screen was given in 1991 [18]. In 1992 a report on controlling a device using CNV potential was given [6]. In addition of solving the CNV-based control of objects as stated in Vidal's challenge [15], it was a first report on interactive EEG-based game between an adaptive brain and an adaptive external device, an adaptive buzzer. In 1992 also a new type of brain potentials were introduced in EEG based control, the steady state visual evoked potentials (SSVEP) [19]. Visual evoked potentials (VEP) were used in 1993 [20].

After the first 10 papers most of the researchers accepted the term Brain-Computer Interface [18][21] proposed in [15]. Let us note that we used the term direct bioelectric control [3].

In addition of listing the first 10 reports in the area of EEG based control, we will also mention the second report on controlling robots using EEG signals [22] which happened in 1999. An invasive EEG recording was applied on open brain, experiments were carried out on monkeys, and a manipulative robot was controlled. The 1988 and 1999 reports were the only ones on EEG controlled robots given in the 20th century, before the year 2000.

9 Conclusion

In 1988 a result was achieved on controlling a physical object, a robot, through EEG signals emanated from a human brain. Although the first report was given in the same year, this paper is more detailed account of the infrastructure developed and signal processing methods used for obtaining the result. This paper also makes an effort to put the 1988 work in the context of the first 10 papers in the area of EEG based control of objects, both physical objects and objects on a computer screen.

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