Elektrotehnički fakultet u Beogradu
Odsek za signale i sisteme

POREĐENJE EVENT-RELATED DESINHRONIZACIJE PRILIKOM VRŠENJA VOLJNIH POKRETA I PRILIKOM IGRANJA WII IGRE

Diplomski rad

student: Nikola Šobajić 06/350

mentor: prof. Dejan B. Popović

Beograd, Oktobar 2010

Table of Contents

Table of Figures

Table of Abbreviations

ALS	Amyotrophic lateral sclerosis
ADC	Analog-digital conversion
BCI	Brain-Computer Interface
DAQ	Data Acquisition
ECG	Electrocorticography
EEG	Electroencephalography
EMG	Electromiography
EOG	Electrooculography
ERD	Event-related desynchronization
ERP	Event-related potential
ERS	Event-related synchronization
fMRI	Functional Magnetic Resonance Imaging
ICA	Independent Component Analysis
IV	Intravenous
LT	Lower treshold
MEG	Magnetoencephalography
NI	National Instruments
PET	Positron Emission Tomography
SNR	Signal-to-noise ratio
SPECT	Single Photon Emission Computed Tomography
SQUID	Superconducting Quantum Interference Device
UT	Upper treshold

Poređenje event-related desinhronizacije prilikom vršenja voljnih pokreta i prilikom igranja Wii igre

Diplomski rad

I. Introduction

Today, much effort is dedicated to the development of Brain Computer Interface (BCI) systems that would allow direct brain interaction with the environment. The reason for the use of the BCI is that it could accept commands directly from the human brain without actual physical activity (movement, voice command, sipping and puffing, etc.).

One important task for the BCI is to detect the intention to move. Voluntary movement results from the complex interaction between different cortical and subcortical circuits. The neuronal activity that has been suggested for the recognition of intention for movement includes event-related desynchronization (ERD) [1] and event-related synchronization (ERS) [2] from the skull recordings (EEG). The analysis of ERD and ERS provides information on the dynamic pattern of cortical activation and idling occurring before motor activity.

ERD BCI systems encompass the range of BCIs that analyse and classify the dynamics (ERD and ERS) of either one single-frequency component, such as a BCI based on μ or ß rhythms or multiple components of sensorimotor rhythms [3], [4]. One of the first reports on classifying ERD/ERS patterns induced by motor imagery appeared in the early 1990s [5]. Several years later, other systems began to use ERD/ERS patterns as features for single-trial EEG classification [6]. A recent study on 14 fully BCI-naive subjects in [4] showed that more than half of them can perform at >84% accuracy in their very first BCI session, using spatial filters that maximize variance of signals of one condition and at the same time minimize variance of signals of another condition. Another research used spatio-temporal analysis to classify the EEG recorded during voluntary left versus right finger movement tasks and produced a classification accuracy of up to 92.1% on the data from five subjects [7]. Work published in [8] combined the ERD and steady-state visual evoked potential approach to designing BCI systems and had a mean success rate of 75% for the ERD and 80% for the hybrid.

In this thesis, I present results from the study that included five healthy subjects. I studied the detection of movement in two conditions: 1) movements during playing a Nintendo Wii game, and 2) self-paced voluntary wrist movements but when the Nintendo Wii game was turned off.

The goal of this reseach was to determine if the established ERD-based movement detection method can be used while playing a video game, and not just in laboratory conditions. The results of this study are of interest for developing the technique that can be used for the therapy of post-stroke hemiplegic individuals [9].

This thesis is presented in six sections. This first chapter was introductory, serving to inform the reader of the goal of the eperiment and the history of similar experiments. Second chapter eplains the theoretical concepts behind the research. Basics of electroencephalography, neurological sources, and the means of acquisition are given. In the third chapter, the used equipment is described, as are the methods used for data acquisition and signal processing. Results of the experiment are listed in the fourth chapter, and discussed in the fifth.

II. Brain activity measurement

A. Brain-Computer Interface (BCI)

BCI is a direct communication pathway between a brain and an external device. It gives its users communication and control channels that do not depend on the brain's normal output pathways of peripheral nerves and muscles. BCIs are often aimed at assisting, augmenting or repairing human cognitive or sensory-motor functions. BCI systems, therefore, are especially useful for severely disabled, or locked-in, individuals with no reliable muscular control to interact with their surroundings. Locked-in syndrome can be caused, for example, by amyotrophic lateral sclerosis (ALS), brainstem stroke, mitochondrial disease, spinal-cord injury, traumatic-brain injury and even later-stage cerebral palsy. Despite these sufferers being completely physically paralyzed and unable to speak, they are however, cognitively intact and alert and thus have a need to communicate. Despite this being a principal motivation, more and more media attention has been attributed to exploring the full potential of this communication medium for the wider audience in areas such as multimedia applications and video games.

A number of invasive or noninvasive techniques exist that can monitor brain activity. These include, for example, functional Magnetic Resonance Imaging (fMRI), Magnetoencephalography (MEG), Positron Emission Tomography (PET), Single Photon Emission Computer Tomography (SPECT) and Electroencephalography (EEG). Of these, EEG is the only one extensively used in BCI research because it is the least expensive, the equipment is portable, and has a high enough temporal resolution to facilitate real-time implementation [10]. Thet is why the rest of this chapter will be dedicated to EEG-based BCI solutions.

Communication or control based on BCI technology requires patterns of brain activity that can be consciously generated or controlled by a subject and ultimately clearly recognizable by a computer system. The performances of different mental tasks generate different EEG responses and hence can be translated into a control codebook for the user, assuming the BCI system can be trained to decipher the associated EEG activity. The simplest approach to generating different EEG patterns is to ensure that the mental tasks activate different parts of the brain. For example, the imagination of right hand movements

should activate the left motor cortex and the imagination of left hand movements the right motor cortex. Another approach requires the user to perform lengthy training sessions in a biofeedback environment to master the skill of being able to self-regulate one's brain activity.

A BCI system comprises a set of sensory components (electrodes positioned on the skull for recording the electrical field from the neurons in the brain, magnetic sensors, like superconducting quantum interference devices (SQUID), positioned in the vicinity of the skull assessing the magnetic field generated by the neurons [11]) that enables the acquisition, a system for signal processing and intelligent recognition of events, and an external device to interact with the environment.

A BCI can be either synchronous, when mental activities are triggered by external stimuli or asynchronous, in which the user decides that the resultant control signal be generated. The former case is computer-driven and only a small segment of the EEG that is time-lockd to the trigger has to be analyzed. The latter is user-driven and the EEG signals have to be continuously analyzed and classified.

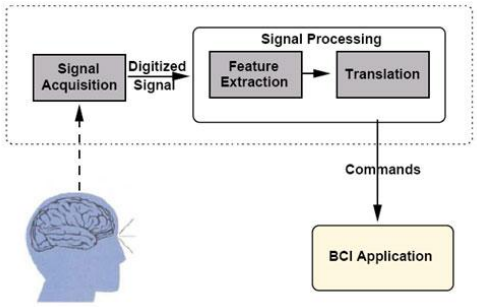


Figure 1. Simplified processing stages in a BCI system

B. Electroencephalography (EEG)

EEG is a noninvasive technique for the recording of electrical activity along the scalp produced by the firing of neurons within the brain [12]. Neurons, or nerve cells, are electrically active cells that are responsible for carrying out the brain's functions. Neurons create action potentials, discrete electrical signals that travel down axons and cause the release of chemical neurotransmitters at the synapse, which is an area of near contact between two neurons. The neurotransmitter causes an electric current within the dendrite or of the post-synaptic neuron. This neuron then synapses on other neurons, and so on. The activity of a single cortical neuron cannot be measured on the scalp due to thick layers of tissue (fluids, bones, and skin) which attenuate the electrical signal when it propagates toward the electrode. However, the joint activity of millions of cortical neurons, at a depth down to several millimeters, produces an electrical field which is sufficiently strong to be measured on the scalp [13].

Richard Caton was the first scientist to have recorded the electrical activity of the brain in 1875. He had used a galvanometer to observe electrical impulses from the surfaces of living brains in animal subjects. In 1929. Hans Berger recorded human EEG in the duration of one to three minutes on photographic paper, and it included the description of the alpha rhythm

as the major component of the EEG signals. Subsequent research revealed a connection between the EEG physiological states, such as sleep and wakefulness.

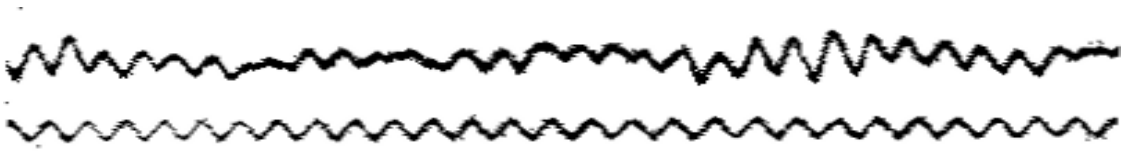


Figure 2. First published Electroencephalogram of a human. The top trace is the EEG recorded from a young boy, the bottom trace is a 10 Hz frequency reference. [14]

Ongoing brain activity is recorded in the absence of an explicit task, such as sensory input or motor output, as opposed to the recording of evoked potentials, i.e. brain activity that is induced by sensory stimuli or motor responses. Evoked potential amplitudes tend to be low in comparison to the background of ongoing EEG and other biological signals and ambient noise, so signal averaging is usually required. The signal is time-locked to the stimulus and most of the noise occurs randomly, allowing the noise to be averaged out with averaging of repeated responses.

1. Electrode cap
2. Amplifier and filter
3. ADC and data storage

Figure 3. An example of EEG recording equipment

The electrical signal which originates from the brain's spontaneous activity is variable and irregular in nature, and is classified as a continual stochastic signal. Simultaneously, distinctive rhythms exist and change with age and from one state of to another, such as wakefulness and sleep. Signals recorded from the scalp have, in general, amplitudes ranging from a few microvolts to approximately 100 μV and a frequency content ranging from 0.5 to 30-40 Hz. The amplitude of the EEG signal is related to the degree of synchrony with which the cortical neurons interact. Synchronous excitation of a group of neurons produces a large-amplitude signal on the scalp because the signals originating from individual neurons will add up in a time-coherent fashion. On the other hand, asynchronous excitation of the neurons results in an irregular-looking EEG with low-amplitude waveforms. High-frequency/low-amplitude rhythms reflect an active brain associated with alertness or dream sleep, while low-frequency/large-amplitude rhythms are associated with drowsiness and nondreaming sleep states. "This relationship is logical because when the cortex is most

actively engaged in processing information, whether generated by sensory input or by some internal process, the activity level of cortical neurons is relatively high but also relatively unsynchronized. In other words, each neuron, or very small group of neurons, is vigorously involved in a slightly different aspect of a complex cognitive task; it fires rapidly, but not quite simultaneously with most of itsneighbors. This leads to low synchrony, so the EEG amplitude is low. By contrast, during deep sleep, cortical neurons are not engaged in information processing, and large numbers of them are phasically excited by a common, rhythmic input. In this case synchrony is high, so the EEG amplitude is large [15]".

Electroencephalographic rhythms, also referred to as background rhythms, are conventionally classified into five different frequency bands. The interpretation of these bands in terms of "normal" or "abnormal" is relative and depends on the age and mental state of the subject. To some degree, these frequency bands are a matter of nomenclature (i.e., any rhythmic activity between 8–12 Hz can be described as "alpha"), but these designations arose because rhythmic activity within a certain frequency range was noted to have a certain distribution over the scalp or a certain biological significance. Most of the cerebral signal observed in the scalp EEG falls in the range of 1–20 Hz (activity below or above this range is likely to be artifactual, under standard clinical recording techniques). Abovementioned ranges are named with letters of the Greek alphabet, and are, as follows:

1. Delta waves lie within the range of 0.5–4 Hz, and have a very high amplitude (75-200 μV). These waves are primarily associated with deep sleep. They are present frontally in adults, and posteriorly in children. It may occur focally with subcortical lesions and in general distribution with diffuse lesions, metabolic encephalopathy hydrocephalus or deep midline lesions.

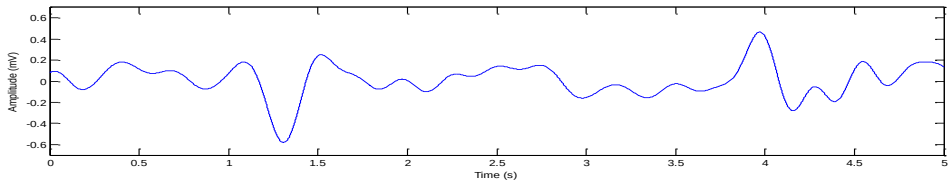


Figure 5. Delta wave

2. Theta waves lie within the range of 4–7.5 Hz. Theta waves appear as consciousness slips towards drowsiness. Theta waves have been associated with access to unconscious material, creative inspiration and deep meditation. They can be observed over the parietal and temporal lobes in younger children. Larger contingents of theta wave activity in the waking adult are abnormal and are caused by various pathological problems. It can be seen in generalized distribution in diffuse disorder or metabolic encephalopathy or deep midline disorders or some instances of hydrocephalus.

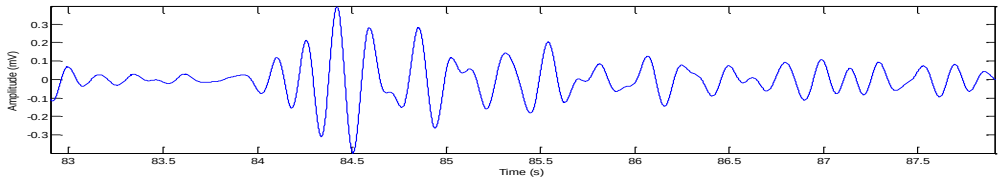


Figure 4. Theta wave

3. Alpha is the frequency range from 8 Hz to 12 Hz. Alpha waves appear in the on both sides of theposterior half of the head and are higher in amplitude on dominant side.

This rhythm is most prominent in normal subjects who are relaxed and awake with eyes closed. It is suppressed by opening the eyes, hearing unfamiliar sounds, by anxiety, or mental concentration or attention. An alpha wave has a higher amplitude over the occipital areas and has an amplitude of normally less than 50 μV. Alpha can be abnormal; for example, an EEG that has diffuse alpha occurring in coma and is not responsive to external stimuli is referred to as "alpha coma" [16]. An alpha-like variant called mu (μ) can be found over the motor cortex (central scalp) that is reduced with movement, or the intention to move.

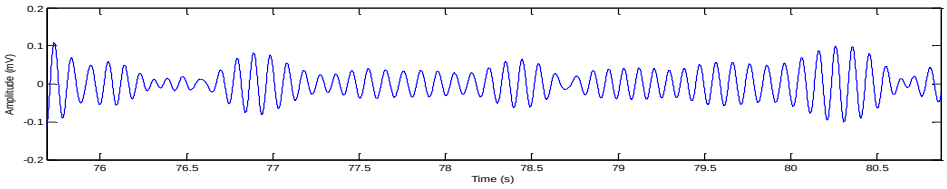


Figure 6. Alpha wave

4. Beta waves lie within the range of 14-30Hz with an amplitude of under 30 μV. The beta rhythm is mainly observed in the frontal and central regions of the scalp. It is seen usually on both sides in symmetrical distribution. A beta wave is the usual waking rhythm of the brain associated with active thinking, active attention, focus on the outside world, or solving concrete problems, and is found in normal adults.

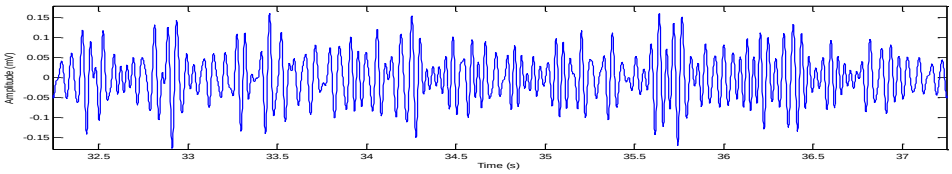


Figure 8. Beta wave

5. The frequencies in the range of 30-100 Hz (mainly up to 45 Hz) correspond to the gamma range (sometimes called the fast beta wave). The amplitude of this rhythm is very low. Gamma rhythms are thought to represent binding of different populations of neurons together into a network for the purpose of carrying out a certain cognitive or motor function. The gamma wave band has been proved to be a good indication of event-related synchronization (ERS) of the brain and can be used to demonstrate the locus for finger, toe, and tongue movement [17]. Many neuroscientists are not convinced of the gamma wave argument - it has been suggested that EEG-measured gamma waves could be in many cases an artifact of electromyographic (EMG) activity [18].

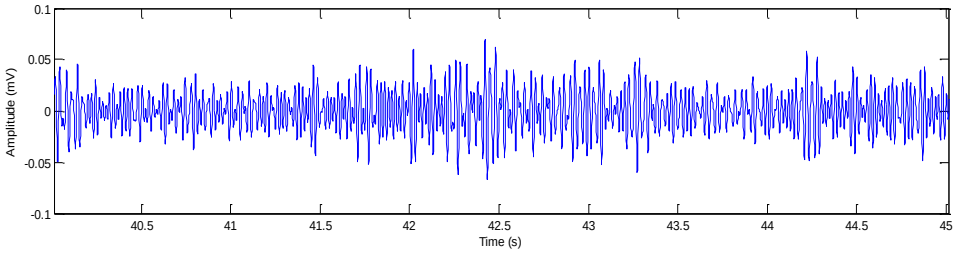
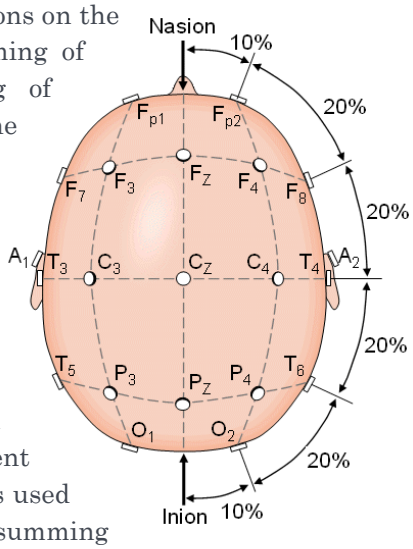


Figure 7. Gamma wave

In conventional scalp EEG, the recording is obtained by placing electrodes on the scalp with a conductive gel or paste, usually after preparing the scalp area by light abrasion to reduce impedance. Electrode locations and names are specified by the International 10–20 system [19] which employs 21 electrodes attached to the surface of the scalp at locations defined by certain anatomical reference points; the numbers 10 and 20 are percentages signifying relative distances between different electrode locations on the skull perimeter. This standardization ensures that the naming of electrodes is consistent across laboratories. The spacing of electrodes with this system is relatively sparse: the interelectrode distance is approximately 4.5 cm on a typical adult head. Improved spatial resolution can be acheved by using high-density arrays with additional electrodes placed in-between the existing 10-20 system. In some applications, such as ERP analysis and brain computer interfacing, a single channel may be used. In such applications, however, the position of the corresponding electrode has to be well determined. EEG recording can be bipolar, where each channel represents the difference between two adjacent electrodes, or unipolar, in which a single reference electrode is used for all the channels. That reference can be constructed by summing and averaging all of the used channels, or it can be one designated electrode, such as vertex (Cz), linked-ears, linked-mastoids, ipsilateral ear, contralateral ear and tip of the nose [20]. A modification of the averaged reference electrode called Laplacian montage where each channel represents the difference between an electrode and a weighted average of the surrounding electrodes.



EEG signals have amplitudes of the order of microvolts and contain frequency components of up to 100 Hz. To retain as much as possible of the information the signals have to be amplified before the analog-to-digital conversion (ADC) and filtered, either before or after the ADC, to reduce the noise and make the signals suitable for processing and visualization. Filtering is usually done with several filters: a highpass filter with a cutoof frequency of less than 0.5 Hz is used to remove the very low frequency components (such as breathing), a lowpass filter is used to remove the high-frequency noise (usually over 50-70Hz), and a notch filter with a null frequency of 50 Hz (or 60 Hz) to reject the power supply. ADC quantization is usually performed with 16 bit per sample to preserve as much information as possible.

The greatest problems one has to tackle in biomedical signal recording and processing are the detection of and removal of artifacts. One useful categorization of artifacts is based on their origin, to those of biological or technical origin. Biological artifacts include breathing, eye movement and blinks, cardiac activity, and muscle activity.

As mentioned earlier, **breathing artifacts** are removed by using a highpass filter with a cutoof frequency of <0.5 Hz.

Eye movement produces electrical activity, called the electrooculogram (EOG), which is strong enough to be clearly visible in the EEG. The EOG reflects the potential difference between the cornea and the retina which changes during eye movement. When the eyes and eyelids are completely still, the corneo-retinal dipole does not affect EEG. However, the eye

movements occur several times per second. The strength of the interfering EOG signal depends primarily on the proximity of the electrode to the eye and the direction in which the eye is moving, i.e., whether a horizontal or vertical eye movement takes place. The EOG artifact can sometimes be confused with slow EEG activity, e.g., theta and delta activities. Another common artifact is caused by eyelid movement ("blinks") which also influences the corneal-retinal potential difference. The blinking artifact usually produces a more abruptly changing waveform than eye movement, and, accordingly, the blinking artifact contains more high-frequency components. It is of note that blinking artifacts in the frontal electrodes is substantially larger than that of the background EEG. EOG signal can be recorded with the use of electrodes placed near the eye since these signals are correlated with the EOG in the EEG and, accordingly, are useful for artifact cancellation purposes.

Another common artifact is caused by electrical activity of contracting **muscles**, measured on the body surface by the EMG. This type of artifact is primarily encountered when the patient is awake and occurs during swallowing, grimacing, frowning, chewing, talking, sucking, and hiccupping [13]. Distribution of spectral components of the EMG considerably overlaps with beta activity in the 15-30 Hz range. Unfortunately, this disadvantage is further aggravated by the fact that it is impossible to acquire a reference signal containing only EMG activity which would be useful for artifact cancellation.

Electrical **activity of the heart** is another type of biological artifact. ECG amplitude is two orders of magnitude lower than spontaneous EEG, and the repetitive, regularly occurring waveform pattern which characterizes the normal heartbeats fortunately helps to reveal the presence of this artifact. However, the spike-shaped ECG waveforms can sometimes be mistaken for epileptiform activity when the ECG is barely visible in the EEG. Even bigger problems occur in the presence of cardiac arrhytmias, when they exhibit considerable variability in the interbeat interval.

EOG, ECG and breathing artifacts can be removed by recording the required signal as a separate channel and substracting them from the EEG, but this is not the case with muscle artifacts where other mothods are required. Studies have shown that independent component analysis (ICA) can effectively detect, separate, and remove contamination from a wide variety of artifactual sources in EEG records with results comparing favorably with the aforementioned methods [21], [22].

Artifacts that originate from the equipment, including electrodes, cables and components used in the equipment construction are called technical artifacts. Movement by the patient, or even just settling of the electrodes, may cause electrode pops, usually manifested as an abrupt change in the baseline level, followed by a slow, gradual return to the original baseline level. If the electrode wires are not shielded, they are susceptible to electromagnetic fields caused by currents flowing in nearby powerlines or through the wires themselves. As a result, 50/60 Hz powerline interference is picked up by the electrodes and contaminates the EEG signal. A third source of possible interference can be the presence of an IV drip; such devices can cause rhythmic, fast, low-voltage bursts, which may be confused for spikes. Other technical artifacts are those produced by internal amplifier noise and clipping caused by an ADC with a dynamic range which is too narrow for the recorded signal [13].

C. Event-related synchronization/desynchronization (ERS/ERD)

Brain's response to sensory, motor, cognitive or emotional stimuli can manifest itself in EEG either as classical, phase-locked event-related potentials (ERP), or non-phase locked

changes in the EEG activity [23]. ERPs are clearly visible on the time average of properly synchronized EEG responses. On the contrary, non-phase locked activity cannot be extracted by a simple linear method, such as averaging, but may be detected by frequency analysis. This means that these event-related phenomena represent frequency specific changes of the ongoing EEG activity and may consist, of either decreases or of increases of power in given frequency bands. This happens due to a decrease or increase in synchrony of the underlying neuronal populations, respectively. The former case is called event-related desynchronization or ERD [1], and the latter event-related synchronization (ERS) [2]. Classically, induced ERD and ERS are quantified by the following procedure: the most reactive frequency bands were chosen by a trial-and-error procedure, and then signals, band-pass filtered within those bands, were squared before averaging.

Voluntary movement results in desynchronization in the upper alpha and lower beta bands, localized close to sensorimotor areas, starting about 2 s prior to movement onset, and is observable in the μ and central ß rhythms [24]. ERS is similarly defined as an increase in power in a frequency band. The μ ERD is most prominent over the contralateral sensory-motor (SM) areas during motor preparation and extends bilaterally with the onset of movement [25]. The ERD and ERS must be observed in relation to the baseline activity measured some seconds before the event. It is now well established that even just the imagination of movement produces an event-related desynchronization (ERD) over the sensorimotor areas. The main difference between the imagination and execution of movement is that in the former case execution would be blocked at some cortico-spinal level.

III. Methods

A. Data Acquisition

We studied five healthy volunteers (1 female and 4 male), aged 21-27 years (mean 23 years), all of them right-handed and in different physical shape. None of the subjects had any experience with the BCI. The subjects were familiarized with the technique required to control the Wii console (Wiimote) and the rules of the game that was to be played. The chosen game was Wii Bowling, a virtual simulation of a game of ten-pin bowling. It is played holding a WiiMote, and swinging as a bowling ball. These moves are sudden and involve a lot of activity from the whole body, so they were simplified to use a computer mouse. The WiiMote was attached to a DC motor whose power and direction were controlled using a slider in an existing LabView program. Subjecets were required to click on the slider and swing it from left to right and back. This caused the Wiimote to rotate and throw the ball.

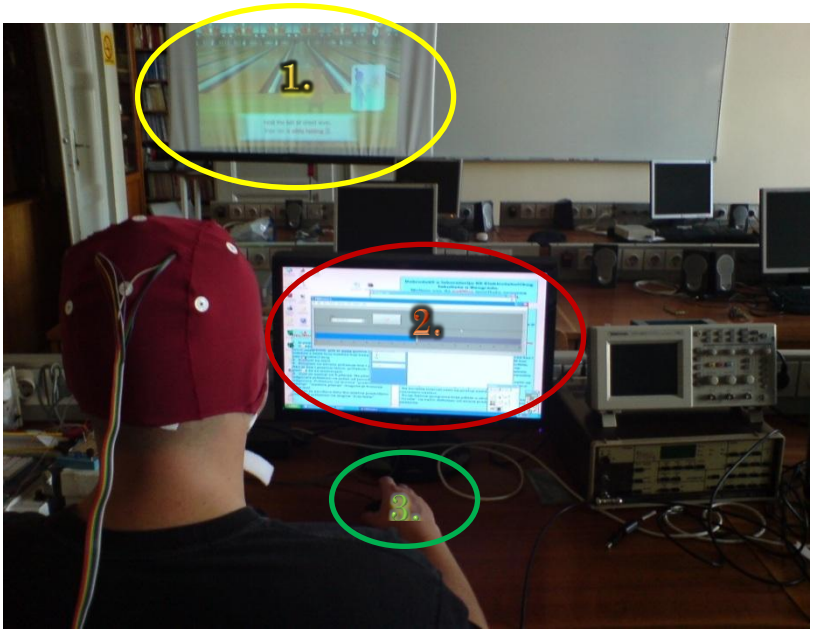
Figure 9. Nintendo Wii console

Figure 10. A screenshot of Wii Bowling

Each subject took part in two recording sessions: 1) self-paced rotation of the wrist whilst holding the mouse as if the game were being played, with the console itself turned off, for a duration of ~2 minutes, and 2) playing one ten-frame game of Wii bowling, using the same movements as in the first

session. The duration of the recording for the second session was determined by the players' skill (3-5 minutes). Intentionally, the experiments were conducted is a room with heavy traffic where other students work on their projects. This environment was selected in order to test the system in the conditions similar to those where the system will be utilized. Each participant sat comfortably in a chair, hands holding an ordinary computer mouse in front of a projection screen with the game on it. They were asked not to make any excessive movement not required to play the game.

The EEG was recorded with an Electro-Cap of an elastic spandex-type fabric with recessed, pure tin electrodes attached to the fabric in the standard 10-20 method of electrode placement [19]. Bipolar EMG recording was conducted on the right flexor carpi ulnaris muscle [26] with the two Ambu Neuroline 720 electrodes. The cap and the EMG electrodes were connected to a PsychLab EEG8 amplifier. The amplifier was connected to a NI BNC-2090 terminal block and further to NI DAQCard-6062E A/D converter in a standard notebook computer's PCMCIA slot. The sampling frequency was set to 1 kHz. One EEG channel was used for bipolar recording between the C3 and C4 electrodes, placed above the primary motor cortex [27]. Trials were made with a different configuration: unipolar recording of the signals on C3 and C4 referenced to the electrode placed on the ear lobe, but the results were significantly worse. Electrooculogram was not recorded. LabView vas used to store recorded data on a hard disk.



1. Wii Bowling
2. Labview slider program used to control the rotation of the Wiimote
3. The slider is controlled via a computer mouse

Figure 11. The experimental setup used fot recording; the screen in the back shows a Wii Bowling game, the monitor in the front is used for the control of the game

B. Signal Processing

Because the signal-to-noise ratio (SNR) of the movement induced EEG to spontaneous EEG is very low, the recordings are highly variable even when the same movements are repeated. Relevant phenomena for this algorithm are ERD and ERS in the μ band (8-12Hz). In order to make ERD noticeable, I filtered the recorded EEG data. All processing was performed in MATLAB. I utilised two filter designs: a 10^{th} order filter with a 9-12 Hz

passband and a slow roll-off, and a 24th order filter with a 8-10 Hz passband and a steep roll-off. Both filters had a minimal stopband gain of -80 dB. Samples of filtered sequences were squared and filtered with a simple moving average filter to compute the short-time power of the EEG in the filtered band.

The detection algorithm used the two thresholds to reach a decision: upper (UT) and lower threshold (LT). The first assumption was that during an idle state, without movement, the power of the μ band was higher than the UT. Lowering the UT would cause the detections to be too narrow, and too high a value would cause a lot of false positives, detections when there was no movement, due to the stochastic nature of the EEG signal. This is why we introduced LT, with a low enough value to avoid potential false positives. The algorithm claims that the movement is occurring when the power drops beneath LT and that the movement stopped when the power is higher than LT. We now used UT to improve on our detections. The algorithm moved back along the signal, until it found the moment at which the power of the signal was higher than UT. This moment was declared as the new start of the movement. Same technique was applied to the estimated end of the movement, but in the opposite direction along the signal. This enabled us to choose low values of LT and still retain a reasonable ability to determine the onset and ending of a movement. After this, we rejected all detected movements with a too short duration, and too frequent movements. In all, four different real-valued variables were used (LT, UT, shortest detectable movement duration, shortest time between two consecutive movements) and one binary variable (filter type).

EMG sequence processing consisted of baseline removal and rectifying the signal so the movements could easily be spotted. The algorithm didn't use EMG for detection.

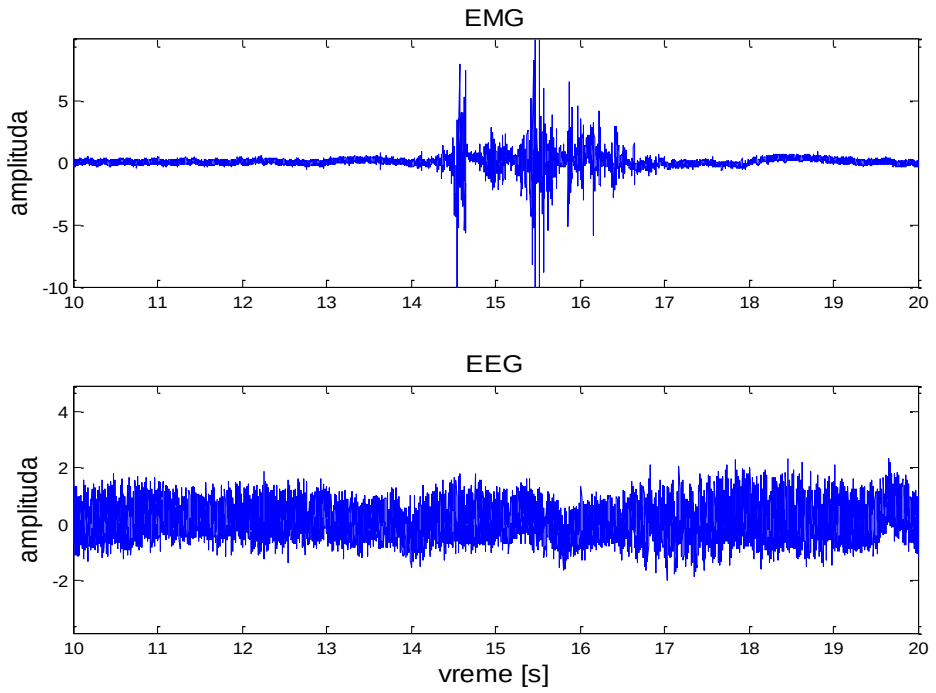


Figure 12. A segment of the recorded data on subject IA before processing

IV. Results

Figure 12 shows a recorded segment from one of the subjects before any processing has taken place. The plots that the algorithm had produced as its output were analysed and certain important features were selected for the quality assessment of the algorithm. Since the EMG and EEG recordings were synchronized, and each movement is easily seen in the EMG, it was used as a reference for the accuracy of the detections. As ERD/ERS are time-locked to the event, but aren't phase-locked, they can be seen on a time-frequency representation, such as a spectrogram (Figure 13). Because the ERD is localized to a narrow frequency band (μ band), the signal was bandpass filtered to retain only those frequencies (Figure 14).

The same segment from the Figure 12, only after the EMG has been rectified and EEG has been filtered and the detection took place, is shown on Figure 15. Green (dotted line) and red (solid line) lines are the detected starts and ends of the movements. Horizontal lines on the lower subplot are LT and UT. Values VZ and VC, used for the quality assessment are illustrated on the plot: VZ is the difference between the actual and detected movement starting time, and VC is the difference between the detected and actual end of movement.

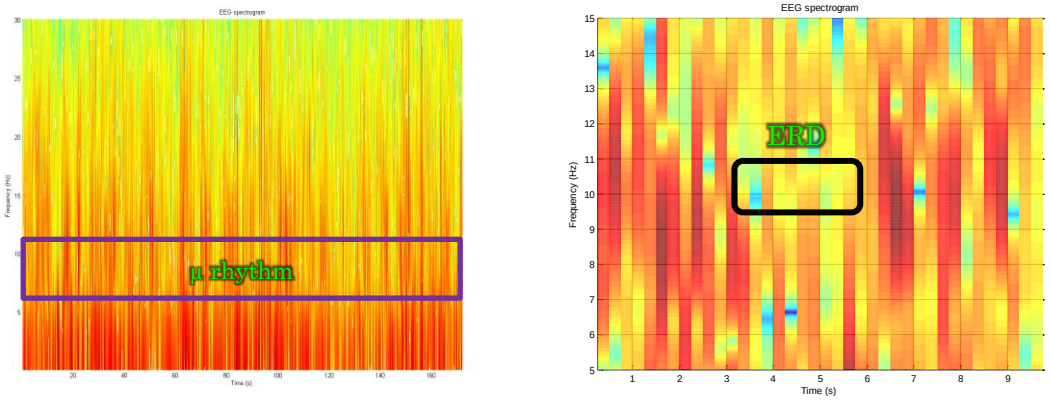


Figure 13. (left): Spectrogram of the whole EEG sequence, and (right): a part of the sequence with ERD clearly highlighted

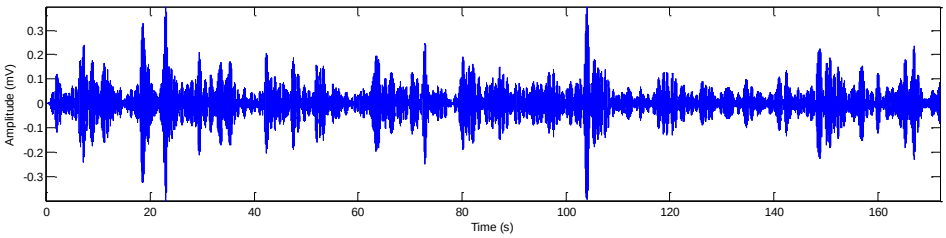


Figure 14. An EEG sequence filtered to retain only the μ-band

Ellipses on Figure 15 mark the phenomena also used to evaluate the success of the algorithm; left image on Figure 15 shows an occurrence of a *False Positive* (type I error), that is a movement was detected which didn't happen, or at least can't be seen in the EMG (maybe it originated from a different muscle, or it was imagined); the image on the right depicts two other events: the solid line marks a *False Negative* (type II error), meaning that the movement which is clearly seen in the EMG wasn't detected, and the dotted line marks a *True Positive*, where the movement happened, originated from the observed muscle, and was successfully detected from the EEG data.

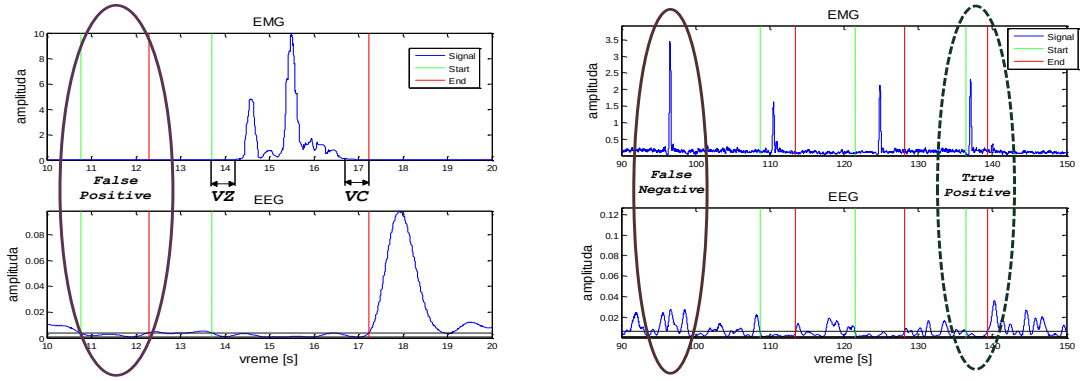


Figure 15. *(left)*: Fully processed segment (subject IA), showing the detected word starts (dotted line) and ends (solid line); the ellipse marks the False Positive event, the detection of a nonexistent movement; VZ and VC are the difference between the detection times and actual movement times; *(right)*: Fully processed segment (subject MK) showing the detected word starts and occurrences of False Negative (an undetected movement) and True Positive (correctly detected movement)

The results for each of the subjects for both sessions and a summary are given in

Table **1**. The quality of the algorithm is described using several parameters. One is a number of correctly detected movements N_T and a percentage of N_T in relation to the number of actual movements N_P

$$TP = \frac{N_T}{N_P}$$

Other parameters are: a number of false negatives N_F, VZ and VC.

The success of the algorithm depends heavily on the choice of these parameters. To ensure that their values are optimal, each sequence has been tested with at least a dozen different combinations. To illustrate how crucial these values are, Figure 16 is showing a result of the algorithm using a good combination, and Figure 17 is showing an example of bad parameter choice.

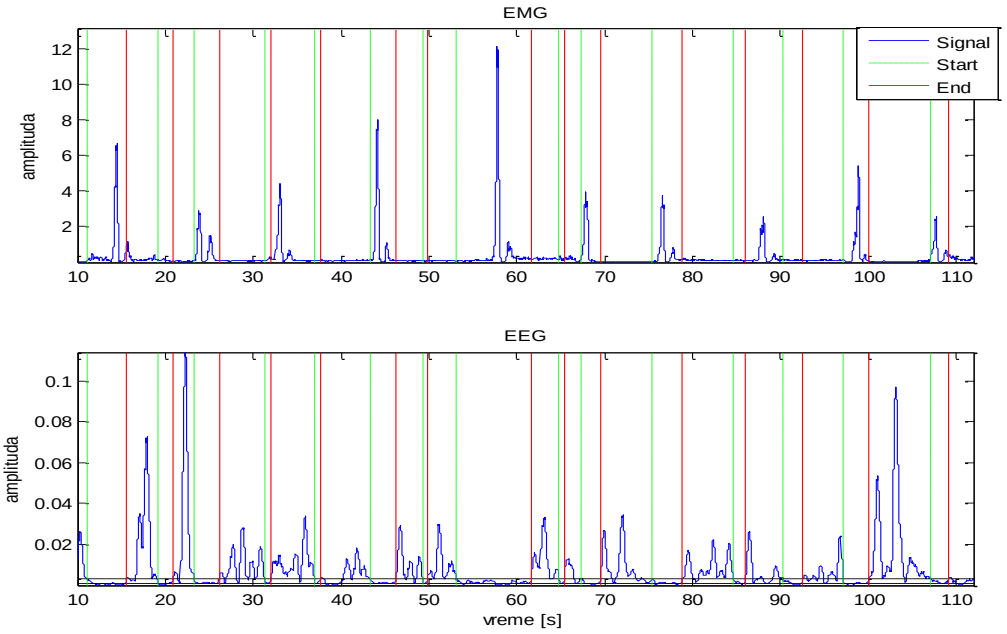


Figure 16. A sequence from the subject ML illustrating a good choice of parameter values

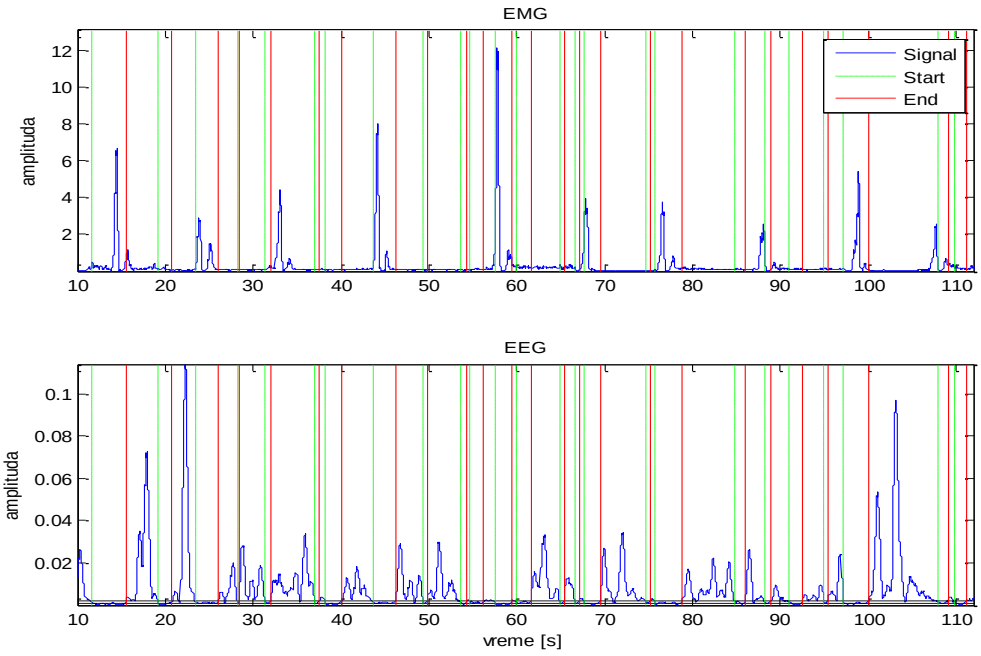


Figure 17. The same sequence as in Figure 16, with a bad choice of parameter values

TABLE 1. COMPILED RESULTS FOR THE ERD-BASED MOVEMENT DETECTION METHOD FOR EACH OF THE SUBJECTS

Name	*Age*	*Gender*	*Session*	*TP*		*FP*	*VZ [s]*	*VC [s]*
IA	27	M	1	100%	(11)	3	0,6±0,8	0,4±1,1
			2	75%	(9)	1	1,2±0,8	0,9±1,5
LJ	22	M	1	75%	(15)	2	0,0±0,7	0,3±0,8
			2	70%	(14)	3	1,1±0,8	1,1±1,2
ML	23	M	1	94%	(16)	6	0,2±1,4	0,9±1,0
			2	74%	(17)	5	-0,3±1,8	0,1±0,6
MŠ	22	M	1	83%	(15)	6	0,0±0,7	0,0±0,9
			2	73%	(11)	3	-0,7±2,0	-1,2±2,0
MK	21	F	1	71%	(12)	0	0,5±1,0	0,4±0,8
			2	81%	(17)	4	1,0±1,3	-0,8±1,5
TOTAL			1	83%	(69)	17	0,2±1,0	0,4±1,0
			2	75%	(68)	16	0,4±1,3	0,0±1,6

Session 1 – without the use of Wii console, Session 2 – With use of Wii console; TP is the ratio of True Positives and all movements, and a number of True Positives (in parenthesis); FP is the number of missed detections; VZ and VC are the differences between the detected and actual start and end of the movement, respectively, here presented as mean + standard deviation

V. DISCUSSION

Four out of five subjects had over 75% of true positive detections, which is in accordance with the results of other similar experiments [6], [7], [28]. The second session, with the Wii console turned on, produced worse results in four subjects, as expected, but performed well with over 70% detected movements. The ERD was mostly detected before the onset of movement, confirming that it is a result of the planning activity of the brain. It is noticeable that the subjects that presented fewer false positives, also presented fewer true positives. This can be explained with the different choice of values for LT and UT, resulting in the stricter criteria for the ERD detection, and a certain trade-off is required. Movements were easily recognized from the self-paced sessions, but with Wii sessions certain problems presented themselves; namely, because of the way the game is controlled, some of the throws were unsuccessful, resulting in several consecutive swings in a short time-span, making them hard to separate in the EMG. Failed throws resulted in frustration as well, which manifested itself as artefacts in the EEG. While playing the game subjects were less concentrated on the wrist itself, due to the immersion in the game and the results of each throw, making small movements, spotted as low amplitude peaks in the EMG, and also

observable in the EEG. One of the subjects reported a higher level of competitive spirit and reacted to the results of the throws causing false positive detections to appear between some throws [29].

It is of importance to mention that EOG wasn't recorded, because the game itself asks the players to follow the ball swiftly along the screen, and to switch their gaze from the screen to the controller. Even though the scalp electrodes were placed over the motor cortex, far from the eyes themselves, sudden movements could cause significant artefacts in the EEG.

The cap used for the EEG acquisition had a standard 10-20 system of electrodes. It is possible that a different, more dense layout [7], [30] would yield better results due to the ability to pinpoint the cortical structures responsible for the examined movement with greater accuracy. This would, potentially, improve the SNR of the evoked activity to the spontaneous brain activity, consequentially reducing the order of the used filters and facilitating signal processing.

VI. Bibliography

1. **Pfurtscheller, Gert and Aranibar, A.,** *Event-related cortical desynchronization detected by power measurements of scalp EEG.* 6, June 1977, Electroencephalography and Clinical Neurophysiology, Vol. 42, pp. 817-826.

2. **Pfurtscheller, Gert,** *Central beta rhythm during sensorimotor activities in man.* 3, March 1981, Electroencephalography and Clinical Neurophysiology, Vol. 51, pp. 253-264.

3. **Pfurtscheller, G., et al,** *15 years of BCI research at graz university of technology: current projects.* 2, Graz : s.n., June 2006, Neural Systems and Rehabilitation Engineering, IEEE Transactions on, Vol. 14, pp. 205-210.

4. **Blankertz, B., et al.,** *The Berlin Brain--Computer Interface: Accurate Performance From First-Session in BCI-NaÏve Subjects.* 10, Berlin : s.n., April 2008, Biomedical Engineering, IEEE Transactions on, Vol. 55, pp. 2452-2462.

5. **Pfurtscheller, Gert, Flotzinger, Doris and Kalcher, Joachim,** *Brain-Computer Interface--a new communication device for handicapped persons.* 3, July 1993, Journal of Microcomputer Applications, Vol. 16, pp. 293-299.

6. **Lisogurski, D. and Birch, G.E.,** *Identification of finger flexions from continuous EEG as a brain computer interface.* 1998. Engineering in Medicine and Biology Society, 1998. Proceedings of the 20th Annual International Conference of the IEEE. Vol. 4, pp. 2004-2007.

7. **Li, Yong, et al,** *Classification of single-trial electroencephalogram during finger movement.* 6, June 2004, Biomedical Engineering, IEEE Transactions on, Vol. 51, pp. 1019-1025.

8. **Allison, BZ, et al,** *Toward a hybrid brain–computer interface based on imagined movement and visual attention.* 2, April 2010, Journal of Neural Engineering, Vol. 7.

9. **Lum, Peter S., et al,** *Robot-assisted movement training compared with conventional therapy techniques for the rehabilitation of upper-limb motor function after stroke.* 7, July 2002, Archives of physical medicine and rehabilitation, Vol. 83, pp. 952-959.

10. **Smith, Raymond Carl,** *Electroencephalograph based Brain Computer Interfaces.* University College Dublin. Dublin : s.n., 2004. A thesis presented in fulfilment of the requirements for the degree of Master of Engineering Science.

11. **Cohen, David,** *Magnetoencephalography: detection of the brain's electrical activity with a superconducting magnetometer.* 2, February 1972, Science, Vol. 175, pp. 664-666.

12. **Niedermeyer, E and da Silva, F.L.,** *Electroencephalography: Basic Principles, Clinical Applications, and Related Fields.* s.l. : Lippincot Williams & Wilkins, 2004.

13. **Sörnmo, Leif and Laguna, Pablo.,** *Bioelectrical Signal Processing in Cardiac and Neurological Applications.* s.l. : Elsevier Academic Press, 2005.

14. **Berger, Hans,** *Über das Elektrenkephalogramm des Menchen.* 1929, Archives für Psychiatrie.

15. **Bear, Mark F., Connors, Barry W. and Paradiso, Michael A.,** *Neuroscience: Exploring the Brain.* s.l. : Lippincott Williams & Wilkins, 2002.

16. **Wikipedia contributors.** Electroencephalography. [Online] Wikipedia, The Free Encyclopedia., 8 October 2010. [Cited: 9 October 2010.] http://en.wikipedia.org/w/index.php?title=Electroencephalography&oldid=389592088.

17. **Pfurtscheller, G., Flotzinger, D. and and Neuper, C.,** *Differentiation between finger, toe and tongue movement in man based on 40 Hz EEG.* 6, June 1994, Electroencephalography and Clinical Neurophysiology, Vol. 90, pp. 456-460.

18. **Whitham, E.M., et al,** *Scalp electrical recording during paralysis: Quantitative evidence that EEG frequencies above 20 Hz are contaminated by EMG.* 8, August 2007, Clinical Neurophysiology, Vol. 118, pp. 1877-1888.

19. **Klem, G. H., et al,** *The ten-twenty electrode system of the International Federation.* 1958, Electroencephalography and Clinical Neurophysiology, Vol. 10, pp. 371-375.

20. **Bickford, R. D.** Electroencephalography. [ed.] G. Adelman. *Encyclopedia of Neuroscience.* Cambridge (USA) : Birkhauser, 1987, pp. 371–373.

21. **Jung, T.-P., et al,** *Removing electroencephalographic artifacts by blind source separation.* s.l. : Blackwell Publishing, March 2000, Psychophysiology, Vol. 37, pp. 163-178.

22. **Joyce, C.A., Gorodnitsky, I.F. and Kutas, M.,** *Automatic removal of eye movement and blink artifacts from EEG data using blind component separation.* 2, March 2004, Psychophysiology, Vol. 41, pp. 313-325.

23. **Pfurtscheller, Gert,** EEG event-related desynchronization (ERD) and event-related synchronization (ERS). [ed.] E Niedermayer and F. Lopes Da Silva. *Electroencephalography: Basic Principles, Clinical Applications and Related Fields.* 4th. s.l. : Williams & Wilkins, 1999, pp. 958-965.

24. **Jasper, Herbert and Penfield, Wilder,** *Electrocorticograms in man: effect of the voluntary movement upon the electrical activity of the precentral gyrus.* 1-2, 1949, European Archives of Psychiatry and Clinical Neuroscience, Vol. 183, pp. 163-174.

25. **Neuper, Christa, Wört, Michael and Pfurtscheller, Gert,** ERD/ERS patterns reflecting sensorimotor activation and deactivation. [ed.] Christa Neuper and Wolfgang Klimesch. *Event-Related Dynamics of Brain Oscillations.* 2006, Vol. 159, pp. 211-222.

26. **Youm, Y., et al.,** *Kinematics of the wrist. I. An experimental study of radial-ulnar deviation and flexion-extension.* 4, s.l. : Journal of Bone and Joint Surgery, Inc, 1978, The Journal of Bone and Joint Surgery, Vol. 60, pp. 423-431.

27. **Kuhlman, William N.,** *Functional topography of the human mu rhythm.* 1, January 1978, Electroencephalography and Clinical Neurophysiology, Vol. 44, pp. 83-93.

28. **Levine, S.P., et al,** *A direct brain interface based on event-related potentials.* 2, June 2000, Rehabilitation Engineering, IEEE Transactions on, Vol. 8, pp. 180-185.

29. **Curran, Eleanor A. and Stokes, Maria J.,** *Learning to control brain activity: A review of the production and control of EEG components for driving brain–computer interface (BCI) systems.* 3, April 2003, Brain and Cognition, Vol. 51, pp. 326-336.

30. **Oostenveld, Robert and Praamstra, Peter,** *The five percent electrode system for high-resolution EEG and ERP measurements.* 4, April 2001, Clinical neurophysiology, Vol. 112, pp. 713-719.