Comparison of the event-related desynchronization during self-paced movement and when playing a Nintendo Wii game

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***Abstract* - We compared pre-movement event-related desynchronization (ERD) of μ rhythm over the primary motor cortex using surface electrodes in a group of five healthy subjects during self-paced wrist movement and the wrist movement when playing a Nintendo Wii. We present a method that uses ERD to detect the onset of movement in single-trial electroencephalographic (EEG) data. This algorithm produced a mean detection accuracy of 83% for the self-paced movement and 75% for the Wii-included sessions, without requiring subject training. This technique can be employed in an EEG-based brain–computer interface due to its high recognition rate and simplicity in computation.**

***Keywords*—Brain-computer interface, Event-related desynchronization (ERD), Electroencephalogram (EEG), Nintendo Wii.**

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.). 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 [1]) that enables the acquisition, a system for signal processing and intelligent recognition of events, and an external device to interact with the environment.

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) [2] and event-related synchronization (ERS) [3] from the skull recordings (EEG). The analysis of ERD and ERS provides information on the dynamic pattern of cortical activation and idling occurring before a motor activity. ERD can be seen as a correlate of an activated cortical area, and presents itself as a decrease in power in certain frequency bands in the EEG starting about 2s prior to movement onset, and is observable in the μ and central β rhythms [4]. 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 [5]. The ERD and ERS must be observed in relation to the baseline activity measured some seconds before the event.

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 β rhythms or multiple components of sensorimotor rhythms [6], [7]. One of the first reports on classifying ERD/ERS patterns induced by motor imagery appeared in the early 1990s [8]. Several years later, other systems began to use ERD/ERS patterns as features for single-trial EEG classification [9]. A recent study on 14 fully BCI-naive subjects in [7] 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 [10]. Work published in [11] 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 paper we present results from the study that included five healthy subjects. We 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 results of this study are of interest for developing the technique that can be used for the therapy of post-stroke hemiplegic individuals [12].

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II. 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 (Wii mote) 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. The moves required in order to play the game are sudden and involve a lot of activity from the whole body, they were simplified to use a computer mouse.

Each subject took part in two recording sessions: 1) self-paced rotation 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 in 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 [13]. Bipolar EMG recording was conducted on the right flexor carpi ulnaris muscle [14] 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 [15]. 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 was used to store recorded data on a hard disk.

B. Signal Processing

Because the signal-to-noise ratio (SNR) of the movement evoked 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, we filtered the recorded EEG data. All processing was performed in MATLAB. We utilised two filter designs: a 10^{th} order filter with a 9-12 Hz passband and a slow roll-off, and a 24^{th} 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 lots 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 HT 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 HT. This moment was declared as the new start of the movement. The 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, HT, shortest detectable movement duration, shortest time between two consecutive movements) and one binary variable (filter type).

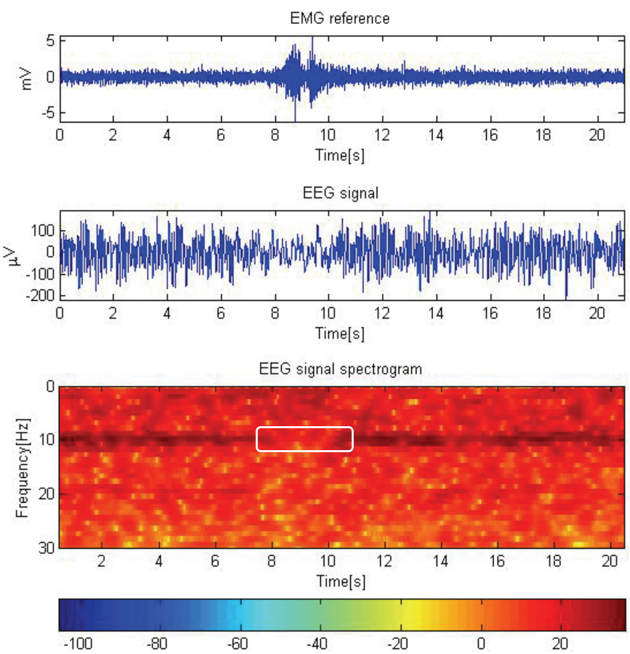

Fig. 1. Top plot: EMG signal recorded during one task execution. Middle plot: raw EEG signal recorded during the same trial. Bottom image: EEG signal spectrogram with μ ERD marked.

EMG sequence processing consisted of baseline removal and rectifying the signal, so the movements could easily be spotted. EMG served as a reference for determination of actual onsets and offsets of the movements.

III. Results

Middle plot of Fig. 1 shows a recorded EEG 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 (Fig 1.) 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. Time-frequency EEG signal representation with pronounced ERD is shown in the bottom image of Fig.1. Because the ERD is localized to a narrow frequency band (μ band), the signal was bandpass filtered to retain only those frequencies. The same segment from Fig. 1, only after the EMG has been rectified and EEG has been filtered and the detection took place, is shown in Fig. 2.

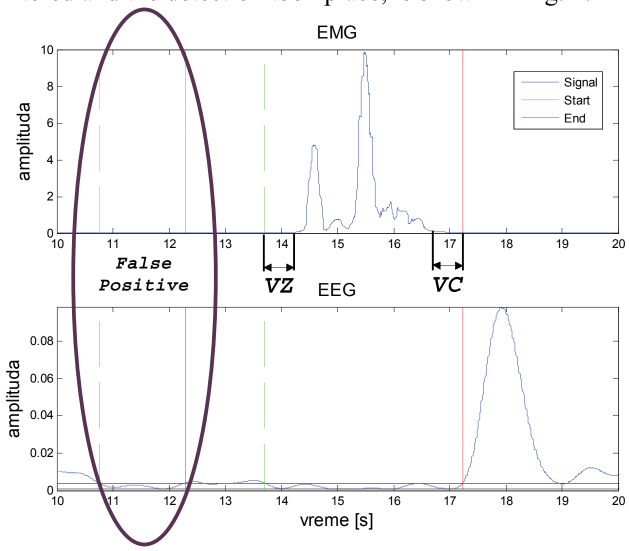

Fig. 2. Fully processed segment (subject IA), showing the detected word starts (dotted line) and ends (solid line); the ellipse marks the False Positive event, the detection of a nonexistent movement; VZ and VC are the difference between the detection times and actual movement times.

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 HT. 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. Ellipses on Fig. 2 and Fig. 3 mark the phenomena also used to evaluate the success of the algorithm; Fig. 2. 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); Fig 3. 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.

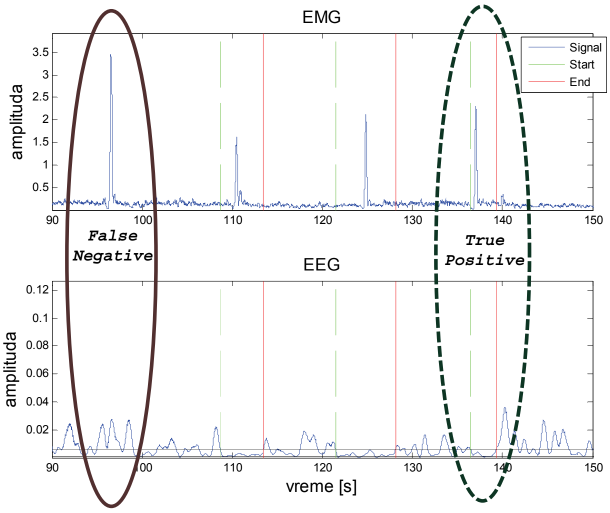

Fig. 3. Fully processed segment (subject MK) showing the detected word starts and occurrences of False Negative (an undetected movement) and True Positive (correctly detected movement).

The results for each of the subjects for both sessions and a summary are given in Table 1. The quality of the algorithm is depicted using several parameters. One is the number of correctly detected movements N_T and the percentage of N_T in relation to the number of actual movements N_P

$$TP = \frac{N_T}{N_P}. \quad (1)$$

Other parameters are: the 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.

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 the use of Wii console; TP is the ratio of True Positives and all movements, and the 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.

IV. Discussion

Four out of five subjects had over 75% of true positive detections, which is in accordance with the results of other similar experiments [9], [10] and [16]. 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, presented fewer true positives also. This can be explained with the different choice of values for LT and HT, resulting in 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 [17].

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 [10], [18] 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.

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