Prosthetic Control by an EEG-based Brain-Computer Interface (BCI)

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Abstract. The real-time analyses of oscillatory EEG components during right and left hand movement imagination allows the control of an electric device. Such a system, called brain-computer interface (BCI), can be used e.g. by patients who are totally paralyzed (e.g. Amyotrophic Lateral Sclerosis) to communicate with their environment.
The paper demonstrates a system that utilizes the EEG for the control of a hand prosthesis.

1. Introduction

There are different ways to control a prosthetic hand: with a shoulder harness, myo-electrically or for example with a WILMER elbow [9]. A shoulder harness can simply be used to control a hand prosthesis by moving the upper arm or shoulder. Alternatively, a below-elbow prosthesis can be controlled myo-electrically. Therefore, some residual nerve functions or muscle activity in the amputated extremity of the amputee must be used in order to control the assistive limb. But the effectiveness is limited because the nerve endings can lose effectiveness due to amputation. Sometimes the nerve endings do not even exist. The WILMER elbow utilizes the motion of the elbow, instead of shoulder or upper arm movements, to control a hand. The opening width of the hand prosthesis is determined by the flexion angle of the elbow.

All these commercial available prosthetic systems require some measure of voluntary motor control and, therefore, are not useful for patients who are totally paralyzed. But an Electroencephalogram-based brain-computer interface (EEG-based BCI) provides a new control channel to individuals with severe motor impairments (e.g. late stage of Amyotrophic Lateral Sclerosis) [3, 12, 13]. A possible application is e.g. to select letters or words by moving a cursor [13], to control a Functional Electrical Stimulation device for patients with spinal cord lesions [10] and also to control a prosthetic device. Such an approach was realized with a phase-locked loop (PLL), which detects motor actions of an amputee from the EEG in order to control an externally powered prosthesis device (EPPD) during grasping with the hand [6]. But the PLL caused a high amount of false alarms.

BCI applications can be controlled by at least one binary output signal of the BCI, which is obtained, for example, by classification of EEG-patterns during imagination of left and right hand movements. It was shown recently that unilateral hand movement imagery results in a contralateral event-related desynchronization (ERD) close to primary motor areas and, in certain cases, in parallel to an ipsilateral event-related synchronization (ERS) of sensorimotor rhythms [7]. A minimum of EEG channels is therefore assembled close to primary hand areas (electrode positions C3 and C4) as an array of electrodes overlying motor and somatosensory areas. The use of oscillatory EEG components as input signals for a BCI requires on-line analysis of EEG signals with the extraction of reliable parameters. The paper shows how to combine recent BCI developments with a modern prosthetic tool.

2. Hardware and Software of the BCI System

The BCI consists of an IBM compatible Pentium II PC operating at 233 MHz and an RTI800a data acquisition board (DAQ) from Analog Device (Analog Device, Norwood, USA) as shown in Figure 1. The digital input/output channels are used to control a remote control (transmitter and receiver) which is connected to a microcontroller to control the prosthesis (see Figure 2). The microcontroller receives commands from the remote control and regulates the grip speed.

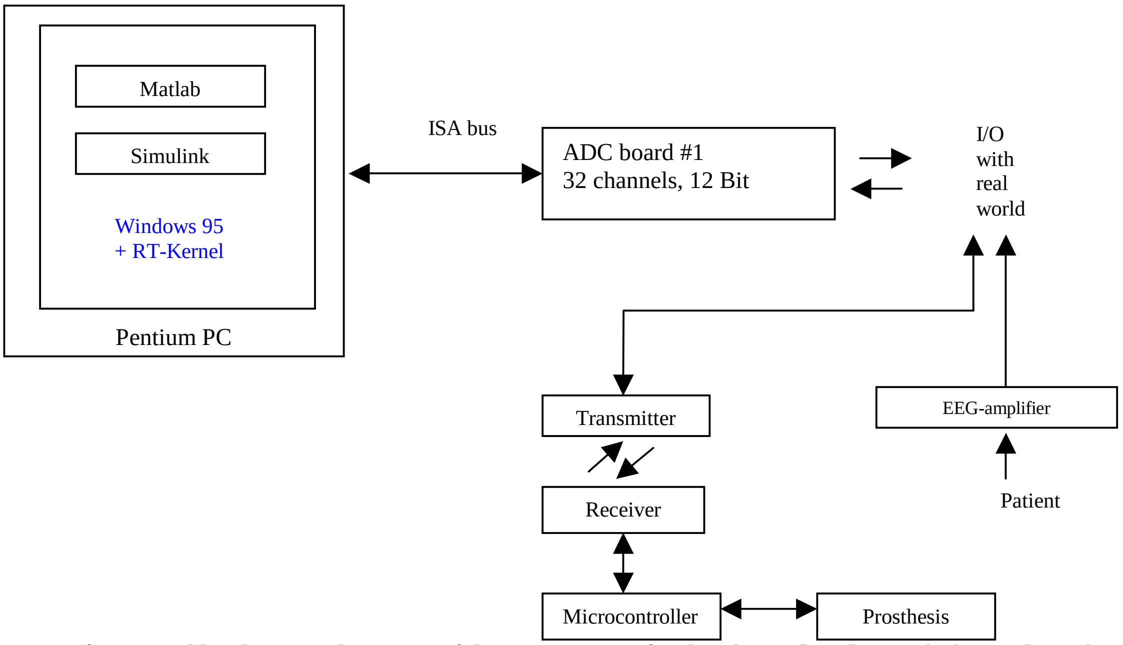

Figure 1: Software and hardware architecture of the BCI system, for details see [1, 2]. Simulink (MathWorks, Inc., Natick, USA) is used for the calculation of different parameters, which describe the current state of the EEG in real-time (after real-time code generation), while Matlab (MathWorks, Inc., Natick, USA) handles the data acquisition, timing and presentation of the experimental paradigm.

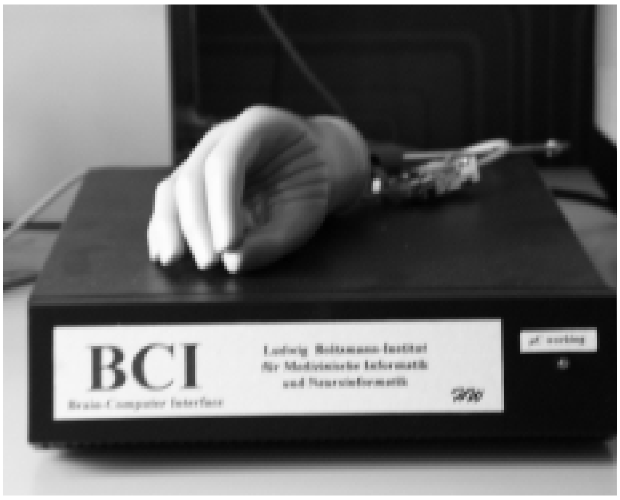

Figure 2: Hand prosthesis and control unit.

3. Parameter Estimation and Classification

An appropriate parameter estimation method for an EEG-based BCI is e.g. the adaptive autoregressive (AAR) model. An AAR model describes a signal in the following form:

$$x_k - a_{1,k} x_{k-1} - \ldots - a_{p,k} x_{k-p} = \varepsilon_k$$

The EEG sample x_k is predicted from a number of samples in the past with a resulting error ε_k for every iteration k. The model is of order p and $a_{1,k} \ldots a_{p,k}$ are the time varying AR-coefficients, which are estimated with the recursive least square (RLS) algorithm. For a detailed description see [8, 11].

A linear classifier is used to differentiate between EEG patterns associated with left and right movement imagery (see next section). The on-line classification result is used to control the movement of the prosthesis.

The AAR-model was implemented with Simulink as shown in Figure 3. The algorithm was initialized at the beginning of every trial to avoid instabilities [2].

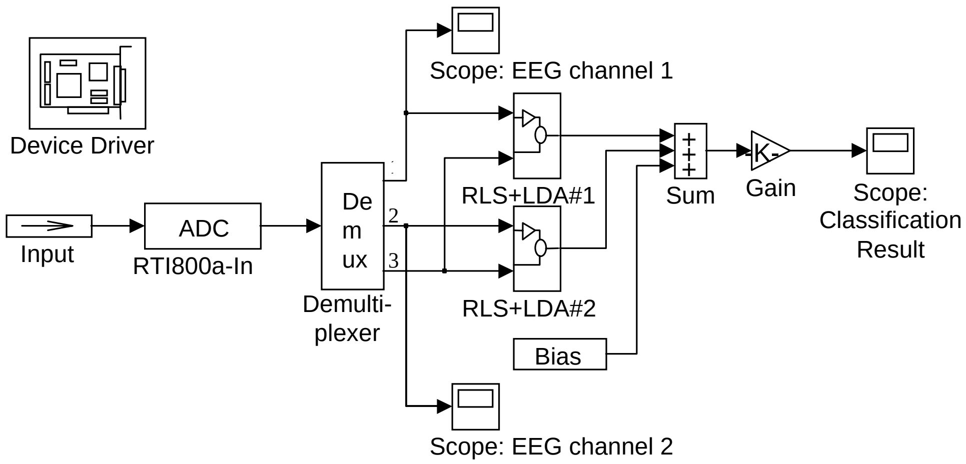

Figure 3: A device driver for the RTI800a board (DAQ board from Analog Device) realizes the connection to the real world. In this case the input block represents analog input channel 1 to 3 (bipolar EEG channel C3, bipolar EEG channel C4, Trigger) and reads the data into the Simulink environment with a sampling frequency at 128 Hz. Channel 1 and 2 are connected to the 'RLS+LDA' algorithm blocks and channel 3 is the trigger signal used to initialize the RLS-algorithms at the beginning of every trial. ‘RLS+LDA’ calculate the RLS-algorithm with a sampling rate inherited from the blocks driving them (128 Hz). The output of the RLS-algorithms consists of six (p=6) time varying AR-coefficients for each EEG channel and is classified with a weight vector previously obtained from a linear discriminant analysis (LDA). The on-line classification result is gained and displayed with the Scope block 'Classification Result' and controls also the movement of the prosthesis. Either outcome of this real-time process (greater or lower than zero) will close or open the prosthesis a little bit more. The complete closing or opening time was set to 1 second. This means if the classification output was greater than zero for at least 1 second, then the prosthesis was closed for sure.

4. Experimental Paradigm

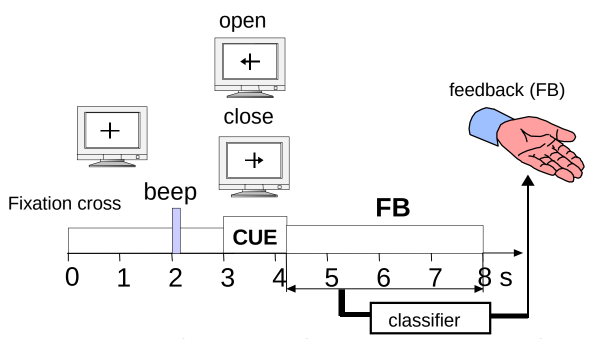

Figure 4: Timing of one trial of the experiment with feedback.

The experiment started with the display of a fixation cross that was shown in the center of a monitor (see Figure 4). After two seconds a warning stimulus was given in form of a "beep“. From second 3 until 4.25 an arrow (cue stimulus), pointing to the left or right, was shown on the screen. The subject was instructed to imagine a left or right hand movement, depending on the direction of the arrow. Between second 4.25 and 8 the EEG was classified on-line and the classification result was used to control the prosthesis. If the person imagined a left movement, then the prosthesis was closed a little bit more and vice versa (correct classification assumed). One session consisted of 160 trials. Three sessions were made with subject i6.

5. Results

Classification results obtained with one healthy subject are graphically presented in Figure 5. Session 1 and 3 were performed with a weight vector obtained from an earlier session, where the feedback was given in form of a moving horizontal bar [2, 5]. For session 2 the data of session 1 was used to set up a weight vector. The AAR-coefficients of the classification time points with the lowest classification error were used to set up the weight vector with the LDA for the following sessions. The weight vector that was used for session 1 and 3 was calculated from the data at second 6, the vector for session 2 at second 6.5.

The lowest error rate in session 1 (10 %) was observed at second 6, in session 2 (17.5 %) at second 6.5 and in session 3 (11.25 %) at second 6. Therefore, the best classification time point always corresponded to the weight vector calculation time point.

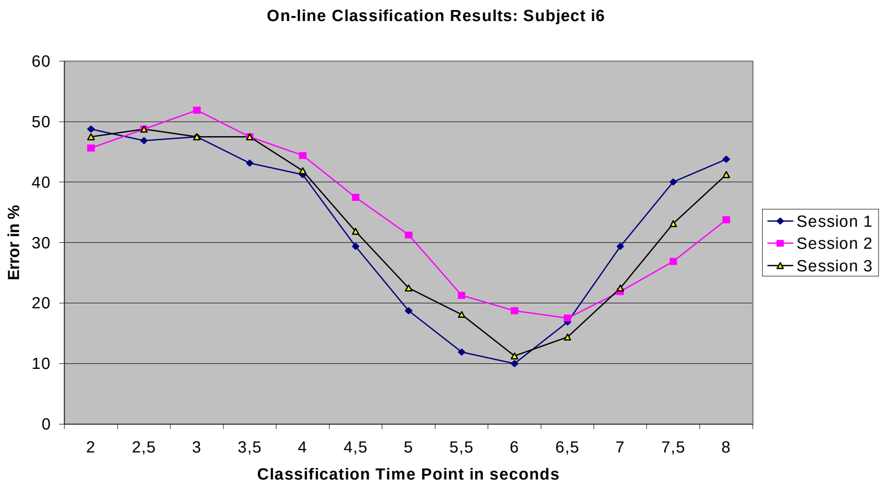

Figure 5: The error rate (100 % minus correct classification) is displayed over classification time points and different sessions for one subject.

6. Discussion

For the first time it was shown that an EEG-based BCI system allows to control a hand prosthesis by imagination of left and right hand movement. The subject was able to achieve an accuracy of about 82.5, 88.75 and 90 %. The best classification time point always corresponded to the calculation time point of the linear classifier. The accuracy is in the same range as achieved with other studies made with the same subject [2]. The subject needed approximately 3 to 3.5 seconds after cue onset to reach the minimum error rate. A difference is the increasing error rate at the end of the sessions. The error increased from 10 to 43.8 % (session 1), 17.5 to 33.8 % (session 2) and from 11.25 to 41.3 % (session 3). An explanation might be, that most of the time the prosthesis was already in the expected position (closed or opened) at second 6 or 6.5, respectively, and therefore the subject stopped to imagine the movement. After seeing the prosthesis moving in the wrong direction the subject was not able to react fast enough. This caused a problem when trying to grasp an object. The object would fall down at the end of the trial with the increasing error of classification. A solution would be to lock the prosthesis at the reached position at second 6 or 6.5, respectively.

The most consistent complaint about non-EEG-based control of a prosthesis is that it requires a high amount of attention of the subject [6]. Therefore, the most suitable way of controlling a hand prosthesis would be to detect signals from the sensorimotor area of the brain to close or open the hand. Ideally, the control signal would be the same as if there would be no movement disorder. Just by attempting to close or open the hand, the prosthesis should be controlled. In order to use this approach for our system it is necessary to increase the spatial resolution by implanting electrodes over the sensorimotor areas [4]. Such an electrode array would allow to record data from a small neuronal population and this would allow to discriminate between the attempt of closing or opening the hand.

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