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Non-invasive Control of Neuroprostheses for the Upper Extremity: Temporal Coding of Brain Patterns

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Abstract— **Spinal cord injury (SCI) results in deficits of sensory, motor and autonomous functions, with tremendous consequences for the patients. The loss of motor functions, especially grasping, leads to a dramatic decrease in quality of life. With the help of neuroprostheses, the grasp function can be substantially improved in cervical SCI patients. Nowadays, systems for grasp restoration can only be used by patients with preserved voluntary shoulder and elbow function. In patients with lesions above the 5th vertebra, not only the voluntary movements of the elbow are restricted, but also the overall number of preserved movements available for control purposes decreases. A Brain-Computer Interface (BCI) offers a method to overcome this problem. This work gives an overview of the Graz BCI used for the control of grasp neuroprostheses as well as a new control method for combining grasp and elbow function is introduced.**

I. INTRODUCTION

The consequences of a spinal cord injury (SCI), which results in a loss of sensory, motor and autonomous functions, are tremendous for the patients. The loss of motor functions, especially of grasping function, leads to a life-long dependency on other persons and thereby to a dramatic decrease in quality of life. With the help of so-called neuroprostheses, systems based on functional electrical stimulation (FES), the grasp function can be substantially improved. All established FES systems for grasp restoration can only be used by patients with preserved voluntary shoulder and elbow function. The limited possibilities for functional restoration in case of extended paralysis as well as inexperienced controllers are the main barriers for a broad use of neuroprosthetic systems outside of research laboratories. Brain-Computer Interfaces (BCI), systems which transform mentally induced changes of brain signals into control signals [1], might serve as an alternative human-machine interface. The ideal solution for voluntary control of a neuroprosthesis would be to directly record motor commands from the corresponding areas of the cortex, convert these into control signals and transfer these control signals to the neuroprosthesis itself, thereby realizing a technical bypass around the interrupted nerve fiber tracts in the spinal cord (Figure 1).

First attempts into the direction of EEG-based control systems for restoration of the hand function were performed by Pfurtscheller et al. [2] who described the control of a grasp orthosis by motor imagery. Heasman et al. [3] reported on the control of a neuroprosthesis controlled with the alpha rhythm modulated by opening and closing the eyes. The aim of this paper is to give an overview of the collaboration work of the Graz BCI group and the Heidelberg neuroprosthetics group in this topic [4], [5], [6]. The use of different brain switches used for control are demonstrated in more detail.

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II. METHODOLOGY AND RESULTS

A. Neuroprostheses

In general, neuroprostheses for the upper extremity restore with the use of electrical impulses lost control/motor- or sensory functions of the body after lesions of the central nervous system [7]. In case of restoration of motor functions, the neuroprostheses deliver short current impulses eliciting action potentials on the efferent nerves, which provoke contractions of the innervated, yet paralyzed muscles. Here, FES artificially compensates for the loss of voluntary muscle activation. The easiest way of improving weak or lost grasp function is the application of multi-channel electrical stimulation with surface electrodes. Generally, the major advantage of these non-invasive systems is that they can be offered to patients at a very early stage of rehabilitation. Limitations regarding selectivity, reproducibility and handling of these systems can be overcome by implantable neuroprostheses, where electrodes, cables and the electrical stimulator are surgically placed under the skin (Freehand, [8]).

B. Brain-Computer Interface

Brain-Computer Interfaces are able to detect thought-modulated changes in electrophysiological brain activity and transform those signal characteristics into control signals. One option for measurement of the brain signals is to place electrodes on the scalp (electroencephalogram, EEG). One common mental strategy to operate a BCI is imagination of limb movements (motor imagery, MI). MI induces measurable changes of oscillatory components in the ongoing EEG over sensorimotor areas known as event-related (de)synchronization (ERD, ERS, [9]). Independent from the signal used, features have to be extracted and classified to distinguish between different brain patterns. Very often, training sessions have to be performed several times over days or weeks to achieve a useful classification result [10].

C. BCI Control and Hand Function

The problem in high SCI patients (lesion above cervical level C4) is that these patients lose control over their grasp function and also their elbow function. In addition to these functional deficits, the ability to control external levers or joysticks also decreases. Eye-tracking systems e.g., in combination with a computer screen can be easily used for spelling. In the case of a prosthesis control, the user has to watch his moving arm; therefore, the use of an eye-tracker is difficult in such a scenario.

To overcome the problems with reduced control possibilities or controllers which are not appropriate for daily activities, the use of a Brain-Computer Interface might be a good solution. The ideal case would be to record motor commands from the scalp and transfer the converted control signals to the neuroprosthesis, realizing a bypass around the interruption in the high spinal cord. A BCI in general is based on the measurement of the electrical activity of the brain, in case of EEG in the range of μV. In contrast, a neuroprosthesis relies on the stimulation of nerves by artificial electrical current pulses in the range of up to 40mA. One of the major points in combining these two methods was to investigate whether it is possible to realize an artefact free control system by using a BCI.

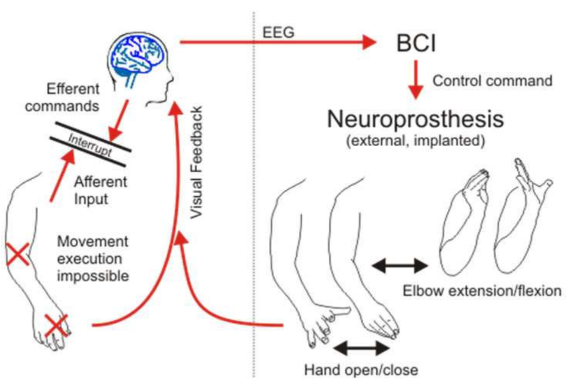

Fig. 1. Principle of the BCI controlled neuroprosthesis. The BCI detects brain patterns of motor intentions and feeds resulting control signals to the neuroprosthesis.

Two SCI patients participated in a feasibility study (Figure 2, [6]). Both suffer from traumatic SCI below the 5th cervical vertebrae and are therefore not able to grasp with their hands and fingers. The EEG was recorded over sensorimotor areas. Input features in both experiments were band power time series. For classification, a linear classifier was used. After training and classifier setup, the patients were able to switch through a grasp sequence, which was generated by a neuroprosthetic device controlled by imagination of a dedicated movement. In case of patient A this was foot MI (recorded from Cz) and in case of patient B it was left hand MI (recorded from Cz and C4). A neuroprosthesis with surface electrodes was set up for patient A such that a palmar grasp pattern was achieved [4]. By flexion of the fingers, small objects can be held between the fingers, thumb and palm. The activation pattern of the muscles was divided into the following four sequential grasp phases: (i) hand opening, (ii) closing of fingers and thumb, (iii) opening of hand, (iv) idling state, and (v) = (i). Patient B was provided with an implantable neuroprosthesis, the Freehand-system. Two basic grasp patterns (lateral grasp and palmar grasp) could be generated with this system, from which the lateral grasp pattern was chosen for the coupling with the BCI [5].

More details about the above described studies on establishing the brain switch can be found in [6].

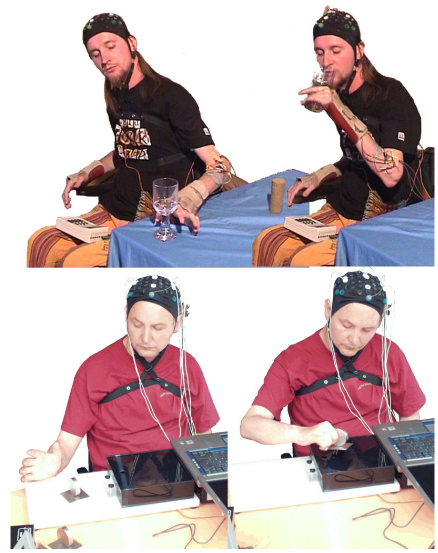

Fig. 2. Patient A with BCI and neuroprosthesis based on surface electrodes on the left hand (upper row) and patient B with implanted neuroprosthesis in the right hand.

D. BCI Control and Hand & Elbow Function

The two case studies presented show clearly that a BCI can be used as a control device for a neuroprosthesis. However, controlling the hand grasp is not the final goal since patients suffering from an SCI at level C4 have lost their voluntary elbow movements and a limited shoulder control. Here, a BCI would be more beneficial, and thus the restoration of the elbow function also has to be taken into account. A BCI provides only a reduced set of commands and is therefore limited for control. In a basic study, a control method was investigated were only one MI pattern was trained and used for control of hand and elbow function of a robotic arm.

Ten healthy subjects (mean age 28.1 years, 4 female, 6 male) participated in a screening study. During screening sessions, 3 types of MI (left hand, right hand, and foot) had to be performed. By means of the Distinction Sensitive Learning Vector Quantization (DSLVQ) algorithm [11], one Laplacian channel and two best separating MI were selected. After this screening, 3 subjects quit. The 7 remaining subjects took part in the cue-based training, and 5 reached a classification accuracy of about 80% in a two class paradigm (basket game, [12]). During this training, they learned to establish two different brain patterns by imagining hand and/or foot movements. After classifier output analyses, the MI which was not preferred (biased) by the classifier was selected for self-paced training.

For this purpose, a computer game-like paradigm was created in form of a Jump and Run game. Subjects controlled a jumping ball and had to leapfrog obstacles presented in random intervals between 10s and 15s along the way. The obstacles were presented in form of small hills with the length of 1 or 3s. Each time the classifier output exceeded a selected threshold (TH = class mean plus one time its standard deviation, obtained from Basket training), the difference between the actual classifier output and the threshold was mapped to the height of the ball. Subjects were instructed to perform MI only to over jump the obstacles and not in the periods in-between. Six runs (each lasted 300 s) with ten short and ten long obstacles each were performed. Four subjects succeeded and learned to establish short and long lasting MI patterns which were necessary to control the robotic arm.

A Laplacian EEG derivation (orthogonal derivation) was realized either from C3, Cz or C4, dependent on the results of the screening procedure performed prior. EEG was recorded with a 0.5 to 100 Hz band pass filter, notch filter on, and a sensitivity of 100μV. The sampling rate was 250 Hz.

The two different durations of the mental activity obtained from training were used to operate a pulse-width-modulated (PWM) switch. The output of the PWM-switch was depending on the threshold TH, and the durations tshort and tlong. Each time the classifier output exceeded TH for $t > tshort$, the output was 1; for $t > tshort$ and $t > tlong$, the output was 2. Otherwise the output was 0. The two states were alternatively mapped to the commands hand open/close (state 1) and elbow flexion/extension (state 2). After movement triggering, a refractory period of 5 s was added so that the robotic device could execute the movement.

To get control and evaluate the performance subjects had to perform a predefined movement sequence: hand open (O), hand close (C), elbow flexion (F), elbow extension (E), O and C. The evaluation was performed in the "error ignoring" mode. This means that the robotic device only accepted commands in the correct order. Wrong commands were ignored. Subjects trained with the PWC to get familiar with the system. To evaluate performance, the experiment was repeated in two different ways (4 runs each): First, after a 1-min period of no movement execution (non-control), subjects had to perform the sequence as fast as possible. Another 30-s period followed and the sequence had to be performed a second time. A non control period of 1 min finalized each run. Second, subjects had to perform the movement sequence according to the timing indicated by the experimenter.

The whole procedure allowed us to identify true positive (TP) and false negative (FN) decisions during a movement sequence and false positive (FP) detections during non-control periods (see Table I, Figure 3), as well as the time needed by the user to establish a certain movement (not presented here). A more detailed description can be found in [13].

III. Discussion

The successful implementation of an EEG-based brain-switch in two patients shows in principle that thought-based control of grasp neuroprostheses is possible. However, one prerequisite for coupling of both systems is the possibility to generate characterstic brain patterns by motor imagery and to detect these significant changes in the EEG-signals.

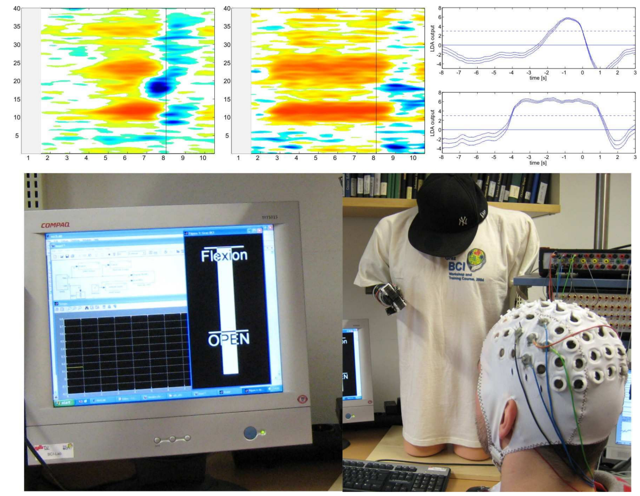

Fig. 3. Pulse width coded brain switch. The upper line shows time frequency maps of one subject (al4) during short (first) and long (second) MI. The thrid plot in this line shows the averaged classifier output for both MI patterns. Pictures in the lower part display the feedback screen (left) and the experimental setting with robot, subject and electrode montage (right).

TABLE I

Results of the evaluation procedure of 4 subjects. True positive (TP) and false negative (FN) movement selections are obtained from control state. False positive (FP) number of movements occurred during the non-control state. Numbers in parentheses give the results from the first 4 runs. * This subject participated only in the first 4 runs of the evaluation procedure.

Subject	TP (control)	FN (control)	FP (non-control)
al4	96 (70)	24 (11)	21 (15)
al9	94 (70)	50 (35)	23 (16)
al10*	58	52	2
ak10	99 (75)	52 (32)	39 (31)

In the second part, we reported on a pulse-width modulated brain switch which allows a user to control a two-axis robotic arm by the induction of only one specific brain pattern. After screening of three types of MI and training with the two best separating MIs, one individual pattern was selected. Here, EEG was recorded from one Laplacian channel only. Four subjects were included in the final evaluation. The main problem using only one pattern is to optimize the LDA threshold in a way to minimize FPs during non-control state and to select the two time intervals to distinguish between the two states. If the second time interval (tlong) is too long, FNs (grasps) are elicited very easily, if it is too short, FNs (elbow) are triggered. However, there are still possibilities to be investigated for the setup of such BCI control. An interesting approach is described in [14]. Here, hand movement direction was decoded by the use of MEG and EEG. However, the classification accuracy has still potential to be improved.

The application of invasive, intracortical electrodes has shown a possible way to decode the intention of movement with high signal quality and transfer rates in primates' experiments [15], [16]. However, besides cost and the inherent risk for infections, implantable systems have to prove their long-term stability over years in clinical trials. This is a mandatory prerequisite for the usability of BCIs for real-word control of neuroprostheses or artificial arms in humans.

Before a BCI-based control of a neuroprostheses can be offered to tetraplegic patients under real world conditions, several practical issues have to be solved. EEG amplifiers are already small and wireless interfaces for the cable-free transmission of the recorded signals have been introduced recently. However, there is still potential for developing much smaller devices, because miniaturization has not been an important research topic so far. At the current state of the art, wet sensors are used for recording. For applying a BCI on a daily basis, dry electrodes mounted in a kind of cap/hat should be available for fast and uncomplicated application - first prototypes already exist (e.g., [17]). Nowadays, BCI algorithms (feature extraction, classification) need a lot of manual expert work. Adaptive algorithms which allow the algorithm to adapt to changes in the users' EEG (mood, fatigue, workload,...) are currently under investigation.

In summary, many neurophysiological basics about the interaction between the brain and the BCI have to be further investigated and a considerable amount of technical issues have to be solved within the next decade to achieve the ultimate goal of a thought-controlled complete restoration of arm, hand and finger function including sensory feedback to the corresponding cortices [18].

IV. Acknowledgments

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