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Design Principles for Noninvasive Brain-Machine Interfaces

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Abstract—**With the advent of sophisticated prosthetic limbs, the challenge is now to develop and demonstrate optimal closed-loop control of the these limbs using neural measurements from single/multiple unit activity (SUA/MUA), electrocorticography (ECoG), local field potentials (LFP), scalp electroencephalography (EEG) or even electromyography (EMG) after targeted muscle reinnervation (TMR) in subjects with upper limb disarticulation. In this paper we propose design principles for developing a noninvasive EEG-based brain-machine interface (BMI) for dexterous control of a high degree-of-freedom, biologically realistic limb.**

I. Introduction

Electromyography (EMG)-based systems have shown reasonably reliable 7-degrees-of-freedom (DOF) control of a prosthetic limb using EMG after TMR – a surgical technique pioneered by Dr. Kuiken involving the transfer of residual nerves in the amputated arm to the remaining muscle, which then provide EMG signals that correlate to the original nerve functions allowing a virtual or physical prosthetic arm to respond directly and more naturally to the brain signals [1]-[2]. Some critical challenges of this approach concern the stability of EMG recordings, interference from muscles controlling remaining joints, effects of tissue loading, control of fine dexterous movements, and the cognitive burden of operating the device [1]. Thus, it is desirable to develop noninvasive neural interfaces that directly use brain signals, such as scalp electroencephalography (EEG), to control fine dexterous movements.

Most EEG-based brain-computer/machine interface (BCI/BMI) systems are based on (for a review, see [3]): 1) slow cortical potentials, including the so-called (low-frequency) readiness potentials that appear prior to the onset of movement, commonly used for the control of spelling devices in locked-in patients; 2) event-related potentials that are large-scale, low-frequency changes observed in response to neural events or triggered by external stimuli, and have been used in spelling devices and for controlling wheelchairs; 3) sensorimotor rhythms, such as alpha and beta rhythms in the 8-24 Hz range, that have been used for BCI cursor control (up to 3D) and other low degree-of-freedom (DOF) robotic applications. These approaches usually require several months of training, lack robustness, do not seem to scale well to tasks requiring > 3 DOF, and/or are slow in their response outputs. Together with physiological and non-physiological sources of noise or artifacts, and because the scalp-skull interface is thought to act as a low-pass filter thereby limiting the range of frequencies that can be recorded with EEG, these factors may have contributed to the widespread perception that EEG is not a suitable signal for complex, natural, volitional BCI/BMI applications. Here, we propose new design principles for the development of EEG-based multifunctional neuroprosthetics that can overcome these perceived limitations of EEG as a source signal for neural interface applications. The challenge is to develop an EEG-based BMI system that can control an upper limb prosthetic naturally and which functions and feels like a real limb [4].

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II. Design Principles for EEG-Based Neuroprosthetics

A. Design Principle I (Input Feature Space): Time-Domain, Delta-Band, Amplitude-Modulated (AM) EEG Carries Decodable Movement Information

Which EEG signal component in the time or frequency domain carries the most information about natural dexterous movement? Many decoding or BCI/BMI studies based on ECoG recordings have generally focused in the identification of the optimal frequency band(s) for spectral-power-based decoding [5]-[8]; with the underlying assumption that spatially-resolved gamma band frequencies are critical for movement decoding. However, recent studies have evaluated decoding from movement-related potentials (time-domain) and from spectral amplitude modulations (frequency-domain) in very low frequencies and in the high gamma band. Specifically, Ball et al. reported high decoding accuracy of arm movement direction based on amplitude modulation both in the delta band (<2 Hz) and in the high gamma band (52–128 Hz), yielding considerably higher decoding accuracy than the alpha, beta and low gamma bands [5]. Ince et al. examined decoding of movement target direction based on SUA and LFP signals, and reported that 1) the decoding accuracies from simultaneously recorded SUA and LFP signals were similar; 2) directional information varied with the LFP frequency sub-band, being greater in low (0.3–4 Hz) and high (48–200 Hz) frequency bands than in intermediate bands. They attributed the high decoding accuracy from LFP signals to the spatial organization of the LFP signals over the recorded areas (M1 and PMd) [9]. Zhuang et al. showed decoding of 3D reach-to-grasp movements from LFP signals based on delta and gamma band information [10]. Acharya et al. found a median decoding accuracy of r = 0.51 for finger movements in a slow grasping task based on moving-average filtering (time constant = 2s) from ECoG [11]. Overall, it seems that detailed information about movement is carried in amplitude modulations of the smoothed ECoG or LFP signals in the delta (0.1-4 Hz) bands originating from a small group of neurons in specific and detailed brain regions. Although EEG recordings represent the activity from large and separated groups of neurons, it can be argued that these amplitude modulations can also be recorded from EEG: a) decoding accuracies from ECoG, LFP and EEG using time-domain amplitude modulations are comparable, b) low-frequency, delta band signals are unlikely to be significantly affected by the conductivity of the brain tissues, and c) these low frequencies are of course easily recorded using EEG and also less susceptible to artifactual components. In this regard, it has been shown that EMG and ocular artifacts do generally occur mainly at frequencies higher than 8 Hz, which is 2 times higher than the upper frequency cutoff of 4 Hz in the delta band [12]. Indeed, we have showed that the relevant input feature space for reconstructing multidimensional natural movement lies in the time-domain modulations of the smoothed (< 4 Hz) amplitudes of high-density scalp EEG, which allow us to selectively read out brain activity patterns naturally correlated with movement intentions [13]-[17].

B. Design Principle II (Decoder Calibration): Calibration Based on Observed Movement

One method to train a neural decoder for BMI applications that does not require actual movement of the user is to use movement observation as a teaching signal during kinesthetic visuomotor imagery. This is essential in the case of a person with an upper limb disarticulation, who cannot move his/her arm for purposes of calibrating the decoder. As in [18], we asked subjects to imagine manually tracking a screen cursor that moved in two dimensions on the computer screen [16]. The movements of the computer-controlled cursor were generated by replaying a 10-min recording of a pilot subject's brain-controlled cursor movements from one of his practice runs (this pilot subject did not participate as one of the five subjects in our study [16]). EEG data acquisition and cursor movement were synchronized (i.e., aligned at the time of cursor movement onset). Our decoding procedure [11] was subsequently executed to find the decoder weights that best mapped 34 EEG signals to observed horizontal and vertical cursor velocities; thus the decoder (a Wiener filter with memory – signals up to 100 ms in the past were used as inputs to the decoder) was created (offline) to map EEG signals to the observed cursor movements. The accuracy of the decoder (Pearson's r), that is, the degree of correlation between the reconstructed (i.e., inferred) cursor trajectories and the actual cursor movements is shown in Figure 1. Examples of reconstructed and measured cursor movement velocities along the X and Y-axes are shown in Figure 2.

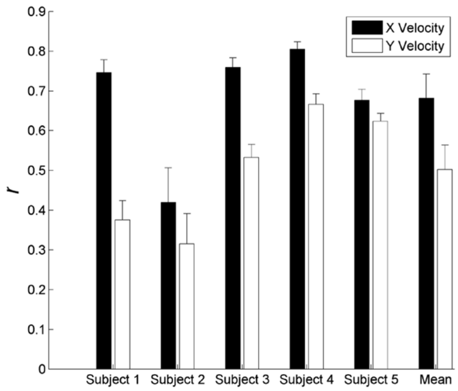

Fig. 1. EEG decoding accuracy of observed cursor velocity. Mean ± standard error of the decoding accuracies (r values) across cross-validation folds (n = 10) for each subject for x (black) and y (white) cursor velocities. Adapted from [16], with permission.

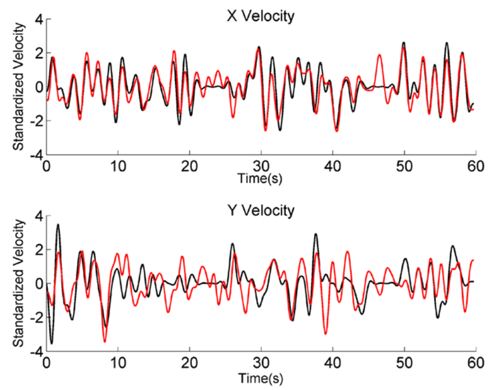

Fig. 2. Superimposed reconstructed velocity profiles (red) and actual velocity profiles (black) matched well (data from Subject 1). Adapted from [16], with permission.

Importantly, analysis of the lags of the decoder most relevant to prediction of observed cursor movement indicated the presence of planning activity that peaked at 50 ms in the past, therefore excluding the decoding of passive viewing as an explanation and suggesting predictive decoding informed by forward models [19].

In the case of multifunctional prosthetic limbs, calibration based on observed movement could be performed by initially having an experimenter or computer program drive the prosthetic limb independent of the influence from the patient's neural signals. The upper limb amputee would be asked to imagine performing a function (e.g., reach-to-grasp movement) while 'wearing' the upper limb prosthetic. While the user tries to perform the dexterous gesture, the experimenter or computer program would command the prosthetic limb to perform the predefined action(s). The brain activity from various electrodes would then be measured during the entire reach-to-grasp gestures as the user watches the prosthetic limb move as if he/she is performing the actions. Thus, the visual feedback acts to reinforce the kinesthetic imagery generated by the user. Of course, the gestures would be repeated together with other gestures to maximize generalization of the decoder.

C. Design Principle III (Internal Model): Fast Attainment of Brain Control with EEG Signals

Linking physical response to neural actions is how people learn. This is similar to the way one learns to play a new videogame or use a novel tool; through practice the brain builds an internal model (or representation) of how the body interacts with the prosthetic limb, including the neural interface itself. As the neural activity is correlated with the behavior, brain control becomes intuitive and training time is reduced [16], [20]. Indeed, cortical control of neuroprosthetic systems is known to require adaptation in neural networks involved in motor planning and motor execution [21]-[23]. Although the long-term use of a BMI device has been shown to result in the formation of a stable, addressable and robust cortical map for 2D prosthetic control [21], little is known about the nature of the cortical representation for prosthetic control of dexterous hand movements at the macro-scale of scalp EEG. Our work suggests a large, but sparse network engaging frontal, temporal and parietal scalp areas that represents angular kinematics of dexterous fine finger gestures [17].

Returning to our example of decoder calibration with observed cursor movement, the linear decoder can be used to decode activity and drive a 'neural cursor' in 2D space in a closed-loop BCI system. For example, we have recently shown in [16] that following a ~20 min practice phase with the neural cursor with no task, subjects moved a cursor with their EEG signals to acquire targets that appeared one at a time pseudo-randomly at the left, top, right, or bottom of a 2D workspace. Four 10-minute runs of target acquisition were then performed with a 1-minute rest interval between runs. The overall means (SE) of the hit rate and movement time (MT) were 73 ± 4% and 5.40 ± 0.27 s. To our knowledge, this is the first noninvasive EEG-based BCI study to employ continuous decoding of imagined/observed natural movement, in which users can achieve 2D brain cursor control in a single session [16]. Previous work in EEG-based BCI systems for cursor control required subjects to overcome an initial disconnect between intended movement and neural activity in order to learn how to modulate their sensorimotor rhythms to control the cursor. These studies based on sensorimotor rhythms required weeks to months of training before levels of performance were deemed sufficient for reporting [24]. We suggest that the combination of using a decoder based on imagined/observed natural movement (as opposed to neurofeedback training of sensorimotor rhythms), in conjunction with the capability of the brain to update internal models, reduced the subject training requirements of our target acquisition phase to only a single brief practice session, and allowed for performance improvement during a single session. An important aspect of decoder design is the analysis of the "long-term stability". Most current EEG-based systems (and even invasive systems) require periodical recalibration, which is due to the variability and deterioration of the signals across time due to changes in electrode impedance, EEG electrode cap repositioning or movement, changing environments, or even changes in neural activity due to normal aging.

D. Design Principle IV (Injured Brain): Calibration and Closed-Loop BCI after Brain Reorganization

With the exception of a few studies in humans involving spinal cord injury, epilepsy and other clinical populations (e.g., [6], [8], [11], [18], [24]), most decoding and BCI/BMI studies are based on brain signals acquired from healthy brains. Since the completion of the 2D BCI study described in [16] and summarized in the previous sections, we have tested an additional subject with left wrist disarticulation (aged 55 y, post-amputation time = 54 years, the subject uses a cosmetic hand). From the decoder calibration phase using imagined/observed cursor movement, the mean (SE) r values for x and y were 0.45 (0.08) and 0.39 (0.08), respectively, for this subject. The median MT was 5.33 s, and the hit rate was 85%. We chose the best (mirrored, given his left hand amputation) 34 sensors we found in our previous study [13] for decoding and BCI control purposes. However, non-mirrored electrodes produced similar decoding accuracies as 27 out of the 34 sensors were shared by the two sets of sensors. Figure 3 depicts the average spatial trajectories to the four peripheral targets during BCI operation during a single BCI session.

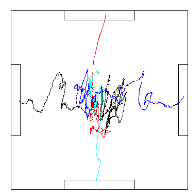

Fig. 3. Mean brain-controlled cursor paths in a subject with wrist disarticulation. Each colored path is the mean of the length-normalized trials for a single direction (left, top, right, or bottom) across all trials of all runs for a subject. Trials in which the subject did not acquire the target within 15 s (time-out) were excluded from analysis.

In regard to other BCI/BMI studies with clinical populations, Hochberg et al. reported results for a tetraplegic human (MN) implanted with a 96-microelectrode array in M1 [18]. Subject MN was able to achieve, in the course of 57 consecutive sessions over 9 months, BCI control of 2D cursor movement that MN used to open and close email, operate devices such as a television and open and close a prosthetic hand to grasp and transport an object from one location to another. In particular, subject MN was able to achieve 2D target hit rates of 73-95% (mean motion completion time ~ 2.51 s) over 6 sessions. Recently, McFarland et al. used an EEG sensorimotor rhythm-based BCI to demonstrate 3D BCI cursor control in a subject (User 2) with spinal cord injury (T7) confined to a wheelchair [25]. User 2 achieved a mean correlation of the control signals, for vertical, horizontal and depth dimensions, of r^2=0.29, 0.37, and 0.16, respectively, with each signal correlated exclusively or most strongly with its own dimension of target location. This performance was obtained over 26 sessions (total of 10.4 h with an additional 367 h of BCI experience in lower dimensional control tasks).

Importantly, the evaluation and validation of non-invasive neuroprosthetics should be done in realistic situations (e.g. reaching operations, activities of daily living, grasping & multi-tasking), preferably with both healthy and impaired subjects to demonstrate the correct operation of the BMI system. The evaluation step should include different validation methodologies; including ruling out the potential influence of eye movements and muscle activity [13], [16], as well as assessment scales (according to the type impairment of the potential users) to study the degree to which the user is improving or recovering lost movements. This is important to demonstrate that the system is not only able to reconstruct real movements, but the user is benefiting from the device. Another critical design issue is need for asynchronous operation of EEG-based neuroprosthetics – an important yet unresolved limitation with most current BMI systems. In order to construct BMI's where the users can perform natural movements, no explicit cues (synchronization signals) must be provided to mark the onset (or the end) of the movements.

III. Conclusion

Few BMI studies have been done with prosthetic limbs. Carmena et al. showed brain control of 3-DOF reach-to-grasp movements using a 6-DOF robotic arm equipped with a 1-DOF gripper with the robotic arm constrained to planar movements in 2D (i.e., in the X-Y coordinates) lasting ~ 2.5s [26]. Over a period of 14 sessions, accuracies (r^2) were achieved of 0.36 (2D endpoint velocity) and 0.68 (force). Feedback of the robot state was provided via a visualization apparatus that displayed end-point position and gripper force as a screen cursor movement and size, respectively. Velliste et al. showed 4-DOF BMI control of self-feeding movements lasting ~3-5s (monkey A) that achieved a success rate of 61% over a period of 2 daily sessions (a second monkey B achieved 76% over 13 days) [22]. These studies were however done in nonhuman primates. Given that noninvasive EEG does not add any risk to the BMI user, we expect that the design principles summarized in this paper will lead to EEG-based BMI control of multifunctional prosthetic limbs in the near future such as the 22-DOF DARPA Modular Prosthetic Limb (MPL) – with the look, weight, strength, dexterity, natural movement, and toughness of an intact arm.

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