

TOWARDS AN IMPLANTABLE BRAIN-MACHINE INTERFACE BASED ON EPICORTICAL FIELD POTENTIALS

T. Ball^{1*}, M.P. Nawrot^{3*}, T. Pistohl³, A. Aertsen³, A. Schulze-Bonhage¹, C. Mehring^{2*}

¹Epilepsy Center, University Clinics, Albert-Ludwigs-University Freiburg, Germany

²Institute for Biology I, Albert-Ludwigs-University Freiburg, Germany

³Institute for Biology III, Albert-Ludwigs-University Freiburg, Germany

ball@nz.ukl.uni-freiburg.de

Abstract—Today, a major challenge in neuro-engineering is to develop a brain-machine interface (BMI) suitable to restore communication and motor control in paralyzed patients. One fundamental, unresolved question is which neuronal signal type should be recorded and decoded for such purposes. Here we review work on neuronal population activity, i.e. the ensemble activity of local groups of neurons, as a control signal for BMIs. Further, we propose a BMI approach based on population activity recorded directly from the human cortical surface. Using a finger movement task, we evaluate movement related changes in epicortical potentials across a broad frequency range and we show that the side of index finger flexions can be inferred from primary motor cortex population activity with up to 100% accuracy from single trial data.

Keywords— brain-machine interface, neuronal motor prosthesis, field potentials, neuronal population activity

Introduction

Bioelectrical activity recorded from cerebral motor areas may be of practical use for controlling a neuronal motor prosthesis. According to Craggs [1], this idea was proposed by G. S. Brindley already in 1968, but an experimental proof of this concept has been provided only in recent years by a series of animal studies. These BCI models in rats and monkeys have demonstrated that the activity of multiple single neurons in cerebral motor areas can be used for the control of a screen cursor or a physical actuator in 3D space [2-4].

Yet, several important issues remain to be solved on the way to a neuronal motor prosthesis that is clinically applicable in humans. One crucial question is which neuronal signal should be recorded and decoded for neuro-prosthetic movement control. Three types of neuronal activity which have been proposed in this context are: single neuron activity (SUA), the electroencephalogram (EEG), and neuronal population activity.

SUA, obtained using intracortical microelectrodes, has been used in several animal models of BMIs for motor control [2-4]. Single neuron recordings have also been achieved in paralyzed humans, using electrodes consisting of small hollow glass conical tips filled with neurotrophic factors which were implanted into cortical motor areas [5]. In the months following implantation, neurites of adjacent neurons were induced to grow into these electrodes.

Alternatively, several BMI approaches have used EEG non-invasively recorded from the head surface [6,7]. There, for instance learned self-regulation of slow potential shifts [e.g. 6] or both time and frequency domain EEG changes associated with the movement of different extremities [e.g. 7] have been used as a basis for BMI-mediated communication or for moving a screen cursor.

Both, SUA- and EEG-based approaches have been extensively reviewed elsewhere recently [2-4,7]. Here, we focus on an alternative approach that utilizes neuronal population signals. Such signals can be measured using electrodes implanted either intracortically or on the brain surface, and reflect the ensemble activity of local populations of neurons. Thus, population signals represent an intermediate range of spatial resolution between the single neuron level and the level of mass activity in EEG measurements.

Here we describe an approach currently developed in our research group, which aims at decoding parameters of voluntary movement from population signals measured directly from the surface of the human cortex by means of arrays of densely spaced electrodes. Using data obtained in a patient undergoing pre-neurosurgical diagnostics, we evaluated the involvement of different frequency bands in movement related changes, indicating their potential usefulness for decoding of movement parameters. We describe a method for inferring movement parameters from single trial data and show results from decoding the side of index finger movements performed either with the right or the left hand. Topographic mapping of the spatial distribution of decoding power revealed a maximum of 100% correct inference within the hand area of primary motor cortex.

Neuronal population activity as a potential basis for BMIs

Two forms of neuronal population activity have been proposed as a BMI control signal: local field potentials (LFPs) measured with penetrating, intracortical electrodes, and epicortical field potentials measured with non-penetrating electrodes placed directly on the brain surface.

Investigating eye movement related LFP activity in monkey parietal cortex, Pesaran et al. [8] have reported that LFP oscillations in the gamma range can be used to

* These authors contributed equally to this work.

differentiate between two possible saccade directions. The representation of arm movement parameters in LFPs recorded from monkey motor cortex was investigated by Mehring et al. [9]. They compared the quality of decoding movement parameters from SUA and from local field potentials (LFPs) recorded from the same electrodes. The low-frequency component of the LFP signal was used to infer the direction and velocity of arm movements and for the reconstruction of arm movement trajectories. Single trial inference based on LFPs was found to be approximately as efficient as inference based on multiple SUA. The highest accuracy, however, was achieved using a combination of SUA and LFPs. Interestingly, preliminary results indicate that also oscillatory LFP activity in the gamma range contains directional information about arm movements [10]. In summary, these studies show that LFPs contain substantial information about parameters of voluntary movements.

A potential use of epicortical field potentials for a BMI has been extensively studied by Levine and colleagues [e.g. 11], analyzing electrocorticograms (ECoGs) from epilepsy patients. In their approach, signal ‘templates’ corresponding to specific movement types (such as wrist extension or tongue protrusion) were first constructed from trigger-averaged signals. Then, a running cross-correlation was used to detect the trial-averaged prototypes in continuous recordings. This way, reliably detected movement types can be used for binary decision steps or for communication in a ‘Morse alphabet’ style.

Could epicortical potentials also be used to decode kinematic arm movement parameters from single trial data, similarly to the approaches taken in the LFP studies cited above? Toro et al. [12] investigated the representation of movement parameters in the 8-12 Hz component of ECoG recordings. Spatial patterns of these oscillations were found to be modulated by both, amplitude and direction of arm movements, but analysis was restricted to averaged data from 20 and more trials for each movement condition.

However, results from an ongoing study in our research group indicate that arm movement direction can indeed be accurately inferred from single trial epicortical potentials [13, 14]. In the following section we describe our approach in more detail and exemplarily analyze data from an experiment using a left and right index finger movement paradigm.

Decoding movement related information from epicortical field potentials in humans

A female patient (aged 55 years) suffering from intractable pharmacoresistant epilepsy with a right fronto-polar focal cortical dysphasia took part in this study after having given her informed consent. The study was approved by the university clinic’s ethics committee. The patient was strongly right-handed after a modified Oldfield questionnaire and showed no clinical signs of pareses or other movement disorders. A platinum grid electrode

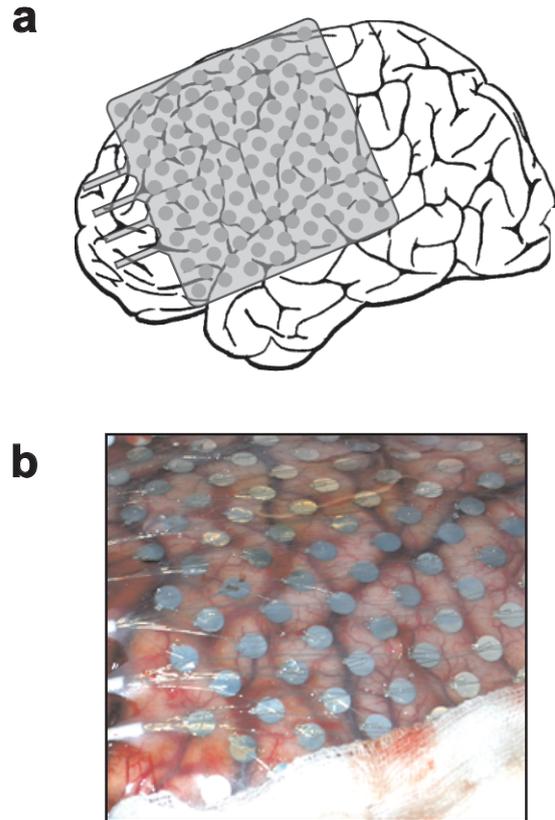


Figure 1: (a) Position of the grid electrode over the left cerebral hemisphere, covering part of the prefrontal, premotor, primary motor, parietal, and temporal cortex. (b) Intraoperatively taken photograph of subdural grid electrode implantation.

(4 mm electrode diameter, 112 contacts, 7.1 mm inter-electrode distances) was subdurally implanted above the left fronto-parieto-temporal region (Fig. 1) for pre-neurosurgical diagnostics.

The subject was instructed to perform self-paced index finger flexions of either the left or the right hand with inter-movement intervals of at least 4 s. Electrocorticograms (ECoGs) were recorded using a clinical AC EEG-System (IT-Med, Germany) digitized at 256 Hz and band-pass filtered (0.032 Hz to 97 Hz). Onset of index finger movement was determined in the electromyogram (EMG) of the *M. flexor digitorum superficialis, pars indicis*. Electrical stimulation was performed with stimulator INOMED NS 60 (INOMED, Germany) to demarcate the eloquent brain areas. The intensity of stimulation was gradually increased up to 15 mA or to the induction of sensory and motor phenomena. All sites with arm or hand motor responses were located outside the ictal onset zone. A structural MRI data set with full head coverage was acquired on the day after electrode implantation using a T1 MPRAGE sequence. The motor cortices were identified according to anatomical landmarks (for references see ref. 15). The exact relation of the individual electrode contacts to the cortical anatomy was then determined using curvilinear reconstructions [16].

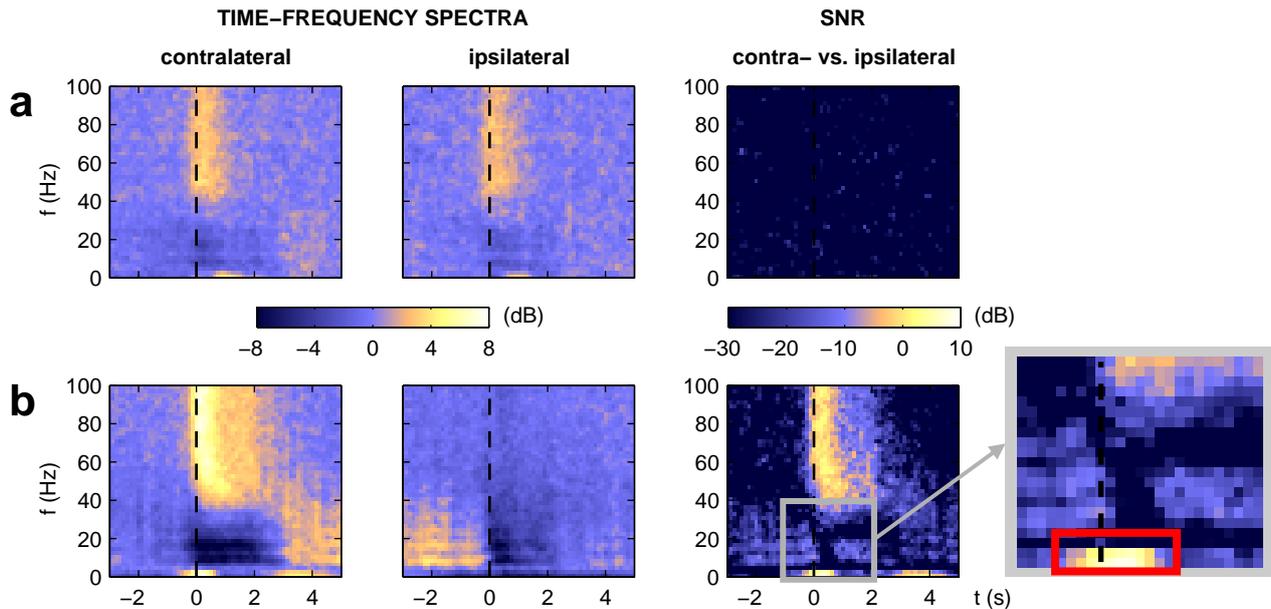


Figure 2: Time-frequency analysis of movement related epicortical potentials for two electrodes placed on (a) the premotor cortex and (b) the arm area of primary motor cortex (M1). Baseline normalized amplitude spectra (left two columns) for both electrodes showed task related spectral power changes in alpha, beta, gamma, and the low-frequency components. Significant differences between movements of the ipsi- and contralateral finger in the signal-to-noise ratio (SNR, right column) plots were observed in electrode (b), but not in (a). The box in the lower part of the magnified SNR plot marks the low-frequency SNR peak corresponding to the signal component we used for movement inference.

Time-frequency analysis

We performed a time-frequency analysis of movement related ECoG-potentials by calculating trial-averaged time-resolved spectra for each electrode separately, using the Fourier transform in overlapping time windows of 0.5 s length, which were subsequently normalized by the trial averaged power during the preceding baseline period. To quantify the reliability of the differences in signal power with respect to ipsi- and contralateral movement, we calculated the signal-to-noise ratio (SNR), defined as the quotient of the signal variance, i.e. the variance of the power for left and right finger flexion, and the combined trial-by-trial variance from all left and right trials [9]. Classical movement related changes of oscillatory activity were found in the alpha/beta range and in the gamma range, with decreased and increased spectral power, respectively [7].

Figure 2 shows examples of two electrodes, both with clear movement related power changes in a broad frequency range. However, as seen in the SNR plots, significant differences for the two movement types were present in the electrode above the hand area of primary motor cortex (M1), but not in the premotor electrode. The strongest local SNR maximum was observed for frequencies below 5 Hz, immediately before and after movement onset. A second local SNR maximum was found in the gamma range during movement execution. Both these components are thus promising candidates for movement inference, in line with the above summarized results on LFPs recorded from monkey motor cortex. Here, in a first step, we used only the low-frequency component for movement inference.

Movement inference

The side of index finger movement was inferred from single-trial ECoG signals by penalized linear discriminant analysis [9]. After smoothing with a Savitzky-Golay filter and resampling at 16 Hz, for each trial and electrode we constructed a 16-dimensional vector by using the resampled signal between EMG-onset and 1s after EMG-onset. For a given set of N electrodes, these vectors were concatenated yielding a $16 \times N$ -dimensional neuronal signal vector for each trial. We decoded this high-dimensional signal vector in three steps [9]: Firstly, it was linearly projected to a 3-D space by penalized linear discriminant analysis. Secondly, we computed the conditional probability for the projected neuronal signal vector given a certain direction by modelling the projections for each direction by a multivariate Gaussian density with diagonal covariance matrix. Thirdly, we used Bayes' rule to infer the conditional probability for each direction given a neuronal signal vector and chose the movement direction with the highest probability.

To calculate the percentage of correctly decoded trials - termed decoding power (DP) - we performed leave-one-out cross-validation. Thus, trials used to train the discriminant and the Gaussian density model were not included in the test set for decoding. Local DP was determined by decoding from local groups of five electrodes, corresponding to an area of 1 cm x 1 cm.

Ipsi- and contralateral movement could be discriminated with a DP of 100%. Mapping of the spatial distribution revealed a maximum of local DP localized in the area of primary motor cortex (M1) showing index finger movement upon direct electrical stimulation (Fig. 3).

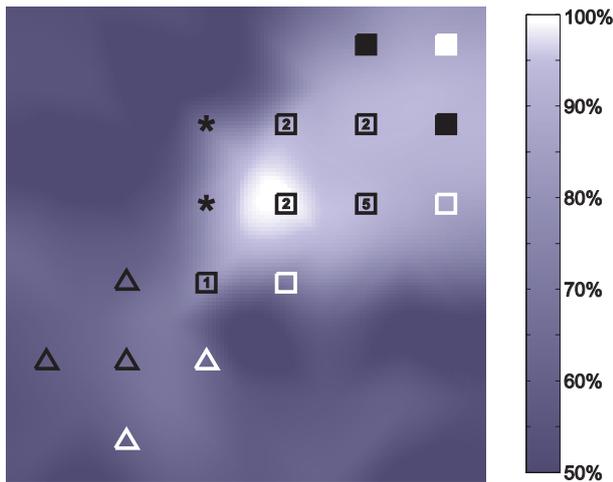


Figure 3: Map of decoding power (DP, in % of correctly inferred trials) corresponding to the area covered by the grid electrode. Black symbols: electrodes with motor responses upon electrical stimulation (■ arm, □ finger with 1 = thumb, 2 = index finger, 5 = little finger, Δ oro-facial, * eye), white symbols: sensory responses. Maximal DP of 100% was found at an electrode within M1 where electrical stimulation elicited index finger movement.

Discussion

We have described an approach to infer movement parameters from epicortical potentials in humans based on recordings from dense electrode arrays. With this technique, the direction of arm movements can be accurately inferred from single trial data [13, 14]. Here we show that the side of index finger flexions can be inferred with up to 100% accuracy. Time-frequency analysis showed that not only low-frequencies, but also the gamma band are promising for movement decoding from human epicortical potentials, corresponding to results from LFPs in monkeys [10]. The distribution of decoding power was found to be quite focal, with a single maximum corresponding to the M1 index finger representation. Thus, recordings from dense electrode arrays may allow for individual finger control.

Currently, developments directed at neuro-interfacing motor commands are based on different types of invasively and non-invasively measured brain signals. It is not yet clear how these different approaches will finally compare in regard to control performance, safety issues, biocompatibility, and long-term signal stability. With respect to the latter, population signals are possibly advantageous over recordings from single neurons for which it is highly demanding to achieve stable recordings over long periods of time. Moreover, epicortical potentials can be expected to bear advantages over methods using penetrating electrodes in view of their reduced risk to lesion intact brain tissue. Finally, they offer superior spatial resolution, better recording stability, and a higher signal-to-noise ratio as compared to the EEG. In summary, the work we have reviewed here and our own results indicate that neuronal population activity may provide a suitable control signal for neuronal motor prostheses in humans.

Acknowledgements

We thank Dr. J. Honegger for providing the photograph used in Figure 1b. The WIN-Kolleg of the Heidelberg Academy of Sciences and Humanities and the German Ministry of Education and Research (BMBF-DIP) supported this project.

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