Decoding of Picture Category and Presentation Duration - Preliminary Results of a Combined ECoG and MEG Study

T. Pfeiffer^{1,*}, C. N. Heinze^{1,*}, E. Gerber², L. Y. Deouell², J. Parvizi³, R. T. Knight⁴ and G. Rose¹

¹ Institute for Medical Engineering, Otto-von-Guericke-University Magdeburg, Magdeburg, Germany, ² Department of Psychology, Edmond and Lily Safra Center for Brain Sciences, The Hebrew

University of Jerusalem, Jerusalem, Israel

³ Department of Neurology and Neurological Sciences, Stanford University, Stanford, USA

⁴ Helen Wills Neuroscience Institute, University of California, Berkeley, USA

* These authors contributed equally to this work

tim.pfeiffer@ovgu.de

Abstract

Limited recording times and different placement of electrocorticography (ECoG) grids over patients can make it necessary to adjust certain paradigms designated for ECoG data acquisition. The present study compares the accuracies of decoding picture categories and the corresponding presentation durations using data acquired by means of ECoG and magnetoencephalography (MEG). The results - decoding accuracies of up to 95 % in ECoG data and up to 85 % in MEG data (chance 20 %) as well as similarity in selected channels for both modalities - indicate that assumptions can be made from MEG data about the outcome of the same paradigm run on ECoG patients for any kind of grid position. Therefore, MEG provides a way to improve paradigms designated for ECoG studies and thus use the limited recording times more effectively.

1 Introduction

Over the last decade, studies more and more suggest ECoG to be the preferred method for acquiring high spatial and temporal resolution data to be used in brain-computer-interfaces (BCI) [1]. Besides its many advantages, acquisition of ECoG data turns out to be a difficult and demanding procedure. It is invasive and provides only limited recording times. Also, because purely based on medical necessity, the placement of the implanted electrode grids rarely covers all brain areas essential for BCI studies. Making best use of the limited patient collective and recording time should therefore be of strong priority. Former studies combined the high spatial resolution of magnetic resonance imaging (MRI) and high temporal resolution of electroencephalography (EEG) [2] to achieve similar signal characteristics to ECoG while being non-invasive. Here we investigate MEG data, which to a certain degree combine the advantages of both imaging modalities [3], and compare it to ECoG. The comparison is based on results of a picture category/duration decoding paradigm using state-of-the-art features and classification routines. Because of its immobility, MEG is not a solution for acquiring data in real-life BCIs. However, with the limited access to ECoG data it is helpful to test paradigms with other modalities and make assumptions about the possible outcomes in ECoG. By showing similarities and differences between MEG and ECoG findings, we conclude that MEG can provide just that.

2 Material and Methods

Data ECoG data were recorded from two volunteering patients (right handed males). Both received subdural electrode implants for pre-surgical planning of epilepsy treatment at Stanford, CA, USA. Electrode grids were solely placed based on clinical criteria and covered a variety of cortical areas including lateral occipital and medial temporal areas. All patients gave their informed consent before recordings started. The ECoG was recorded with a sampling frequency of 3051.7 Hz. Pre-processing steps included high pass filtering (cut-off: 0.5 Hz) as well as notch filtering around the power line frequency (60 Hz). The electric potentials of all electrodes were re-referenced to Common-Average-Reference. Afterwards, the time series were visually inspected for artifacts (e.g. epileptic activity) and epoched into trials representing the interval between -100 ms and 2000 ms with respect to picture onset times. MEG data were recorded with a bandwidth of 100 Hz (sampling frequency: 1017.25 Hz), using a whole-head 248-sensor BTi Magnes system (4D-Neuroimaging, San Diego, CA, USA). Data have been acquired from four healthy volunteers (age 25-28, one female, one left-handed). Like the ECoG, MEG data were epoched into trials containing the interval [-100 ms, 2000 ms].

Task Pictures from four different categories, namely objects, faces, watches and clothing, were presented to the subjects. Presentation durations were randomly chosen from five different time spans (300, 600, ..., 1500 ms). Intervals of varying duration (600, 750,..., 1200 ms), in which only a focus is visible, intersect the pictures. Stimuli were shown either on a projection screen (MEG data) positioned 1 m away from the subject or on a notebook screen (ECoG data) within the patients reach. Subjects were requested to respond to the presentation of a piece of clothing with a button press. Target stimuli (i.e. clothing) accounted for approximately 10 % of the total trial count.

Feature Extraction and Selection Two different feature types have been extracted for this study, namely low-frequency time domain (LFTD) and high gamma (HG) features. LFTD features were obtained by low-pass filtering in Fourier domain with a cutoff frequency of 30 Hz (MEG: 10 Hz) and subsequent down sampling of the time series. For the computation of HG features, spectral power was measured using a sliding Hann-window approach (window length = 250 ms). For each window the square root of the power spectrum was computed by Fast Fourier Transform (FFT). The resulting coefficients were then averaged in the frequency band of 70-200 Hz. Feature selection is performed on training data only using an algorithm based on the Davies-Bouldin index. Full details on feature selection (as well as extraction) routines can be found in our previous study [4]. The algorithm was employed to select a set of the twenty (MEG: ten) most informative channels corresponding to the actual class separation problem (i.e. either discrimination of picture categories or presentation durations).

Classification Linear Support-Vector-Machines (SVM) were used in one-vs-one mode for both classification problems, picture category and duration. The influence of the constant C was analysed on a single data set for each modality. We found the influence of C to be minimal, as long as not chosen too small ($C < 2^{-15}$). Consequently, we chose $C = 2^{-5}$ (MEG: $C = 2^{-10}$) across all datasets.

3 Results

In order to restrict information to any kind of visual processing within the brain, target stimuli (i.e. clothing) have been omitted for the analysis of decoding accuracies. Otherwise, activation of motor areas during subjects' button presses might influence the decoding.

Signal-to-noise ratio in the high gamma band of the MEG data was too low to be used for single trial analysis. Therefore, only LFTD feature accuracy is plotted for the MEG datasets.



Figure 1: a), b) LFTD features for a dominantly selected channel (trials sorted by duration) c), d) Decoding accuracies (in %) for both classification tasks (i.e. category and duration) and both feature types (i.e. LFTD and HG features; ECoG only).

Decoding accuracies have been computed for all datasets by means of a 50-times-5-fold cross-validation procedure. The results for all ECoG and MEG datasets can be found in figure 1 c) and d). Figure 2 shows a comparison of the averaged decoding accuracies of both acquisition modalities. Chance levels for the two classification tasks are 20% (duration, five classes) and 33% (category, three classes) respectively.

We also found that the dominantly selected MEG channels were located in the same areas as the dominantly selected ECoG channels. This holds true for duration detection as well as picture category decoding.

4 Discussion and Future Work

The results show that MEG can classify picture category and presentation duration with high accuracy on a single trial basis, though not as stable as ECoG. More importantly, spatial resolution of the MEG seems to be high enough that only channels from the area expected to have highest activity for the given task are selected by our routines. By manually restricting MEG data to certain channels, decoding accuracies of different ECoG grid placements might



Figure 2: Comparison of the decoding accuracies (in %) of both recording modalities

be roughly assessed. This is helpful to test and improve paradigms designated for ECoG studies. The results also imply a superiority of high frequency information for neural decoding. Because of that, future studies will address gamma activity in MEG in order to get a better comparison. Also, we will investigate simultaneous decoding of both, stimulus category and duration. Findings are expected to be of high interest for BCI due to possible analogies between visual and motoric scenarios. Decoding stimulus quality (here: picture category) and quantity (here: stimulus duration) could translate into the possibility to detect an intended movement direction and duration at the same time, when it comes to realizations of robotic BCI systems.

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