Single Trial Detection of Hand Poses in Human ECoG using CSP based Feature Extraction

C. Kapeller*, C. Schneider*, K. Kamada, H. Ogawa, N. Kunii, R. Ortner, R. Prückl, C. Guger
Authors equally contributed to the presented work.

***Abstract*— Decoding brain activity of corresponding high-level tasks may lead to an independent and intuitively controlled Brain-Computer Interface (BCI). Most of today's BCI research focuses on analyzing the electroencephalogram (EEG) which provides only limited spatial and temporal resolution. Derived electrocorticographic (ECoG) signals allow the investigation of spatially highly focused task-related activation within the high-gamma frequency band, making the discrimination of individual finger movements or complex grasping tasks possible. Common spatial patterns (CSP) are commonly used for BCI systems and provide a powerful tool for feature optimization and dimensionality reduction. This work focused on the discrimination of (i) three complex hand movements, as well as (ii) hand movement and idle state. Two subjects S1 and S2 performed single 'open', 'peace' and 'fist' hand poses in multiple trials. Signals in the high-gamma frequency range between 100 and 500 Hz were spatially filtered based on a CSP algorithm for (i) and (ii). Additionally, a manual feature selection approach was tested for (i). A multi-class linear discriminant analysis (LDA) showed for (i) an error rate of 13.89 % / 7.22 % and 18.42 % / 1.17 % for S1 and S2 using manually / CSP selected features, where for (ii) a two class LDA lead to a classification error of 13.39 % and 2.33 % for S1 and S2, respectively.**

I. Introduction

A Brain-Computer Interface (BCI) provides an alternative way for interaction that bypasses the brain's normal output pathways of peripheral nerves [1]. A BCI can be realized following different strategies and most of them rely on processed electroencephalographic (EEG) data containing event-related potentials (ERP) or oscillations showing event-related desynchronization/synchronization (ERD/ERS) [1], [2]. The EEG is widely spread because of its low cost and easy setup, as well as its very high temporal resolution [3]. However, the weak spatial resolution is limiting many EEG based BCI applications in combination with a low signal-to-noise ratio.

Changing to invasive EEG recording techniques like electrocorticography (ECoG) can overcome these limitations [4]. While non-invasive EEG signals have carry information in the range of 0 – 40 Hz, ECoG signals provide information up to 500 Hz [5]. This broader bandwidth covers the movement related increase in bandpower for frequencies above 40 Hz, which is called high-gamma activation (HGA) [6]. Such a task related HGA is highly focused at specific cortical regions.

As the small exposure diameter and the dense alignment of ECoG electrodes lead to a much higher spatial resolution than in EEG, the ECoG signals allow mapping of functional brain regions more precisely. Even individual finger movements can be detected from ECoG signals [7]. Recent studies also decoded hand movement trajectories [8] and developed ECoG BCI applications based on motor imagery [9].

In order to provide a more intuitive way to interact with the environment, it is required to analyze more complex tasks than isolated hand or finger movement. To optimize the movement behavior of neuroprosthetic devices two different grasping tasks were distinguished [10]. While changes in low frequencies are very similar over large cortical regions for slightly different tasks, the highest decoding accuracies were achieved with frequencies above 50 Hz. Such high-level tasks might be very useful for more complex intention recognition, as this seems to be the way we usually interact with our environment.

In this work we are attaching to the idea of identifying high-level tasks. Common spatial patterns (CSPs) have so far mainly been utilized on the alpha and beta frequency bands for motor imagery tasks [12], [13], [16]. For motor execution it was shown that the HGA spectrum displays most of the movement related brain activity [14]. Therefore a novel four-class model for three different hand poses and the resting condition 'idle' has been developed using CSP features on high gamma activity of human ECoG data. The aim of the study is to determine whether it is possible to discriminate three different hand poses and the idle state with single trial analysis, and to compare the results to a manual selection of optimal channels and frequency bands.

II. Methods

A. Subjects

Two patients who underwent neuro-monitoring for surgical treatment of intractable epilepsy volunteered for participation in the experiment. The first patient (S1) in the Asahikawa Medical University as well as the second patient (S2) in the University of Tokyo had subdural electrodes (Unique Medical, Tokyo, Japan) implanted to localize the

Research supported by the European Union FP7 Integrated Project VERE (No. 257695) and the EU project 'High Profile' (grant agreement number 269356).

C. Kapeller, C. Schneider, R. Ortner, R. Prückl and C. Guger are with g.tec Guger Technologies OG, Schiedlberg, Austria. (Corresponding author: C. Kapeller. Phone: 0043 7251 22240; e-mail: kapeller@gtec.at).

K. Kamada and H. Ogawa are with the Department for Neurosurgery, Asahikawa Medical University, Asahikawa, Japan.

N. Kunii is with the Department for Neurosurgery, The University of Tokyo, Tokyo, Japan.

978-1-4244-7929-0/14/$26.00 ©2014 IEEE

epileptogenic zones. The used platinum electrodes had an inter-electrode distance of 1.0 cm and an exposure diameter of 2.3 mm. Table 1 and Fig. 1 show more details about the subjects.

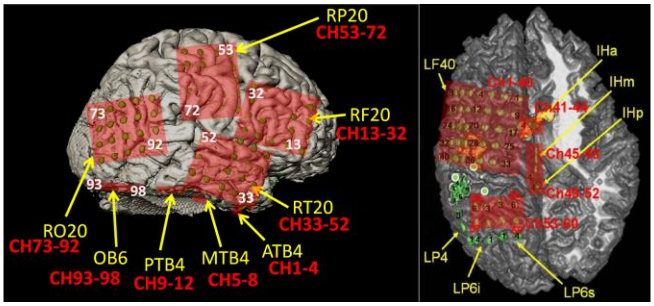

Figure 1. Electrode configuration of subject S1 with coverage of the lateral side of the right hemisphere (left) and subject S2 with coverage of the left frontoparietal and the interhemispheric cortex (right).

TABLE I. SUBJECT DETAILS

Subject	Gender	Age	Dominant Hemisphere	Number of Electrodes
S1	female	35	right	98
S2	male	22	left	60

B. *Experimental Design*

The subjects were asked to remain silent and follow the instructions presented on a screen that was placed bedside to the patient. For stimulus presentation the MATLAB/Simulink rapid prototyping environment was used. The paradigm comprised of the tasks (i) make a fist, (ii) show the peace gesture (V-sign) and (iii) open the hand. Due to limited experimental time the subjects had to perform slightly different paradigms, both with a varying inter-trial length to prevent subject adaptation. While S1 performed 90 trials in total, each consisting of a 1.5 s (± 10 %) baseline and a 1.5 s active period, subject S2 performed 120 trials with 2 s (± 25 %) baseline and 2 s active period. During every single trial exactly one hand pose was performed. The number of trials for each hand pose was equally distributed.

C. *Data Acquisition*

The ECoG data was recorded at bedside using a g.HIamp biosignal amplifier (g.tec medical engineering GmbH, Schiedlberg, Austria) with a sampling rate of 1200 Hz and its built-in band-pass filter set to the range from 0.5 to 500 Hz. For subject S2 the hand movement onset was determined via electromyogram (EMG) on the right hand and stored as additional channel in the same recording.

D. *Pre-processing*

The data from both subjects was band-pass filtered from 100 to 500 Hz (high gamma range) with additional notch filters at all harmonics h_i of the 50 Hz power line frequency. All filters were designed as Butterworth filter of order 5 with a notch width of h_i ± 5 Hz. Then the data was triggered 500 ms before and 1500 ms after the stimulus onset of each task which results in an overall trial length of 2 s.

E. *CSP Feature Extraction and Classification*

Common Spatial Patterns (CSPs) are a standard method for EEG data to extract optimal discriminant features in movement (or movement imagination) tasks. In this paper a two-stage process is described where in a first step movement is told apart from the idle state and in a second step the three different hand poses are decoded in a ‘one vs. all’ comparison [15]. Since the experimental paradigm did not contain a separate class of idle trials, such a set was created offline by looping the data sets once and shifting the trigger channel in the second part so that the new trial periods cover the inter-trial periods of the original data (see Fig. 2). In the case of subject S2 a left-shift of 2 s moves the end of the idle trials to the onset of the original trials. For subject S1 this is achieved by a left-shift of 1.5 s.

To prevent influence of visual or auditory stimuli onto the classification, the CSPs were run exclusively on the electrode grids covering the motor cortex. These are the channels 53 – 72 on grid RP20 for S1 and the channels 1 – 40 on grid LF40 for S2 (see Fig. 1). Error rate based search algorithms yielded the optimal parameters listed in table 2 for both data sets S1 and S2.

The CSP weight matrix calculated with the optimal window size was then used to spatially filter the ECoG signal, and the four most discriminant feature channels were selected per decision pair (two largest eigenvalues from each

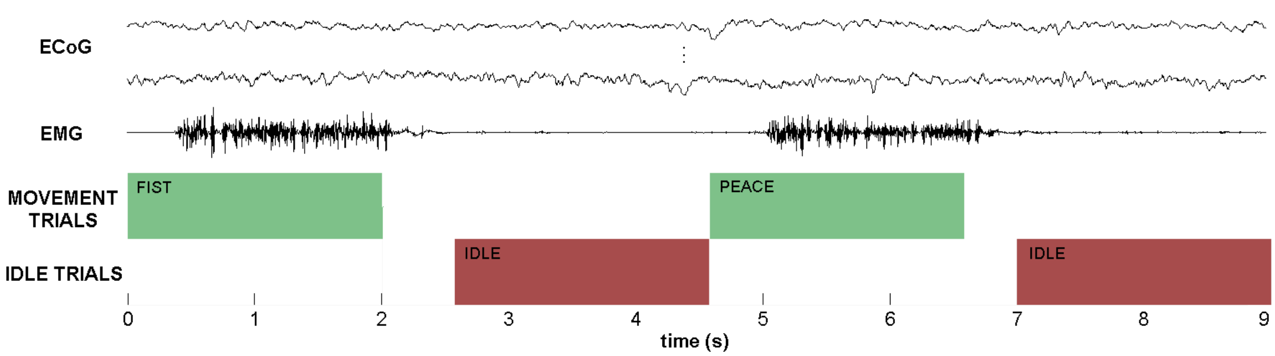

Figure 2. Arrangement of ‘movement’ trials (green) and left-shifted ‘idle’ trials (red) in context with the ECoC and EMG data. Due to irregular inter-trial intervals and triggering 0.5 s before trial onset the ‘idle’ trials are often contaminated with ongoing movement from the previous ‘movement’ trial as can be seen by comparing with the EMG amplitude.

side of the spectrum). Then the signal variances were computed and the resulting channels were normalized and had their logarithm taken for numeric stability.

Based on those features a two-class linear discriminant analysis (LDA) for the case ‘movement’ vs. ‘idle’, or a multi-class LDA (MLDA) for the hand pose decryption was calculated using 10×10 fold cross-validation [11]. This was done for equally spaced time points (1/16 of sampling frequency) in the range of 0.5 s before and 1.5 s after stimulus onset, yielding a set of 32 different classifiers.

TABLE II. OPTIMAL SIGNAL BUFFER LENGTH

Discriminated States	**CSP Window in Trial**	**Signal Variance Window Length**
Movement vs. Idle	500 – 1500 ms	500 ms
Fist vs. Peace vs. Open	1000 – 1500 ms	500 ms

F. *Manual Feature Extraction and Classification*

The ERD/ERS was computed based on a 300 ms reference interval before the stimulus onset. Visual inspection of the time-frequency plots (0 – 200 Hz) showed that the channels 64, 65, 69, 70 and 71 were coding the individual hand poses for S1, while the channels 28, 35, 37 and 38 were doing the same for S2. Channels with strong task-related high-gamma activation (>60Hz) were considered for feature extraction.

For each of the selected channels the signal power within the 60 – 90 Hz, 110 – 140 Hz and 160 – 190 Hz bands was estimated using a Butterworth filter of fourth order, followed by squaring and averaging over consecutive samples of a 500 ms window. All feature values were then logarithmically scaled. Based on the given bandpower features, a multi-class linear discriminant analysis (MLDA) was performed to compute a set of 32 linear classifiers, each represented the features for a given time point [11]. As in the CSP case, a 10×10 cross-validation was used to determine the classifier error rate.

To determine the significance level of distinct distribution means between the two feature extraction methods, the nonparametric McNemar’s test for paired nominal data was used with three different test statistics: exact binomial confidence intervals, Yates continuity correction, and Edwards continuity correction.

III. RESULTS

A. *Discrimination of Hand Poses*

Using the manual feature selection, the subjects S1 and S2 showed a minimal detection error for the three different hand poses of 13.89 % and 18.42 %, respectively. In contrast, the CSP based features led to a minimal classification error of ‘fist’, ‘peace’, and ‘open’ hand poses of 7.22 % and 1.17 % for S1 and S2, respectively.

Fig. 3 shows more details about the error rate of all the 32 different classifiers in the 2 s trial window for both subjects and methods. The shaded areas in Fig. 3 represent the 95 % (dark gray) respectively the 99 % (light gray) significance level for the McNemar test in all three test statistics.

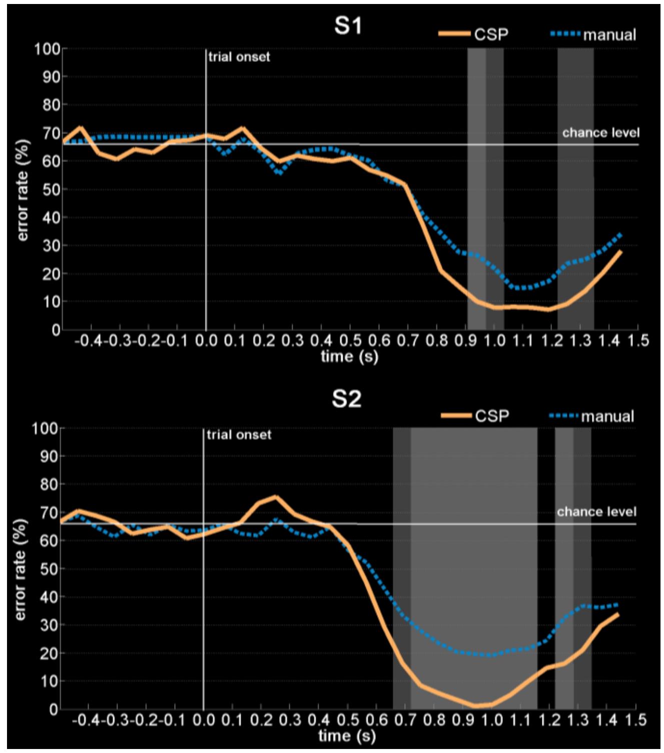

Figure 3. Averaged 3-class detection error for a single trial using manual (dashed lines) and CSP (contionuous lines) feature extraction. The vertical line represents the timepoint of the visual stimulus that showed the subject which hand pose to perform. The gray bars represent the areas of significant differences between the two feature extraction method means; dark gray indicates $p < 0.05$ and light gray $p < 0.01$.

B. *Discrimination of Movement and Idle State*

The discrimination of movement containing ‘fist’, ‘peace’, and ‘open’ hand trials against the relaxed ‘idle’ state showed a classification error of 13.39 % and 2.33 % for S1 and S2, respectively (see Fig. 4).

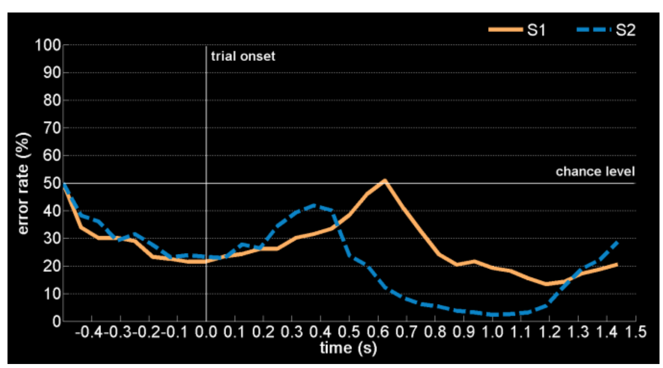

Figure 4. Averaged 2-class (‘movement’ vs. ‘idle’) detection error for a single trial using the CSP feature extraction. The vertical trial onset line is identical with the onset of the green ‘movement’ and red ‘idle’ blocks in Fig. 2. The non-random classification behavior before 0.4 respectively 0.65 s stems from previous movements contaminating the fake ‘idle’ trials.

IV. Discussion

Fig. 3 shows the error rates of the linear 3-class classifiers along the different time points of trial duration. It can be seen that the CSP based feature extraction expresses significantly lower error rates in detecting the correct hand poses compared to the manual feature selection. The error rates drop from 13.89 % to 7.22 % for S1 and from 18.42 % to 1.17 % for S2. This yields a maximal mean accuracy rate of 95.8 % by gaining on average 11.96 %.

Due to the 500 ms signal buffer for the bandpower computation and the reaction time of the subject, the movement type features were most discriminant in a window between 800 and 1200 ms after trial onset (300 – 500 ms after cue presentation). Furthermore, the features only remained stable for around 300 ms, which leads to long phases of random state classification in an online experiment.

Therefore additional discrimination between the 'movement' and 'idle' state was used to minimize these false positive assignments. Fig. 4 shows that the respective error rates drop with the beginning of the movement around 500 to 800 ms after the trial onset. The bowl-shaped deviation from the 50 % chance level for the classification error in the window from -0.5 to 0.65 s (S1) and -0.5 to 0.4 s (S2) stems from contamination with the end of the movement period of the previous trial. This is a direct consequence of the generation of the 'idle' trials via trigger shifting (see section II E). The contaminated window for S2 is shorter because of the longer inter-trial period compared to S1. Visual inspection of the video material of the hand movements during the experiments reveals a possible reason for the weaker movement/idle discrimination of S1: it can clearly be seen that the flexion and extension of the fingers was executed much more powerful by subject S2.

The presented experiments further show a strategy how to detect specific hand movements in an online environment. The presented two-step BCI system allows the detection of movement in the first place, followed by a movement discrimination step. These two steps are computed in parallel (using their distinct CSP filters and classifiers). If 'movement' is classified the classification output of the 3-class hand pose is emitted, otherwise the state 'idle' is shown. Compared to the manual feature extraction the CSP filtering process stands out by the higher classification accuracy and the inherent dimensionality reduction, which decreases the computational effort tremendously and is an important factor for real-time computation within an online BCI system. In contrast to CSP based classification algorithms for EEG data (e.g. [17]), it stands out that similar accuracies can be achieved for more classes, shorter trial periods, and without the need of extra subject training.

In conclusion, the presented ECoG based BCI system provides an accurate and fast configuration for a corresponding online setup.

References

[1] J.R. Wolpaw, N. Birbaumer, D.J. McFarland, G. Pfurtscheller, and T.M. Vaughan, "Brain-computer interfaces for communication and control." *Clinical neurophysiology : official journal of the International Federation of Clinical Neurophysiology*, vol. 113, (no. 6), pp. 767-91, Jun 2002.

[2] J.R. Wolpaw and E.W. Wolpaw, "Something new under the sun?" in *Brain-Computer Interfaces: Principles and Practice: Oxford University Press*, Inc., 2012, pp. 3-14.

[3] S.G. Mason, A. Bashashati, M. Fatourechi, K.F. Navarro, and G.E. Birch, "A comprehensive survey of brain interface technology designs." *Annals of biomedical engineering*, vol. 35, (no. 2), pp. 137-69, Feb 2007.

[4] E.C. Leuthardt, G. Schalk, J.R. Wolpaw, J.G. Ojemann, and D.W. Moran, "A brain-computer interface using electrocorticographic signals in humans." *Journal of neural engineering*, vol. 1, (no. 2), pp. 63-71, Jun 2004.

[5] R.J. Staba, C.L. Wilson, A. Bragin, I. Fried and J. Engel. "Quantitative analysis of high-frequency oscillations (80–500 Hz) recorded in human epileptic hippocampus and entorhinal cortex." *J. Neurophysiol*. 88 1743–52. 2002.

[6] Crone NE, Miglioretti DL, Gordon B, Lesser RP "Functional mapping of human sensorimotor cortex with electrocorticographic spectral analysis. II. Event-related synchronization in the gamma band." *Brain* 121:2301–2315. 1998.

[7] K. J. Miller, S. Zanos, E.E. Fetz, M. den Nijs, and J.G. Ojemann. "Decoupling the cortical power spectrum reveals real-time representation of individual finger movements in humans." *The Journal of Neuroscience* 29.10 (2009): 3132-3137.

[8] G. Schalk, J. Kubanek, K.J. Miller, N.R. Anderson, E.C. Leuthardt, J.G. Ojemann, D. Limbrick, D. Moran, L.A. Gerhardt and J.R. Wolpaw. "Decoding two-dimensional movement trajectories using electrocorticographic signals in humans." *J. Neural Eng.* **4.** 264–275. 2007.

[9] K.J. Miller, G. Schalk, E.E. Fetz, M. den Nijsb, J.G. Ojemann, and R.P.N. Raoa. "Cortical activity during motor execution, motor imagery, and imagery-based online feedback." *Proceedings of the National Academy of Sciences.* 107.9 (2010): 4430-4435.

[10] T. Pistohl, A Schulze-Bonhage, A. Aertsen, C. Mehring, T. Ball. "Decoding natural grasp types from human ECoG." *NeuroImage* 59 248–260. 2012.

[11] C.M. Bishop. "Neural Networks for Pattern Recognition." *Clarendon Press*, Oxford, 1995.

[12] C. Liu, H.B. Zhao, C.S. Li, H. Wang. "Classification of ECoG Motor Imagery Tasks Based on CSP and SVM." *2010 3rd International Conference on Biomedical Engineering and Informatics* (BMEI 2010)

[13] L. Li, D. Xiong, X. Wu. "Classification of Imaginary Movements in ECoG" Bioinformatics *and Biomedical Engineering,(iCBBE) 2011 5th International Conference on.* IEEE, 2011.

[14] I. Onaran, N.F. Ince, A.E.Cetin, A. Abosch. "A Hybrid SVM/HMM based System for the State Detection of Individual Finger Movements from Multichannel ECoG Signals." *Proceedings of the 5th International IEEE EMBS Conference on Neural Engineering* Cancun, Mexico, April 27 – May 1, 2011.

[15] Y. Fang, M. Chen, X. Zheng, R.F. Harrison. "Extending CSP to Detect Motor Imagery in a Four-class BCI." *Journal of Information & Computational Science* 9: 1 (2012) 143-151.

[16] J. Mueller-Gerking, G. Pfurtscheller, H. Flyvbjerg. "Designing optimal spatial filters for single-trial EEG classification in a movement task." *Clin. Neurophysiology*, vol 110, pp. 787-798, 1999.

[17] C. Guger, H. Ramoser, G. Pfurtscheller. "Real-time EEG analysis with subject-specific spatial patterns for a brain-computer interface (BCI)." *Rehabilitation Engineering, IEEE Transactions on* , vol.8, no.4, pp.447,456, Dec 2000.