Epidural ECoG Online Decoding of Arm Movement Intention in Hemiparesis

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***Abstract*—Brain-Computer Interfaces (BCI) that rely upon epidural electrocorticographic signals may become a promising tool for neurorehabilitation of patients with severe hemiparatic syndromes due to cerebrovascular, traumatic or tumor-related brain damage. Here, we show in a patient-based feasibility study that online classification of arm movement intention is possible. The intention to move or to rest can be identified with high accuracy ($\sim$90%), which is sufficient for BCI-guided neurorehabilitation. The observed spatial distribution of relevant features on the motor cortex indicates that cortical reorganization has been induced by the brain lesion. Low- and high-frequency components of the electrocorticographic power spectrum provide complementary information towards classification of arm movement intention.**

I. Introduction

Brain impairment is one of the largest health-related, socio-economic burdens. In particular, stroke is the most frequent cause of long-term motor disability among adults [1]. Patients with severe motor impairment are not sufficiently addressed by current rehabilitation methods. Significant functional recovery after one year is rare – despite novel interventional approaches for application in the chronic stage such as bilateral arm training or constraint-induced movement therapy [1].

Electrocorticographic (ECoG) based Brain-Computer Interfaces (BCI) [2] in combination with robot-assisted therapy may provide an alternative approach to neurorehabilitation, particularly for patients with severe motor deficits. We assume that a brain signal-based haptic reinforcement of a patient's intent to move the arm with the support of a robot arm may induce cortical plasticity and functional improvement of the paretic arm. Here, Hebbian rule-based learning is the presumed underlying biological mechanism [3], [4]. A key step in realizing such a scenario is the online decoding of the patient's intent to move the impaired arm. In this paper, we investigate the feasibility of this approach using *epidural* ECoG in a stroke patient, a safer alternative to intraparenchymal electrodes or subdural devices for BCI applications [5].

In primates, spike signals recorded from the motor cortex have been shown to provide information about position or velocity of real arm movements [6]. Off-line reconstruction of 2-D real arm movement trajectories has been posible using the firing rates of several neurons [7]. There is evidence that intracortical local field potentials (LFPs) in primates or fields potentials measured directly from the brain surface (*subdural* ECoG) may also be used in humans for decoding substantial information on the patient's arm movements [2], [8]. Off-line reconstruction of 2-D real arm movement trajectories of epileptic human subjects has proven possible [9].

Motor imagery has been employed to control the 1-D or 2-D trajectory of a device (e.g., the cursor on a screen). However, in most cases, the system relies on combinations of imagined movement for different parts of the body or extensive training of the patient who learns how to modulate different frequency bands: Subdural ECoG features recorded from several locations over the same hemisphere in epileptic subjects have been used in a two-dimensional four-target center-out task [10]. A linear combination of EEG left and right hand imagery features recorded from healthy subjects has been used to perform a two-dimensional center-out task with eight targets [11]. The modulation of μ-rhythm generated magnetoencephalography (MEG) features recorded from stroke patients has been used to control a 1-D cursor with an accurate direction classification of (65%-90%) [1].

In our scenario, real movement decoding is not possible due to the paralysis caused by the brain lesion. Using features resulting from different types of imagined movements (tongue, arm, etc.) as control signals in a robot-assisted therapy in stroke patients is not reasonable when aiming at the restoration of the impaired arm. Instead, we are aiming at decoding movement intention that mimicks the desired motor trajectory of the affected arm and may, thereby, be useful in robot-assisted training of hemiparetic patients.

To the best of our knowledge, this is the first BCI application using *epidural* ECoG in a stroke patient, studying prospective neuromotor rehabilitation. This study employs online classification of arm movement intention over a fixed trajectory using *epidural* ECoG signals. We show how low-frequency (2-40 Hz) and high-frequency (40-80 Hz) power spectral densities provide complementary information that can be combined to improve the classification accuracy. A comparison among power spectral densities in different spatial locations over the motor cortex provides evidence of cortical reorganization caused by the brain lesion.

II. Materials and Methods

Human subject. The subject was a 65-year old male with a right-sided chronic hemiparesis following a hemorrhagic stroke in the left thalamus. Electrode grid implantation was performed within a treatment protocol for intractable pain and was determined solely by clinical criteria.

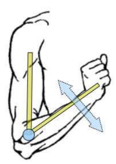


Figure 1. Subject's task

Tasks. The subject's task consisted of trying to move his paretic forearm forward or backward, using his elbow as the single degree of freedom during the movement (Figure 1). In order to facilitate the movement, the forearm was lying laterally on a small platform. As this task consists of a forward movement followed by a backward movement, it mimics a pointing movement with the forearm and it is an essential component of a grasping movement. The subject was not capable of performing this movement appropriately, thereby resulting in a movement intention rather than the movement itself. In each block, there were 15 visual and auditory cues (”Move forward”, ”Move backward”) for each movement direction and 30 visual and auditory cues (”Relax”) for rest, delivered as a text at a distance of 1.5m from the subject, alternating between 5s movement periods and 3s rest periods. In each block, online visual feedback was provided after an initial training period consisting of 15 seconds for each condition. Here, an arrow moved forward, backward or stopped every 300 ms based on the online decoding of the ECoG signal. More detail will be provided in Section III. Cues of both types of movement directions were interleaved randomly in a way that the movement direction could not be inferred a priori. The subject's movement intent was always cued for the arm contralateral to the side of the brain lesion and the cortical grid.

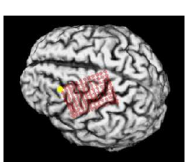


Figure 2. MRI of the subject's brain with an overlay x-ray of the electrode grid.

Recording. The platinum electrode array (by Ad-Tech, Corp.) consisted of 96 electrodes, configured as a 8 $\times$ 12-electrode grid. The electrode pads had 4-mm diameter (2.3 mm exposed) and 5-mm interelectrode distance. The electrode array covered parts of the premotor cortex, primary motor cortex and somatosensory cortex, as shown in Figure 2. The electrode with index 1 corresponds to the top right corner, and indices increase in columns from top to bottom and right to left. Electrode 89 (top left corner, in yellow) was used as reference. ECoG signals were fed into a stack of BrainAmp (by Brain Products GmbH) amplifiers in the first session and into a Quickamp (by Brain Products GmbH) amplifier in the second session, both with a 250Hz sampling rate. ECoG signals were acquired from the amplifiers using the general-purpose BCI2000 software [12], and the additional module BCPy2000 [13] was used for online signal processing and statistical learning.

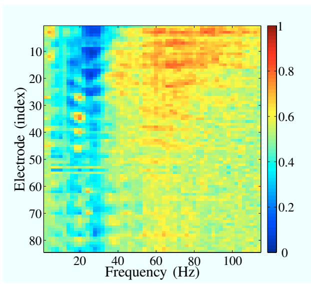
Signal Analysis. Initially, common average reference (CAR), band pass filtering (2-115 Hz), and notch filtering (50 Hz power line) were carried out over the raw signals. Normalized average power spectral densities in 2 Hz frequency bins for each electrode were used as features, as previously used in motor imagery and for real movement decoding [9], [10]. Welch's method was used to compute an estimation of the power spectral density (PSD). During the experiment, the estimation was computed on-line over incrementally overlapping bigger time segments during each 5s movement or 3s resting periods. Larger segments provide less noise and more reliable estimates while smaller time segments are necessary to enable online classification already at the beginning of every trial.

Online decoding. Online classification was carried out between movement and resting, providing online feedback. A linear support vector machine (SVM) classifier [14] is generated on-line after a short initial training period in which spectral estimates for 15 seconds of each condition (both movement directions and rest) are computed. In addition, the parameters of a sigmoid function to map the SVM outputs into probabilities are also estimated.

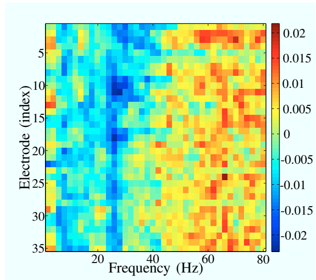
III. Results

Spatial and Spectral Features. To gain more insight into the discriminative power of every feature, the area under the receiver operating characteristic curve (AUC) [15] is computed for both pairs of conditions (move forward vs rest and move backward vs rest) for every feature, i.e. electrode and frequency bin. Figure 3(a) shows the AUC values for every feature when comparing move backward vs rest (a similar figure was obtained when comparing move forward vs rest and it is omitted). Areas with values closer to zero (shown in blue) and values closer to one (shown in red) correspond to a decrease and increase in spectral power, respectively, when carrying out the movement. Similar to preceding subdural ECoG studies [16], also in our data there is a spectral power decrease in the low-band frequency regime and a spectral power increase for high-band frequencies during movement. In low-band frequencies, we did not find a significant μ rhythm (9-13 Hz) desynchronization. Instead, we observed a strong β rhythm (18-24 Hz) desynchronization. This finding might be related to different factors most likely due to the underlying pathology.

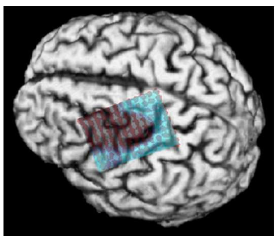
Moreover, we integrate the values in Figure 3(a) over a low-frequency band (2-40 Hz) and a high-frequency band (40-80 Hz) and we map them to their spatial locations, as shown in Figures 3(c) and 3(d), where light blue and red colors indicate greater statistical significance. This provides evidence of cortical reorganization caused by the brain



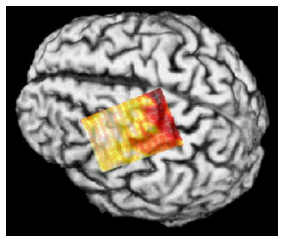
(a) AUC



(b) Classifier weights



(c) Average AUC (2-40Hz)



(d) Average AUC (40-80Hz)

Figure 3. **Discriminative power of the features**: (a) AUC and (b) classifier weights per electrode and frequency bin, (c) average AUC per electrode for low-frequency band and (d) average AUC per electrode for high frequency band for moving backward vs resting. A similar figure was obtained when comparing move forward vs rest and it is omitted. Refer to Fig. 2 for the subject's brain with an overlay x-ray of the electrode grid.

lesion. The most active areas during movement intention of the arm do not entirely match the expected somatotopic representation within the motor cortex.

Most of the discriminative power lies in electrodes covering the motor and somatosensory cortex, and thus we used the first (in terms of index) 35 electrodes for online classification. Interestingly, when focussing on the average classifier weights across blocks, it can be observed that they mimic the results of the AUC. However, note that no additional constraint in the classification problems was added to bias the solutions towards these electrodes or frequency bins. Hence, no screening session with manual feature selection is needed. The average classifier weight distribution for the case of moving backward vs resting is presented in Figure 3(b).

Performance. We evaluate the performance achieved in terms of classification accuracy with *epidural* ECoG for two different online decoding schemes and for one off-line decoding algorithm. In the first online decoding scheme, overlapping segments between 500 ms and 5 seconds are used in both the training set and the test set for every block. None of the segments of the training set overlaps with segments in the test set. In the second online decoding scheme, 500ms non-overlapping segments are used in both the training and the test set for every block. In the off-line decoding algorithm, full trials are used in both the training set and the test set. For every case and every block, samples in the training set occurred earlier in time than the ones in the test set. During the experiment with the patient (on-site), online decoding with overlapping segments was used.

Figure 4 shows the average test accuracy and test range accuracy across blocks when considering a low-frequency band (2-40 Hz), a high-frequency band (40-80 Hz) and a broadband (2-80 Hz). Two binary classification problems were studied: move forward vs rest and move backward vs rest for the three different decoding schemes. Using confusion matrices, it was verified that the classification was not skewed towards one class. Table I shows the confusion matrices of both classifiers for the frequency band 2-80 Hz. Both low-frequency (2-40 Hz) and high-frequency (40-80 Hz) bands seem useable for classification purposes. The best results are achieved using the broadband that contains both low-frequency and high-frequency components. This might indicate that low-frequency and high-frequency components provide complementary information.

Our results are comparable with previous off-line 2-class classification accuracy, i.e., 95% for real movement and 80% for imagined movement vs rest for epileptic patients who were not compromised in their motor performance [16]. In contrast, our patient had a hemiparetic arm and was not able to perform the instructed movement. Importantly, we provide on-line instead of off-line (full-trial based) classification. Hence, we provide the first proof of concept that online BCI control can be applied in hemiparetic patients.

Decoding of the direction of arm movement (move forward vs move backward) was also attempted. Relatively low performance (40-67%, with average values around 55-60%) was achieved. This may be caused by inconsistencies in the subject's movement direction intention during some trials, i.e. the patient mixed forward and backward directions during a single trial. This occurred specially during the second session. Thereby, for online decoding based on low-frequency components, we attained an accuracy of 61.3% during the first session but only chance level during the second session. Hence, this prevents us from drawing further conclusions.

IV. Discussion

Our study forms a first step in exploring the feasibility of *epidural* ECoG signals for creating BCI-based rehabilitation devices for hemiparetic patients. These devices would consist of a brain signal-based haptic reinforcement of a patient's intent to move the paretic arm with the support of a robot arm. In this scenario, the robot arm control must provide real-time haptic feedback in response to the patient's intent to move or stop and thus, online decoding of the brain signals is necessary. We have shown that online classification of arm movement intention of a stroke patient with *epidural* ECoG is possible even in a hemiparetic patient. High accuracy ($> 90\%$) was achieved when comparing movement with respect to a resting condition, allowing an implementation

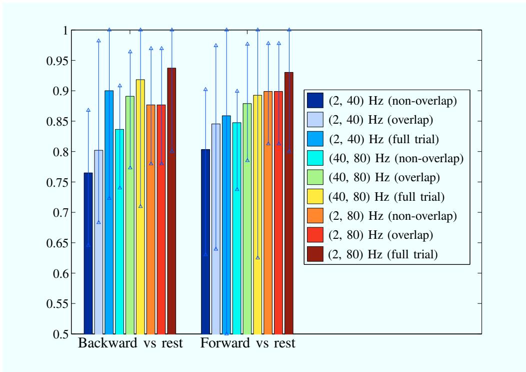


Figure 4. **Classification accuracy:** The figure shows the average test accuracy and test accuracy range across blocks for both binary classifiers (forward vs rest and backward vs rest) and three frequency ranges (2-40, 40-80 and 2-80 Hz).

for rehabilitation purposes. Our study was carried out without intensive training, requiring as little as 15 seconds of data per class per run (i.e., training and test period), and it does not rely on off-line analysis or computation. These results support the feasibility of *epidural* ECoG as a viable and safer alternative to intraparenchymal electrodes or subdural devices for BCI applications [5], having a greater spatial resolution and less amount of artifacts than EEG.

Power spectral analysis shows a surprising lack of significant μ rhythm (9-13 Hz) desynchronization and instead a strong β rhythm (18-24 Hz) desynchronization, probably related to the underlying pathology. The analysis of AUC and the classifier weights provides empirical evidences for cortical reorganization caused by the brain lesion. In particular, the somatotopic arm representation has been shifted within the motor cortex. Our approach allows addressing different feedback strategies with respect to individual reorganization patterns for neurorehabilitation in future studies. A study with more stroke patients is under progress.

Classifier	**Actual**	**Predicted**	
		Rest	Backward
Backward vs rest (non overlap)	Rest	0.8452	0.1548
	Backward	0.0834	0.9166
		Rest	Forward
Forward vs rest (non overlap)	Rest	0.8948	0.1052
	Forward	0.1094	0.8906
		Rest	Backward
Backward vs rest (overlap)	Rest	0.8257	0.1743
	Backward	0.0721	0.9279
		Rest	Forward
Forward vs rest (overlap)	Rest	0.8890	0.1110
	Forward	0.0911	0.9089
		Rest	Backward
Backward vs rest (full trial)	Rest	0.9322	0.0678
	Backward	0.0576	0.9424
		Rest	Forward
Forward vs rest (full trial)	Rest	0.9597	0.0403
	Forward	0.0990	0.9010

Table I
CONFUSION MATRICES FOR FREQUENCY BAND 2-80 HZ

REFERENCES

[1] E. Buch *et al.*, "Think to move: a neuromagnetic brain-computer interface (BCI) system for chronic stroke," *Stroke*, vol. 39, no. 3, p. 910, 2008.

[2] E. Leuthardt *et al.*, "A brain–computer interface using electrocorticographic signals in humans," *J. of Neural Engineering*, vol. 1, pp. 63–71, 2004.

[3] T. Murphy and D. Corbett, "Plasticity during stroke recovery: from synapse to behaviour," *Nature Reviews Neuroscience*, vol. 10, no. 12, pp. 861–872, 2009.

[4] L. Kalra, "Stroke Rehabilitation 2009: Old Chestnuts and New Insights," *Stroke*, vol. 41, no. 2, p. e88, 2010.

[5] T. Valderrama *et al.*, "Gain of the human dura in vivo and its effects on invasive brain signal feature detection," *J. of Neuroscience Methods*, 2010.

[6] J. Kalaska *et al.*, "Cortical mechanisms related to the direction of two-dimensional arm movements: relations in parietal area 5 and comparison with motor cortex," *Experimental Brain Research*, vol. 51, no. 2, pp. 247–260, 1983.

[7] W. Wu *et al.*, "Bayesian population decoding of motor cortical activity using a Kalman filter," *Neural Computation*, vol. 18, no. 1, pp. 80–118, 2006.

[8] C. Mehring *et al.*, "Comparing information about arm movement direction in single channels of local and epicortical field potentials from monkey and human motor cortex," *J. of Physiology-Paris*, vol. 98, no. 4-6, pp. 498–506, 2004.

[9] T. Pistohl *et al.*, "Prediction of arm movement trajectories from ECoG-recordings in humans," *J. of Neuroscience Methods*, vol. 167, no. 1, pp. 105–114, 2008.

[10] G. Schalk *et al.*, "Two-dimensional movement control using electrocorticographic signals in humans," *J. of Neural Engineering*, vol. 5, pp. 75–84, 2008.

[11] J. Wolpaw and D. McFarland, "Control of a two-dimensional movement signal by a noninvasive brain-computer interface in humans," *Proc. of the National Academy of Sciences*, vol. 101, no. 51, p. 17849, 2004.

[12] G. Schalk *et al.*, "BCI 2000: A General-Purpose Brain-Computer Interface(BCI) System," *IEEE Transactions on Biomedical Engineering*, vol. 51, no. 6, pp. 1034–1043, 2004.

[13] http://bci2000.org/downloads/BCPy2000/.

[14] V. Vapnik, *The nature of statistical learning theory*. Springer Verlag, 2000.

[15] M. Hollander and D. Wolfe, "Nonparametric statistical methods," 1973.

[16] P. Shenoy *et al.*, "Generalized features for electrocorticographic BCIs," *IEEE Transactions on Biomedical Engineering*, vol. 55, no. 1, p. 273, 2008.