Gernot Müller-Putz*, Markus Crell, Johanna Egger, Patrick Suwandjieff and Kyriaki Kostoglou

Towards Implantable Brain-Computer Interface for Communication in Locked-In Syndrome patients

An introduction to INTRECOM

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Abstract: Locked-in Syndrome (LIS) severely restricts the communication abilities of individuals due to extensive paralysis. The Intracranial Neuro Telemetry to Restore communication (INTRECOM) project aims to aid patients in overcoming these limitations by developing a fully implantable brain computer interface (BCI) system based on state-of-the-art technology holding great promise in revolutionizing the lives of LIS patients. In this project, the Graz BCI group, with its expertise in understanding brain dynamics associated with movement, focuses on the algorithmic development of advanced decoders that enable the user to execute specific commands by simply attempting corresponding movements. Our preliminary findings using electrocorticography (ECoG) data obtained from one individual with LIS that underwent implantation of a BCI communication system demonstrate the applicability of a 'brain switch' function that detects brain signals associated with attempted movements. This switch can then be used to translate the intention of the user into a click/select function on a screen.

Keywords: INTRECOM, Implantable BCI, Locked-In Syndrome, Attempted Movement, Pole Tracking, ECoG

1 Introduction

The possibility of being conscious but unable to communicate is a distressing prospect for countless individuals all over the world. Motor neuron disorders, trauma or stroke can lead to a condition called Locked-In Syndrome (LIS), characterized by a complete loss of muscle control and diminished quality of life. It imposes an immense burden of care not only on the affected individuals but also on their families and care givers. The Intracranial Neuro Telemetry to Restore Communication (INTRECOM) project (https://intrecom.eu/) is dedicated to transforming the lives of people experiencing LIS. Through the development of a fully implantable Brain-Computer Interface (BCI), INTRECOM facilitates real-time speech/movement decoding and use in the home environment. By incorporating state-of-the-art hardware and software solutions based on Artificial Intelligence (AI), this system will enhance the overall quality of life of people affected by LIS.

In this work, we give an overview of the INTRECOM project and detail its objectives. Furthermore, we give an example on some of the methods we plan to employ using prior recorded electrocorticogram (ECoG) data from one individual with LIS.

1.1 The INTRECOM Project

INTRECOM is a project funded by the European Innovation Council (EIC) Pathfinder, and coordinated by the University Medical Center Utrecht, the Netherlands (UMCU) and partnered by the Wyss Center (Geneva, Switzerland), CorTec GmbH (Freiburg, Germany) and us. It builds upon five primary objectives that form its core, aiming to substantially advance BCI technology and validate its efficacy in people with LIS within their home environment. These objectives are:

1. Development of a fully functional high-density BCI prototype device with 128 channels and brain surface-lining electrode grids. This advanced device ensures both safety and reliability while allowing continuous recording of high-quality brain signals.
2. Development of decoding algorithms that can translate brain signals to real-time computer speech and/or character selection and cursor control, thereby restoring communication abilities to patients by the end of the project.
3. Implantation of the developed prototype device in 2 people with LIS. We will accomplish home use with basic functionality within weeks after implantation.
4. The data obtained during this project will be openly shared, contributing to the advancement of scientific knowledge in areas such as human brain function and BCIs.

*Corresponding author: Gernot Müller-Putz: Institute of Neural Engineering, Graz University of Technology, Stremayrgasse 16/4, 8010 Graz, Austria, e-mail: gernot.mueller@tugraz.at
Gernot Müller-Putz: BioTechMed Graz, Austria
Markus Crell, Johanna Egger, Patrick Suwandjieff, Kyriaki Kostoglou: Institute of Neural Engineering, Graz University of Technology, 8010 Graz, Austria

5. By the end of this project, we aim to demonstrate the acceptability of the system among participants, caregivers and healthcare professionals.

1.1.1 Specific aims for the Graz BCI group

The Graz BCI group focuses on building decoders that can translate brain activity into control commands. Our initial objective is to build a brain 'switch' associated with attempted hand movements. This brain switch serves as a means for the BCI system to understand the user's intention and carry out corresponding actions, such as selecting an item from a menu on the screen. This function will then be enhanced by introducing further degrees of freedom. This involves allowing the user to freely navigate and interact within the screen environment. In the following section, we present our initial findings regarding the development of a brain switch using ECoG data obtained from an individual with LIS.

2 A brain switch based on Pole Tracking

2.1 Methods

The data was previously collected by UMCU from an individual with late-stage amyotrophic lateral sclerosis (ALS) (diagnosed in 2008). This individual underwent implantation of an ECoG-based BCI communication system in 2015 as a part of the Utrecht NeuroProsthesis (UNP) study [1] (referred to as participant UNP1 in [1]). To capture neural activity, subdural electrode strips were positioned over the sensorimotor hand area (Fig.1).

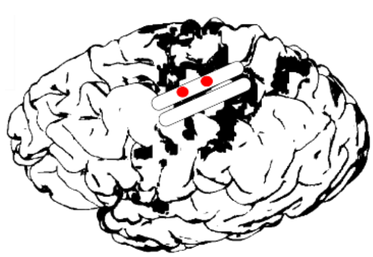

Figure 1: Subdural electrode strips were positioned over the sensorimotor hand area. The location of the analyzed electrodes is denoted with red dots.

The ECoG signals were recorded during the Localizer Task runs, which involved a series of repetitive attempts of right hand and finger tapping or periods of rest lasting 15s. Each trial was preceded by a 1-second preparation phase. Our primary objective was to assess the distinguishability between the resting and attempted movement conditions three years after implantation (i.e., in 2018). The separability of these two conditions enables the implementation of a brain switch function. The recorded data (sample frequency was 200 Hz) consisted of a total of five runs. Each run included 4 trials of rest and 4 trials of attempted movement, resulting in a total of 40 trials.

The raw signal of the bipolar electrode pair was high-pass filtered at 0.3Hz (two-way least squares FIR filtering) to eliminate slow drifts and DC offsets. In order to analyse the oscillatory patterns during attempted movements and resting states, the data was divided into epochs of [-1 15] s relative to the 'Go' cue onset. Time-frequency maps of event-related desynchronization and synchronization (ERD/ERS) were then computed across a range of frequencies [2].

To classify the two conditions, we applied pole tracking (PT) based on Autoregressive (AR) models [3] along with shrinkage Linear Discriminant Analysis (sLDA) [4]. Time-varying (TV) AR models are widely used to track changes in the power of a signal. This is typically accomplished by segmenting the data into quasistationary epochs. A more intuitive approach involves independently tracking the poles of the signal-generating system by reformulating the AR model as a cascade of second-order filters. This formulation assumes that the ECoG signals can be described as the outcome of white noise passing through this cascade of filters. The magnitude and the frequency of the poles represent the strength and the frequency of the most dominant oscillatory components in the signal. Since the reformulated model is nonlinear in its coefficients, tracking can be achieved through extended Kalman Filtering (EKF). The TV frequency and magnitude of the poles are then used as features for sLDA-based classification (this combined model is referred to herein as PT-sLDA).

Training of the PT-sLDA model involves two steps. Firstly, the EKF hyperparameters for PT are optimized by minimizing the mean squared error between the predicted and the observed ECoG signals. This ensures that the EKF captures accurately the underlying dynamics. It's important to note that in this study, only one pole was tracked. Secondly, an sLDA model is trained using the magnitude and the frequency of the estimated TV poles as features. These features are employed to predict whether the participant is resting or attempting finger movements at each time point. To evaluate the performance and the generalization capabilities of the model, we used data that were not utilized during the training phase. Specifically, we trained a PT-sLDA model using the initial run of year 2018 (consisting of 8 trials) and we then applied the model to the subsequent runs of the same year. To assess the performance of a random classifier, we followed a similar evaluation procedure, but with one key difference: we

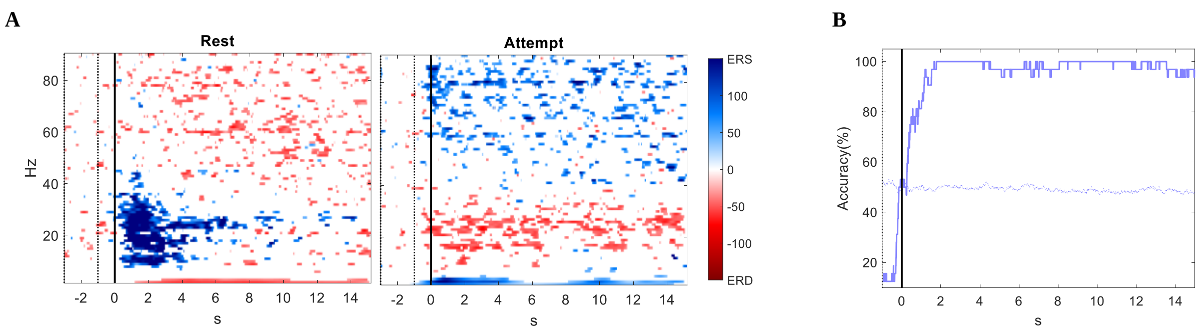

Figure 2: **(A)** ERD/ERS maps during resting (left panel) and finger movement attempts (right panel). ERD and ERS is represented by red and blue, respectively. The vertical dashed line at -1s indicates the 'Ready' cue onset (preparation phase), while the vertical bold line at 0s indicates the 'Go' cue onset (i.e., start of movement attempts or rest for 15s). The reference period was selected between [-2 0]s. (**B**) Time-varying classification accuracy between rest and movement attempts relative to the 'Go' cue onset. The purple line corresponds to training the model on the first run of year 2018 and testing it on the subsequent runs of the same year. The dashed purple line (around 50%) refers to the time-varying accuracy of a random classifier.

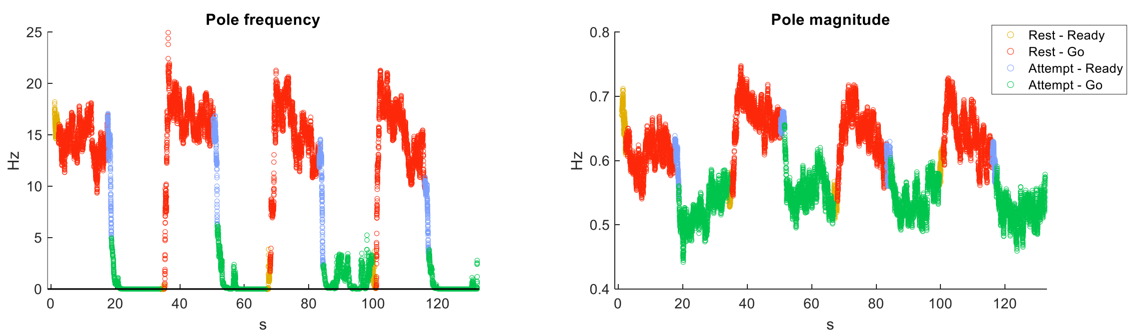

Figure 3: Time evolution of the average (over all runs) pole frequency (left panel) and magnitude (right panel) within a run. Different colors correspond to different phases (i.e., preparation phase for rest and attempt are color coded with yellow and blue, respectively. Rest and attempt trials are indicated by red and green, respectively).

randomly permuted the labels (i.e., 'rest' and 'attempt') 100 times.

2.2 Results

Figure 2A illustrates the estimated time-frequency ERD/ERS maps contrasting rest vs finger movement attempts. These maps cover a range of frequencies ([1 90] Hz with a step of 1 Hz) and provide visual depiction of the ERD/ERS patterns during both resting and movement attempts. Only statistically significant values, determined using a bootstrap technique, are displayed on the maps. The ECoG dynamics exhibit the well-established patterns of alpha/beta (especially beta) desynchronization and gamma synchronization during movement attempts [5]–[7]. Additionally, there is evident alpha/beta synchronization within the initial seconds of the resting trials. This observation potentially suggests inhibition of movement attempts, or a post movement beta synchronization generated by the offset of a previous attempt trial. As depicted in Fig. 2B, the PT-sLDA model achieves a testing accuracy of 100% by only using one run of the data for training. This high accuracy is achieved within 1.5 to 2 seconds after the 'Go' cue onset.

Figure 3 presents the average time evolution of the frequency and magnitude of the estimated pole within one run. Resting trials exhibited oscillatory patterns in the alpha/beta band (pole frequency between 15-20 Hz and pole magnitude of 0.7-0.8). Conversely, during movement attempts there was a noticeable decrease in pole frequency towards the delta range accompanied by a simultaneous decrease in magnitude indicating alpha/beta desynchronization (which aligns with the observations in the ERD/ERS maps). At the end of each attempt, we also observed a beta rebound (i.e., ERS) (i.e., pole frequency overshooting towards the beta range followed by concurrent increases in magnitude indicating amplification of beta oscillatory activity).

3 Discussion

Our results indicate that a brain switch function can be successfully employed in a LIS patient. The system achieves a remarkable accuracy of 100% in detecting movement attempts. This is in line with previous work from members of the INTRECOM consortium [1], [6]–[8], indicating the feasibility and continued effectiveness of the brain switch over an extended period of use. As these findings are preliminary, our future work will focus on investigating the impact of incorporating a larger number of poles, encompassing both real and complex poles. In the current study, we tracked only one complex pole, since complex poles are linked to oscillatory components in the data. We will also explore the use of autoregressive moving average models (ARMA), which offer higher flexibility compared to AR models. Alternative types of features such as time-domain features and frequency-domain features, or a combination of both, will also be considered. Another important area of focus is optimizing the training procedure to minimize calibration time while maximizing the accuracy of detecting movement attempts. These efforts are crucial for advancing the performance and usability of the brain switch function, while also paving the way for the development of more sophisticated and advanced functionalities.

4 Conclusion

We introduced the INTRECOM project (https://intrecom.eu/) which aims to develop a fully implantable BCI system for home use environment. The Graz BCI group plays a vital role in the project by focusing on implementing brain decoders that can effectively translate movement attempts into useful BCI commands. Our initial findings on a LIS patient have shown promising results and we expect to further enhance our knowledge through continued research and development in this field.

Author Statement

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