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Multi-way Decoding of Wirelessly Transmitted ECoG Signals from WIMAGINE® Implant for Self-Paced Brain Computer Interface

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Abstract

The multi-way decoding algorithms are adapted to incomplete wirelessly transmitted data and integrated to CLINATEC® BCI platform. The platform includes wireless 64-channels ElectroCorticoGram (ECoG) recording implant WIMAGINE® and BCI software environment associated to a 4-limbs exoskeleton EMY.

1 Introduction

Multi-way (tensor-based) analysis was recently reported as an effective tool for neuronal signal processing. It was applied for Brain Computer Interface (BCI), e.g., (Li & Zhang, 2010). Movement-related BCI aims to provide an alternative non-muscular communication pathway for individuals with severe motor disability to send commands to the external world using measurements of brain activity. Generally, a common approach for brain signal analysis consists in the extraction of the information from spatial, frequency and/or temporal domains. The commonly used time-frequency decomposition of the signals leads to a matrix valued process. Introducing delays in time leads to the observations stored in a 4th order tensor. For the decoding model identification, a projection of the high dimensional tensor of observation to low dimensional space is generally applied using unfolding procedure or various tensor decomposition technics. The multi-way decoding was chosen for BCI project in CLINATEC®, CEA, Grenoble (Eliseyev, et al., 2011; Eliseyev & Aksenova, 2013). The goal of the project is to allow a tetraplegic subject to control external effectors, such as an exoskeleton. Despite encouraging success, movement related BCIs have yielded limited application outside of the laboratory, mainly due to unsolved problems of efficiency and long-term stability. The key criterion for clinical applications is reliable BCI devices and their stable and robust functioning. Moreover, the self-paced BCI system should be activated by users whenever they want. The important requirement is fast and easy calibration of the BCI system. In addition, to be comfortable for users, the high decision rate and low latency are desirable. The latency comprises algorithm delay, as well as

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data transmission and computation time. To approach the requirements of the clinical applications, a set of tensor-based algorithms were developed in CLINATEC®, CEA. The Recursive block-wise N-way PLS (Eliseyev & Aksenova, 2013) provides the progressive adaptive learning of the BCI system. L1-penalized N-way PLS algorithm performs the slice-oriented tensor decomposition that allows the selection of the groups of informative features (Eliseyev, et al., 2012). Sparse models reduce the computation time, increase the decision rate and, thus, improve the latency of the BCI system. The algorithms were tested in self-paced mode in series of preclinical experiments in animals, namely, the brain switch in freely moving rats (Eliseyev, et al., 2011), as well as brain switch and upper limb trajectory reconstruction in minimally restricted nonhuman primates (Eliseyev, et al., 2012; Eliseyev & Aksenova, 2013). In parallel, to estimate the performance, the publically evaluable data (Shimoda, Nagasaka, Chao, & Fujii, 2012) were analyzed (Eliseyev & Aksenova, 2013). The algorithms' delays were evaluated in series of experiments in rats and nonhuman primates. The negative delay of the decoder was observed in the brain-switch BCIs (Eliseyev, et al., 2011; Eliseyev, et al., 2012). The next step is integration and testing of the decoding algorithm at clinical BCI platform.

The CLINATEC® BCI platform includes ECoG recording implants WIMAGINE® which wirelessly transfer neural activity of the brain to a PC and the software environment associated to an effector. The wireless connection may introduce temporal loss of the signals. Moreover, the important point of the real time functioning of BCI system is the delay of the signal processing: signal acquisition, transmission, and the commands generation. To ensure stable system functioning, a set of gaps' filling algorithms was investigated. Then, preclinical experiments were carried out to study the latency and the performance of the system in a realistic context.

2 Methods

2.1 CLINATEC® BCI Platform

For real-life applications, the decoder is to be integrated to BCI environment. The CLINATEC® clinical movement related BCI platform is based on a wireless 64-channels ECoG recording implant WIMAGINE®, designed for the long-term clinical application (Charvet, et al., 2013). Two implants will record simultaneously the neural activity of the brain for wireless transfer to the base station, then a PC. The BCI software environment is associated to a 4-limbs exoskeleton EMY (Enhancing MobilitY) dedicated to medical purposes (Perrot, Verney, Morinière, & Garrec, 2013).

2.2 Integration of Decoder to BCI Platform

As the physical conditions are changing (quality of the wireless link, perturbations, interference) the bitrate of a radio frequency transmission inevitably varies. Thus, the wireless connection could introduce temporal loss of the data. To define the best strategy of decoding in the case of incomplete data, a set of computational experiments were carried out. The goal of the experiments was a comparison of different strategies of signal recovering and an evaluation of decoder robustness. For this study, the problem of reconstruction of hand trajectory was considered. The publically available ECoG recordings (Shimoda, Nagasaka, Chao, & Fujii, 2012) were corrupted with artificial sequences of the gaps. They were generated according to the gaps' distribution in the wirelessly transmitted signals in CLINATEC® BCI Platform. The sequences were imposed on the gaps-free data. The medians of the gaps segment were about 20 ms and 30% of the gaps do not exceed 5 ms. The number of the gaps was increased 100 times to obtain an upper estimate of the prediction biases. A set of algorithms for gaps' filling was studied: Zero-Order Hold, First-Order Hold, Autoregressive Model (8^{th} Order), Spline Cubic Interpolation, Piecewise Polynomial Interpolation, Sinusoidal Amplitude L1 Estimation, and Sinusoidal Amplitude and Phase L1 Estimation (Cowpertwait & Metcalfe, 2009). In

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all the cases, the algorithm has demonstrated significant robustness. The biases of the prediction (relative root mean squares error) were, 1.4%, 1.4%, 1.4%, 3.6%, 1.4%, 1.8%, 1.3%, and 1.3% respectively. Thus, even in the simplest case of the filling, namely, Zero-Order Hold, the influence of the data loss on prediction was negligible.

2.3 Preclinical Test

Integrated to the BCI platform, the decoder was tested in real-time in preclinical experiments carried out in non-human primates in CLINATEC®. Ethical approval was obtained from ComEth in accordance with the European Communities Council Directive of 1986 (86/609/EEC). Designed to be compatible with human's skull, WIMAGINE® cannot be implanted directly to primates. Thus, a silicone/platinum-iridium cortical electrode array was implanted in the region of monkey's left motor cortex and connected to the recording electrodes of the WIMAGINE® implant by means of a connector. Then, it was integrated to the BCI platform. The setup of the experiment is shown in Figure 1. The monkey was trained to reach an exposed target using the right hand. The hand movements were recorded by an optical motion capture system Vicon (Motion Systems, Oxford, UK). During the calibration stage, the monkey's ECoG data were used together with information about the hand position to identify a prediction model. For the BCI system, the calibration training tensor was formed using 1-second epochs of training recording. Normalized absolute values of complex wavelet coefficients (Morley) in logarithmic scale were considered as features. Feature tensor (6000 epochs) is split into training tensor to identify coefficients (4000 epochs) and validation tensor (2000 epochs). L1-penalised tensor decomposition was applied for features selection (frequencies and channels). Sparse model provided reducing of computation time with slight improvement of decoding performance (about 6% of improvement for the validation tensor). The correlation of the observed and the decoded trajectories was varying in the range of 0.4-0.8.

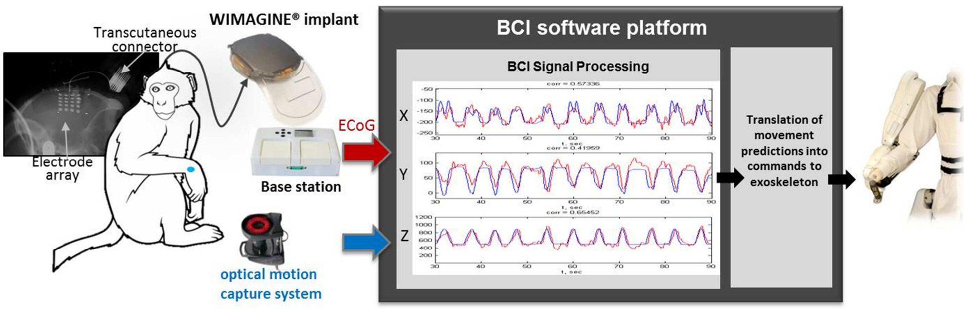

Figure 1: Preclinical experiments using CLINATEC® BCI Platform. Recording of ECoG activity of the brain is transmitted wirelessly by the WIMAGINE® implant. ECoG data are analyzed in real-time to send the commands to the external effector.

Figure 2 illustrates the relative weights of the linear model coefficients in the spatial and frequency domains for both full and sparse models. In the frequency domain, high frequencies 80-130 Hz have the highest contribution. At the same time, the frequencies 35-40 Hz as well as around 7 Hz are informative.

During the online experiments, the control commands were generated with decision rate DR=10 Hz. The estimated delay of the signal processing, including the signal acquisition, transmission, as well as the commands generation, was approximately equal to 300 ms. The next step of the CLINATEC® project is optimization and adjusting of all the components of the BCI system. Additional tests in animals are in progress to better estimate system performance (more animals, various experiment protocols etc.).

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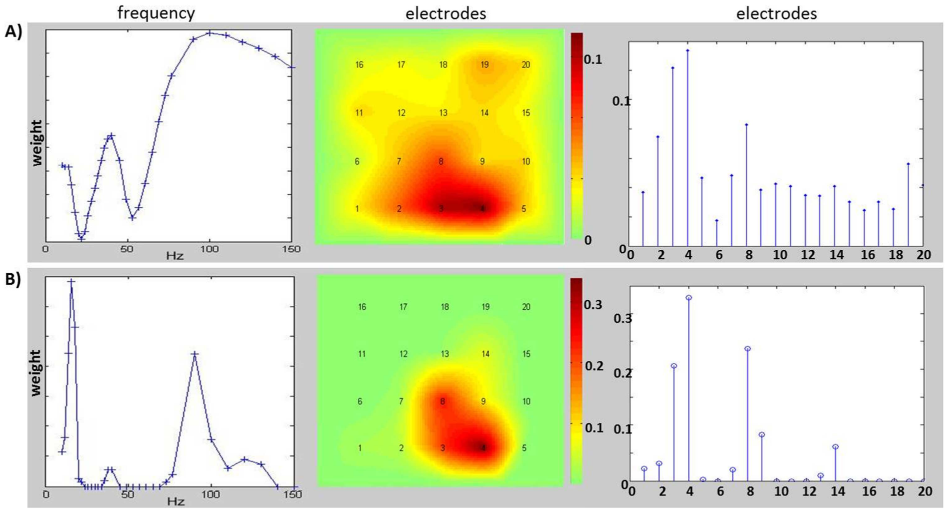

Figure 2: Relative weights of the linear model coefficients in the spatial and frequency domains for both full (A) and sparse (B) models.

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