ECoG Real Time Signal Processing for Clinical Self paced BCI Application

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1 OBJECTIVES

The overall goal of the Brain Computer Interface (BCI) project led at CEA/LETI/CLINATEC® is to improve the quality of life of quadriplegic subjects. BCI will allow them to control effectors such as an exoskeleton, through recording and processing of the electrical activity of their brain. To do this, a wireless 64-channel ElectroCorticoGram (ECoG) recording device WIMAGINE® (Wireless Implantable Multi-channel Acquisition system for Generic Interface with NEurons) has been designed for long-term human implantation to interface an electrode array to an external computer (Charvet *et al* 2013). To decode the ECoG data, high resolution algorithm has been constructed at CLINATEC® (Eliseyev et al., 2011); (Eliseyev and Aksenova 2013). Once the data are treated, they are used to control the external effectors.

To reach the overall goal, it is crucial to construct a whole software system working in real time. In order to prepare the BCI software system for the clinical trials, we demonstrated online real time Electrocorticogram (ECoG) signal processing using Monkey ECoG recordings corresponding to an arm movement (Shimoda et al., 2012). The algorithm of N-way Partial Least Square (NPLS) regression family (Eliseyev and Aksenova, 2013) is applied to extract linear model from the recordings. The model is used to control the robotic arm JACO (KINOVA) as a demonstrator.

2 METHODS

Figure 1 shows the schematic data flow for our BCI system. The raw data should contain high temporal resolution which does not limit to specific data acquisition, e.g. EEG, MEG and ECoG. Accumulation of data from several channels is represented in *Acquisition* box in Figure 1. After the data are collected in some buffer size, they are mapped by the continuous wavelet transform (CTW) to the temporal-frequency-spatial space (Acar *et al* 2008). Then they are sent to the linear prediction model. To create the model, the algorithm of PLS family (Eliseyev and Aksenova, 2013) is applied. PLS is a statistical method for data analyses particularly suited for high dimensional variables (Geladi and Kowalski, 1986). PLS algorithms provide stable linear models, which can then be used to decode neuronal signal into commands for external devices. Both CWT and prediction are represented in *Algorithm* box in Figure 1. The data transmission is represented in *Effector application* box in Figure 1.

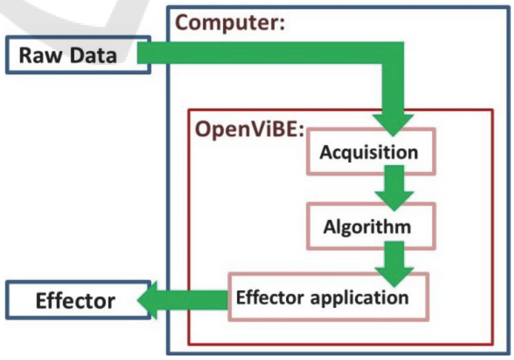

Figure 1: Flow of data decoding.

2.1 Specific Application

To test the system, publically available raw data are considered (Shimoda et al., 2012), which contains nine dimensional arm trajectory (shoulder, elbow and wrist of x- y- z- coordinated captured by VICON system) of Japanese macaque as well as epidural ECoG signals of monkey's brain (64 electrodes, sampling rate 1 kHz).

For decoding, block-wise Recursive N-way PLS regressing is used (Eliseyev and Aksenova, 2013), which can show correlation of 0.62, 0.80 and 0.85 of shoulder, 0.54, 0.84 and 0.83 of elbow and 0.63, 0.85 and 0.82 of wrist for x- y- z- coordinates

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respectively. To form training tensor, 64 electrodes ECoG signal and 1000ms window of analysis are considered. The CWT with 84 frequencies between 0.6 and 300 Hz are performed with additional 100ms tails using FFTW software (Frigo and Johnson, 2005). Then the signal was decimated in 100ms with 200ms sliding window. Using this training tensor, predictive model is constructed. After the training phase, the same features are considered for online prediction. All of the computations are integrated with OpenViBE (http://openvibe.inria.fr/) and finally connected with the JACO robotic arm as shown in Figure 2.

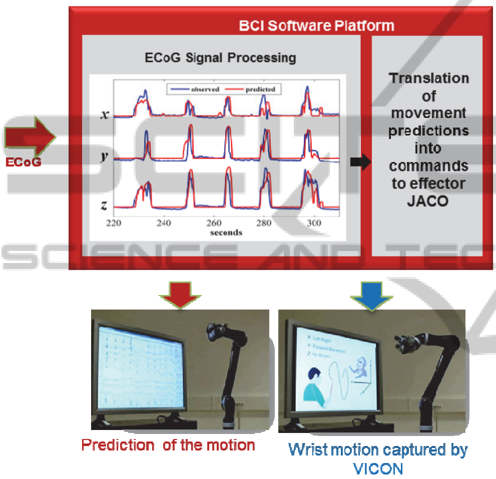

Figure 2: Comparison of predicted and actual movement.

3 RESULTS

To achieve real time, whole computation has to be completed within the buffer size. With the specific application from previous section, the temporal-frequency-spatial dimension is 537600 and predictive space has 9 degrees of freedom, namely shoulder, elbow and wrist of x- y- z- coordinates. With buffer size 100ms, the algorithm itself takes 83.81ms in average and simulating real time using OpenViBE reach real time for more than 10 minutes.

4 DISCUSSION

The system can be applied to different algorithms and data sets. The different model from PLS method (Chao et al., 2010) is also tested. From the specific applications, it is feasible to conclude that the model using less than 64 channels, 84 frequencies and 1000ms window has decision rate at least 10Hz.

This is directly related to the CLINATEC BCI project with ECoG signals of 64 channels using linear predictive models.

ACKNOWLEDGEMENTS

The authors wish to thank the technical staff of CLINATEC for their profound involvement in the success of the project. The project received financial support through grants from the French National Research Agency (ANR-Carnot Institute), Fondation Motrice, Fondation Nanosciences, Fondation de l'Avenir, and Fondation Philanthropique Edmond J. Safra.

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