Prediction of the Saccadic Eye Movement: Using Epidural ECoG in Non-Human Primate

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Abstract

Recently, several studies have reported use of epidural electrocorticogram (eECoG) for brain computer interface (BCI). However, the feasibility and performance of eECoG on BCI were not fully evaluated yet. In this study, we verified the usability of implanted eECoG in non-human primate by predicting saccadic movement using eECoG signals. Two micro electrode patches (32 channels) were inserted over duramater on rhesus monkey. The monkey performed four directional eye movement tasks responding to target's color change. As results, we classify the eye movement directions using eECoG and showed significant and stable decoding performance over two months. This could support the efficacy of BCI using eECoG.

1 Introduction

On brain computer interface (BCI), decoding and predicting intention of the subject is one of main issues. In primates, saccadic eye movements are often used to fixate objects of interest. The frontal eye field (FEF), supplementary eye field (SEF), and superior parietal lobule (SPL) including Intraparietal sulcus (IPS) are known as principal neocortical regions involved in the execution of both saccadic and pursuit eye movements. However it is not fully understand because of the limited measurement equipment such as fMRI, which has low time-resolution (LunaB, ThulbornK, StrojwasM, SweeneyJ, 1998) or depth electrode, which has low spatial-resolution (LeeK, AhnK, KellerE, 2012).

Recently, epidural electrocorticogram (eECoG) is widely known to give a great SNR, high spatialresolution, and broad frequency bandwidth. In this study, we verified the usability of implanted eECoG in non-human primate by predicting saccadic movement using eECoG signals. We used implanted multi channels micro electrode for non-human primate and eye movement behavioral task for verification.

2 Materials and Methods

2.1 Surgical Procedure

All surgeries were carried out in the animal surgical suite at the Primate Center of Seoul National University Hospital. Throughout the surgery, body temperature, heart rate, blood pressure, oxygen saturation and respiratory rate were continuously monitored. The adult male rhesus monkey (Macaca mulatta) was then placed in a stereotaxic frame before the incision of the scalp. After skin incision, a craniotomy of 2cm radius was conducted. Then, the monkey was implanted epidurally with two micro

electrode patches (32 channels, 4 by 8), positioned in the left hemisphere including dorsal parietal cortex and posterior part of frontal cortex (Figure 1). It covered the SEF, FEF and SPL including IPS, which were well-known as related to saccadic behavior. The implanted electrode grids consisted of gold electrodes that were embedded in poly-imide and spaced at an inter-electrode distance of 3 mm.



Figure 1: Position of the implanted electrode patches

2.2 Behavioral Task

Monkey was trained to perform a choice saccade task (LeeK, AhnK, KellerE, 2012). In Figure 2, upper panel shows the pre-trained location and color association, e.g. red is associated with the upperright visual field. Lower panel depicts a task procedure. A trial began when the monkey fixated at a central gray disc. After the fixation, four gray targets appeared in the peripheral visual field, and after 500ms the central disc changed to one of the four colors which associated with a particular target location. After 600ms, the central disc disappeared, which was the cue for the monkey to make a saccade response. The mapping between color and location was held constant throughout the training and experiments. Electrical recordings were started a week after the surgery, to allow sufficient time for recovery and three recording sessions were performed over two months.



Figure 2: "Choice saccade" task paradigm

The performance in the task was monitored by infrared video-oculography with a sampling rate of 500Hz (Eyelink2, SR Research Ltd, Kanata, Ontario, Canada). Saccade behavior was measured off-line using programs written in MATLAB (The Mathworks, Natick, MA, USA). The onset and offset of saccades were determined by velocity criteria (30°/s radial velocity for onset and 10°/s for offset).

eECoG signals were recorded with a sampling rate of 512Hz per channel, using data acquisition system (Brainbox EEG-1164 amplifier, Braintronics B. V., Almere, Netherlands). 60 Hz analog notch filter was used during the data acquisition.

2.3 Data Analysis

All data were band-pass filtered from 1 Hz to 170 Hz for processing. For pre-processing, trials with artifacts were excluded by the visual inspection, baseline remove, and the ICA decomposition was conducted to remove artifacts. The analysis epoch was -500 to 0ms relative to saccade execution time. For each channel and each 100ms time period (stepping by 10ms), normalized average power spectral densities were computed in 10 Hz frequency bins using Wavelet. 4 frequency bands were used, α -band (8~13Hz), β -band (18~26Hz), low γ -band (30~50Hz), and high γ -band (70~170Hz). The powers of each frequency, time window and channel were used as input features (a feature vector) for classification analysis (35 time bins × 4 frequency bands × 64 channels; total of 8960 features). The feature vector obtained from each trial was labeled by the target direction (left: 135 degree and 225 degree / right: 45 degree and 315 degree). We used a linear support vector machine (SVM) classifier (BoserB, GuyonI, VapnikV, 1992; VapnikV, 1999) to decode target direction and dimensionality of feature vectors was reduced by adopting SVM-based recursive feature elimination (SVM-RFE) (GuyonI, WestonJ, BarnhillS, VapnikV, 2002). We ranked the features by the weights value and selected top features above +2 standard deviation. The classification accuracy was calculated with a 10 fold cross-validation process.

We also quantified the spatio-spectro-temporal contribution of brain activity for predicting each target direction, by calculating weight contribution ratio value from the features' weight magnitude which was derived from adopting the SVM-RFE algorithm (GuyonI, WestonJ, BarnhillS, VapnikV, 2002).

W(ch) quantifies the spatial contribution ratio of each channel for predicting across all frequency bins and time bins, W(freq) quantifies the spectral contribution of each frequency bin across all recording channels and time lags, and W(time) quantifies the temporal contribution of each time bin across all channels and frequency bins. (ChaoZ, NagasakaY, FujiiN, 2010)

3 Results

We measured the eECoG's impedance to observe the impedance change after implantation. As a result, *in-vivo* impedance test showed stable values as time passes. Electrodes had impedance of 5.492 ± 0.046 k Ω , 5.470 ± 0.048 k Ω , 5.392 ± 0.050 k Ω and 5.358 ± 0.047 k Ω (mean \pm SEM for 64 electrodes at 1 kHz), from 1st to 4th week, respectively.

The eECoG decoding processing was carried on three sessions to predict the monkey's saccadic movement. The classification accuracies were 87%, 86% and 89% for predicting saccade eye movement's direction, from 1st session to 3rd session, respectively. Calculating the weight contribution ratio in decoding models revealed that the greater spatial contributions were found in SEF, FEF and SPL, which are consistent with previous reports and support the feasibility of eECoG based on neuroscientific background. In addition, Contribution of temporal information was significantly higher as closer to saccade onset time. The spectral contributions were greater in β (18~26Hz) band than other frequency bands.



Figure 3: Time-Weight graph of the each session's β (18~26Hz) band

4 Discussion

The 4-direction classification accuracies, which were 53%, 66%, and 56%, were higher than a chance level (25%). The left/right classification accuracies were significantly higher than a chance level (50%). It shows that 2-direction classification is much more efficient than 4-direction classification at BCI. Moreover, the prediction accuracy of eECoG-based decoding showed no significant monotonic decrease for 2 months. This result indicates that eECoG has durability and that the signal quality of the eECoG was maintained for several months at least.

As seen in the Figure 3, the weight of β -band was increased gradually over time and the highest at just before the physical eye movement. It seems that the β -band played a large role in saccadic plan and execution.

In the present study, we predicted saccadic eye movement using eECoG and investigated the feasibility of long term implanted eECoG on BCI. This work demonstrated that it was possible to detect the eye movement's direction before physical eye movement using eECoG, which reflects the possibility of eECoG for brain signal decoding and BCI study.

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