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High Gamma Oscillations Enhance the Subdural Visual Speller

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Abstract— **The N200 speller is a non-flashing visual brain-computer interface (BCI) using motion-onset visual evoked potentials (mVEPs). Previous N200 speller was implemented at the scalp EEG level. Compared to scalp EEG, electrocorticography (ECoG) provides a broader frequency band that could be utilized in BCI. In this study, we investigated whether the high gamma brain activities recorded from human intracranial electrodes can enhance the performance of the subdural speller. The ERP and high gamma responses of one most task-related subdural electrode were used together for BCI classification and showed that high gamma responses did enhance the performance for the subdural visual motion speller resulted in an average increase of over 8% (p<0.05, paired t-test).**

I. Introduction

The N200 speller is a recently proposed brain-computer interface (BCI) system [1-2]. Similar to the classical P300 speller [3- 4], the N200 speller consists of a 6×6 character matrix. In contrast to the visual flashes used in the P300 speller, brief visual motions are presented at the locations of these characters in a column / row manner. The column and row associated with the overtly attended (i.e. eye gaze) visual motion stimulus elicits a more negative peak (N200) around 200 ms after stimulus onset, constituting the basis of BCI classification. The N200 speller was named after N200, which is the most prominent component of motion-onset visual evoked potentials (mVEPs) [5]. The N200 speller has been demonstrated to achieve a comparable performance with that of the P300-speller [2]. Along with the lower inter- and intra-subject variability of mVEPs [6] and less user fatigue for long-time use brought by the nature of the non-flash visual stimuli, the mVEP based BCI has been proposed to be a promising candidate of practical human-computer interface applications [7].

While most of currently reported BCIs are using the non-invasive electroencephalographic (EEG) recordings from the human scalp [8-11], increasing interests have been drawn toward electrocorticography (ECoG) [12]. ECoGs are directly recorded from the surface of the brain, which is capable of capture brain activities of a broader frequency band, compared to the non-invasive EEGs. Specifically, the brain activities in the gamma band (i.e. 40-200 Hz) have been proposed to be highly correlated with the execution of a variety of cognitive tasks such as motor intention, speech production, attention etc. [12-14]. For BCI applications, classifications of different motor/language intentions and visual attention statuses have been achieved using ECoGs [15-17].

The N200 speller is likely to benefit from the broad frequency distribution of ECoGs as well. It has recently been shown that visual motion stimuli induces a significant increase of high gamma band activities in ECoG electrodes that covered the fMRI-defined hMT+ [18], which is a special area for processing visual motion. The hMT+ high gamma activity had a different time course and power change characteristic compared to the event-related potentials (ERP) recorded in parallel, indicating that the high gamma responses might provide independent information. However, it is still unclear whether the visual motion related high gamma activity is subject to human attentional modulation, which is critical for BCI controls.

In this study, we investigated whether the high gamma brain activity recorded from human subdural electrodes over visual motion area can enhance the performance of the N200 speller. ECoG data were recorded from two epilepsy patients with ECoG electrodes placed over the hMT+ regions for the purpose of identifying the epileptic zone. The patients participated in an offline N200 speller experiment. One subdural electrode with most prominent ERP and high gamma responses was selected for BCI classification. The contribution of the high gamma responses was evaluated in terms of BCI classification accuracy.

II. Methods

A. Patients

The experiment was conducted with two patients (see Table I for additional information) who suffered from intractable epilepsy and underwent temporary placement of intracranial ECoG electrode arrays to localize seizure foci prior to surgical resection. The patients gave informed consent prior to the implantation of electrodes and the study was approved by the Ethics Committee of the affiliated Yuquan Hospital, Tsinghua University.

TABLE I. PATIENT INFORMATION

Patient	Age	Sex	Electrode Grid Placement
A	12	Male	Right TL, PL and OL
B	24	Male	Right TL and PL

TL, temporal lobe; PL, parietal lobe; OL, occipital lobe.

The patients had a 32- or 64-electrode grid (4 mm electrode diameter and 1 cm inter-electrode distance) placed

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over the parietal-temporal-occipital region. Grid placement and duration of ECoG monitoring were entirely based on the clinical requirements, without any consideration of this study.

B. Paradigm

The subject sat about 60 cm in front of a 19-inch LCD monitor with a 60 Hz refresh rate and 1280×1024 resolution. A demonstration of the N200 speller interface [2] is shown in Fig. 1, which is a 6×6 screen virtual keyboard with embedded visual motion stimuli. In each virtual button, a vertical bar appeared (motion-onset) at the right border of a vacant rectangle and moved leftward at the velocity of 2.00°/s before it disappeared (motion offset), forming a brief motion stimulus. The entire process of onset, motion and offset took 150 ms. The stimulus onset asynchrony (SOA) between two motion stimuli was 200 ms. The motion stimuli in the virtual buttons occur in a random order by row/column, with random color (red, green, blue, brown, yellow and cyan). Presentation of the stimuli was programmed in Matlab (The Mathworks, USA) using Psychophysics Toolbox 3.0 extensions [19-20].

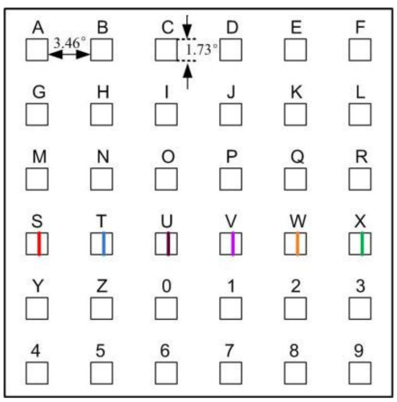

Figure 1. The N200 speller interface.

C. Procedure

The experiment was carried out in an offline manner. The visual stimuli were presented in an epoch-trial-block way. A stimulus epoch was defined as a motion stimulus of one row or one column. One trial of stimulus presentation consisted of 12 stimuli epochs in a random order, corresponding to the six rows and six columns respectively. A block contained 10 or 15 continuously presented trials with the same virtual button as the 'target' for overt attention. Depending on the subjects' attention task, the stimulus epochs were categorized into target epochs where the corresponding stimuli epoch included the virtual button as the subjects' attention focus, and non-target epochs where not including the attended virtual button. While watching the target, the subject was also instructed to mentally count the number of times the moving bar appeared in the attended button. Patient A participated in 6 blocks (15 trials/block). Patient B participated in 6 blocks (10 trials/block). The amount of data obtained from each patient varied due to their physical state and willingness.

D. ECoG Recordings and Electrode Localization

ECoG was recorded from implanted electrodes using the g.USBamp amplifier/digitizer system (g.tec, Graz, Austria). The amplifier sampled the signal at 1200 Hz using a high-pass filter with a 0.1 Hz cutoff frequency and a notch filter at 50 Hz to remove power noise. Four inactive epidural electrodes facing the skull were served as ground and reference.

Before the implantation surgery, the patients' MRI imaging was acquired with a 3T Philips scanner, covering the whole brain. After the placement of the subdural grid, the 3D head CT image was obtained by a Siemens SOMATOM Sensation 64 CT to verify its location. The three-dimensional cortex segmentation in MRI head model was implemented with BrainVoyager software (http://www.brainvoyager.com/). Afterwards, the post-operative CT was co-registered with the pre-operative MRI, using 3D Slicer (http://www.slicer.org/). After co-registration, the locations of implanted electrodes were marked on the patients' individual 3D cortex.

E. Data Analysis

The visual motion onset elicited brain responses in both the low frequency band (i.e. ERP) and the high frequency band (i.e. high gamma) were extracted separately for BCI classifications. To extract the ERPs, the ECoG data were first digitally filtered using a bidirectional linear filter (pass band 1-20 Hz). Single-epoch data were derived in association with each stimulus, beginning 200 ms prior to the motion-onset and lasting for 1000ms. All epochs were baseline corrected with respect to the mean voltage over the 200 ms preceding the motion stimulus onset. To explore possible high frequency responses, the ECoG data were band-pass filtered to 60-140 Hz and the time-varying high gamma envelops were extracted by Hilbert transform. The high gamma envelops were then baseline corrected following the same procedure as done for the ERP feature.

Before BCI classifications, we searched for single 'optimal' subdural electrode for both the ERP and high gamma features. The optimal electrode was defined as the electrode with maximal correlated activity with the attention task. Here the task correlation was evaluated by calculating the square of the Pearson correlation (r^2) between the target and non-target responses. The optimal electrode was chosen (i.e. showing the largest r^2) separately for ERP and high gamma features. The ERP responses between 50 ms and 350 ms after stimulus onset were then downsampled to 30 Hz, forming a 10-dimension feature vector. Likewise, the high gamma feature was consisted of a 15-dimension feature vector, which was the downsampled (also 30 Hz) high gamma power envelop between 0 ms and 500 ms.

The classification was carried out in two steps. First, in order to assess the BCI contribution of both ERP and high gamma feature separately, two support vector machine (SVM) classifiers were constructed for discriminating target responses from non-target responses, using either ERP or high gamma features. The output of these SVM classifiers were further translated into p-values, describing the probability of one particular epoch to be a target epoch [21]. Second, a 2-dimnesion feature vector was formed using the probability outputs of the two SVM classifiers and submitted to a Fisher linear discriminate analysis to obtain a classification accuracy with combined contributions of both the ERP and high gamma features.

The classification algorithm was implemented in Matlab with LibSVM toolbox [21]. The first 3 blocks of data were used for training the classifier and the rest 3 blocks were used for validation. Only classification accuracies on the rest 3 blocks were reported.

III. RESULT

A. *Intracranial mVEPs and High Gamma Oscillations*

The overt attention led to a negative ERP peak (Fig. 2, left), with a latency of ~180-240 ms post-stimulus, similar to the scalp N200 responses [2]. The high gamma (60-140 Hz) power envelop increase occurred around ~150 ms after motion onset and lasted ~200 ms (Fig. 2, right). The time periods with a significant difference (paired-sample T-test, $p < 0.005$) between the responses of target and non-target stimuli were highlighted in grey.

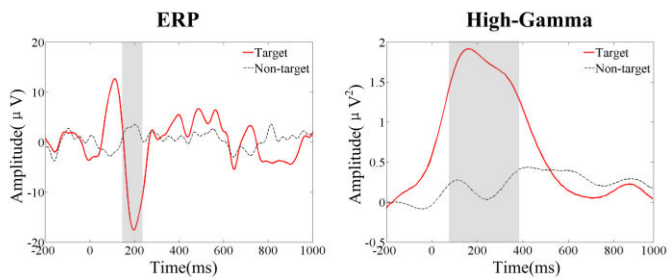

Figure 2. Averaged temporal patterns of ERP and high gamma power envelop of Patient B

B. *Single Electrode Selection*

Fig. 3 showed the r^2 results for both ERP and high gamma features, mapped on the patient's own cortex surface. The subdural electrode with the largest r^2 was then chosen as the 'optimal electrode' for BCI classifications. For both the two patients, the ERP and high gamma power envelop showed maximal discriminability between target and non-target responses at the same electrode (marked by the arrows).

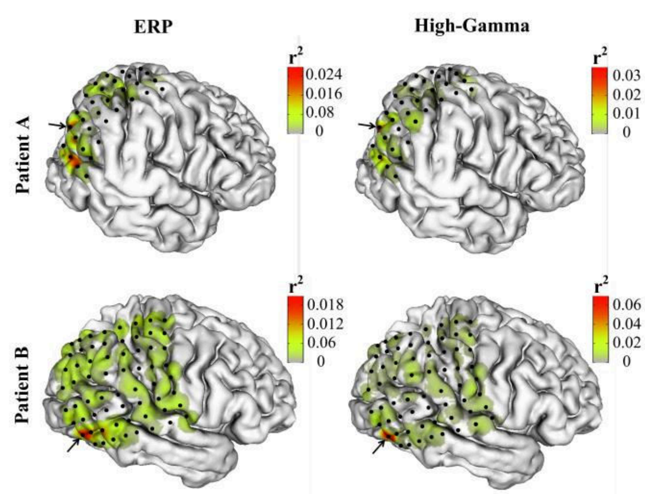

Figure 3. r^2 mapping of ERP and high gamma

C. *BCI Classification*

The classification accuracies using only ERP features and combined features (i.e. ERP & high gamma) were presented in Fig. 4. Following the traditional ERP BCI approaches, the classification accuracies were calculated as the function of number of epochs being temporally averaged. For both these two patients, the classification accuracies were increased when introducing the high gamma features. On average, a ~8% ($p<0.05$, paired t-test) increase was observed.

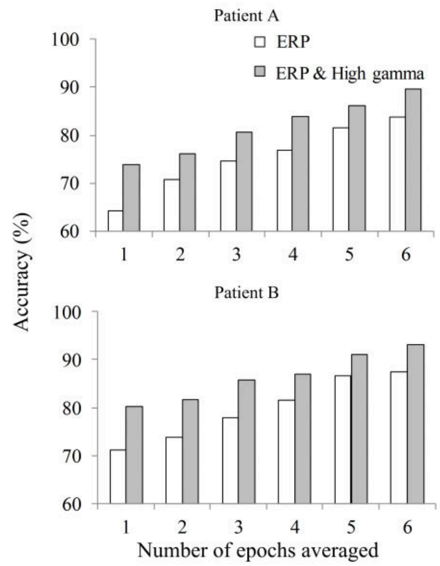

Figure 4. BCI classification accuracies

IV. DISCUSSIONS AND CONCLUSIONS

In this paper, the possibility of implementing an ECoG based N200 speller was assessed. We observed both increases of the high gamma (60-140 Hz) power after the overtly attended visual motion stimuli, and ERPs that was similar to the scalp mVEPs. Interestingly, the ERP and high gamma features had similar spatial distribution, thus the same single subdural electrode was used for BCI classification. Comparing with traditional EEG-based classification method using only ERPs features, classification with high gamma feature showed an average increase of over 8% ($p<0.05$, paired t-test).

The frequency range and time course of the high gamma responses were similar to characteristics reported in [18]. Also, the observed intracranial ERPs were also consistent with previous ECoG studies on visual motion processing [22]. However, here we further extended their findings, showing that these responses can be modulated by overt attention, thus allowing BCI controls.

To investigate whether high gamma responses had independent contribution for BCI classification, we further analyzed the independence of ERP and high gamma features. Fig. 5 shows that the two features contributed somehow independently, as the optimal classification boundary was likely to be the diagonal of the two-dimension feature space. Considering the different time course of the ERP and high gamma feature, they might reflect different brain mechanisms for processing the attended visual motion stimuli.

EEG studies on visual motion processing has already suggested that the recorded mVEPs (especially the N200 component) might originate from hMT+ [5], which was a relatively small brain region. As here we found that both ERP and high gamma responses showed high task specificities in a very localized area (Fig. 3), the recorded responses were likely to be from the hMT+ as well. One remaining issue is how to determine the spatial location of the single subdural electrode for BCI classification. As high gamma activity has been reported to be spatially correlated with fMRI BOLD responses [23-24], it may be possible to determine the location of the single electrode for BCI application using non-invasive imaging technology, prior to the implantation surgery. Nevertheless, the highly localized brain responses shed lights on the practicability of the ECoG based N200 speller: only a small brain region and a single subdural electrode may provide sufficient information for operating an N200 speller, therefore a minimally invasive BCI can potentially be achieved.

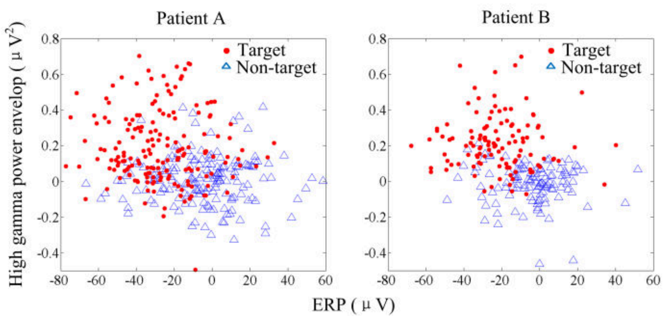

Figure 5. Target and non-target samples marked by the amplitudes of ERP (N200) and high gamma power envelop

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