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Usability of EEG Cortical Currents in Classification of Vowel Speech Imagery

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***Abstract*—With the purpose of providing assistive technology for the communication impaired, we propose a new approach for speech prostheses using vowel speech imagery. Using a hierarchical Bayesian method, electroencephalography (EEG) cortical currents were estimated using EEG signals recorded from three healthy subjects during the performance of three tasks, imaginary speech of vowels /a/ and /u/, and a no imagery state as control. The 3-task classification using a sparse logistic regression method with variational approximation (SLR-VAR) revealed that mean classification accuracy of cortical currents was almost two times greater than chance level and significantly higher than that using EEG signals. The results suggest the possibility of using EEG cortical currents to discriminate multiple syllables by improving the spatial discrimination of EEG.**

Keywords-component; BCI; EEG; Inverse Problem; speech;

I. Introduction

Among brain-computer interfaces (BCIs) which can be used as a means of communication for handicapped individuals, a few studies have attempted to discriminate differences in brain activity during syllable phonation [1] or vowel imagery [2]. In [2], pairwise classification of imagined vowels, /a/ and /u/, and a no imagery state, resulted in classification accuracies ranging from 68 to 78% using EEG signals. To further improve practical applicability, multi-class discrimination is necessary. However, EEG might be insufficient for classifying multiple syllables due to its inherent low spatial discrimination. In this study, we examined the possibility of using EEG cortical currents isolated from EEG sensor signals. Thousands of cortical currents were estimated using a hierarchical Bayesian inverse method that solves an inverse problem by incorporating functional magnetic resonance imaging (fMRI) activity as a hierarchical prior [3]. Performing multi-class discrimination of 3 imagery states, /a/, /u/, and a no imagery state, and using a sparse logistic regression with variational approximation (SLR-VAR) [4], vowel-classification accuracy using cortical currents was found to be higher than that using EEG sensor signals.

II. Methods

A. Paradigm and Data Collection

Three healthy subjects, 1 female and 2 male, participated in the study. The experiment was performed in accordance with protocol approved by a local ethics committee of the National Center of Neurology and Psychiatry, and all subjects gave written informed consent.

Subjects were instructed to perform one of three tasks on appearance of a visual cue: 1) /a/, i.e. task /a/ with imagined mouth opening for pronouncing vowel /a/, 2) /u/, i.e. task /u/ with imagined lip rounding for pronouncing vowel /u/, and 3) /+/, i.e. control task with no imagery. The vowels /a/ and /u/ were chosen due to their dissimilar muscle activations during real speech production [5].

For EEG recordings, one trial consisted of 3 periods: pre-task (2-3 s), task (2 s) and rest (3 s) periods. Eye-blinking was allowed only during the rest period. 50 trials were performed for each task in random order, resulting in a total of 150 trials per subject. EEG signals were recorded using a 32 channel BioSemi ActiveTwo system with a sampling rate of 512 Hz. Recorded data were downsampled to 256 Hz and zero-phase band-pass filtered at a range of 1-45 Hz. 50 epochs per task were extracted in reference to task onset. Each epoch had a duration of 3 s, 1 s of pre-onset and 2 s of post-onset. The epoch data were used for cortical current estimation.

An fMRI experiment was also conducted to identify brain activation areas and intensities for use as hierarchical priors

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when estimating cortical currents from EEG signals with a hierarchical Bayesian method [3]. A session was composed of alternating periods of imagery (3 s) and rest (7-11 s) periods. Subjects performed each task 20 times in random order. fMRI data were acquired with a T2*-weighted gradient-echo echoplanar imaging (EPI) sequence (repetition time = 2 s; echo time = 30ms; flip angle = 90˚; voxel size = 3 x 3 x 3 mm) using a 3-T Magnetom Trio MRI scanner. In total, 374 volumes were acquired. T1-weighted structural images were also acquired with 1 x 1 x 1 mm resolution with a magnetization-prepared rapid gradient-echo sequence.

B. Cortical Current Estimation using a Hierarchical Bayesian Method

EEG cortical currents were estimated using a hierarchical Bayesian method described in [3]. For each subject, we estimated approximately 2,900 (mean: 2,936, SD: 99) current dipoles on the cortical surface, which were distributed within regions of interests (ROIs) consisting of Brodmann areas 1, 2, 3, 4, 6, 9, 22, 39, 40, 41, 42, 44 and 45 relating to speech-related brain activity [1]. *t*-values of fMRI statistical maps obtained from SPM5 software were used as current amplitude priors for the current dipoles in the ROIs. The method calculates an inverse filter to estimate the cortical current for each dipole from EEG sensor signals. The inverse filter was estimated using all trial data of each task, and the filter was applied to sensor signals in each trial to calculate cortical currents.

C. Classification

We chose a SLR-VAR classifier from the Sparse Logistic Regression toolbox (SLR toolbox) [4] in consideration of computational speed and memory requirements. With SLR, we are able to automatically select relevant currents while estimating their weight parameters for classification. Furthermore, this method is applicable in higher-dimensional classification problems because the weight parameters are learned in a sparse way.

EEG sensor signals and cortical currents were low-pass filtered with a cut-off frequency of 10 Hz followed by downsampling by a factor of 16. Classification was performed using data ranging from -250 ms to 500 ms in reference to task onset, i.e. 25 time points at an interval of 750 ms. We then divided the data into training (40 epochs) and testing (10 epochs) subsets to perform a 5x5-fold cross validation.

III. Results and Discussion

Fig. 1 compares mean accuracies using EEG sensor signals and cortical currents in a 3-task classification for 3 subjects. Both accuracies were above chance level of 33.3%, and cortical currents showed a significantly higher accuracy of 61.2% in comparison to 49.9% using EEG sensors (paired t-test, $p<0.05$).

Mean numbers of sensors and currents selected by SLR-VAR, shown in Table 1, did not vary greatly between the two methods even though the original number of currents was much larger than the number of EEG sensors. This suggests that only currents which highly contributed to vowel imagery were used for classification. In fact, most of the selected current sources

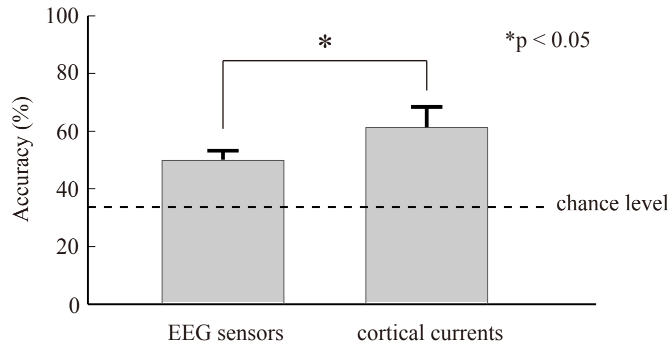

Figure 1. Mean accuracies with standard deviations for 3-task classification of /a/, /u/, and control. In comparison to EEG sensors, cortical currents showed a significantly higher accuracy at almost twice chance level.

TABLE I. MEAN NUMBER OF SENSORS AND CURRENTS SELECTED BY SLR-VAR IN CROSS-VALIDATION.

Subject	Selected numbers by SLR-VAR		*Original number of currents*
	EEG sensors [a]	*Currents*	
S1	21	18	2829
S2	25	33	3024
S3	24	33	2956

a. Original number of EEG sensors was 32

were distributed within reasonable areas for the experimental tasks of mouth movement imagery, such as the supra-marginal gyrus related to body-part recognition, Wernicke's area, the somatosensory area, and the motor area. On the other hand, EEG sensors were selected from broad areas of the brain. The results suggest that localization of EEG current sources and isolation of cortical currents from EEG sensor signals are effective for classifying differences in brain activity during different vowel imagery tasks. In future work, if we can identify syllable-specific current sources by classifying additional vowels or syllables, we believe that this approach will have significant potential as a BCI-based speech prosthesis for helping disabled people regain an improved quality of life through silent communication.

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