9th International IEEE EMBS Conference on Neural Engineering
San Francisco, CA, USA, March 20 - 23 , 2019

Bi-directional Visual Motion Based BCI Speller

Dingkun Liu, Chang Liu, and Bo Hong, *Member, IEEE*

***Abstract*— Motion-onset visual evoked potential (mVEP) has been successfully used for spelling in both EEG and intracranial EEG based brain-computer interface (BCI). However, its speed is relatively slow compared to P300 and SSVEP paradigms. In order to improve the speed, we proposed a novel bi-directional (leftward and rightward) visual motion BCI paradigm, which decreased the stimulus presentation time of single trial by 50%. Offline experiments were conducted on 5 subjects, which revealed a unique symmetrical spatial and temporal mVEP pattern. The N200 peak of mVEP first appeared on the hemisphere contralateral to the visual motion onset position of stimuli, which reflected the hemisphere transmission delay caused by the optic chiasm. Based on this observation, we developed a BCI system capable of discriminating not only target mVEP responses from non-target ones, but also response to leftward motion from rightward ones. Our new system achieved an averaged AUC 0.93 ± 0.044 in BCI classification, and an information transfer rate (ITR) boost of $43 \pm 16\%$ over original uni-directional mVEP BCI in offline evaluation. The results demonstrated the capacity of bi-directional visual motion paradigm in doubling the BCI spelling speed, and laid the foundation for a high speed online visual motion BCI.**

I. INTRODUCTION

Visual motion evoked potentials (mVEPs) based BCI speller (also known as N200 speller) is a well established non-flashing visual BCI paradigm utilizing the overt attention modulation effects on mVEP[1][2]. N200 BCI speller has been implemented in both EEG[2] and intracranial EEG (iEEG)[3], and been developed into a practical BCI system with extra non-control state detection[4]. Compared to SSVEP based BCI system, it is more comfortable for users since its non-flashing characteristics. And compared to P300 paradigm, the responses of visual motion stimuli are local and stable. However, its relative low BCI speed has been dragging down its development. With smart stopping algorithm, mVEP based BCI reached an information transfer rate (ITR) to 50.2 bits/min with iEEG electrodes[5]. But the speed was still unsatisfactory compared to P300 and SSVEP paradigms. New approaches need to be developed to elevate its speed to a comparable level of other visual BCI, while keeping its advantage of non-flashing stimulus.

Preview studies have explored the directional modulation effects on cortical response to visual motion stimulus. Kamitani et al. successfully decoded moving dots in 8 different directions with fMRI BOLD signals from visual pathway, including V1-V4 and MT[6]. Meanwhile, Mercier et al. demonstrated that differential extrastriate activation at around 200 ms after visual motion onset accounted for different mVEPs generated by visual motion stimuli of different directions[7].

Inspired by these results, we postulated that direction of visual motion could be employed as an additional dimension to encode BCI speller targets. In this study, a novel bi-directional mVEP BCI paradigm was proposed and tested on 5 subjects. The offline analysis revealed a unique and distinguishable symmetrical spatial and temporal mVEP pattern, which supported an averaged ITR boost of 0.43 ± 0.16 over the original uni-directional visual motion BCI.

II. METHODS

A. Experimental Setup

In order to shorten the stimulus presentation time and to speed up the mVEP BCI system (also known as N200 speller), we proposed a new bi-directional visual motion paradigm on the basis of the original uni-directional one. The visual stimuli, with viewing distance of 50 cm, were displayed on a 23-inch LCD monitor with 60 Hz refresh rate and 1920×1080 resolution. 6×6 rectangle virtual buttons were placed uniformly on the speller interface (Fig.1a). For leftward stimulus, a vertical bar moved from the right border of rectangle virtual button and stoped at $1/3$ width from the left border and then disappeared. Similarly, for rightward stimulus, the bar moved from the left and stoped at $1/3$ width to the right. In one epoch, two lines (row or column) of bars, typically three lines apart, moved simultaneously in different directions for 150 ms. The intervals between epochs are 50 ms(Fig.1b). One complete trial consists of 6 different epochs, with 3 for rows and 3 for columns. For the first to third row/column, the bars are moving leftward, while moving rightward for the forth to sixth row/column. In this way, the 6×6 speller can be divided into four quadrants with combination of different directional stimuli (e.g. targets in the second quadrants, which lies in the 1-3 rows and the 4-6 columns, were encoded by row and column stimuli leftward and rightward respectively). In this way, the stimulus presentation time of each trial were reduced to 1200ms, which is half of the original uni-directional visual motion paradigm. The software for online stimulus display was developed with Psychopy[8].

During the experiment, subjects were required to gaze at the letter showing in the center of the target virtual buttons, and in the meantime distinguish colors of moving bars appeared inside the attended target. 12 virtual buttons on the diagonal and counter-diagonal were sequentially assigned as attended targets (”AHOV29FKPUZ4”). Each target was repeated for 10 times as one block.

*This work was supported by National Science Foundation of China (NSFC grant 61473169).

D. Liu, C. Liu and B. Hong are with the Dept. of Biomedical Engineering, School of Medicine, Tsinghua University, Beijing 100084, China. Email: hongbo@tsinghua.edu.cn

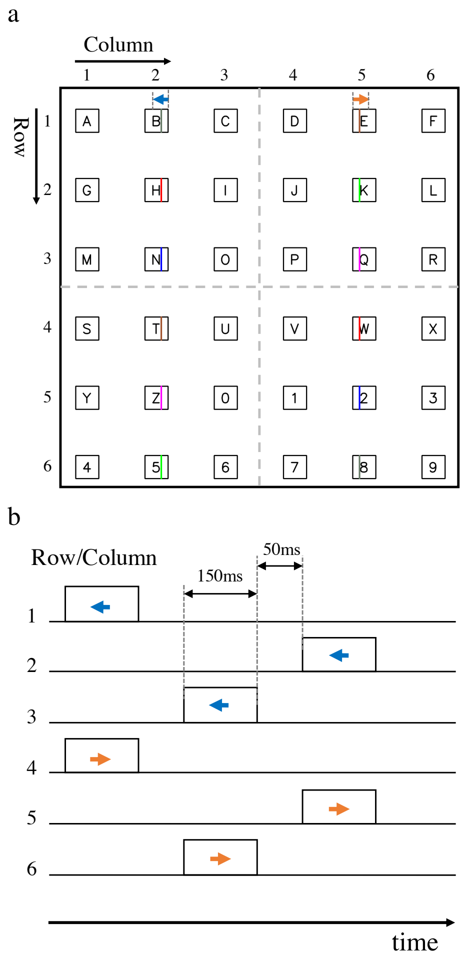

Fig. 1: Bi-directional visual motion paradigm (Leftward in blue and rightward in orange). (a) N200 speller interface. (b) Temporal scheme of visual-motion stimulus presentation.

B. Subjects and Data Recording

Five male volunteers aged 20-24 were recruited to participate the study. All subjects gave informed consent and were paid for their participation. Each subject showed normal or corrected to normal eyesight, without clinical visual disease. The EEG data were recorded from 8 electrodes using an wireless EEG amplifier(NeusenW, Neuracle Inc.), following the international 10-20 system. Electrode P7, P8, P3, P4, Pz, O1, O2 and Oz were selected in this study, with CPz and AFz chosen as REF and GND respectively. In order to visualize spatial pattern from the whole scalp, 64-channel wireless EEG (NeusenW, Neuracle Inc.) were also employed to collect data for subject S2. All electrodes' impedance were reduced to 10 $k\Omega$ before data recording. Signals were sampled at 1000 Hz. Trigger events were acquired simultaneously with stimulation onset.

C. Data Processing and BCI Classification

First, data were digitally filtered with a 200 order FIR bandpass filter (pass band 1-20 Hz[5]) to minimize high frequency noise. Independent component analysis(ICA) was applied to remove EOG artifacts[9]. The raw signals were decomposed to 25 independent components. The first component located on the prefrontal area and showed strange variances between epochs compared to normal EEG was set to zero. EEG epochs were derived according to the onset time of each stimulus, from 300 ms prior to the stimulus onset to 600 ms after. Then, linear detrending was made to minimize DC drifts. Next, baseline correction was applied by subtracting mean value of 300 ms preceding motion onset. Finally, epoch data were downsampled to 40 Hz and all 8 channels in the time window of 0-500 ms were concatenated together to form a 200-dimension feature vector. For each trial, there are two target epochs for leftward or rightward stimuli and four non-targets.

Logistic regression classifier plus "OVR" strategy were adopted to discriminate leftward, rightward and non-target stimuli. Like usual N200 paradigm based BCI system, average over trials is needed in most times. But during online experiments, the time of average is undetermined, so that we will need a series classifiers trained with data averaged with different times. So, here we adopted a method that averaged predictions of several single epoch data together to replace directly averaging over data, so that we could train one single classifier with single epoch data and used it with any average times during online phase. The classifier was trained with single epoch data, while predictions of the classifier were averaged with their n (2 or 3) neighboring epochs (same class) during validation. The trained model was evaluated with 20-fold validation, whose training and validation sets were uniformly sampled from each class of original data.

All data analyses were carried out using Python (Python Software Foundation) with Numpy[10], Scipy[11], Scikit-learn[12] and MNE[13].

III. Result

A. Temporal Pattern of Bi-directional Visual Motion Response

To implement a bi-directional visual motion BCI, two requirements need to be met: 1) Both leftward and rightward target stimuli are able to evoke distinguishable brain response over non-target stimuli; 2) Patterns of leftward and rightward target stimuli responses themselves are discriminable. Fig.2 showed averaged ERP waveform of bi-directional visual motion stimuli from subject S1. Since the 200 ms regular interval bar-moving induced a relatively strong SSVEP of 5 Hz, target response were subtracted by averaged non-target response to better present ERP waveform in Fig.2. Clustering permutation test[14] was applied to each channel to find the time window in which leftward and rightward stimuli responses were significantly different (shadowed area in Fig.2 indicates $p < 0.05$).

Responses of leftward, rightward and non-target stimuli showed differences on both amplitude and phase. On the one hand, both hemisphere revealed prominent N200 components, with electrodes on the left side(P3, P7 and O1) showing larger amplitude than the right hemisphere electrodes (P4, P8 and O2). On the other hand, a phase delay between mVEP of two directions was clearly observed, which was further clarified by estimating local maximum of cross correlation function between leftward and rightward mVEP response of each channel. Leftward mVEP response(blue lines) was 46 ± 18.5 ms ahead of rightward ones(orange lines) on the left hemisphere. On the contrary, rightward mVEP advanced for 73 ± 13.4 ms on the right hemisphere.

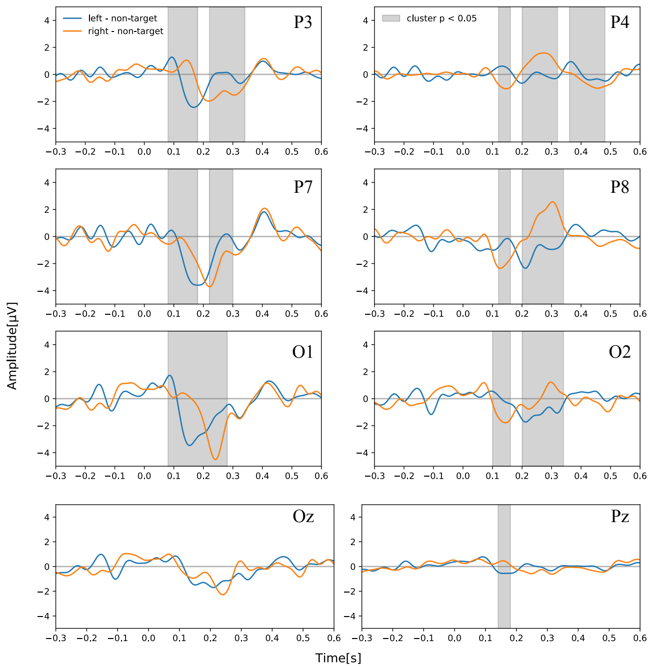

Fig. 2: Temporal pattern of bi-directional visual motion paradigm. Blue lines represented leftward target responses subtracted by non-target responses, while orange lines represented rightward minus non-target. The gray lines ($y = 0$) were a baseline. Gray shadows indicated regions where leftward and rightward target responses were significantly different($p < 0.05$) under clustering permutation F-test[14].

The above symmetric delay between responses to leftward and rightward stimuli could be explained by their relative positions in the field of view. Since the subject was asked to gaze at the center of the target button, the leftward moving bar started from the right visual field, causing a quicker response on the left hemisphere because of the fiber crossing at optic chiasm. And similarly, rightward stimuli responses appeared earlier on the right hemisphere.

B. Spatial Pattern of Bi-directional Visual Motion Response

Besides temporal pattern discussed above, spatial pattern of bi-directional mVEPs of subject S2 (Fig.3) further supported the assumption that differences between leftward and rightward stimuli were caused by their position in the field of view.

The time window of 150-250 ms and 250-350 ms after visual motion onset were selected to compute mean amplitude of N200 (Negative peak at around 200 ms after stimulus onset) and P300 (Positive peak at around 300 ms after stimulus onset) respectively. For leftward stimuli(Fig. 3a3), the N200 components were biased to the left hemisphere, while the rightward stimuli (Fig.3b3) were the opposite. For leftward visual motion stimuli, channels on the left hemisphere (P3, P7, O1) had significantly stronger N200 than channels on the right hemisphere (P4, P8, O2) (T-Test, $p = 3.73 \times 10^{-7}$). Meanwhile, for rightward stimuli responses, the N200 components were dominant on the right hemisphere (T-Test, $p = 5.85 \times 10^{-3}$).

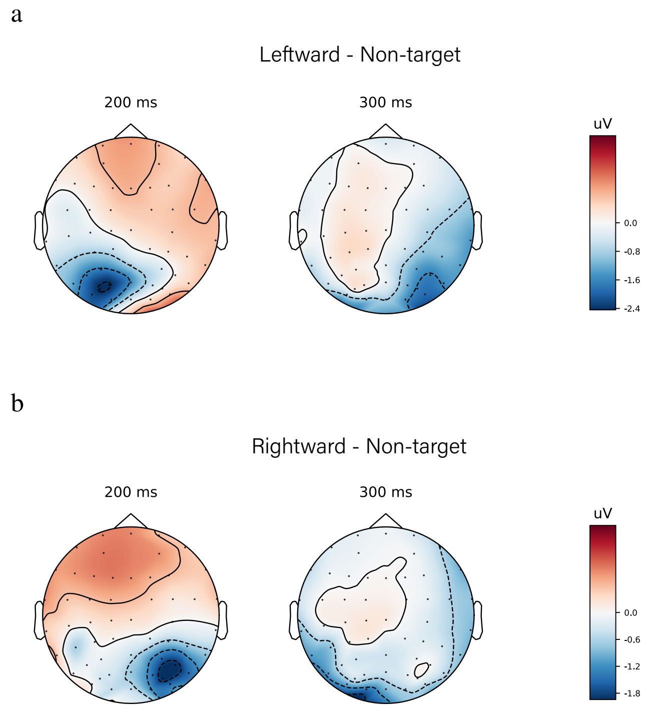

Fig. 3: Spatial pattern of bi-directional mVEPs of subject S2. (a) Scalp topomap of mean response amplitude of leftward N200 and P300 subtracted by non-target response. (b) Scalp topomap of mean response amplitude of rightward N200 and P300 subtracted by non-target response.

C. Performance of Offline Bi-directional mVEP Speller

Based on the ERP analyses above, we believed that bi-directional visual motion paradigm was capable of supporting a faster BCI spelling than original uni-directional one. Thus, offline BCI classification were made to evaluate the new paradigm's performance on BCI spelling.

The classifier's performance was evaluated with AUC (Area under the ROC curve, see Equation.1, where T is the threshold of the classifier, TPR is for the true positive rate and FPR for false positive rate.)

$$AUC = \int_{\infty}^{-\infty} TPR(T)FPR^{'}(T)dT \qquad (1)$$

The speed of BCI was estimated by Information Transfer Rate (ITR, bits/min, see Equation.2, where N is the number of possible choices in one trial, P ($1/N < P < 1$) is the accuracy of the selection, and t is the average time of one single trial. [15]). As discussed above(sec.II-C), the classifier was trained with single epoch data and the predictions were averaged two times with their same class neighbors.

$$ITR = [log_2(N) + Plog_2(P) + (1-P)log_2(\frac{1-P}{N-1})]/t \quad (2)$$

Fig.4a shows the ROC curve for subject S1, with $\overline{AUC} = 0.9905 \pm 0.0008$. All three curves in Fig.4(a) representing ”leftward stimuli responses versus rest”, ”rightward stimuli responses versus rest” and ”non-target responses versus rest” had AUC above 0.98. All 5 subjects in this study had AUC ($\overline{AUC} = 0.93 \pm 0.044$) significantly higher than chance level ($AUC = 0.5$) (Fig.4b upper panel), which proved the trained classifier’s validity.

Fig.4b (lower panel) shows ITRs of each subject. For ITR calculation, t in Equation.2 was $2 \times 200ms$ since $n = 2$ average was used here. And N was 3 for there were three different choices (leftward, rightward and non-target) in one single trial. To simplify comparison between ITR of bi-directional paradigm and uni-directional one, only single epoch ITR was used and compared in this study. Treating P in Equation.2 equaled to 1, we could obtain the theoretical ITR ratio between bi-directional and uni-directional paradigm ($\frac{ITR_{bi}}{ITR_{uni}} = \frac{log_2 3}{log_2 2} \approx 1.58$). In current study, the real mean ITR ratio of all 5 subjects was 1.43 ± 0.16, which was very close to the theoretical value. Moreover, the fact that the ITR ratio was significantly greater than one well supported the speed superiority of the bi-directional visual motion BCI.

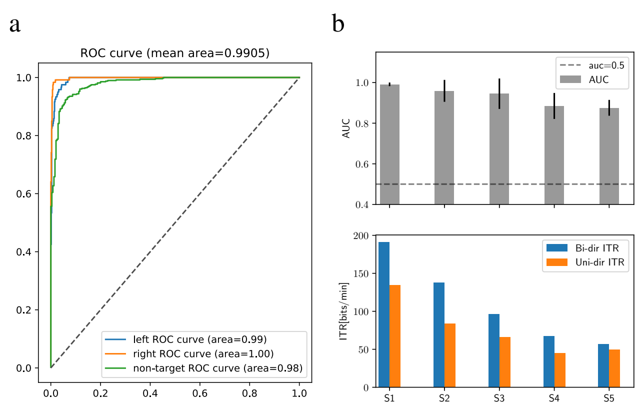

Fig. 4: Performance of Offline bi-directional N200 speller. (a) ROC curve of subject S1 for three class classification. (b) Mean AUC for all five subjects, and comparison for ITR between bi-directional and uni-directional paradigm.

IV. Discussion

The proposed bi-directional visual motion paradigm keeps the advantage of original uni-directional speller that N200 responses are reliable and local at bilateral middle temporal(MT) visual area[2][4], while overcomes its drawback of low BCI speed. The next step of our work is to build an online BCI typing system with the bi-directional visual motion paradigm. With our best subject, 1-2 trials average was sufficient, which corresponded to a spelling speed of 1.2-2.4 s/character. With accuracy above 85%, the ITR can get to approximately 95-190 bits/min. The new bi-directional visual motion paradigm has the capacity of reaching a comparable speed with SSVEP BCI, while keeping its non-flashing characteristic.

Acknowledgment

The authors would like to thank Dan Zhang and Jingjing Chen for their comments on BCI paradigm design and implementation, and Xiaoshan Huang for EEG data collection.

References

[1] F. Guo, B. Hong, X. Gao, and S. Gao, “A brain–computer interface using motion-onset visual evoked potential,” *Journal of neural engineering*, vol. 5, no. 4, p. 477, 2008.

[2] B. Hong, F. Guo, T. Liu, X. Gao, and S. Gao, “N200-speller using motion-onset visual response,” *Clinical neurophysiology*, vol. 120, no. 9, pp. 1658–1666, 2009.

[3] D. Zhang, H. Song, R. Xu, W. Zhou, Z. Ling, and B. Hong, “Toward a minimally invasive brain–computer interface using a single subdural channel: a visual speller study,” *Neuroimage*, vol. 71, pp. 30–41, 2013.

[4] D. Zhang, H. Song, H. Xu, W. Wu, S. Gao, and B. Hong, “An n200 speller integrating the spatial profile for the detection of the non-control state,” *Journal of neural engineering*, vol. 9, no. 2, p. 026016, 2012.

[5] D. Li, H. Han, X. Xu, Z. Ling, and B. Hong, “Minimally invasive brain computer interface for fast typing,” in *Neural Engineering (NER), 2017 8th International IEEE/EMBS Conference on*. IEEE, 2017, pp. 477–480.

[6] Y. Kamitani and F. Tong, “Decoding seen and attended motion directions from activity in the human visual cortex,” *Current biology*, vol. 16, no. 11, pp. 1096–1102, 2006.

[7] M. Mercier, S. Schwartz, C. M. Michel, and O. Blanke, “Motion direction tuning in human visual cortex,” *European Journal of Neuroscience*, vol. 29, no. 2, pp. 424–434, 2009.

[8] J. Peirce, “Psychophysics software in python,” *Neurosci Methods*, vol. 162, no. 1-2, pp. 8–13, 2007.

[9] T.-P. Jung, S. Makeig, C. Humphries, T.-W. Lee, M. J. Mckeown, V. Iragui, and T. J. Sejnowski, “Removing electroencephalographic artifacts by blind source separation,” *Psychophysiology*, vol. 37, no. 2, pp. 163–178, 2000.

[10] T. E. Oliphant, *Guide to NumPy*, 2nd ed. USA: CreateSpace Independent Publishing Platform, 2015.

[11] E. Jones, T. Oliphant, P. Peterson, *et al.*, “SciPy: Open source scientific tools for Python,” 2001, [Online]. [Online]. Available: http://www.scipy.org/

[12] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay, “Scikit-learn: Machine learning in Python,” *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.

[13] A. Gramfort, M. Luessi, E. Larson, D. A. Engemann, D. Strohmeier, C. Brodbeck, L. Parkkonen, and M. S. Hämäläinen, “Mne software for processing meg and eeg data,” *Neuroimage*, vol. 86, pp. 446–460, 2014.

[14] E. Maris and R. Oostenveld, “Nonparametric statistical testing of eeg-and meg-data,” *Journal of neuroscience methods*, vol. 164, no. 1, pp. 177–190, 2007.

[15] J. R. Wolpaw, N. Birbaumer, W. J. Heetderks, D. J. McFarland, P. H. Peckham, G. Schalk, E. Donchin, L. A. Quatrano, C. J. Robinson, and T. M. Vaughan, “Brain-computer interface technology: a review of the first international meeting,” *IEEE transactions on rehabilitation engineering*, vol. 8, no. 2, pp. 164–173, 2000.