Classification of visual stimuli with different spatial patterns for single-frequency, multi-class SSVEP BCI

C.-H. Han, H.-J. Hwang and C.-H. Im

A new approach for a multi-class steady-state visual-evoked potential (SSVEP)-based brain–computer interface (BCI) is proposed. It was demonstrated through preliminary experiments that spatial patterns of SSVEP responses recorded using high-density electroencephalography while presenting pattern reversal checkerboard stimuli with different spatial patterns can be classified with fairly high accuracy. The average classification accuracies in two of the three subjects were 91.7% (12-class) and 93.3% (15-class), suggesting that the proposed visual stimulation can potentially be used for multi-class SSVEP-based BCI.

Introduction: The brain–computer interface (BCI) can provide paralysed individuals with a direct communication channel between the brain and the external world [1]. Among the various brain signals used to realise electroencephalogram (EEG)-based BCIs, steady-state visual-evoked potential (SSVEP) has received increasing attention because it can provide a high information transfer rate and generally requires little user training, compared with the BCIs based on the other brain signals [2, 3].

The SSVEP response is evoked by a visual stimulus flickering or reversing with a certain frequency. In the conventional multi-class SSVEP-based BCI studies, different flickering frequencies have been used to generate the corresponding number of commands. However, the number of available frequencies is often restricted, especially when a computer monitor is used to present the visual stimuli [2]. This is because (i) the stimulation frequencies have to be the sub-harmonics of the monitor refresh rate for accurate SSVEP detection, (ii) frequencies that elicit strong SSVEP responses are dependent on the participants and (iii) it has been known that the alpha band (8–13 Hz) should be carefully selected because its use can cause a larger number of false positives. For these reasons, increasing the number of visual stimuli with a limited number of stimulation frequencies has been a challenging issue in BCI.

Previous studies have introduced methods to increase the number of visual stimuli with fewer stimulation frequencies [4–6]. Theoretically, these methods could generate ${}_NC_2$ (Shyu *et al.* [4]), ${}_NC_2 + N$ (Hwang *et al.* [5]) and N^2 (Zhang *et al.*[6]) stimuli using N different flickering frequencies. These approaches could increase the number of visual stimuli, but they still require a considerable number of stimulation frequencies.

In the work reported in this Letter, we investigated whether visual stimuli with a variety of spatial patterns and a single reversing frequency could be classified from a high-density EEG recording. In our preliminary study, EEG signals were recorded while three participants were gazing at 200 visual stimuli with randomly generated spatial patterns. To decode the visual patterns from the EEG signals, an artificial neural network (ANN) was used. We estimated the cross-correlation between the original and the decoded visual patterns, which was then used for the classification. To verify the proposed approach, we conducted realistic simulations, for which distorted SSVEP responses were used as the test datasets.

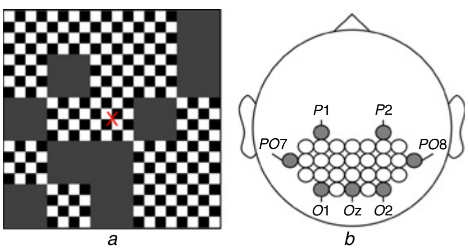

Fig. 1 *Experimental conditions*
a Example of randomly generated visual stimuli
b Electrode configuration used for EEG recording

Experimental conditions: A total of 200 different visual patterns were randomly generated in a 5 × 5 square matrix by placing a 4 × 4 black–white checkerboard pattern in each of the randomly selected elements. Fig. 1*a* shows an example of the visual stimuli. The checkerboard pattern was modulated at a reversing frequency of 6 Hz to evoke SSVEP at the corresponding frequency (6 Hz). A fixation cross was used to prevent the participants from moving their eyes during the experiments.

Three participants (all males; 25, 26 and 27 years) took part in this study. They were asked to gaze at the fixation cross for 6 s. The visual angle of each stimulus was set to 5.7° × 5.7°. Each session consisted of 20 trials, and a total of 10 sessions were conducted with each participant. The inter-trial interval was randomly set to 2–3 s, and the participants took a rest for 5–10 min between sessions. EEG signals were recorded from 30 electrodes densely attached on the participants' occipital areas (Fig. 1*b*). The reference and the ground electrodes were placed behind the right and left ears, respectively. The EEG signals were sampled at 512 Hz, and an anti-aliasing bandpass filter with cutoff frequencies of 0.7 and 50 Hz was applied.

Construction of ANN model: The SSVEP amplitudes at the modulation frequency (6 Hz) were calculated for all the electrodes and for all the visual stimuli using fast Fourier transform. The SSVEP amplitude of each electrode was then normalised with respect to the mean of all the electrodes for each trial. We then constructed an ANN model with 30 input nodes corresponding to the normalised SSVEP amplitudes of the 30 electrodes and with 25 output nodes corresponding to a 5 × 5 matrix-shape visual pattern. Either +1 or −1 was assigned to each output node: +1 was assigned to an element with the reversing checkerboard pattern and −1 was assigned to an element filled with a black background. A single hidden layer consisting of 40 nodes was used, and the weights of the network were trained using the 'train()' function implemented in the neural network toolbox of MATLAB 2009a (The MathWorks Inc., Natick, MA, USA). The ANN model was constructed using the normalised SSVEP amplitudes at the 30 electrodes and the corresponding visual patterns (coded with +1 and −1) from all the 200 trials. To improve the network generalisation as well as to avoid over-fitting, an early-stopping method was applied [7].

Estimation of visual patterns under no-noise condition: After the construction of an ANN model, we first tested whether the constructed model could accurately decode the presented visual stimulus patterns from the spatial distributions of the SSVEP amplitudes. The 200 normalised SSVEP patterns were fed again to the constructed ANN model, and their output visual patterns were also quantised to be either +1 or −1 by multiplying the output values with a Signum function. Then, the cross-correlations between each decoded visual pattern and the 200 original visual patterns were evaluated, and the visual pattern showing the highest correlation with the predicted pattern was selected. The classification accuracy was evaluated by determining whether the predicted visual patterns matched the original patterns. Basically, this simulation assumed that identical SSVEP responses would be generated for the same visual stimulus, which is not the case in practice.

Estimation of visual patterns under realistic conditions: To be more realistic, we tested the constructed ANN model with perturbed SSVEP responses to verify whether the proposed approach could be used in realistic scenarios. To generate the perturbed SSVEP responses, the test–retest variability of SSVEP amplitudes was estimated by presenting the same visual stimulus (Fig. 1*a*) to a participant (subject 1) repeatedly in 10 different trials. Then, the normalised SSVEP responses were evaluated for each of the 10 repeated recordings. The standard deviation of the 10 normalised SSVEP responses was 7.64% with respect to the mean SSVEP responses. Based on this, we generated 200 perturbed SSVEP responses by adding random Gaussian white noise with a standard deviation of 7.64% to the original 200 normalised SSVEP responses of each channel. The perturbed SSVEP responses were fed into the ANN model that was created using the original SSVEP responses, and then the decoding accuracy was estimated using the same correlation-based method that was used for the no-noise condition tests. This 'perturbing-testing' procedure was repeated 10 times for each participant. Visual stimuli with decoding accuracies of over 70% were then selected. The same decoding procedure was repeated using only the selected visual stimuli (the decoded patterns were compared only with the selected patterns).

Results: Fig. 2 shows examples of the normalised SSVEP responses evoked by different visual patterns, from which it was confirmed that different visual patterns could generate different spatial distributions of SSVEP responses due to the retinotopic characteristics of V1 [8, 9].

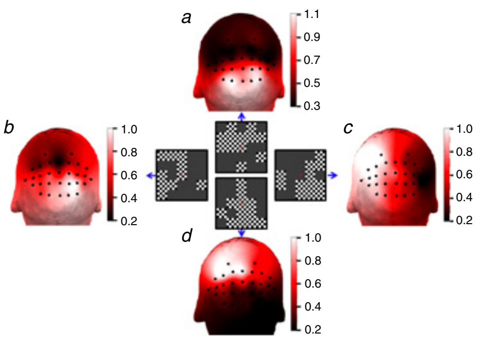

Fig. 2 *Examples of topographical distributions of SSVEP responses*

Fig. 3 shows the cross-correlation between the 200 original visual patterns and those decoded from the corresponding SSVEP responses without any perturbation. The average cross-correlations between the original and the decoded visual patterns were 0.54, 0.47 and 0.41 for subjects 1, 2 and 3, respectively. The average classification accuracies of the three experiments were 59.5% (= 119/200), 55.5% (= 111/200) and 30% (= 60/200). We then evaluated the classification accuracy for each visual pattern from 10 repeated realistic simulations with perturbed SSVEP responses. The numbers of visual stimuli correctly classified with over 70% accuracy were 12, 15 and 0 out of the 200 visual patterns.

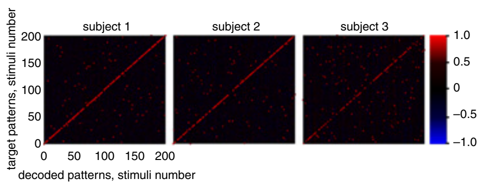

Fig. 3 *Cross-correlation between original and decoded patterns*

Table 1 shows the results of the second simulation test performed with only the selected visual patterns that were correctly decoded with over 70% accuracy. Subject 3 was excluded in this test because the subject had no visual patterns that were correctly decoded with over 70% accuracy. All the classification accuracies in each of the 10 virtual trials with differently perturbed SSVEP responses were high enough (> 80%) to be applied to practical BCI systems, and the average accuracies were reported to be 91.7% for subject 1 and 93.3% for subject 2.

Table 1: Classification accuracy (%) for 10 trials (*S*1 and *S*2: subjects)

Trials	1	2	3	4	5	6	7	8	9	10	Avg.
*S*1	83	92	92	100	100	92	92	83	83	100	91.7
*S*2	93	87	100	87	93	100	93	100	87	93	93.3

Conclusion: In this preliminary study, we investigated whether visual stimuli with different spatial patterns flickering at a single frequency could be classified from the SSVEP responses recorded at electrodes that were densely located around the occipital area. Simulation studies using perturbed SSVEP responses showed a high classification accuracy in two out of three participants (91.7% in the 12-class classification and 93.3% in the 15-class classification), demonstrating that single-frequency modulation of different spatial patterns could potentially be used for a multi-class SSVEP-based BCI system. In future studies, we plan to apply our approach to develop online multi-class BCI systems.

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One or more of the Figures in this Letter are available in colour online.

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References

1 Wolpaw, J.R., Birbaumer, N., McFarland, D.J., Pfurtscheller, G., and Vaughan, T.M.: 'Brain-computer interfaces for communication and control', *Clin. Neurophysiol.*, 2002, **113**, (6), pp. 767–791
2 Hwang, H.J., *et al.*: 'Development of an SSVEP-based BCI spelling system adopting a QWERTY-style LED keyboard', *J. Neurosci. Meth.*, 2012, **208**, (1), pp. 59–65
3 Vialatte, F.B., Maurice, M., Dauwels, J., and Cichocki, A.: 'Steady-state visually evoked potentials: focus on essential paradigms and future perspectives', *Prog. Neurobiol.*, 2010, **90**, (4), pp. 418–438
4 Shyu, K.K., Lee, P.L., Liu, Y.J., and Sie, J.J.: 'Dual-frequency steady-state visual evoked potential for brain computer interface', *Neurosci. Lett.*, 2010, **483**, (1), pp. 28–31
5 Hwang, H.J., Kim, D.H., Han, C.H., and Im, C.H.: 'A new dual-frequency stimulation method to increase the number of visual stimuli for multi-class SSVEP-based brain-computer interface (BCI)', *Brain Res.*, 2013, **1515**, pp. 937–950
6 Zhang, Y., Xu, P., Liu, T., Hu, J., Zhang, R., and Yao, D.: 'Multiple frequencies sequential coding for SSVEP-based brain-computer interface', *Plos One*, 2012, **7**, (3), pp. e29519
7 Caruana, R., Lawrence, S., and Giles, L.: 'Overfitting in neural nets: backpropagation, conjugate gradient, and early stopping' in Leen, T.K., Dietterich, T.G., and Tresp, V. (Eds): 'Advances in neural information processing systems' (Massachusetts Institute of Technology, Cambridge, MA, USA, 2001), pp. 402–408
8 Yan, Z., *et al.*: 'A half-field stimulation pattern for SSVEP-based brain-computer interface'. 31th Annual Int. Conf. IEEE EMBS, Minneapolis, MN, USA, 2009, pp. 6461–6464
9 Materka, A., and Byczuk, M.: 'Alternate half-field stimulation technique for SSVEP-based brain–computer interfaces', *Electron. Lett.*, 2006, **42**, (6), pp. 321–322