1-F-59 Primitive shape imagery classification from electroencephalography

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Introduction: Brain-computer interfaces (BCIs) augment traditional interfaces for human-computer interaction and provide alternative communication devices to enable the physically impaired to work. Imagined object/shape classification from electroencephalography (EEG) may lead, for example, to enhanced tools for fields such as engineering, design, and the visual arts. Evidence to support such a proposition from non-invasive neuroimaging techniques to date has mainly involved functional magnetic resonance tomography (fMRI) [1] indicating that visual perception and mental imagery show similar brain activity patterns [2] and, although the primary visual cortex has an important role in mental imagery and perception, the occipitotemporal cortex also encodes sensory, semantic and emotional properties during shape imagery [3]. Here we investigate if five imagined primitive shapes (sphere, cone, pyramid, cylinder, cube) can be classified from EEG using filter bank common spatial patterns (FBCSP) [4]. Material, Methods, and Results: Ten healthy volunteers (8 males and 2 females, aged 26-44) participated in a single session study (three runs, four blocks/run, 30 trials/block (i.e., six repetitions of five primitive shapes in random order)). Trials lasted 7s as shown in Fig. 1 and ended with an auditory tone. Thirty EEG channels were recorded with a g.BSamp EEG system using active electrodes (g.tec, Austria). [Fig.1 HERE] EEG channels with high-level noise were removed. Signals were band-pass filtered in six non-overlapped, 4Hz width bands covering the 4-40Hz frequency range. Filter bank common spatial pattern (FBCSP) based feature extraction and mutual information (MI) based feature selection methods provided input features for 2-class classification using linear discriminant analysis (LDA) for target shape versus the rest, separately. The final 5-class classification was decided by assessing the signed distance in the 2-class discriminant hyperplane for each of the five binary classifiers as shown in Fig. 1. Classifiers were trained on two runs and tested on the one unseen run (i.e., 3 fold crossvalidation). A Wilcoxon non-parametric test was used to validate the difference of DA at end of the resting period (-1s) and at the maximal peak accuracy occurring during the shape imagery task (0-3s) is significant ($p<0.001$). Fig. 1 shows the between-subject average time-varying classification accuracies with standard deviation (shaded area). Discussion: The results indicate that there is separability provided by the shape imagery and there is significantly higher accuracy compared to the ~20% chance level prior the display period with maximum accuracy reaching 34%. In [5] classification of five imagined primitive and complex shapes with 44% accuracy is reported using a 14 channel Emotiv headset. Differences in performance reported may be influenced by EEG recording (EEG in [5] appears to have different dynamics (significant mean shifts)), the study had more sessions/trials, applied ICA for noise removal and the participants had designer experience whilst our study did not. Improvement of our methods is required to achieve higher accuracy rate. It is unclear if an online feedback to shape imagery training and learning will an impact performance - a multisession online study with feedback is the next step in this research. Significance: To best of our knowledge this is only the second study of shape imagery classification from EEG. Acknowledgement: supported by the UK EPSRC grant nos. EP/M01214X/1 and EP/M012123/1 References [1] T. Horikawa and Y. Kamitani, "Generic decoding of seen and imagined objects using hierarchical visual features," Nat. Commun., vol. 8, no. May, pp. 1-15, 2015. [2] G. Ganis, W. L. Thompson, and S. M. Kosslyn, "Brain areas underlying visual mental imagery and visual perception: An fMRI study," Cogn. Brain Res., vol. 20, no. 2, pp. 226-241, 2004. [3] D. J. Mitchell and R. Cusack, "Semantic and emotional content of imagined representations in human occipitotemporal cortex.," Sci. Rep., vol. 6, no. December 2015, p. 20232, 2016. [4] Kai Keng Ang, Zheng Yang Chin, Haihong Zhang, and Cuntai Guan, "Filter Bank Common Spatial Pattern (FBCSP) in Brain- Computer Interface," 2008 IEEE Int. Jt. Conf. Neural Networks, pp. 2390-2397, 2008. [5] E. T. Esfahani and V. Sundararajan, "Classification of primitive shapes using brain-computer interfaces," CAD Comput. Aided Des., vol. 44, no. 10, pp. 1011-1019, 2012.