BRAIN CONTROLLED ROBOTIC PLATFORM USING STEADY STATE VISUAL EVOKED POTENTIALS ACQUIRED BY EEG

S. Dasgupta, M. Fanton, J. Pham, M. Willard, H. Nezamfar, B. Shafai, D. Erdogmus

Cognitive Systems Laboratory, ECE Department, Northeastern University, Boston, MA

ABSTRACT

This paper describes a capstone design project by four undergraduate students (first four authors listed in alphabetical order by last name). A noninvasive brain computer interface (BCI) based on the steady state visual evoked potential (SSVEP) has been developed and utilized in controlling an iRobot platform remotely in real-time closed-loop fashion using video feedback from the robot's eye view to the operator over the internet. The operator selects commands by focusing gaze on one of four flickering checkerboards surrounding the video feedback window in order to navigate the robot as desired. The intended/desired control commands are sent to a laptop controlling the iRobot platform via remote wireless connection. Naive subjects are able to control and navigate the robot via the designed interface with minimal practice and classifier calibration. Typical command selection accuracy is over 95% within 4 seconds of the desired transition; most subjects are able to achieve such high accuracies with a 1 second delay.

***Index Terms*—** EEG, SSVEP, Brain Control

1. INTRODUCTION

Brain computer interfaces (BCI) have emerged as a promising new human computer interface modality in the last decade or so with the merger of various technological and theoretical developments [1]. BCI research had been divided into two primary camps: (i) invasive microelectrode array based acquisition of brain activity, which focuses on acquiring highly localized single unit spike activity from one or more cortical areas and attempting to build highly detailed neuronal response models based on basic neuroscience models such as tuning curves coupled with advanced statistical (Bayesian) dynamic recursive state estimation tools, such as particle filters [2, 3, 4, 5, 6, 7, 8, 9, 10], (ii) noninvasive electroencephalography (EEG) based acquisition of brain activity, which focuses on macroscopic responses of various cortical areas to external stimuli such as in P300-based paradigms or internal subject-induced brain activity such as motor imagery, followed by statistical pattern recognition approaches for signal detection or discrimination citeAll10, Kue05, Hua09, Tow10, Tre10, Vau06, Bin09a, Bin09b, Liu10, Luo10, Mul05, Qia10. Electrocorticography (ECOG) based BCI research had been pursued by some [23], however, not as widely as neither microelectrode array nor EEG based approaches, primarily due to the lack of access to subjects given the invasive cortical surface measurement requirements of this acquisition approach. There is also some interest in using near-infrared spectroscopy (NIRS) as a brain activity sensing modality in various brain interface contexts [24, 25, 26].

On the EEG front, typical signals that have been exploited by various groups include single- (or multi-) trial event related potentials (such as the P300 signal that is generated in response to a novel stimulus or one that matches an expected target; P3a vs P3b) [13, 14, 15, 16], motor imagery induced cortical potentials (which provide the subject to voluntarily and asynchronously generate command signals by imagining the performance of a body/limb movement) [11, 12], and steady state visual evoked potentials (SSVEP) which is the natural periodic response of the visual cortex to a periodic visual stimulus pattern [17, 18, 19, 20, 21, 22]. The latter signal is generated when the gaze of the subject is focused on a flickering visual pattern, such as a high-contrast checkerboard that oscillates between two inverted color states periodically at a predetermined frequency (typically around 5Hz-15Hz). While photosensitive seizures might be a concern for some subjects (estimated at 1 in 4000 people), in most subjects the flickering frequencies are considered safe and too low to induce such seizures - nevertheless, proper precaution must be taken and visual stimuli must be terminated immediately at first sign of a problem since there might be subjects who are unaware of their condition as such visual stimuli are unnatural and not common.

This work is supported by NSF under grants ECCS0929576, ECCS0934506, IIS0934509, IIS0914808, BCS1027724 and by NIH under grant 1R01DC009834-01. The authors also acknowledge the REU supplement provided by NSF under grant IIS0914808 that enabled the travel of the undergraduate authors to NCUR 2010 at the University of Montana. The opinions presented here are those of the authors and do not necessarily reflect the opinions of the funding agencies. Please contact Deniz Erdogmus about with inquiries about this paper.

2. METHODS

In order to exploit the strong signals generated by the visual cortex in the SSVEP paradigm, we have built a remote robot navigation interface using this approach as the basis of a brain interface and have tested the designed prototype successfully on various volunteer operators. The system consists of the following components: (i) an iRobot platform that acceptsand executes motion commands through a serial port (four commands are used in this prototype: turn left/right go forward, stop); (ii) video feedback from the robot's perspective via a webcam and Skype, (iii) visual stimulus display to induce unique frequencies in visual cortex activity corresponding to each desired command (four checkerboards flickering on the screen with periods coinciding with the monitor refresh rate and approximately at 7Hz, 9Hz, 11Hz, and 13Hz); (iv) multichannel EEG acquisition and frequency detection/classification algorithm using a g.USBamp amplifier with g.Butterfly active electrodes (G.tec, Austria). Gaze tracking is a routine technique employed for assessing the focus of attention of the subject on a screen - for instance in assistive technology applications [27]. The designed system essentially achieves gaze based selection of commands from a screen by processing visual cortex signals directly and it is estimated to be a better indicator of attention than the pupil position surrogate - this claim, however still needs to be evaluated in experiments.

The iRobot platform provides a convenient API to communicate with and control the robotic platform. A laptop is mounted on the robot and this laptop both received commands from the brain interface for the robot via remote wireless connection and transmitted to the operator's screen video feedback from the robot's perspective using a Skype video connection. The visual stimulus was in the form of 4 checkerboards (8x8 grid of black/white squares) positioned on each corner of the screen, occupying slightly less than one quarter of the monitor (typically Dell 22" widescreen LCD, but also tried stand-alone Mac monitors as well as Mac laptops of various sizes). The checkerboards have been separated by a relatively thin black + spanning the horizontal and vertical length of the monitor separating the screen into quadrants. The Skype video feedback window was overlaid on the checkerboards, centered on the screen, and occupied approximately one third of the screen area. The subject was initially positioned directly in front of the monitor at a distance of approximately 50cm; however, the subject was free to move the head and torso and reposition himself as desired to maximize comfort and change positions if desired. The checkerboard state transitions were synchronized to the retracing of the screen (60Hz) using OpenGL in order to ensure perfect periodicity.

The visual cortex activity was measured using up to 8 electrodes at 256Hz sampling rate from the occipital regions using the g.GAMMAcap positions at the back of the head around O1 & O2 sites in the International 10-20 configuration. Active g.Butterfly electrodes were used to acquire EEG activity, an acquisition driver and software written by our team from scratch was used to read the signals into a computer through a USB port. The signal from each electrode was processed by a Welch periodogram with 512 FFT points and a sliding (at 125ms intervals) window of variable length (typically set to an integer length in seconds such as 1s, 2s, 3s, or 4s) were used to estimate the energy at and around the known flickering frequencies of the checkerboards (7, 9, 11, 13 Hz and their neighboring half frequencies were monitored as features). The 12 time-frequency features were acquired for each window (8 times per second), and classified by a multiclass SVM frequency detector. The frequency decisions for all channels were then subjected to a majority vote fusion scheme in order to obtain a joint frequency selection that would then send the corresponding command to the robot to be executed. The classifiers also featured a reject option which was used when the operator focused gaze on the Skype video feedback rather than a flickering checkerboard. The reject vs frequency detector was calibrated prior to each session by asking the operator to focus gaze on each checkerboard and then the static Skype video screen sequentially for about 10 seconds each - the total calibration time in this manner usually took less than one minute.

3. RESULTS

The designed prototype brain controlled robot navigation interface has been tested on various subjects successfully. Depending on the subject and session (i.e. electrode connection and signal quality), sometimes fewer than 8 electrodes have been used. Most of the time, it has been observed that even a single electrode (specifically O1 or O2) can be sufficient to achieve 100% accuracy among 4 frequencies and reject as described above. For different subjects, the periodogram window length had varied between 1s and 4 s but all subjects we have experimented with achieved 100% correct classification with 4s windows and none needed a longer window. Of course, a longer window causes transitions between two separate commands to be delayed by up to the window length since the periodogram calculations are based on a longer window containing portions of two separate frequencies. Some subjects achieve 100% correct decision using a 1s window; we have not attempted to reduce the window length further for such subjects, but it is expected that as small as 285ms (one period of the longest flickering period corresponding to 7Hz) could work with multiple high SNR electrodes. A video demonstration of one subject operating the robot through the described brain interface platform is available here: http://www.youtube.com/watch?v=cuC0RTf1taw.

4. DISCUSSION

SSVEP paradigm is a particularly interesting BCI design approach because it requires minimal subject training and system calibration. Compared to motor imagery, which requires extensive subject training, and P300, which is not very reliable at single-trial mode and requires high level of cognitive effort (though not as much as motor imagery perhaps) from the subject, SSVEP paradigm is based purely on the sensory signal generated in the brain at an early stage and requires no effort from the subject to be generated, apart from focusing the gaze at the desired location. Of course, one could think of this system as a fancy eye tracker - however, there might be advantages to external eye tracking: the signals are measured directly from the visual cortex and while signal strength might be influenced by contrast and visual angle it occupies (depending on size on screen and distance from subject's eyes), the method does not suffer from miscalibration difficulties encountered by eye trackers that require subjects to move minimally to maintain calibration accuracy. For SSVEP-BCI the flickering patterns can be transparently embedded into the images/icons representing functions and possibly optimized in terms of contrast and frequency to be effective (generate measurable visual cortex response), safe (avoid photosensitive seizures) and comfortable (perhaps at higher frequencies that are not perceived by the user). Alternative flickering patterns are also possible. For instance m-sequences have been investigated in vision psychophysics experiments as well as BCI applications as the flickering pattern of the visual stimulus [28, 29, 30]. We have obtained initial results using m-sequence flickering sequences for checkerboard stimuli. Specifically, our recent experiments revealed that using a simple template matching classifier (i.e. a matched filter) we can achieve 99% classification accuracy using 60 or 70 training samples to create the average template for each m-sequence response (our results are submitted for publication in another venue). In our experiments, we used four separate 31-bit m-sequences with pairwise correlation coefficients less than 0.3 in amplitude. Flickering at 30 bits per second, the calibration time needed was about one minute per m-sequence. Our future work will continue to investigate these improvements as well as alternative applications; currently, we are starting to explore the application of this technique in flight simulator control and wheelchair control.

5. REFERENCES

[1] SG Mason, A Bashashati, M Fatourechi KF Navarro, GE Birch, "A Comprehensive Survey of Brain Interface Technology Designs," Annals of Bioemdical Engineering, vol. 35, no. 2, 2007.

[2] Chapin, J.K., Moxon, K.A., Markowitz, R.S., Nicolelis, M.A.L. Realtime control of a robot arm using simultaneously recorded neurons. Nature Neuroscience, 2(7):1-7, 1999.

[3] Gage GJ, Ludwig KA, Otto KJ, Ionides EL, Kipke DR, "Naive Coadaptive Cortical Control," Journal of Neural Engineering, 2(2):52-63, 2005.

[4] LR Hochberg, MD Serruya, GM Friehs, JA Mukand, M Saleh, AH Caplan, A Branner, D Chen, RD Penn, JP Donoghue, "Neuronal Ensemble Control of Prosthetic Devices by a Human with Tetraplegia," Nature, vol. 442, (7099), pp. 164-171, 2006.

[5] S.P. Kim, J.C. Sanchez, Y.N. Rao, D. Erdogmus, J.C. Principe, J.M. Carmena, M.A. Lebedev, M.A.L. Nicolelis, "A Comparison of Optimal MIMO Linear and Nonlinear Models for Brain-Machine Interfaces," Journal of Neural Engineering, vol. 3, pp. 145-161, May 2006.

[6] MA Lebedev, MA Nicolelis, "Brain Machine Interfaces: Past, Present, and Future," Trends in Neurosciences, vol. 29, no. 9, pp. 536-546, 2006.

[7] M Schreuder, B Blankertz, M Tangermann, "A New Auditory Multi-class Brain Computer Interface Paradigm: Spatial Hearing as an Informative Cue," PLoS One, 5(4):e9813, 2010.

[8] DM Taylor, SI Tillery, AB Schwartz, "Direct Cortical Control of 3D Neuroprosthetic Devices", Science, vol. 296 (5574), pp. 1829, 2002.

[9] J.C. Sanchez, D. Erdogmus, M. Nicolelis, J. Wessberg, J.C. Principe, "Interpreting Spatial and Temporal Neural Activity Through a Recurrent Neural Network Brain Machine Interface," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 13, no. 2, pp.213-219, 2005.

[10] MA Nicolelis, J Wessberg, CR Stambaugh, JD Kralik, PD Beck, M Laubach, JK Chapin, J Kim, et al., "Realtime Prediction of Hand Trajectory by Ensembles of Cortical Neurons in Primates," Nature, vol. 408, (6810), pp. 361, 2000.

[11] BZ Allison, C Brunner, V Kaiser, GR Muller-Putz, C Neuper, G Pfurtscheller, "Toward a Hybrid Brain Computer Interface based on Imagined Movement and Visual Attention," Journal of Neural Engineering, vol. 7, no. 2, 2010.

[12] Kuebler, A., Nijboer, F., Mellinger, J., Vaughan, T. M., Pawelzik, H., Schalk, G., McFarland, D. J., Birbaumer, N., Wolpaw, J. R. Patients with ALS can use sensorimotor rhythms to operate a brain-computer interface. Neurology, 64(10):1775-1777, 2005.

[13] Y. Huang, D. Erdogmus, M. Pavel, K.E. Hild II, S. Mathan, ”A Hybrid Generative/Discriminative Method for EEG Evoked Potential Detection,” Proceedings of NER 2009, pp. 283-286, Antalya, Turkey, Apr 2009.

[14] G Townsend, BK LaPallo, CB Boulay, DJ Krusienski, GE Frye, CK Hauser, NF Schwartz, TM Vaughan, JR Wolpaw, EW Sellers, ”A Novel P300-based Brain Computer Interface Stimulus Presentation Paradigm: Moving Beyond Rows and Columns,” vol. 121, no. 7, pp. 1109-1120, 2010.

[15] MS Treder, B Blankertz, ”(C)overt Attention and Visual Speller Design in an ERP-based Brain Computer Interface,” Behavioral and Brain Functions, 6(1): 28, 2010.

[16] Vaughan, T.M., McFarland, D.J., Schalk, G., Sarnacki, W.A., Krusienski, D.J., Sellers, E.W., Wolpaw, J.R. The Wadsworth BCI Research and Development Program: At Home With BCI. IEEE Trans Neur Sys Rehab Eng, 14(2):229-233, 2006.

[17] G Bin, X Gao, Y Wang, B Hong, S Gao, ”VEP-based Brain-Computer Interfaces: Time, Frequency, and Code Modulations,” IEEE Computational Intelligence Magazine, 2009.

[18] G Bin, X Gao, Z Yan, B Hong, S Gao, ”An Online Multio-channel SSVEP-based Brain Computer Interface Using a Canonical Correlation Analysis Method,” Journal of Neural Engineering, 6(4), 2009.

[19] T Liu, L Goldberg, S Gao, B Hong, ”An Online Brain Computer Interface Using Nonflashing Visual Evoked Potentials,” Journal of Neural Engineering, vol. 7, no. 3, 2010.

[20] A Luo, TJ Sullivan, ”A User Friendly SSVEP-based Brain Computer Interface Using a Time-Domain Classifier,” Journal of Neural Engineering, vol. 7, no. 2, 2010.

[21] GR Muller-Putz, R Schrerer, C Brauneis, G Pfurtscheller, ”Steady-state visual evoked potential (SSVEP)-based Communication: Impact of Harmonic Frequency Components,” Journal of Neural Engineering, vol. 2, no. 4, 2005.

[22] K Qian, P Nikolov, D Huang, DY Fei, X Chen, O Bai, ”A Motor Imagery-based Online Interactive Brain Controlled Switch: Paradigm Development and Preliminary Test,” Clinical Neurophysiology, 2010.

[23] Miller, K.J., Leuthardt, E.C., Schalk, G., Rao, R.P.N., Anderson, N., Moran, D.W., Ojemann, J.G. Spectral changes in cortical surface potentials during motor movement. Journal of Neuroscience, 27(9):2424-2427, 2007.

[24] Coyle SM, Ward TE, Markham CM. Brain-computer interface using a simplified functional near-infrared spectroscopy system. J Neural Eng. 2007 Sep;4(3):219-26.

[25] Nagaoka T, Sakatani K, Awano T, Yokose N, Hoshino T, Murata Y, Katayama Y, Ishikawa A, Eda H. Development of a new rehabilitation system based on a brain-computer interface using near-infrared spectroscopy. Adv Exp Med Biol.2010;662:497-503.

[26] Izzetoglu M, Bunce S, Izzetoglu K, Onaral B, Pourrezaei K, ”Functional Brain Imaging Using Near Infrared Technology for Cognitive Activity Assessment,” IEEE Engineering in Medicine and Biology Magazine, Special issue on on the Role of Optical Imaging in Augmented Cognition, 26(4):38-46, 2007.

[27] Donegan, M., Oosthuizen, L., Bates, R., Istance, H., Holmqvist, E., Lundalv, M., Buchholz, M., and Signorile, I., ”Report of User Trials and Usability Studies: Communication by Gaze Interaction (COGAIN),” http://www.cogain.org/w/images/1/15/COGAIN-D3.3.pdf (last accessed on 11 June 2010).

[28] Buracas GT, Boynton GM, ”Efficient Design of Event-related fMRI Experiments Using M-sequences,” Neuroimage, 16(3 Pt 1):801-813, 2002.

[29] Cohn, M., Lempel, A. ”On Fast M-Sequence Transforms,” IEEE Trans. Information Theory, vol. IT-23, pp. 135-137, 1977.

[30] Golomb S, Shift Register Sequences, San Francisco, Holden-Day, 1967.