ESANN'2009 proceedings, European Symposium on Artificial Neural Networks - Advances in Computational Intelligence and Learning. Bruges (Belgium), 22-24 April 2009, d-side publi., ISBN 2-930307-09-9.

Multiclass brain computer interface based on visual attention

Rolando Grave de Peralta Menendez [1,2] Jorge Manuel Miranda Dias [3], José Augusto Soares Prado [3], Hadi Aliakbarpour [3] and Sara Gonzalez Andino [1]

1-Electrical Neuroimaging Group, Department of Clinical Neurosciences, Geneva University Hospital, Geneva 1211, Switzerland.
2- Neurodynamics Laboratory, Department of Psychiatry and Clinical Psychobiology, University of Barcelona, Barcelona 08035, Catalonia, Spain.
3- Laboratory of Systems and Automation, IPN, Coimbra 3030, Portugal.

Abstract. Recent public demonstrations showed that a system based on imagination does not always work [1]. On the other side predicting limb movement based on scalp activity has proved to be hazardous [2] and thus other alternatives are needed. This paper describes the asynchronous Geneva-BCI based on EEG and visual attention to external stimulus able to send commands every 0.5 (or 0.25) seconds with very high (98.88%) correct classification rates and optimal (178 bits/min) theoretical bit rate. This high performance allows for the distant real time control of robots using four commands.

1 Introduction

Research on brain computer interface has been running for several decades. Despite the considerable investment of researchers in the field, the level of success achieved in converting theoretical and technical advances into clinical applications remains scarce. Thus far, no patient in a complete locked in state has been able to systematically control any of the existing devices [3].

Communication devices can be based on monitoring eye movements which can be coupled to on-screen virtual keyboards allowing patients to control his environment (e.g. lights). Not all patients are however able to control such devices because of increasing fatigue of eye movements and the lack of reliable voluntary muscle movement.

A second type of devices is based on the direct monitoring of neural activity either invasively (spikes/LFP/ECoG) or non-invasively (EEG or MEG). Four types of signals, three based on EEG activity and one on MEG activity, have been more thoroughly tested in non-invasive BCI research. A slow cortical potential (SCP)-based spelling BCI has been developed to allow severely paralyzed patients to communicate [4], a system originally tested in patients with intractable epilepsy. Sensorimotor rhythms (SMRs) have been used as the critical EEG oscillation for control of a BCI device [5] [6]. Another extensively tested BCI controller is the P300 event-related brain potential (ERP) BCI developed by Donchin [7]. SCP control and SMR (often called mu rhythm) control are learned through visual and feedback and reward and might need 5-20 training sessions before significant production of SCPs or mu rhythms is achieved, while the P300 BCI needs no training at all. We would note that although some motor imagery BCI system (e.g. IDIAP BCI from J. del R. Millan and coll.) failed to work in public [1], other promising systems, requiring short training sessions (e.g. Berlin BCI [8]or Graz BCI [9]), are already available in the literature.

Devices based on the invasive or non-invasive monitoring of the brain electrical activity might provide a communication channel for patients however, the results of the clinical tests are not however yet at the level of expectancies. For instances, Birbaumer [3] described the results obtained in a cohort of patients at different stages of debilitating diseases who require the use of communication devices. While patients at intermediate and early states achieved relatively good control using at least one of the two modalities (either P300 or SCP), the results were surprisingly bad for patients at the complete locked in state (CLIS). None of the patients diagnosed as CLIS was able to communicate using BCI devices.

It general, BCI systems relying upon relatively automatic brain responses (such as the P300) and requiring no learning and little training might be the most promissory for those cases. The use of steady states visually evoked responses (SSVEP) as a BCI modality control considered on what follows belongs to this later category.

On this manuscript we aim at proposing a Brain-Computer Interface using SSVEP that could satisfy the following ideal constraints:

1) Non-invasiveness, i.e., based on EEG or derived measures.
2) High transfer rate: Able to send orders each half or quarter of seconds.
3) Minimal training requirements: Avoid long training periods, reusing classifiers obtained in previous sessions.
4) Able to function in real life conditions (environmental noise), i.e., allowing the subject to control the robot while other people talk with him as in a diary life.
5) Require low level of artificial intelligence to reduce the price of the system.
6) Able to deal with several classes (˜6).

In particular we present a solution which respond satisfactory to the first 5 points while solving only partially constraint 6 since only four classes have being so far properly identified and its preliminary results for the case of healthy subjects.

The Geneva Brain-Computer Interface (G-BCI) described here is based on spatial visual attention and the so-called steady state visual evoked potentials. While the basic experimental design resembles those previously described elsewhere [10-12] the main difference remains the feature selection algorithm called the discriminative power (DP) [13]. For each feature, the DP estimates the number of true positive given that the number of false positive is zero. Using this measure we rank the features and build a linear classifier based on the best features and the Proximal SVM approach (PSVM) with hyperparameter nu estimated from the training set. Finally a heuristic filtering strategy is added to the output of the classifier to suppress false positives. For

ESANN'2009 proceedings, European Symposium on Artificial Neural Networks - Advances in Computational Intelligence and Learning. Bruges (Belgium), 22-24 April 2009, d-side publi., ISBN 2-930307-09-9.

now on the term classifier will refer to both the PSVM and the filtering strategy of the output scores. As for features we use the oscillatory activity in the EEG extracted with a simple FFT algorithm. In summary the brain computer interface presented here is based on fast algorithms that allow for an efficient online implementation.

The development of the BCI system was done in two stages. In the first part a theoretical study with three subjects and three classes (two frequencies) was conducted. Based on the encouraging results of first stage we entered the second stage. An additional class (i.e. three frequencies) was included and the system was tested online. First subjects drove a virtual wheelchair in a virtual environment. In a second experiment two subjects were able to control a robot via internet.

In addition we assessed the artificial intelligence (AI) level needed for virtual and real scenarios and confirmed that although scarcely used, a simple stop before collision agent (SBCA), was enough to warrant correct execution of the tasks. Thus complex obstacle avoidance agents or expensive sensors were not needed.

1.1 First Stage: Two frequencies

1.1.1 Theoretical results: off line analysis

The data from two healthy subjects participating in 4 sessions were used to evaluate theoretically the methodology proposed here. The results from all subjects were very similar. Using two visual stimuli (corresponding to Right or Left movements of the robot), we were able to correctly identify 100% of the stimuli in ½ second and no less than 95% in ¼ second using a 10 folds cross-validation procedure. Since the quarter of second is probably not useful for the tas k presented here, we will consider classifications based only on half a second in the following. This corresponds to 120 decisions per minute or a maximum transfer rate of 120 bits/minute. In addition similar (about 99%) classification rates were obtained using classifiers build on different sessions. That means that the classifier can be computed in a single training session.

1.1.2 Simulation results: online analysis

On this setting we need to transmit 3 commands to the robot, i.e., Left, Right or Continue to move. Since we know precisely the class labels of each EEG windows, we can use the well know formula of Wolpaw to estimate the theoretical bit rate. Using a sliding window on the training data with 3 classes, we estimated a (very pessimistic) lower bound of 87% for the first stage. This value would correspond to a bit rate of 107.7 bits/min that surpass most of the methods presented so far based on visual attention or other (e.g. motor imagination) strategies. We would emphasize that these values remain a theoretical reference since for the case of self paced BCIs, as the one presented in this paper, the subject intent is in general not observable.

Experimental results during real time control of a robot simulator by the two subjects, using classifiers stored from a training session of a previous day confirm that for practical purposes, the classifier can be computed in advance. In addition the trajectory described by the robot denoted the (almost complete) absence of false positives obtained, nevertheless, at the price of certain rigidity of the “steering wheel” induced by the filtering.

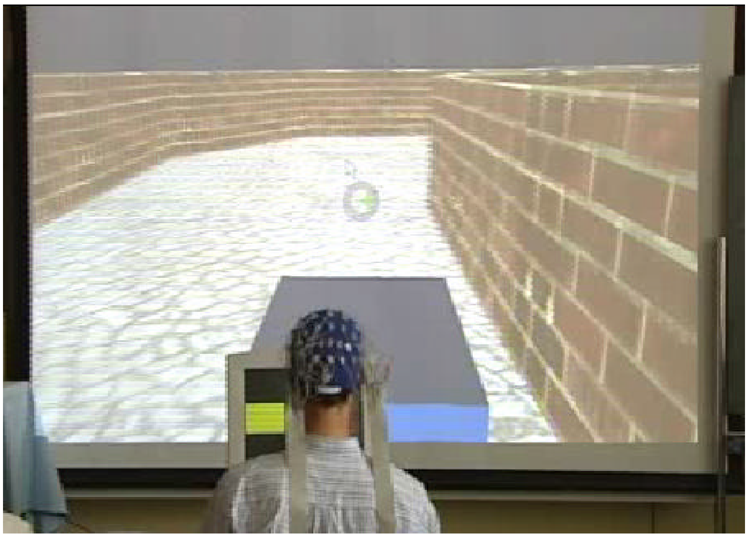

Figure 1: The subject controls the robot simulator in virtual environment using Steady State Visual Evoked Potentials. To simulate a realistic condition the robot moves at 0.8 m/s.

Regarding the environmental noise, the subjects refer very low disturbance even if people are talking to them. Furthermore the subjects can switch their attention from the robot to the speakers without affecting the robot control. However, if the subjects try to talk or move, false positives might appear, then, at current stage of development, we recommend the subject to refrain from talking while transiting by a narrow lane.

For the sake of simplicity the robot simulator included a “stop before collision agent” (SBCA) that reduces the robot speed in the vicinity of an obstacle and stops if a collision seems unavoidable. Nevertheless, the robot simulator displays whether the command is sent by the subject or the SBCA. From these simulations it was clear that the SBCA was scarcely (and only) used during the first minutes of user control. However, although not really relevant for the real control, we think that SBCA is a very important element for the safety the human user and the integrity of the robots.

To check the consistency of this methodology, a third subject with 100% (0.5 sec) in training data (offline analysis) was able to easily control the robot simulator.

1.2 Second stage: Three frequencies

Results from previous stage suggested that further classes could be included without additional off line analysis. Nevertheless, the main limitation was that the visual stimulations were provided using a standard PC display with a very simple graphic card. Under these conditions only another class, i.e., frequency, producing no overlap with the frequencies already in use, was available. Nonetheless, the inclusion of another stimulation frequency allowed for the definition of four classes and thus to control a real robot in real time.

Since the goal of this work was to provide real control to real subjects, we passed directly to the online control of a robot simulator in a virtual scenario. As expected the inclusion of four classes presented no additional difficulties and after a short training session of 20-30 minutes the two subjects were ready to try the control in a realistic environment. See Figure 1 for a snapshot of the user and the robot simulator.

During the experiment, subjects controlled the remote robot using a camera on the top of the robot as feedback. While the camera provided detailed information about textures and colors, distance information was rather poor, nevertheless, users were able to follow a person in the distant lab avoiding all the obstacles and thus driving the robot to any desired position. While there was no objective value of the amount of commands coming from the user and the SBCA, we observed that the robot was rarely close to the objects, and thus that the SBCA was almost never used. This is probably due to the speed of the real robot which was notably lower than the speed used for training in the virtual environment.

1.3 Conclusions

Steady state visual evoked potentials provide an efficient way to develop Human machine interfaces characterized by high transfer rates and minimal errors. Such technique used conjointly with a remotely controlled robot should enable telepresence using minimal artificial intelligence levels, i.e., simple stop before collision agents based on very cheap sensors. Future work will focus on increasing the number of possible commands and the test with disabled patients.

References

[1] TSR, "Lire dans les pensées.," in *Video Two* www.electrical-neuroimaging.ch\download, 2007.

[2] R. Grave de Peralta Menendez, P. Morier, R. Millan J. del, and S. L. Gonzalez Andino, "Accurate hand trajectory prediction by real and synthetic EEG," presented at 3rd International Brain-Computer Interface Workshop & Training Cours, Graz, 2006.

[3] N. Birbaumer and L. Cohen, "Brain-computer interfaces: communication and restoration of movement in paralysis," *The Journal of Physiology*, vol. 579, pp. 621, 2007.

[4] N. Birbaumer, N. Ghanayim, T. Hinterberger, I. Iversen, B. Kotchoubey, A. Kubler, J. Perelmouter, E. Taub, and H. Flor, "A spelling device for the paralysed," *Nature*, vol. 398, pp. 297-298, 1999.

[5] 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 Trans Rehabil Eng*, vol. 8, pp. 164-73, 2000.

[6] J. Wolpaw and D. McFarland, "Control of a two-dimensional movement signal by a noninvasive brain-computer interface in humans," *Proceedings of the National Academy of Sciences*, vol. 101, pp. 17849-17854, 2004.

[7] L. Farwell and E. Donchin, "Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials.," *Electroencephalogr Clin Neurophysiol*, vol. 70, pp. 510-23, 1988.

[8] B. Blankertz, G. Dornhege, M. Krauledat, K. R. Muller, V. Kunzmann, F. Losch, and G. Curio, "The Berlin Brain-Computer Interface: EEG-based communication without subject training," *IEEE Trans Neural Syst Rehabil Eng*, vol. 14, pp. 147-52, 2006.

[9] C. Vidaurre, A. Schloogl, R. Cabeza, R. Scherer, and G. Pfurtscheller, "A fully on-line adaptive BCI," *IEEE Trans Biomed Eng*, vol. 53, pp. 1214-9, 2006.

[10] M. Cheng, X. Gao, S. Gao, and D. Xu, "Design and implementation of a brain-computer interface with high transfer rates," *IEEE Trans Biomed Eng*, vol. 49, pp. 1181-6, 2002.

[11] S. P. Kelly, E. C. Lalor, C. Finucane, G. McDarby, and R. B. Reilly, "Visual spatial attention control in an independent brain-computer interface," *IEEE Trans Biomed Eng*, vol. 52, pp. 1588-96, 2005.

[12] P. Martinez, H. Bakardjian, and A. Cichocki, "Fully online multicommand brain computer interface with visual neurofeedback using SSVEP paradigm," *Computational Inteligence and Neuroscience*, vol. 2007, pp. 9 pages, 2007.

[13] S. L. Gonzalez, R. Grave de Peralta, G. Thut, R. Millan Jdel, P. Morier, and T. Landis, "Very high frequency oscillations (VHFO) as a predictor of movement intentions," *Neuroimage*, vol. 32, pp. 170-9, 2006.