Telepresence based on remote real time control of a robot with brain waves

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Abstract

The term brain computer interface (BCI) is used to denote a direct communication pathway between the brain and an external device. In this poster we propose a BCI based on Steady State Visual Evoked Potentials (SSVEP). This BCI system attains the maximum theoretical transfer rates and an empirical transfer rate that surpass largely all the systems based on movement imagination.

As additional features, the system false positive rate is negligible and with a minimal attention of the subject. This means that the subject can follow a conversation or divide visual attention without compromising the control of the external device. Expected to work for several classes, current version allow sending 4 different commands. Using this system we perform a telepresence experiment where one subject at our lab explored another lab several miles away by controlling in real time a robot through Internet.

1. Introduction

The main goal of our project is the development of a Brain-Computer Interface able to satisfy the following constraints:

1) Non-invasiveness, i.e., based on EEG or derived measures.
2) High transfer rate: Able to interact with the robot at least every ½ second.
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).

On this poster 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.

The Geneva Brain-Computer Interface (coined 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 [1,2], the main difference remains the feature selection algorithm called the discriminative power (DP) [3]. 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). Finally a heuristic filtering strategy is added to the output of the classifier to suppress false positives. For 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 very fast algorithms that allow for an efficient online implementation.

The development of the BCI system was done in two stages. In the first a theoretical study with two subjects and three classes was conducted. Based on the encouraging results of first stage we entered the second stage. An additional class was included and the system was tested online. First the subject drove a virtual wheelchair in a virtual environment. In second experiment the subject was able to explore a remote lab by means of a robot controlled via internet.

In addition we assessed the need for different artificial intelligence levels in both virtual and real scenarios. The extremely low level of false positive required only simple anti collision system.

2. First Stage

2.1 Theoretical results

The data from two healthy subjects participating in 4 sessions were used to evaluate theoretically the methodology proposed here. The results from both 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 task 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 [4]. 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.

2.2 Simulation results

In practice we need to transmit 3 commands to the robot, i.e., Left, Right or Continue to move. Using a sliding window on the training data with 3 classes, we estimated a (very pessimistic) lower bound of 87% for the first classification stage. This value corresponds 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. imagination) strategies.

These values are compatible with experimental results during real time control of a robot simulator by one subject, using a classifier stored from a training session of a previous day. This confirms that for practical purposes, the classifier can be also computed in advance. In addition the trajectory described by the robot denotes the (almost) absence of false positives obtained, unfortunately, at the price of certain rigidity of the "steering wheel".

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.

3. Second Stage

Based on the results of previous stage we concluded that the inclusion of further classes should not be a problem. 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 not to study any general theory but 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 couple of sessions of 20-30 minutes the subject was ready to try the control in a real environment. See Figure 1 for a snapshot of the user and the robot simulator.

For the telepresence experiment, a robot with 4 control commands similar to the robot simulator was considered. In this experience the robot was equipped with a single system that reduces the robot speed in the vicinity of an obstacle and stops if a collision seems unavoidable. In that way the user keeps the full autonomy while enjoying the privilege of the anti-collision feature.

During the experiment the subject 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 really poor and a navigation map provided by the laser sensors of the robot was additionally transmitted to the user. On these conditions the user was able to follow a person in the distant lab avoiding all the obstacles and thus driving the robot to any desired position.

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 of severely disabled patient. Future work will focus on increasing the number of possible commands and test with disabled patients.

References

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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.