Hybrid Brain-Robot Interface for telepresence

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Abstract. Brain-Computer Interface (BCI) technology allows to use brain signals as an alternative channel to control external devices. In this work, we introduce an Hybrid Brain-Robot Interface to mentally drive mobile robots. The proposed system sets the direction of motion of the robot by combining two brain stimulation paradigms: motor imagery and visual event related potentials. The first enables the user to send turn-left or turn-right commands to the robot by a certain rotation angle, while the second enables the user to easily select high level goals for the robot in the environment. At the end, the system is integrated with a shared-autonomy approach in order to improve the interaction between the user and the intelligent robot, achieving a reliable and robust navigation.

Keywords: Human-centered systems, Human-robot interaction, Machine learning

1 Introduction

In the last few decades, scientific, medical and industrial research communities have shown a greater interest to the field of health care, assistance and rehabilitation. The result has been a proliferation of Assistive Technologies (ATs) and healthcare solutions designed to help people suffering from motor, sensor and/or cognitive impairments due to degenerative diseases or traumatic episodes [1]. In this context, researchers highlight the importance to design innovative and advanced Human-Robot Interfaces in order to combine the user's intentions decoded directly from (neuro)physiological signals and translate them into intelligent actions performed by external robotic devices such as wheelchairs, telepresence robots, exoskeletons and robotic arms [2–4]. With this regards, Brain-Computer Interface (BCI) systems enable users to send commands to the robots using their brain activity (e.g. based on Electroencephalography (EEG) signals) by recognizing specific task-related neural patterns [5]. For instance, the user is required to imagine the movements of the hands and the feet in order to turn the robot respectively in the left and the right directions [4] or to open/close the hand of an exoskeleton [6].

Despite in the last years BCI studies show promising results in different applications, such as device control, target selection, and spellers [7], the BCI system still remains an uncertain channel of communication through which the users are able to deliver only few commands and with a low information transfer rate. Moreover, the workload required to both healthy and disabled users is still high [8], slowing down the expansion of these neurorobotics systems and their translational impact [9, 10]. In the assistive robotics literature, the principle of the shared-autonomy demonstrates how it is possible to partially overcome this limitation by adding a low-level intelligence on the robot, thanks to which it is able to contextualize the few high-level commands received by the user according to the environment and the data from its sensors [4, 11, 12]. The agent maintains some degree of autonomy avoiding obstacles and determining the best trajectory to follow when the user cannot deliver new commands. Once a new command is sent from the user, the robot simply adjusts its current behaviour.

In this work, we propose to combine shared-autonomy approach with an additional intelligent layer between the user and the robot, inferring the user intention by mixing two kinds of brain stimulation paradigms. In details, we present a preliminary Hybrid Brain-Robot Interface for robot navigation, in which the user pilots the robot through 2-class Motor Imagery (MI), but simultaneously he/she can be stimulated through a visual event related potentials (P300) to reach predefined targets. At the end, the output of the system represents the predicted direction along which the robot has to move.

2 Materials and methods

In this study we consider two kinds of standard BCI paradigms: motor imagery (MI) and visual event related potentials (P300). The first is designed to make the robot turn left/right through the imagination of motor movements (e.g. hands vs. feet). The other makes the robot move in the direction of a specific target chosen according to where the user focuses his/her attention while he/she is stimulated through visual flashes. When the user does not send any command, the robot keeps moving along its current direction. Behind the system, after the processing of the EEG signals, two classifiers infer the presence of a motor imagery (MI) or a visual event related potentials (P300) commands based on the computed raw probabilities and the evidence accumulation. For more mathematical details on the specific BCI classification methods please refer to [4] and [13] respectively. Then, to predict the direction of the robot chosen by the user, we combine the last outcome from the BCI classifiers with the history of the previous decisions. The aim is to smooth the uncertainties of the single BCI command by integrating the information about user intention over time, therefore reducing the side effects of involuntary commands delivered by the user. An overview of the entire pipeline is shown in Fig. 1. With this regards, we design a mathematical model to estimate the new direction based on a weighted sum of Gaussian ($\mathcal{N}(\cdot)$) distributions: the first $\mathcal{N}(x_t, \sigma_t)$ is the distribution over the new predicted command and the second $\mathcal{N}(x_{t-1}, \sigma_{t-1})$ is the distribution over the previously predicted command. In details, we compute at each t the following distribution:

$$D_{t|t_0:t-1} = \mu_0 \cdot \mathcal{N}(x_t, \sigma_t) + \mu_1 \cdot \mathcal{N}(x_{t-1}, \sigma_{t-1}) + \mu_2 \cdot D_{t-2|t_0:t-3} \qquad (1)$$

where $\mu_0, \mu_1, \mu_2 \in R^n$ such that $\mu_0+\mu_1+\mu_2 = 1$. The term $D_{t-2|t_0:t-3}$ represents a memory term to keep memory of the past decisions. The shapes of the normal distribution are related to the outcome of the two classifiers. Further details are presented in the following paragraphs, showing how the probability distribution $D_{t|t_0:t-1}$ and therefore the kind of movements performed by the robot change according to three possible situations: a) no new command delivered by the user, b) the prediction of a new motor imagery command and c) the prediction of a new P300 command. At the end, the final predicted direction is given in input to our shared-autonomy algorithm [4], to manage the movements of the robot ensuring obstacle avoidance and a reliable navigation.

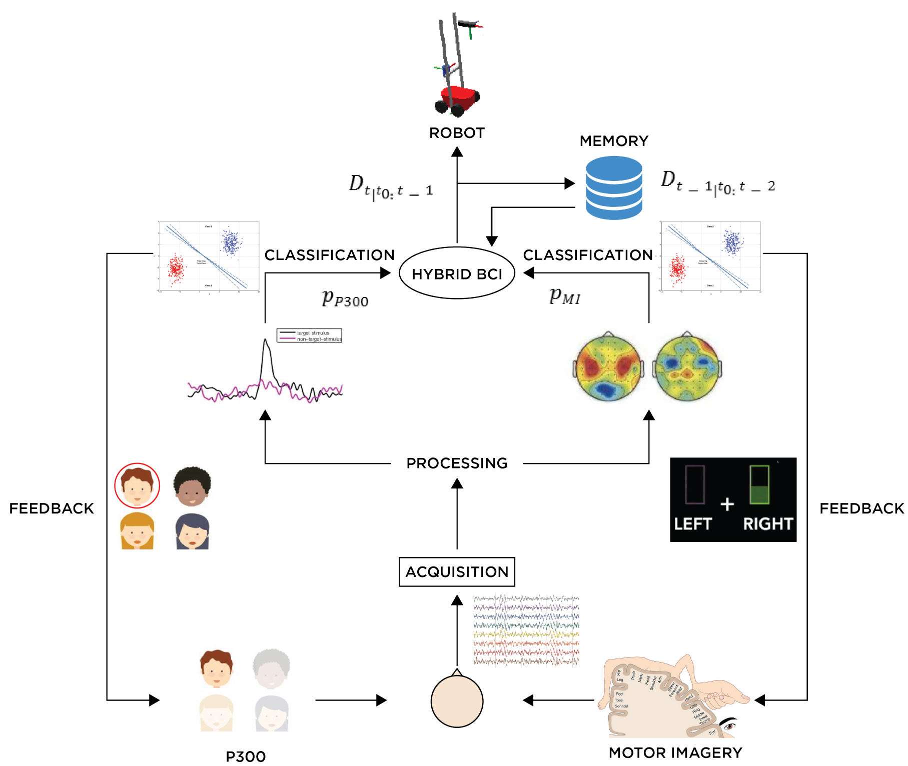

Fig. 1. A visual representation of the data processing pipeline. The subject is required to perform motor imagery task (MI) for driving the robot left and right. At the time, he/she is stimulated through visual flash (P300) to select targets for instance people in the environment. The EEG signal are acquired and analysed both in frequency domain to identify MI features and in time domain in the case of P300. Underlying the system there are two classifiers whose output (probability distributions) are combined by our proposed model. This model considers also a memory term based on the previous distributions of the directions followed by the robot. At the end, the telepresence robot performs the predicted command.

2.1 No new command from the user

When the user does not send commands for a specific amount of time, we assume the robot is moving in the direction desired by the user. In this case, the probability distribution of Eq 1 becomes the following ($\mu_0 = 0$), thanks to which the robot keeps its current orientation θ:

$$D_{t|t_0:t-1} = \mu_1 \cdot \mathcal{N}(x_{t-1}, \sigma_{t-1}) + \mu_2 \cdot D_{t-2|t_0:t-3} \tag{2}$$

An illustrative example is shown in Fig. 2.

2.2 The prediction of a new motor imagery command

When a new motor imagery command is predicted by the BCI classifier, the normal distribution $\mathcal{N}(x_t, \sigma_t)$ is centered in the current position of the robot and the corresponding σ_t is set according to the rotation angle the robot has to turn in the left/right direction (e.g. $\pm 45°$). An illustrative example is shown in Fig. 3.

2.3 The prediction of a new P300 command

When a new P300 command is predicted by the BCI classifier, the normal distribution

$$\mathcal{N}(x_t, \sigma_t)$$

is characterized by a mean equal to the direction of the target chosen by the user. An illustrative example is shown in Fig. 4.

2.4 Implementation

We implement our system exploiting the standard and the tools provided by Robot Operating System (ROS), in view of establishing a standardized research platform for neurorobotics applications [9,10]. It includes three main nodes managing the *hybrid_bci_node*, *robot_controller_node* and the *interface_node* through which the user is stimulated and receives the feedback from the system.

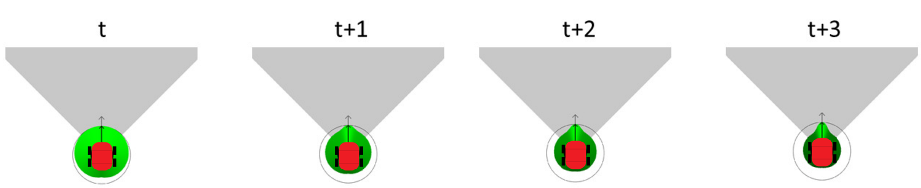

Fig. 2. The trend of the distribution probability (in green) when the user delivers any commands. The robot keeps its current direction (in grey).

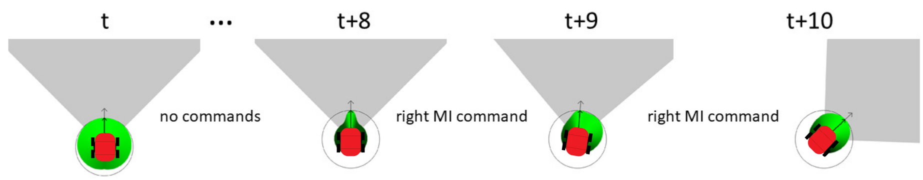

Fig. 3. The trend of the distribution probability (in green) when the user delivers two consecutive right motor imagery commands. The robot turns in the right direction (in grey).

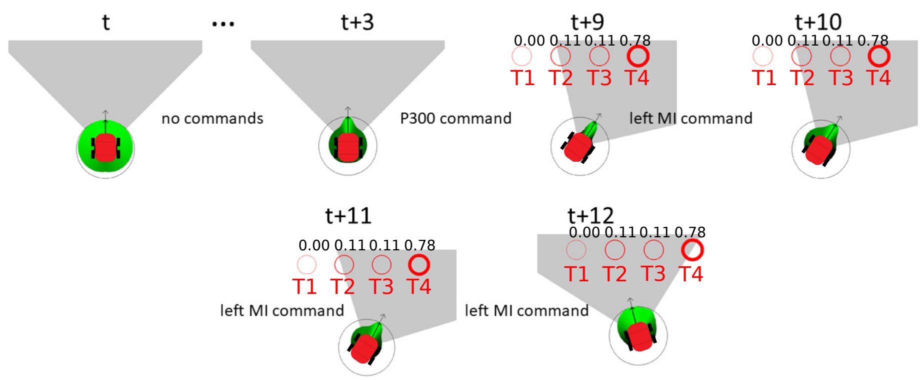

Fig. 4. The trend of the distribution probability (in green) when the user delivers a P300 command and three consecutive left motor imagery commands. The robot moves along the target direction at the beginning and then turns left.

3 Conclusion

In this work, we introduce a preliminary Hybrid Brain-Robot Interface for robots' navigation that enables the user to interact with the robot based on two brain stimulation paradigms. The coupling between a probabilistic model to infer the user's intention and the robot's intelligence might guarantee the robot to perform the appropriate movements in the environment. The main limitation of this study is the missing of numerical results to demonstrate the benefits of fusing the proposed two brain stimulation paradigms, motor imagery and visual event related potentials, to mentally drive telepresence robots. With this regards, future directions include to test and validate our system on a physical robot. In addition, we will study properly the resulting brain signals when the user is involved simultaneously in dual mental tasks.

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