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Real-Time Mobile Robot Obstacles Detection and Avoidance Through EEG Signals

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***Abstract*—Human-Machine Interface (HMI) and Brain-Computer Interface (BCI) have recently emerged as an efficient solution for many machine controlling or computer application in order to send direct controls' commands or provide feedback to correct some robot actions during task execution [1], [2], [3]. However, there are many challenges for designing an efficient and effective BCI system that requires less mental effort involving humans brain, so that it could be a practical tool for daily-task without to request extra brain effort. In the related works, Electroencephalographic (EEG) signals, acquired by external electrodes placed on the human scalp, are used as input for the implemented algorithms to correct possible faults and errors during the robot's task performance [4], [5]. Although there are many works focused on the use of BCI with the goal of real-time feedback based on EEG signals detection, the idea of using them as input to algorithms in order to correct possible faults and errors during the robotic task, as in the proposed case of obstacle avoidance during navigation of this paper, still remains a challenging goal [6]. In addition, most existing BCI protocols for involving humans in the robot control's loop, require the user observes a full visual and brain concentration in order to have good signals for different cognitive situations [1].**

The aim of this study is to design a BCI-based protocol to be used with a wheelchair-robot control system for safe navigation in an indoor scenario, that can avoid obstacles not detected by the on-board sensor equipment. Moreover, the design of a specific protocol has the aim of evoking and collecting EEG data for training and testing the BCI system which will be integrated with ROS (Robotics Operation System). In ROS environment, the BCI will be lined with a package, already developed [7]–[9], that generates virtual obstacles and supports the human in the loop approach integration. The designed protocol has been implemented by using a simulation platform (i.e., Gazebo), including both an environment and a specific mobile robot, namely a smart wheelchair. The smart wheelchair can navigate autonomously in the indoor scenario, avoiding possible obstacles without any human intervention using only the available sensors that equip the smart wheelchair. However, in the case that the sensors can fail in the obstacle detection, due to occlusions or unexpected obstacle positions, the involvement of human in the robot path planning control improves the human safety. During the training phase with the BCI system, the user is asked to observe a video during which the robot is trying to avoid the obstacles (i.e., holes positioned in the floor), placed along the path, particularly focusing when the smart wheelchair fails the task (e.g., runs into a hole in the floor). According to the well-known "oddball paradigm" [10], used to elicit the P300 ERP (Event-Related Potential), a sequence of events, that can be classified into two categories, is presented to the subject at a very fast rate. In general, events of one category, that can be considered as "target stimuli", must have a lower frequency of occurrence with respect to the other. By engaging the subject in a cognitive task, for example by instructing him/her to progressively and mentally count the number of times the target stimulus appears, the P300 is generated. In this way, presenting to the subject the smart wheelchair that passes through the obstacle or turns around it, the user's brain is expected to generate particular EEG signals, namely the ERPs. These EEG signals will be recorded and sent to the BCI system that processes them and classifies the event. The recognized ERPs are then used as input signals for a developed Matlab-Simulink algorithm. In particular, the Simulink file runs a node that publishes a trigger topic, through cloud service, for the robot, in a ROS-based architecture that integrates the robot navigation packages with the signal recognition provided by the BCI system. The data have been collected from 10 healthy subjects, and each of them performed 150 trials, in 25 minutes. This data is then divided for training and testing phases. The data has been processed in a Matlab environment, basically in EEGLAB and BCILAB. EEGLAB has been used to process all data off-line in order to investigate all the neurophysiology properties (i.e., signal shape and potential activation zones), which will be better optimized for the classification, among them the best channel and the optimum frequency bandwidth for the interesting events. Instead, the BCILAB has been used for all event classification and reprocessing online and offline. The pre-processing step has been tuned based on the results obtained from EEGLAB. The paradigm with the best classifications accuracy and fewer computation efforts has been used for the online integration with ROS. The overall results show that the area under the curve for training and testing respectively are 0.73 and 0.59, while the standard deviation for training and testing are 0.11 and 0.07 respectively. Different simulation results will be presented in the extended version of this work.

In conclusion, this study shows the possibility of using human brain signals, recorded through a BCI system, in order to provide a real-time human-in-the-loop approach for monitoring

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the reliability of a robot while executing the obstacle avoidance task. The obtained results show that the proposed solution can significantly improve safety conditions during human-robot interaction, providing feedback accordingly.

Index Terms—**Human-in-the-loop, BCI system, ERP detection,EEG Brain Robot interface, Obstacle avoidance, Robot navigation.**

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