Shared Intelligence for User-Supervised Robots: From User's Commands to Robot's Actions

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Abstract. This paper introduces a novel form of cooperation between the humans and user-supervised robots that we name *shared intelligence*. The fundamental principle at the base of *shared intelligence* is that the user's commands are equally processed with the robot's perception in order to create a successful interaction. We investigate a first *shared intelligence* system to mentally teleoperate a mobile robot via brain-machine interface. The preliminary results promote the introduction of *shared intelligence* to augment the human-robot interaction without prefixing specific constraints (environment-dependent) thanks to the coupling between the human and the robot.

Keywords: Neurorobotics · Brain-machine interface · Telerobotics and teleoperation · Behavior-based systems

1 Introduction

Thanks to the continuous advancements in robotics and machine learning areas, it has been possible to develop intelligent robots with increasing abilities. These robots are considered intelligent because they abstract the biological intelligence through the canonical paradigm "*plan*, then *sense-act*". Hence, the robotic intelligence consists of four main functions: *reaction* to stimuli, *recognition* of symbols, *deliberation* and the *interaction* with the environment and the others. In particular, in this paper we focus on the *interactive functionality* and we introduce the *shared intelligence* referring to a form of cooperation between the human and robot that share a common goal [1]. This research can have an impact on many human-in-the-loop applications where the user is actively involved in determining the actions performed by the robot such as in the case of robot-assisted surgery, remote space exploration, assistive devices, and telepresence robots. In all these scenarios, the user interacts with the robot by sending commands through a particular interface. However, the main idea underlying the *shared intelligence* provides that the robot is not passive during the human-robot interaction. On the contrary, the robot is able to lead the humans by interpreting

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their intentions and evaluating the inputs received according to the context. The robot contributes to the decision-making process by questioning the user's commands on the base of the information acquired through its sensors (e.g., laser rangefinder, camera) and with the possibility of taking the control over the human in case of emergency situations. It is worth highlighting that the user always supervises the robot and can interact at any time. This means that the user adjusts the next robot's action by delivering new commands if undesired robot's behaviors occur.

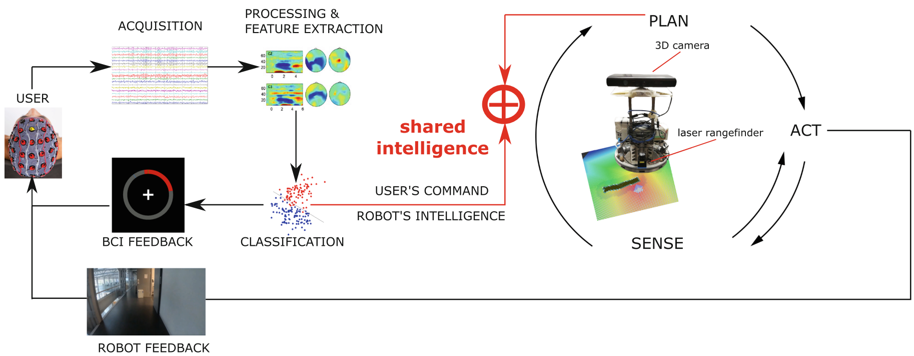

Fig. 1. *Shared intelligence* for controlling mobile robots via brain-computer interface. The user is required to perform a mental task to deliver new commands to the robot. The user's intention to interact with the robot is directly decoded from the acquired brain signals according to a subject-specific classifier. The decoded BCI commands are equally fused with the perception's of an intelligent robot. The robot is involved in the canonical *plan-sense-act* paradigm and contextualises the received user's commands in according to the context.

In this work, we address *shared intelligence* to the robot's teleoperation through an uncertain communication interface (see Fig. 1). Specifically, the user interacts via brain-computer interface (BCI) an interface that provides an alternative interaction channel that does not depend on the brain's normal output pathways of peripheral nerves and muscles [2,3]. Because of the non-muscular nature, BCIs is mainly introduced to allow people suffering from severe motor impairments to interact with external devices (e.g., interface, prosthesis, exoskeletons, wheelchairs, telepresence robots) directly according to their brain activity [2–8]. However, BCIs are characterised by low bit rate and noise due to the instability of the neurophysiological signals; which means the user can only interact with the robot by delivering sparse discrete commands. Moreover, the user's commands might be wrongly decoded in the BCIs system introducing the send of unintentional user's commands. These limitations motivate our hypothesis to rely on the robot's low-level intelligence to achieve an effective control thanks to the cooperation between the human and the robot.

2 Methods

In this section, we present the key characteristics of our *shared intelligence* approach to teleoperate a telepresence robot via BCI.

2.1 Brain-Computer Interface System to Detect the User's Commands

In our system, we exploit a 2-class BCI based on the sensorimotor rhythm (SMR) paradigm to detect the user's commands. In the neurorobotics field, SMR BCIs have been widely used to control external devices (e.g., in [7,9–11]) because contrariwise to exogenous approaches [8,12,13] enable users interact without the need of any external stimulation. The user learns how to voluntary modulate his/her brain rhythms. Specifically, to interact with the robot, the user is requested to perform specific mental tasks, namely the imagination of the movements of both hands and both feet, that activate the well-localized regions in the motor cortex area. We acquire the EEG signals from 16 channels placed on the sensorimotor cortex area (i.e., Fz, FC3, FC1, FCz, FC2, FC4, C3, C1, Cz, C2, C4, CP3, CP1, CPz, CP2, CP4 according to the international 10–20 system layout) and recorded through the g.USBamp, Guger Technologies, Graz, Austria amplifier 512 Hz sampling rate. The acquired signals are then processed to detect specific patterns associated with the mental tasks and correlated to the user cognitive states. In SMR BCI, according to the neuroscience findings, these patterns correspond to amplitude increment and decrement of the rhythmic activity during the imagination of both hands and feet movements that are called event-related desynchronization (ERD) and synchronization (ERS) [14]. We exploit ERD and ERS events to create subject-specific models (i.e., calibrated on the single person) using supervised machine learning techniques that optimize the discrimination between the two classes. In detail, we process the EEG signals by applying a laplacian spatial filter. The power spectral density (PSD) of the signal was continuously computed via Welch's algorithm in the μ (8–12 Hz) and β (16–30 Hz) bands activated during the required motor task. The selected features (channel-frequency pairs) are the basis of a Gaussian classifier trained with a set of samples acquired during a calibration phase to decode the user's intention of performing the specific mental tasks. Indeed, with this purpose, before controlling the robot, the user is instructed to perform the same two mental tasks but in specific windows of time in order to acquire the training dataset and the related labels of the two classes (see Fig. 2).

Finally, the posterior probabilities in output from the classifier are communicated to the user through a visual feedback (see Fig. 2). Furthermore, by comparing the posterior probabilities with respect to a threshold, new discrete commands are identified and given in input to the shared intelligence system, that congruently translates them into movements of the robot.

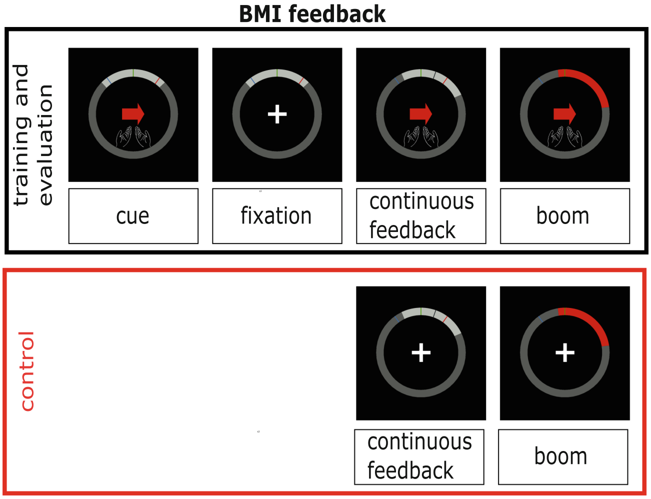

Fig. 2. SMR BCI feedback. In the *BCI calibration* and *evaluation* runs the users were instructed with a visual signal (cue) about the mental task to perform. During the *control*, no cue is provided because participants decided by their own the command to deliver. In both cases, they received a continuous feedback representing their mental state. When a new command was detected the wheel reached the extremity in the corresponding direction (boom).

2.2 The Fusion of the User's Commands with the Robot's Intelligence

In this work, we propose a first simple version of a *shared intelligence* system designed for the robot's navigation based on the information about obstacles, the natural direction of motion, the preferable ranges of the robot's step during the navigation, the user's inputs. Since the robot's intelligence depends on different factors influencing the robot's motion, we design the system in a modular and flexible way. Each factor determines a sort of behavioral guideline for the robot (i.e., the robot should move far from obstacles, the robot should reach the target, the robot should implement the user's commands if possible), that we represent in the form of *policy*. The choice of the *policy* is motivated by the fact that in *shared intelligence* system, the robot's behavior is not pre-coded according to procedures, but it results from the interaction between the user and the robot as agent au pair [1]. In other words, in contrast to other approaches in the literature, the robot does not select a single behavior implemented separately, namely we do not include any arbiter or mechanism that selects a single policy as in the "winner-takes-all" approach. On the contrary, all these *policies* equally contribute in determining the robot's motion and the final robot's behavior results only from their fusion.

Specifically, in our system, each *policy* is a function that encodes the situation around the robot according to the behavioral guideline conditioning the

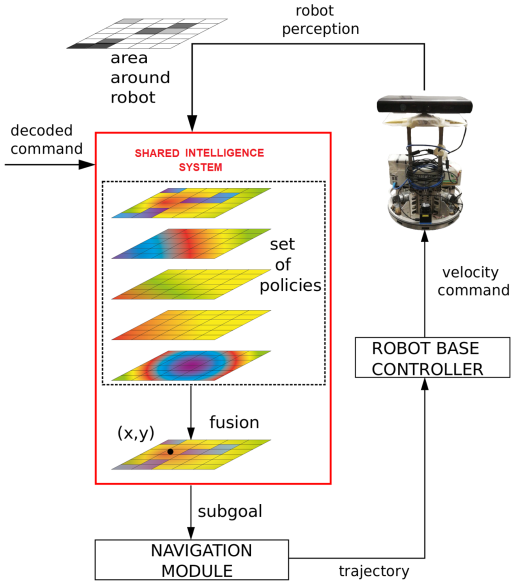

Fig. 3. An illustrative scheme of the proposed *shared intelligence*. The system is based on a set of *policies*. Each *policy* is associated with a factor that can influence the robot's motion: for instance in the case of the robot's teleoperation via BCI, we consider the distribution of obstacles, the user's inputs, the preferable direction of motion, the preferable ranges of the robot's step during the navigation. The *policies* compute probability grids in the local area of the robot. All the *policies* simultaneously determine the next robot's movements. Specifically, the fusion of all the *policies* outputs a position in the environment representing a target for the robot. Finally, the navigation module plans the best trajectory for the robot to move towards that position.

navigation and the related input (e.g., the distribution of obstacles, the user' s commands, the current robot direction, the minimum/maximum admitted step). Let $\mathcal{A}$ be the area around the robot by size s (in our case $s = m \times n$) and I_t the input of the policy at time t, in our system, a *policy* p is defined as follows:

$$p : \{I_t \rightarrow [0, 1]^s \mid \forall x, y \in \mathcal{A},\ p(x, y) \in [0, 1]\} \tag{1}$$

namely a *policy* outputs a probability grid in the neighborhood of the robot starting from the given input and it assigns a value between 0 and 1 for each position of the probability grid. Then, all the probabilities grids returned by N *policies* are fused together

$$\Sigma_p = \prod_{k=1}^{N} p_k \tag{2}$$

and the result is then normalised to obtain again a probability grid Σ'_p, calculated on each position (x, y) in the area around the robot $\mathcal{A}$. From the fused probability grid Σ'_p, we select one position (the most probable), called *subgoal*, that represents a temporary target for the robot. Finally, to avoid falling into local minima, a navigation module based on a motion planning optimizes the robot's motion towards that position determining the best trajectory for the robot, while the robot base controller is in charge to determine the velocity commands according to the trajectory calculated. An illustrative representation of the key principle underlying our system is shown in Fig. 3.

It is worth highlighting that in our system, we only exploit the information from the robot's perception in its local area in order to extract the distribution of obstacles. Indeed, the strength point of our approach is the independence from specific information of the environment (e.g., global map) nor procedures strictly linked to the kind of the landmarks inside (the passage through doors or the alignment with respect to the corridor) in contrast to [11,15–17]. This aspect simplifies its reproducibility in different everyday life contexts because any pre-setup phase is not required.

3 Experiments

The presented *shared intelligence* system was evaluated with 13 healthy subjects without any previous experience in a pilot experiment. All the participants signed a written informed consent in accordance with the principles of the Declaration of Helsinki. The study was approved by the Cantonal Committee of Vaud (Switzerland) for ethics in human research under the protocol number PB_2017-00295.

The participants were asked to mentally navigate the robot in an unmodified office environment with seven target positions in Fig. 4.

We compare the performance of the proposed *shared intelligence* system driven by brain-computer interface with respect to a manual teleoperation based on joystick that is taken as reference as best teleoperation interface (since the user can control any single movements of the robot at any time). Each participant repeats the navigation task via BCI four times. An illustrative video is available at https://aixia2020.di.unito.it/awards/premio-pietro-torasso.

4 Preliminary Results

The first tests were successful in demonstrating the flexibility of the presented *shared intelligence* in the typical circumstances of the indoor environment as in our setup (see Fig. 4): the free space area, door passage, corridor, crossroad, areas covered by obstacles. We evaluate the performance using the following quantitative metrics that are typically considered in the case of BCI driven mobile robots: the number of commands, the spent time and the path length in the two conditions (BCI vs. joystick). The results are shown in Fig. 5. We perform multiple two-sided Wilcoxon rank-sum to verify statistically significant difference between the two modalities.

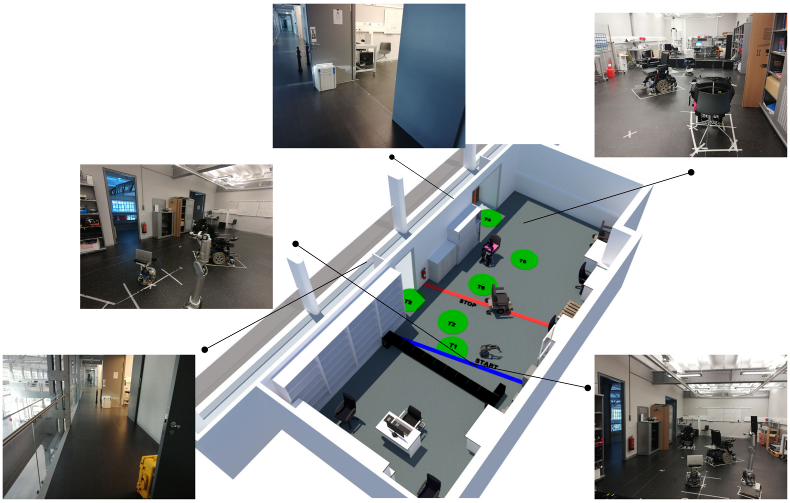

Fig. 4. Experimental setup. The participants control the robot in the represented unmodified environment with the seven target positions (in green). (Color figure online)

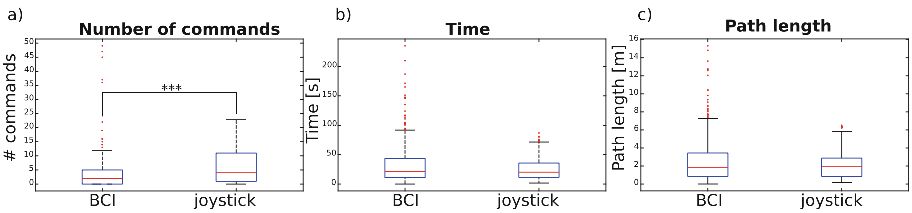

Fig. 5. Boxplots of the performances in terms of number of commands delivered (a), time spent (b) and path length per modality. The box edges signify the 75th (top) and 25(th) (bottom) percentiles and the horizontal line represents the median of the corresponding distribution. The whiskers extend to the largest and smallest non outlier values. Outliers are marked with red crosses. Statistically significant differences are shown with two-sided Wilcoxon rank-sum (***): $p < 0.001$. (Color figure online)

As expected, BCI users delivered a significant reduced number of commands with respect to the teleoperation through a joystick (BCI $= 3.99 \pm 6.66$, joystick $= 6.01 \pm 6.25$, p $= 0.00093$). The average time with BCI is slightly longer and the path length higher than joystick but any statistical difference was found (respectively BCI $= 34.89 \pm 38.74$ s, joystick $= 26.50 \pm 22.3198$ s for the time and BCI $= 2.74 \pm 2.94$ m, joystick $= 2.20 \pm 1.86$ m in terms of path length).

Finally, participants gave qualitative feedback through a questionnaire based on a 5-point Likert-type scale. They reported that the robot helped them to reach the target positions (3.38 ± 0.86) and the robot's behavior was expected through the BCI (3.153 ± 0.98).

5 Conclusion

In this paper, we introduce the concept of *shared intelligence* to combine the user's commands with the robot's perception to navigate a mobile robot via BCI. Despite the flourishing of many brain-actuated robots during the three decades of BCI research, in most of the state-of-the-art studies the interaction between human and robot is still rudimentary in which the robot implements the user's commands passively [11,18]. Herein, on the contrary, we promote the applications of artificial intelligence algorithms and robotic knowledge to create an effective and ecological system that enhances the role of the robot. In particular, we simultaneously fuse the different information relevant in the robot's navigation into a modular system based on *policies* that put on the same level the robot's inputs according to its perception with the user's commands. Since our system does not make any assumption about the kind of environment but rather it is based on the cooperation between the user and the robot, our approach might facilitate the transfer of BCI driven robots outside the laboratory. The preliminary results suggest performance comparable with a joystick teleoperation despite the limitation interaction derived from BCI. Furthermore, participants confirmed that the system supported them and that the robot's behavior was in line with their intentions. This aspect is a major point in developing user-centric solutions and in guaranteeing user's acceptance.

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