Emulated haptic shared control for brain-computer interfaces improves human-robot cooperation

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***Abstract*— Today, technology provides many ways for humans to exchange their points of view about pretty much everything. Visual, audio and tactile media are most commonly used by humans, and they support communication in such a natural way that we don't even actively think about using them. But what about people who have lost motor or sensory capabilities for whom it is difficult or impossible to control or perceive the output of such technologies? In this case, perhaps the only way to communicate might be to use brain signals directly. The goal of this study is therefore towards providing people with tetraplegia, who may be confined to their room or bed, with a telepresence tool that facilitates the daily interactions so many of us take for granted. In our case, the telepresence tool is a robot that is remotely controlled. It can act as a medium for the user in their everyday life with the design of a virtual link with friends and relatives located in remote rooms or places or with different environments to explore. Therefore, the objective is to design a Human-Machine System that enables the control of a robot using thoughts alone. The technological part is composed of a brain-computer interface and a visual interface to implement an "emulated haptic shared control" of the robot. Shared motion control is implemented between the user and the robot as well as an adaptive function allocation to manage the difficulty of the situation. The control schema that exploits this "emulated haptic feedback" has been designed and evaluated using a Human-Machine Cooperation framework and the benefit of this type of interaction has been evaluated with five participants. Initial results indicate better control and cooperation with the "emulated haptic feedback" than without.**

Keywords—disability, brain-computer interface, human-machine cooperation, adaptive level of automation

I. Introduction

Our long-term vision is to improve quality of life for people who may be confined to a bed and are unable to use conventional interfaces, e.g. perhaps due to tetraplegia. The aim of this study is to develop an assistance system to compensate the user's inabilities, consequently enabling interactions with parents, friends and environment using a brain-controlled telepresence system. In particular, we apply the principles of Human-Machine Cooperation (HMC) to understand how the human will be able to operate the device effectively. The results of this new five-participant experiment, build upon our previous single-user case-study [1].

The HMC approach has been designed and applied in several different domains [2], [3] and especially in ground robotics [4]. The main purpose of this approach is to design and use a generic method that supports designers in identifying how the user may cooperate with an assistance system, especially regarding the dynamic selection of suitable adaptive levels of automation [5], whilst improving their performance, safety [6] and their confidence [7].

Key concepts in the fields of HMC and brain-computer interfaces (BCI) are briefly presented in order to introduce the specific challenges of our cooperative system. We then present the new experiment conducted with five able-bodied participants, before discussing the results. Finally, we conclude that "emulated haptic feedback" is a good way to support Human-BCI-Robot cooperation. Nevertheless, we propose further refinements to improve system usability.

II. Related work

In this section we present the key concepts used to design such a Human-Machine System (HMS). They deal with models of cooperative agent, Brain-Computer Interfaces (BCI) as well as cooperative design.

A. *Model of cooperative agent*

The objective of the Human-machine cooperation approach is a find the best balance between the Know-How (KH) of the human and the machine to perform a function, whilst taking into account their abilities to cooperate with the other, called the Know-How-to-Cooperate (KHC).

The KH relates an agent's competences (abilities) and capacity (workload or attention for example) to control a process or an environment as if this agent were to do it alone. The agent has more or less expertise or training to fulfil functions (based on knowledge, rules and skills [8]), linked to expertise, experience and practices of agents with these functions. Human information processing might be sometimes very complex, but we used a framework to reduce the complexity into four main functions [6]: information gathering on the environment; analysis of information in order to identify its state (diagnosis/prognostic); decision making regarding its control; and action implementation. In our study, the user and the robot both have to be aware of their abilities to get information about the environment in which the robot is running, to analyze information, avoid obstacles and reach the goals.

The KHC is the ability of agents to obtain information about other agents reaching the same goals or using the same procedures, and to provide them with information about themselves and their own activity in order to make the cooperative activity easier [2]. The support of the KHC, so called the Common Work Space, enables agents to be aware of environment, but is also enriched by the team situation awareness dealing with past, current and future activity of other agents [9].

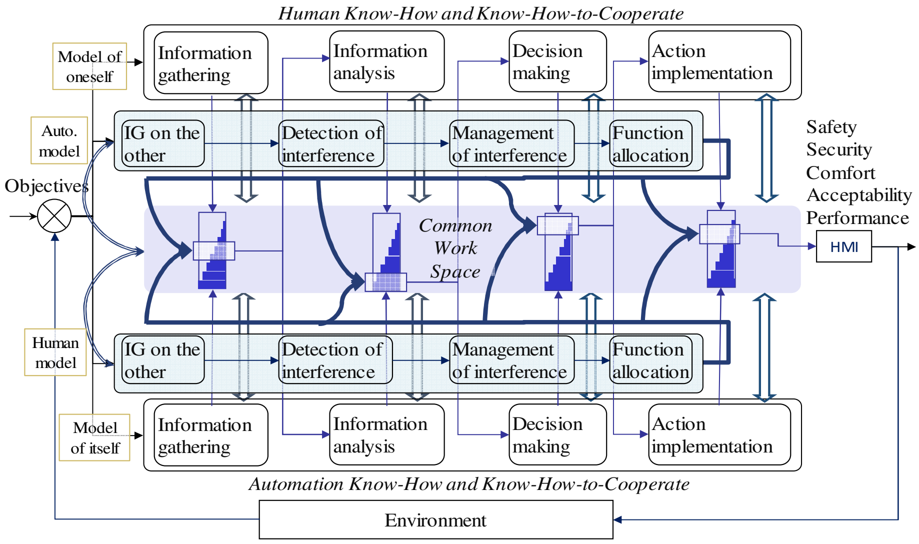


Fig. 1. Human-machine cooperation model [10].

Thanks to this cooperative capability, agents may build up a model of others by learning, training and exchanging with other agents. With this model they can then be able to infer their KH and KHC.

Using the artificial intelligence point of view, and more particularly the multi-agent approach, KH and KHC define two interwoven functions described by four sub-functions as presented in Fig. 1. The Common Work Space, represented by the central rectangle, supports interactions between agents and to decide function allocation. They compare the inference of results stemming from the information processing of the other, to their own results (interference detection and management) to adjust the position of the four sliders that describe the functions allocation (scales represented in the Common Work Space). The position of a slider on a scale defines the percentage of sharing between the human and the automation function. It is not only decided according to the agents' KH but also according to the complementarity between these KHs analyzed through their KHCs. For example, two agents can be completely complementary regarding their KH, but if they have no KHC they cannot take into account the others' activity to adjust their own activity and reach their common goal.

These definitions and concepts can be used as a methodology to follow to identify and design cooperation between a robot and a human through the BCI system that is now presented.

B. Brain-Computer Interface (BCI)

We use the same fundamental BCI that we developed for our original case-study [1], which was constructed around CNBI's motor imagery protocol [11]. The user can perform one of two tasks: either imagine moving their left or right hand and these are then decoded by the BCI, giving two classes for control. A third implicit class exists, when the user does not imagine moving either hand and in this case the control authority is delegated entirely to the robot. This self-paced, asynchronous BCI has been demonstrated to be a potentially viable in many different application areas, ranging from wheelchairs [12] to exoskeletons [13] and is of particular interest, since it is skill-based.

In the CNBI protocol, the electroencephalogram (EEG, or electrical activity of the brain) is recorded non-invasively at 512Hz, using the g.GAMMA system by g.Tec GmbH. Sixteen electrodes are placed directly over the Motor Cortex. After Laplacian filtering the EEG to improve the signal-to-noise ratio, we use Welch's method to estimate the power spectral density (PSD) for the previous one second, every 62.5ms (from 4 to 48Hz, with 2Hz bins [14]). Using canonical variate analysis (CVA), we then select the features for each participant that maximally separate the classes, whilst being most stable [15]. A Gaussian classifier is then trained on these features, which, in line with the literature, are typically found within in the mu-band (~8-13Hz). Classifier accuracy within the BCI community is often reported to be good at only around 70%. However, this is insufficient for our real-time control task, since any error in sending commands to the robot could add a substantial penalty in terms of time and effort taken to correct it. Therefore, to improve the accuracy at the level of commands sent to the robot, the instantaneous classifier outputs were passed through an exponential smoothing probability integration framework [16]. Once the accumulated value reached a participant-specific threshold, a command was finally delivered; e.g. left hand motor imagery was mapped to issue a turn left command to the robot.

C. Human-BCI-robot cooperation

The design of HMS usually requests the analysis of the overall system according to levels of abstraction of activity. Whatever the domain of application, the more common levels are the strategic, tactical and operational ones. From these levels, which are more focused on individual activity, the layers of cooperation were defined [17].

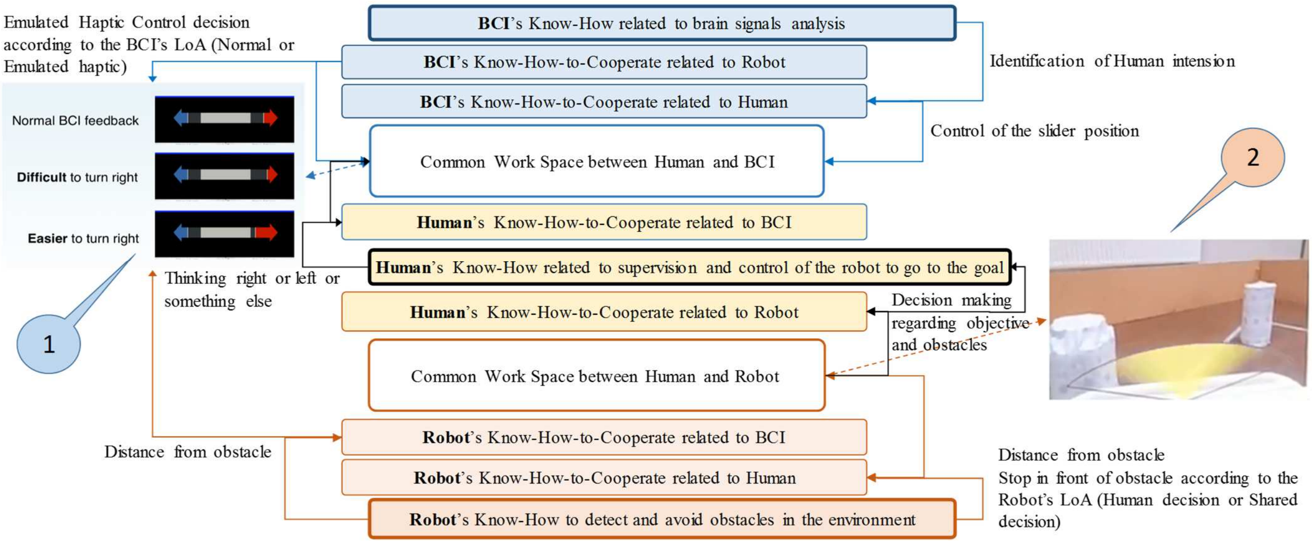


Fig. 2. Model of cooperation between Human, BCI and Robot according to their Know-How and their Know-How-to-Cooperate, Common Work Space between BCI and Human (1), Common Work Space between Human and Robot (2)

Layers deal with cooperation between levels to ensure a longitudinal control from navigation, to guidance and command. In this HMS composed by a user, a BCI and a robot, two layers have been studied and defined. The operational layer deals with the obstacle avoidance (OA), which both agents can manage. The tactical layer updates the plan of the activity, by modifying the trajectory to reach the goal and controlling avoidance of unexpected obstacles, when this can currently only be managed by the user.

Indeed, in this case of telepresence, human has no real goals but may have several small ones according to opportunities such as searching information, meeting different people. Moreover, providing precise goal with position for example to the robot is almost impossible, due to the relatively low resolution and throughput of the BCI as an interface. The robot cannot yet recognize human intention and is so unable to define the trajectory itself to reach it. Therefore, the robot has no KH or KHC at the tactical layer.

At the operational layer, both human and robot can control trajectory and obstacle avoidance (OA). The human detect obstacles through a live video stream of the environment from the robot's perspective (cf. Fig. 2, (2)) ; and the robot detect obstacles thanks to its ultrasonic sensor (shared information gathering and analysis). Both make decisions (shared decision), but the robot is the only one which can execute the decision and update the trajectory.

Both the human and the robot get information about each other. Interferences might be detected and managed, like the detection of obstacle or wrong command by the way of the Common Work Space (cf. Fig. 2: KHC). Nevertheless, the final decision to move to the right or the left is made by the robot, mainly due to the limited capacity of the human to react quickly to an unexpected situation. That is an inherent constraint of the current state-of-the art in this type of BCI and indeed is always a challenge in teleoperation situations, where unpredictable transmission delays may occur. In order to compensate such a behavior, we defined the "emulated haptic shared control" [1]. This specific type of control is based on the detection and management of interference, functions of the KHC.

Haptic control is used for a long time in robotics, aeronautics and in car driving adding a force feedback in the command device, sticks or steering wheel [18]. The concept we propose has been based on a similar principle. However, when a command is sent via a BCI, no muscles can oppose or follow the direction provided by the system, then it is not a real haptic feedback. Therefore, the idea is to emulate this haptic behavior by changing the behavior of the classifier output and illustrating this on a visual display. The robot/BCI system makes the action implementation easier or more difficult, in terms of (mental) effort, for the human, according to where obstacles are detected. The ease or difficulty is conveyed to the user through our standard visual feedback (cf. Fig. 3, (1)). When the user performs motor imagery, the grey bar moves to the left or right depending upon which hand the user focuses on. When the grey bar touches right or left arrows, it delivers the corresponding turn command. Updating of the size of the arrow according to the modification of the thresholds to deliver BCI commands makes the implementation of the turn or no turn (mentally) easier or more difficult. This gives the illusion of a "haptic" feedback, although no real contact forces or muscle activations are involved. This new concept was first presented in a single user case study [1] but is now explored in much greater detail here with our five-participant study.

III. Implementation and Tests

This experiment aims to evaluate the potential of "emulated haptic feedback" to control a robot with a BCI. An initial pilot experiment was conducted to validate technical feasibility and human ability to control such a system [1]. A new complete experimental protocol has now been proposed and is explained as follows.

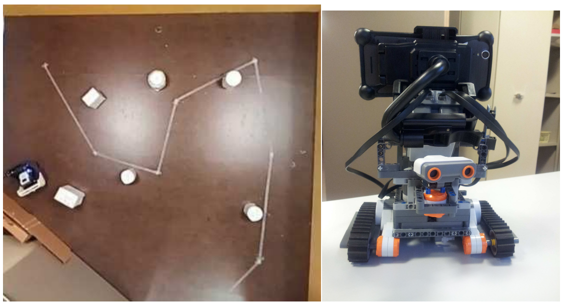
A. *Use case*

During the experiments the participants had to control the robot in order to follow the trajectory indicated by the white tape on the floor, whilst avoiding the obstacles (cf. Fig. 3 (a)). The robot is not able to follow the proposed trajectory because it cannot perceive the tape, just as it would not know where a user would like it to go with a remote control. However, this serves as a ground truth for the human "intention".

B. *Experimental platform*

1) *Mobile robots*

The mobile robot is a Lego Mindstorms NXT (cf. Fig. 3 (b)). It is a small, low-cost robot, supporting rapid prototyping to study cooperation between robot and human.



(a) Experimental room (b) Lego Mindstorms NXT

Fig. 3. Experimental environment and telepresence robot platform

The robot sends its information analysis based on its 3 sensors (ultrasonic, gyroscope and contact) through an XBee module, and video feedback by Wi-Fi with the smartphone. It receives commands from the user through the same XBee module. The 3 motors of the robot control the two wheels (speed: 0.06 m/s) and the lateral rotation of the ultrasonic sensor (60° angle).

When the robot detects an obstacle less than 40cm away, it only notifies the human. However, when the distance is less than 10cm, the robot stops. When the user sends a command to go on the right or left, the robot performs a 45° turn in the requested direction.

2) *Control interface*

The visual interface proposed to the user is presented on Fig. 4. Two displays are used, a video feedback provided by the robot about the environment, and the emulated haptic feedback to send the command (right or left) to the robot.

First, the users are trained with the BCI, and the BCI trained with the user to build a model (mutual learning, cf. II.B). For the users to be able to control the robot, they have to relax their hands loosely on their lap and must imagine the kinesthetic movement of their left or the right hand. It is not so easy, but when they succeed, the grey bar rendered on the screen moves in the direction corresponding to the imagined hand movement. The motion of the grey bar may represent the intention of the user if the model the BCI uses regarding the user is well-trained and correctly calibrated.

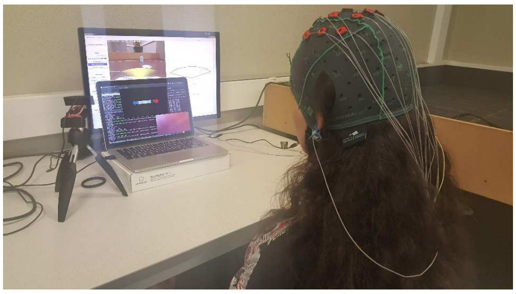


Fig. 4. BCI/Emulated haptic control interface. Visual feedback is provided about the state of the BCI system as well as the environment in which the robot is operating.

Controlling this type of device requires the user to be very focused on a single task to prevent interferences in the detection and analysis of signal. They have to avoid contracting muscles, even the position of the eyes. However, such a request is unfortunately easier to respect for people with tetraplegia, since they have few volitional control of large muscle groups. Nevertheless, before gaining approval to work with tetraplegic users, we must first evaluate the prototype with healthy, able-bodied participants.

IV. Experimental protocol

The training session is split into three stages. 1) Using only the BCI, the computer learns the specific patterns of the participant's brain signals, initially without them directly controlling the feedback (offline). 2) Once an initial classifier has been built, the user directly controls the motion of the visual feedback bar with the BCI and the classifier is updated using this (online) training data. 3) Finally, the user learns to operate the robot with the BCI in a free exploration task; the participant trains both with and without emulated haptic feedback in this stage. Two experimental conditions have been defined, combining the possibility to use emulated haptic feedback or not. we present the results relating to the Emulated Haptic (HE) vs. No Emulated Haptic conditions (HNE).

The results presented in the next section stem from the analysis of video records, combined with a data log recorded during the experiments performed by the five healthy participants with randomized conditions.

V. Results and discussion

The results are stemming from objective and subjective data analysis. A coding of participants' and robots' actions has been undertaken in order to identify the global performance for each experimental condition and to value the quality of cooperation. The global performance has been calculated according to the number of sections of the trajectory the participants correctly traversed (cf. Fig. 5), as well as the number of loops they made in order to complete each section correctly.

The quality of cooperation has been evaluated according to the number of interferences between the participants and the robot. The first type of interference occurs when the robot does not take into account the command from the participant because of (occasional) communication problems with the Xbee, which is not an unrealistic scenario for telepresence systems. The second type of interference relates to the stopping of the robot when it is too close to an obstacle (< 10 cm).

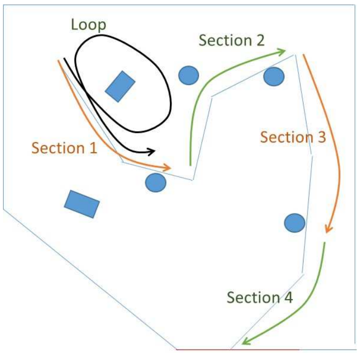


Fig. 5. The four sections of the trajectory (orange and green sections from 1 to 4) and an example of loop (black drawing)

The next type of data that has been analyzed is the action performed by the participants and the robot. The number of commands could indicate the level of cooperation; e.g. when the participant "fights" against robot's decision to go in the opposite to their desired direction, the number of commands increases. The last type of data is the number of collisions the robot encounters.

A. *Results*

1) *Objective data*

In the HE experimental condition, the robot makes fewer stops than in the other condition (cf. Fig. 6). This result is perhaps thanks to the Emulated Haptic feedback, which makes it more difficult for the participant to send the robot in a direction where there is clearly an obstacle.

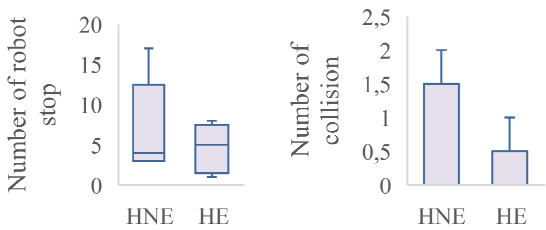


Fig. 6. Number of stops of the robot because it detects an obstacle, and number of collisions per experimental condition

The mean number of collisions is not very substantial (less than 1 on average per condition), nevertheless it is smaller with emulated haptic feedback (cf. Fig. 6).

There is not much difference in the total number of commands sent by the participants in both conditions (cf. Fig. 7). Similarly, the number of loops in both conditions is comparable. Nevertheless, the results highlight more inter-individual differences in HNE than in HE. A hypothesis could be an effect of homogenization with emulated haptic feedback. On average, users complete more "correct" sections of the trajectory with HE.

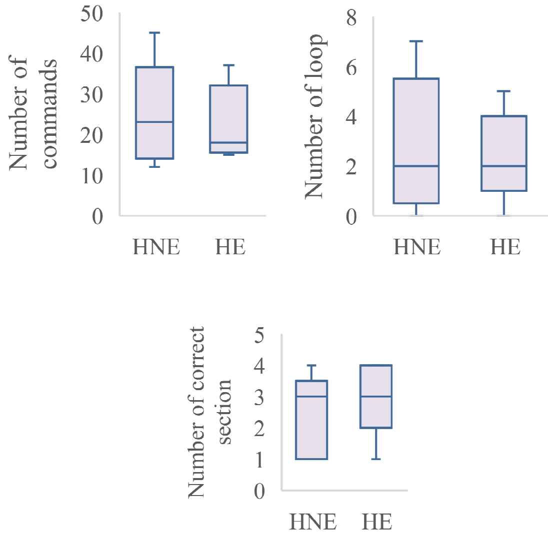


Fig. 7. Number of command sent by the participants, number of loops, and number of correct sections for each experimental condition.

2) *BCI Accuracy: Objective and subjective data*

The BCI command accuracy was calculated at the end of the training session, just before the experimental sessions. The score is very good (mean: 92%; std: 5%). This result is consolidated by the results from questionnaires concerning the evaluation of training from the participant point of view:

- Were you trained sufficiently to use the BCI? (from 1 (not at all) to 7 (absolutely))
- Were you trained sufficiently to use the BCI and the robot? (from 1 (not at all) to 7 (absolutely))

Participants felt they were sufficiently trained with BCI and with BCI and robot at the same time (first question (mean: 6.6, std: 0.54); second question (mean: 6.2, std: 1.30)). The control of BCI and robot at the same time is more difficult because participants had more tasks to perform to control the environment and the robot.

BCI accuracy is correlated to two objective results: the number of commands (r: 0.77); and the number of sections that had been followed correctly (r: 0.77). We can suppose that the participants who felt in control of the BCI were not afraid to send several commands and were able to better adapt the trajectory in a manner that more closely respected the requested trajectory.

3) *Results stemming from subjective data records*

a) *Questionnaires: Expertise of participants*

A performance score has been calculated for each participant for each experimental condition. It is the sum of the number of collisions (coef.: -0.5), plus the number of loops (coef.:-0.5), plus the number of correct sections traversed (cf. Fig. 8). An expertise score has been calculated according to the participant's expertise regarding the control of robot and the use of BCI. The participants had to answer to the two next questions by selecting one choice.

The sum of the two answers provides the score: Never (0), Occasionally (0.5), Sometimes (1), Often (1.5), Always (2).

Questions to evaluate participant expertise:

- Have you ever used a BCI before the experiment?
- Have you ever used a robot before the experiment?

Questions to know preferred experimental condition:

- Which interface did you prefer? (Without emulated haptic support, With emulated haptic support)

There is a strong correlation (r: 0.9) between the expertise score and the score of the preferred experimental condition (type of system). The less the participant felt expert the worse the participant performed in their preferred experimental condition. The more the participant felt expert, the more likely they would make a good decision, the more the robot needed to stop (r: 0.79) and the fewer the number of resultant loops (r: -0.71). One explanation could be, the more the participant is expert the better the participant can manage interferences with the robot and the BCI to achieve good overall performance.

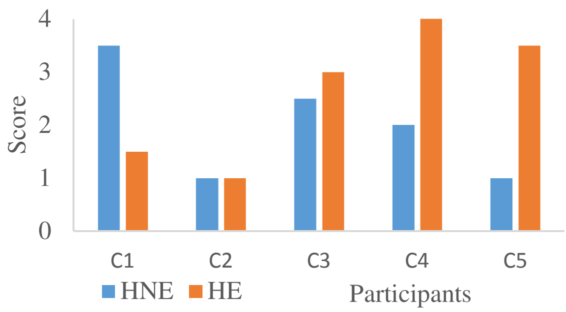


Fig. 8. Performance score for each participant (C1 to C5) for each experimental condition

VI. CONCLUSIONS AND PERSPECTIVES

We have presented a human-robot cooperation system whose ultimate goal is to allow people with tetraplegia to cooperate with and remotely control a robot using a BCI. This paper reported an empirical study with five able-bodied participants to evaluate the cooperation between human and robot. The cooperation is designed using the human-machine cooperation model and is evaluated using both objective and subjective data. Generally, the results highlighted a better cooperation under the *emulated haptic* support mode.

In future work, we would like to give more assistance to the human operator by adapting dynamically the behavior of the robot according to the human state. In fact, we assume that such a task required a high level of concentration and mental workload. In this regard, we envisage a BCI able to monitor human operator states [19]. In addition, we aim to reduce the number of false positives or indeed to help the BCI to (continuously) retrain the classifier [20]. The robot behavior could then be improved by dynamically adapting its level of automation [5], i.e. increase the level of automation of the robot when the level of human mental workload is high.

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