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Towards a Brain-Robot Interface for children

Gloria Beraldo[1], Stefano Tortora[1] and Emanuele Menegatti[1]

Abstract— **Brain-Computer Interface systems have been widely studied and explored with adults demonstrating the possibility to achieve augmentative communication and control directly from the users' brain. Nevertheless, the study and the exploitation of the BCI in children seems to be limited. In this paper we propose and present for the first time a Brain-Robot Interface enabling children to mentally drive a robot. With this regards, we exploit the combination of a P300-based Brain-Computer Interface and a shared-autonomy approach to achieve a reliable and safe robot navigation. We tested our system in a pilot study involving five children. Our preliminary results highlight the advantages of using an accumulation framework, thanks to which the performance of the children reached the 81.67 % $\pm$ 12.7 on average in terms of accuracy. During the experiments, the shared-autonomy approach involved a low-level intelligent control on board of the robot to avoid obstacles, enabling an effective navigation also with a small number of commands.**

I. INTRODUCTION

Brain-Computer Interfaces (BCIs) are a well-known technology able to detect and translate electrical signals produced by the brain activity into outputs communicating the user's intent without the participation of peripheral nerves and muscles [1]. For people with neurodegenerative diseases, these interfaces can provide an alternative form of communication, implementing a direct mind-control of external devices. In this perspective, thanks to the knowledge acquired over the last 15 years about the brain functions and the progress in robotics, people have been able to control different devices such as new generation of neuroprostheses, wheelchairs, telepresence robots and robotic arms [2], [3], [4].

Despite BCI systems have been widely investigated and explored over the years in different contexts, most studies focused the attention on adult subjects. To the best of our knowledge, the exploitation of BCI in children seems to be strongly limited. Surely the lack of procedures, guidelines and recommendation according to the evidence-based medicine paradigm plays a significant role. However, as mentioned in [5], the incident rates of severe neurological disorders in children should be not overlooked. The consequences of them can be various and severe depending on lesion location and size, its cause and the age of the young patients: motor disorders, seizures, cognitive and neuropsychological disturbances [6]. Nevertheless, effective medical treatments and rehabilitation approaches can significantly influence the therapy outcome and especially in children it can be more promising than in adults thanks to their brain plasticity [7]. In this context, the exploitation of advance techniques like BCI might be a future prospective for neurological rehabilitation and physiotherapy for children with severe neurological deficits.

[1]Intelligent Autonomous System Lab, Department of Information Engineering, University of Padova, Padua, Italy. beraldog, tortora, emg@dei.unipd.it

Fig. 1. A child mentally navigating a service robot by the proposed Brain-Robot Interface

In this paper we propose a preliminary system to navigate a robot by a Brain-Robot Interface. To the best of our knowledge, this is the first one which enables children to mentally control a service robot in a non structured environment (see Fig. 1). To this aim, we adapted our previous system, based on a semi-autonomous navigation algorithm, which was already tested in adults [8]. In that work, the robot takes as input high level commands from the user and autonomously deals with low level problems, such as obstacle avoidance and the search of the best trajectory to arrive to the destination. However, in comparison to our previous work, in order to facilitate the control of the robot for children, we simplified the system both in the BCI protocol and in the feedback given to the user. In details, we used the intuitive BCI based on visual event-related potentials (P300) [9] and we modified the graphical interface to give a richer feedback to the children. All these aspects are particularly important when users are children [10] and motivated our designed choices. This work aims at developing a preliminary Brain-Robot Interface enabling children to mentally drive robots. We assume that this kind of system can be useful also to expand the knowledge about BCI in children. Indeed, the presented work is inserted in a long term project with the purpose of validating the proposed Human-Robot Interface in a paediatric context with the collaboration of neurophysiologists, psychologists and children experts.

This paper is organized as follows. Section II describes the BCI system, the robot and our semi-autonomous navigation algorithm. In Section IV we show and we evaluate our preliminary results. Finally in Section V we discuss the

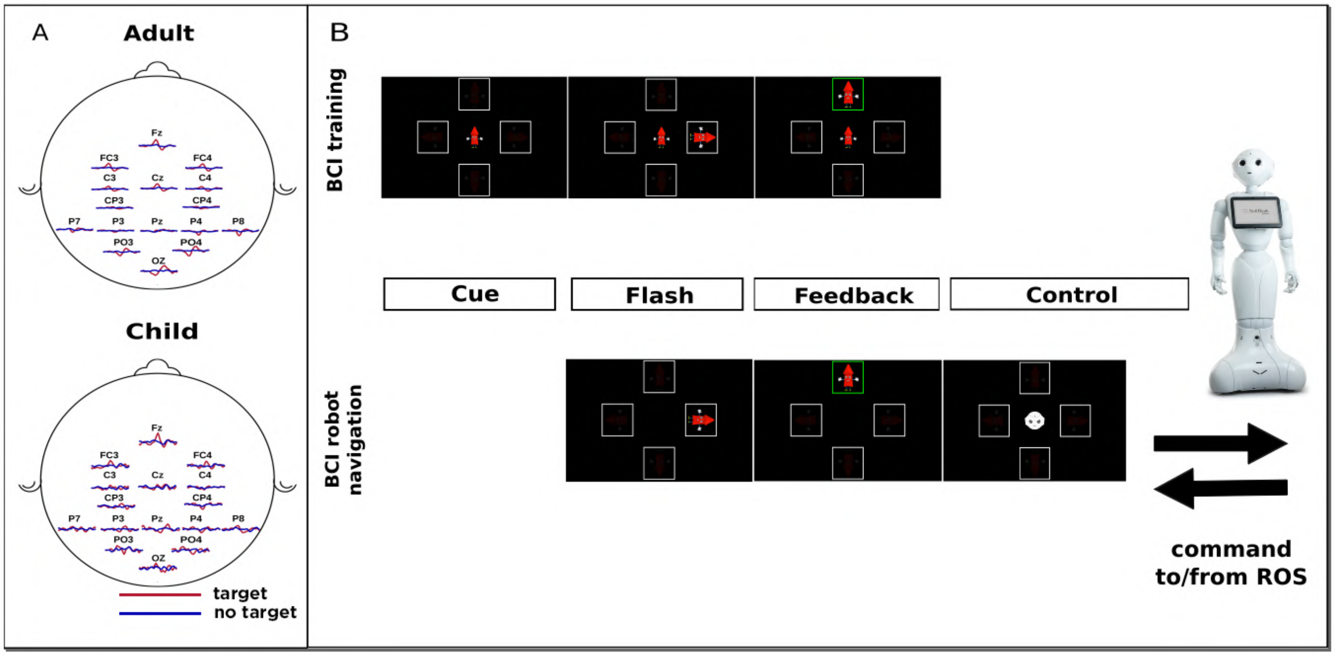

Fig. 2. A) Topographic distribution of P300 potentials in a sample of adult and children subjects. B) Schematic representation of the visual graphical interface used to stimulate the subjects. Top row: the protocol we used during the training is shown. The user was instructed by a symbolic cue appearing in the centre of the screen about the target image he/she has to focus his/her attention. Then, all the images flash block-randomized for several blocks. Thus, a visual feedback is provided to the user based on the BCI prediction, indicating the end of the trial. A green (if classified image is equal to the target)/red (otherwise) box is added around the classified image. During the BCI training we did not use the robot, therefore no feedback is provided by it. Bottom row: The protocol during the robot navigation through the BCI is the same as during the training with the exception that there is no cue because the user decides autonomously on which image he/she focus his/her attention. When the BCI system has a new outcome, the classified image was highlighted with a green box and the corresponding command is sent to the ROS infrastructure. While the robot is performing the current behavior, the user is not stimulated until an image representing the robot's face appears in the centre of the graphical interface. It represents an additional feedback from ROS system indicating the execution of the command by the robot and a signal for recalling the user's attention to send the next command.

proposed system and we present our future directions.

II. METHODS

A. Brain-Computer Interface system

From the point of view of the BCI system, we chose to apply an visual P300 BCI [9]. Indeed, as previous studies with adults showed [11], [12], the P300 signal is easy to recognize in almost every person. For further information, the Fig. 2A shows the P300 waves of the children and adults subjects involving in this study.
Moreover, P300 approach is more intuitive than other BCI paradigms (e.g those based on Sensorimotor Rhythm (SMR)). Therefore, also the task required to the subject is very simple to be explained by the operator and especially to be understood by children. At the end, extensive training is not necessary, reducing the risk of losing the attention and the participation of the children.

In the following parts, we briefly describe the different components of the BCI system we used for the study.

- ***Paradigm***
  The user can drive the robot by concentrating on the graphical interface depicted in the right box of Fig. 2B. In order to elicit the P300 visual event-related potential, four coloured arrows are flashed in a random sequence in the four boxes on the top, bottom, left and right positions, corresponding respectively to the following four commands for the robot: FORWARD, STOP/GO BACK, TURN LEFT, TURN RIGHT. The flashing arrows appear in a random sequence with permutation without repetition; the sequence is called a *block*. We set the flash period (i.e. the interval in which the arrow is turned on) to 0.15 s and the inter-flash period (the amount of time between two consecutive flashes) to 0.55 s, resulting in an inter-stimulus interval (ISI) of 0.7 s. Thus, each block lasts for 2.8 s. The sequence of blocks is grouped in a *trial*. At the end of each *trial*, the BCI classifier, based on the P300 signals of the user, predicts the command selected by the user and shows it on the screen (the green box in Fig. 2B). The command is sent to the robot for the execution. After the execution a new *trial* starts. At the beginning of a trial a small icon with the face of the robot is shown for 1 s to be sure the children do not miss the first flashes of the first block. Several *trials* are grouped in a *run*.
- ***EEG Acquisition and Preprocessing***
  EEG data was recorded using a portable g.tec system (g.tec medical engineering, Austria), receiving in input 16 channels. Electrodes were placed over the frontal and parieto-occipital areas (Fz, FC3, FC4, C3, Cz, C4, CP3, CP4, P7, P3, Pz, P4, P8, PO3, PO4, Oz) according to the international $10-20$ system layout (see Fig. 2A). Samples were recorded at 512 Hz sampling rate.

The signal inside the 0.45 s time-window epoch after every stimulus was acquired and a butterworth 4^{th} order digital band pass filtered in the range 1-24 Hz was applied, to remove baseline drift and high-frequency noise. Then, a common average reference (CAR) filter was performed and the signal was decimated by a factor of 8. To reduce the effect of eye-blink, eye-movement and muscle artefact, the signal from each channel was winsorized, by computing the 10^{th} and 90^{th} percentiles of the signal amplitude and by replacing every sample outside this range with the value of 10th and 90th percentile, respectively. Finally, we applied a z-score normalization to account for trial-to-trial and day-to-day variability.

- ***Feature extraction and Classification***
The resulting samples for each channel were concatenated, creating a features vector for each trial (the length of feature vector was 64 Hz/(1/0.45 s) samples $\times$ 16 channels = 464). Offline evaluation of the system was performed for each subject by means of a 4-fold cross-validation over the training dataset. Once this set of features $\hat{\mathbf{x}}$ was extracted, the next step was the classification phase. In this system, we applied the Bayesian Linear Discriminant Analysis (BLDA), that was extensively studied for P300 classification problems [13], [14], [15]. Briefly, BLDA can be seen as a regularized version of Linear Discriminant Analysis (LDA), in which the *weight vector* $\mathbf{w}$, such that the discriminant function is equal to $t(\mathbf{x}) = \mathbf{w}^T\mathbf{x}$, is assumed to be a latent variable and estimated using Bayesian inference [13]:

$$P(\mathbf{w}|\beta, \alpha, \mathbf{D}) = \frac{P(\mathbf{D}|\beta, \mathbf{w})P(\mathbf{w}|\alpha)}{\int P(\mathbf{D}|\beta, \mathbf{w})P(\mathbf{w}|\alpha)dw} \quad (1)$$

where $\mathbf{D}$ is the training dataset, $P(\mathbf{D}|\beta, \mathbf{w})$ and $P(\mathbf{w}|\alpha)$ are the likelihood function and prior of the weights, assumed to be Gaussian. The likelihood function of the weights is estimated from the training dataset $\mathbf{D}$, while the prior distribution is set equal to a isotropic multivariate Gaussian, with diagonal covariance matrix of value α. Finally, β and α are hyperparameters of the classifier and can be iteratively estimated from the training dataset, maximizing the likelihood. Detailed description and implementation of the algorithm can be found in [13], [16], [17].
At each trial, when a new feature vector $\hat{\mathbf{x}}$ is received, the output of the classification was given by $\mathbf{w}^T\hat{\mathbf{x}}$ with $\mathbf{w}$ equal to the mean of $P(\mathbf{w}|\beta, \alpha, \mathbf{D})$, representing the raw posterior probability to belong to the target class. However, to accumulate evidence of the user's, the raw probabilities were integrated linearly over blocks of stimulus N_b. More precisely, the classifier provides four posterior probabilities (one for each class) computed by summing over blocks for each image. The class C, maximizing that sum, is selected and converted to the corresponding command to send to the robot:

$$C = \underset{c \in \{1,2,3,4\}}{\operatorname{argmax}} \sum_{b=1}^{N_b} \mathbf{w}^T \hat{\mathbf{x}}_{b,c} \quad (2)$$

The user is informed about the output of the classification through a visual feedback.

- ***Feedback***
The system provides to the user two different feedbacks (see Fig. 2B). One is designed to inform the user about the input detected by the BCI (a box around the classified image). The other aims to notify the user about the execution of the received command from the robot side. It consists in a small image representing the robot's face that appears in the centre of the graphical interface, when it is going to finish the execution of the current command and start the next planning. The aim is to draw the attention of the user on focusing again on the graphical interface to send the next command. Indeed, in the case of exogenous BCI, it is crucial the user is heedful to the graphical interface since it represents also the medium through which they are stimulated.

B. Robot

In this work, we exploited Pepper robot[1], designed by Aldebaran Robotics and released in 2015 by SoftBank (see Fig. 2B). It is a human-shaped robot that was created to be a day-to-day companion. Thus, it was optimized for human interaction and it is able to engage with people. The robot is 121 cm tall and it features 20 DOFs for natural and expressive movements. It has a 1.9 GHz quad-core Atom processor and 4 GB of RAM. For the navigation purposes, it is equipped with an omnidirectional base (0.480 $\times$ 0.425 m), two sonars, three bumpers, three laser sensors, an inertial unit and actuators. It provides also 2D and 3D cameras, touch sensors, LEDs and microphones for multimodal interactions.

III. Experimental design

The experiments were performed in two separate days (two sessions) per subject in order to reduce the workload required to the children. The first day is dedicated to the explanation of the protocol and to the BCI training, while the second one to the control of the robot. In details the training consisted in three runs including 8 trials per run (2 per each target image). The number of blocks N_b per trial during the training was chosen randomly between 7 and 9 in order to avoid habituation and expectation in the user. The subject was instructed by a symbolic cue appearing in the centre of the screen, about the target image on which he/she has to focus his/her attention (see Fig. 2B). In addition he/she was asked to not move, speak or blink during each run. The duration of each run was 3 minutes on average. After each run we included breaks and talks with the user.

We decided to calibrate the system after the first run, in order to engage more the child by providing a visual feedback based on the outcome of the BCI starting from the second run. Precisely, a green (if classified image is equal to

[1] https://www.softbankrobotics.com/emea/en/pepper

Fig. 3. The experimental environment: the user sat at position S and the robot is positioned in R at the beginning. The user was asked to mentally drive the robot from R to the three target locations T1, T2, T3 consecutively.

the target)/red (otherwise) box is added around the classified image in Fig. 2B. Then we trained the classifier after each run using all the available data.

In the second day, the user was required to perform only a new training run before driving the robot. We updated the classifier using the last three runs (2 acquired in the first day, 1 in the second day) and we chose manually the N_b to be used during the navigation phase according to the presence of a plateau in the average accuracy resulting in output from the cross-validation.

During the robot's navigation, the subject sat in front of a laptop at 1 m distant from a 15.6" display at position S. At the beginning, the robot was positioned in R and it is partially viewed by the user. The user was asked to move the robot from S, going consecutively through three target positions T1, T2, T3, by sending mental commands via the BCI (see Fig. 3). The user was aware of the robot's movements by watching its position in a map of the environment, that is provided to the robot for localization and navigation purposes.

A. Subjects

Five healthy children subjects (age 10.4 ± 2.19, 1 female) without any previous experience with BCI accepted to take part to the study and whose parents signed the consent form. In addition, in this study, we considered also 3 healthy adult subjects (age 26.33 ± 1.53, 1 female), on which we evaluated the feasibility of the protocol before testing on children. They did not try the P300 BCI system before. The project was also approved by the Ethics Committee for Clinical Trials of the Azienda Ospedaliera of Padua. All the experiments were conducted in accordance with the ethical guidelines of the 1975 Declaration of Helsinki.

B. Semi-autonomous navigation system

The core functionality underlying the navigation system is to provide an intelligent motion control of the robot according to the commands sent by the user through the P300 BCI. The motivation is to reduce as much as possible undesirable behaviors of the robots that could make tired and annoyed the child. With this regard, we extended our previous semi-autonomous navigation based on a shared control for BCIs and exploiting Robot Operating System (ROS) [8]. According to our algorithm, the user drives the robot by sending commands corresponding to change of its direction and at the same time, the latter performs obstacle detection and avoidance, computing the best trajectory to arrive to the goal. More precisely, the robot performs its default behaviour that makes it moving forward avoiding obstacles when it is necessary. Whenever the BCI system has available a new output, it is converted into the corresponding command. Furthermore, with the aim of making the robot moving smoothly, it receives a navigation subgoal, that is continuously updated based on the actions the user wants that the robot performs. Moreover, to achieve a stronger and a more reliable navigation, the robot uses a priori knowledge as well as a dynamic perception of the environment to move. Thus, the robot receives at the beginning two static global maps of the environment, thanks to which it localizes and it is aware about the fixed obstacles. In addition, it estimates its pose in the environment by fusing both odometry and the output of a localization module. Please refer to [8] for further details.

In the new protocol, the user can deliver four steering commands - GO, STOP/GO BACK, TURN LEFT, TURN RIGHT - to drive the robot. The commands TURN LEFT (left image in the P300 interface) and TURN RIGHT (right image in the P300 interface) makes the robot turn to the corresponding direction. When the user focuses his/her attention on the up or on the down images in the P300 interface, the user choice is mapped to different resulting actions according to the previous behaviour performed by the robot and its current status. In details, when the bottom image is chosen, it is converted to the STOP/GO BACK command. Precisely, if the robot is moving (speed different from 0), it has the function to stop the robot (STOP). Otherwise in the case the robot is still idle, it actives the GO BACK ACTION that makes the robot move backwards. This operation represents a kind of alternative RECOVERY BEHAVIOUR, that can be chosen voluntarily by the user, for example to correct commands misclassified by the BCI system or to unblock the robot when it is not able to reach the current target subgoal. Whereas, the selection of the image at the top — GO command — corresponding to the default behavior of the robot making it going straight. This can be used to reactivate this behavior after the selection of the STOP/GO BACK command or in case the robot is moving to keep it.

IV. RESULTS

A. Training phase

In this section we present the results of the classification based on the training dataset with children and adults subjects. In Fig. 4 and 5, we show the average accuracy over the iteration given in output by the cross-validation for each subject. The same curves are used by the operator to understand the performance of the system and to select manually the number of blocks N_b to be used during the

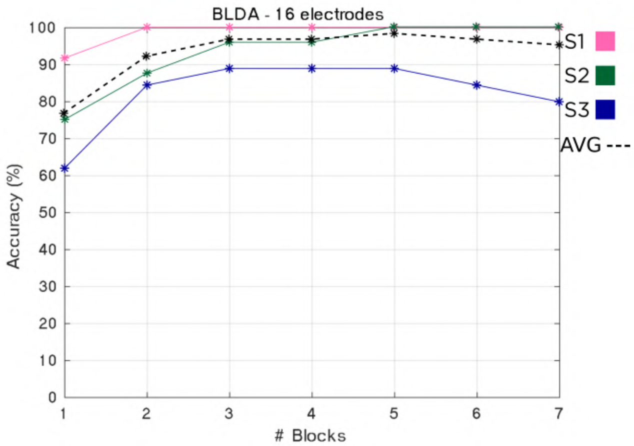

Fig. 4. Classification accuracy obtained by integrating over the blocks of stimulus for each adult subject. The dashed curve represents the average accuracy across adults.

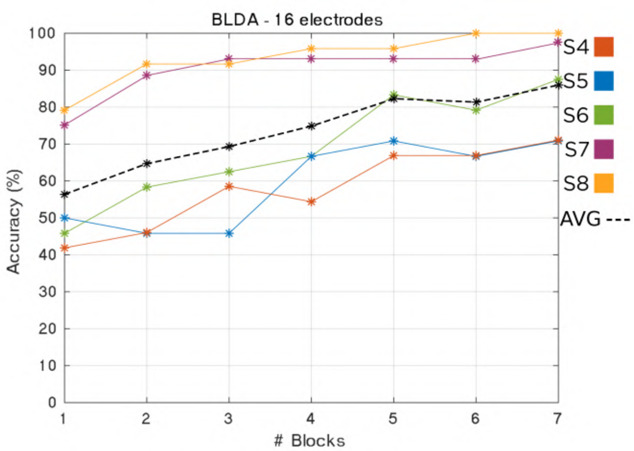

Fig. 5. Classification accuracy obtained by integrating over the blocks of stimulus for each children subject. The dashed curve represents the average accuracy across children.

navigation phase according to the presence of the plateau in the performance. In the case of the adults the average accuracy across subjects reached the 93.06% ± 12.03 after accumulating over 7 blocks starting from 76.39% ± 14.63. This was even more substantial with the children where the performance was increased from 58.33% ± 17.43 to 85% ± 15.86. With regards to the selection of the number of blocks N_b during the navigation, we considered 3 (average accuracy equal to 94.44%) as a good choice for adults, while in the case of children we selected generally 5 blocks (average accuracy equal to 81.67%), by taking into account both the performance and the time required to deliver commands (it increases with the increase of N_b). However, as shown in Table I and II, N_b was adjusted by the operator according to the status and the level of attention of each user. In Table I and II we present both the performance of our proposed framework based on the evidence accumulation and the corresponding one that would have been achieved by classifying after each flash (single epoch classification),

TABLE I

TRAINING PERFORMANCE WITH ADULT SUBJECTS

Subjects	Evidence accumulation			Single Epoch			
	N_b chosen	Accuracy	Chance level	Accuracy	Recall	Specificity	Chance level
S1	2	**1.0**	0.4	0.75	0.93	0.69	0.6
S2	3	**0.96**	0.4	0.74	0.86	0.69	0.6
S3	3	**0.88**	0.4	0.66	0.84	0.60	0.6

TABLE II

TRAINING PERFORMANCE WITH CHILDREN SUBJECTS

Subjects	Evidence accumulation			Single Epoch			
	N_b chosen	Accuracy	Chance level	Accuracy	Recall	Specificity	Chance level
S4	5	**0.67**	0.4	0.56	0.78	0.48	0.6
S5	5	**0.71**	0.4	0.60	0.73	0.56	0.6
S6	5	**0.83**	0.4	0.63	0.82	0.57	0.6
S7	5	**0.92**	0.4	0.64	0.88	0.56	0.6
S8	6	**1.0**	0.4	0.65	0.85	0.60	0.6

with respect to the corresponding chance level [18]. In particular, as expected, the accuracy is higher when evidence accumulation is applied: it rose by a factor of about 23% in both adult and children.

Moreover, to describe better the performance of the classifier, we considered also the recall and the specificity values in the case of single epoch classification, indicating respectively the probability of detecting the desired selection and the probability of correctly rejecting the wrong choices. Overall, in both adults and children subjects, the recall presented high values (87.67% ± 4.72 in adults and 81.12% ± 5.89 in children), while the specificity appears quite low (66.00 % ± 5.20 in adults and 55.4% ± 4.44 in children).

B. BCI driven robot navigation

In this section we present the results of the final experiment in which children and adults were asked to mentally drive the robot from S through the three target positions T1, T2, T3 consecutively (see Fig. 3). An illustrative video is available at `https://youtu.be/7GJE0aDmkxA`.

Among the children subjects, three of them (S4, S6, S8) took part to the final part of the experiment, making the robot navigate in the environment through the BCI. Unfortunately the other two subjects (S5, S7) performed only the training phase because they did not show up the second day for finishing the protocol. In addition, S6 and S8 tried to move the robot going through the three target positions T1, T2, T3 for three times, while S4 performed only one attempt because he was demotivated by using BCI and too attracted by the robot. Regarding the control of the robot, we considered the navigation accuracy computed as number of times each target position was reached over the number of total attempts across the subjects (see Fig. 6): the robot arrived in T1 driven by the children 100% of the total attempts, in T2 the 71.43% and in T3 28.57%. In addition, regarding the incorporation of the shared control, we analyzed also the number of the BCI commands delivered by the subjects and the time necessary to reach the three targets (in Fig. 6). On average children delivered 3.00 ± 1.15 commands to reach T1, 3.80 ± 4.66 for T2 and 2.00 ± 1.15 for T3. In terms of time, on average, 68.57 ± 27.17 s were taken to make the robot arrive in T1, 84.00 ± 82.96 s in T2 and 62.5 ± 27.17 s in T3. The high standard deviation related to the target T2 was due to an

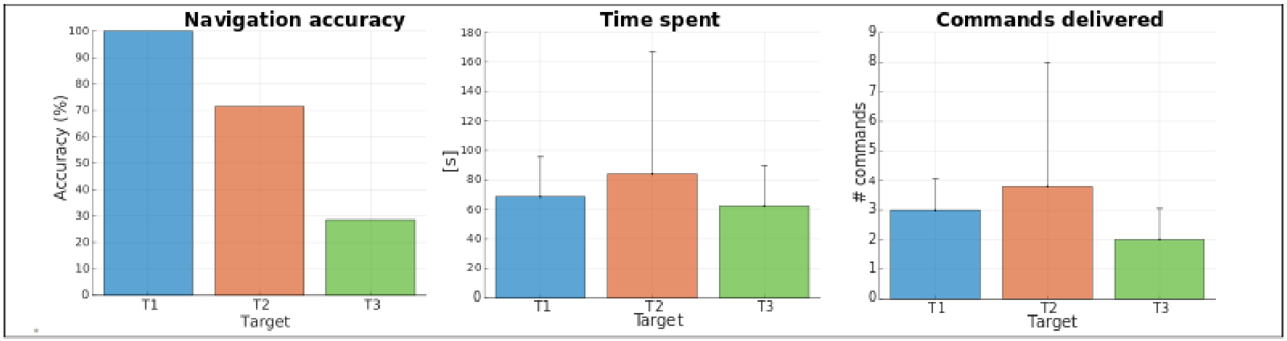

Fig. 6. Navigation accuracy, average and standard deviation of time spent and number of commands sent across the children subjects to reach each of the target positions T1, T2, T3.

attempt in which a lot of wrong BCI commands were sent by S6.

Also one adult (S1) controlled the robot through the BCI along the three target positions and repeated it for three times, by sending on average 7.00 ± 6.08 commands to reach T1, 2.00 ± 0 for T2 and 2.66 ± 0.57 for T3. However, in the P300 BCI the number of sent commands are strongly dependent on the number of the blocks used (N_b), 2.00 per adult and 5-6 for children. As regards to the time required to navigate the robot, in the case of the adult S1, on average 76.00 ± 64.11 s were necessary to make the robot arrive in T1, 23.0 ± 1 s in T2 and 28.66 ± 9.29 s in T3.

V. DISCUSSION

The main purpose of this paper was to present for the first time a Brain-Robot Interface to enable children to mentally drive robots. With this regards, the combination of an intuitive BCI paradigm and a shared-autonomy approach allowed also children to control robot only via BCI. Indeed, although in the current literature, endogenous system such as Sensorimotor Rhythm (SMR) have been mainly exploited to successfully control mobile devices [4], [19], [20], in this work we used an easier BCI paradigm based on a visual event-related potentials (P300). Surely on one hand, the endogenous BCI are more appealing because the user decides when starting the mental task independently of any external stimulus, on the other, the main advantages of exogenous BCIs such as P300 is that they are based on a very simple task suitable also for children and requires a limited training. Nevertheless, in our Brain-Robot Interface, the slowness, derived by using an exogenous BCI, is compensated from the robotics side thanks to the low-level intelligence on board of the robot. Our system demonstrated that the robot can avoid obstacles and determine the best trajectory to follow also in the situation when user cannot deliver new commands.

Since the exploitation of the BCI in children seems to be in its infancy, comparing our results with the different BCI systems tested on adults could be meaningless. However, it is worth highlighting that the results we achieved on adults are in line with those presented in [13] in terms of classification accuracy. Both works reported the same trend related to the increasing of the accuracy by accumulating over the number of blocks. Our preliminary results encouraged that 3 blocks on average are good choices for adults and only 5 for children.

This particular aspect becomes fundamental when this kind of BCI is used to control an external device such as robots. Indeed, by increasing the number of blocks, the system can detect better the intention of the user reducing the misclassified commands, but the time requested before sending a command increases with the risk to get the user bored and unable to drive the robot. With this regards, we evaluated also the possibility to design a Brain-Robot Interface based on a single epoch framework in which after each flash a new output of the classifier is available and therefore a new command is sent to the robot [21]. Our preliminary results showed that in the case of a single epoch classification, the system seems less robust in rejecting the response to undesired flashing (low specificity), increasing the possibility that user sends wrong commands to the robot and get demotivated especially when he/she is a child. However, the single epoch classifier presents high recall values, meaning that it is able to recognise well the presence of P300 wave in the EEG signals when the target is flashed. Therefore applying evidence accumulation framework provides both a good detector of the P300 pattern and at the same an improvement of the performance by discarding better negative events. Since the BCI remains a very uncertain channel, the difficulty to classify the intention of the user when subjects are children might increase: the P300 pattern in children appear less defined than in adults (see Fig. 2A) and thus the accuracy of the classifier was lower. Our preliminary results highlight the possible advantages to accumulate the evidence of the subject for a limited number of blocks.

From the point of view of navigation, the proposed Brain-Robot Interface showed the possibility that also children can control successfully a robot through BCI. By evaluating the performance of the navigation in children and adults, the adjustments we made for simplifying the Brain-Robot Interface (such as the use of a shared autonomy algorithm to control the robot, the add of a dual feedbacks to limit the sending of wrong commands, the introduction of a command to activate the STOP/GO BACK actions, etc.) are brought out. Indeed our preliminary results shows that in the case of children, the time required to reach the target position T1 and T3 was less than in adults. A possible motivation is that the robot is more autonomous when it is driven by children, because, as previously explained, in order to simplify the system, it accumulates the evidence for a higher number of blocks limiting the number of commands that children can deliver in comparison to adults. Nevertheless, we found that the performance related to the navigation were strongly dependent on the level of attention, in agreement with [22].

Despite these expedients we took into account to simplify and facilitate the control of robots in order to make the system usable also by children, the protocol might be improved. Although children were able to drive the robot, the procedure we adopted and the kind of experiments we performed might be still complex and too much close to the typical experimental design exploited with adults. For example, children involved in the study pointed out that the training phase was boring. Clearly testing and studying BCI for children require extra cares than doing experiments with adults. In this context, this work aimed at promoting the collaboration of multiple disciplines and therefore it is inserted into an already active long term project in which we will evaluate and validate the system in a paediatric context with the collaboration of neurophysiologists, psychologists and children experts by involving a big sample of children. Future directions of the proposed work will consider at first making the graphical interface more attractive and engaging in order to keep children attention longer. Furthermore, we will experiment the possibility to exploit the robot also during the training phase in order to motivate the children and create a pleasant atmosphere. In particular, an additional advancement in this direction will consist to integrate also some social behavior performed by the robot including for example communication capabilities. In addition, other improvements will be addressed to the BCI system. In the future we are planning to add an additional control based on the level of the attention of the child in order to avoid the sending of involuntary commands due to the loss of his/her concentration.

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