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Using Brain-Computer Interface to Steer a Humanoid Robot

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***Abstract*—This work presents the use of a brain-computer interface (BCI) system in order to steer a humanoid robot. We aim at designing a ready-to-use system allowing the user to manipulate the robot in an unknown environment. This design induces some constraints on the BCI system design that we present in this paper. Given these constraints, two steering paradigms based upon the steady-state visually evoked potentials (SSVEP) phenomenon are proposed, implemented on the HRP-2 humanoid robot, and compared on the basis of both robotics and interface criteria through an usage case study.**

I. INTRODUCTION

Among the most challenging advances in human-machine interfaces is the use of brain-computer interfaces to communicate users' intentions to the computer bypassing the classical hand input interfaces such as keyboard and mouse. What can be processed as intentions can also be used to control systems connected to the BCI. Recent work has demonstrated impressive capability for controlling mobile robots, virtual avatars and even humanoid robots [1] [2] [3].

The challenges that are to be made are well illustrated in recent fiction such as the Avatar or Surrogates movies. This challenge has been taken up by the VERE project and current progress is reported in this paper.

As we are trying to achieve the embodiment of one's conscience into a humanoid robotic avatar using a brain computer interface, the ability to freely and safely steer the robot in its environment is an essential step towards more complex applications. However these interfaces have limitations such as high latency or low bit rate, which cannot be tolerated for control interfaces in this context.

The ability to control a humanoid robot with a brain-computer interface was already demonstrated in [4]. In this work, the users were able to select an object in the robot's environment - seen through the robot's cameras - and put it in a desired area in the environment - seen through an overhead camera. The user was only interacting with the robot to select objects and drop spot to cope with the defects of brain-computer interfaces previously mentionned.

In this paper, our approach aims at bringing the capacity for the user to tightly control the robot's steering thanks to recent progress made in the robot's walking control and in the recognition's speed and accuracy of the steady-state visually evoked potentials (SSVEP) method we used. We present a highly interactive BCI application to steer a humanoid robot using a brain-computer interface based on the well known SSVEP brain pattern. The user, that controls the robot thanks to an electroencephalography (EEG) cap, is fed with direct visual feedback from robot embedded cameras where visual stimuli, designed to induce SSVEP responses. This allows fine and reactive control of the robot's speed and direction after a short training session.

This approach is assessed in an experiment using the HRP-2 humanoid robot controlled via g.BCIsys (g.tec medical engineering GmbH, Austria). Five users are asked to steer the robot; we requested them to move the robot from known location 'A' to another known location 'B' while passing through viapoints with position and orientation constraints. This scenario was tested with two different steering paradigms and the results are compared on the basis of some mission performance related metrics, e.g. achievement time and robot's trajectory, but also from the user interface's perception by the users in order to empirically evaluate the cognitive load of both interfaces based on their feedback.

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II. BRAIN-COMPUTER INTERFACE

A brain-computer interface, as first described in [5], establishes a communication channel between a human brain and a computer. Since then, these interfaces have been used in a wide variety of applications [6]. In recent years, several frameworks such as OpenViBE [7] or BCI2000 [8] have introduced a similar three-layer model to produce BCI application as shown in Fig. 1.

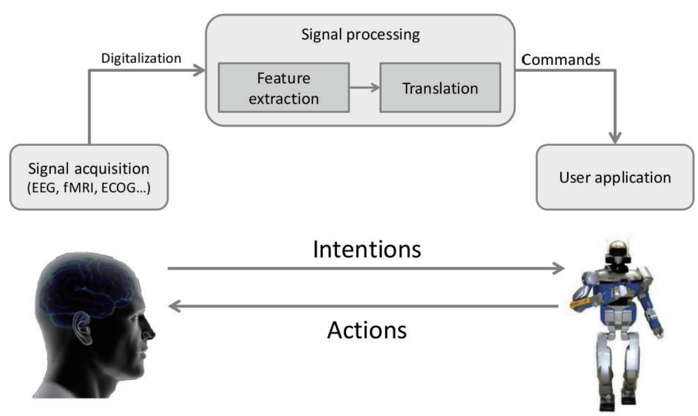

Fig. 1. General design of a BCI system according to the BCI2000 formalism

The signal acquisition layer samples the physiological signals from the brain through one or several physical devices and digitizes these signals to pass them onto the signal processing unit. The signal processing unit is in charge of extracting

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features —e.g. power spectrum, signal energy— from the raw signals and pass them onto a classification algorithm to distinguish the intentions of the user. Finally, these decoded intentions are passed onto the user application which can take many forms from a virtual keyboard to a humanoid robot.

Our intention was to design a BCI application that is ready-to-use and allow the user to steer the robot in an unknown environment. Therefore, this section focuses on the two first layers of this model to present and explain the choices we had and the choices we made within the scope of this application.

A. Acquisition method

The reading of one's brain signals can be done via different techonologies such as electroencephalography, EEG, or functional magnetic resonance imaging, fMRI. They can be characterized from a signal analysis point-of-view, for example, the quality of the recorded signals or their spatial localization accuracy - i.e. how precisely you can tell from where in the brain a signal originates. But we also have to take into account practical issues such as cost and more importantly the intrusiveness level. Indeed some acquisition systems, e.g. electrocorticography, ECoG, might require expensive medical equipment or heavy surgical intervention to obtain the signal from the user's brain.

In a recent work, the precision level obtained by such intrusive acquisition system has allowed the steering of a robotic arm [9] by mapping the intracortical motor signals - i.e. precise movement intentions - of a person to a robotic movement. However, since we are trying to produce a ready-to-use, and so, non invasive solution, such technologies are not used in our work.

For BCI applications, EEG proved to be the most used technology, even though it suffers from a poor spatial localization accuracy and signal to noise ratio, it has remarkable practical qualities such as cheap cost, real-time acquisition and most importantly non-invasiveness which is the reasons why we adopted it in the scope of our problem.

B. Feature selection

In the field of neuroscience a tremendous work is done to identify brain signal patterns relating to one's intentions or emotions. However three major methodologies are used in the BCI field because of their consistency among different untrained users.

Motor imagery [10] consists in detecting so-called event related desychronization —*ERD*— and event related synchronization —*ERS*— which are the decrease or increase of power in the alpha (8–13Hz) and beta (14–30Hz) frequency ranges of the brain activity and which occurs when the user executes or, more interestingly, imagines a movement. This method has been used before to steer a wheelchair [1] for example. Yet, while progress is made, this method still requires a long training with the user to achieve useful performance when the system distinguishes multiple classes of movement. As we try to achieve a ready-to-use system, we decided that this method would not be used for the moment.

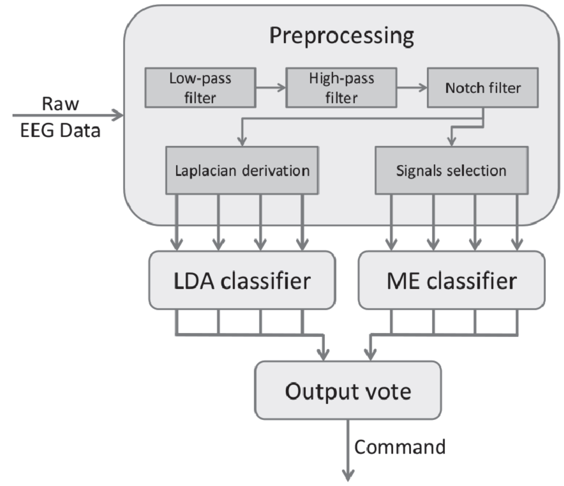

Fig. 2. Extraction of the SSVEP feature from the EEG signal

P300 [11] describes a positive wave in the cerebral activity which occurs 300ms after the occurrence of a rare but expected event among other similar events. It is really adapted for system with a very large number of choices - e.g. selecting keys on a keyboard [12] - and has proven to provide very good performance with little training among the population. In [13], a study conducted with 100 persons showed that 90% were able to achieve an accuracy level between 80 and 100% after a 5 minutes training. However, to obtain this kind of performance it is better to have the rare event occur multiple times to properly detect the P300, therefore, while a high bitrate can be achieved with this paradigm, the decision rate is rather low, typically reaching 3 to 4 decisions a minute which is not enough to properly steer a robot.

The SSVEP [14], describe the activities that the brain generates at given frequency when the user observes visual stimuli flickering at this frequency. The stimuli can be of various types, including physical LEDs to on-screen flickering objects. State-of-the-art detection systems [15] can operate at a good success rate, i.e. above 80%. The method relies uniquely on the user's attention to the stimulus, it also allows to detect that the user is maintaining his attention on a given stimulus and to detect a shift of attention in a few seconds. We therefore decided to use the SSVEP paradigm to steer a robot.

III. Method Overview

A. SSVEP extraction

The process we used to extract the SSVEP from the brain signals has been provided by g.tec as described in [16]. Fig. 2 illustrates the overall extraction process.

The pre-processing step first filters the signal by applying a band filter of 2-60Hz and a 50Hz notch filter to get rid of the power line noise. It also takes advantage of the multi-electrodes system by using Laplacian derivations of the signals from an electrode and its neighbors thus allowing to enhance the signal to noise ratio. The linear coefficients used in the application are given in [16].

The output of the different laplacian derivations are then fed directly to four classifiers which use a classic Fast Fourier Transformation, *FFT*, to generate the frequency spectrum of the signal and a feature vector is extracted by taking the values of the stimulus frequency and its first and second harmonics. A linear discriminant analysis, *LDA*, is then trained with data from a training session the user undergoes before using the complete system. Once the system has been trained it can classify the signal input to one of the stimulus frequency.

Different combinations of the filtered EEG signals are also fed to four minimum energy classifiers, *ME*, which was introduced in [17]. This method requires no training of the system and no tuning of the channel combination as it automatically selects the best combination. It relies on an estimation of the noise present in the EEG signals through the use of an artificial oscillations at the stimulus frequency and harmonics. The different channels are then combined to minimize the energy of the output of the linear combination. Finally a statistical test determines the outcome of the classifier based on the signal to noise ratio between the analyzed signal and the noise estimation.

Finally, the outputs of the eight classifiers are fed to a voting mechanism. When 6 out of the 8 classifiers (a ratio decided empirically) agree upon one frequency, it will be the output of the signal processing unit, otherwise the system considers that the user is not attending to any stimulus, thus providing a zero-class implementation.

This method provides a 70% success rate, and even over 90% when not considering the 'no decision' outcome as a miss-classification error, a conservative assumption in the context of robot control. These performances were not reassessed with a live video feedback during the robot's manipulation but are conclusive with performances measured with a static video feedback and with the feeling of control reported by the user. This method also provides us a zero-class implementation which will prove very useful in the scope of the steering problem. Finally, the system outputs a new command every 250ms which is a very satisfactory performance for a BCI system. However, while it will output a new decision at this rate, since the FFT method relies on a 2 seconds window, a user shift of attention cannot be detected in less than 2 seconds.

B. Interface design

Our aim is to allow the user to input commands to the robot while seeing through the robot's "eyes". Therefore the user interface shows the live feed of the robot's embedded cameras and the SSVEP stimuli needed to induce the SSVEP response in the brain are shown on the screen. These stimuli are associated to the robot's center of mass (CoM) velocity the user wants to impose to the robot.

To allow us to insert the robot's view feedback, the stimuli are presented on-screen as a flickering red transparent mask. In this work we chose four different stimuli flickering at 5, 7, 9 and 12Hz. We were able to produce such frequencies on-screen thanks to the square function presented in [18] which allows us to display any given frequency on-screen without the usual constraints imposed by the screen frequency. These frequencies were chosen since they do not have any common first or second harmonics and are within a safe range to minimize the risk of eliciting an epileptic crisis in healthy subjects [19].

The different paradigms presented in this section make different usage of these stimuli to steer the robot which result in different qualities and defaults regarding the robotic performance and the interface acceptance by the user.

In previous works where SSVEP has been used to steer a robot or a virtual avatar, such as [3], [16] or [20], the stimuli are statically associated with speed input for the controlled object as illustrated in Fig. 3.

The main advantage of this kind of interface is that it is very intuitive for the user. Indeed, it is basically a joypad that you can control with your brain. However, this type of steering interface suffers from two major drawbacks. First, the steering is very rigid. For example, when steering a robot this means you can only go forward, backward and rotate on place. Ultimately, it vastly under-uses the capacities of complex avatars such as virtual humans or, in our case, a humanoid robot, and generates awkward trajectories over complex steering missions. Second, in such interfaces, to maintain the direction of the directed object, the user has to keep focusing on the stimulus related to the current desired direction. Given the nature of the stimuli it might also feel tiring to the subject after a long usage of the interface.

A possible solution to the steering rigidity of such systems is to extend the number of stimuli presented to the user. For example in [21] a virtual car is driven through a circuit with 8 stimuli thus allowing to go in diagonal direction in addition to forward, backward, left and right. However, increasing the number of stimuli also increases the time needed to train the user as well as the error rate of the system. Moreover, in the scope of our application, increasing the number of stimuli also clutters the video feedback from the robot, leaving a very narrowed field of view. Finally, it does not address the tiring issue as continuous attention to a stimulus is still required.

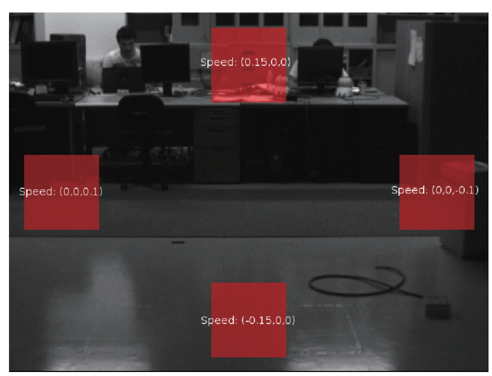

Fig. 3. Static interface with speed (forward, sideway, rotation) in m/s associated to the stimuli (capture of a video streaming feedback from the embedded robot camera).

To cope with these problems we designed an interface that evolves with the decisions of the user. Initially the user is presented with the static interface described above where each stimulus is associated with a speed. As long as the user doesn't focus on a particular stimulus, the robot remains still. Once the user shifts his attention to a particular stimulus, the associated speed is sent to the robot and the interface adapts itself: it is recentered on the previous stimuli and the associated speeds are changed as illustrated in Fig. 4. From this point, when the user doesn't focus on a particular stimulus, the robot maintains the previous input speed. This interface was implemented with two levels of evolution, i.e. once you have accelerated twice in a particular direction the interface won't let you accelerate further in that direction. To facilitate the steering of the robot, once the maximal speed in a direction is reached, the interface adds a stimulus to stop the robot.

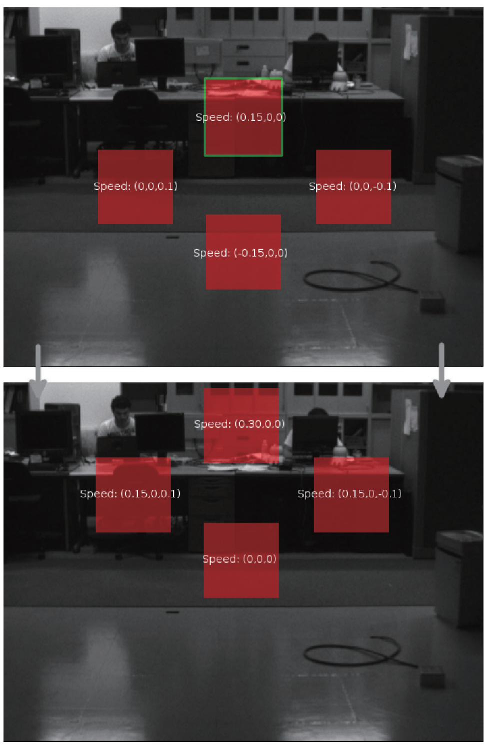

Fig. 4. Adaptive interface, upper part is the interface at beginning and down part is after the selection of top stimulus.

This makes the interface potentially less tiring in the sense that the user only has to focus on a particular stimulus when he want to change the direction or the speed of the robot. Also, it offers a lot more possibilities in trajectory generation than the static interface while still using a minimal number of stimuli thus reducing the error rate and time needed for training, for example, with four stimuli and two levels of evolution we offer 25 different speeds.

C. Pattern generator

In [22], a pattern generator is presented that allows control of the walk of the robot by simply giving it the CoM velocity. To do so, the robot is modeled as a linear inverse pendulum and a Linear Model Predictive Control is used to compute the footsteps which minimize the difference between the input, a reference CoM velocity, and the previewed CoM velocity. These footsteps are then passed onto the robot controller that will execute them as illustrated in Fig. 5.

Our work relies on this pattern generator to steer the robot by associating BCI commands to the robot's CoM velocity.

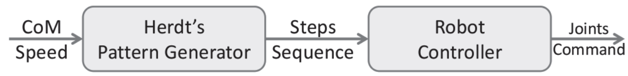

Fig. 5. Pattern generator overview

D. Integration

Fig. 6 illustrates how the modules are integrated and describes the data flow between these modules.

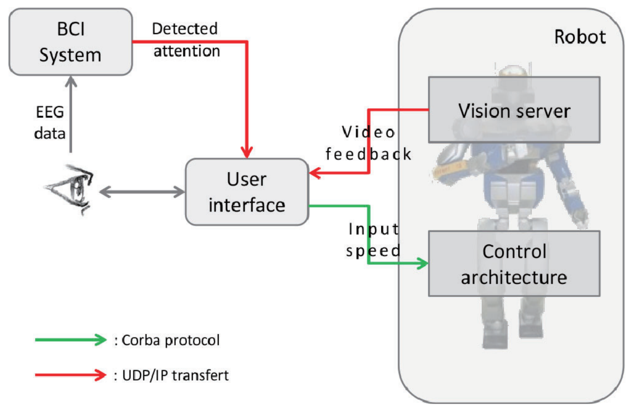

Fig. 6. Overall architecture

The link between the BCI system and the user interface relies on a very simple protocol that transmits the identified attention of the user - each frequency is therefore associated to a unique identifier. The link between the user interface and the vision server is also very simple, the user interface requests the image from one of the robot's cameras and the vision server then transmits this image to the user interface. However, since the cameras are providing 640×480 grayscale image at 30fps, the images are downscaled in order to obtain a fluid stream with little to no lag. Finally the link between the user interface and the control system is ensured by the well-known inter-process communication protocol CORBA.

As shown in Fig. 6, the link between the robot and the user interface relies on internet protocols and can therefore be used to teleoperate the robot. Since the command scheme incorporates a high level of abstraction, the major difficulty lies in the user anticipation of the robot's trajectory. When the distance between the two operation sites grow enough to induce an important lag in the images received by the user, it will become more difficult for the user to properly steer the robot as its feedback would be greatly delayed. Avoiding obstacles in these conditions would be especially difficult.

IV. Experiments

A. Scenario and objectives

In these experiments, 5 users were required to accomplish a simple “slalom” scenario: going from one location to another by passing through a “door” defined by two poles. To do so, the user has to use the BCI system described in this paper and use the two paradigms we propose. For each paradigm the protocol we defined was the same. After a short training of the BCI system, the user could exercise with the paradigm by freely steering the robot in an empty (i.e. obstacle-free) environment in order to understand how the system works and become accustomed to the visual feedback from the robot. After this period, the user is asked to perform the slalom mission. Each user would experience both paradigms —in different orders however— so that they could compare them in terms of sensation.

The purpose of the experiment was to compare the two paradigms that we proposed to steer a robot through a BCI using the SSVEP phenomenon: a static interface and an adaptive interface. Since the BCI performance is the same for both paradigms, the comparison was based on the time it took a user to accomplish a given route and the trajectory the robot took to accomplish this route as we expect that the adaptive interface will allow smoother trajectories since it uses more of the robot’s capabilities.

Since the adaptive interface has a more significant cognitive load associated to it we also wanted to assess that this would not affect the capability of the user to properly manipulate the robot. The paradigms were therefore also compared in terms of the subjective views of the users.

B. Material

The experiment was carried out using the HRP-2 humanoid robot. We used EEG cap from g.tec with 8 Ag/AgCl electrodes placed over the visual cortex on positions POz, PO3, PO4, PO7, PO8, O1, O2 and Oz of the international 10-20 system.and the system described earlier to analyze SSVEP responses. The interface was displayed on a 15.4” laptop screen.

C. Results

Every user was able to successfully perform in the slalom mission with both paradigms with consistent feedback and performance. Fig. 7 illustrates the trajectories of the robot’s center of mass generated from one user’s intentions for both paradigms. The data was captured using a motion capture system. The sway motion that we can observe on these curves is not related to the interface decisions but to the way the robot walks in a biped mode.

The strategy each user used to pass through the door was similar. From the starting point, they would steer the robot in the direction of the door, then move towards the door, then, if necessary, stop and adjust their approach at proximity of the door and finally go through the door to achieve the mission.

While most users used the supplementary capacities of the adaptive interface to turn while advancing, thus optimizing

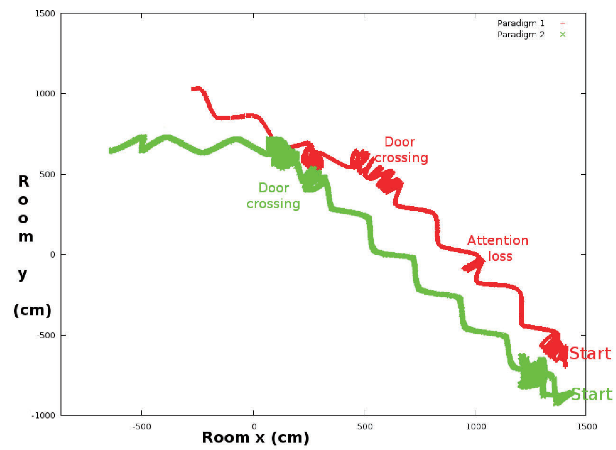

Fig. 7. CoM trajectories for paradigm 1 and paradigm 2

their approach of the door, the acceleration capacity of the adaptive interface were not used much. This results in a superior average achievement time of the mission for the second paradigm since the speed associated to stimuli in the static paradigm is twice the initial speed, before acceleration, as in the adaptive paradigm.

However, as we can observe in Fig. 7, the first paradigm introduces unintended stops as the system wrongly detects that the user stopped focusing on a stimulus —i.e. when a false negative answer is given. This error was observed consistently over the subjects and it is bound to happen as the users would eventually blink longer or get slightly distracted by their environment. Since the second paradigm expects the users to focus on the intended stimulus only when wanting to shift their current speed, the issue of undesired stop is not observed.

Both paradigms are well received by the users. On the positive side, the users reported to feel in control of the robot and appreciated the visual feedback as they felt “inside” the robot. The control scheme was also reported as being intuitive to use as you look towards the direction you want to steer the robot. They also reported that the adaptive paradigm was more difficult to grasp, yet still felt natural to use after the training ride. However, the adaptive interface felt cluttered to some users since it was displayed on a 15.4” monitor where the interface had to be concentrated on a small portion of the screen.

While subjects were not made aware of the technical aspects of the process, one of them explicitly noticed the two seconds lag —technically due to the Fourier window— between his shift of attention and the actual command input. It is interesting to note that once he noticed it, he began to anticipate the robot’s actions to take into account this delay.

D. Discussion

The most important defect we witnessed in the experiment was the underuse of the acceleration capacity of the interface. The combination of the delay in the translation of the user’s intention to a robotic command and the operational space available to the robot during the experiments may explain this phenomenon. Indeed, the experiment room was about 15×10 meters, thus the door was about 7 meters away from the robot. The initial input forward-speed of the robot in the adaptive paradigm being 0.1m/s, it would be able to go there in about a minute. With the delay between the user's intention and its detection, he may not feel very comfortable trying to go faster although he would have been able to stop the robot easily once at maximum speed. A more extensive training, which emphasize on the existence of a quick-stop functionality, might have allowed for a better usage of the adaptive interface.

Additionally, a third paradigm could be investigated that would combine the static and adaptive paradigm. The static interface would be used but the speeds associated to the stimuli, as well as the neutral speed, would evolve as the user gives new inputs. This interface would therefore allow freeing the user's field-of-view by relieving him from the constant attention needed to a stimulus while still allowing him to finely steer the robot, thus providing advantages from both paradigms.

V. CONCLUSION

We presented a BCI system to steer a humanoid robot with the constraints of being ready-to-use, with the user not having to be a robotic or BCI expert to properly steer the robot, as well as allowing a fine control of the robot in an unknown environment. We therefore proposed, implemented and compared two paradigms, both using the SSVEP: a classical one inspired from state of the art methods to control an avatar using SSVEP-based BCI and a novel one that better suits the robot capacities while trying to relieve the user's strain: the adaptive paradigm.

Both paradigms were compared through a case study that confirmed the expected defaults of classical approach such as a rigid steering or continuous need for user's focus which are less vivid in the adaptive paradigm, while also shedding the light on problems specific to the adaptive paradigm, particularly related to its interface.

We believe the results of these experiments shape a third paradigm at the crossroad of the static and adaptive interface that would allow a control as fine as the adaptive interface while keeping the interface as straight-forward as the static interface.

VI. ACKNOWLEDGMENTS

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