Brain-Computer Interface-based autonomous communicating robot for disability assessment

Amin Zammouri, M'Hammed Sahnoun, Soufian Zerouali

Brain-Computer Interface-based autonomous communicating robot for disability assessment

Amin Zammouri*
Euro-Mediterranean University of Fez
Fez, Morocco
a.zammouri@ueuromed.org

Mhammed Sahnoun
CESI-Centre Nord-Ouest
Mont-Saint-Aignan, France
msahnoun@cesi.fr

Soufian Zerouali
CESI-Centre Nord-Ouest
Mont-Saint-Aignan, France
s.zerouali@cesi.fr

***Abstract*— Designing intelligent and assistive devices for disabled persons' mobility requires appropriate assistive tools and techniques in order to insure efficiency and security in use. In this work we present a new architecture of an autonomous and communicating mobile robot for disability assistance. This architecture represents a first step towards an implementation to an intelligent wheelchair for the mobility of individuals with motor impairment. The proposed design provides two use modules namely the navigation based only on the brain signals and the intramural mapping of buildings. For the first use module, our approach exploits the statistical characteristics of the brain signal to extract eye movements and transform them into commands to control the robot. Concerning the intramural mapping module, our proposed solution is based on an obstacle detection algorithm implemented on a Raspberry PI 3 board using the ROS system.**

Keywords*— *EEG; BCI; Eye mouvements; Intramural mapping; Autonomous mobile robot

I. INTRODUCTION

In the field of robotics a booming market is installed. This is a direct consequence of the decline in costs since the 90s and which covered all types of robots namely domiciliary, industrial and leisure robots. This decrease in robot costs has made it possible to extend applications of this field to the military, industrial and medical areas. In the context of locomotion, the first designed robots were limited by the constraint of stability. This, because it is a discipline that requires skills in robotics, artificial intelligence (AI), industrial and computer engineering [1].

Nowadays, increasing the autonomy of people in situations of disability is in an increasing interest. This may be justified at a first time by the phenomenon of aging but also accidents and chronic diseases take part in this situation. As an example, the legal definition of disability according to the French law of 2005, it covers any limitation of activity to the restriction of participation in life. According to this example, more than two million individuals are administratively recognized as disabled in France, and 60% of whom have motor impairment. In this French example, 12% of the reported impairments are attributed to accidents. On another hand, 10% are due to "early" causes such as complexity of pregnancy, congenital malformation and even hereditary diseases. In this context, assistance robotic has become one of the most invested sectors [2]. This covers sectors from helping robots to auxiliary robots in life.

With the advent of artificial intelligence, rapid advances have been made in robotics. These advances have made it possible to increase the degree of interaction between humans and robots. The refinement of such interaction has allowed the appearance of what is called "Assistive Robotic" (AR) [3]. The aim of such a discipline is to improve the autonomy and life quality of persons with disabilities. In this context, understanding the needs of disabled persons and adapting these needs to robotic services is the serious challenge of any assistive robotic system. Given this constraint, assistive robotic has been regrouped in different axes in order to offer a diversity of choices in disability assistance.

In terms of physical assistance, which is considered to be the direct application of AR, designed systems aim to increase the individual's independence during a physical task. For example in the case of muscle degeneration in the upper limb, self-feeding becomes a tedious, or even an impossible task. To overcome this deficiency, works from assistive robotics propose the use of a robotic arm. In this context, the Assistive Robotic Manipulation (ARM), known as MANUS [4], represents one of the most commonly studied robots in literature works. Based on six degrees of freedom and an end effector, the MANUS is intended to be mounted on a wheelchair for a general handling. This robotic device has been designed for clinical cases where there is a quadriplegic patient or suffering from a neuromuscular disease. In addition to self-feeding, the MANUS offers its users simple aids such as opening the door of a room or wearing glasses. As MANUS, several approaches are proposed in the literature and are based on the residual motor abilities of the individual. However, in the case where no motor ability is available, these robotic systems are of no use. In such a situation, the use of other approaches is necessary. These approaches can rely on voice recognition or eye-tracking in order to have a controlling tool of a robotic device. However, in cases of extreme disability, i.e. no standard neuromuscular peripheral is functional; the use of brain signals represents the only overcoming reliable approach to increase the dependence of the patient [2].

In the case of a total motor deficiency, i.e. no residual motor ability is present; a possibility to overcome this isolation can be implemented using paradigms based on non-muscular information pipes. These information channels could be like

the Heart Rate Variation (HRV), the Galvanic Skin Response (GSR), eye movements recorded on an eye tracker and brain signals which result in respect to the electrical brain activities, i.e. Electroencephalogram signals (EEG) [5]. However, taking into account the inter-individual variability, brain signals-based paradigms represent the most reliable solution for creating communication systems. The use and the analysis of brain activity in relation to intelligent systems has always been referred to the concept of Brain-Computer Interfaces (BCI) [6][7][8][9]. These interfaces allow communication which does not require any muscular ability and the user intentions are mediated through brain signals. Related to the mobility assistance, Rebsamen [10] seeks to generate, in the user's brain, a response following the presentation of a stimulus. In this paradigm, randomly flashed choices are presented to the user. When the user's intended selected choice is flashed, a cerebral response is generated at the central brain area. This response is a large positive deflection in the brain signal after the reception of a stimulus. This deflection is known as the P300 Event Related Potential (ERP) component [11]. This component is generated at the central brain area 300 milliseconds after the reception of the stimulus. To allow navigation in a typical building, the user selects his desired direction on a GUI. Apart from the ERP paradigm, BCI can be designed through exploiting the asynchronous brain signals. Unlike ERPs, these signals are voluntarily generated by the user and no stimulation is used. In such a context, the imagination of movements is the most used approach through literature works. In this realm, Tonin [12] designed control architecture for a telepresence robot based on asynchronous BCI. This system, based on the imagination of hand movements, allows patients in clinics to control a telepresence robot situated from more than 100 Km. In order to focus patients' attention on movements imagination, shared control is introduced and is based on automatic obstacle avoidance.

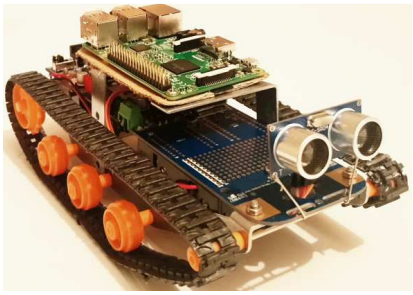
In this work, we present a new architecture of a communicating autonomous robot. The proposed design provides two modules of the robot use, namely (1) the control of the robot using only EEG signals and (2) the intramural mapping of a building. In the first module, our control approach is based on the detection of eye movements on the EEG signal. This approach exploits the statistical characteristics of the EEG signal. On a graphical user interface (GUI), and based on his eye movements, the user moves a cursor to select the robot movement direction. For the test and the validation of this module, our experimentations were conducted using a reference EEG assembly with a dry active electrode placed at the Fp1 position according to the 10-20 international system. On another hand, and for a first validation of the proposed use mode, this experimental protocol included a mal participant with any eye or cognitive impairment. As a test task, the participant was asked to move the robot from a departure point and going through three stations before reaching the arrival point. Experimental results from this first module show that the precision of the proposed approach reached 86%. This result allows us to postulate that such an approach could be one of the alternatives for the control of a wheelchair by persons with severe motor disability. For the second module, the intramural mapping represents a useful feature for patients with disabilities. To do this, our adopted approach is based on obstacle avoidance and wall tracking. In order to demonstrate and validate the capabilities of this module, a case study was discussed. In this case, the robot simultaneously locates, browses and builds a map of its environment.

The remain of this paper is organized as follow. In section 2 we give a presentation on our adopted model. We present each of experimental setups and the adopted approaches for both use modules. In section 3, we present the obtained results in relation to each use module. These results are then discussed in the same section. Finally, perspectives and future works are introduced in the conclusion.

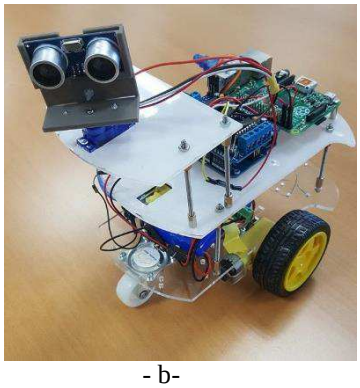
II. ADOPTED MODEL

A. *Experimental setups*

Since in this work we propose a system with two modules of use, two versions of architecture have been proposed. The "light" version implements only the intramural mapping module. In the "complete" version we have implemented the two modules. In the two proposed versions the logical processes are carried out based on a Raspberry PI embedded system which has an ability to implement the Robot Operating System (ROS). For interfacing the different actuators, the two versions are based on Arduino boards. In order to enhance the robot autonomy in terms of obstacle avoidance and wall tracking, we relied on an ultra-sound sensor. The two designed robots are presented on Figure 1. The common architecture of the two versions is presented in Figure 2. Concerning the navigation module using the brain signals, our experimental protocol consists of using a single active EEG electrode (Ag/Cl electrode) placed at the Fp1 position according to the 10-20 international system.



- a-



- b-

Fig. 1 "Complete" version of the designed robot –a- and "Light" version of the designed robot

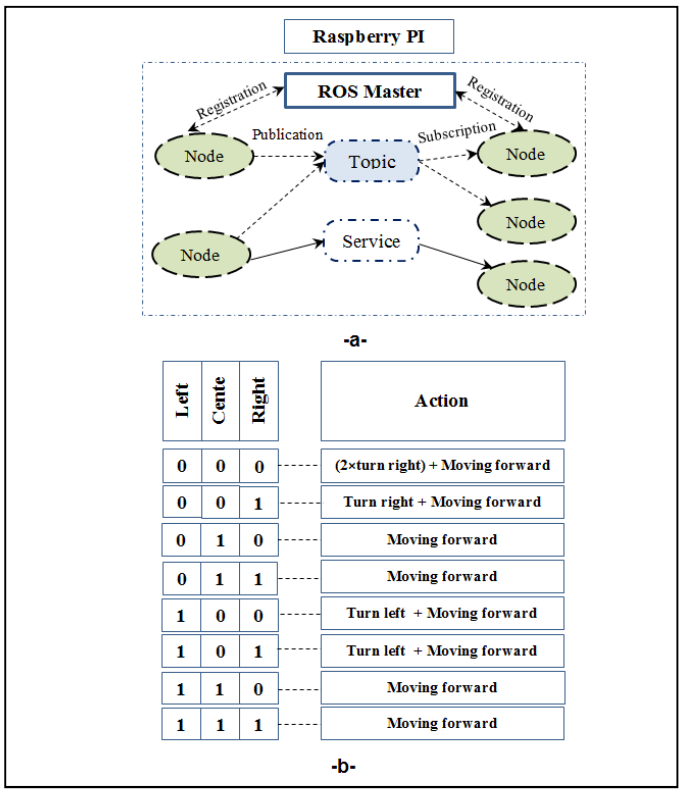


Fig. 2 –a- ROS communication structure. ROS starts by executing the Master which allows to all the ROS executables (Nodes) to meet and inter-communicate. –b- Robot states and actions diagrams. On the left side of the figure "1" represents a distance greater than the safety distance regarding the obstacle.

For the validation of the navigation module, the experimental protocol was tested on a volunteer subject from the project team. The subject was trained in the method with which he has to use the system for experimentation. The experimentation consists of placing the participant in front of a GUI on which we present a cursor and the possible directions for moving the robot on the plan. The participant moves his eyes to select the desired direction for moving the robot.

B. Intramural mapping module

The robot autonomy in the mapping module mainly concerns obstacle avoidance and wall tracking using an ultrasonic distance sensor. In our approach, we chose to connect the different sensors and actuators to the Raspberry PI which is considered as the logic processing unit in our architecture. We chose an implementation using the ROS. The choice of such a system is justified by its fundamental concept which offers parallel operations of a large number of executables (called Nodes) in order to make them exchanging information in a synchronous way (called Service) or asynchronous (called Topic).

At the ROSSERIAL stack, communication between ROS on the Raspberry PI and the Arduino board can be established. To allow the estimation of the position of the robot during a movement, the ultrasonic sensor allows a measurement starting from a known departure position. For such an estimation of the position and the trajectory based on the odometric measurements, we propose the models, presented on figure 4, for the robot displacement.

C. Eye movements-based navigation module

Our approach for controlling the mobile robot based only on brain signals consists on using and improving an eye movement detection algorithm from our previous works [13]. This improvement consists in taking into account a new parameter which is the power spectral density (PSD) of the alpha brain wave [8-12 Hz] during the production of an eye movement. For the sake of a lack understanding, we give a brief description of this algorithm. Our approach is based on detecting eye movements with the shape of a blink. Such an approach requires a calibration session in which we try to measure a typical eye blink for each user. During this session, the user blinks his eyes in different times. The importance of the typical blink, which is specific to each user, lies in the refinement of the detection process during experiments through parametric comparisons. The use of this typical blink is explained later in this paper.

The proposed blink detection process is based on statistical characteristics of the EEG signal. Let $s(t_i)$ be the measurement of the EEG signal by the electrode Fp1 at the instant t_i. For each participant, we demonstrate that $s(t)$ follows a Normal Gaussian Law, i.e. $s(t) \sim \mathcal{N}(\mu_s, \sigma_s^2)$ where μ_s and σ_s^2 represent the EEG signal mean and variance respectively. The EEG data normality leads us to postulate that the pure EEG data, which are not contaminated by other external signals, are within the Gauss' confidence interval. Taking into-account the inter-individual variability, this confidence interval, denoted by I_C, is defined as presented in Eq.1. In our experiments, we chose to vary the parameter p from 1 to 5 so as to exclude the least percentage of pure EEG data from the interval I_c.

$$I_c = [\mu_s - p * \sigma_s, \mu_s + p * \sigma_s] \qquad \text{Eq.1}$$

The next step in a blink identifying process is seeking a point from the signal which verifies $(t_i) \notin I_c$. Once this point is identified we seek to determine the first $s(t_j)$ which verifies $s(t_j) \approx 0$ and $t_j < t_i$. On the other hand, we seek to identify the third point verifying $s(t_{j'}) \approx 0$ and $t_{j'} > t_i$. The instants t_j and $t_{j'}$ represent the estimated times of starting and ending of the eye movement. A graphical representation of these parameters is given on Fig. 3. As a third step in the identification process, we apply a Fisher-Senedecor test for a comparison based on the typical blink and the blink supposed to be identified between instants t_j and $t_{j'}$.

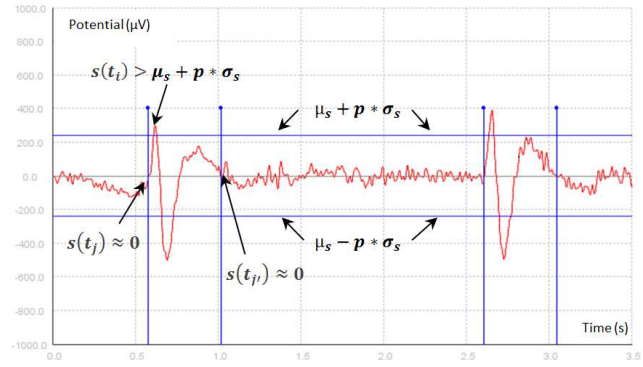


Fig. 3 Detection of an eye blink using the signal statistical parameters.

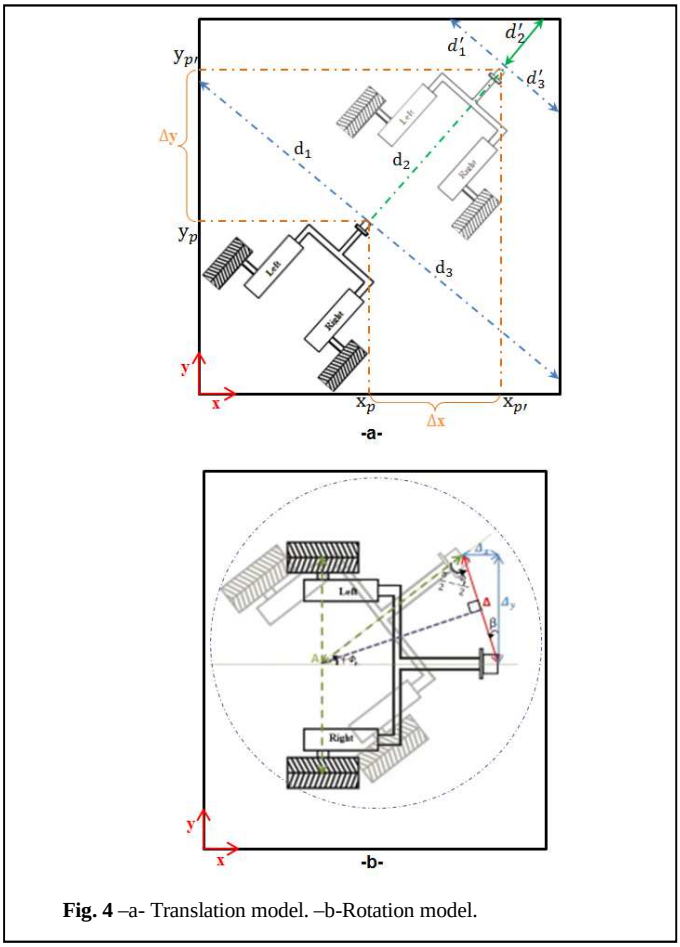


Fig. 4 –a- Translation model. –b-Rotation model.

The use of the Fisher-Snedecor test aims at comparing if two samples belong to the same population. In our case, the two samples are the typical blink and the estimated blink. Let s_e be the EEG signal delimited by instants t_j and $t_{j\prime}$. And let s_b be the EEG signal which composes the typical blink. We denote by n_{s_e} and n_{s_b} sizes of s_e and s_b respectively. The experimental variances of s_e and s_b are, respectively $S_{s_e}^2$ and $S_{s_b}^2$ as shown in equations Eq.2 and Eq.3. μ_{s_e} and μ_{s_b} are means of s_e and s_b respectively.

$$S_{s_e}^2 = \frac{1}{n_{s_e}} \sum_{i=1}^{n_{s_e}} \left(s_e(t_i) - \mu_{s_e}\right)^2 \qquad \text{Eq.2}$$

$$S_{s_b}^2 = \frac{1}{n_{s_b}} \sum_{i=1}^{n_{s_b}} \left(s_b(t_i) - \mu_{s_b}\right)^2 \qquad \text{Eq.3}$$

The two equations lead us to postulate two hypotheses. Null Hypothesis (H_0) corresponds to the case where $S_{s_e}^2 = S_{s_b}^2$. The Alternative Hypothesis (H_A) represents the case of $S_{s_e}^2 \neq S_{s_b}^2$. The statistic of the Fisher-Snedecor test is defined as follow:

$$F = \frac{S_{s_e}^2}{S_{s_b}^2} \qquad \text{Eq.4}$$

Based on a bilateral test with a specific confidence threshold λ. The test can rejects the H_0 hypothesis with a ρ risk if $F > \lambda$. In the case where $F \leq \lambda$, H_0 is accepted.

III. Results and Discussion

In order to test and validate the capabilities of the mapping module, we discussed the case study described in Figure 5. In this case study, the robot locates tracks and simultaneously builds a map of its environment. Such a test can be considered as a first step in the SLAM machine learning. In Figure 5 we present each of the environments where the robot performs its movements and the results obtained in terms of mapping and trajectory estimation without going through the wheels encoders. Figure 5 shows that the robot is able to map the entire test environment and to accurately estimate its positions. On another hand, results from Figure 5 present a limitation in mapping. This limitation is translated by the robot's inability to accurately map the corners of the environment. This is shown on Figure 5 by phenomena "Pheno1" and "Pheno2". Indeed, the principle of the robot navigation consists of two steps. The first consists of a 180° scan of the environment with the ultrasonic sensor through sampling three points (0°, 90°, 180°). Subsequently, the robot moves according to what it has just detected based on the algorithm of Figure 2. Thereafter, it returns to scanning. The "Pheno2" is justified by the servomotor pitch that we have fixed to 90° and also by the ultrasonic sensor field which detects a wall on the side despite having already passed it. On the other hand, Figure 5 shows an approximation between the robot placements ("Pheno3"). This is due a purely technical problem related to the battery. Indeed, when the battery charge decreases, the motor lacks power and this affects its displacement, including the rotation which requires more power.

For the navigation module, the validation process was performed based on a mal participant. This validation process focused on measuring the performance, in terms of accuracy, we used metrics of Sensitivity (Sen) and Specificity (Spe) as defined in the following equations:

$$Sen = \frac{TP}{TP + FN} \qquad \text{Eq.5}$$

$$Spe = \frac{FP}{FP + TP} \qquad \text{Eq.6}$$

where TP represents the number of real detection, done by the algorithm, and which are also annotated by a human expert. FN, represents the number of detections made by the human expert which were not made by the algorithm. Finally, FP represents the number of detections made by the algorithm and which are not made by the human expert.

In Tab. 1 we present the results of the chosen evaluation process. For the selected representative participant, the obtained results represent a sensitivity rate of 86% and a

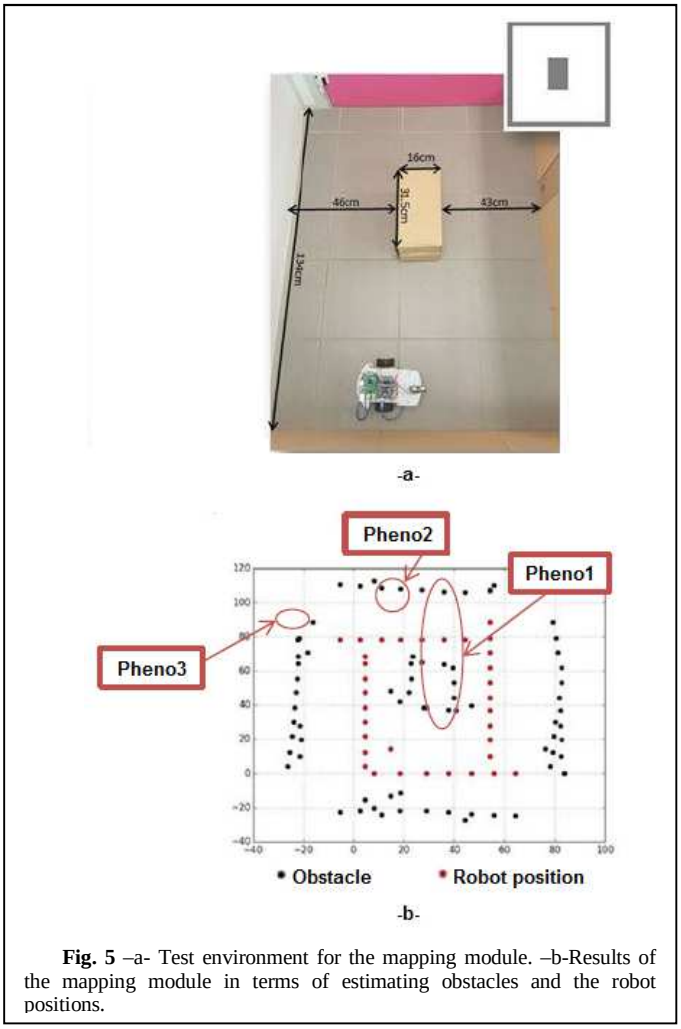


Fig. 5 –a- Test environment for the mapping module. –b-Results of the mapping module in terms of estimating obstacles and the robot positions.

specificity of 69%. The first metric value reflects the precision of the proposed algorithm to detect true eye movements. However, concerning the second metric value, we explain it by the test environment influence on the EEG acquisition system. Indeed, since the acquisition system uses a Bluetooth-based information transmission, this transmission channel could be disturbed by the magnetic waves which could be f an origin of the test environment devices. On another hand, we explain the second metric value by the influence of the participant's other biological signals on the EEG acquisition system. Indeed, the participant's cheeks and neck movements (muscle movements in general) generate electrical potentials which are intercepted by the EEG acquisition system.

Tab. 1 Metrics of the eye movement detection algorithm

	Sen	***Spe***
Representative participant	86%	69%

IV. Conclusion

In this paper we presented a new architecture of an autonomous mobile robot intended for motor disability assistance through a future implementation on a wheelchair. The designed architecture offers two modules of use. The first module allows the intramurals mapping in a typical building. Through experimentation, we have demonstrated that it is possible to map based on a combination of distances and angles measured by an ultrasonic sensor and servomotors. However the approach incorporated in this fist module presented some limitations, especially in corners mapping, we can overcome these limitations by using a filter layer applied on the resulting map in order to eliminate unnecessary points. Another improvement could be envisaged by using data fusion based on Bayesian networks to improve the robot position estimation.

References

[1] G. K. Kraetzschmar, N. Hochgeschwender, W. Nowak, and F. Hegger., S. Schneider, R. Dwiputra, J. Berghofer and R. Bisschoff, "Robocup@work: competing for the factoryof the future." *in RoboCup2014: Robot World Cup XVIII*, Springer, 2014, pp. 171–182.

[2] E. K. Kalunga, S. Chevallier, O. Rabreau, and E. Monacelli. "Hybrid interface: Integrating BCI in multimodal human-machine interfaces," in *Proc. AIM*, 2014, pp. 530–535.

[3] S. W. Brose, D. J. Weber, B. I. Salatin, G. G. Grindle, H. Wang, J. J. Vazquez and R. A. Cooper, "The role of assistive robotics in the lives of persons with disability" *Am. J. of Phys. Med. Rehabil.*, vol. 89, no. 6, pp. 509–521, Jun. 2010.

[4] S. Jain, A. Farshchiansadegh, A. Broad, F. Abdollahi, F. Mussa-lvaldi and B. Argall, "Assistive Robotic Manipulation through Shared Autonomy and a Body Machine Interface" *in IEEE Int. Conf. Rehabil. Robot.*, IEEE, 2015, pp. 526–531.

[5] C. Mühl, C. Jeunet, and F. Lotte, " EEG-based workload estimation across affective contexts" *Front. Neurosci.* 8, 2014.

[6] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan. "Brain-computer interfaces for communication and control." *Clin. Neurophysiol.*, vol. 113, no. 6, pp. 767–791, Jun. 2002.

[7] R. Rupp, S. C. Kleih, R. Leeb, J. del R. Millan, A. Kübler, and G. R. Müller-Putz. "Brain–Computer Interfaces and Assistive Technology," in *Brain-Computer-Interfaces in their ethical, social and cultural contexts*, vol. 12, G. Grübler and E. Hildt, Eds. Dordrecht: Springer Netherlands, 2014, pp. 7–38.

[8] C. J. Bell, P. Shenoy, R. Chalodhorn, and R. P. N. Rao. "Control of a humanoid robot by a noninvasive brain–computer interface in humans." *J. Neural Eng.*, vol. 5, no. 2, pp. 214–220, Jun. 2008.

[9] G. Cisotto, S. Pupolin, M. Cavinato, and F. Piccione. "An EEG-Based BCI Platform to Improve Arm Reaching Ability of Chronic Stroke Patients by Means of an Operant Learning Training with a Contingent Force Feedback." *Int. J. E-Health Med. Commun.*, vol. 5, no. 1, pp. 114–134, 2014.

[10] B. Rebsamen, E. Burdet, C. Guan, C. L. Teo, Q. Zeng, M. Ang, and C. Laugier. "Controlling a wheelchair using a BCI with low information transfer rate," in *Proc. ICORR*, 2007, pp. 1003–1008.

[11] R. van Dinteren, M. Arns, M. L. A. Jongsma and R. P. C. Kessels,. "Combined frontal and parietal P300 amplitudes indicate compensated cognitive processing across the lifespan." *Front. Aging Neurosci*,. 6, 2014.

[12] L. Tonin, T. Carlson, R. Leeb, and J. del R Millan. "Brain-controlled telepresence robot by motor-disabled people," in *Proc. EMBC* 2011, pp. 4227–4230.

[13] A. Zammouri and A. Ait Moussa. "Eye blinks artifacts detection in a single EEG channel." *Int. J.Embdedd Systems* 2017, vol. 9, no. 4, pp. 321–337.