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A new BMI Based Method for Wheelchair Robot Navigation

[Marsel Mano, Zulkifli Mohamed, Mitsuki Kitani and Genci Capi]

Abstract— Recent research has shown that Brain Machine Interface (BMI) can be used to assist disable people in navigating a robotic wheelchair by using voluntary mental intentions. BMI based navigation is a very challenging task. In this paper we present a novel adaptive method to improve BMI based robotic wheelchair navigation. The robot is controlled by an adaptive navigation platform that provides the user with scalable navigation assistance. The platform is able to detect and avoid collisions by using a laser range finder sensor. Furthermore, by using computer vision it can read assistive information for visually impaired people (tactile paving) on the floor and autonomously navigate the robot following tactile paving directions. Based on user intentions and environment context, the robot navigation adaptively changes between assisted and unassisted mode. Experimental results show that with the assistance of the adaptive navigation platform the robot navigation improves significantly. Furthermore, the user's mental focus is reduced and BMI classification accuracy is improved as a consequence.

***Keywords*—Brain machine interface, rehabilitation, robot navigation**

I. Introduction

Brain Machine Interface (BMI) has attracted a great deal of research attention. BMI systems enable humans to communicate with machines by using their brain activity, generally measured by Electro Encephalography (EEG) [1]. Non-invasive BMI generally consists of EEG signals recorded by electrodes placed on the human scalp. Depending on the recorded signals and the brain activity, different methods to establish a non-invasive BMI communication channel exist [2]. A commonly used communication channel is based on the detection of event related synchronization/de-synchronization of brain's motor rhythms, generated while performing motor imagery of limb movements. In this method, the subject voluntarily performs motor imagery mental tasks, which are later classified and send to a computer or a machine.

Its unique ability to communicate with machines only by brain signals opens a very wide area of applications for BMI. Recently, different research teams are focused on combining BMI capabilities with assistive technologies, to provide solutions that can benefit patients with motor disability, when no other means are possible. A detailed review of BMI applications for improvement of assistive technology is shown in [3]. BMI usage to support human's motor disability is a very important application.

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There are two BMI aspects that make the task of controlling a wheelchair very challenging. First, it is the low-bitrate nature of the communication channel. BMI can efficiently classify only up to three or four mental tasks, which limits the user's available actions and affects directly the control performance. Second, the brain signals change from one state of a human to another and from human to human. This makes generalized models inefficient for mental task classification which directly affects performance.

These aspects have been previously investigated in BMI based control of either real [4, 5] or simulated [2] robots. In order to deal with the individuality and the dynamic nature of brain signals, subject's specific predictive models are commonly acquired prior to BMI operation. Furthermore, during BMI operation the user is asked to repeat the same exact mental task many times, which leads to a high mental workload and makes the whole navigation experience tiring.

A very useful application is the combination of BMI with intelligent robotic wheelchairs. The shared control or shared autonomy approach [4] is proposed as an effective way to deal with the low bitrate nature of BMI. In this approach, the robotic wheelchair is equipped with different assistive modules to complement BMI and assist control, based on robot intelligence and environment situation. This has shown to improve the navigation experience, but the user's mental workload is still very high since continuous focus is needed to steer the robot. Furthermore, modules used to assist navigation require specific prior information (e.g. the goal location for orientation recovery module). The semi-autonomous strategy introduced in [4], reduces user's mental workload, by autonomously navigating the robot, and by requiring user involvement for simple yes or no decisions. This method allows the user to relax and get involved only when a navigation choice has to be done, but the user here doesn't have full control on navigation when he wants it. Furthermore, prior to navigation the robotic wheelchair has to be trained in the same environment, which makes it closely environment dependent.

In this paper, the BMI based control of a robotic wheelchair is considered. We propose a novel adaptive navigation platform (ANP) for the BMI based robotic wheelchair navigation scenario. The ANP uses tactile paving for visually impaired people as assistive information to autonomously navigate the robot. It reduces user's mental workload by switching to autonomous navigation based on user preference. ANP has a modular architecture that allows it to be flexible and scalable according to environment and navigation scenarios.

Experimental results show that when robot navigates using the ANP modules and the assistive information, the number of required mental tasks, the navigation time and the number of collisions per trial, are reduced significantly. Furthermore, no prior environment training or environment information (i.e.

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goal position, layout map, etc.) are used by ANP during robot navigation.

II. BMI

The EEG signals were recorded on scalp using 15 EEG electrodes mounted on an electrode cap (F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4 and T6) positioned as shown on Fig. 1, with ear average reference. The electrodes are connected to the Mitsar-EEG 201 electrode box/amplifier, and collected at 250Hz on PC.

During robot navigation, an online predictive module (OPM) was used to filter, extract features and classify the EEG signals. The OPM was built from an offline recording session. During offline sessions, three cues, representing three different mental tasks (*left hand*, *right hand* and *foot*), were shown on the computer screen. The user was asked to perform the mental task on the cue for 3s. In total, 120 trials (40 per task) were taken offline. The BMI paradigm used to build the classifier is as follows:

1. Epochs were extracted on the 0.5-3s window after each cue.

2. Spatio-temporal filters were optimized for feature extraction with spectrally weighted common spatial pattern CSP method [6-8].

3. Features extracted from the EEG recordings were used to build a classifier based on linear discriminant analysis.

The classification is in the form of probability distribution over three tasks, thus the output is defined by the class with the highest probability and can take one of the following values: *left*, *right*, *forward* (foot) and *uncertain*. A threshold probability (0.48) is established to define the output. If this threshold value is not achieved by any of the classes, classification is labeled '*uncertain'*.

III. Robotic wheelchair navigation

The diagram of the system (Fig. 1(b)) has two parts: 1) the robot, that includes the wheelchair equipped with AC motors, laser range finder (LRF) sensor, camera and the user with the EEG acquisition device, 2) the adaptive navigation platform (ANP), which integrates navigation modules and is responsible for user–robot interaction.

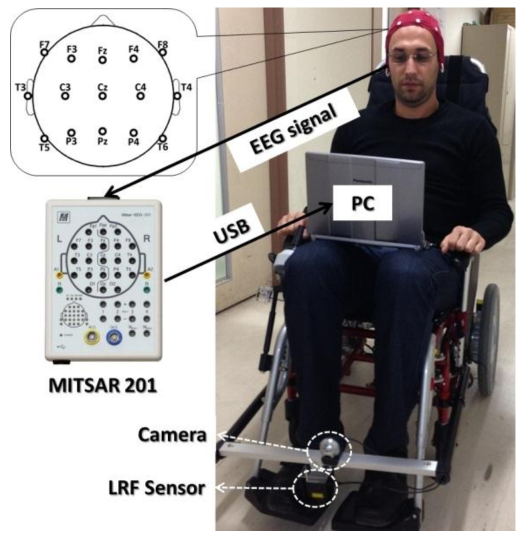
A. *Navigation Modules*

We have created three modules to facilitate the robot navigation:

a) The unassisted module (DCM) is used to navigate the robot in a basic turn-by-turn style. It can turn the robot left, right or follow straight ahead with a constant speed of 0.5m/s.

b) The collision detection module (CDM) uses LRF data to avoid collisions. The target sensor distance is set to 0.5m. The measuring area is virtually divided in three subareas: left, forward and right subarea. When an obstacle is detected in any of the subareas the robot turns in the opposite direction to avoid it.

c) The autonomous navigation module (ANM) is used to navigate the robot autonomously, based on the assistive information found on the floor. The assistive information consists of existing tactile paving used for visually impaired people (Fig. 2). The assistive information is classified into assistive lines and decision points. Decision points are called areas where tactile lines cross each-other, in front elevators or doors, etc. The ANM uses the tactile lines to navigate the robot autonomously. Any time a decision point is detected; the robot stops and allows the ANP to ask the user for the next action.



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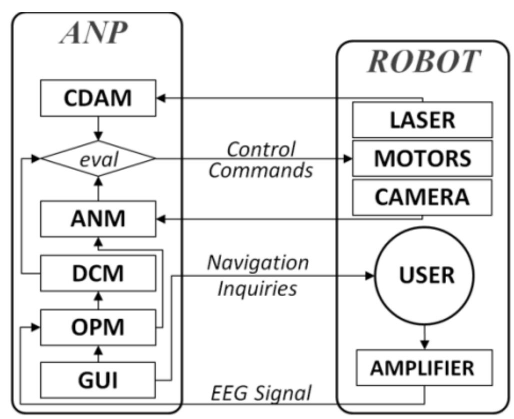


(b)

Figure 1. (a) BMI based robotic wheelchair system. (b) System diagram.

(a) (b)

Figure 2. Tactile paving used as assistive information: (a) straight line (b) cross section.

B. *Adaptive navigation platform*

The role of ANP is to adapt navigation based on the environment context in order to reduce the user's mental workload, eliminate collisions and facilitate robot navigation experience. The ANP integrates the user's mental task predictions with the robot sensing information to navigate the robot. A graphical user interface and popup windows are used to send inquiries to the user.

In our experiment navigation is done in two different modes:

1) Unassisted mode, where the user navigates the robot turn-by-turn using BMI. The user fully controls the robot during navigation. Every mental task translates into a robot moving direction change following Table 1.

2) Assisted control mode, where the autonomous navigation module navigates the robot following assistive information. When a decision point is detected the mental task prediction translates into a direction change following Table 1.

In both modes, the collision detection module is available and has the highest priority. The ANP uses the graphical user interface and popup windows to ask the user to: 1) activate ANM in the beginning of navigation, 2) select navigation mode and 3) select next direction.

Changing from unassisted to assisted mode can be done only when assistive information is available. While in unassisted mode, if a tactile line is detected, the user is asked to switch mode. If declined, the navigation will continue in unassisted mode. Otherwise, navigation will change to assisted mode and the robot will follow the assistive information. Mode selection is done using only mental tasks; usually *left hand* or *foot* means "yes" and *right hand* or *uncertain* means "no"; they are decided by the user.

Changing from assisted to unassisted mode can be done when a decision point is detected; the user is asked to switch between modes. When the line is lost (i.e. line is covered or is not available anymore) or an obstacle is detected during autonomous navigation, the navigation will immediately switch to unassisted mode without asking the user.

IV. Experiments

The experimental environment (Fig. 3) is an office building with assistive information for visually impaired people. During the experiments all objects were static in the environment. Anyway, if the robot encounters a moving object or human the collision detection module treats it as a routine collision detection scenario.

TABLE I. ROBOT ORIENTATION CHANGE BASED ON OPM OUTPUT

OPM output	Robot Orientation Change	
	Unassisted control	Assisted Control
left	$\psi^{a} + \pi/4$	follow left line
right	$\psi - \pi/4$	follow right line
foot /uncertain	$\psi + 0$	follow line ahead

a. ψ is the robot direction

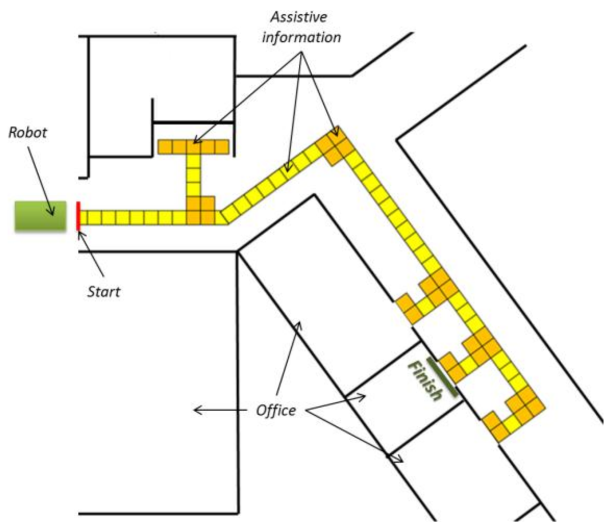


Figure 3. Experimental environment.

First, the subject used a pushbutton interface (instead of BMI) to navigate the robot (around 10 min) in order to familiarize with the wheelchair navigation. The task is to navigate the robot from start to the goal (Fig. 3). Sessions are approximately two hours, including cap installation, electrode impedance correction and navigation trials. Longer sessions cause fatigue and the subject's focus declines; headache may occur due to pressure on scalp caused by electrodes.

In order to evaluate the adaptive navigation platform we conducted the same number of assisted and unassisted experimental trials in each session. At the beginning of each trial the subject was able to select assistance from ANP by using BMI. The trials' sequence was evenly distributed over the three sessions with random variations of control modes.

V. Results

A. *BMI*

For every pair of mental tasks spatial-temporal patterns (filters) corresponding to the three biggest/smallest eigenvalues were optimized (Fig. 4) and linear classifier was trained with filtered signals. Pattern optimization and classifier training were done simultaneously.

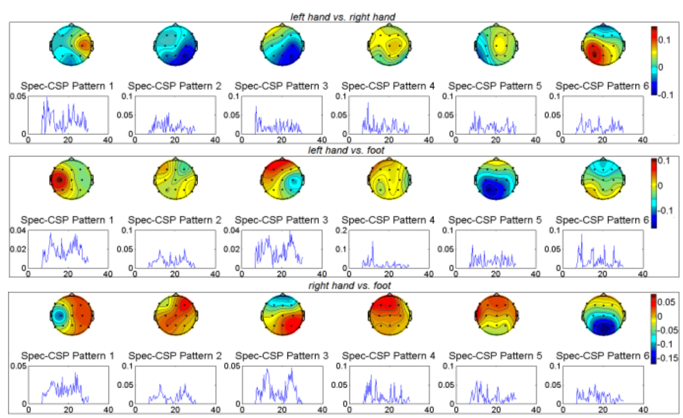


Figure 4. Spatial patterns (CSP) and their corresponding frequency filters.

The mean BMI online classification accuracy results are shown on Fig. 5. The BMI accuracy during assisted navigation trials is higher compared to unassisted navigation trials. Although there is no direct correlation between BMI classification algorithm and ANP, the results show improved classification in assisted navigation. The mental tasks performed during assisted navigation are less than those performed in unassisted navigation mode and the user can relax longer between mental tasks in assisted navigation which results in improved BMI accuracy.

B. *Navigation*

The camera input is processed online to extract assistive information (Fig. 6). The online navigation results are summarized in Table 2. Each subject performed 18 trails, 9 assisted and 9 unassisted trials. The navigation performance metrics are: 1) the number of mental tasks or BMI predictions, 2) the navigation time, 3) the number of collisions detected.

In assisted mode, all three performance metrics improve (Table 2). The average number of mental tasks is reduced by more than 34%, the navigation time decreased by more than 14% and the number of collisions was reduced by more than 77%. This shows that ANP with assistive information improves the navigation quality significantly by keeping the robot on the best route and avoiding collisions.

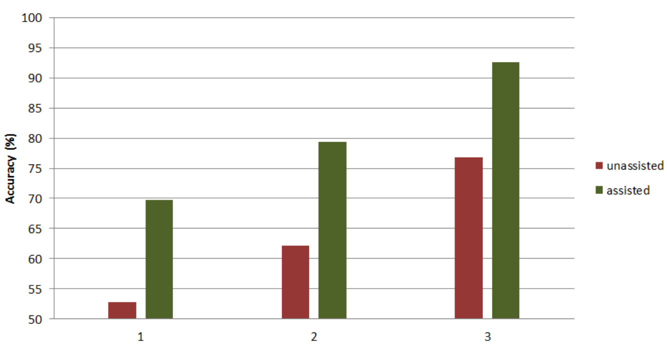
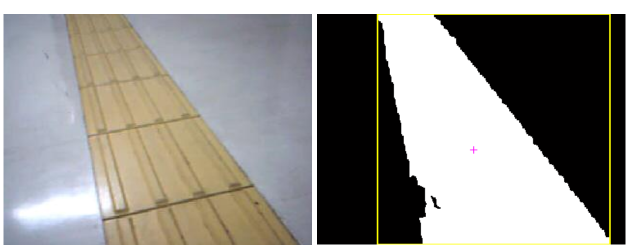


Figure 5. Mean BMI accuracy over sessions in assisted/unassisted mode.



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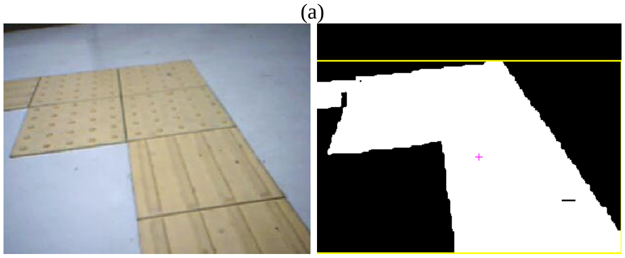
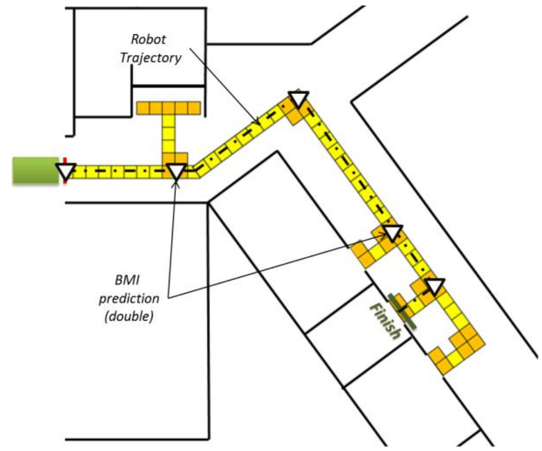


(b)

Figure 6. Assistive information extraction: a) tactile paving line, b) decision point.

Fig. 7 (a) shows the robot navigation route in a trial conducted in assisted mode. Here navigation started in unassisted mode and after the first mental task the camera detected the tactile paving. The subject was asked to switch mode and assisted mode was selected. In total there are two mental tasks (double MI task) at the same place. At the first decision point, the robot stopped and the subject was asked again to switch control mode. Assisted control was selected again. Immediately after, the movement direction was asked and forward was selected (double MI task again). Following navigation according to the dotted line, the robot arrived at the finish line.



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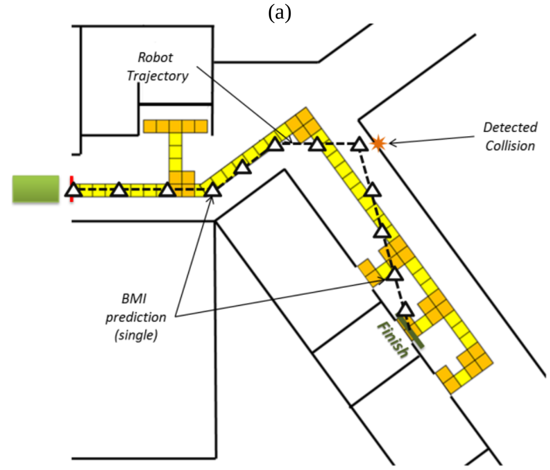

(b)

Figure 7. A navigation trial conducted in a) assisted mode b) unassisted mode.

TABLE II. ROBOT NAVIGATION RESULTS

Mode	Sessions	*Mental predictions*		*Detected collisions*		*Time*	
		mean	*std*	*mean*	*std*	*mean*	*std*
Unassisted	1	31.4	7.0	16.0	5.1	298.2	61.9
	2	30.4	3.0	9.6	3.3	262.6	29.4
	3	17.4	3.3	5.5	2.1	157.8	24.9
	Avg.	**26.4**	**4.4**	**10.4**	**3.5**	**239.6**	**38.7**
Assisted	1	22.5	4.1	4.7	0.0	256.7	56.9
	2	17.8	1.9	1.8	0.5	212.6	23.9
	3	11.3	0.9	0.6	0.9	148.2	18.6
	Avg.	**17.2**	**2.3**	**2.4**	**0.5**	**205.8**	**33.2**

Fig. 7 (b) shows the robot navigation route in a trial conducted only in not assisted mode. In this trial we have only one mental task at a location since the user was never asked to switch mode. During this trial a collision was detected and later avoided by the collision detection module.

VI. Conclusions

The paper proposed an adaptive platform for the BMI navigation of a robotic wheelchair. The advantages of the proposed platform were proved by its application in experimental trials. We found that by using the ANP, the number of mental tasks, the number of collisions and the navigation time improved significantly. Furthermore, the BMI classification accuracy was improved in assisted navigation. In addition the navigation performance improves considerably when the users gain experience. The navigation assistance used in our method is not restrictive because the subject is able to reject it and directly control the robot. In our approach the assistive information helps to autonomously navigate the robot without any prior training.

References

[1] G. Pfurtscheller and C. Neuper, Motor imagery and direct brain-computer communication. Proceedings of the IEEE, vol.89, no.7, pp.1123–1134, 2001.

[2] G. G. Gentiletti, J. G. Gebhart, R. C. Acevedo, O. Yáñez-Suárez, V. Medina-Bañuelos, Command of a simulated wheelchair on a virtual environment using a brain-computer interface. Irbm, vol.30, no.5–6, pp.218–225, 2009.

[3] J. D. R. Millán, R. Rupp, G. R. Müller-Putz, R. Murray-Smith, C. Giugliemma, M. Tangermann, el al, Combining Brain-Computer Interfaces and Assistive Technologies: State-of-the-Art and Challenges. Frontiers in neuroscience, vol.4, September, pp.1–15, 2010.

[4] X. Perrin, R. Chavarriaga, F. Colas, R. Siegwart and J. D. R, Millán, Brain-coupled interaction for semi-autonomous navigation of an assistive robot, Robotics and Autonomous Systems, vol.58, no.12, pp.1246–1255, 2010.

[5] J. S. Lin and W. C. Yang, Wireless Brain-Computer Interface for Electric Wheelchairs with EEG and Eye-Blinking Signals, International Journal of Innovative Computing, Information and Control, vol.8, no.9, pp.6011-6024, 2012.

[6] R. Tomioka, G. Dornhege, G. Nolte and B. Blankertz, Spectrally weighted Common Spatial Pattern algorithm for single trial EEG classification. University of Tokyo. 2006.

[7] O. Aydemir and T. Kayikcioglu, Comparing common machine learning classifiers in low-dimensional feature vectors for brain computer interface applications, International Journal of Innovative Computing, Information and Control, vol.9, no.3, pp.1145-1157, 2013.

[8] B. Blankertz, R. Tomioka, S. Lemm, M. Kawanabe and K. Muller, Optimizing Spatial filters for Robust EEG Single Trial Analysis, IEEE Signal Processing Magazine, vol.25, no.1, pp.41–56, 2008.

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