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# AN ADAPTIVE BMI BASED METHOD FOR REAL TIME WHEELCHAIR NAVIGATION

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Abstract. *Recent research has shown that Brain Machine Interface (BMI) can be used to assist disabled people in navigating a robotic wheelchair by using voluntary mental intentions. 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 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 (tactile paving for visually impaired people) on the floor and autonomously navigate the robot. Based on user intentions and environment context, the robot adaptively switches between assisted and unassisted navigation mode. Experiment results show that with the assistance of the adaptive navigation platform the robot navigation improves significantly. Furthermore, the user's mental workload is reduced, resulting in a higher BMI classification accuracy.*
**Keywords:** Brain machine interface, Robot navigation, Rehabilitation

1. **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, which is generally measured by Electroencephalography (EEG) [1]. Non-invasive BMI consists of EEG signals recorded by electrodes placed on the human scalp. There exist different methods to establish a non-invasive BMI communication channel [2], depending on the recorded signals and the brain activity. One commonly used BMI communication channel is based on the detection of spontaneous signals, more precisely event related synchronization/de-synchronization of brain's motor rhythms, generated while performing motor imagery of limb movements [3]. In this method, the user voluntarily performs motor imagery mental tasks, which are later classified and sent to a computer or a machine. Other signals used for BMI include non-motor imagery spontaneous signals and also another class of electrophysiological signals called evoked potentials. Typical examples of the second class are the steady state visually evoked potentials and the P300 [4,5].

The unique ability to communicate with machines only by brain signals opens a very wide area of applications for BMI. Recently, different research teams have 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 [6].

BMI usage to support human's motor disability is a very important research field. A very useful application is the combination of BMI with robotic wheelchairs in order to provide mobility independence to severely disabled people [7]. Although the idea of controlling a wheelchair by using only brain signals sounds very appealing, 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 [8].

These aspects have been previously investigated in BMI based control of either real [9,10] or simulated [2,11] robots. In order to deal with the individuality and the dynamic nature of brain signals, user's specific predictive models are commonly acquired prior to BMI operation [8]. 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 [6].

In other works, the researchers have combined residual motor functions with BMI to improve control of the wheelchairs. For instance, eye gaze is coupled with EEG based BMI to control a wheelchair in [12] or eye-blinking is used in [13]. This approach requires the user's ability to perform motor functions and also his full control over them. In the case of fully paralyzed patients this is not possible, and the users must rely only on their brain signals to control the wheelchair.

To increase bitrate, evoked potential based BMIs are proposed in [14,15]. In both these cases the user is able to navigate the wheelchair, but in order to generate the required brain signals the user must be continuously focused on a screen (or LED) where the external stimuli or cues are presented, which results in users getting tired. Furthermore, the BMI control is fully synchronized.

The shared control or shared autonomy approach [9,14,16-19] 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 reduce BMI 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 due to the continuous focus needed to steer the robot. Furthermore, modules used to assist navigation require prior specific environment information (e.g., the goal location, environment map) [9,20]. The semi-autonomous strategy introduced in [9], reduces user's mental workload, by autonomously navigating the robot, only requiring user's involvement for simple yes or no decisions. Through this method, the user can relax as he is only involved in the process when a navigation choice has to be made. On the other hand, the user cannot have full control on navigation when he would like to have it. He can control the robot only when the semi-autonomous system allows it. The system is always in charge of the navigation and the user control over the robot is reduced significantly. Furthermore, prior to navigation the robotic wheelchair has to be trained in the navigation environment, which makes it highly environment dependent.

In this paper, an adaptive navigation platform (ANP) for BMI based control of a robotic wheelchair is considered. The BMI is based on the voluntary motor imagery signal classification. The ANP uses a camera to read assistive information (tactile paving for visually impaired people) in order to autonomously navigate the robot and laser range finder (LFR) data to avoid collision. Furthermore, no prior environment training or environment information (i.e., goal position, layout map) is used by ANP during robot navigation. ANP has a modular architecture that allows it to be flexible and scalable according to different environment and navigation scenarios. The user is able to accept or reject assistance offered by ANP at any time by only using his brain activity measured by EEG.

Experimental results show that ANP based robot navigation reduced significantly the number of required mental tasks, the navigation time and the number of collisions. In addition, the user's mental workload was reduced since no user input was required during autonomous navigation.

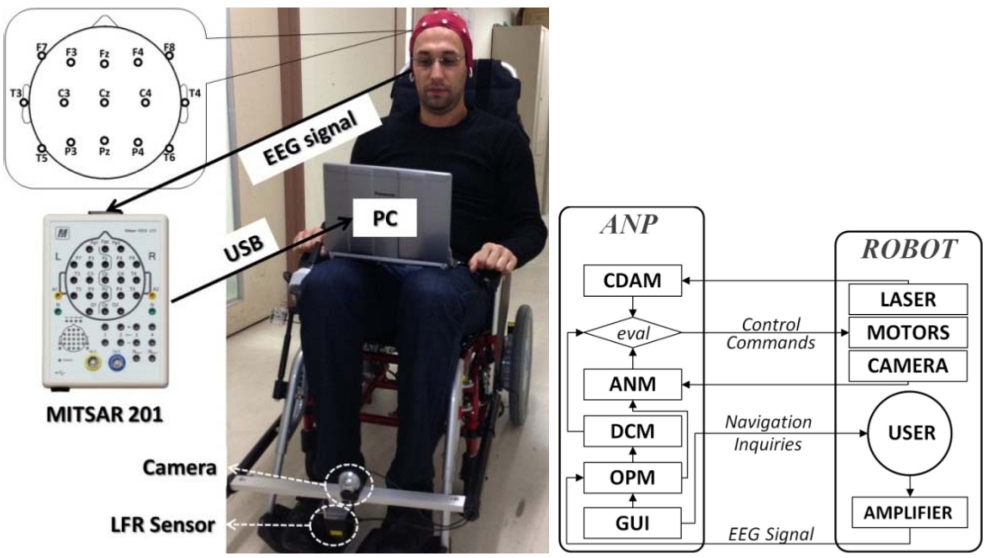
2. **Brain Machine Interface.** The EEG signals are recorded on scalp using 15 electrodes mounted on an electrode cap (F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4 and T6) as shown in Figure 1, with ear average reference. The electrodes were connected to the Mitsar-EEG 201 electrode box/amplifier, 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 motor imagery 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 algorithm used to build the BMI classifier offline is as follows:

1. Epochs were extracted on the 0.5s – 3s window after each cue.
2. Spatio-temporal filters were optimized for feature extraction with spectrally weighted common spatial pattern CSP method [21-23].
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*'.

3. **Robotic Wheelchair Navigation.** The diagram of the system (Figure 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




(a) (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.

navigation platform (ANP), which integrates navigation modules and is responsible for user-robot interaction.

3.1. **Navigation modules.** Three modules were created to facilitate the robot navigation:

a) The direct control module (DCM) is used to navigate the robot in a basic turn-by-turn style. It can turn the robot left, right or continue straight ahead with a constant speed of 0.5m/s.
b) The collision detection module (CDM) uses LRF data to avoid collision. 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 (Figure 2). The assistive information is classified into assistive lines and decision points. Decision points are: the intersection areas, in front of elevators, room entrance, etc. The ANM uses the tactile lines to navigate the robot autonomously. When a decision point is detected, the robot stops and allows the ANP to ask the user for the next action.

3.2. **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 is used to send inquiries to the user.

In our experiment navigation is done in two different modes:

1) Unassisted mode, where the robot is navigated turn-by-turn using BMI output. 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 robot navigates autonomously following the assistive information. When a decision point is detected the mental task prediction translates into a direction change as shown in Table 1.

TABLE 1. Robot orientation change based on OPM output

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

In both modes, the collision detection module is available and it has the highest priority. The ANP uses the graphical user interface to ask the user to: 1) activate ANM at 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; *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.

4. **Experiments and Results.** The experimental environment (Figure 3) is an office building floor. During the experiments, if the robot encounters any static object, moving obstacle or human, the collision detection module is automatically activated.

First, the subject used a pushbutton interface (instead of BMI) to navigate the robot (around 10min) in order to become familiar with the wheelchair navigation. The task is

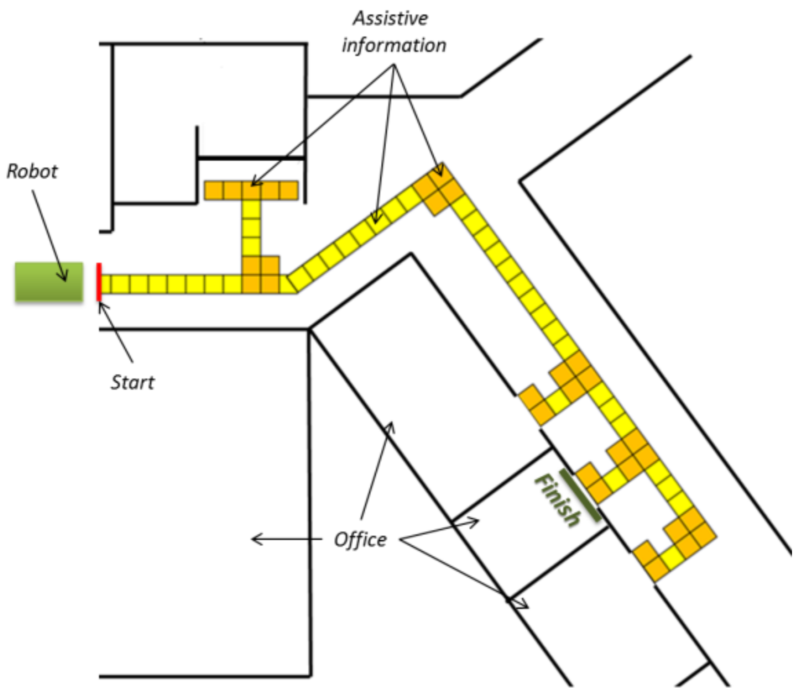



FIGURE 3. Experimental environment

to navigate the robot from start to the goal (Figure 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 ANP assistance by using BMI. The trials' sequence was evenly distributed over the three sessions with random control modes.

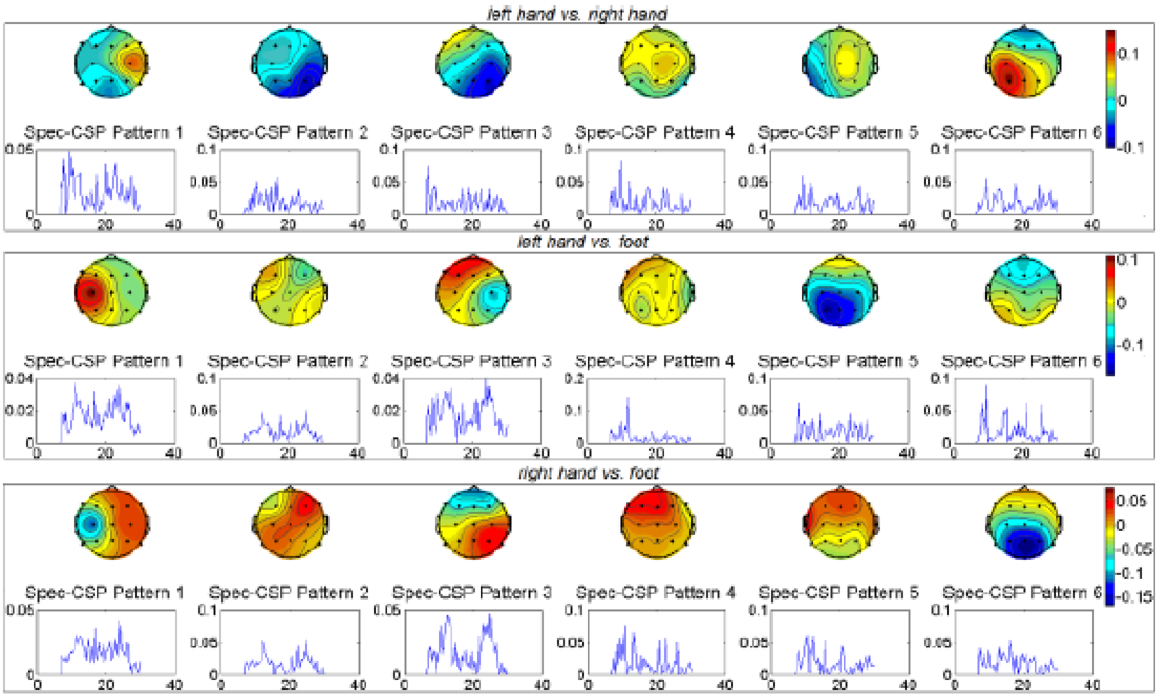



FIGURE 4. Spatial patterns (CSP) and their corresponding frequency filters

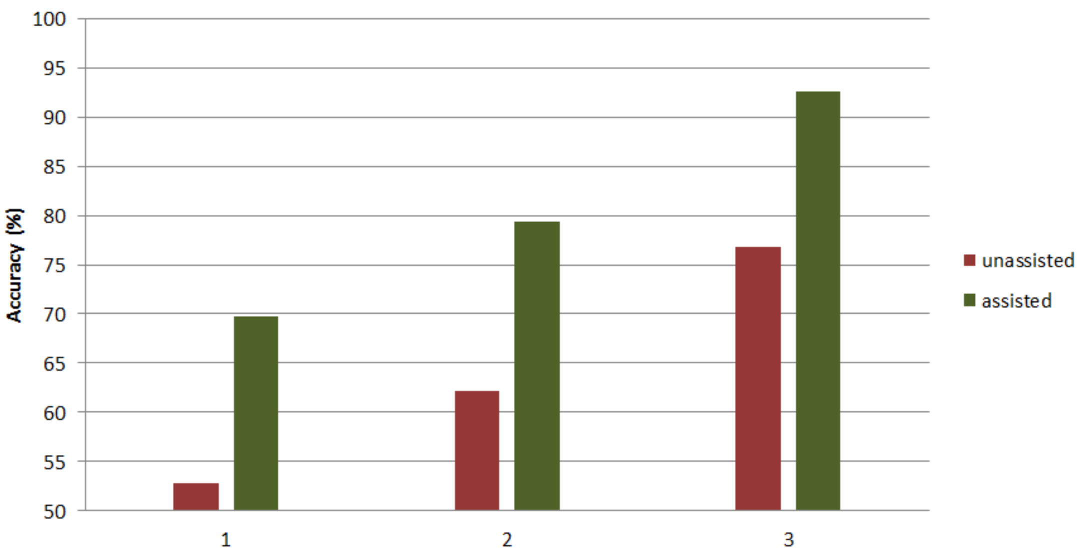
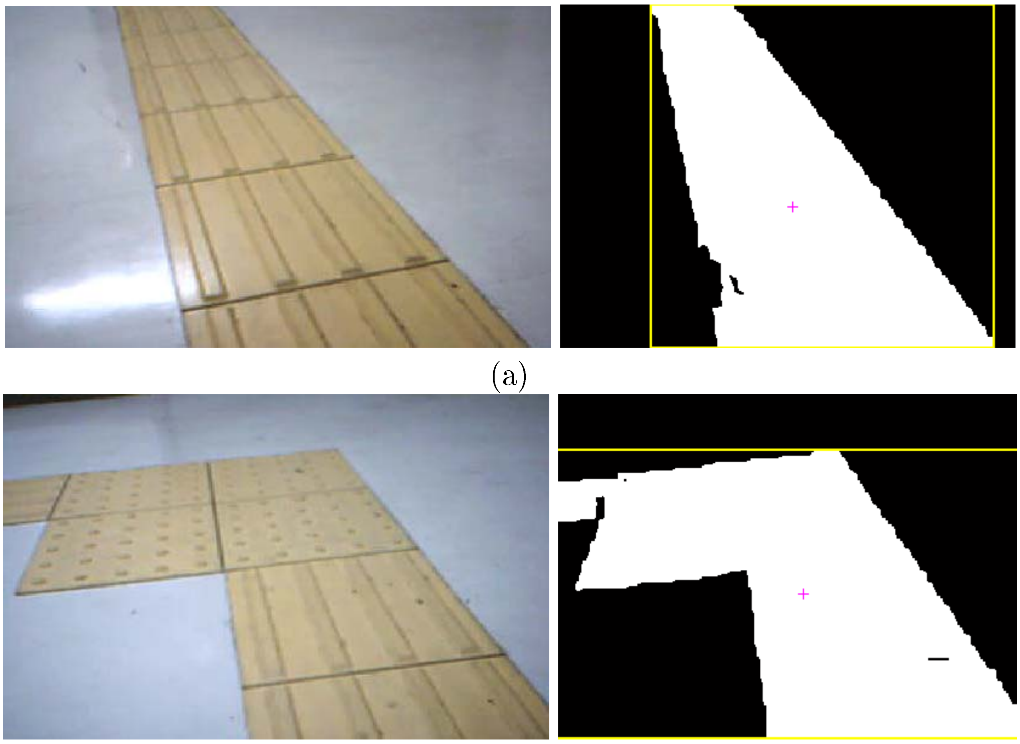



FIGURE 5. Mean BMI accuracy over sessions in assisted/unassisted mode

4.1. **Brain machine interface results.** For every pair of mental tasks, spatial-temporal patterns (filters) corresponding to the three biggest/smallest eigenvalues were optimized (Figure 4). Then, the linear classifier was trained with filtered signals. Pattern optimization and classifier training were done simultaneously.

The mean BMI online classification accuracy results are shown in Figure 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 that in assisted navigation the classification rate is higher than in unassisted navigation. This is because the mental tasks performed during assisted navigation are less than those performed during unassisted navigation; the subject can



(a)

(b)

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

Table 2. Robot navigation results

| Mode | Sessions | *Mental predictions* | | *Detected collisions* | | *Time* | |
|---|---|---|---|---|---|---|---|
| | | *mean* | *std* | *mean* | *std* | *mean* | *std* |
| Unassisted | 1 | 31.3 | 7.1 | 16.0 | 5.3 | 298.2 | 61.9 |
| | 2 | 30.7 | 3.2 | 9.7 | 3.1 | 262.6 | 29.4 |
| | 3 | 17.3 | 3.5 | 5.3 | 3.8 | 157.8 | 24.9 |
| | **Avg.** | **26.4** | **8.0** | **10.3** | **5.9** | **239.6** | **72.9** |
| Assisted | 1 | 22.7 | 4.0 | 5.0 | 0.0 | 256.7 | 56.9 |
| | 2 | 17.7 | 2.1 | 1.7 | 0.6 | 212.6 | 23.9 |
| | 3 | 11.3 | 0.6 | 0.7 | 1.2 | 148.2 | 18.6 |
| | **Avg.** | **17.2** | **5.4** | **2.4** | **2.0** | **205.8** | **57.2** |

relax longer between mental tasks during assisted navigation which results in improved BMI accuracy.

4.2. **Navigation results.** The camera input was processed online to extract assistive information (Figure 6). The online navigation results are summarized in Table 2. In total, 18 trails (9 assisted and 9 unassisted) were performed. The navigation performance metrics are: 1) the number of mental tasks or BMI predictions, 2) the navigation time, 3) the number of collisions detected.

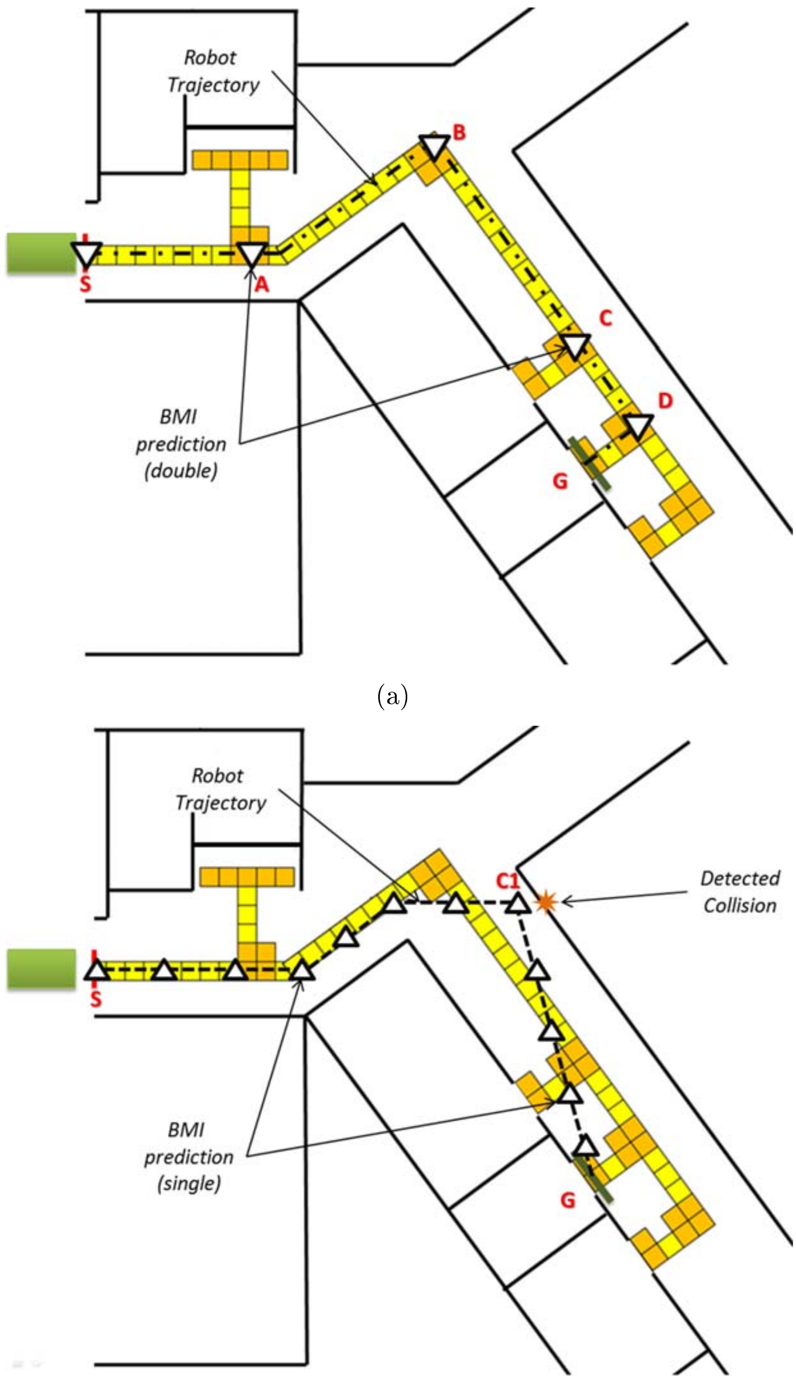



FIGURE 7. A navigation trial conducted in (a) assisted mode (b) unassisted mode

The assisted mode outperformed unassisted mode in all three metrics (Table 2). The average number of mental tasks was 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 navigating the robot on a good trajectory and avoiding collision.

Figure 7(a) shows the robot navigation in assisted mode. The navigation started in unassisted mode and after the first mental task the camera detected the tactile paving. The subject switched to assisted mode at point 'S'. In total there are two mental tasks (double MI task) at the same place. At the first decision point (A), 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 direction was selected (double MI task again). Following navigation according to the dotted line, the robot arrived at the goal location 'G'.

Figure 7(b) shows the robot navigation route in a trial conducted only in unassisted mode. In this trial, we have only one mental task at each location since the subject was never asked to switch mode. During this trial, a collision was detected at 'C1' and avoided utilizing the collision detection module.

5. **Conclusions.** The paper proposed an adaptive platform for the BMI navigation of a robotic wheelchair. The advantages of the proposed platform were proved experimentally. It was 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 was improved considerably when the users gained experience.

The navigation assistance used in our method is not restrictive thus the user 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.

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