Semantic Mapping for Safe and Comfortable Navigation of a Brain-Controlled Wheelchair

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Abstract. This paper presents a novel navigation system designed for a brain-controlled wheelchair, which interacts with human user by the low throughput interface. The navigation system proposes the semantic map, which is integrated with the navigation points, semantic targets and local 3D map, to a human user who can choose one of the navigation points as a goal for navigation. The semantic targets provide category, geometry and functionality information of the recognized objects, such as a table which can be docked. The local 3D map provides the navigation points in the traversable areas. The human-wheelchair interactive system shows the semantic map to user, and the user selects the goal via a brain-computer interfaces (BCI). Therefore, this method can help the wheelchair implement accurate navigation (e.g. docking) with a low throughput interface and the safety and comfortability are improved. Our navigation system is successfully tested in real environment.

Keyword: Smart Wheelchair, 3D Semantic Map, Brain-Computer Interfaces.

1 Introduction

The smart wheelchairs play more and more important roles in disabled and elderly people's life. Most wheelchairs are controlled by the interface such as joystick, touch screen or voice. For the people who cannot control these interfaces, the brain-computer interfaces (BCI) based on electroencephalography (EEG) is made. But BCI is a low throughput device, whose result is only in a limited number of classes and determined in 0.5-1 Hz [1]. Therefore, it is difficult to control a wheelchair safely and comfortable, using only the outputs of a BCI.

In this paper, a navigation system integrated with semantic mapping is proposed. Semantic mapping is used to extract obstacle, provide the navigation points at the traversable areas, and analyze environment to recognize objects, in order to propose probable action (e.g. docking, door passage) to the user [2, 3]. The user's workload is reduced to choose either a navigation point or a probable action via BCI to control the

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wheelchair. In addition, a wheelchair controlled by the navigation system is safer than controlled directly by human user command.

In these years, many brain-controlled wheelchairs were proposed. Carlson et al. [4] developed a vision-based shared control for a BCI wheelchair, in which method, the vision system provided obstacle avoidance and the wheelchair interpreted the high-level BCI commands such as go left and go right. Mandel et al. [5] proposed the combination of a BCI interpreting steady-state visual evoked potentials and an environment analyzing system. This system analyzed a local 2D map to extract the route graphs. The user could choose a route with the four commands of BCI. Iturrate et al. [6] described a brain-controlled wheelchair, on which a screen displayed a real-time virtual reconstruction of the environment and the target location that wheelchair could arrive. The EEG signals of user were processed to detect which target location the user wanted to choose. And then an autonomous navigation system controlled the wheelchair move to the target while avoiding collisions with obstacles. Perrin et al. [7] presented a semi-autonomous navigation for the robot by analyzing the environment to determine the probable action of robot, and the human user can decide whether to implement the action or not. The probable action of robot was extracted by recognizing the places of interest where a human–robot interaction should take place (e.g. crossings). The user could choose the target by means of a button or a brain–computer interface (BCI).

All the methods above can analyze the environment and provide probable routes or actions to user who will choose one of them to drive the wheelchair. But the routes or actions those providing are crude, such as follow a route or turn left. They can hardly implement accurate navigation of the wheelchair, such as docking, which is our aim. Consequently, our navigation system can reduce the operation of user and improve comfortability. Furthermore, as pose and category of the target is known, our navigation system can plan an optimum trajectory, which is safer than the passive obstacle avoidance.

In this article, system architecture of semantic mapping for safe and comfortable navigation of a brain-controlled wheelchair is presented. A local 3D map is built online using Rao-Blackwellized particle filter (RBPF). The local 3D map is used to extract navigation points and semantic targets. The user selects the goal from the navigation points or semantic targets. And the wheelchair is autonomous navigated to the goal. A smart wheelchair equipped with a RGB-D sensor and a laser range finder (LRF) is developed as experimental platform for studying the effectiveness of the proposed method.

2 System Architecture

As shown in Fig. 1, our approach has two loops: human loop and machine loop, and semantic map is the bridge between these two loops. In machine loop, a semantic map including a real-time virtual reconstruction of the local environment, combined with navigation points and semantic targets, is built. In human loop, the user faces a screen displaying the semantic map, and uses EEG signals to select a goal from the navigation points and semantic targets in the semantic map. Once the goal is selected, the motion control module will calculate the speed of wheelchair considering with obstacles.

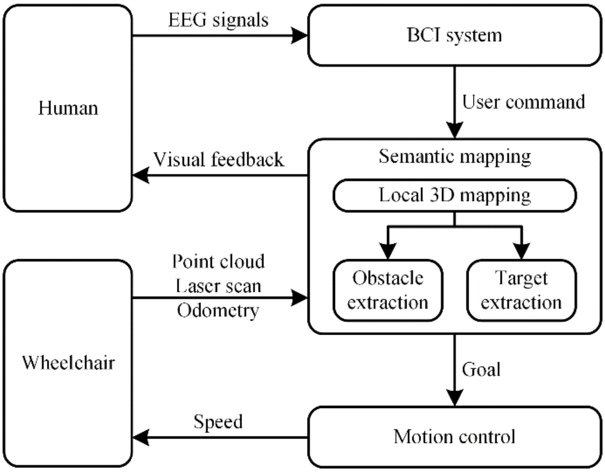


Fig. 1. System architecture

3 BCI System

EEG is one type of biological electrical signals. EEG can be divided into four types of wave: delta (1-3Hz), theta (4-7Hz), alpha (8-13Hz), beta (14-30Hz). The expressions of user have relationship with beta waves, since beta waves with multiple and varying frequencies are often associated with active, busy, or anxious thinking and active concentration [8]. Consequently, the expressions of user can be recognized by BCI to control the navigation system.

A linear classifier is used to recognize the expressions of user. The feature is the integral of energy of a set of channels in a period of time. The first step is feature selection, that we select one set of channels of EEG whose changing are conspicuously associated to one expression. For different expressions, several sets of channels are selected. The second step is to train the system via offline experiments, where user makes some kind of expression several times. The data of selected channels are recorded and used to train the linear classifier. Finally, the trained linear classifier is used to recognize the expression. In this article, four commands (forward, backward, left, right) are recognized and used in our navigation system.

4 Semantic Mapping

The semantic map is a bridge connecting user and machine. It presents a virtual reconstruction of environment additional with navigation information including obstacles, navigation points and semantic targets. The user can select the goal interactively via BCI, referencing the feedback shown on the semantic map, and the motion control module will navigate the wheelchair to the goal.

4.1 Local 3D Mapping

To extract the traversable area and obstacles around the wheelchair, a local 3D map is needed. In this paper, Rao-Blackwellization particle filter (RBPF) [9, 10], an implementation of SLAM problem, is used to localize the pose of wheelchair and build local 3D map. SLAM is a problem that estimates $p(x_{1:t}, m|z_{1:t}, u_{1:t-1})$, the joint distribution over the wheelchair trajectory $x_{1:t}$ and the map m, by sensor observations (laser scans) $z_{1:t}$ and control signals (odometry) $u_{1:t-1}$. Rao-Blackwellization is expressed by the following equality:

$$p(x_{1:t}, m|z_{1:t}, u_{1:t-1}) = p(m|x_{1:t}, z_{1:t}) \cdot p(x_{1:t}|z_{1:t}, u_{1:t-1}). \tag{1}$$

which decouples the trajectory estimation problem $p(x_{1:t}|z_{1:t}, u_{1:t-1})$ from the map computation $p(m|x_{1:t}, z_{1:t})$.

The map computation problem can be solved by assuming that wheelchair trajectory is known and using inverse laser range finder model. The map is stored in a grid map. Each ceil of the grid map expresses the probability of occupancy. The occupancy probability of each ceil is updated by sensor observations [11]. Rather than directly register the raw data of sensor, the occupancy probability representation can reduce noise of sensor and ignore the dynamic obstacles such as people.

For the trajectory estimation problem above, a non-parametric implementation of the Bayes filter is implemented. The Bayes filter is based on a set of particles. Each particle associates with a weight, and each particle represents a trajectory hypothesis for the wheelchair up to time t. Since we assume that the movement of our wheelchair is restricted in the 2D plane, the trajectory of wheelchair consists of a set of poses $x_{1:t-1} = (x, y, \theta)$, including position and orientation. The particle filter performs following three steps between $p(x_{1:t-1}|z_{1:t-1}, u_{1:t-1})$ and $p(x_{1:t}|z_{1:t}, u_{1:t})$: predicting the pose of wheelchair by the motion model and odometry, updating the weight of particles by matching laser scans, and resampling the distribution of particles if necessary.

In order to building local 3D map online, at each time the SLAM updating the pose of wheelchair, a frame of point cloud obtained by RGB-D sensor is inserted into the local 3D map, and the point clouds, which are obtained far from the current position, are discarded.

4.2 Obstacle Extraction

The obstacles are extracted from the local 3D map in order to mark the navigation points. Since the wheelchair only travel in the 2D ground, the wheelchair can be considered as a cube and all obstacles can be project to the ground. Supposing the wheelchair can go through the obstacle lower than H_{min} and the height of wheelchair is H_{max}, the obstacles can be represented by the follow equation:

$$P_{obstacle} = \{(x, y)|(x, y, z) \in P_{3D}, H_{min} < z < H_{max}\}. \tag{2}$$

where P_{3D} is the points of local 3D map.

4.3 Semantic Target Extraction

The shape-based method is used to build 3D semantic map, referencing to our previous work [2, 3]. The local 3D map is processed by three steps:

1) Data preprocessing: using pass though filter and down-sample to reduce the amount of data;
2) Segmentation: using RANSAC algorithm and European clustering to segment the point cloud into horizontal planes and vertical planes;
3) Recognition: matching the segments to a priori model library in order to identify the semantic targets.

Finally, the semantic targets are marked on the local 3D map.

4.4 Visual Feedback

The semantic map integrated with local 3D map, semantic targets and navigation points is displayed on the screen as a visual feedback to the user (Fig. 2). The user can control the wheelchair by selecting the goal from the navigation points via BCI.

The distribution of navigation points is inspired by the article [6]. The ground is divided by a grid, and each intersection between circular arcs and radial lines is a possible position that a navigation point can locate. Considering both accurate control and fast move ability of wheelchair, the closer from the wheelchair, the thicker distribution of navigation points is, and vice versa. So the appropriate grid is like Fig. 2-b. On each intersection, if the minims distance to the obstacle is larger than a threshold, this point is a navigation point (the white points in Fig. 2-b). And the semantic target (the white frame in Fig. 2-b) is binding on the nearest navigation point. The goal, as a selected navigation point (the green point in Fig. 2-b), will be delivered to the motion control module for driving the wheelchair.

(a) (b)

Fig. 2. (a) Snapshot of a user navigating along a corridor; (b) Detail of the screen displayed in (a)

5 Motion Control

Driving the wheelchair to a normal navigation point and a semantic target are different, because the pose of a semantic target includes position and orientation meanwhile a navigation point only contains position.

The navigation system controls the wheelchair to a semantic target according to the relative position of the wheelchair and the semantic target. A real-state feedback controller [12] is used to calculates the linear and angular velocity (v and ω) (Eq. 3).

$$\begin{cases} \mathrm{v} = k_r r \\ \omega = k_a a + k_b b \\ \mathrm{r} = \sqrt{\Delta x^2 + \Delta y^2} \\ a = -\theta + \operatorname{atan2}(\Delta x, \Delta y) \\ b = -\theta - a \end{cases} \quad (3)$$

where Δx and Δy are position error between the wheelchair and the semantic target, θ is the orientation of wheelchair, r is the distance between the wheelchair and the semantic target, a and b are intermediate variables. k_r, k_a and k_b are constants.

The method to navigate the wheelchair to a normal navigation point is a simplification of above method as shown in Eq. 4.

$$\begin{cases} \mathrm{v} = k_r r \\ \omega = k_a \operatorname{atan2}(\Delta x, \Delta y) \\ \mathrm{r} = \sqrt{\Delta x^2 + \Delta y^2} \end{cases} \quad (4)$$

where the meanings of all parameters are similar with above.

In order to guarantee the safety of motion, MVFH&VFF methods [13, 14] are used to implement obstacle avoidance, as modifying the linear and angular velocity command according to the laser scan.

6 Experiment and Results

6.1 Wheelchair Prototype

The wheelchair prototype [2, 3] based on an ordinary electric wheelchair, equipped with several mobile robot sensors including a Kinect, a LMS200 LRF, odometry, and an Emotiv EPOC EEG Neuroheadset etc., is shown in Fig. 3. There are two computer on the wheelchair, one runs Linux to implement semantic mapping and motion control, and another one runs Windows for BCI. And these two computer communicate with each other by Ethernet. The motion control commands are executed by the Smart Motion Controller (SMC) of wheelchair in 20Hz. Both laser scans of LRF and point clouds of Kinect are obtained for semantic mapping. The local 3D mapping algorithm is performed using a ROS implementation of GMapping [10] from OpenSLAM. The semantic map update frequency is 1Hz. The EPOC is connected to the computer by Bluetooth for obtaining BCI commands in 3Hz. The system software is developed based on ROS [15] and PCL [16].

The 14 channels of the EPOC distribute in accordance with International 10-20 system [17] as shown in Fig. 4. Three sets of channels are used in our system: [AF3, AF4, F7, F8], [T7, F7, FC5], [T8, F8, FC6] (Fig. 4). The period of integral is 0.3 second. Four expressions are recognized in our system: lifting brows, biting the teeth on the left, biting the teeth on the right, and biting the teeth on both side. These expressions can lead to significant changes in EEG, and do not affect the user operating the wheelchair (e.g. moving eyes will affect the user observing screen).

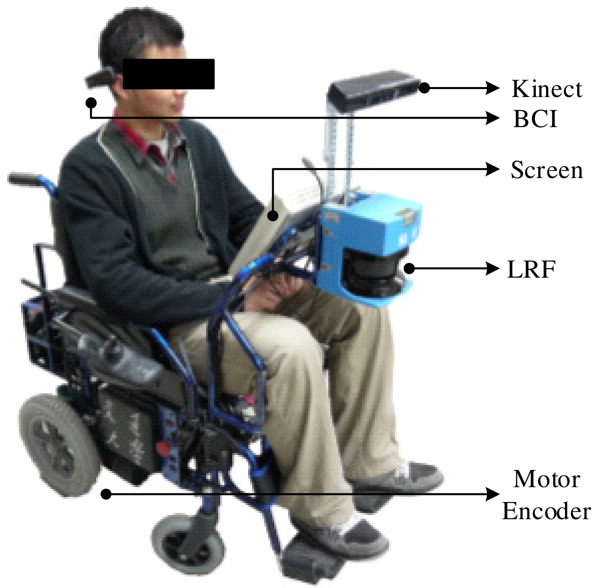


Fig. 3. Wheelchair prototype

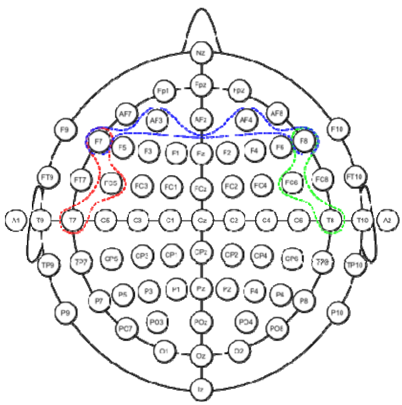


Fig. 4. Electrodes of International 10-20 system for EEG [18]

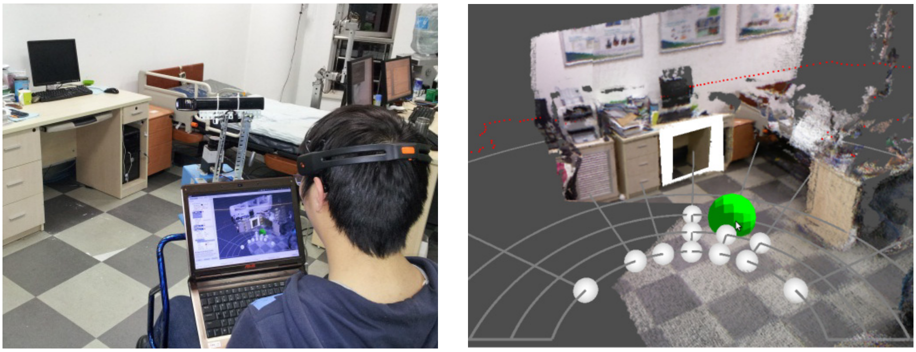
6.2 Experimental Environment and Task

The environment for experiment is shown in Fig. 6-a. The tasks include passing through a doorway and docking into the table.

The blue line in Fig. 6-a is the path of wheelchair. The path of wheelchair controlled automatically, when the user selects a semantic target, is marked as dashed.

6.3 Semantic Mapping

Fig. 5 illuminates an example of semantic mapping test. Fig. 5-a is a snapshot of experimental environment, and Fig. 5-b is the screenshot of semantic map at that moment. In the semantic map, the white points are navigation points, the green point is the goal, and the white frame marks the semantic target (a table).



(a) (b)

Fig. 5. (a) Snapshot of a user preparing to dock into table; (b) Detail of the screen displayed in (a)

6.4 Performance Evaluation

This section describes a general evaluation of the brain-controlled wheelchair and compares our navigation system with the similar system only controlled with navigation points excluding semantic targets. We call our navigation system as system I and the comparative system as system II. The metrics to evaluate the wheelchair performance are:

1) Task success: degree of accomplishment of the navigation task;
2) Path length: distance traveled to accomplish the task;
3) Time: time taken to accomplish the task.

The metrics to evaluate the comfortability are:

1) High ω ratio: the ratio of the control steps whose angular velocity is higher than 8 deg/s to the total control steps;
2) BCI commands: number of BCI commands.

The metrics to evaluate the safety are:

1) Collisions: number of collisions;
2) Obstacle clearance: minimum and mean distance to the obstacles.

Fig. 6-b shows the comparison of trajectories two systems and the results are summarized in Table 1 to Table 3. In five experiments of each system, all experiments succeed with system I but only once succeeds with system II, since it's barely docking into the table without semantic map. The path of system I is longer, because the autonomous navigation to the semantic target needs a longer path which is far from obstacles and smooth (the ratio of high angular velocity is lower), in order to guaranteeing the safety and comfortability. System II costs more time to complete the task since manual control need more adjustment by the user. Similarly, the user sends mort BCI commands to system II to control the wheelchair. And both of these two systems are safe enough to protect wheelchair from collisions. The obstacle clearance is measured when the wheelchair is passing through a door.

Table 1. Metrics to evaluate the wheelchair performance

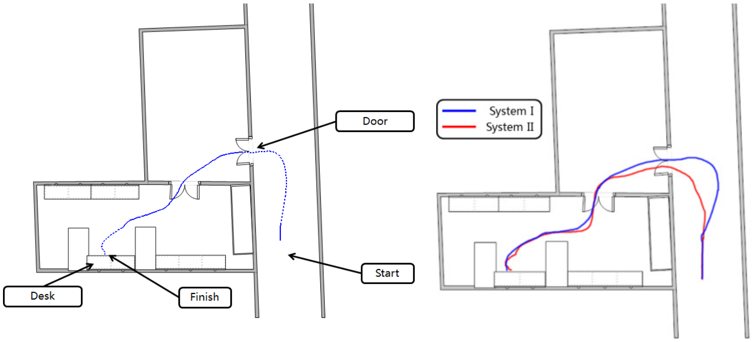
	System I		System II	
	mean	std.	mean	std.
Task success	1	-	0.2	-
Path length (m)	28.5	0.3	23.2	0.6
Time (s)	96	8	116	10

Table 2. Metrics to evaluate the comfortability

	System I		System II	
	mean	std.	mean	std.
High ω ratio (%)	3.4	1.1	7.6	1.2
BCI commands	19	2	37	5

Table 3. Metrics to evaluate the safety

	System I		System II	
	mean	std.	mean	std.
Collisions	0	0	0	0
Clearance mean (m)	1.56	0.03	1.33	0.03
Clearance min (m)	0.65	0.07	0.44	0.16



(a) (b)

Fig. 6. (a) Experimental environment and tasks; (b) Comparative experiment

7 Conclusion and Future Works

This paper presents a smart wheelchair navigation system relying on semantic map controlled via brain-computer interface. Semantic map is used to analyze the environment and extract semantic targets. When the user selects the semantic target, our system can actively navigate the wheelchair, which plans a smooth path far from obstacles and accurately navigate the wheelchair to the goal. And autonomous navigation to the semantic target significantly reduces operation of user. Consequently, both safety and comfortability are improved. The experiments validate the proposed method with the real wheelchair and in the real world. In the future, the BCI will be improved to adapt different people, and the robustness and stability of semantic mapping should be enhance.

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