2013 IEEE/RSJ International Conference on
Intelligent Robots and Systems (IROS)
November 3-7, 2013. Tokyo, Japan

A Waypoint-Based Framework in Brain-Controlled Smart Home Environments: Brain Interfaces, Domotics, and Robotics Integration

Atsunori Kanemura*, Yoichi Morales, Motoaki Kawanabe, Hiroshi Morioka, Nagasrikanth Kallakuri, Tetsushi Ikeda, Takahiro Miyashita, Norihiro Hagita, and Shin Ishii

***Abstract*— The noninvasive brain-machine interface (BMI) is anticipated to be an effective tool of communication not only in laboratory settings but also in our daily livings. The direct communication channel created by BMI can assist aging societies and the handicapped and improve human welfare. In this paper we propose and experiment a BMI framework that combines BMI with a robotic house and autonomous robotic wheelchair. Autonomous navigation is achieved by placing waypoints within the house and, from the user side, the user performs BMI to give commands to the house and wheelchair. The waypoint framework can offer essential services to the user with an effectively improved information-transfer rate and is an excellent examples of the fusion of data measured by sensors in the house, which can offer insight into further studies.**

I. Introduction

The current forefront of noninvasive brain-machine interface (BMI) is coming along with attempts to assist aging societies, but still BMI's information-transfer rate is limited to 35 bits per minute (bpm) for the best subjects [1], which is not enough. This fact necessitates a framework to execute commands safely and reliably to let the elderly and physically impaired to use BMI in their life even with insufficient accuracy of BMI. To this end, the combination of BMI with robotics can provide a promising framework by enhancing the limited information-transfer rate through the application of effector devices, sensing networks, and autonomous navigation embedded in a smart home environment.

Smart homes [2], [3] offer essential automation services for the elderly and physically impaired; e.g., automation for doors and windows, lighting adjustment, indoor temperature, etc. As a step forward to comfortability in houses, we constructed a smart house system that can be controlled by commands from the user through BMI. A central server in the house controls house appliances, detects the status of them, and remotely receives commands through wireless network.

BMI is an input technology that connects the brain directly to external effectors. With this interface, people do not need to rely on commands provided by speech, a joystick, or a computer to interact with their physical world and to navigate

This research was supported by the Ministry of Internal Affairs and Communications, Japan, with a contract entitled "Novel and innovative R&D making use of brain structures."

The authors are with Advanced Telecommunications Research Institute International (ATR), Kyoto 619-0288, Japan (Email: {atsu-kan,yoichims, kawanabe,morioka,srikanth,ikeda,miyasita,hagita,ishii}@atr.jp).

*Now with ISIR, Osaka University, Osaka 567-0047, Japan (Email: kanemura@ar.sanken.osaka-u.ac.jp)

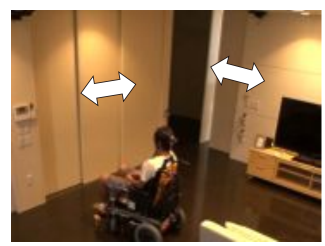
(a) Smart house facade.

(b) House entrance.

(c) The height of kitchen is automatically adjusted to the height of the wheelchair user. Water supply is also controlled from the server.

(d) The elevator for wheelchairs at the entrance works automatically.

(e) Household electrical appliances are controlled from the server.



(f) Doors are controlled according to the navigation plan.

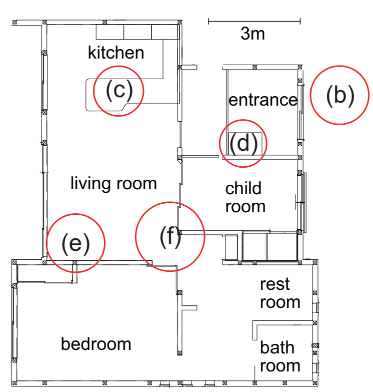


Fig. 1. Overview of the smart house. Installations are fully electrical powered. It has an area of 95.25 square meters.

through it. Conventional BMI wheelchair controllers [4], [5] continuously reads brain activities during the entire operation period, following user's instant commands. This continuous control requires the user to persistently concentrate, making the user tired. Therefore this is not always suitable for daily living without a practical design. Although many researchers have devoted their efforts in increasing the information-transfer rate by improving decoding techniques, currently it is reaching the ceiling.

As output means for mobility, we use a robotic wheelchair that can navigate autonomously between different locations in a living environment. Decision making of the target location is given by the user through BMI whereas the wheelchair navigates to its destination passing through doors and detecting and avoiding obstacles. The wheelchair manages a multi-map system in which maps are switched according to the status of the environment installations, i.e., the states of doors, curtains, etc. This characteristic allows mobile platforms to adapt to the dynamic status of the environment. The wheelchair localizes itself with a particle filter that corrects the position of the robot based on laser scans where a pre-processing method of laser data allows the robot to localize itself even in the presence of multiple people around.

Here in this paper we use a moderately low information-transfer rate decoding technique but we increase an effective information-transfer rate by exploiting the robotic home environment. Based on two kinds of available information, i.e., 1) the status of household equipment and electric appliances and 2) the position of the user (wheelchair), we design an efficient framework, which we call waypoint-based BMI. Basically BMI is used for sensing the user's wants; for the navigation task, BMI read the location in the house that the user wants to go, and robotics executes the command in an automatic and safe manner. Waypoints are located on landmark spots in the living environment; they are selected manually at the front of the entrance door, living room, bedroom, kitchen, in front of television, etc. At each waypoint there is a list of possible actions, from which the user chooses one to be executed. The user controls the wheelchair and house equipments only by conducting BMI at the waypoints. Our framework stands independently with specific BMI tasks and in principle can be applied to any task. In addition, to provide safe mobility to users, we propose the use of a semi-autonomous robotic wheelchair which communicates with the house installations achieving smooth navigation. This is the first report that constructed the brain-controlled robotic home.

The rest of the paper is organized as follows: Section II presents the related works, Section III describes the system overview, Section IV describes the field trials and reports the experimental results, with discussion of the system advantages and limitations. Finally Section V presents the conclusions and future works.

II. Related Works

A. BMI

Blankertz et al. [1] examined nine subjects and reported only three subjects achieved the peak information-transfer rate of BMI above 35 bpm, above 23 bpm for two subjects, and above 12 bpm for three, while one subject could not control BMI. Noninvasive BMI has been used for the control of electric devices including electric wheelchairs, mainly using P300, motor imagery, and SSVEP (steady-state visual evoked potential). They can be divided into two categories: synchronous and asynchronous. In a synchronous scenario, subjects only performs BMI at discrete timings, and thus subjects are able to relax often. Aloise et al. [6] proposes a synchronous P300-based approach, where a threshold classification system for domotic appliances is described; however, they did not performed experimentation in a real home environment. Iturate et al. [7] developed a BMI navigation system with subgoals that are combinations of the distance (close, mid, and far) and direction (left, ahead, and right). Benefits from asynchronous approaches include that subjects can determine the timing of BMI control, but they have to concentrate continuously. Carlson and Millán [4], [8] presents asynchronous motor-imagery BMI approaches where a shared control architecture couples the user's desires with the precision of a powered wheelchair. Rebsamen et al. [9] integrated a slow but reliable P300-based BMI to select a destination amongst a list of predefined locations with a wheelchair which can autonomously follow smooth trajectories towards selected destinations in virtual environments, with a similar philosophy to our work. Mandel et al. [10] used SSVEP with a continuous control design with an extra monitor attached to the wheelchair.

In this work we use two-class motor imagery (left or right hand) to select destinations of the wheelchair and to control the electric appliances in our smart house, because it can be naturally associated with the direction of movement, has relatively solid justifiability from neuroscience background, and does not require an extra monitor for destination selection.

B. Robotic Wheelchairs

Robotic wheelchairs provide users with mobility autonomy and safe navigation [11]. Autonomous wheelchairs providing mobility services have been product of previous research and implemented [12], [13], [14]. For example, regarding navigation, [15] proposes a system which integrates a multiple representation of the spatial knowledge for navigation. Regarding BMI controlled wheelchairs, [5] proposed a wheelchair controlled by BMI in which the user can continuously give locomotion commands to the wheelchair. The main difference of the wheelchair presented in this work and previous works is the seamless interaction with the user and the smart house. Through seamless communication the wheelchair can report its pose and velocity and the smart house can report its facility present state (doors, windows, etc.). In this way, the wheelchair can switch between a multiple map system to localize itself and the house can operate doors to allow the wheelchair navigation. This design avoids the necessity to have additional hardware to manipulate and handle the house installations. To increase user comfortability, in the proposed system, the user on the wheelchair does not need to concentrate and control it continuously, he just need to take decisions in waypoints set in the house to decide his destination.

C. Smart Houses

Domotics as a research field has been established as an extension of ubiquitous computing [16] and contributes to enhance research and development of in ambient intelligence for smart environments [17]. There is research reporting advances in smart rooms and homes [18], however, a home system involving direct human control through a brain interface combined with a robotic wheelchair has not been reported. In addition to the common characteristics of a smart environment, this work proposes the addition of user mobility with a robotic wheelchair as an extension of the ambient intelligence. The wheelchair communicates to the house through a central server, as the house is equipped with laser sensors, it can inform the wheelchair navigational system if a certain path is free and clear to go through.

In this work we present a BMI system which fully controls the smart house and the mobility in it in the shape of a robotic wheelchair.

III. System Overview

A. Brain Data Acquisition

One healthy male subject (23y; right-handed) participated in a series of experiments to construct and test the waypoint BMI system. EEG signals were recorded with a mobile EEG amplifier (g.MOBIlab+ by g.tec medical engineering GmbH, Austria) using 8 Ag/AgCl electrodes at FC3, FC4, C3, Cz, C4, CP3, CP4, and Pz in the extended 10-20 system to cover motor-related areas and sampled at 256 Hz.

To build a database for BMI classification, the subject conducted the two-class motor imagery task in which one of left/right-hand movements was imaged for 5 seconds according to different visual cues ("$<$" for left and "$>$" for right). Over 11 days, 71 runs with 30 trials of each motor condition were recorded ($71 \times 30 \times 2 = 4260$ trials in total).

B. BMI Decoder

To estimate the subject's intention, we constructed a BMI decoder utilizing the database. Usually BMI decoders consist of two steps: feature extraction and classification. We applied a widely-used spatial filter called a common spatial pattern (CSP) [19], [20] with appropriate regularization [21], and employed the log power of the first two CSP components in the alpha band (9–13 Hz) as the input feature. A CSP component has large variances in one motor condition, while its variance is small in the other case, which can enhance pattern differences of rhythmic brain activities between the two classes. As is known in neurophysiology literature, we usually observe event-relate desynchronization (ERD) in the motor areas contralateral to the imagined hands. The obtained CSP filters have weights with opposite signs on the bilateral motor areas in order to capture the contralateral ERD in the alpha band.

Although linear classifiers such as linear discriminant analysis (LDA) with appropriate regularization are commonly used to determine the imagined limbs [22], in our implementation, we used k-nearest neighbor classifier with $k = 10$ based on the tagged brain patterns stored in the database. Our motivation behind the choice is that a data-driven approach is more suitable for BMI. In the smart house, more and more data are obtained and stored anyway during daily usage of BMI and, in contrast to standard linear classifiers, no re-training or online adaptation are necessary to utilize the growing dataset.

C. Waypoints

Since our BMI decoder can only make a binary decision, at each waypoint the system makes a branch for two actions. At some waypoints two actions correspond to two moving directions, and at other waypoints two actions are associated with commands to appliances; for examples, at the waypoint just after entering to the living room, the user can choose the way to go from "in front of TV" or "the kitchen," and at the waypoint in front of TV, the action list consists of two TV channels.

D. Smart House

To increase the reliability of daily life using a BMI-based wheelchair, we use a smart house that monitors and supports the wheelchair and the user living there. The smart house installations are fully electrical powered and controlled from the central server, and many kinds of sensors are installed to understand behavior of people and provide safe navigation of the wheelchair. Since BMI-based control is still not very stable, the smart house server will stop or modify the command from user when it will result in collision the smart house system. Fig. 1 shows the overview of the smart house.

1) Control System: The central server communicates with peripheral devices and controls a relay system for the manipulation of the electrical facilities. Fig. 2 shows the block diagram of the smart house system. The wheelchair is connected to the central server through a wireless connection. Air-conditioners, televisions, water pots, doors, windows, curtains, wheelchair lift, etc. can be electronically controlled through socket connection. Output of a BMI decoder that analyzes brain activities gives control commands to the server. The field together with the wheelchair constitutes a fully autonomous ubiquitous system. For example, in the case of doors, when the central server sends a target waypoint to the wheelchair, the server checks the status of the doors on the way, opens the doors if closed, and closes the doors as the wheelchair passes as the server receives notifications from the wheelchair position. When the wheelchair (or the user) comes to a waypoint, the central server invokes a BMI and waits the decision. The server sends a command to a device defined on the waypoint.

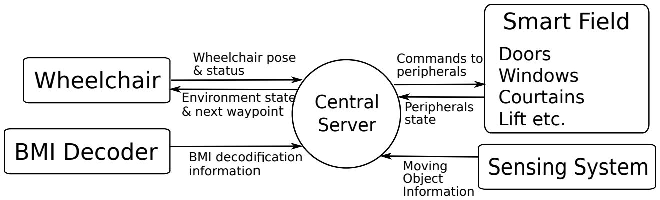
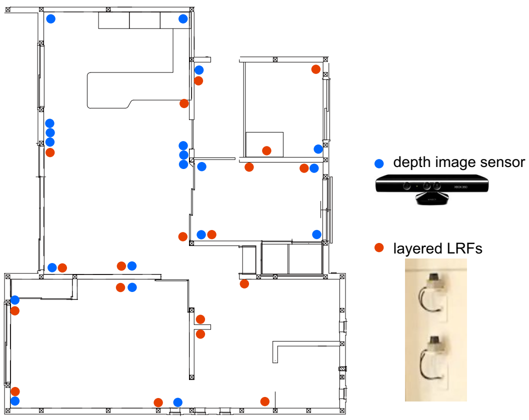


Fig. 2. Communication between the server, wheelchair, and peripherals.



(a) Sensor placement. Red circles show pair of LRF on the wall, blue circles show depth sensors on the ceiling.

(b) Sensors that monitors a wheelchair in the living room.

Fig. 3. Sensing system in the smart house.

2) *Sensing System:* The sensing network system in the smart house consists of depth sensors and laser range finders (LRFs) (Fig. 3). Pairs of LRFs (Hokuyo URG-04LX) are put on the wall at each location to track the positions of moving target precisely and recognize types of moving objects. Depth sensors (Microsoft Kinect) are installed on the ceilings to understand various daily behaviors. Household electrical appliances and doors are connected to the central server and the server understands behavior of the people in the house through their status.

The LRF system used in this work [23] tracks the positions at intervals of 5 cm and a frequency of 10 Hz. The system assigns a consistent ID to each moving object and performs object recognition to detect the type of target (human or wheelchair). Fig. 4 shows the LRF system track people in the living room.

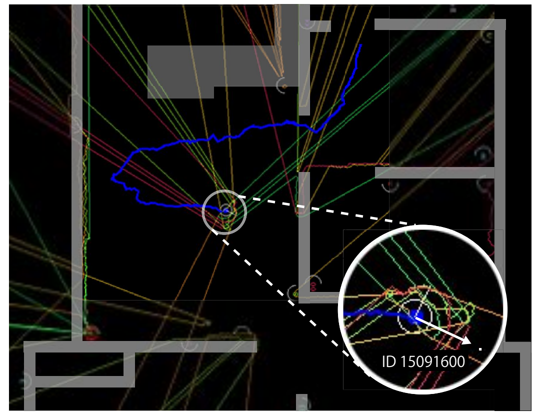


Fig. 4. People tracking using LRFs. The blue circle is the location of a person, whose trajectory is the blue line, and the white arrow points toward the moving direction of the person. Green, yellow, and red lines are the observations from LRFs. A unique ID is assigned to each moving object.

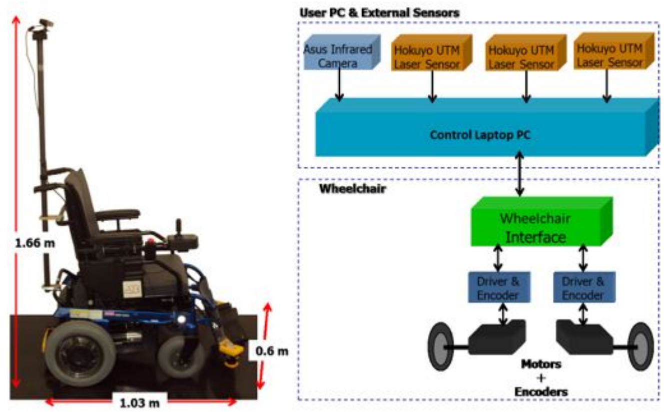


Fig. 5. Autonomous robotic wheelchair equipped with wheel encoders, three laser sensors, and a depth RGB infrared camera.

E. Autonomous Robotic Wheelchair

The robotic wheelchair is equipped with wheel encoders, three Hokuyo UTM-30LX laser sensors, and one ASUS Xtion PRO sensor tilted down (Fig. 5). See Fig. 6 for data flow. The laser sensors are used for map-building, localization, and obstacle avoidance. The ASUS infrared camera is used to detect obstacles at different heights.

1) *Map Building and Handling:* House maps were built from laser scans and odometry data from the robot manually driving through the environment by using SLAM (simultaneous localization and mapping) framework [24]. We built several grid maps with a cell resolution of 5 cm in pgm format representing the different states of the house. According to the information provided by the central server, maps are switched and used for robot localization. Fig. 7 shows the grid map, where the robot can traverse on white areas, black areas represent solid objects, red lines represent the doors, and the blue square the wheelchair lift.

2) *Localization:* We used a particle filter with 200 particles for wheelchair localization towards the grid map. Each particle contains a pose given by state vector $\hat{x} = \{x, y, \theta\}$, with positions x and y and orientation θ of the robot. We

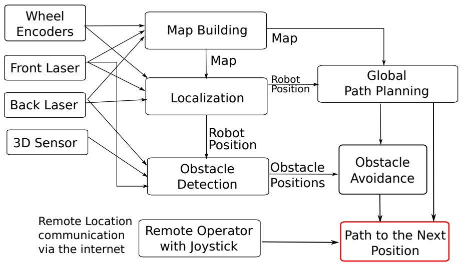


Fig. 6. Data flow.

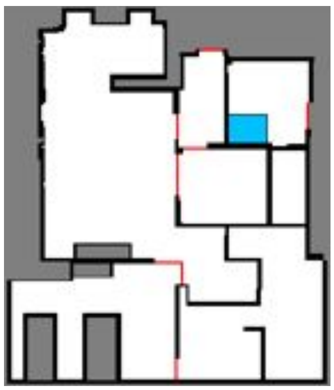


Fig. 7. Grid map of the smart living environment. Doors are represented in thin red lines and the elevator in light blue.

used the ray tracing approach likelihood model in [25] to compute the particle weights and the vehicle pose is given by the average weight of the particles.

3) Autonomous Navigation: For autonomous navigation, we pre-defined points in which the wheelchair can freely navigate such as entrance, living room, kitchen, bedroom. The person on the wheelchair through the BMI decides the goal location, the smart house opens and closes the doors to clear the path and the wheelchair moves towards the goal location. Autonomous navigation reduces stress and load of the user of having to control the wheelchair continuously with BMI. In the case of obstacles, the wheelchair would try to avoid them using a variant of the dynamic window approach [26], in the case there is no free space to pass it would stop and call an operator.

IV. Experimental Results and Discussion of System Limitations

This section presents the experimental results of the wheelchair autonomously navigating in the smart living environment. Fig. 8 presents the localization results of the wheelchair after autonomous navigation runs. First, the trajectories in light blue present the results of seven different runs of the wheelchair starting outside the main entrance (1), entering through the main door (2) (Fig. 9(a)), changing level through the elevator (3) (Fig. 9(b)) and entering the living room (4) (Fig. 9(c)). The trajectories in dark blue show seven different routes of the wheelchair navigating inside the living environment, between the kitchen (5) (Fig. 9(e)) and the bedroom (6) in both ways. Fig. 9 shows a series of images

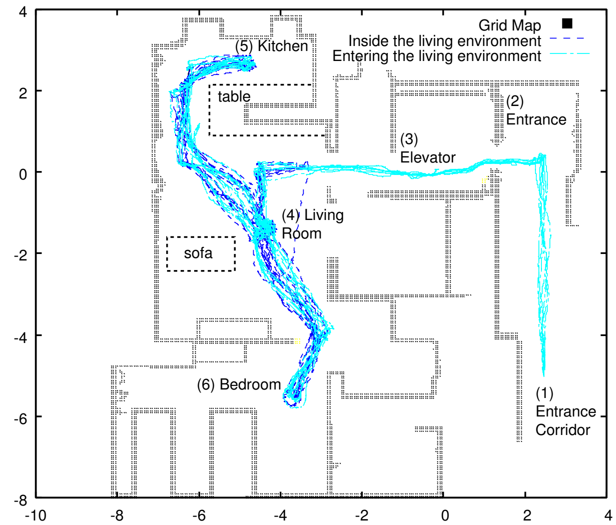


Fig. 8. Trajectories of the wheelchair during autonomous navigation. The grid map is shown in black, objects not visible at the height of the laser (table and sofa) are shown in dotted lines.

of the BMI user using the wheelchair.

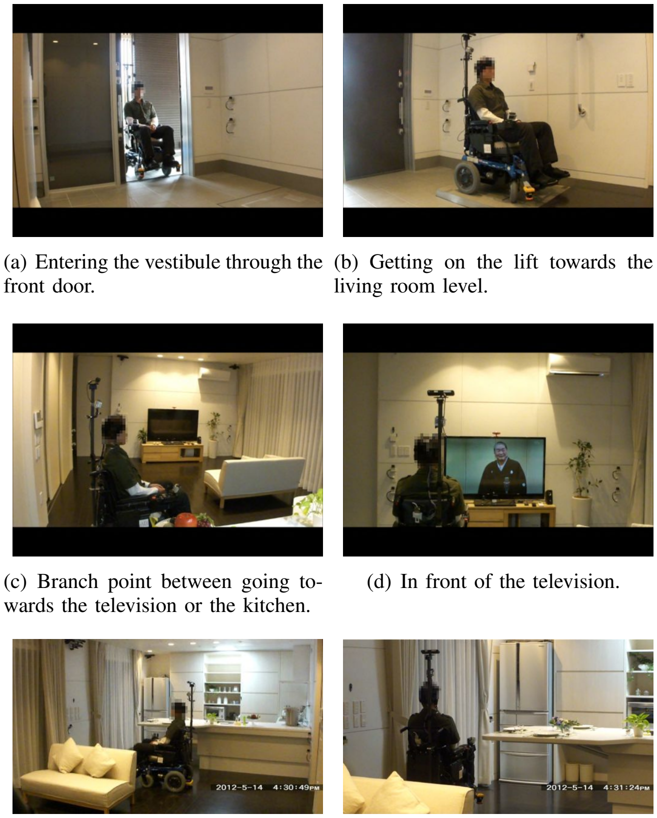
We performed an open demonstration of the whole operating system on November 1st, 2012, where the success ratio of the BMI decoding in the live demo was $11/12 = 91.7\%$. From the current state of the EEG-BMI technology, this accuracy is an excellent performance. However, once among the 12 trials, the subject went to the kitchen, although he wanted to move to the bedroom, which should not occur in daily life usage. Since it is impossible to achieve 100% precision by BMI, a practical solution would be introducing a mechanism to stop in the middle to the selected goal and retry BMI there.

EEG signals show non-stationary changes and session-to-session variabilities by many reasons: impedance changes, concentration levels, learning effect, fatigue and so on. The subject's performance can drop to about 70% on some days when he cannot concentrate to generate discriminative brain activities. This is still one of the unsolved important topics in BMI. We need to understand backgrounds of such non-stationarity and to develop robust machine learning techniques against it.

Our BMI decoder based on 10-nearest neighbors search from the database achieved 78.1% accuracy by offline cross-validation analysis with a part of the acquired data, while a linear classification technique (SLR; sparse logistic regression), predicted 79.8% of test trials correctly on average. It is known that with an appropriate input feature, usually simple linear classifiers work best for motor imagery tasks. Thus, in this problem, the more flexible data-driven decoder was not better than the state-of-the-art methods in classification performance, in particular, with the current middle-sized database.

V. Conclusions and Future Works

We implemented a waypoint BMI system for controlling wheelchair and electric appliances in a smart house to assist



(a) Entering the vestibule through the front door.

(b) Getting on the lift towards the living room level.

(c) Branch point between going towards the television or the kitchen.

(d) In front of the television.

(e) Going towards the kitchen.

(f) Turning on the kitchen.

Fig. 9. Experimentation in the living environment.

daily-life activities of its users. It was demonstrated online by a subject who achieved an excellent performance. Further works should be done to ensure reasonable performance everyday dispute of day-to-day variability of EEG signals and to make the waypoint BMI system more flexible, e.g., including a mechanism for correcting previous commands and retrying BMI in the middle of trajectories towards wrong destinations.

ACKNOWLEDGMENT

We thank T. Condon, T. Ochi, and H. Moriyama for software development, J. Abdur-Rahim, S. Morimoto, and Y. Shikauchi for experimental and K. Fujii and Y. Ishiyama for network assistance. Some facilities were installed by Sekisui House, Ltd. EEG device was provided by Shimadzu Corporation.

REFERENCES

[1] B. Blankertz, G. Dornhege, M. Krauledat, K.-R. Müller, and G. Curio, "The non-invasive Berlin brain-computer interface: fast acquisition of effective performance in untrained subjects," *NeuroImage*, 2007.

[2] J. L. Ryan, "Home automation," *Electron. Commun. Eng. J.*, vol. 1, no. 4, pp. 185–192, 1989.

[3] C. Reinisch, M. J. Kofler, and W. Kastner, "Thinkhome: A smart home as digital ecosystem," in *IEEE Int. Conf. Digital Ecosystems and Technologies (DEST)*, 2010, pp. 256–261.

[4] T. E. Carlson and J. d. R. Millán, "Brain-actuated wheelchairs: A robotic architecture," *IEEE Robot. Autom. Mag.*, vol. 20, no. 1, pp. 65–73, 2013.

[5] F. Galán, M. Nuttin, E. Lew, P. W. Ferrez, G. Vanacker, J. Philips, and J. d. R. Millán, "A brain-actuated wheelchair: Asynchronous and non-invasive brain-computer interfaces for continuous control of robots," *Clin. Neurophysiol.*, vol. 119, no. 9, pp. 2159–2169, 2008.

[6] F. Aloise, F. Schettini, P. Aricó, F. Leotta, S. Salinari, D. Mattia, F. Babiloni, and F. Cincotti, "Toward domotic appliances control through a self-paced P300-based BCI," in *Int. Conf. Bio-Inspired Systems and Signal Processing (BIOSIGNALS)*, 2011, pp. 239–244.

[7] I. Iturrate, J. Antelis, A. Kubler, and J. Minguez, "A noninvasive brain-actuated wheelchair based on a P300 neurophysiological protocol and automated navigation," *IEEE Trans. Robot.*, vol. 25, 2009.

[8] J. d. R. Millán, F. Galan, D. Vanhooydonck, E. Lew, J. Philips, and M. Nuttin, "Asynchronous non-invasive brain-actuated control of an intelligent wheelchair," in *Annu. Int. Conf. IEEE Engineering in Medicine and Biology Society (EMBS)*, 2009, pp. 3361–4336.

[9] B. Rebsamen, C. Guan, H. Zhang, C. Wang, C. Teo, M. H. Ang, and E. Burdet, "A brain controlled wheelchair to navigate in familiar environments," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 18, no. 6, pp. 590–598, 2010.

[10] C. Mandel, T. Lüth, T. Laue, T. Röfer, A. Gräser, and B. Krieg-Brückner, "Navigating a smart wheelchair with a brain-computer interface interpreting steady-state visual evoked potentials," in *IEEE/RSJ Int. Conf. Intelligent Robots and Systems (IROS)*, 2009.

[11] E. Wästlund, K. Sponseller, and O. Pettersson, "What you see is where you go: testing a gaze-driven power wheelchair for individuals with severe multiple disabilities," in *Symp. Eye-Tracking Research & Applications (ETRA)*, 2010, pp. 133–136.

[12] E. Prassler, D. Bank, and B. Kluge, "Key technologies in robot assistants: Motion coordination between a human and a mobile robot," *Trans. Control Autom. Syst. Eng.*, vol. 4, pp. 56–61, 2002.

[13] Y. Kobayashi, Y. Kinpara, T. Shibusawa, and Y. Kuno, "Robotic wheelchair based on observations of people using integrated sensors," in *IEEE/RSJ Int. Conf. Intelligent Robots and Systems (IROS)*, 2009.

[14] A. A. Argyros, P. Georgiadis, P. Trahanias, and D. P. Tsakiris, "Semi-autonomous navigation of a robotic wheelchair," *J. Intell. Robot. Syst.*, vol. 34, 2001.

[15] P. Beeson, M. MacMahon, J. Modayil, A. Murarka, B. Kuipers, and B. Stankiewicz, "Integrating multiple representations of spatial knowledge for mapping, navigation, and communication," in *AAAI Spring Symp. Interaction Challenges for Intelligent Assistants*, 2007.

[16] E. Aarts and B. de Ruyter, "New research perspectives on ambient intelligence," *J. Ambient Intell. Smart Environ.*, vol. 1, pp. 5–14, 2009.

[17] D. J. Cook, "Multi-agent smart environments," *J. Ambient Intell. Smart Environ.*, vol. 1, pp. 51–55, 2009.

[18] C. D. Kidd, R. Orr, G. D. Abowd, C. G. Atkeson, I. A. Essa, B. MacIntyre, E. D. Mynatt, T. Starner, and W. Newstetter, "The aware home: A living laboratory for ubiquitous computing research," in *Int. Workshop Cooperative Buildings, Integrating Information, Organization, and Architecture (CoBuild)*, 1999, pp. 191–198.

[19] K. Fukunaga, *Introduction to Statistical Pattern Recognition*, 2nd ed. Academic Press, 1990.

[20] Z. Koles and A. Soong, "EEG source localization: Implementing the spatio-temporal decomposition approach," *Electroencephalogr. Clin. Neurophysiol.*, vol. 107, pp. 343–352, 1998.

[21] F. Lotte and C. Guan, "Regularizing comon spatial patterns to improve BCI designs: Unified theory and new algorithms," *IEEE Trans. Biomed. Eng.*, vol. 58, pp. 355–362, 2010.

[22] F. Lotte, M. Congedo, A. L Secuyer, F. Lamarche, and B. Arnaldi, "A review of classification algorithms for EEG-based brain-computer interfaces," *J. Neural Eng.*, vol. 4, 2007.

[23] D. F. Glas, T. Miyasita, H. Ishiguro, and N. Hagita, "Laser-based tracking of human position and orientation using parametric shape modeling," *Adv. Robot.*, vol. 23, pp. 405–428, 2009.

[24] G. Grisetti, C. Stachniss, and W. Burgard, "Improved techniques for grid mapping with Rao-Blackwellized particle filters," *IEEE Trans. Robot.*, vol. 23, no. 1, pp. 34–46, 2007.

[25] D. Fox, W. Burgard, S. Thrun, and A. B. Cremers, "Position estimation for mobile robots in dynamic environments," in *Nat. Conf. Artificial Intelligence (AAAI)*, 1998.

[26] D. Fox, W. Burgard, and S. Thrun, "The dynamic window approach tocollision avoidance," *IEEE Robot. Autom. Mag.*, vol. 4, no. 1, pp. 23–33, 1997.