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A Fuzzy-based Shared Controller for Brain-actuated Simulated Robotic System

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***Abstract*—The primary problems of brain-computer interface (BCI) are the low channel capacity and high error rate. Therefore, an assistive motion control method is important for the brain-actuated robot to realize real-time and reliable control. To make the brain-actuated robot respond to the external environments with more flexibility, a shared control method based on fuzzy logic is proposed. Experimental results obtained with ten healthy voluntary subjects show that the proposed fuzzy-based shared controller has improved performance compared with direct control approach.**

I. INTRODUCTION

THE idea of mentally controlling a device is a technical and social dream that now is turning into reality. Among the many BCI modalities, the non-invasive techniques, such as electroencephalography (EEG) recorded from the scalp, is of particular interest. It bears advantages of less workload for the brain and low cost. However, the low channel capacity offered by such non-invasive signals makes their use in controlling rapid and complex sequences of robot movements difficult [1,2]. An approach to alleviate this relies upon machine learning techniques to find subject-specific EEG features with maximal inter-task differences, and to train classifiers that minimize the classification error rates. Another solution to the low bandwidth problem of BCI is to incorporate increasing adaptive shared autonomy in the agents that execute BCI commands, such as a wheelchair with obstacle avoidance [3,4].

The shared control techniques has a profound impact on the BCI performance for a robotic assistance [5]. A next step in the development of shared control techniques would be to make the system more capable of handling real world uncertainty and knowledge representation to maximize user control of the brain-actuated robot. In this paper, we propose a fuzzy-based shared control method and implement it between the BCI and the robot. One advantage of this control method resides in that the fuzzy logic approach can deal with various situations without analytical model of the environments [7-9]. Moreover, it allows robotic system to reason more closely as humans. As a result, the system can execute effectively high-level commands associated with the users' mental commands for obstacles avoidance and smooth turns.

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II. METHOD

A. Brain-actuated Robotic System Structure

Fig. 1 shows a schematic representation of the shared control architecture for the brain-actuated robotic system. The system consists of two parts, namely, the BCI system and the intelligent robotic system. Our BCI system is implemented with the general-purposed BCI 2000 software [6]. The robot used is an ActivMedia *Pioneer P3-DX* robot with three wheels equipped with different sensors including a pan-tilt camera, SICK LM200 laser and sonar for environmental information acquisition.

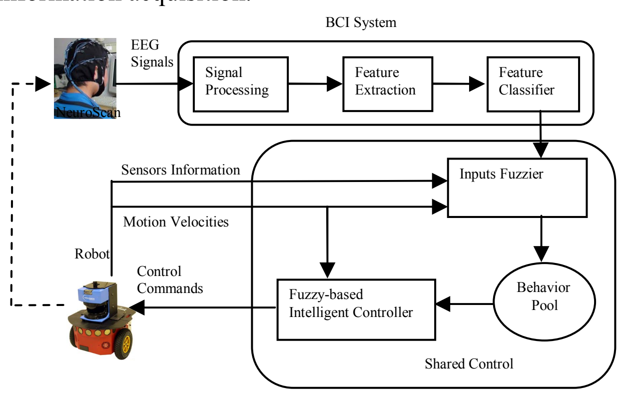
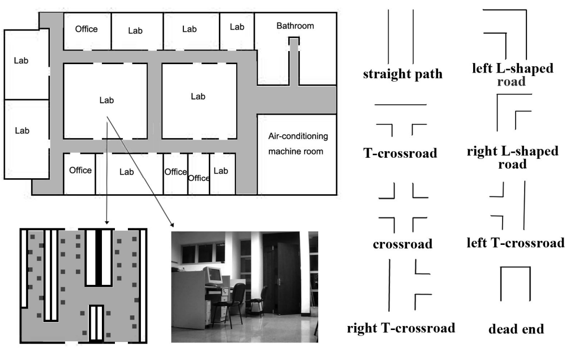


Fig.1. Architecture of the brain-actuated robotic system.

The shared control module consists of inputs fuzzier, behavior pool and fuzzy-based intelligent controller. In our controller, both the users' mental state, the robot's sensory information, motion behavior and velocities are the inputs to the shared controller which translates the inputs to proper motor commands, represented by a translational (υ) and rotational (ω) velocities. Given the environmental information, each behavior calculates its appropriateness based on fuzzy rules. The controller then applies fuzzy control rules again to determine which behavior in the behavior pool is activated. The shared controller chooses appropriate behavior combining the recognition results and operator's commands. Therefore, the intelligent robot with fuzzy-based shared control will alleviate the problem associated with the low accuracy or signal rate in BCI.

B. *Fuzzification of the Input-output Variables*

Fig. 2(a) shows the layout of robot indoor navigation environment. It has several labs and offices along the corridor. The bottom left picture is the map of one typical lab, in which the white sticks and black spots represent lab tables and chairs, respectively. The bottom right of Fig. 2(a) is a snapshot of the lab. A pattern matching algorithm is implemented to map the raw laser sensory readings into 8 classes of environmental states (i.e. the robot's perceptual states) as shown in Fig. 2(b). They are "straight path", "left L-shaped road", "T-crossroad", "right L-shaped road", "crossroad", "right T-crossroad", "left T-crossroad", and "dead end".



(a) (b)

Fig. 2 (a) The layout of typical office environment for mobile robot navigation (b) Path shapes.

The behaviour of the robot is determined by the three mental states (forward, left, right) of the user as well as the 8 perceptual states of the environment determined by the robot's sensory readings. Moreover, the controller uses two other inputs, internal memory variables for the current behaviour, such as the distance to the wall and motion velocities. A linguistic variable x in a universe of discourse U is characterized by $T(x)=\left\{T_x^1,T_x^2,...,T_x^k\right\}$ and $M(x)=\left\{M_x^1,M_x^2,...M_x^k\right\}$, where $T(x)$ is the term set of x with each value T_x^i being a fuzzy number with membership function M_x^i defined on U. So $M(x)$ is semantic rule that associates each value with its meaning. For our system, the input vector X includes four input linguistic variables $X=\{x_1,x_2,x_3,x_4\}=\{S,C,B,V\}$, where S, C, B and V indicate sensory information, mental commands, behaviors and motion velocities respectively. Therefore, we have

T_{x_1} = {ST,L,R, LRC, LC, RC, CROSS, END}, with the corresponding meaning of {straight path, left L-shaped road, right L-shaped road, T-crossroad, left T-crossroad, right T-crossroad, crossroad, dead end};

T_{x_2} = {L,R,S}, with the corresponding meaning of {left turn, right turn, stop};

T_{x_3} = {b-ST,b-L,b-R,b-LW,b-RW,b-STOP,b-SLOW,b-FAST}, with the corresponding meaning of {straight, left turn, right turn, along the left wall, along the right wall, stop, slow down, accelerate}.

The motion velocities vector x_4 have two inputs variables, i.e. υ and ω. Therefore, $x_4=\{x_{41},x_{42}\}=\{v,w\}$. Since the rotation velocity provides more information about the behaviour of the robot, seven fuzzy sets are used to define it, while five terms are assigned to the translation velocity. v and w are expressed by linguistic values {NB,NS,ZO,PS,PB} and {NB,NM,NS,NO,PO,PS,PM,PB}, respectively. The linguistic term symbols have the following meanings:

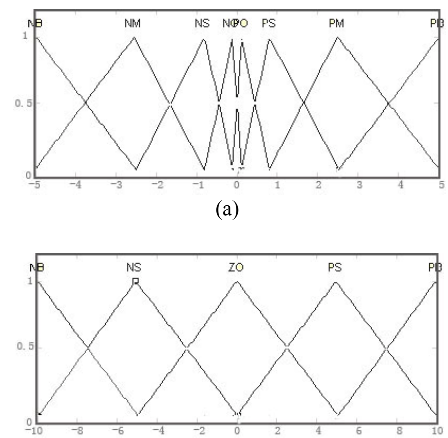
N: Negative B: Big M: Middle
S: Small Z: Zero P: Positive.

Following the above definition, the input vector X and the output state vector Y can be defined as

$$X=\left\{\left(x_i,U_i,\left\{T_{x_i}^1,T_{x_i}^2,...,T_{x_i}^{k_i}\right\},\left\{M_{x_i}^1,M_{x_i}^2,...,M_{x_i}^{k_i}\right\}\right)\Big|_{i=1...n}\right\} \quad (1)$$

$$Y=\left\{\left(y_i,U_i',\left\{T_{y_i}^1,T_{y_i}^2,...,T_{y_i}^{l_i}\right\},\left\{M_{y_i}^1,M_{y_i}^2,...,M_{y_i}^{l_i}\right\}\right)\Big|_{i=1...m}\right\} \quad (2)$$

The membership functions of the fuzzy sets defined for the υ and ω are shown in Fig. 3. In this study, triangular shapes are chosen to simplify the computation.



(a)

(b)

Fig. 3 (a) Membership function curves of angular velocity (b) Membership function curves of linear velocity.

C. *Rule Base Construction*

The rule bases for realizing each behavior can be constructed based on human experience. However, using a fuzzy logic controller (FLC) for mobile control has the problem that rules increase exponentially with the number of variables involved. Since the robot has five inputs in our study, this results in the rule bases as large as 6720 (8×8×7×5×3), which causes problems for the robot's real-time performance and the FLC design. To cope with this problem, a optimization strategy is applied to hierarchically decompose the control problem. Moreover, we break down the input space for analysis by sharing it among multiple low level behaviors, each of which responds to specific types of situations, and then integrate the recommendations of these behaviors. For example, on the 'straight' path, both translation and rotation velocities have no effect on the behavior choice. In the 'left turn,' 'right turn,' and 'dead end,' cases, the amplitude of translation velocity has no relation to the behaviour choice. When a 'stop' mind command is issued, the 'stop' behavior would be selected no matter how much each of the other input is. After the decomposition, the total number of control rules reduces to 83. The rule bases for the behaviors consist of the rules taking the form of IF-THEN statements:

$$R_n^k : IF(\mathrm{X}{=}\mathrm{T}_n)THEN(Y=[v_k, w_k]) \tag{3}$$

where R_n^k denotes the n[th] rules associated with the k^{th} behavior. Also, T_n with $n=1,2,...,N_k$ are the linguistic value vectors. The rule based for the k^{th} behavior R^k can be represented as the union

$$R^k = \left\{ \bigcup_{n=1}^{N_k} R_n^k \right\}. \tag{4}$$

The nth rules are the fuzzy relations in product spaces, $U_{x_1} \times U_{x_2} \times U_{x_3} \times U_{x_4} \times U_w \times U_v$. Thus, the rules can be implemented as fuzzy relations with corresponding membership functions. The membership values of n[th] rule will be denoted by μ_w and μ_v. When the input $X=\{S',C',B',V'\}$ are given, the fuzzy control actions V' and W' are inferred by

$$\begin{aligned} V' &= (S',C',B',V') \circ \bigcup_{n=1}^{N_k} R_n^k(v) \\ W' &= (S',C',B',V') \circ \bigcup_{n=1}^{N_k} R_n^k(w) \end{aligned} . \tag{5}$$

where $\circ$ denotes the maximum-minimum composition.

In order to determine the output action, $\vec{v}^i$ and $\vec{w}^i$, for the i^{th} behavior from the fuzzy control actions, V' and W', a defuzzification process is required. When the method of the center of gravity [9] is used for defuzzification in the case of discrete universe, crisp control actions are expressed by

$$\begin{aligned} \vec{v}^k &= \left\{ \sum_{i=1}^{p} v_n \mu_{V'}^k(v_n) \Big/ \sum_{i=1}^{p} \mu_{V'}^k(v_n) \right\} \\ \vec{w}^k &= \left\{ \sum_{i=1}^{q} w_n \mu_{W'}^k(w_n) \Big/ \sum_{i=1}^{q} \mu_{W'}^k(w_n) \right\} \end{aligned}, \tag{6}$$

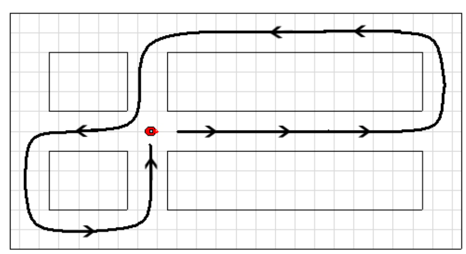
where p and q denote the number of quantization levels of the fuzzy output actions, V' and W', in each behavior, respectively.

III. Experimental Results

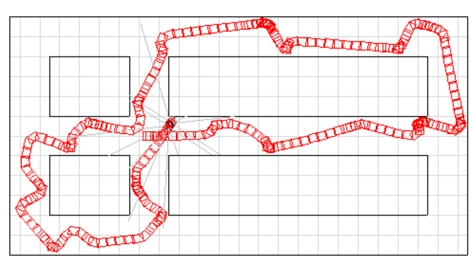
The objective of this experiment is to investigate the performance of fuzzy-based shared control method for BCI-robot navigation task. Moreover, the impact of the signal arriving time (SAT) and the control modes are also studied in this test. The main hypothesis for this experiment is that the participants should navigate the robot to the destination better under shared control mode than direct control (human commands only). It is expected that the increase of SAT would affect the performance of tasks.

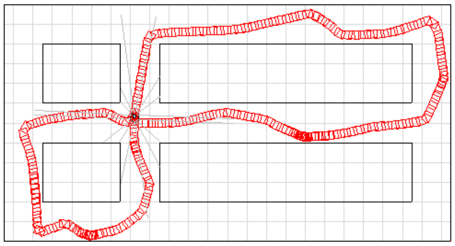
Experiments were carried out in a simulated environment based on our developed BCI-Mobilesim system [6]. The whole experiment data were obtained from 10 volunteers, eight females and two males. The average age of the participants was 26 years (SD = 2.36), with a range from 24 to 30 years. Regarding to control tasks, all participants had no prior experience. The subjects were instructed to navigate the simulated robot through a way to the target in as short time as possible without hitting anything as depicted in Fig. 2(a). To compare the performance under two control modes fairly, 4 times random wrong operations were added to simulate BCI system performance. In our setting, the universe of discourse U_{41} of translation velocity (υ) is [-300,300] (mm/s) which is the settings of the real robot. It is discretized into 21 levels {-10, -9, -8, -7, -6, -5, -4, -3, -2, -1, 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10} with five terms defined for it. The universe of discourse U_{42} of rotation velocity (ω) is [-50,50] (rad/s). With the quantization level, the universe discourse is discretized into 11 segments between [-5,5]. U_4 is transformed into the normalized closed interval [-1,+1] with the normalization factor 1/10.

Experimental procedures were developed for both training and testing sessions. During the one hour training session, subjects were introduced to the system operation and experimental protocol. Two variables were manipulated in the experiment including SAT and control mode. There were two SAT conditions including 0.5b/s and 1b/s. Each participant experienced two kinds of control mode, including direct control and shared control. The number of effective operation (correct actions to navigate the robot to the destination), misoperation, collision, completion time, and total distance were recorded during the experiments as the performance metrics.

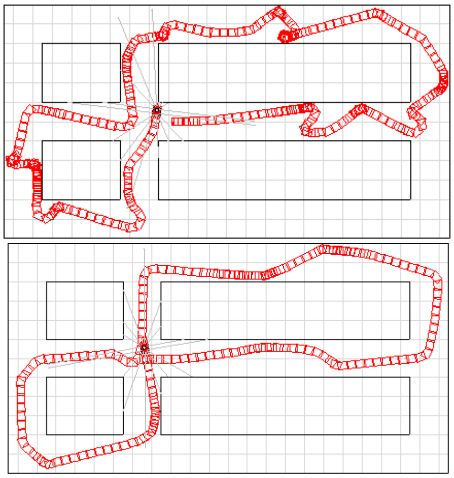


(a) The environment in which the experiment was performed and the pre-specified path.





(b) The robot trajectories for direct control (up) and control with shared control method (down) when the SAT is 0.5b/s.



(c) The robot trajectories for direct control (up) and control with shared control method (down) when SAT is 1b/s.

Fig 3 The control trajectories comparison between direct control and control with shared controller under different transformation rate.

TABLE I
STATISTICS OF PERFORMANCE

Performance	SAT 0.5b/s		SAT 1b/s	
	Direct	Assistive	Direct	Assistive
Effective operation (Times)	28	16	27	14
Misoperation (Times)	6	2	4	4
Completion Time (s)	112	91	103	86
Collision (Times)	17	4	13	3
Distance (cm)	28.00	22.75	25.75	21.50

All the ten subjects successfully completed the four-section experiment. They were able to navigate the simulated robot from the starting position to the target. The evidence values for the same control task under different control conditions are shown in table I while the comparative trajectories for the experiment under different conditions are shown in Fig. 2(b) and Fig. 2(c). Analyses of variance (ANOVAs) were applied to the various dependent variables to investigate the influence of control mode on the task performance. The results were significant with $p<0.05$. Correlation analyses were also conducted to identify any significant relationships among completion time, number of misoperation, collisions and effective control and total distance.

Fig. 3 shows that the subject does make some loops under direct control mode. The mobile robot can smoothly navigate through environment. Thus, fuzzy-based shared controller could definitely help here. The results of an ANOVA on the entire performance variables under the two control modes revealed that there was significant main effect of shared control mode on task completion time. The correlation analyses indicate a significant positive interaction between control mode and SAT on completion time and total distance: $F = 1.24$ and $p = 0.2734$, $F = 1.97$ and $p = 0.1685$. However, there is less interaction on the number of effective operation, misoperation and collision. These results reflect the fact that the control mode is beneficial to the whole control performance.

IV. CONCLUSION

In this paper, a fuzzy logic based shared controller was developed for the motion control of the brain-actuated robot. The performance of the adaptive shared control strategy suggests the fuzzy logic technique may provide an effective solution to design a shared control BCI system. It has been proved successfully in combining the obstacle awareness sent by the laser sensor with the intentions of the operator to provide near optimum navigation without prior knowledge of the environment. The overall performance of the robotic system was improved significantly by correctly matching the selected task to a given situation.

We are currently planning more extensive tests to evaluate the adaptive fuzzy shared strategy with real-time online BCI control. In these tests the robot will be required to perform a number of tasks with increasing difficulty.

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