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Adaptive Shared Control Strategies Based in the Bayesian Recursive Technique in an Intelligent Wheelchair

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***Abstract*—In this paper we present an adaptive shared control method for an intelligent wheelchair based on the Bayesian recursive technique to assist a disable user in performing obstacle avoidance tasks. Three autonomous tasks have been developed for different types of environments to improve the performance of the overall system. The system combines local environmental information gathered using a laser range finder sensor with the user's intentions to select the most suitable autonomous task in different situations. The evidences of these tasks are estimated by the Bayesian recursive technique during movements of the wheelchair. The most appropriate task is chosen to be the with the highest evidence value. Experimental results show significant performance improvements compared to our previously reported shared control methods.**

I. Introduction

The percentage of the population considered to be elderly or to have a disability is increasing. Within this section of the community many are considered to have functional impairments. The aim of rehabilitation technology is to improve the quality of life of people with disabilities. For example intelligent wheelchairs are developed to assist people with mobility impairments. The provision of independent mobility, has potential to benefit substantial, the development and/or maintenance of physical, cognitive, communication and social skills in both children and adults [1].

Several contemporary shared control strategies have been developed for various wheelchair platforms such as *SENA* [2], *Rolland* [3] and *Navchair* [4]. However, these methods were unable to facilitate wheelchair operation in a dynamic environment, having either no capacity for combining the user's intentions with data about the local environment or requiring prior knowledge of this environment. In addition, these methods would require further development to facilitate real-time operation.

In this paper, we present an assistive wheelchair system that utilises an adaptive shared control strategy based on the Bayesian recursive technique to select which autonomous task to use in different situations. To improve the wheelchair's performance in different environments three autonomous tasks have been developed: general obstacle avoidance, corridor and wall following and door passing [5]. As the wheelchair moves it takes into account both the user's intentions and local environment data to estimate each tasks' evidence. The task chosen being the one with the highest evidence value. System trials show significant performance improvement compared to our previously reported methods [6].

The paper is organised as follows. The second section presents the shared control strategy based on the Bayesian recursive technique. The following section introduces the experimental results. While in the last section we present our discussion and conclusions.

II. Adaptive Shared Control Strategy Based on the Bayesian Recursive Technique

A. Bayesian recursive for wheelchair's shared strategy

The information in regard to the local environment and the user's intentions is continuously updated. While the raw laser data provides the position of surrounded obstacles, it needs to be refined further to determine the most suitable autonomous task. Specifically, the system needs to use this data to identify environment features such as corridors, walls and doors in addition to general obstacles that need to be avoided. Hence a model of the local environment has to be produced.

Let us assume that the environment model is already available and at time t the wheelchair controller has observed a stream of information, I, as follows.

$$I = \{U_1, D_2, U_2, D_3, \ldots, U_{t-1}, D_t\} \tag{1}$$

Where

U_t: the user command at time t,

D_t: the environment model information at time t.

To estimate the current state of the wheelchair the Markov assumption is used, fig. 1, so that the values in any state are only influenced by the values of the state that directly preceded it. This assumption significantly reduces the computational complexity by allowing the removal of previous states that no longer effect the current state.

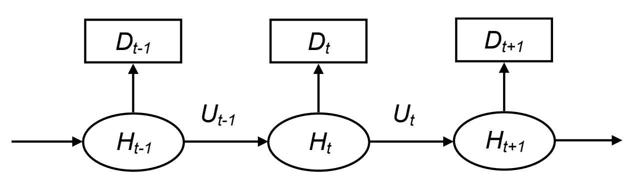

Fig. 1. The Markov chain for the wheelchair application. H is the wheelchair state. U is the user's action. D presents environment data.

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To select the appropriate task at time t, H_t, the posteriors of these autonomous tasks, known as evidences, have to be estimated based on the information of the environments and the user's intentions, D_t and U_{t-1} respectively, as follow

$$Evi(H_t) = P(H_t \mid U_1, D_2, U_2, D_3, ..., U_{t-1}, D_t). \qquad (2)$$

Using the Bayesian theorem to take into account the environment information:

$$Evi(H_t) = \frac{P(D_t \mid H_t, U_1, D_2, ..., U_{t-1})P(H_t \mid U_1, D_2, ..., U_{t-1})}{\int P(D_t \mid H_t, U_1, D_2, ..., U_{t-1})P(H_t \mid U_1, D_2, ..., U_{t-1})dH_t}. \qquad (3)$$

Based on the Markov assumption,

$$Evi(H_t) = \frac{P(D_t \mid H_t)P(H_t \mid U_1, D_2, ..., U_{t-1})}{\int P(D_t \mid H_t, U_1, D_2, ..., U_{t-1})P(H_t \mid U_1, D_2, ..., U_{t-1})dH_t}, \qquad (4)$$

$$Evi(H_t) = \eta_t P(D_t \mid H_t) P(H_t \mid U_1, D_2, U_2, D_3, ..., U_{t-1}),$$

Where

$$\eta_t = \int P(D_t \mid H_t, U_1, D_2, U_2, D_3, ...U_{t-1})P(H_t \mid U_1, D_2, U_2, D_3, ...U_{t-1})dH_t.$$

Take into account the user's intentions, the evidences are

$$P(H_t \mid U_1, D_2, U_2, D_3, ...U_{t-1}) = \int P(H_t \mid U_1, D_2, U_2, D_3, ...U_{t-1}, H_{t-1}) P(H_{t-1} \mid U_1, D_2, ..., U_{t-1})dH_{t-1}. \qquad (5)$$

From equations 4 and 5, we have

$$Evi(H_t) = \eta_t P(D_t \mid H_t) \int P(H_t \mid U_1, D_2, U_2, D_3, ..., U_{t-1}, H_{t-1}) P(H_{t-1} \mid U_1, D_2, ..., U_{t-1})dH_{t-1},$$

$$Evi(H_t) = \eta_t P(D_t \mid H_t) \int P(H_t \mid U_{t-1}, H_{t-1}) P(H_{t-1} \mid U_1, D_2, ...U_{t-1})dH_{t-1}$$

$$Evi(H_t) = \eta_t P(D_t \mid H_t) \int P(H_t \mid U_{t-1}, H_{t-1}) Evi(H_{t-1})dH_{t-1}. \qquad (6)$$

In our discrete application with only three operating modes, the evidences for these tasks are simplified as:

$$Evi(H_t) = \eta_t P(D_t \mid H_t) \sum_{i=\{GOA,CWF,DP\}} P(H_i^t \mid Ut-1, Ht-1) Evi(H_i^{t-1}) \qquad (7)$$

Where

$$\eta_t = \sum_{i=\{GOA,CWF,DP\}} P(D_t \mid H_i^t, U_1, D_2, ...U_{t-1})P(H_i^t \mid U_1, D_2, ...U_{t-1}) \qquad (8)$$

The appropriate task being selected based on its evidence's value.

B. *Shared control strategy framework*

The framework for the adaptive shared control strategy is presented in the fig. 2. Initially, at $t = 0$ as there is no prior environment information nor user's intentions, the priors are assumed to be equal for all autonomous tasks. When new information arrives, the initial evidences are calculated using the environment model data, equation 4. The final values are then determined after considering the latest user intentions, equation 7. Finally the most suitable autonomous task is selected as being the one with the highest evidence.

As previously mentioned some wheelchair applications have used offline environmental data, such as the use of a topology map in *Navchair* [4]. This however means that the wheelchair can only operate in a known environment. In this paper we introduce a novel method of using laser images to classify the local environment. The locations of corridors, walls, doors and general obstacles are determined from the raw laser data. Again we apply the Bayesian neural network framework, as in [5, 6], as follows:

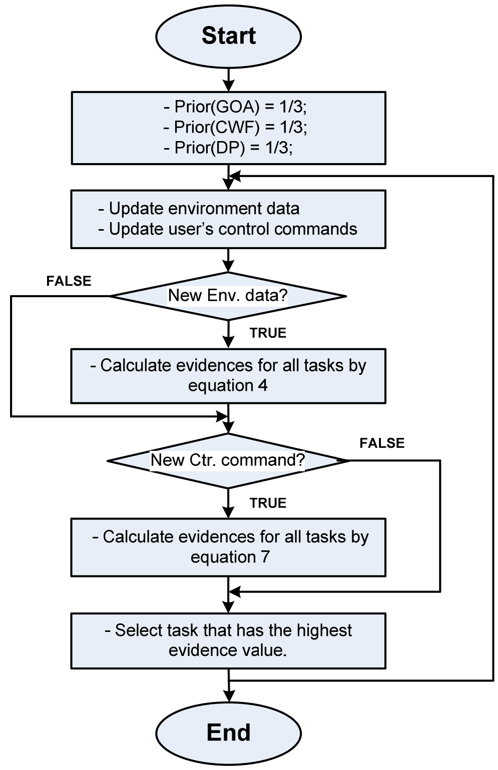


Fig. 2. The adaptive shared control strategy framework.

- *Step 1*: collect the training patterns from various environments.
- *Step 2*: apply the Bayesian framework to determine the optimal neural network structure and to train this network for better generalization.

Experimental results using this method are presented in the next section.

III. Experimental Results

A. *Environmental model – training results*

To collect data to be used for training the wheelchair travelled through three different environments that contain corridors, walls, doors and general obstacles. A dynamic window technique is used to scan over the laser images to look for features of the environment and provides 30 data points as inputs to the neural network. The data is split into training and testing sets that include 3416 patterns each. The training conditions are organised as follow:

- 30 inputs, corresponding to 30 data points from the dynamic window,
- Two outputs, each corresponding to one of the classes: wall/corridor and general obstacle,
- The numbers of hidden nodes are varied from one to eight.

The training results are presented in fig.3 below. The result shows that the network with four hidden nodes produced the highest evidence and is hence the most optimal structure for this application. The testing set was used to test the performance of the network which was found to have. 93.6% accuracy (Table I).

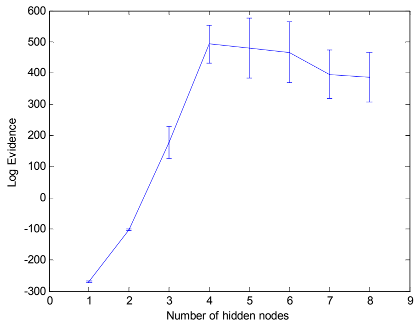


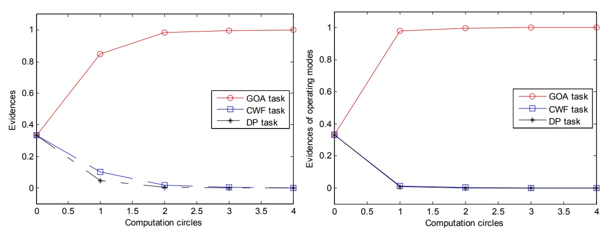
Fig. 3. The training result for the environment model networks.

TABLE I: TESTING RESULT

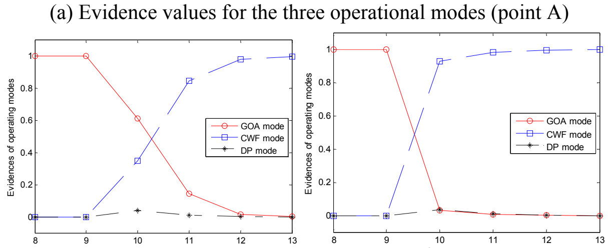
			Environment model results	
Test set			Wall/Corridor	General Obs.
1	Actual Environment	Wall/Corridor	1688	131
		General Obs.	1509	88
		Accuracy (%)	**93.6**	

Environment model – training results

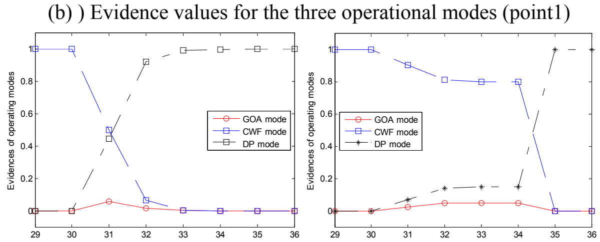
Two experiments were designed to compare the performance of the new shared control strategy to the previously reported cost function shared method [6]. In the first, the wheelchair moved through three distinct environments, while in the second the environment included a number of possible paths. In both experiments data was recorded at 100 milliseconds intervals (computation circles).



(a) Evidence values for the three operational modes (point A)



(b)) Evidence values for the three operational modes (point1)



(c)) Evidence values for the three operational modes (point 2)

Fig. 4. Evidence values calculated using the recursive Bayesian technique. The results for the full Bayesian shared control framework are shown on the right, while the results without consideration of the user's intentions are shown on the left.

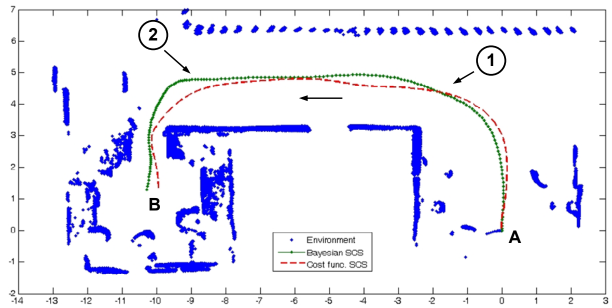
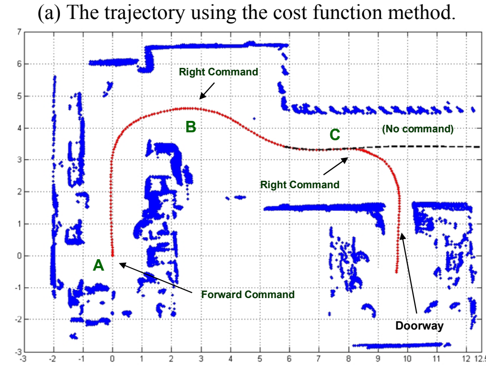


Fig. 5. Comparative trajectories of the adaptive shared control strategy and cost function shared method for the first experiment.

(a) The trajectory using the cost function method.



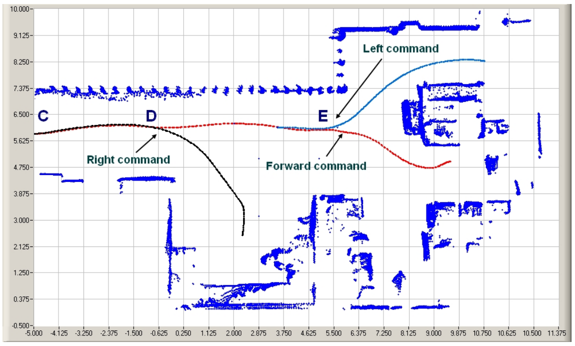
(b) The trajectory using the adaptive Bayesian shared strategy.

Fig. 6. Comparative trajectories of the cost function method (a) and adaptive shared control strategy (b) for the second experiment.

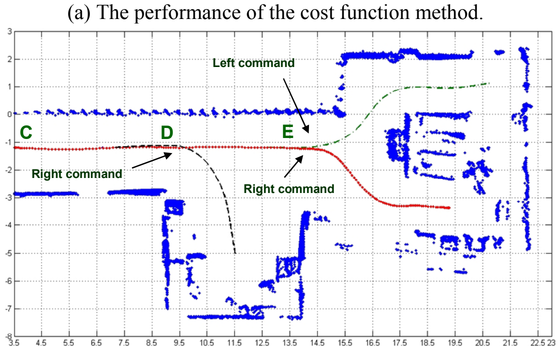
The evidence values for three autonomous tasks are shown in fig. 4 while the comparative trajectories for the first experiment are shown in fig. 5. The wheelchair started from point A in an environment that contained only general obstacles. Figure 4a shows that the evidence increases for the general obstacle avoidance mode while decreasing for the two other modes. Hence the wheelchair chooses to operate in the general obstacle avoidance mode.

This mode of operation is maintained until the wheelchair reaches point 1 where it detects a corridor and receives a left turn command from the user. Figure 4b shows the adaptive shared strategy's reaction to this situation with the corridor following mode evidence increasing and the evidence of the other two modes decreasing. Hence the wheelchair switches to run in the corridor following mode.

Figure 4c (left) shows the evidence for the door passing mode increasing at point 2 in fig. 5 confirming the systems detection of the approaching doorway. However, with no change in intention from the user fig 4c-right (computation



(a) The performance of the cost function method.



(b) The performance of adaptive Bayesian shared strategy.

Fig. 7. The performances of two shared method in the second experiment.

circle 30 to 34) shows that the overall value of evidence for this mode only increases a small amount to be slightly higher than the evidence for the general obstacle avoidance mode but significantly less than the evidence for the corridor following mode, hence at this point the wheelchair remains in the corridor following mode.

At point 3 (fig 5) the user indicates their intention to turn left towards the doorway. At this point (computation circle 35 in fig.4c-right) the evidence for the door passing mode increases to the highest value of all three modes. The wheelchair switches to the door passing mode and confidently navigates through the doorway.

This experiment was repeated but this time using the cost function shared strategy as reported in [6]. A comparison of the trajectories for each implementation is presented in figure 5. The figure clearly shows the inferior performance of the cost function shared strategy. Compare to the shared control strategy, the wheelchair trajectory using the cost function strategy meanders around the optimum route and results in the wheelchair making an early left turn narrowly missing the left side of the doorway (the dotted line in fig.5).

The second and more extensive experiment confirmed this result. By selecting the most appropriate autonomous task in a given situation, the adaptive shared control strategy showed a significant performance improvement, fig. 6b and 7b comparing to the cost function method, fig. 6a and 7a. When using the adaptive shared control strategy the wheelchair followed a smooth and near optimal path in negotiating the doorway after which the wheelchair moved towards the middle of the doorway at point C. Furthermore, the wheelchair maintained a relatively constant speed and direction throughout the corridor and wall following tasks.

This resulted in the wheelchair travelling almost parallel to the left-hand side wall between points C and E, before the wheelchair turns confidently to enter one of the two small free-spaces, as chosen by the user, in front of point E (fig. 6b and 7b). In comparison when using the cost function shared strategy (fig. 6a and 7a) the wheelchair frequently meanders around the optimum path and moves closer to obstacles providing less clearance, for example when negotiating door frames (fig 6).

IV. Discussion and Conclusion

The reported performance of the adaptive shared control strategy suggests that the Bayesian recursive technique may provide an effective solution to designing a shared control autonomous system. It proved successful in combining the obstacle awareness provided by the laser sensor with the intentions of the user to provide near optimum navigation without prior knowledge of the environment. The overall performance of the wheelchair system was improved significantly by correctly matching the selected autonomous task to a given situation.

We are currently planning more extensive tests to evaluate the adaptive Bayesian shared strategy. In these tests the wheelchair will be required to perform a number of tasks requiring increasing difficulty, initially with able-bodied users, then contingent on the success of these trials, with operators who have a disability including those with spinal cord injuries. To allow comparisons and evaluation the performance of the participants will be recorded in both the manual and semi-autonomous modes.

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