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Shared Control Strategies for Human – Machine Interface in an Intelligent Wheelchair

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***Abstract*— In this paper, we introduce a shared control mechanism for an intelligent wheelchair designed to support people with mobility impairments, who also have visual, upper limb, or cognitive impairment. The method is designed to allow users to be involved in the movement as much as possible, while still providing the assistance needed to achieve the goal safely. The data collected through URG-04LX and user interface are analyzed to determine whether the desired action is safe to perform. The system then decides to provide assistance or to allow the user input to control the wheelchair. The experiment results indicate that the method performs effectively with high satisfaction.**

I. Introduction

Commercial electric – powered wheelchairs traced to the 1950s have been providing functional mobility for people with both lower and upper extremity impairments. These include various overlapping motor, perceptual, or cognitive impairments such as spinal cord injury, or cerebral palsy. With the assistance of the wheelchair, their quality of life is significantly improved [1]. Although the benefits of powered wheelchairs are well-documented, safety issues and difficulties associated with their operation and control often prevent clinicians and rehabilitation professionals from prescribing powered mobility [2]. According to a recent study [3], 61% to 91% of all wheelchair users in the US would benefit from the assistance of an intelligent wheelchair.

One of the prime issues to be considered in any intelligent wheelchair is a shared control strategy which focuses on combining the instructions of a user with the autonomous behaviors of the wheelchair. Although intelligent wheelchairs can operate without user control, this may lead to loss of residual skills and frustration as the user is not involved in the navigating process. Conversely, some systems require the driver to continuously specify precise, low-level control input. Unfortunately, many users lack these fine motor skills to navigate the chair through narrow openings such as a doorway. Thus, it is essential to establish a shared control approach which allows both the wheelchair and the user to contribute to the control.

Shared control approaches can be implemented based on the user's ability to decide the level of combination between the user and autonomous commands. Some simply estimate the consistency of the user input [4]. Others measure the user's driving skills or their health conditions, and then decide at which level the autonomous system needs to assist users [5, 6]. The difficulty of these approaches is to indentify the user's intention, and they are usually applicable for only a specific individual.

Other possible shared control strategies are based on a set of predefined autonomous behaviours such as FollowWall, CrossDoor, AvoidObstacle or PassDoorway [7]. The user is responsible for high level planning by selecting intermediate goals and the wheelchair activates an appropriate mode to autonomously navigate with safety to these intermediate goals. Our previous work [8] for the semi – autonomous machine – (SAM) can be classified into this type. The difference is, instead of switching between different modes for different environment types, SAM uses a non-collision navigation neural network which is trained to control the wheelchair according to the surrounding environment. This avoids unstable trajectories caused by the mode switching. This shared control type is especially suitable for people with severe physical disabilities who are able to interact only through low rate information interfaces such as brain-computer interfaces (BCIs). However, for those who are able to use high rate information interfaces such as a joystick or head movement capable of providing both the direction and velocity for the vehicle, they often wish to be involved in the navigating process .They require high level planning and low level control for easy tasks, and seek the support from the machine for difficult tasks such as entering narrow openings.

To accommodate this population, we propose a shared control methodology that allows the user to be actively involved in the navigation as much as possible while still providing the assistance needed to achieve the manoeuver safely. The method is designed to verify that the user's intentions are safe to perform based on the local environment, and when necessary, activates the non-collision navigation algorithm to provide the assistance. This paper is organized as follows. In Section II, the method will be presented. In section III, experimental results of the proposed method are described to demonstrate the performance of the assistive navigation system. Finally, a conclusion of our study is drawn in Section IV.

II. Method

A. Intelligent wheelchair

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Our SAM, as shown Fig.1, is a commercial wheelchair which has been modified to include the following items: a minicomputer, user interfaces, and measurement sensors. This modification allows the user to operate in either manual mode or assistive mode. In the manual mode, SAM acts as a normal powered wheelchair in which the operator simply uses joystick to drive the wheelchair.

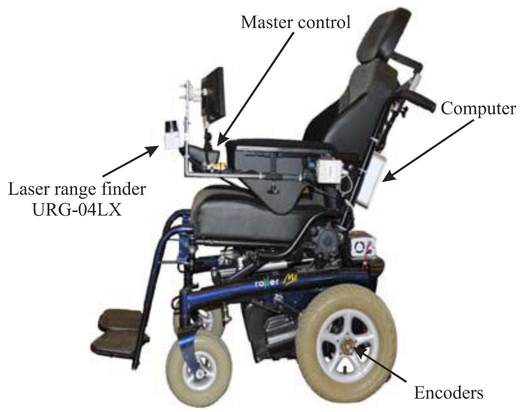

Fig.1. A prototype of intelligent wheelchair at the Centre for Health Technologies, University of Technology, Sydney.

In assistive mode operation, the on-board computer plays a central role in controlling the wheelchair. Instead of using the joystick, the on-board computer generates appropriate control signals following calculations of assistive navigation software to control the wheelchair. The software does so by relying on both user intentions and surrounding obstacle information. In this mode, the user can use one of four available interface types developed for SAM: joystick, head movement, brain computer interface (BCI), and iPhone4/iPad. SAM automatically detects and reads signals whenever these interfaces are connected to the system. Through these signals, the SAM is able to monitor what the user wants it to do. Another important information source used to make navigation decisions comes from the laser URG-04LX-based obstacle detection. The computer triggers the sensor to produce measured distance and angle data of surrounding obstacles in front of the vehicle with maximum radius of 4m and angular resolution of 1.08^0.

Assistive navigation software is written to provide two different levels of shared controls depending on the level of disability of a user. For those who are only capable of using low rate information interfaces such as BCI, the software just provides the shared control level which is called mode 2 as detail described in our previous work [8], the limited command information is combined with the environment data to find the most appropriate direction of travel under the Bayesian recursive method, then non-collision navigation neural network developed in [9] generates the control signals to drive the wheelchair following the direction. For those who are able to use high rate information interface such as a joystick or head movement, besides the shared control mode 2, the software permits the user to choose involving more in the navigating process - call the shared control mode 1. The next sections explain in detail the shared control mode 1 and the non-collision navigation neural network.

B. User-Machine Shared Control

In this framework, our goal is to allow the user to take part in the navigating process as much as possible, and we focus towards people with physical disabilities who can use an analog joystick or head movement interface.

At first, SAM collects information from the surrounding environment and a user interface. Then, the information is analyzed to determine whether the intended direction of travel of the wheelchair is safe to perform in the vicinity of obstacles. If no collision threat is detected, SAM allows the user to take full control of the system. However, whenever collision risks appear, the system either activates the non-collision navigation neural network to provide assistance or immediately stops the wheelchair if the obstacles are too close to the wheelchair.

The assessment the collision risks is implemented based on both surrounding environment information gathering through the URG-04LX and a user's intention through user interface signals. As shown in Fig.2, the environment information is process to build a polar obstacle map which displays the distance of obstacles to the wheelchair, while the intended navigation area (green shade) is defined as space near the direction of travel based on the user interface position. The space around the wheelchair is assigned into one of three regions.

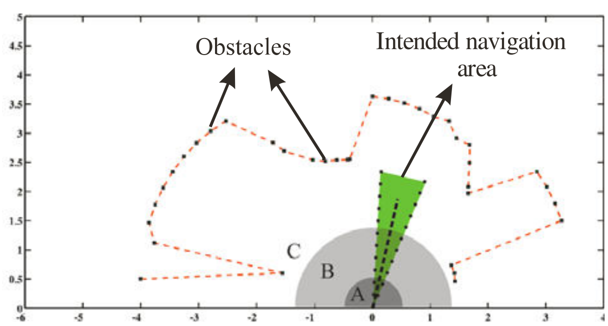

Fig.2. Pre-defined regions and surrounding environment information

High collision risk region (A): This region is nearest to the wheelchair. An obstacle in this region is highly likely to cause a collision. Thus obstacle avoidance assistance or stop wheelchair action is needed to prevent the system from crashing into the obstacles.

Collision risk region (B): A collision might occur if there are obstacles in this region and the intended navigation area. SAM provides non-collision navigation assistance if there are obstacles detected in the overlap between region B and the intended navigation area.

Safe region (C): The region is the farthest away from the wheelchair. Having an obstacle in this region will not effect the movement of the wheelchair. The user safely and freely drives the wheelchair with no modification made.

Based on the intended direction of movement and obstacle distribution around the wheelchair, SAM makes one of three choices:

1. Do not change the input speed and direction of travel provided by the user if there are only obstacles in the region C and/or in the region B but outside the intended navigation area.

2. Stop the wheelchair immediately if there are obstacles found the current navigation direction area in the region A. This is necessary for delay caused by computing process.

3. Active the non-collision navigation neural network to modify the original user signals in order to avoid obstacles or to assist to navigate in other cases of obstacle distribution. It is also activated if the user stops to provide commands. When this occurs, SAM understands that the user is unable to be involved in the navigating process, thus it takes full control of the system based on the latest commands given by the user. In other words, the system automatically switches to the shared control mode 2.

C. Non-Collision Navigation Neural Network.

When assistance is needed, a trained neural network is used to generate control signals to control the wheelchair. Our latest work [9] presented the design of the network. In general, this technique relies on the ability of a neural network to learn how to drive the wheelchair in certain situations through a number of patterns.

In particular, a feed forward neural network with hidden neurons and linear output neurons is recruited to learn to navigate without collisions. Its inputs include 36 transformed URG04-LX data points and a direction of travel. Output layer comprises of two outputs corresponding to steering angle control and velocity control. A number of hidden nodes are determined during training process under Bayesian supervision.

Based on a number of collected patterns, Bayesian framework has been carried out within the Levenberg – Marquardt optimization approach to find the most optimal network structure and weights. While training, the number of hidden nodes varies, and the assessment process for each network structure is taken as follows. At first, the values of the hyper-parameters and weights' value of the network are randomly initialized, then the Levenberg - Marquardt optimization algorithm updates these weights value in order to minimize the total error function. Finally, the evidence value of the structure is estimated when the optimization algorithm converges. The most suitable network is selected with the highest evidence value.

III. EXPERIMENT RESULTS

In order to investigate the feasibility of the developed shared control framework, five able-bodied users who already have experience to use joystick to control the wheelchair are recruited to perform all performance testing in an office environment.

A. Experimental design and results

Participants are asked to perform a blue dash trajectory in our laboratory room organized as Fig.3 by using a standard joystick. The entire trajectory is organized into five sections with different environment characteristics: AB – general avoidance, BC – door passing, CD – wall following, DE – general avoidance and EF - door passing. Each participant takes about 30 min to learn the task as well as becomes familiar with the system and 30 min to complete the trajectory in three operating modes that correspond to different levels of machine autonomy.

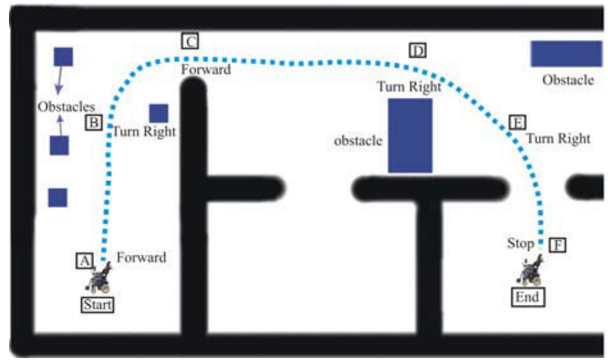

Fig.3.Testing trajectory with different environment types

Manual mode: The user drives the wheelchair by the joystick without any navigation support. In this mode, the system sends control signals to the motor controllers that are identical to the signals received from the joystick. For safety reasons, obstacle distances to the wheelchair are always updated to remove the control signals which could lead to a collision, and in these cases, a neutral signal (stop command) is sent to the motor controller instead.

Shared control mode 1: Individuals share control with the wheelchair as the mechanism described in section II.B. This support method is explained to the users before testing and they are encouraged to drive the wheelchair in a way they prefer. During navigation, the system automatically decides to modify or preserve the user control signals without any warning to the users.

Shared control mode 2: Users still have the opportunity to share the control with the wheelchair but in a different scenario. The user input is only used to imply general directions such as Forward, Left, Right, or Stop, and the system generates control signals based on the non-collision navigation neural network. Usually, generated control signals are different with those received from the joystick to control the wheelchair. Although all participants are guided to give appropriate commands at the points A, B, C, D, E, F as the Fig 3 to complete the trajectory, they are free to choose commands in the navigating process.

For consistency, each participant uses each mode to repeat the trajectory three times. In experiments, we measure and compute several average quantities of different sections per each mode to compare these modes of operation, including average completion time, average speed of the system, number of interactions, and number of collisions, and level of system control. The results are shown in the Table 1.

B. Discussions

The first factor whenever we consider the assistive mobile system for a human user is numbers of collision. This is the number of times when the wheelchair collides with obstacles

	Manual mode					Shared control mode 1					Shared control mode 2				
	Tc(s)	Va(m/s)	Ni	Lc	Nc	Tc(s)	Va(m/s)	Ni	Lc	Nc	Tc(s)	Va(m/s)	Ni	Lc	Nc
AB	5.5	0.84	12.3	10	0	5.1	0.82	8.2	9	0	5.2	0.78	2.3	6.2	0
BC	2.5	0.42	7.6	10	0	3	0.34	4.2	8	0	3	0.35	1.3	7.1	0
CD	7.9	0.81	8.6	10	0	8	0.71	3.5	9.5	0	8	0.67	1.5	8	0
DE	4.2	0.75	5	10	0	4.1	0.72	2.5	9.3	0	4	0.62	1.7	6	0
EF	3.1	0.45	8	10	0	3.9	0.39	4.2	7.8	0	4	0.32	1.2	7.5	0
Overall	**23.2**	**0.72**	**41.5**	**10**	**0**	**24.1**	**0.64**	**22.6**	**8.72**	**0**	**24.2**	**0.59**	**8**	**6.96**	**0**

Tab.1**.** Average measurable quantities per each section of three modes in all experiments. Tc(s) : Average completion time; Va (m/s): average speed; Ni: Number of interactions between the user and wheelchair; Nc: Number of collisions; Lc: Level of system control

or the wheelchair is forced to stop to avoid a collision. As shown, none of collision times are recorded for three modes in all these experiments.

In terms of average speed and time to completion, although the total time to complete the whole trajectory is almost similar between three modes, the average speed of the system is the fastest with the manual mode (0.72m/s) with able-bodied experienced users and the slowest with the shared control mode 2 (0.59 m/s) with control signals generated by the neural network. This means that the non-collision navigation network might control the wheelchair in shorter trajectories. During these experiments, we also realize that in the shared control mode 1, the user input is mostly accepted to be sent to motor controllers in sections AB, DE as the obstacles are distant. The users' input is often overwritten by the network outputs as the wheelchair is approaching the narrow openings such as door sections BC, or EF. Therefore, measured values in the shared control mode 1 are quite close to those in manual mode in sections AB, DE and those in shared control mode 2 in sections BC and EF.

Another factor to assess the system is the number of interactions which is the number of times the user has to move the joystick to control the system. In order to complete the entire trajectory, the manual mode requires the most effort from the user with average 41.5 times, while shared control mode 2 only needs 8 interaction times (there are three users who only use 6 interaction times during the shared control mode 2). Although the average number of interactions with the shared control mode 1 is 22.6, this number can be understood as a preferable interaction times that the users would like to take the control of the system when we consider the level of system control which shows that participants much prefer mode 2 to mode 1.

At the end of tasks, users are asked to assess the level of system control for each mode per each section with a scale from zero to 10. This parameter reflects their feeling for controlling the system as well as the degree they agree with the way the system is controlled. The results show that users feel the most confident with manual mode (10), then shared control mode 1 (8.72) and shared control mode 2 (6.96). This confirms that new method has improved the users' satisfaction of the system.

IV. CONCLUSION

A new shared control between human – machine has been presented for an intelligent wheelchair. The experimental results indicate that the proposed method has enabled people to drive the wheelchair safely while reducing demands on visual attention, cognitive workload, and manual dexterity. This means that experienced wheelchair users who are mobility impaired, but still able to operate joysticks or head movement with a reasonable degree of precision will enjoy the new developed navigation strategy, by which they can have more involvement in the navigation process, which is rarely found in other systems.

REFERENCES

[1] E. Trefler, S. G. Fitzgerald, D. A. Hobson, T. Bursick, and R. Joseph, "Outcomes of wheelchair systems intervention with residents of long-term care facilities," Assistive Technology, vol. 16, pp. 18-27, Sum 2004.

[2] D. Gavin-Dreschnack, A. Nelson, S. Fitzgerald, J. Harrow, A. Sanchez-Anguiano, S. Ahmed, and G. Powell-Cope, "Wheelchair-related falls - Current evidence and directions for improved quality care," Journal of Nursing Care Quality, vol. 20, pp. 119-127, Apr-Jun 2005.

[3] R. C. Simpson, E. F. LoPresti, and R. A. Cooper, "How many people would benefit from a smart wheelchair?," Journal of Rehabilitation Research and Development, vol. 45, pp. 53-71, 2008 2008.

[4] S. P. Parikh, V. Grassi Jr, V. Kumar, and J. Okamoto Jr, "Integrating Human Inputs with Autonomous Behaviors on an Intelligent Wheelchair Platform," Intelligent Systems, IEEE, vol. 22, pp. 33-41, 2007.

[5] C. Urdiales, B. Fernandez-Espejo, R. Annicchiaricco, F. Sandoval, and C. Caltagirone, "Biometrically Modulated Collaborative Control for an Assistive Wheelchair," Neural Systems and Rehabilitation Engineering, IEEE Transactions on, vol. 18, pp. 398-408, 2010.

[6] D. Vanhooydonck, E. Demeester, A. Hüntemann, J. Philips, G. Vanacker, H. Van Brussel, and M. Nuttin, "Adaptable navigational assistance for intelligent wheelchairs by means of an implicit personalized user model," Robotics and Autonomous Systems, vol. 58, pp. 963-977, 2010.

[7] R. C. Simpson and S. P. Levine, "Automatic adaptation in the NavChair Assistive Wheelchair Navigation System," IEEE transactions on rehabilitation engineering : a publication of the IEEE Engineering in Medicine and Biology Society, vol. 7, pp. 452-63, 1999-Dec 1999.

[8] A. V.Nguyen., S. Su., and H. T.Nguyen., "Development of a Bayesian Recursive Algorithm to Find Free-Spaces for an Intelligent Wheelchair.," in 33 rd Annual International Conference of the IEEE EMBS., Boston, Massachusetts USA, 2011.

[9] A. V.Nguyen., L. Nguyen, S. Su., and H. T.Nguyen., "Development of a Bayesian Neural Networks to Perform Obstacle Avoidance for an Intelligent Wheelchair," in 34 rd Annual International Conference of the IEEE EMBS., San Diego, California, USA, 2012.