Proceedings of the 2005 IEEE
International Conference on Robotics and Automation
Barcelona, Spain, April 2005

Usability Study of a Control Framework for an Intelligent Wheelchair

Sarangi P. Parikh*†, Valdir Grassi Jr.†‡, Vijay Kumar†, and Jun Okamoto Jr.‡
* Systems Engineering, United States Naval Academy, USA
† GRASP Laboratory, University of Pennsylvania, USA
‡ Escola Politecnica, University of Sao Paulo, Brazil
sparikh@usna.edu, {vgrassi,kumar}@grasp.cis.upenn.edu, jokamoto@usp.br

***Abstract*— We describe the development and assessment of a computer controlled wheelchair called the SMARTCHAIR. A shared control framework with different levels of autonomy allows the human operator to stay in complete control of the chair at each level while ensuring her safety. The framework incorporates deliberative motion plans or controllers, reactive behaviors, and human user inputs. At every instant in time, control inputs from these three different sources are blended continuously to provide a safe trajectory to the destination, while allowing the human to maintain control and safely override the autonomous behavior. In this paper, we present usability experiments with 50 participants and demonstrate quantitatively the benefits of human-robot augmentation.**

***Index Terms*— Wheelchair navigation, smart wheelchairs, user evaluations, usability studies, wheelchair control.**

I. INTRODUCTION

Human-robot interaction (HRI) has become an increasingly popular research topic. While it is not a new area of research, there are still many aspects of it that have not been well explored. Integrating new technology with humans has been at the level of supervisory control, where the user manages the robotic system while it is performing autonomous behaviors [1], [2]. However, the more complex task of a human user sharing control with a robot to accomplish a mutual goal has received less attention [3], [4]. Mixed-initiative systems allow the human user and robot to share control by allowing both agents to actively participate [5], [6], [7]. By adjusting the autonomy of the system, the user can collaborate with the robot at different levels. Our systematic, empirical research in human-robot collaboration has allowed us to design a human-centered framework for wheelchair users.

There is extensive research on computer-controlled wheelchairs where sensors and intelligent control algorithms have been used to minimize the level of human intervention [8], [9]. There are a number of research groups that have developed novel robotic wheelchairs. Wheelchair researchers have taken different approaches to incorporate human inputs into the control loop. One strategy is to allow the user to command directions to the chair directly and use the autonomous system for ensuring safety by avoiding obstacles. Another is to have the wheelchair perform specified behaviors, such as following a person or tracking a line [10], [11]. At an even higher level, it is beneficial to be able to automatically navigate to locations

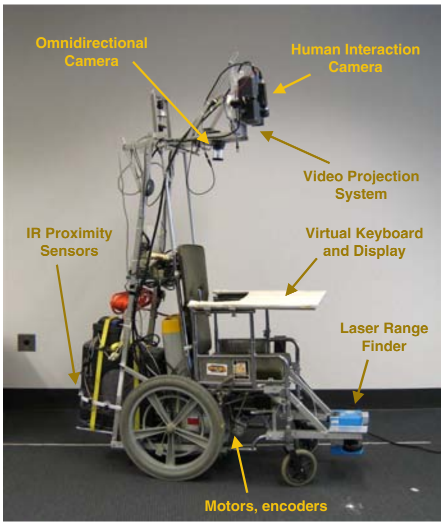

Fig. 1. The GRASP Laboratory SMARTCHAIR

on a map [12]. At this level, landmarks or known targets are used to navigate to the desired location [13], [14].

Our previous research provides an integrated solution to the motion planning and control problem with inputs from three different sources [15]. At the highest level, the human operator can specify goal destinations on a map using a simple visual interface [16]. At this level, a deliberative plan incorporating prior world knowledge is automatically generated. At the intermediate level, obstacles and features that are detected by the sensors must be avoided. This is done using reactive controllers. Lastly, at the lowest level, the human operator can directly provide commands using a joystick.

It is easy to imagine situations where the chair has to respond to all three types of inputs. For example, consider the chair navigating to a user-specified exhibit in a museum using an automatically generated deliberative plan, while avoiding museum visitors via reactive controllers, and being diverted by the human rider for a stop at the water cooler en route to the destination. It is scenarios like this that motivate this work. More generally, this paper addresses experimental studies of a human-in-the-loop motion planning and control framework that can be used for human-robot augmentation in an assistive technology. We systematically bring together three diverse, and at times contradictory, goals in motion planning: deliberative, reactive, and user-initiated. We show that we are able to plan deliberative paths, use reactive controllers for safety, and integrate human inputs into our smart wheelchair system. The usability study presented in this paper, demonstrates the ease with which a human user can interact with the SMARTCHAIR, allowing the user to intervene in real time during the execution of an autonomous task. This flexibility allows the human user and the autonomous system to truly share control.

In this paper, we first briefly describe the SMARTCHAIR platform and the system model. In Section III, we provide a description of the experiments as well as the protocol that was used in this study. Section IV provides experimental results which illustrate the performance and benefits of the human augmented system. Finally, Section V contains a discussion of our conclusions and future work.

II. THE SMARTCHAIR

Our motorized wheelchair is equipped with onboard processing and a suite of sensors as seen in Fig. 1. The omni-directional camera, mounted over the user's head, allows the user to view 360 degrees around the wheelchair. The projector system displays images onto the lap tray and enables the user to send commands to the wheelchair through a visual interface. The projector and camera systems form a feedback system where the user interaction is effected by occluding various parts of the projected image.

Along with the vision system, there is a laser scanner, which is mounted on the front of the wheelchair, under the user's feet. The laser measures distances at every half degree through a 180 degree scan in order to detect obstacles. Similarly, IR Proximity sensors are placed on the back of the chair. Lastly, encoders on the motors provide a dead reckoning system for the wheelchair. This is augmented, when necessary, by vision-based localization with landmarks on the ceiling. The wheelchair platform is discussed in greater detail in [16].

The control framework developed for our wheelchair [15] allows us to operate the chair in three different paradigms. Each operation mode corresponds to a different level of robot autonomy. The three paradigms that we are interested in are: manual control, autonomous control, and shared human-robot control. The user can manually control the chair using a joystick, the wheelchair can autonomously drive by itself with user input only at the highest level, or lastly, the user and the system share control of the motion.

III. USABILITY STUDY

In order to evaluate the usefulness of an intelligent robotic wheelchair and the efficacy of the three paradigms, we conducted a usability study where participants drove the chair using the different control options. In the semi-autonomous paradigm, our algorithm that smoothly combines three different, and at times, conflicting, approaches to motion control (deliberative, reactive, and user-initiated) was of central interest. We investigated the viability of the framework and algorithms, with the goal of evaluating the different levels of human-robot cooperation.

Participants: We recruited 50 individuals for the study. No subjects were excluded because of age, gender, economic status, or race. Each participant spent approximately 1 hour running experiments and answering questionnaires.

Experimental Design: We evaluated three distinct levels of operation. Autonomous control uses a deliberative plan along with local reactive behaviors to guide the wheelchair. Similarly, when the user is manually driving, reactive behaviors allow the user to safely drive the chair without any collisions. The semi-autonomous paradigm incorporates all the behaviors described earlier; a deliberative plan with reactive behaviors and user-initiated inputs. Please refer to [15] for further details about the shared-control framework.

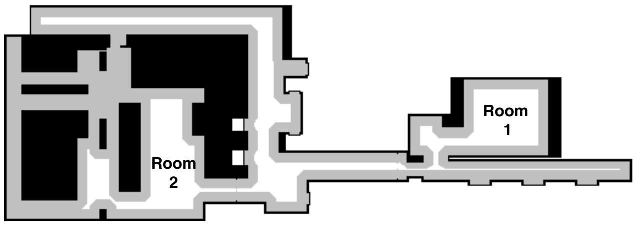

Fig. 2. Overhead map of the environment. The dark regions are tables and other known objects in the environment. The lighter region is an expanded map, which is a safety boundary that takes into consideration the size of the wheelchair.

Fig. 2 shows an overhead schematic of the floor in which the experiments took place. The expanded map seen in the figure (expanded to accommodate the finite footprint of the wheelchair) was used to compute the potential function for navigation.

We represent ground truth using odometry from the wheelchair. Simple tests conducted to observe factors that could contribute to irregularities in odometry, such as belt or wheel slippage, reveal that such slip is minimal or not existent in our test environment [16].

Autonomous System: While running the chair autonomously, the participants were not allowed to provide input to the system after the initial selection. In each environment, a deliberative plan was constructed using a potential field placed on the map [17]. By following the negative gradient of the potential function, the wheelchair was driven from the initial position to the desired destination specified by the user. However, the deliberative controller is locally modified to accommodate obstacles via reactive behaviors.

Fig. 3 shows the path followed by the wheelchair when in the autonomous paradigm. As seen in the figure, the chair is guided by the potential field lines to the selected location. The dashed trajectory is the path the chair would have taken if the environment was completely known and free of unmodeled obstacles. Trajectories taken by different users autonomously driving the wheelchair illustrate that the autonomous system efficiently and predictably drives the wheelchair in the same manner each time.

Manual System: When manually driving, the users were instructed to drive the chair using the joystick. Fig. 4

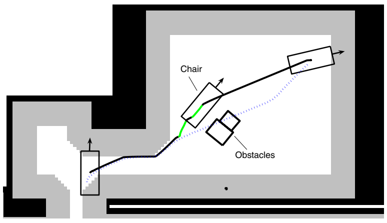

Fig. 3. The autonomous trajectory taken in Room 1 is a result of the deliberative controller (potential field controller) and local, reactive behaviors. The solid line shows when the deliberative controller is invoked. The lighter (green) line segments represent locations where the activated obstacle avoidance behavior is composed with the deliberative behavior. The dashed (blue) line is the trajectory that the chair takes if there are no obstacles.

illustrates a manual path taken by one of the users in Room 1. It should be noted that even when the chair is manually driven, the obstacle avoider is always turned on and the user input is modified by the reactive obstacle avoidance behavior. However, we found that the lack of sensors on the sides lead to a few collisions (a total of 3) that did not occur in the autonomous operation.

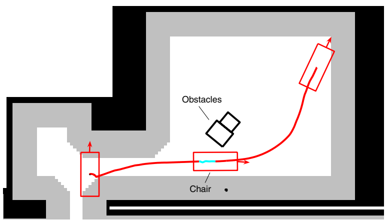

Fig. 4. Sample trajectory (red) taken by the user in Room 1 during the manual mode. The lighter (blue) line segments represent the activation of obstacle avoidance and modification of the human input.

Semi-autonomous System: In the semi-autonomous paradigm, individuals had the opportunity to share control with the wheelchair. Fig. 5 shows a trajectory that one of the users took. In the figure, we point out the different controllers that are used. It can be seen that semi-autonomously driving involves a smooth integration of the deliberative plan with reactive behaviors as well as human inputs. When human inputs are incorporated into the system there are different scenarios that may occur. These are described in greater detail in [15].

Trajectories that different individuals took look similar to the example seen in Fig. 5. However, it should be noted that in this paradigm, there were numerous collisions. All of these collisions were due to the lack of sensors on the side of the wheelchair. Most of the collisions occurred because the user was overly confident in our system's ability to avoid collisions. Although all users were reminded at the beginning of each experiment that there are no sensors on the sides, approximately half of the users had collisions in the semi-autonomous module in one of the two environments. Fig. 6 shows sample trajectories that had collisions. By analyzing these trajectories, we see that all the collisions occurred in a similar location on the chair. Also from observation, we noticed that all the collisions occurred when the chair made a quick turn, hitting the obstacle that was in the blind spot. This type of collision is very similar to collisions that occur when automobiles are changing lanes on a highway. We will discuss our recommendations to avoid these types of collisions later in the paper.

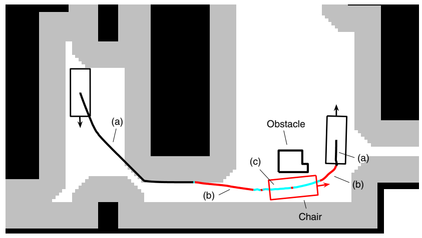

Fig. 5. A sample wheelchair trajectory using a deliberative plan, combined with user input (semi-autonomous paradigm). Part(a) represents the deliberative path taken, part(b) represents the user's input, which is consistent with the deliberative plan, part(c) represents when the obstacle avoidance behavior is activated.

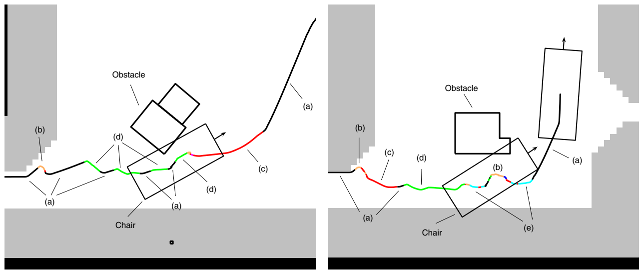

Fig. 6. Collisions that took place while the wheelchair was being driven semi-autonomously. Both rooms are shown in this figure. Part(a) represents the deliberative path taken, part(b) represents the user's input, which is modified so that it is consistent with the potential, part(c) represents the user's input, which is consistent with the deliberative plan, part(d) represents activated obstacle avoidance while the user is in control of the chair, part(e) illustrates when the obstacle avoidance is activated while the chair is driving autonomously.

Method: During our study, each subject experienced each of the three paradigms in both environments. The order of the experiments was randomly assigned to each person so there are no biases related to the sequence of testing.

The user was also given two secondary tasks. All subjects were asked to take a simple math test and pick up a specified object while driving the wheelchair. As suggested by [6], [18], we used the performance in the secondary tasks as a measure in our evaluations. Such secondary tasks are similar to the types of interruptions that may occur during normal operation. It was emphasized to all of the subjects that the math task and picking up the item were not as important as the driving test.

Although each person performed all the experiments, the individuals were divided into four groups based on the order in which they performed the experiments, and in which environment. When evaluating the data, the four groups were treated separately. The groups were combined together only if there was no significant statistical difference (according to a t-test or an ANOVA analysis) between them.

TABLE I
TIME TO COMPLETION

Room, Group	Autonomous Time (sec)	Manual Time (sec)	Semi-Auto Time (sec)
Room 1, Group 1	68.2	69.5	76.7
Room 1, Group 2	67.4	68.6	78.9
Room 1, Group 3	70.5	71.1	77.9
Room 1, Group 4	67.9	71.2	78.9
Room 2, Group 1	71.2	82.8	93.5
Room 2, Group 2	72.0	83.3	85.8
Room 2, Group 3	71.1	83.9	95.2
Room 2, Group 4	70.8	88.4	101.6

A well-defined protocol is used for the usability study. The following steps were then followed for each participant after pre-experimental forms were completed.

Step 1: All subjects spend approximately 15 minutes driving the wheelchair, experiencing each paradigm.

Step 2: Next, the instructions are read and the user is asked to navigate using one of the three paradigms from an initial position to a marked final destination in one of the rooms.

Step 3: After the participant has driven the chair in both environments, a post-task questionnaire and the NASA Task Load Index (TLX) form are filled out to evaluate the method of operation experienced by the user.

The three steps were repeated for the second and third paradigms. After all experiments were run, the user was asked to fill out a post-experimental questionnaire. This allowed users to express their overall reactions to the entire system as well as compare the three paradigms.

IV. EXPERIMENTAL RESULTS

Out of the 50 subjects that participated in the study, we obtained 43 complete data sets, which were used in the evaluations. There were 21 female participants and 22 male participants. Subjects were between the ages of 18 and 49. Demographic data (sex, age, and education completed) was analyzed across all groups by performing an analysis of variance (ANOVA). No significant statistical differences were encountered at a level of significance $\alpha = 0.05$.

A. Quantitative Results

1) Time to Completion: Table I shows the average completion times of the navigation task for each paradigm. The environments and the groups are kept separate in the table. It illustrates that in every group, the semi-autonomous control method requires the greatest amount of time, while the autonomous is the fastest. Since all the groups show exactly the same trend, it can be concluded that in terms of time to completion, the order of the paradigms is not significant. However, there is a large statistical significance between the three operations. From an ANOVA analysis, $F(2, 117, p < 0.001) = 25.04$ in Room 1 and in Room 2, $F(2, 119, p < 0.001) = 89.48$. While both F values are much higher than $F_{critical}$, there is a lesser difference in times to completion between the three methods of operation in Room 1 than in Room 2, resulting in a slightly lower F ratio in Room 1.

2) Human-Robot Interactions: One way to measure complexity of a user operated system is to count the number of times the user needs to interact with the system in order to accomplish the desired task. When autonomously controlling our smart wheelchair, the subject must simply select the destination and the chair will automatically drive to the goal while avoiding collisions. In this scenario there is only one user interaction. In the manual and semi-autonomous systems, we can quantify the number of interactions by counting the approximate number of times the user moves the joystick.

Again, all the analysis is done separately for the four groups. Using ANOVA we deduce that there is no statistical difference between groups 1 and 4 and there is no difference between groups 2 and 3. While groups 1 and 4 had the same order of operation, the two groups had the order of rooms switched. Likewise, groups 2 and 3 performed the experiments in the same operation order, however they began in different rooms. The ANOVA analysis helps us conclude that the order of the environments is not statistically significant, given $\alpha = 0.05$. We are able to combine the four groups into two groups, which have different operation orders. Group A (originally groups 1 and 4), has performed the manual experiments first, followed by autonomous, and finally semi-autonomous. Group B (groups 2 and 3), began with the autonomous mode, then the manual mode, and lastly the semi-autonomous mode. Table II shows the average number of human-robot interactions, the average frequency of interactions, and the calculated F ratio. The F ratio allows us to compare the variance between the manual and semi-autonomous paradigms.

From the data collected, it can be seen that twice as many human-robot interactions occur when subjects manually drive the chair as compared to using the semi-autonomous operation. We can conclude that manual driving requires more effort by the user than driving the system semi-autonomously. The calculated value of F in each case is much greater than $F_{critical}(1, 40) = 4.085$ for $\alpha = 0.05$. Thus, this allows us to conclude that there is a significant statistical difference between the two and they cannot be grouped together.

3) Cognitive Complexity: Another measure of complexity can be made by observing an individual's cognitive abilities. In our experiments, we asked the user to perform a secondary task, which can be used to study the complexity of the primary task. Individuals were asked to solve math problems while driving the wheelchair. The number of math questions answered correctly per minute was used to measure cognitive complexity in each paradigm. We can analyze the math tests in terms of efficiency and compare the three paradigms (Table III).

We observed that individuals solve more problems correctly per minute when autonomously operating the system compared to the other two paradigms. However, when comparing the manual and semi-autonomous paradigms, the results are inconclusive. It was also observed that individuals who did not perform more efficiently during

TABLE II
HUMAN-ROBOT INTERACTIONS

	# HRI (manual)	HRI/min. (manual)	# HRI (semi-auto)	HRI/min. (semi-auto)	F ratio
Room 1, Group A	44.1	37.8	18.2	13.8	$F(1,40,p<0.001)=121$
Room 1, Group B	34.8	30.0	16.7	12.6	$F(1,42,p<0.001)=46.6$
Room 2, Group A	47.1	33.6	26.4	16.2	$F(1,40,p<0.001)=55.5$
Room 2, Group B	36.7	26.4	20.6	13.8	$F(1,42,p<0.001)=33.5$

TABLE III
COGNITIVE COMPLEXITY

Efficiency Order	Percentage of Total Subjects
Autonomous > Semi-autonomous	60.9 %
Semi-autonomous > Autonomous	34.8 %
Autonomous = Semi-autonomous	4.3 %
Autonomous > Manual	67.4 %
Manual > Autonomous	28.3 %
Autonomous = Manual	4.3 %
Semi-autonomous > Manual	41.3 %
Manual > Semi-autonomous	39.1 %
Semi-autonomous = Manual	19.6 %

the autonomous operation, appeared to be more distracted with the secondary task of picking up the object. It should be noted that the path the wheelchair takes autonomously makes picking up the object very difficult. Although individuals were told to pick up the object only if possible, some people were distracted because they were unable to reach the object and as a result, stopped solving the math problems. On the other hand, there were also a few individuals who devoted more cognitive resources to answering math problems and consequently did not make an attempt to pick up the specified object. Anecdotal evidence suggests that as an individual's experience increases with the intelligent wheelchair system, the cognitive workload decreases in the automated and semi-automated methods of operation.

4) Distance Traveled: When analyzing navigation tasks, another method of measuring effectiveness is the distance traveled. The autonomous system always takes the path that requires the least amount of travel. In Room 1, there is about half a meter difference between the manual and autonomous paths. However, in Room 2, there is about a 1 meter difference between the two modes of operation. In this case, the manual system is within 0.2 meters of the semi-autonomous path taken. This result indicates that in terms of the distance traveled, there is not a significant difference between the manual and semi-autonomous systems, but the autonomous controller is definitely most efficient.

When analyzing the distance traveled in each of the rooms, there is no difference between the four groups. However, path length analysis indicates that there is a significant difference between the paradigms, $F_{Room1}(2,119,p < 0.001) = 62.64$ and $F_{Room2}(2,121,p < 0.001) = 50.02$. This indicates the fact that the autonomous system takes the shortest path is statistically significant, given $\alpha = 0.05$.

B. Observations and Qualitative Results

Throughout the experiments, the navigation task remains the same. This allows us to focus our attention on the effectiveness of the different methods of operation. An overwhelming majority of the participants (greater than 90%), were satisfied with the system and found it easy to use. Users were also able to judge their performance in each of the paradigms. After each operation, users were asked to rate the system on a scale from zero to ten in various categories. In terms of safety, over 93% of the users rated all three of the paradigms at 5 or higher. On the other hand, when asked whether or not they felt in control of the system, only 40% rated the autonomous system above 5. However, over 90% of participants felt in control when driving semi-autonomously and manually.

The level of frustration appears to be related to how much control the user felt in each case. Users were most frustrated when autonomously driving, where they also felt that they had the least amount of control. Participants did find the manual system the least frustrating and also felt that it allowed them to have the most amount of control. While a little over half the participants found the semi-autonomous system more frustrating then the manual, 91% of the total subjects felt in control while sharing control with the robotic system.

A majority of users (90%) thought that the manually driving the wheelchair required more effort than autonomously driving. 60% of the individuals felt that the manual system required more effort than the semi-autonomous. 90% of the users felt that the autonomous system required the least amount of effort.

V. DISCUSSION

The goal of this paper was to evaluate a framework that systematically combines three different approaches to motion control: deliberative plans, local reactive behaviors, and human inputs. Usability studies with 50 participants helped evaluate three different levels of human-robot autonomy, ranging from complete manual control to a purely autonomous system. Participants were able to experience each paradigm and assess the system as well as their own performances. A statistical evaluation of the recorded performance was correlated with the user's qualitative impressions.

As expected, the autonomous paradigm requires the least amount of effort from the user, and is the most efficient method of operation in terms of distance traveled and time to completion. On the other hand, it is the most rigid paradigm and does not allow the user to make minor changes to the planned path to accommodate last minute user decisions. For instance, during our experiments users were unable to modify the path to get within range of the object which needed to be picked up. This lack of interaction and control over the chair causes frustration in situations like the one described.

Manually driving requires the most amount of effort from the user. In spite of this, it was considered the least frustrating paradigm. This is mainly associated with the fact that it gives the user complete motion control and therefore, the user is able to drive the chair to any desired position.

The semi-autonomous paradigm requires less effort from the user than the manual. It is also observed that the number of human-robot interactions in the semi-autonomous operation is significantly less than the number of interactions in the manual one. Along with less workload, semi-autonomously driving gives control to the user over the wheelchair whenever the user wants, allowing the user to make small changes in the path. Despite these advantages, as we have mentioned previously, there is an inverse relationship between "feeling in control" and "feeling frustrated". Since individuals have less control in the semi-autonomous operation than the manual operation, they did find it more frustrating. In addition, we believe that there is another reason for this observation. It is important to note that there are no sensors on either side of the wheelchair, thus many individuals collided with obstacles as the chair was turning, which can lead to feeling more frustrated.

We have two recommendations for improving the frustration level and safety when driving semi-autonomously. The easy fix to the system would be to place sensors on the sides and therefore, let the obstacle avoidance algorithm handle all objects near the chair. Another way to avoid side collisions is to enhance the reactive obstacle avoidance behavior. In other words, as the system detects unmodeled static obstacles via the front laser, record the obstacles in short-term memory. Using this memory of the obstacle, the chair can continue to avoid a collision if the object remains close to the chair, even though it may no longer be visible by the laser.

We believe the approach presented here is generally applicable to a wide range of systems in which commands come from both humans and machines. This control framework is unique in that it reconciles different, possibly conflicting inputs, at the level of continuous. However, as documented, the results of the usability studies do not always follow intuition. The most significant finding is that although the overwhelming majority of users preferred semi-autonomous control over the manual or autonomous, the autonomous system performed consistently better in most quantitative comparisons. This suggests that it may not be feasible to integrate disparate control commands at the continuous level and points to the need for a hierarchical, discrete plus continuous framework for control.

ACKNOWLEDGMENTS

The authors would like to thank the many individuals who participated in this study. The authors would also like to acknowledge support from NSF (grants IIS00-83240 and IIS02-22927), CAPES-Brazil (grant BEX0112/03-8), and FAPESP-Brazil (grant 02/00225-8).

REFERENCES

[1] R. Murphy and E. Rogers, "Cooperative assistance for remote robot supervision," 1996. [Online]. Available: citeseer.ist.psu.edu/murphy96cooperative.html

[2] S. Thrun, M. Bennewitz, W. Burgard, A. Cremers, F. Dellert, D. Fox, D. Hahnel, C. Rosenberg, N. Roy, J. Schulte, and D. Schulz, "Minerva: A second generation museum tour-guide robot," in *Proc. of IEEE Int. Conf. on Robotics and Automation*, Detroit, MI, May 1999.

[3] H. Yanco and J. L. Durry, "A taxonomy for human-robot interaction," in *AAAI Fall Symposium on Human-Robot Interaction, AAAI Technical Report FS-02-03*, Falmouth, Massachusetts, November 2002, pp. 111–119.

[4] J. Scholtz, B. Antonishek, and J. Young, "Evaluation of a human-robot interface: Development of a situational awareness methodology," in *Proc. of the 37th Hawaii Int. Conf. on System Sciences*, Big Island, Hawaii, January 2004.

[5] K. S. Ali and R. C. Arkin, "Multiagent teleautonomous behavioral control." *Machine Intelligence and Robotic Control*, vol. 1, no. 2, pp. 3–10, 2000.

[6] J. L. Marble, D. J. Bruemmer, D. A. Few, and D. D. Dudenhoeffer, "Evaluation of supervisory vs. peer-peer interaction with human-robot teams," in *37th Hawaii International Conference on System Sciences*, Hawaii, 2004.

[7] M. Nicolescu and M. Mataric, "Linking perception and action in a control architecture for human-robot interaction," in *Hawaii Int. Conf. on System Sciences, (HICSS-36)*, Hawaii, USA, January 2003.

[8] J. Wagner, H. V. der Loos, N. Smaby, K. Chang, and C. Burgar, "Provar assistive robot interface," in *International Conference on Rehabilitation Robotics*, Stanford, CA, 1999.

[9] R. A. Cooper, L. M. Widman, D. K. Jones, and R. N. Robertson, "Force sensing control for electric powered wheelchairs," *IEEE Transactions on Control Systems Technology*, vol. 38, pp. 112–117, 2000.

[10] R. C. Simpson and S. P. Levine, "Automatic adaptation in the navchair assistive wheelchair navigation system," *IEEE Transactions on Rehabilitation Engineering*, vol. 7, no. 4, pp. 452–463, December 1999.

[11] U. Borgolte, H. Hoyer, C. Buhler, H. Heck, and R. Hoelper, "Architectural concepts of a semi-autonomous wheelchair," *Journal of Intelligent and Robotic Systems*, vol. 22, pp. 233–253, 1998.

[12] G. Bourhis and Y. Agostini, "Man-machine cooperation for the control of an intelligent powered wheelchair," *Journal of Intelligent and Robotic Systems*, vol. 22, pp. 269–287, 1998.

[13] T. Gomi and A. Griffith, "Developing intelligent wheelchairs for the handicapped wheelchair," in *Assistive Technology and Artifical Intelligence*. New York: Springer, 1998, pp. 151–178.

[14] J. D. Crisman and M. E. Cleary, "Progress on the deictic controlled wheelchair," in *Assistive Technology and Artificial Intelligence*, V. Mittal, H. Yanco, J. Aronis, and R. Simpson, Eds. New York: Springer, 1998, pp. 137–149.

[15] S. Parikh, V. Grassi, V. Kumar, and J. Okamoto, "Incorporating user inputs in motion planning for a smart wheelchair," in *International Conference on Robotics and Automation*, New Orleans, LA, 2004, pp. 2043–2048.

[16] R. Rao, K. Conn, S. Jung, J. Katupitiya, T. Kientz, V. Kumar, J. Ostrowski, S. Patel, and C. Taylor, "Human robot interaction: Applications to smart wheelchairs," in *International Conference on Robotics and Automation*, Washington, DC, 2002.

[17] E. Rimon and D. E. Koditschek, "Exact robot navigation using artificial potential functions," *IEEE Trans. on Robotics and Automation*, vol. 8, no. 5, pp. 501–518, 1992.

[18] J. W. Crandall and M. A. Goodrich, "Characterizing efficiency of human robot interaction: A case study of shared-control teleoperation," in *Proc. of the 2002 IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, Lausanne, Switzerland, October 2002, pp. 1290–1295.