Shared Control for Obstacle Avoidance in Intelligent Wheelchairs

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Abstract—**Intelligent wheelchairs operating in dynamic environments need to sense its neighborhood and adapt the control signal, in real-time, to avoid collisions and protect the user. In this paper we propose a robust, real-time obstacle avoidance extension of the classic potential field methodology. Our algorithm is specially adapted to share the wheelchair's control with the user avoiding risky situations. This method relies on the idea of virtual forces, generated by the user command (attractive force) and by the objects detected on each ultrasonic sensor (repulsive forces), acting on the wheelchair. The resultant wheelchair's behavior is obtained by the sum of the attractive force and all the repulsive forces at a given position. Experimental results from drive tests in a cluttered office environment provided statistical evidence that the proposed algorithm is effective to reduce the number of collisions and still improve the user's safety perception.**

Keywords—**Intelligent wheelchairs, obstacle avoidance, potential field**

I. INTRODUCTION

This Motivated to answer to numerous mobility problems, many intelligent wheelchair related projects have been created in the last years [1]. In fact, intelligent wheelchairs (IWs) are a very good solution to assist handicapped people who are unable to operate classic electric wheelchairs by themselves in their daily activities. While some initiatives have improved the autonomous function of the mobility aid [2], [3], others focused their work in sharing the wheelchair's control with the user [4], [5]. Shared control initiatives take advantage of the user's intelligence and assist the driver in the navigation process when dangerous situations are detected, extending and complementing user capabilities.

In such a way, techniques as obstacle avoidance developed in fields of robotics have the potential to improve user's safety and reduce the navigation complexity. These methodologies consist basically on shaping the robot's path to overcome unexpected obstacles. A number of algorithms were develop to overcome obstacles and differ basically in the sensorial data used and control strategies. However, not all techniques are suitable to be implemented in a shared control paradigm. Some of the desired properties of shared control algorithms are:

- Avoid obstacles in real-time. Since wheelchairs operate in dynamic environments, it is not feasible to implement popular time-consuming global path planners. Instead, such application is more suitable to approaches based on fast response like reactive/reflexive controls.
- Low computational consuming. Low memory and processing consuming algorithms are more likely to achieve a real-time reflexive behavior in embedded systems.
- Increase user safety and user safety perception. Beyond a quantitative reduction in the number of collisions, shared control initiatives may consider qualitative evaluations of the wheelchair's overall behavior. In spite of imposing the control to the wheelchair, the algorithm may adapt the control signal to reduce the discomfort caused in driving tasks.

Furthermore, once intelligent wheelchairs are designed to carry people with disabilities, they should have the same durability, functionality and ergonomics concern of the standard powered wheelchairs. It not only constrains the number of sensors, but their type and position on the wheelchair. Therefore, the shared control algorithm may be robust enough to ensure the user safety even with non-optimal amount of information.

Following the above referred features, this paper proposes and implements an extension of a classic obstacle avoidance technique known as potential field. Special attention was given to user the autonomy, assisting the wheelchair's control just when dangerous situations were detected.

The rest of the paper is subdivided as following: a brief description of some obstacle avoidance methodologies is presented in Section 2. Section 3 presents a Potential Field extension specially designed to assist users in intelligent wheelchair's navigation. Section 4 presents experimental results obtained with both simulated and real drive tests and section 5 presents discussions, final conclusions and some future research topics.

II. RELATED WORK

This section presents a concise summary of some classic obstacle avoidance methodologies developed in robotics. In particular, shortcomings and characteristics of each technique are discussed with focusing its implementation on intelligent wheelchairs with shared control paradigm.

A. *Edge-Detection*

Considered one of the first methodologies proposed to avoid obstacles during robot navigation, edge-detection became popular in late eighties. Through ultrasonic-sensor readings, the algorithm tries to map the position of the vertical edges of every obstacle in the robot surroundings. Then, once new edges are found, a temporary map is updated and an optimum path planning algorithm is applied to plan the subsequent path [6]. Whenever the robot moves, a scanning mode starts taking alternate sonar's samples. Once measures are under a certain safety distance, the robot stops, take a panoramic scan, apply the edge-detection methodology and restart the cycle all over again [7], [8].

Edge-detection methodology is not itself an obstacle avoidance technique. Actually, it can be better described as an approach to represent the environment based on geometrical primitive line segments. Therefore, off-line path planners are still needed in order to yield obstacle-free paths, limiting its implementation in low-resource embedded systems.

B. *Certainty Grids*

Certainty grid (CG) method is a probabilistic representation of obstacles in a grid based world model. This world model has been developed for mobile robots in Stanford and CMU for more than ten years, and was originally designed to handle sonar's inaccuracies shortcomings [9].

In this method, the robot's work area is modeled as a 2-D array of square elements, called cells. Each cell of the grid contains a likelihood estimate (certainty value) that indicates confidence that an obstacle is placed within the corresponding region of space. Once readings are more likely to detect objects closer to the acoustic axis of the sonar, a probabilistic function updates more the certainty value in this region than in the other areas enclosed by the sensor [9], [10].

In spite of some improvements presented by CG methodology, some drawbacks can compromise its implementation in real-time applications. Firstly, the accuracy provided is too much dependent of the cell size. Secondly, as the robot moves over large areas, lots of memory and processing power are required, restricting the application of CG especially in some embedded systems. Finally, the subsequent robot's path shall be computed off-line, by a global path-planning.

C. *Vector Field Histogram*

Introduced by Borenstein and Korem [6], the Vector Field Histogram (VFH) uses a polar histogram instead of a 2-D Cartesian grid to avoid collisions and steer the mobile robot to the target. This method employs a two-stage data reduction process in order to compute the control command to the robot.

In the highest level of data, VFH stores a detailed 2-D histogram grid map of the robot's neighborhood. As just only one cell in the histogram is updated for each range reading, it takes just a small computational overhead. Thus, a probabilistic distribution is obtained by continuously and quickly sampling each sensor while the robot moves [11]. At the second level, data is mapped onto a one-dimensional polar histogram that comprises n angular sections each with width α. Each sector in the polar histogram contains a value representing the polar obstacle density in that direction. Finally, based on the obstacle polar density (1-D histogram), VFH selects the best steering direction for the robot and computes the reference values for driving the robot (third level of data representation) [6].

As can be observed, the VFH overcomes some issues shown by the other methods described above. In fact, the influence of low accuracy distance measures is minimized through the histogram representation. In addition, the world representation is restricted to the robot's surrounding trough a bi-dimensional sliding window, reducing the computational overhead. On the other hand, local minima problems are still not solved by the algorithm itself, which has to invoke a global path planner when these situations are flagged. Finally, like edge-detection and CG methodologies, VFH depends not only from the data gathered by the sonars, but from an accurate localization system. Otherwise, inaccurate robot's position can introduce more errors and disturb the object mapping.

D. *Potential Field Methods*

First suggested by Andrews and Hogan [12] and Khatib [13], the Potential Fields methodologies (PF) relies on a simple and powerful principle, the artificial potential field concept. In this method, the robot is considered immersed in a potential field generated by the target and by obstacles. In this field, obstacles generate imaginary repulsive forces, while the target generates an attractive force to the robot. The resultant robot behavior is obtained by the sum of all attractive and repulsive forces at a robot's given position.

After the original work, a number of improvements and extensions have been published. Krogh [14] has computed forces not only to steer the robot around objects, but to set its speed as well and Seiki [15] has introduced the consideration about the nonholonomic motion constrains and the robots shape into the PF. Khatib and Chatila [16], considered, besides distance, the robot's relative orientation to the obstacle in order to compute forces. Bicho [17] implemented a dynamic approach using low level sensory information, in which each sensor generates a repulsive force that drives the direction and the speed of the robot.

In its original version the PF methodology exhibit many shortcomings, in particular the sensitivity to local minima that arises mostly due to the symmetry of the environment. Furthermore, it tends to be very susceptible to misreading (since it takes into account just one set of data) and to the sonar most common issues. Some versions still assume a known and prescribed world model to evaluate off-line the potential field. Finally, some implementations present significant problems related to oscillations in narrow passages and in the presence of obstacles [6], [18].

III. LOCAL OBSTACLE AVOIDANCE

The potential field concept was chosen as base for our implementation given its simplicity. Especially due to the possibility to easily adapt the algorithm to cover the specific requirements of shared control paradigms and to run it on the limited computational capability of our prototype's embedded system. However, our work differs from the original PF because it does not try to build a world map of the environment. Instead, our approach is closer to the implementation described by Bicho [17], where each ultrasonic range reading is treated as a repulsive force.

Once an object is detected by a sensor S_i, a virtual repulsive force F_i towards the robot is computed. The direction of each repulsive force is determined by the direction of σ_i, from the object point O_i to the Robot Center Point C, Fig.1. Notice that since sonar sensors return radial measures of the environment, it is not possible to determine precisely the angular location of the object. However, it is much more likely that the detected object is closer to the acoustic axis of the ultrasonic transceiver then in the periphery of the conical field of view [13]. Thus, the position of obstacle O_i is computed as the measured distance D_i under the acoustic axis of the sensor.

$$\sigma_i = \arctan\left(O_{iy}/O_{ix}\right) \tag{1}$$

Where(O_{ix}, O_{iy}) is the relative position of obstacle detected by the sensor S_i, and σ_i is the direction from the detected object O_i to the wheelchair's center point $\mathbf{C}$.

In order to keep user autonomy at the utmost, control signals are only adapted in situations which the user faces an eminent risk of collision. Therefore, repulsive forces start acting just when a safety range is reached. Due to inertia, the distance needed to completely stop the wheelchair increases with its speed Sp. Thus, the risk of collision is considered a bi-dimensional variable, both distance and speed dependent.

Such safety range was designed not just to avoid obstacles in the wheelchair's neighborhood, but also to avoid oscillations that non-critical far objects could cause in the control's behavior, and implemented according to the graphics depicted in Fig. 2 and Fig. 3. The magnitude of the repulsive forces grows exponentially accordingly the pair (D_i,Sp):

$$|F_i| = \propto * \, exp(-\beta * D_i + \omega * Sp) * |F_a|. \tag{2}$$

Where $\propto$, β, ω are positive constants deduced from the desired safety range, $|F_a|$ is the magnitude of the attractive force and D_i the distance to an obstacle O_i measured by the sensor Si.

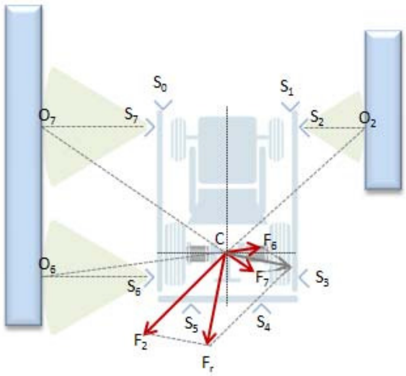

Figure 1. Repulsive forces acting on the wheelchair.

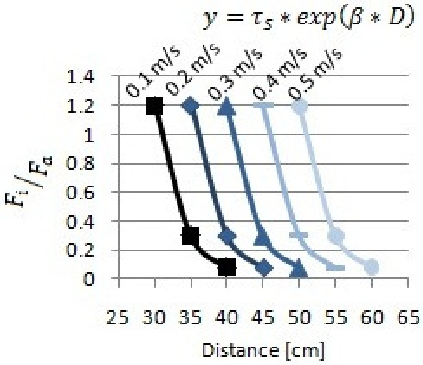

Figure 2. Safety distance range acording to the IW's speed and distance.

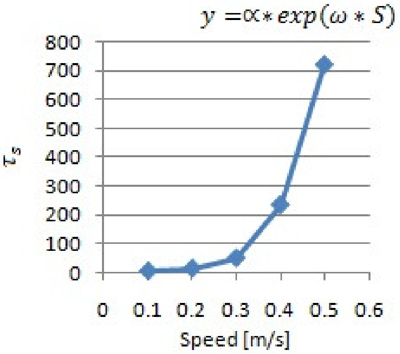

Figure 3. Speed component of the safety range.

Once all repulsive forces are computed, they are added up to yield a resultant repulsive force F_r.

$$F_r = \sum_{i=0}^{n} F_i. \tag{3}$$

Next, the virtual attractive force F_a induced by the target is updated. In the wheelchair implementation F_a is directly proportional to the current user input, which can be either the standard wheelchair's joystick or a special user interface which is based on the user's head position. Summing both the resultant repulsive force F_r and current attractive force F_a it is possible to derive the final force F_t that steers the wheelchair, Fig. 4.

$$F_t = F_a + F_r. \tag{4}$$

IV. EXPERIMENTS

In order evaluate the efficiency of the proposed algorithm eight volunteers performed each one set of four drive tests. Sets were composed four laps: two laps in a simulated environment (with and without the assistance of the algorithm) and two laps in a real environment (with and without the assistance of the shared wheelchair control). All of the eight recruited participants were aged between 26 and 39 years old, and have spent around 40 minutes running the experiments and answering a post-test questionnaire

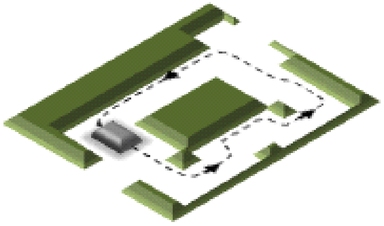

Figure 4. Closed circuit were experiments were conducted.

Figure 5. Intelligent wheelchairr prototype used during the tests inn the real environment.

Based on the work proposed by Parikh [19], a well-defined protocol to conduct the test was designed. It aims to ensure that data were collected accurately and in the same way across the tests, and will be better explained in the next sub-section.

Participants were instructed about the objective of the task and about the closed circuit they should drive, Fig. 4. It was reinforced that their main goal was to drive safely and then to finish each lap as fast as they could. Time was just mentioned as a secondary objective to prevent volunteers from navigating too slowly, and was not used on the evaluation process.

Real tests were run using IntellWheels intelligent wheelchair prototype, Fig 5. It is equipped with 2 encoders, a ring of eight sonars and eight infrared sensors distributed accordingly Fig. 1 and one embedded ATmega1280 microcontroller board to run the algorithm. Due to the measuring rate of the ultrasonic sensors, each algorithm cycle spend 80 ms to be computed. Simulation tests were run under the IntellWheels Simulator, emulating the same characteristics of the real prototype and the real environment. Further details about the prototype and the simulator can be found in [20], [21], [22].

During these trials, some conditions faced by handicapped individuals have been simulated. To accomplish that, all participants were asked not to drive the wheelchair using its standard hand driven joystick. Instead, volunteers were requested to perform all four laps using a special human-machine interface based on the user's head position [21], [23].

A. *Experiments Protocol*

This experiment protocol has been defined to standardize the results of both tests, and consists basically of seven steps:

- Step 1: volunteers have been instructed about test procedure and about their objectives during the four drive tests.
- Step 2: it was given to the participant a 10 minutes driving trial in a simulated environment. Thus, the user could experiment the wheelchair and make the necessary adjustments to the special human-machine interface.
- Step 3: once prepared, the participant was asked to drive the wheelchair (1 lap) through the circuit in the simulated environment with the manual control paradigm.
- Step 4: after the first test, it was asked to the volunteer to drive the wheelchair (1 lap) through the same circuit in the simulated environment, but with the assistance of the shared control.
- Step 5: accomplished both tests in the simulator, the user were asked to drive the wheelchair (1 lap) in the real environment with the manual control.
- Step 6: in the last test the user had to drive the wheelchair (1 lap) in the real environment with the shared control paradigm.
- Step 7: to evaluate the shared control paradigm, the user safety perception and to conclude the set of experiments, a pot-task questionnaire was applied.

B. *Results*

From the set of experiments described above, both quantitative and qualitative data have been generated. All analysis were performed within subjects, which allowed us to estimate if providing assistance actually helped each individual, rather than testing the performance of individuals against each other. Therefore, experimental data were subjected to a nonparametric test for paired samples (Wilcoxon Signed Rank 1-tailed test) [27], which made possible to reach some conclusions with a confidence level of 95% ($p<0.05$).

Based on the number of collisions of each trial, the shared algorithm performance could be evaluated in the simulated (Fig. 6) and real environments (Fig. 7). In the real environment, the results indicate a significant difference between the number of collisions with and without the shared control paradigm ($T= 0.00$, $n=8$, $p= 0.0135$). In addition, the sum of the positive difference ranks ($R\_+=21$) was larger than the sum of the negative difference ranks ($R\_-=0.00$), showing a positive impact from the algorithm. In the simulated environment, results also indicate that there is significant difference between the number of collisions with and without the shared control paradigm ($T= 0.00$, $n=8$, $p= 0.009$).

The sum of the positive difference ranks ($R\_+=28$) was larger than the sum of the negative difference ranks ($R\_-=0.00$), showing a positive impact from the algorithm. Therefore, our analysis provides evidence that the shared control paradigm is providing positive benefits toward the reduction in the number of collisions. On the other hand, it is important to evaluate the algorithm from the user's perspective.

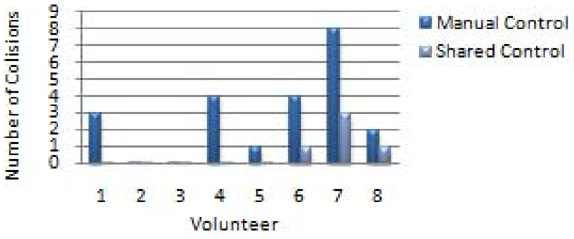

Figure 6. Number of collisions per volunteer on the real environment.

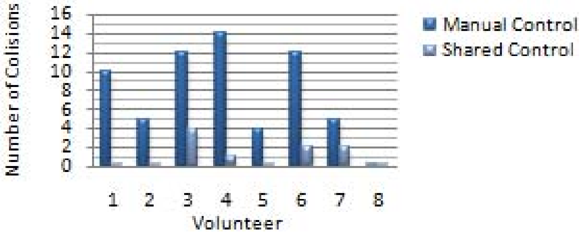

Figure 7. Number of collisions per volunteer on the simulated environment.

Related projects concluded that, despite the reduction in the number of collisions provided by their algorithm, users did not felt safer indeed, preferring the standard driving paradigm (without any assistance).

In order to measure the user feeling, the questionnaire applied was composed of five statements for each control paradigm, in which respondents were invited to specify their level of agreement on a five-point Likert scale (1 = Strongly disagree, 2 = Disagree, 3 = Neither agree nor disagree, 4 = Agree, 5 = Strongly agree):

1. I feel comfortable when driving the wheelchair.
2. I feel that I have the control of the wheelchair behaviour.
3. It is easy to drive the wheelchair in cluttered spaces.
4. Driving the wheelchair requires little attention.
5. The wheelchair has the same behaviour either in the simulated and the real environments.
6. I believe that the shared control helped me during the navigation task.

In our analysis, the user safety perception was treated as an indirect variable measured through the sum of the points of the statements 1,2,3 and 4, Fig. 8. The difference between the user safety perception with and without the shared control paradigm was significantly greater than zero (T= 3.0, n=8, p= 0.027), providing evidence that the shared control is effective to improve user's safety perception.

Another inference can be done regarding to the behavior of the wheelchair in the simulator. Through the fifth statement, we tried to measure how close to the reality the simulated behavior of the wheelchair is. A threshold value of 3 was used to compare results, Fig. 9.

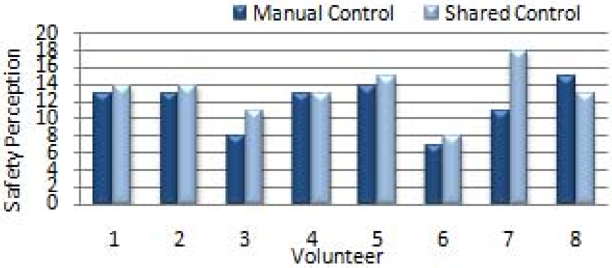

Figure 8. User's safety perception with and without the assistance of the shared control.

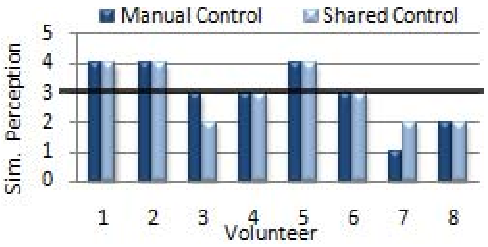

Figure 9. How realistic is the simulator on manual and shared control paradigms.

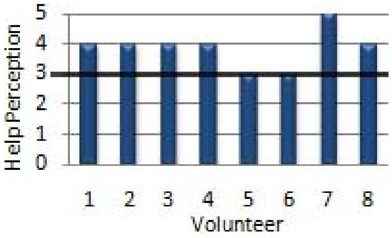

Figure 10. User's help perception with the assistance of the shared control.

Remember that in Likert scale a value of 3 means that respondents neither agree nor disagree with the statement, thus a value greater than 3 means that simulated wheelchairs react just like the real ones in the user's perspective. However, through the Wilcoxon Signed Ranks test it was not possible to state with a confidence level of 95% that the wheelchair has the same behavior in the real and simulated environments for both manual (p = 0.0655) and shared control (p = 0.051) paradigms.

Finally, one last result of the questionnaire is the user's perception of the help provided by the wheelchair. In this case it was evaluated through the statement 6 (only present in the shared control section of the questionnaire), comparing it with a threshold value of 3, Fig. 10. Similar to what was mentioned before, a value greater than 3 means that the user felt helped by the algorithm. The user's help perception variable was significantly greater than the test value 3 (T= 0.0, n=8, p = 0.01), providing evidence that volunteers indeed felt that the shared control paradigm helped then to drive the wheelchair.

V. CONCLUSIONS

This paper presented a new approach to improve safety for wheelchair's users. To assist patients in their navigation tasks, an obstacle avoidance methodology has been adopted. Based on the dynamic approach of the classic field of forces concept, this work extends and complements the potential field methodologies from a shared control perspective. To reduce the computational cost and run the algorithm in real-time, each ultrasonic range reading is treated as a repulsive force. Thus, it is not necessary to build a map of the environment and compute thousands of parameters. Furthermore, as localization is not required, dead reckoning errors are not introduced when computing the distance to obstacles.

On the other hand, such proposal is still very sensor-depended, and does not overcome by itself the intrinsic sonar shortcomings. Further improvements should include some sensor filtering to increase robustness and reduce measures oscillations. Another problem detected during the experiments regards to the prototype and not to the algorithm itself. It was noticed the presence of two small blind spots for object closer than 25 cm, one at each side of the wheelchair. Both of them cannot be reached during a forward/rewind displacement, but only when turning in sharp corners. In our tests it was the main reason of those collisions during the tests with the shared control paradigm, and could be eliminated with the addition of two more sonars.

As depicted in Figure 7, the number of collisions in the simulated environment is clearly much greater, and can be explained through the volunteer's comments and their behaviour during the tests. Apparently, the 3D environment of the simulator could not provide an accurately perception of depth and distance to objects, causing collisions in the cluttered test circuit. However, a second reason is related to the user way of driving. In the simulated environment volunteers tended to relax and to reduce the attention to the circuit mostly because they were not going to suffer the physical damages of a real collision.

Our research has demonstrated that it is possible to increase safety with low cost sensors and improve the acceptance of intelligent wheelchairs. Future work will address the wheelchair simulator by increasing its realism in order to achieve very similar behaviors in real and simulated environments. Future work will also be concerned with increasing the number of volunteers in the drive tests, and testing the algorithm not only in able-bodied individuals, but also on impaired people with different diseases.

ACKNOWLEDGMENT *(HEADING 5)*

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