A New Velocity Planning Method for Autonomous Robots with Varying Mass

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Abstract: Mobile robots are designed to perform different tasks in many different fields such as production, fast delivery, defence industry and space exploration. Advances in mobile robots are crucial as they can perform tasks that are difficult, dangerous or inefficient for humans. In this context, we discuss the improvement of velocity planning in the rapidly evolving field of autonomous mobile robots. In this study, we focus on mobile robots with high variance in their weight. Mobile robots can transport loads or autonomous personal transportation vehicles such as wheelchairs, which can be given as an example of these types of systems. This study focuses specifically on linear velocity planning for providing the same performance for all payloads on the mobile robot considering comfort and safety. For this aim, we propose a new velocity planning method based on fuzzy logic which has several advantages over previous methods. The suggested algorithm is tested in simulations using certain performance measurement metrics. After the observation of successful results, real-world experimental tests are performed to prove the real-time applicability of the proposed approach.

Keywords: autonomous robots; mobile robots; velocity planning; fuzzy logic

1 Introduction

Today, the rapid evolution of technology allows the development of elements such as artificial intelligence, image processing and autonomous systems used in the design of faster, stronger and smarter robots. In parallel with the developments in these fields, robots play a key role in the competitiveness of the industries by reducing production costs and help achieve high quality standards. For this reason, the importance of developments and dissemination studies in the field of robotics is increasing day by day. Various difficulties such as path planning, velocity planning, and obstacle avoidance are encountered in the development of each of the different robots produced for different purposes. This study focuses on mobile robots that carry people where safety and comfort are critically important.

The information about road and vehicle dynamics is commonly used in velocity planning for ground vehicles [1, 2]. In [3], the linear and angular velocity of the vehicle is obtained with vehicle dynamics and tracking error that is the input of the Fuzzy Logic Controller (FLC). In [4], linear velocity reference is calculated by the curvature of the trajectory in an obstacle-free environment. In [5], another velocity planning method is proposed and applied to a car-like robot using an FLC, taking into account the predictive curvature of the road. This increases the tracking performance compared to the classical approaches.

One crucial factor for reference linear velocity calculation is the environmental condition such as object density, distance and angle of the objects from the vehicle. In [1], linear velocity reference is obtained with fuzzy the controller using the curl magnitude of the target velocity field, and extension of the Voronoi Diagram which specifies the location and size of obstacles. [6] calculates reference left and right wheel velocity values using the angular variation from the target and the distance from the nearest obstacle towards left, front and right values using fuzzy rules. In another approach [7], the desired linear velocity is found by considering the minimum distance between obstacle and vehicle, the angle of the nearest obstacle and the steering angle values by using two cascade-connected FLC. In [8], right and left motor velocity are determined according to the surrounding obstacles obtained from the sensors on the vehicle. In another work, angle to the goal and distance and angle to the obstacle values are merged using fuzzy rules in [9].

Another factor that should not be ignored in velocity planning is driving comfort. In [10], an optimized velocity profile is planned by using an offline numerical optimization and a PD controller by considering initial and terminal conditions, road information and comfort criteria. In this study, comfort criteria are lateral and longitudinal acceleration, and lateral and longitudinal jerks constraints. In [11], the velocity planner uses the set of curves of the previous layer to compute analytically a comfort-constrained profile of velocities and accelerations, where the comfort criteria are maximum speed, longitudinal and lateral acceleration, and jerk. [12] proposes an intelligent longitudinal velocity planning method based on a fuzzy neural network to increase the comfort and reduce the complexity of the planning algorithm in autonomous vehicles. In [13] a new approach is given for the jerk constrained velocity optimization problem. The velocity planning problem is formulated as linear programming which takes comfort into account. In another study [14], the velocity planning function generates velocity profile candidates on the planned path using cubic polynomials. Then, the best candidate is selected considering comfort, safety and boundary conditions. Another approach in which the optimization problem is solved by a particle swarm optimization (PSO) algorithm to obtain a time optimal and smooth velocity profile is shown in [15].

None of the above-mentioned methods take into account the mass of the robot in velocity planning. In this paper, a new velocity planning method for mobile robots with varying mass is designed based on fuzzy logic. Fuzzy logic systems, unlike neural networks, can be easily modified and can easily use human expert knowledge. It does not need special datasets and has relatively lower complexity. The proposed fuzzy system is formed by two parallel connected Mamdani-type Fuzzy Inference Systems for obtaining the desired velocity. The method aims to provide a high-level of comfort and safety and the ability to reach the target, regardless of changing masses. The main contribution of the proposed approach is considering the total mass of the robot on velocity planning. To the best of our knowledge, this mass parameter has not been considered in velocity planning before. Another novelty is removing the effect of the actuator limits, which has not been considered in previous works and causes problems in some scenarios for them. Moreover, we define a new parametric danger function for obstacles around. We bring a new perspective to the velocity planning problem by considering; ”previous velocity”, ”reference angular velocity” and ”the danger level of environment” parameters together. In this way, similar performance is achieved for all different mass values. All of these inputs have a critical effect on the velocity plan which are explained in the remaining parts of this paper. The autonomous wheelchair platform is chosen to implement and test the new velocity planning method. There are two main reasons for this choice. The first is that the mass of the whole system is highly affected by the mass of the person on the vehicle. The second is that it is a personal transportation device for which the safety and comfort of the user is paramount.

The paper is organized as follows: A technical approach for the adaptive velocity planning problem is considered in Section 2. Section 3 simulation presents robot modelling, simulations and comparisons. In this section, the proposed approach is compared with a classical approach and constant velocity profiles. The real-world implementation results are discussed in Section 4. Lastly, the paper ends with a summary of the entire work, providing a perspective on further research topics in Section 5.

2 Technical Approach

Velocity planning has a very critical role in the autonomous mobile robot software stack. Different purposes can be set for it which may vary depending on the application. In this paper, the problem is defined as making an efficient velocity plan to obtain a safe travel while providing high comfort and low travel time. In order to achieve these conflicting requirements, we propose a design based on fuzzy logic. Fuzzy logic is a decision-making methodology. which is inspired by human thinking, taking advantage of our ability to reason with approximate data. Previous studies on velocity planning show that fuzzy logic has an efficient performance on mobile robot velocity planning problems. Instead of connecting all inputs to a single fuzzy decision maker which would result in a huge number of rules, two parallel fuzzy blocks are used in this study as shown in Figure 1. The remaining parts of the paper explain each block in detail.

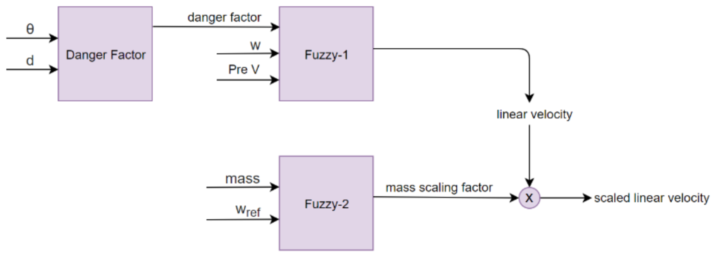


Figure 1
Velocity planner designed for wheelchair platform

2.1 Fuzzy-1 Inference System

Fuzzy-1 structure is created to produce a velocity plan according to safety and comfort which are considered two crucial factors in this study. For any ground vehicle that is capable of moving autonomously, any object in the view of the vehicle can become an obstacle. However, the important point is the danger level posed by the obstacles. When we drive on the road, we analyse the danger level of an obstacle by two criteria; distance from the vehicle to the obstacle and the angle between the obstacle and the vehicle's x-axis [16]. Similarly, we analyse the danger level of an obstacle using the same properties which directly affect the velocity plan.

Another crucial factor is the driving comfort if the mobile robot is carrying a human. The meaning of comfort is to keep the velocity and the acceleration of the wheelchair to be smooth and limited [17]. The acceleration or deceleration of the vehicle and the temporal derivative of acceleration (jerk) significantly affect driving safety and comfort [18]. For this reason, it is recommended to impose restrictions on the acceleration and jerking of vehicle movement. As an example of these limitations, the standard values of acceleration and jerk criteria in public road or rail transport in many countries are limited to 0.9-1.47 $m/s^2$and 0.3-0.9 m/s^3[10,19]. In Section 3.3, lateral and longitudinal accelerations are determined to define a comfort zone in which a comfortable driving experience is possible for a human.

2.1.1 Structure of Fuzzy-1 Inference System

The first fuzzy block has three different inputs which are the danger factor, the previous linear velocity of the vehicle and the angular velocity of the vehicle (Figure 1).

The danger factor is calculated by the distance and angle of objects to the vehicle within the area scanned by any sensor that is capable of measuring the angle and distance. In the design of the danger factor function, it is aimed that the obstacles in front and on the same path with the robot should be evaluated as more dangerous than others.

Sensors that are capable of measuring ranges like LIDAR, Depth Camera and have the angular range or field-of-view. Depending on the sensor's angular resolution in the horizontal plane, the total number of range measurements N, is changed. The index of range measurement is expressed as $i \epsilon Z$. Equation 1 defines the risk factor R_i for each range measurement i. $d_{max} \epsilon R$ is the maximum range that the sensor can measure and $d_i \epsilon R$ is the range value of the related index i. Therefore, $d_i \leq d_{max}$ and d_i / d_{max} is less or equal to 1. $s \epsilon R$ is the degree of the function in equation 1. For instance, i_o is the index of measurement, do is the range value of the corresponding measurement. As s increases d_o / d_max decreases, and risk factor (R_o) is increases. The s value is left as a tuning parameter to get the desired risk calculation.

$$R_i(d_i; s, d_{max}) = \left(1 - \left(\frac{d_i}{d_{max}}\right)^s\right) \quad (1)$$

An object in front of the vehicle is more dangerous than an object on the side of the vehicle. Therefore, an obstacle's angle to the vehicle is a critical parameter of its danger level. A weighting function is required to increase the level of danger when the obstacle is directly in front of the vehicle. The bell-shaped function [20] is chosen to handle these desired criteria.

As mentioned before, the index of the range measurement is i. Using the index, the angle between that measurement and the vehicle's x-axis in the local frame, θ_i, is easily calculated. Since there is no necessity to calculate the risk factor at the backside of the vehicle, θ_i is restricted as $-\frac{\pi}{2} \leq \theta_i \leq \frac{\pi}{2}$.

The weighting factor W_i is given in Equation 2, which determines how much each R_i value is affected by its angle with respect to the vehicle. There are two parameters in Equation 2 that can be set. As the k parameter increases, the dangerous area of the objects on the side of the vehicle increases. This is due to the decrease in the slope of the bell function. On the other hand, when the y parameter increases, the angle of the dangerous area in front of the vehicle increases. W_t is the sum of all values W_i as shown in Equation 3.

$$W_i(\theta_i; k, y) = \frac{1}{1 + \left|\frac{\theta_i}{k}\right|^y} \quad (2)$$

$$W_t = \sum_{i=1}^{N} W_i \quad (3)$$

Finally, D_f which is the total danger factor of the environment is obtained with Equation 4.

$$D_f = \max\left(\frac{W_i}{W_t} x R_i\right) \qquad i = 0, \dots, N \quad (4)$$

For normalization, each weight is divided by the sum of all weights. The maximum value of the multiplication of R_i and corresponding normalized weight is taken as the danger factor. In the light of the various experiments made for three parameters, the coefficients to be used in this study are selected as; $s = 6$, $k = 1$ and $y = 1$. These parameters can be adjusted by the user to get different danger characteristics. The danger factor representation with the determined parameters is shown in Figure 2.

Another input of Fuzzy-1 block is the "previous linear velocity" of the vehicle. This is chosen as an input because of the comfort criteria. Comfort should carefully be taken into account for human-carrying robots and it is affected by both longitudinal and lateral acceleration. The sudden changes in velocity results in sharp transitions in longitudinal acceleration (Equation 5). These sharp transitions in velocity and also the high values of acceleration directly affect human comfort.

$$a_x = \frac{V_t - V_{(t-1)}}{\Delta t} \quad (5)$$

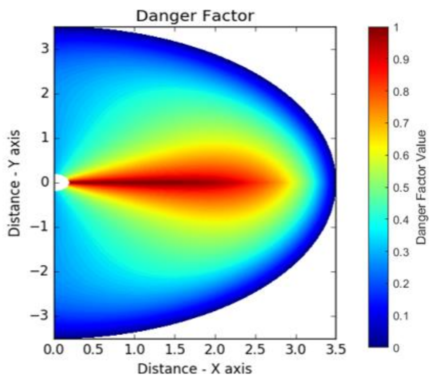


Figure 2

Danger factor representation with the parameters used during the simulations

Another input of Fuzzy-1 block is the "angular velocity" of the wheelchair platform, which is calculated by the local planner to avoid obstacles and track the global path. The reason for taking angular velocity as an input is the lateral acceleration, which is a part of comfort and should be between certain values. The relation between the angular velocity and the lateral acceleration is centrifugal force. The centrifugal force F_c is calculated as shown in Equation 6 where m is the loaded weight of the vehicle, ω is the angular velocity, and r is the turning radius.

$$F_c = m\omega^2 r \quad (6)$$

Since the force is calculated as the multiplication of mass and acceleration in Newtonian mechanics, the lateral acceleration (α_y) is specified as $\omega^2 r$ as provided in Equation 7. Using the relation between angular velocity and linear velocity, the lateral acceleration can be written as the multiplication of linear velocity and angular velocity as in Equation 7.

$$a_y = \omega^2 r = V\omega \quad (7)$$

As it is seen in Equation 7, the lateral acceleration is directly proportional to the angular velocity and the linear velocity.

After taking into account of the provided inputs, the linear velocity is the output of the Fuzzy-1 structure. The fuzzy rules create an adaptive velocity profile according to the obstacles around the vehicle and comfort criteria. The proposed structure is provided in Section 2.1.2.

2.1.2 Rules of Fuzzy-1 Inference System

The increased danger factor means that the danger level of the vehicle's environment increases. In these situations, it is a priority to prevent the vehicle from hitting obstacles and to ensure its safety. The rules are created to reduce the linear velocity and make the vehicle act cautiously in these cases.

On the other hand, rules are created to prevent the wheelchair user from being disturbed by linear and lateral acceleration. According to the rule set, if the angular velocity is large, the linear velocity is reduced for limiting the lateral acceleration. Similarly, the reference velocity is restricted by looking at the vehicle's previous velocity for preventing a high amount of longitudinal acceleration.

The rule base according to the designed strategy is provided in Table 1 and the membership functions are shown in Figure 3.

Table 1

Rules of Fuzzy-1 structure. VS: Very Small, S: Small, M: Moderate, H: High, VH: Very High

		Input 1: W = S					*Input 1: W = M*					*Input 1: W = H*				
		Input 3: Danger Factor					*Input 3: Danger Factor*					*Input 3: Danger Factor*				
		VS	**S**	**M**	**H**	**VH**	**VS**	**S**	**M**	**H**	**VH**	**VS**	**S**	**M**	**H**	**VH**
Input 2: Previous Velocity	**VS**	M	M	M	S	S	M	M	S	S	VS	S	S	S	VS	VS
	S	H	H	H	M	S	H	H	M	M	S	M	M	S	VS	VS
	M	VH	VH	VH	H	M	H	H	M	M	S	M	M	S	VS	VS
	H	VH	VH	H	M	M	H	H	M	S	S	H	M	M	S	S
	VH	VH	H	H	M	M	VH	H	M	M	M	H	H	M	M	M

An example is given to increase the clarity of the logic of the rule sets in Table 1. Linear velocity is moderate (M) if the angular velocity is high (H), the previous linear velocity of the vehicle is very high (VH) and the danger factor is very high (VH). The reason the linear velocity is not kept lower than M is that it is undesirable for comfort to reduce the velocity from" very fast" to" slow" or" very slow" directly.

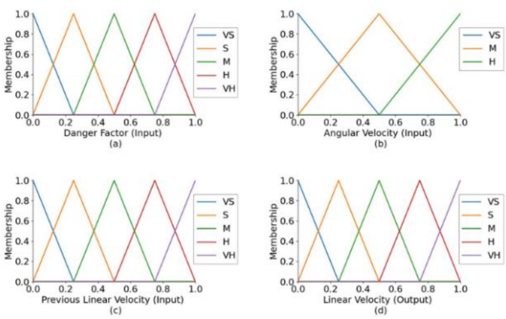


Figure 3
Membership Functions for Fuzzy 1

2.2 Fuzzy-2 Inference System

In some kinds of autonomous robots such as human-carrying vehicles or factory robots which carry heavy loads, sometimes the total mass changes dramatically. The change in the mass value causes safety and performance problems according to the scenario. For this reason, the second fuzzy block is designed to consider the effects of mass on safety and actuator limits.

2.2.1 Structure of Fuzzy-2 Inference System

The proposed fuzzy logic structure has two inputs; the mass and angular velocity and output as the mass scaling factor. The final linear velocity sent to the wheels is obtained by multiplying the mass scaling factor and Fuzzy-1 output as shown in Figure 1.

Mass is the total mass of the vehicle and the payload which can be human. Considering Newton's second law one of the primary factors that affect the acceleration or deceleration of the object is mass [21]. When both the mass and velocity of the robot is high (high momentum) it is harder to decelerate or stop. Hence, the high-mass vehicle can pose a danger when it has high-speed and/or it is close to the obstacle. Therefore, the linear velocity of the high-mass vehicle should be slower than the low-mass vehicle. The first aim of Fuzzy-2 block is to prevent such kinds of dangerous scenarios.

The second part of the Fuzzy-2 block is to prevent the saturation of actuators, which may cause another safety problem. In cases where the reference angular velocity of the vehicle is high, if a high linear velocity is requested, the required amount of power for each motor increases. Since these actuators are not generally selected for the robots for this kind of edge scenario, one or both of the actuators may not provide the requested torque. This may result in dangerous scenarios as it is shown in Section 3.2. In order to prevent these types of accidents, **reference angular velocity** is taken into account together with the total mass, for manipulating the robot's linear velocity.

The output of the Fuzzy-2 is the **mass scaling factor.** This value is multiplied by the Fuzzy-1 output and the scaled linear velocity of the vehicle is obtained. The fuzzy rules create an adaptive scaling factor according to the mass and the reference angular velocity. The proposed structure is provided in Section 2.2.2.

2.2.2 Rules of Fuzzy-2 Inference System

The Fuzzy-2 rules are based on two main purposes. The first is to prevent accidents caused by the control signal from reaching the saturation limit. As the reference angular velocity increases, the linear velocity that the vehicle can reach decreases for the same saturation limit. Therefore, the mass scaling factor must be a small value to decrease the linear velocity demanded. The second is to prevent accidents caused by momentum. As the mass increases at the same speed, the distance is taken to stop the vehicle increases. For safe driving, the vehicle should travel at a slower speed in high masses. Thus, the mass scaling factor should be a smaller value when the mass increases. For example, if the reference angular velocity is small (S) and the mass is very small (VS) then the mass scaling factor is very small (VS) which is the lowest value in the rule set. The rule base according to the designed strategy is provided in Table 2 and the membership functions are shown in Figure 4.

Table 2
Rules of Fuzzy-2 structure.
VS: Very Small, S: Small, M: Moderate, H: High, VH: Very High Input 1: Mass

		Input 1: Mass				
		VS	**S**	**M**	**H**	**VH**
	S	VH	H	H	M	M
Input 2:	**M**	H	H	M	M	S
Ref. Ang. Vel.	**H**	H	M	M	S	VS

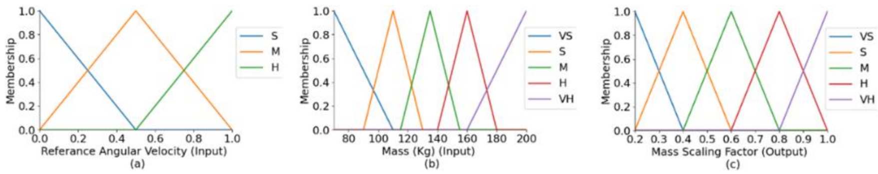


Figure 4
Membership functions for Fuzzy 2

3 Robot Modelling, Simulations and Comparisons

The proposed velocity planner is tested in the simulation environment with various scenarios. A dynamic mathematical model of the conventional differential drive electrical wheelchair is used in experiments. Detailed information about differential drive mobile robot dynamics and mathematical equations can be found in [22]. The reason for using a wheelchair platform is its variable total mass depending on the human weight on it. From a light child to an obese adult, people of many different masses can ride in a wheelchair. Different velocity planners and the proposed method are compared on this platform. This comparison is made within the framework of certain metrics. The results of the metrics are critical to comparing the effectiveness of the proposed method numerically.

3.1 Simulation Environment

In order to analyse the proposed method correctly, the mobile robots must be imported into the simulation environment. The proposed and the reference methods are compared in simulations using MATLAB/Simulink and ROS (Robot Operating System) environment together, as shown in Figure 5. The dynamic model of the wheelchair is created with the help of standard differential drive mobile robot equations [22]–[24], using MATLAB/Simulink. After the creation of a mathematical model in MATLAB, the dynamic model is imported into the ROS-Gazebo environment. Gazebo offers accurate and efficient simulation environments for complex indoor and outdoor scenarios.

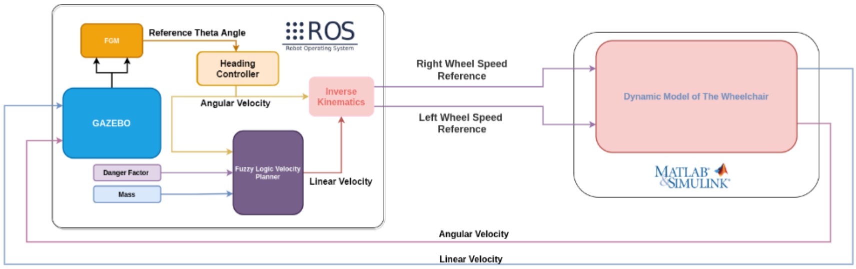


Figure 5
General simulation structure including ROS & MATLAB

Indoor simulation environments where the obstacles can be integrated in random positions are created with this simulator. In order to avoid obstacles and reach to the goal point, Follow the Gap Method (FGM) [16] is used as a local planner which calculates the angular velocity in ROS side. Since we use two different tools for simulations, communication between MATLAB / Simulink and ROS are crucial for experiments. The connection between the two is shown in Figure 5. ROS operates based on publishers and subscribers, in other words, receivers and senders for information sharing. This communication between computer and root is provided by topics and messages. ROS toolbox in MATLAB/Simulink provides significant advantages for data import or export operations, which can be done from the topics and messages in ROS.

3.2 Experiments and Comparison

The proposed velocity planner is compared with three different strategies. The first two have constant velocity values as 1 m/s and 1.5 m/s constant velocities. 1 m/s is an average value and 1.5 m/s is the maximum velocity for the wheelchair platform. The third compared method is a classical fuzzy planner [7] is referred to as "Classic Fuzzy" in the next parts. The classic fuzzy planner's structure is shown in Figure 6.

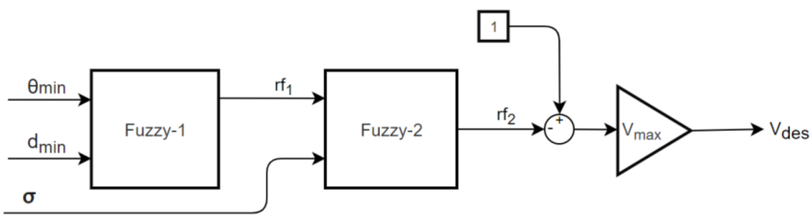
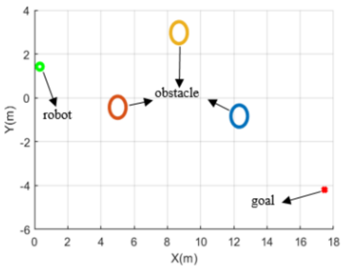
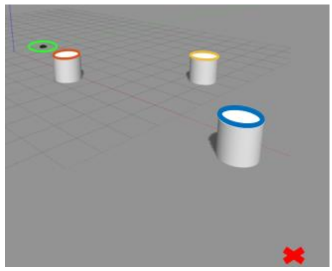


Figure 6
Classic fuzzy velocity planner

In the Classic Fuzzy method, there are 2 fuzzy blocks. The first block has two inputs as distance (d_{min}) and angle of the vehicle from the nearest obstacle (θ_{min}) respectively together with an output as the first risk factor (rf_1). The second fuzzy structure has two inputs as the first fuzzy output rf_2 and steering angle (σ) and an output as a second risk factor (rf_2). Since the velocity should be reduced with high values of risk, rf_2 is subtracted from 1 and multiplied by the maximum linear velocity that the vehicle can reach. More detailed information about this planner can be found in [7]. The last method to be used in the tests is the proposed adaptive velocity planner. All these methods are compared in 10 different test scenarios created with different initial and goal points together with random obstacles.



(a)



(b)

Figure 7

(a) Test environment visualization in MATLAB. (b) Test environment visualization in Gazebo

A sample test environment in Gazebo and MATLAB is shown in Figure 7. In the experiments, it is aimed to observe the performance of vehicles of different masses with 4 different velocity planners in 10 randomly generated simulation environments. The kerb weight of the vehicle is 80 kg and tests are made with 5 different payloads. The total masses used in the tests are selected as 80, 120, 140, 160 and 200. Considering 4 different methods, and 5 different mass values in 10 different environments, 200 experiments are carried out to compare the performances. The numerical comparison depending on the performance metrics is provided in Section 3.3. But before that, to explain the efficiency of the proposed method clearly, several specific experiments are visualized in the following part.

EX 1. The main purpose of this experiment is to show that Fuzzy-2 solves the control signal saturation problem. Two test results are illustrated in Figure 8 where the first one is the proposed method and the second one is the proposed method without Fuzzy-2 block. It should be noted that this specific experiment is outside of the 200 tests mentioned above since we compare the proposed method with itself.

It is seen that the vehicle using Fuzzy-1 as a velocity planner crashed into the obstacle. In order to understand the cause of the accident, the signals sent to the wheels are examined. In Figure 9, the reference and actual angular velocity of wheels are given. This simulation is performed for 200 kg of mass which requires higher motor torques as explained previously.

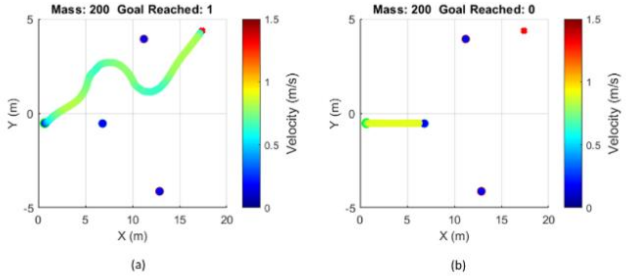


Figure 8

Simulation result for 200 kg

The system tries to turn the left by decreasing the reference angular velocity of the left wheel more than the right wheel. However, the motor's torque is not enough to reach the reference velocity values when the mass is very high such as 200 kg. That's why a vehicle cannot turn and crashes into obstacle.

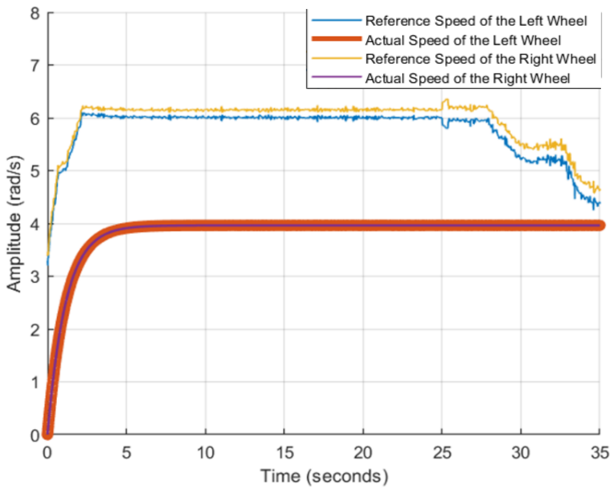


Figure 9

Reference and actual angular velocity of left and right wheel for the simulation given at Figure 8.b

The limit value of the control signal is applied to determine the maximum velocity values that the vehicle travels without the saturation problem. It is seen in Figure 10 that the vehicle cannot reach its maximum velocity without a saturation problem when its mass is more than 140 kg. In cases where the angular velocity reference is changed when the vehicle is travelling faster than the linear velocity which causes saturation, the vehicle cannot respond to the angular velocity demand and resulting in safety problems as shown in Figure 8.

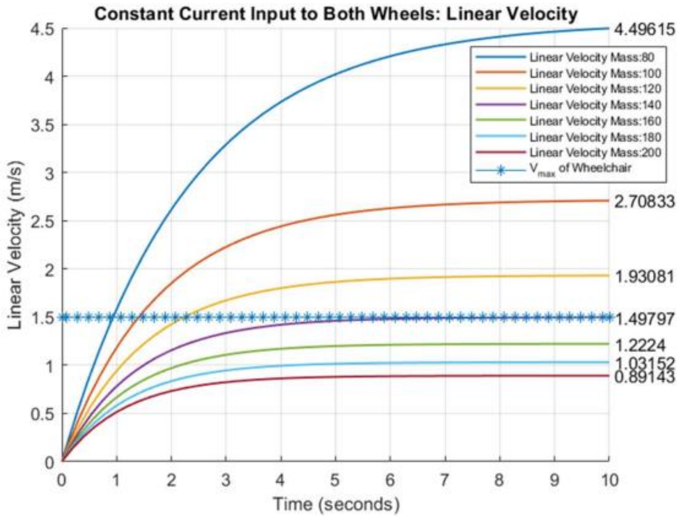


Figure 10

Wheelchair maximum linear velocities for different masses under maximum current

EX 2. The main purpose of this experiment is to show that the New Fuzzy Method gives better results than other velocity planners at high masses. Results are analysed for the second highest mass, as none of the velocity planners achieved the 200 kg target except for the New Fuzzy Method. Four test results are illustrated in Figure 11, all conditions are the same except for the velocity planners. According to the simulations, all methods arrive at the goal excluding Constant 1.5 m/s velocity. It hits the obstacle due to the control signal saturation problem.

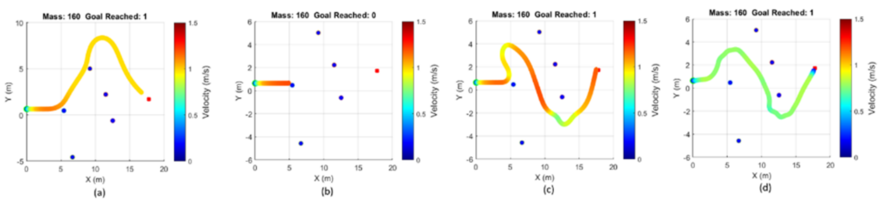


Figure 11

The performances of 4 different velocity planners in the same scenarios. (a) Constant 1 m/s. (b) Constant 1.5 m/s (c) Classic Fuzzy. (d) New Fuzzy

The Fuzzy Method is better than other methods in terms of safety and driving comfort, even if it reaches the target slower than Constant 1 m/s and Classic Fuzzy methods. It can be seen in Figure 11 that the Constant 1 m/s and Classic Fuzzy Methods come very close to the obstacle, which is dangerous for both the user and the environment. The New Fuzzy Method not only solves control signal saturation but also ensures a safer path at high mass.

EX 3. One of the critical goals of the proposed method is to show the same performance for all masses. In Figure 12, the performances of 4 different velocity planners in the same environment can be observed for 5 different masses.

Simulation results show that the velocity profile of the mobile robot changes only in the New Fuzzy Method since other methods do not consider the mass in their 12 strategies. This causes them to hit the obstacle and fail to reach the target in some scenarios. Moreover, the trajectories are very close to the obstacles in some scenarios where the robot reaches the target. On the other hand, it is clear from Figure 12 that the New Fuzzy Method performance is similar and safer for all the masses. It adapts its velocity decisions considering safety and comfort using the mass, angular velocity, danger factor and the previous velocity values as explained.

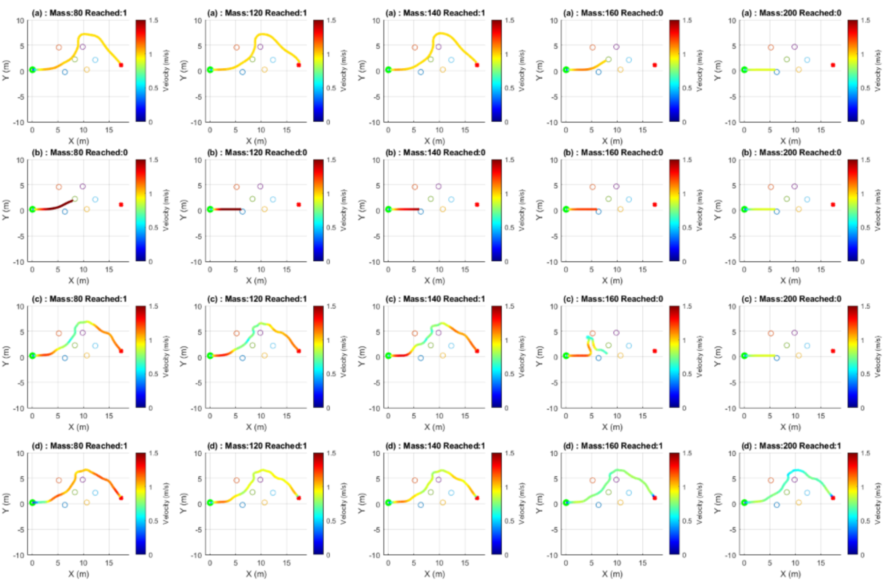


Figure 12

The performances of 4 different velocity planners for 5 different masses under the same initial conditions. (a) Constant 1 m/s Velocity Planner. (b) Constant 1.5 m/s Velocity Planner. (b) Constant 1.5 m/s Velocity Planner. (d) New Fuzzy Velocity Planner

3.3 Evaluation Metrics and Analysis

In order to compare each method numerically, specific metrics are defined. These metrics are" the number of reaching the target"," average travel duration", "safety" and "comfort". As it is explained previously, 50 tests for each method are performed for analysis. As it is illustrated in Section 3.2, the vehicle cannot reach the target in some scenarios. For this reason, the number of arrivals to the target is determined as the first metric. The second metric is chosen as average travel duration. Time until the vehicle reaches the destination is an important criterion for effectiveness

[25]. The third metric is about the safety of the path taken by the robot during the simulation. This metric measures the distance between the vehicle and the obstacle during travel. It records the closest point between the vehicle and obstacles during the simulation.

Table 3

Comparison of different methods with evaluation metrics

	Total Number of Arrivals to the Goal					Average Test Duration (Seconds)					Safety Metric (Meters)					Comfort Metric				
Mass (kg)	80	120	140	160	200	80	120	140	160	200	80	120	140	160	200	80	120	140	160	200
V = 1 m/s	10	10	8	8	0	11	18,703	17,407	16,82	-	0,1537	0,1512	0,1961	0,1416	-	0,0624	0,029	0,0181	0,0003	-
V = 1.5 m/s	7	3	0	0	0	6,443	13,304	-	-	-	0,3317	0,4251	-	-	-	0,1426	0,0093	-	-	-
Classic Fuzzy	10	10	10	5	0	11,214	15,553	18,956	16,358	-	0,8305	0,8015	0,9507	0,4485	-	0,111	0,0332	0,0176	0,0012	-
New Fuzzy	10	10	10	10	10	8,188	15,613	15,36	20,452	22,615	0,8023	0,7885	0,7209	0,7843	0,6996	0,0312	0,0032	0,0019	0,0004	0

The last metric is used to compare the driving comfort of the vehicle. This metric is obtained from the vehicle's longitudinal and lateral acceleration during the simulations. For comfortable driving, longitudinal and lateral acceleration limits are defined to be between -1 and 1 m/s^2, -0.9 and 0.9 m/s^2 values, respectively, as it is taken in [19] for passenger comfort. A comfort zone is drawn from these intervals as shown in Figure 13.

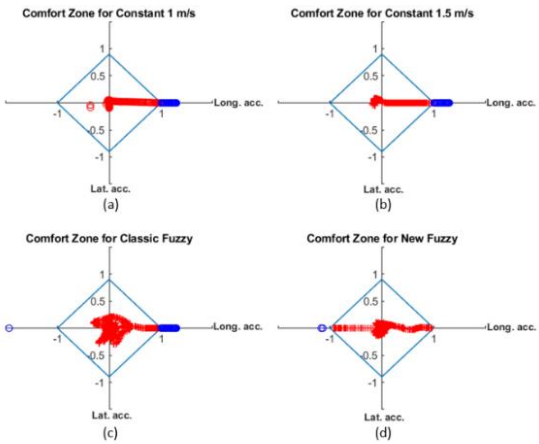


Figure 13

Comfort zone with longitudinal and lateral accelerations.

(a) Constant 1 m/s. (b) Constant 1.5 m/s (c) Classic Fuzzy. (d) New Fuzzy

Then, the longitudinal and lateral acceleration values of the vehicle throughout the tests are collected [26]. To calculate the comfort metric, the number of points outside the comfort zone is divided by the total number of points which is the ratio of uncomfortable travel to the whole motion. The comfortable (red) and uncomfortable (blue) points of each method during the simulations are illustrated in Figure 13. A numerical comparison of different methods with metrics is shown in Table 3.3. The New Fuzzy Method is the only method that can reach the goal in all tests. For example, for 200 kg mass, none of the methods could reach the target due to actuator saturation problem, except New Fuzzy Method. In the Classic Fuzzy

Method [7], when the platform is 160 kg, it can reach the target in 5 out of 10 tests. The Constant 1m/s reaches 8 out of 10 for the 160 kg scenario since it is relatively slower than the classic fuzzy approach, but the average test duration metric becomes worse as expected. The advantage of including mass in the velocity planner is seen in the table. Constant 1.5 m/s is not able to reach the target for the 160 kg condition. This shows that the New Fuzzy Method is the best among others in terms of Arrival to the Goal metric, as the mass increases.

The Average Travel Duration metric should be analysed with safety and comfort metrics since the wheelchair may arrive at the goal faster by compromising safety and comfort. Even though the Constant 1.5 m/s method has the fastest strategy which reduces average travel time, the safety and comfort metrics are worse than New Fuzzy Method.

The New Fuzzy Method is 3 to 10 times better than other methods on the comfort metric. This is due to the consideration of the angular velocity and the previous linear velocity values in the Fuzzy 1 block which is different from other approaches. Since both classic fuzzy and new fuzzy methods consider the risk level of the environment, the safety metric values are close to each other and better than the constant velocity strategies.

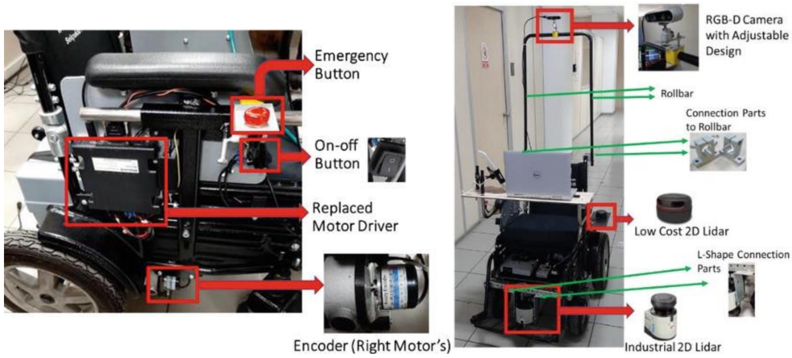
4 Real-World Implementation

After the simulations and comparative analysis, the proposed method is applied on a real autonomous wheelchair platform. The wheelchair used in the tests is converted from a conventional differential drive electrical wheelchair with 80 kg mass and has the dimensions of 120 cm x 65 cm x 100 cm. The conversion procedure includes removing the joystick, mounting a new DC motor driver, adding encoders for each motor and mounting several sensors and computers. Additionally, an on-off button and an emergency button are added to the system for power management and security. The fundamental components added for drive-by wire and the front view of the platform are shown in Figure 14. More detailed information about the design of the autonomous wheelchair platform can be found in [27].

The wheelchair currently has 3 sensors in operation for perception and localization purposes: 1 SICK LMS-151, 1 RPLiDAR-A2M6 and 1 Intel-RealSense D435i camera. The RPLiDAR sensor is used for localization. The other 2 sensors are fused to be used for perception to widen the coverage. Since these two sensors are located at different heights on the wheelchair's body, the wheelchair can detect obstacles efficiently.

The fuzzy velocity planner and the other algorithms related to autonomy are implemented on ROS (Robot Operating System) platform. The autonomy stack uses

Rapidly-Exploring Random Tree (RRT*) [28] as a global planner. In order to follow the path that is produced by RRT*, linear velocity commands are produced by the proposed fuzzy planner and angular velocity commands are calculated by the Follow the Gap Method (FGM) [16]. Adaptive Monte Carlo Localization (AMCL) [29], is used for localization. The planner tests are conducted in Mechatronics Education and Research Center (MERC) at Istanbul Technical University. The grid map of MERC that is used for localization can be seen in Figure 15a.



(a) Side view of the wheelchair (b) Front view of the wheelchair

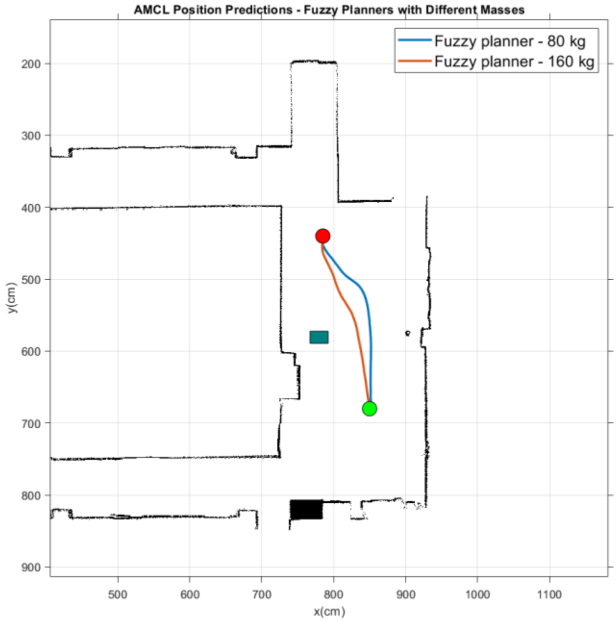
Figure 14

Fundamental components of the wheelchair

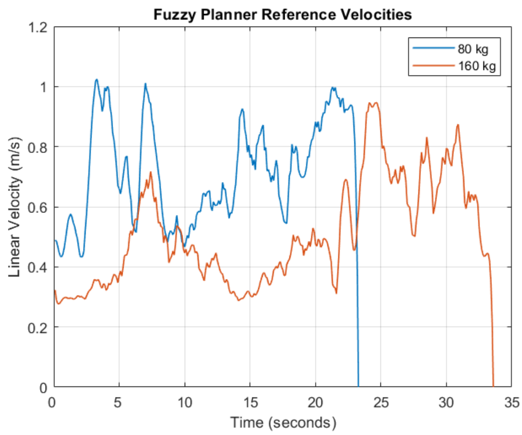
The test scenario consists of an obstacle which blocks the global path of the wheelchair. The planner is tested with 80 kg (empty wheelchair) and 160 kg (wheelchair carrying a person) total weights. The total path of the wheelchair for two different mass values can be seen in Figure 15a. As it is seen, the robot can reach the target successfully in both of the tests. The reference velocities computed by the proposed fuzzy planner during the test can be seen in Figure 15b.

Positions of the wheelchair while crossing the obstacle can be seen in Figure 16 for different masses. The wheelchair crosses the obstacle closer while carrying a person compared to no person case. This is expected since the heavier vehicle turns harder and this matches with the simulation results.

As a result, the proposed method is applied as part of the whole autonomous stack in real-time, without any problem.



(a) Paths followed during the test



(b) Reference velocities from the proposed fuzzy planner

Figure 15
Experiment results

(a) Total Mass is 80 kg (b) Total Mass is 160 kg

Figure 16

Moments when wheelchair of different weights passes the barrier (80 kg – 160 kg)

Conclusions

A new adaptive velocity planner for autonomous mobile robots with varying mass, is presented in this paper. The proposed approach is proven to be successful in an autonomous wheelchair platform. To the best of our knowledge, the new approach is the first velocity planner in the literature which considers mass. Moreover, our approaches a novel risk function to measure the danger level of the environment. As another novelty, we consider the previous velocity and the angular velocity reference values to achieve a comfortable travel. The proposed approach is analysed with systematic simulations using MATLAB/Simulink and ROS simultaneously. The results show the efficiency of the proposed method compared to the classical fuzzy approach and various constant speed strategies. After simulations and analysis, the new method is applied on a real autonomous wheelchair platform to prove its applicability and success in real-world conditions. Measurement noise and uncertainties of the system can be taken into account to obtain a more extensive and robust algorithm as a future work. Further analysis can be done for other types of robots where the total mass dramatically changes; such as autonomous forklifts or load-carrying mobile robots.

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