Robot navigation on inclined terrain using social force model

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ABSTRACT

This research introduces an innovative approach to address the limitations of the commonly used social force model-based robot navigation method on flat terrain when applied to sloped terrain. The incline of the terrain becomes a crucial factor in calculating the robot's steering output when navigating from the initial position to the target position while avoiding obstacles. Therefore, we propose a social forced model-based robot navigation system that can adapt to inclined terrain using inertial measurement unit sensor assistance. The system can detect the surface incline in real time and dynamically adjust friction and gravitational forces, ensuring the robot's speed and heading direction are maintained. Simulation results conducted using CoppeliaSim show a significant improvement in speed adjustment efficiency. With this new navigation system, the robot can reach its destination in 59.935089 seconds, compared to the conventional social forced model which takes 63.506442 seconds, the robot is also able to reduce slip to reduce wasted movement. This method shows the potential of implementing a faster and more efficient navigation system in the context of inclined terrain.

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1. INTRODUCTION

Terrain-based adaptive control has the primary goal of assisting robots in undergoing stable and safe movement, especially when operating on different types of terrain that may differ in characteristics. Achieving this goal requires the robot's ability to accurately identify surface slopes and adapt its actions and responses according to the terrain conditions encountered [1]–[3]. One of the key aspects of this adaptability is the ability to regulate the forces acting on the robot so that changes in speed or direction of movement do not occur suddenly.

In this research framework, the main focus is on developing an adaptive social force model (SFM)-based navigation model, especially in the context of inclined terrain. Previously, social force navigation models have been successfully used in various applications, such as pedestrian avoidance [4]–[10], healthcare robots [11] drones [12], [13], evacuation robots [14]–[17], and navigation of soccer robots [18], [19] some also modify the SFM [20]–[22]. However, in most cases, the use of these models is limited to flat surfaces and does not consider changes that may occur to the robot during travel or navigation.

Therefore, this research aims to develop a SFM system that can adapt to various terrain conditions that may be faced by the robot. This system will be equipped with the ability to detect changes in surface slope in real time and the ability to adjust the forces acting on the robot according to the context of the terrain being traveled. As a result, the acceleration, speed, and heading of the robot can be dynamically adjusted according to the slope of the terrain, allowing the robot to maintain movement stability and respond more effectively to terrain conditions. The forces generated by social force mode will be integrated with other forces that affect the robot's movement, including friction forces that may occur on the robot. Through the integration of these forces, the system will ensure that the speed and heading obtained by the robot remain stable and consistent in the face of diverse terrain conditions. Thus, the robot will have the ability to operate efficiently and safely in a variety of inclined terrains [23]–[25].

2. METHOD

2.1. Social force model

SFM, introduced by Helbing and Molnar [26], [27], is a system used to predict the possible behavioral-based movements of agents or individuals based on the attractive and repulsive forces acting on them. It considers both physical and social factors that influence agent movements. In the SFM, three types of forces influence agent movements, namely an attractive force toward the goal, a repulsive force against a static obstacle (i.e., walls, buildings, roads), and a repulsive force against a dynamic obstacle (i.e., human). Figure 1 depicts the relation between all force components in the SFM framework.

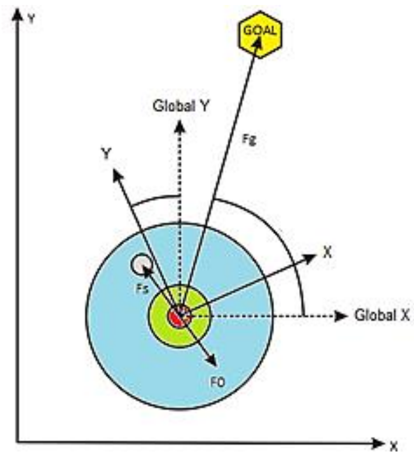


Figure 1. The relation between all force components in SFM framework

The primary objective of the SFM is to determine the navigation force, denoted as F_{nav}, essential for guiding a mobile robot through its environment. This is achieved through the intricate calculation of a resultant force derived from three fundamental components. The first component involves an attractive force directed towards the predefined goal, denoted as F_g. Simultaneously, the second component introduces a repulsive force aimed at mitigating potential collisions with static obstacles, represented by F_s. Lastly, the third component incorporates a repulsive force designed to counteract the influence of dynamic obstacles, expressed as F_d. The formulation of these components is fundamental to achieving a nuanced and balanced navigation force, enabling the mobile robot to navigate effectively by harmonizing attraction towards the goal and repulsion from obstacles, both static and dynamic, within its operational environment.

$$F_{nav} = F_g + F_s + F_d. \tag{1}$$

$$F_g = m \, . \, a \tag{2}$$

The repulsive force against a static obstacle, denoted as F_s, is composed of two main components: the social repulsion force denoted as f_{soc}^{s} and the physical repulsion force denoted as f_{phy}^{s}. The social repulsion force arises from the interactions between the robot and its surroundings, including people or stationary objects. This force captures the social aspect of the robot's environment, reflecting its ability to navigate and interact safely with individuals and objects. On the other hand, the physical repulsion force stems from the tangible interactions between the robot and static objects, such as walls or stationary obstacles. This force is crucial for preventing collisions and ensuring the robot's physical integrity. By summing up these two forces, the overall repulsion force against static obstacles is determined. This comprehensive approach allows the robot to navigate its environment effectively, taking into account both social considerations and physical barriers, ultimately contributing to a more robust and adaptive robotic system.

$$f_{soc}^{s} = k^{s} exp\left(\frac{r_R - d_R^s}{\Psi^s}\right) + e_R^s, \tag{3}$$

$$f_{phy}^{s} = k^{s}(r_R - d_R^s)\, e_R^s, \tag{4}$$

$$F_s = f_{soc}^{s} + f_{phy}^{s}, \tag{5}$$

In the context of the provided formulation, f_{soc}^{s} stands for the robot's social repulsion force against static obstacles, while f_{phy}^{s} represents the robot's physical repulsion force exerted on static obstacles. The parameter r_R corresponds to the radius of the robot's interaction area, and d_R^s denotes the distance from the robot to the nearest static obstacle. The coefficient k^s serves as a gain factor that determines the magnitude of feedback received subsequently. Furthermore, Ψ^s denotes the effective distance value influencing the repulsion force to navigate around dynamic obstacles, and e_R^s is a vector indicating the direction from which static obstacles approach. The repulsive force against a dynamic obstacle F_d arises when there are moving obstacles around the robot. It is also formed through the sum of the social repulsion force and the physical repulsion force. To anticipate the movement of dynamic obstacles, in the SFM framework, a proxemic area radius is given that indicates the possible movements that can occur next.

$$F_d = f_{soc}^{d} + f_{phy}^{d}, \tag{6}$$

$$f_{soc}^{d} = k^{d} exp\left(\frac{r_r^d - d_R^d}{\Psi^d}\right) e_R^d, \tag{7}$$

$$f_{phy}^{d} = k^{d}(r_r^d - d_R^d)\, e_R^d, \tag{8}$$

$$r_r^d = r_R + d_R^d, \tag{9}$$

In the outlined framework, f_{soc}^{d} represents the robot's social repulsion force against dynamic obstacles, while f_{phy}^{d} characterizes the robot's physical repulsion force applied to dynamic obstacles. The parameter r_R signifies the value of the radius defining the robot's detection area, d_R^d indicates the distance from the robot to the nearest dynamic obstacle. The coefficient k^d functions as a gain factor determining the degree of subsequent feedback. Additionally, e_R^d represents a vector indicating the direction from which dynamic obstacles approach, and Ψ^d signifies the value determining the effective distance of the repulsive force to navigate around dynamic obstacles. The parameter r_r^d is derived from the sum of the radius of the robot's proxemics area and the radius of the dynamic obstacle area.

2.2. Inclined force

In this paper, we proposed to consider the inclined terrain factor as shown in Figure 2. Since the robot sometimes needs to navigate in a traverse position on an inclined terrain, a slippery condition may occur and make the robot shift to the side due to gravitation force. The first step in this calculation is to find the value of the normal force (N) acting on the robot, which can be expressed in the following equation related to the forces affecting the robot when traveling on an inclined road, to make the SFM better adapted in its navigation.

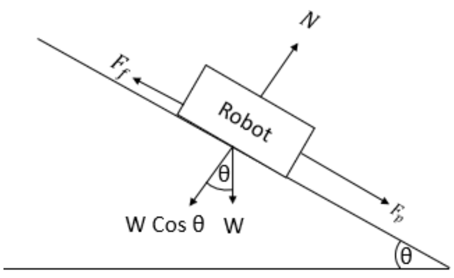


Figure 2. Robot on inclined terrain

$$\Sigma F_y = 0 \tag{10}$$

$$N - W.cos\ \theta\ = 0 \tag{11}$$

$$N = W.cos\ \theta \tag{12}$$

In the context of the given formulation, ΣF_x represents the sum of forces acting on the robot along the x-axis. This includes the weight force, determined by the product of the robot's mass and gravity, and is pivotal in understanding the dynamics of the robot's motion. The angle θ introduced in the formulation signifies the slope of the terrain, measured by the robot's sensor during implementation. This angle enhances the analysis by accounting for the inclination of the surface on which the robot operates. Calculating the resultant force on the x-axis involves determining both the friction force and the parallel force. The friction force arises from the interaction between the robot's wheels or contact points and the surface, opposing motion. The parallel force is a component of the weight force parallel to the terrain's incline.

$$\Sigma F_x = F_p - F_f \tag{13}$$

The parallel force F_p is obtained by multiplying the robot's weight force by $sin\ \theta$, indicating that the greater the inclination of the plane, the greater the parallel force generated. Meanwhile, the friction force F_f is calculated by multiplying the friction coefficient μ by the normal force N, which has been calculated previously. This coefficient of friction depends on the material of the plane being traversed and the material of the robot wheel. In this study, the coefficient of friction is considered constant. In this paper, we ignored the dynamic obstacle since it can be simplified and equated with an approach to static obstacles. The resultant of the robot's force on the x-axis when going through the inclined plane can be added to the SFM so the robot can minimize the force that occurs on the inclined plane.

$$F_p =\ W.sin\ \theta \tag{14}$$

$$F_f =\ \mu\ .N \tag{15}$$

$$F_f\ \ = \mu.(W.cos\ \theta) \tag{16}$$

$$F_{nav} = F_g + F_s +\ F_p - F_f \tag{17}$$

2.3. Fuzzy inference system

The k and Ψ values as shown in (3) and (4) are gain values that are made adaptive based on the fuzzy inference system [18], [19], in previous research, the robot detection area can be divided [7], [8]. Table 1 shows the fuzzy rule for static obstacles which deals with the division of the proxemics area (robot detection area). The k gain function is used to measure the extent to which the robot responds or reacts to the influence of obstacles in this model. A higher value of gain k will result in a stronger response to the obstacle, while a lower value of gain k will result in a weaker response. In this paper, we also ignored the Ψ value, since it does not have a significant impact and can be determined manually.

Table 1. Fuzzy rule for static obstacle

R		Obstacle Distance			
		Intimate	Personal	Social	Public
Obstacle Angle	Front	50	25	25	25
	Side-Front	25	25	12.5	12.5
	Side	12.5	6.25	6.25	6.25

Figure 3 explains the division of the radius of the proxemic area [28], [29], delineating specific zones based on interpersonal distances. These zones include intimate space (less than 45 cm), personal space (45 to 120 cm), and social space (121 to 360 cm), while areas beyond these boundaries are classified as public spaces. In the context of the SFM, the model primarily focuses on detecting and responding to forces within the intimate, personal, and social spaces. Notably, public space, although not directly detected by the SFM, is still factored into the decision-making process through the application of fuzzy logic. Fuzzy logic plays a crucial role in determining the adaptive gain value, enabling the robotic system to dynamically adjust its behavior, considering the broader context of public spaces. This integration ensures a more nuanced and adaptive response, accounting for the subtleties of social dynamics across different proxemic zones.

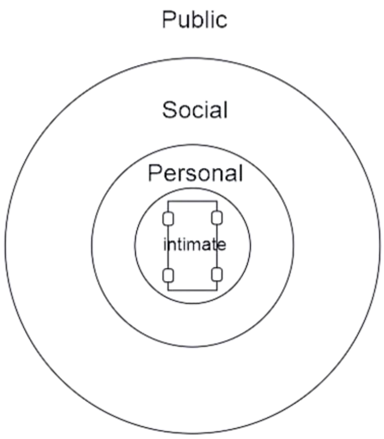


Figure 3. Proxemic area

Based on the partitioning of the proxemic area and the angle of approach by the robot [18], [19], a membership function can be thoughtfully designed, as illustrated in Figure 4. Using this information, the robot gains the ability to discern and react suitably to distinct proxemic zones, thereby optimizing its behavior in alignment with human preferences and interaction constraints. This nuanced approach empowers the robot to operate with heightened adaptability and responsiveness. By incorporating a tailored membership function, the robot not only interprets its surroundings more effectively but also tailors its responses to various proxemic zones, thereby enhancing its overall capacity to navigate and interact in a manner that is attuned to human expectations and preferences.

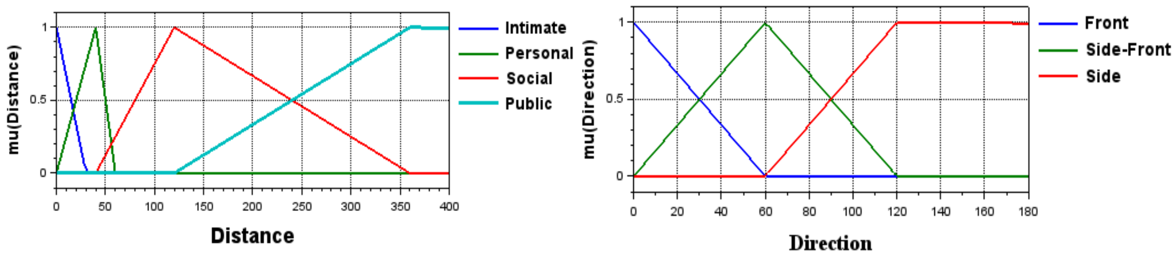


Figure 4. Membership function

3. RESULTS AND DISCUSSION

The SFM simulation was conducted using the CoppeliaSim application using a differential drive mobile robot (DDMR) 4 wheel. This implementation used various programming languages, including C++, Lua, and Python, and connected them through the Robotic Operating System (ROS) communication system, for full specification all hardware and software are in Table 2. The simulation environment used was set up as shown in Table 2. We have developed Lua scripts in CoppeliaSim to control motors within the simulation, enabling both linear and angular speed adjustments as depicted in Figure 5. The SFM algorithm, implemented in C++, includes the calculation of forces on the inclined plane. The implementation of this algorithm is distributed through the ROS communication system. Visualization of the simulation results is displayed using OpenCV with the Python programming language, providing a clear visual representation of the robot’s movement and its interaction with obstacles in the simulated environment. In the context of the robot, its weight is set in the range of about 25 kg and I specified an inclined plane with a slope of approximately 15 degrees. All these settings are designed to achieve accurate and representative simulation results.

Table 2. Simulation specifications

Hardware	Description
Mini PC	IntelNuc
Processor	Intel(R) Core(TM) i5-10210U CPU @ 1.60 GHz
RAM	8192 MB DDR4
HDD	128 GB
Operating System and other Software	Visual Studio Code

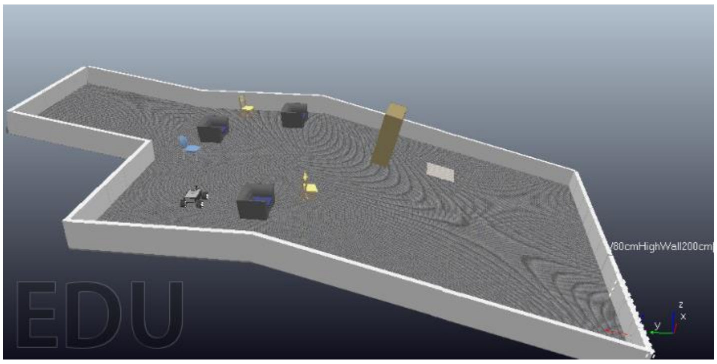


Figure 5. Defined Simulated environment in the CoppeliaSim

The robot will be made to move from the start position to the end position. On this journey, several obstacles will be placed to test the robot's navigation capabilities based on the SFM. Two types of SFM models will be tested. First, the SFM without taking into account the force on the inclined plane is marked with a yellow line, and second, the SFM that takes into account the force on the pre-made inclined plane with a blue line, then the red dots are a representation of the distance reading from the lidar as can be seen in Figure 6, while the corresponding travel times are depicted in Figure 7. The robot successfully navigates and reaches the destination point by avoiding several obstacles using SFM.

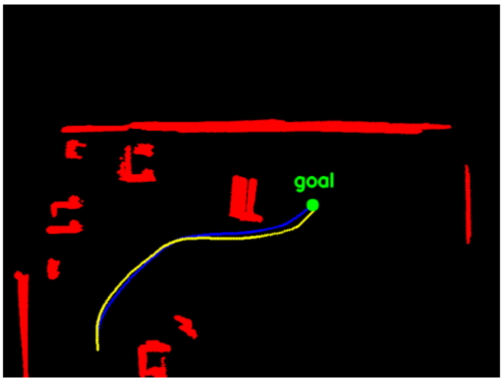
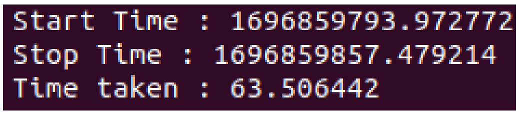
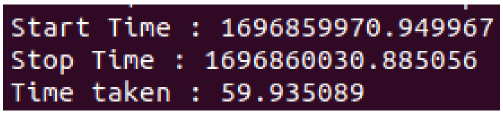


Figure 6. Visualization of robot movement



(a)



(b)

Figure 7. Time taken for the robot to reach the goal (a) without and (b) with force on an inclined plane

The test results reveal a significant difference in the time taken by the robot to reach the finish line. When using the SFM model without considering the forces on the inclined plane, the required time duration is 63.506442 seconds according to Figure 7(a). However, when the robot takes into account the forces on the inclined plane, it can be observed that the robot reaches the goal faster, approximately in 59.935089 seconds according to Figure 7(b). The comparison of values before and after incorporating inclined force calculations is visually presented in Figure 8. A detailed breakdown of these findings is provided in Table 3. Notably, accounting for forces on the inclined plane enables the robot to reach its destination more swiftly by identifying a more efficient route. In practical terms, this optimization reduces slipping and minimizes wasteful movements, contributing to the overall enhanced performance of the robot.

Table 3. Result of the time taken and travel distance

Method	SFM Without Force on an Inclined Plane	SFM With Force on an Inclined Plane
Time	63.506442	59.935089
Distance	16.643172424591	16.095605425016

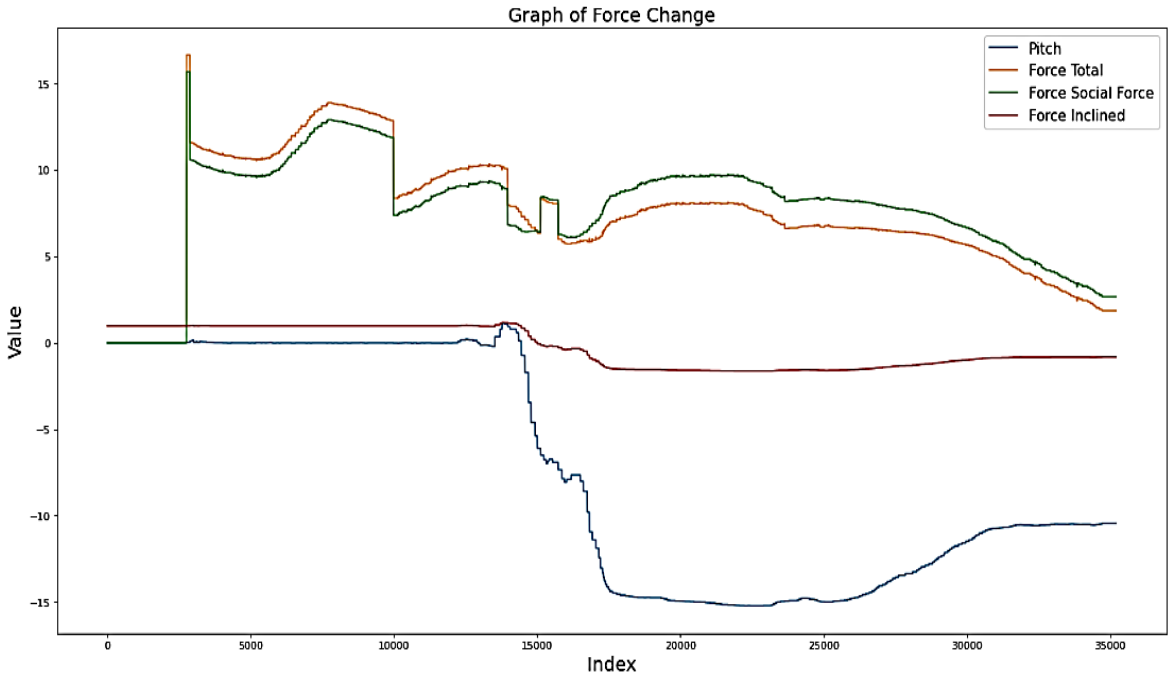


Figure 8. Changes in SFM forces against an inclined plane

In the graphical illustration in Figure 9, the force values in the SFM without considering the inclination of the plane are represented by blue lines, while those that take into account the inclination of the plane are shown in yellow. The force due to the inclination of the plane is represented in red, while the change in pitch on the inclined plane is depicted in blue. It is important to note that when the robot passes through an inclined section that is a descent (being in a downhill position), the system will calculate the force arising from the inclination. As a result, the navigation force in the SFM will decrease, and therefore, the speed of the robot on the inclined plane will also decrease in line with the change in navigation force. By implementing this system, the speed of the robot when using the SFM becomes more adaptive when traveling on an inclined plane. This results in robot navigation that is more stable and responsive to changing terrain conditions, allowing the robot to move efficiently and safely even on surfaces with varying slopes.

4. CONCLUSION

In this work, we successfully overcome the main obstacle of the Social Force Model on inclined terrain by developing an adaptive system that allows the robot to move efficiently and safely on inclined terrain. The force adaptive control we implemented involves real-time detection of changes in surface slope, enabling dynamic adjustment to frictional and parallel forces. Simulation results show a significant improvement in the stability of the robot's movement, reducing the risk of sudden changes in speed and ensuring smoother navigation on inclined terrain. In this context, our research not only enriches the understanding of SFM applications in complex environments but also provides a foundation for the development of future navigation technologies. The ability of robots to dynamically adapt their movements to the terrain will be key in the development of robots that can operate reliably in various environmental conditions. As such, this research not only has an important impact on academia but also opens up new opportunities in the use of robotics technology in various practical applications, including the exploration of difficult environments and hard-to-reach places. We are confident that the findings and approaches we developed in this research will pave the way for further research and development of innovative and reliable robot navigation solutions.

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