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Development of an Omni Directional based Mobile Robot Navigation System using Optimized-Fuzzy Social Force Model

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ABSTRAK

Membangun sebuah sistem navigasi pada mobile robot yang bergerak di ruang sosial perlu memperhatikan beberapa aspek krusial, seperti menghindari rintangan, menjaga arah hadap robot ke tujuan, dan mencapai tujuan dengan cepat. Penelitian ini bertujuan untuk mengembangkan sistem navigasi pada Omnidirectional mobile robot menggunakan Fuzzy-Social Force Model (FSFM). Social Force Model (SFM) mampu menggerakan robot ke tujuan sambil menghindari rintangan. Fuzzy Inference System (FIS) digunakan untuk menghasilkan gain adaptif sebagai salah satu parameter SFM agar respon SFM sesuai dengan masukan dari sensor lidar. Aturan FIS dioptimasi agar mendapatkan nilai optimal menggunakan Particle Swarm Optimization (PSO). Dari hasil percobaan, mobile robot mencapai tujuan lebih cepat dengan selisih 1.59 s dan nilai error heading robot lebih kecil 0.9261 dibandingkan FSFM tanpa optimasi.

Kata kunci*: Sistem Navigasi, Mobile Robot, Fuzzy-Social Force Model, Optimasi, Particle Swarm Optimization*

ABSTRACT

Building a navigation system on a mobile robot moves in social space needs to consider several crucial aspects, such as avoiding obstacles, keeping the robot facing the destination, and reaching the destination quickly. This study aims to develop a navigation system on an Omnidirectional mobile robot using the Fuzzy-Social Force Model (FSFM). The Social Force Model (SFM) guides the mobile robot to its destination while avoiding obstacles. The Fuzzy Inference System (FIS) produces adaptive gain as one of the SFM parameters so that the response of the SFM matches the data of the lidar sensor. The rule base of FIS is optimized to get the optimal value using Particle Swarm Optimization (PSO). From the experimental results, mobile robots reach the destination faster with a difference of 1.59 s and a minor error in robot heading of 0.9261 compared to FSFM without optimization.

Keywords*: Navigation System, Mobile Robot, Fuzzy-Social Force Model, Optimization, Particle Swarm Optimization*

1. INTRODUCTION

In this modern era, developments in robotics continue to increase rapidly. Along with these developments, applications and tasks that robots can perform are becoming increasingly complex and complicated, especially in mobile robots. In addition, mobile robots must also be equipped with good navigation algorithms to move into the target position without crashing into any objects around them while completing their tasks **(Shayestegan & Marhaban, 2012)**. A mobile robot with a holonomic system like Omni directional mobile robot can move freely in all directions without changing its heading orientation **(Afridi & Usman, 2019)**.

While the mobile robot navigates to a certain point, the robot also needs to consider various obstacles around it. There are two categories of obstacles in the environment, non-moving obstacles known as static obstacles and moving obstacles known as dynamic obstacles **(Majeed, et al., 2021)**. Social Force Model introduced by **(Helbing & Molnár, 1995)** states that an agent, in this case, a mobile robot avoids colliding with static obstacle and dynamic while it navigates to the destination point.

Several studies are implementing Social Force Model (SFM) into a mobile robot to navigate **(Tamura, et al, 2010) (Yang, et al., 2019)**. Besides that, several applications of SFM are used for other purposes, such as companion robots **(Ferrer, et al., 2013)**, the human leader following robot **(Kuderer & Burgard, 2014)**, human guide robot **(Dewantara & Miura, 2017) (Muallimi, et al., 2020)**, human-robot collision avoidance **(Ratsamee, et al., 2013)**, social robot navigation **(Kivrak, et al., 2021)**. Other researchers have developed SFM applications in tour-guide robots **(Bellarbi, et al., 2017)**, healthcare robot navigation **(Rifqi, et al., 2021)**, and SFM in quadcopter robots **(Gil, et al., 2021)**. Another research developed SFM for robosoccer navigation purpose **(Dewantara & Ariyadi, 2021)** using Fuzzy-Social Force Model implemented into a ball-playing soccer robot to move from its goalpost to the opponent's goalpost without colliding with another robot.

This research aims to implement a navigation system based on **(Dewantara & Ariyadi, 2021)** with the combination of the Fuzzy-Social Force Model (FSFM) into a mobile robot that can navigate through a social environment that consists not only of humans as the dynamic obstacle but also static obstacles such as walls or cabinets.

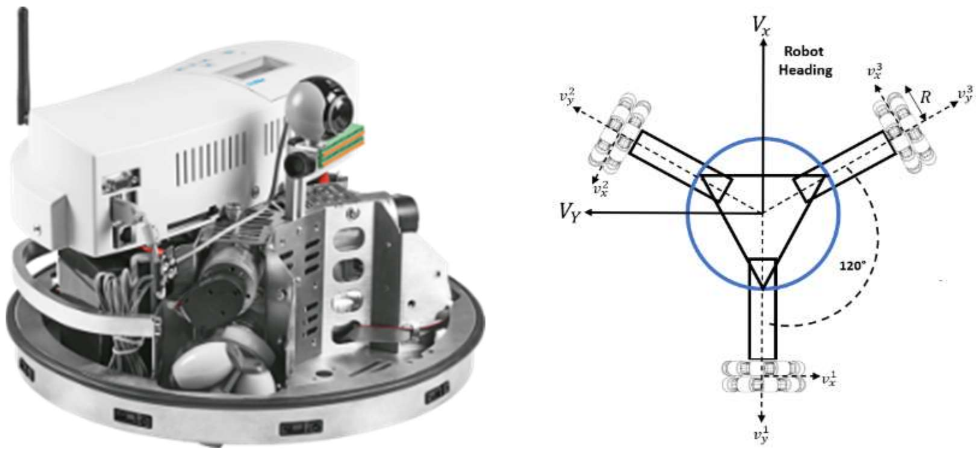
The Social Force Model (SFM) is used to navigate the mobile robot from start to goal while avoiding colliding with static and dynamic obstacles. The fuzzy used to generate gain needed for SFM to perform avoidance movement based on distance and position of the obstacle. We also added Particle Swarm Optimization as optimization for the FSFM so the FSFM can be more adaptable while navigating the social environment. The trial was conducted in realistic 3D simulation software VREP with scene design as a social environment with a mobile robot, human, and object.

The remainder of this paper is organized as follows. Section 2 describes the kinematic of the Omni directional wheel mobile robot and our proposed method. Section 3 describes the result and discussion of the experiment, and Section 4 explains the conclusion of this paper.

2. METHODS

2.1 Omni Directional Mobile Robot

This study experiment uses an Omni directional mobile robot with three-wheeled Omni wheel configuration. The robot model uses the Robotino mobile robot model, as shown in Figure 1.



(a) **(b)**

Figure 1. (a) Robotino Robot (b) Omni directional mobile robot with three-wheeled Omni wheel configuration

The inverse kinematics used is based on **(Dewantara & Ariyadi, 2021)** to move the robot in Equation (1)-(4).

$$V_x = \frac{R(v_X^3 - v_X^2)}{\sqrt{3}} \tag{1}$$

$$V_y = \frac{R(-v_X^1 - 2v_X^2 + 2v_X^3)}{3} \tag{2}$$

$$V_\theta = \frac{R(v_X^1 + v_X^2 + v_X^3)}{3L} \tag{3}$$

$$\begin{bmatrix} V_x \\ V_y \\ V_\theta \end{bmatrix} = \begin{bmatrix} 0 & -\frac{R}{\sqrt{3}} & \frac{R}{\sqrt{3}} \\ -\frac{R}{3} & -\frac{2R}{3} & \frac{2R}{3} \\ \frac{R}{3L} & \frac{R}{3L} & \frac{R}{3L} \end{bmatrix} \begin{bmatrix} v_X^1 \\ v_X^2 \\ v_X^3 \end{bmatrix} \tag{4}$$

Where V_x and V_x are the velocity of the mobile robot in x and y axis movement, V_θ is representing the angular velocity of heading mobile robot, R is wheel radius of the mobile robot use, L is axle length between each mobile robot wheel. v_X^i and $-v_Y^i$ are representing the velocity of each wheel on the x-axis and y-axis.

To generate the velocity of each mobile robot wheel from the information of V_x, V_y, V_θ using Equation (5).

$$\begin{bmatrix} v_X^1 \\ v_X^2 \\ v_X^3 \end{bmatrix} = \begin{bmatrix} 0 & -\frac{1}{R} & \frac{L}{R} \\ -\frac{\sqrt{3}}{2R} & \frac{1}{2R} & \frac{L}{R} \\ \frac{\sqrt{3}}{2R} & \frac{1}{2R} & \frac{L}{R} \end{bmatrix} \begin{bmatrix} V_x \\ V_y \\ V_\theta \end{bmatrix} \tag{5}$$

2.2 Fuzzy-Social Force Model (FSFM) Optimized by PSO

2.2.1 Social Force Model (SFM)

Social Force Model is used based on **(Dewantara & Miura, 2017)** as a navigation system that drives the mobile robot navigation to a goal in the social environment while considering the obstacle around the mobile robot. Social Force Model can consider many objects around the environment as an obstacle which can define into two categories. These are non-moving obstacles called static obstacles dan moving obstacles called dynamic obstacles. When the mobile robot navigates into the social environment, the robot will attract to move toward the goal called attractive force toward the goal $\mathbf{F}^g$ with Equation (6).

$$\mathbf{F}^g = m\frac{\boldsymbol{v}^0 - \boldsymbol{v}^t}{\boldsymbol{\tau}} \tag{6}$$

Where m is the mass of the mobile robot, $\boldsymbol{v}^0$ is desired velocity of the mobile robot (m/s), $\boldsymbol{v}^t$ is the actual velocity of the mobile robot (m/s) and $\boldsymbol{\tau}$ is the relaxation time (s). The avoidance movement of the mobile robot based on obstacle can divide into the force to avoid static obstacle movement called repulsive force toward static obstacle $\mathbf{F}^h$ and force to avoid dynamic obstacle called repulsive force toward the dynamic obstacle $\mathbf{F}^k$. The equation for repulsive force movement avoidance toward static obstacles in Equation (7)-(9).

$$\mathbf{F}^h = \mathbf{F}^h_{soc} + \mathbf{F}^h_{phy} \tag{7}$$

$$\mathbf{F}^h_{soc} = \mathbf{k}^h \, exp\left(\frac{\mathbf{r}_{R_h} - \mathbf{d}_{R_h}}{\boldsymbol{\psi}^h}\right)\mathbf{e}_{R_h} \tag{8}$$

$$\mathbf{F}^h_{phy} = \mathbf{k}^h \, exp\left(\mathbf{r}_{R_h} - \mathbf{d}_{R_h}\right)\mathbf{e}_{R_h} \tag{9}$$

Where $\mathbf{k}^h$ is gain value to navigation avoidance of the static obstacle, $\mathbf{r}_{R_h}$ is total of mobile robot radius added with static obstacles radius when both collide in the social environment, $\mathbf{d}_{R_h}$ is the distance of closest static obstacle to the mobile robot. $\boldsymbol{\psi}^h$ the value representing the effective range of influence of the force related to a static obstacle and $\mathbf{e}_{R_h}$ is the vector of the direction from the static obstacle to the mobile robot. For the repulsive force movement avoidance toward dynamic obstacle in Equation (10)-(12).

$$\mathbf{F}^{k} = \mathbf{F}^{k}_{soc} + \mathbf{F}^{k}_{phy} \tag{10}$$

$$\mathbf{F}^{k}_{soc} = \mathbf{k}^{k}\, exp\left(\frac{\mathbf{r}_{R_k} - \mathbf{d}_{R_k}}{\boldsymbol{\psi}^{k}}\right)\mathbf{e}_{R_k} \tag{11}$$

$$\mathbf{F}^{k}_{phy} = \mathbf{k}^{k}\, exp\left(\mathbf{r}_{R_k} - \mathbf{d}_{R_k}\right)\mathbf{e}_{R_k} \tag{12}$$

Where $\mathbf{k}^{k}$ is gain value to navigation avoidance of the dynamic obstacle, $\mathbf{r}_{R_k}$ is total of mobile robot radius added with dynamic obstacles radius when both collide in the social environment, $\mathbf{d}_{R_k}$ is the distance of closest dynamic obstacle to the mobile robot, $\boldsymbol{\psi}^{k}$ is the value representing an effective range of influence of the force related to a dynamic obstacle and $\mathbf{e}_{R_k}$ is the vector of the direction from the dynamic obstacle to the mobile robot.

2.2.2 Fuzzy Design

Fuzzy is used to produce adaptive gain value k from information of obstacle position and distance. The gain value is needed for SFM to give an exact response based on obstacles around the mobile robot and navigate to avoid static and dynamic obstacles. The mobile robot will be divided into four areas, shown in Figure 2, and the membership function of fuzzy is shown in Figure 3. The membership function of the fuzzy consists of the distance and position of the obstacle to the mobile robot with the aim of more adaptive robot navigation depending on that information. The gain value of SFM in the fuzzy rule is set in a more significant value when the obstacle is near the robot, so the robot is more reactive to avoiding and does not crash into the obstacle. The robot is also more reactive if the obstacle is in front of the robot, which has the potential to hinder the robot's navigation to the goal.

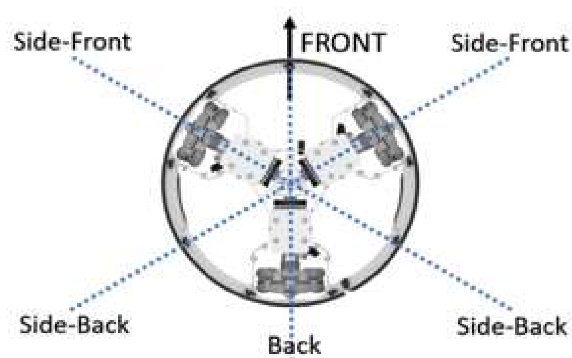
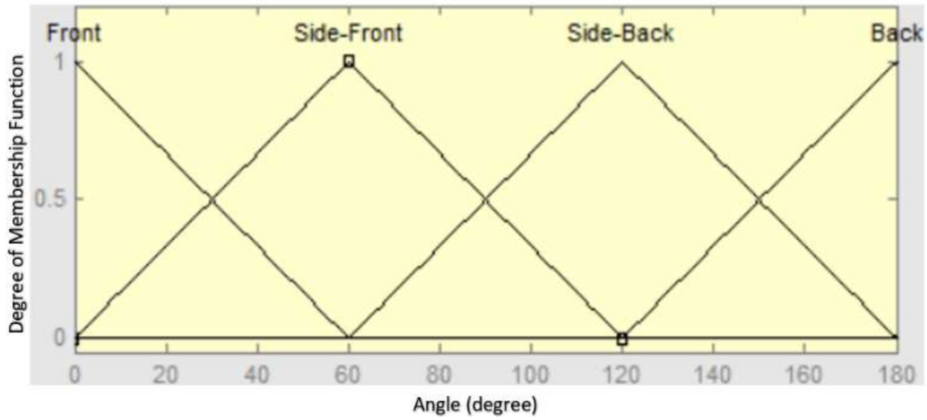
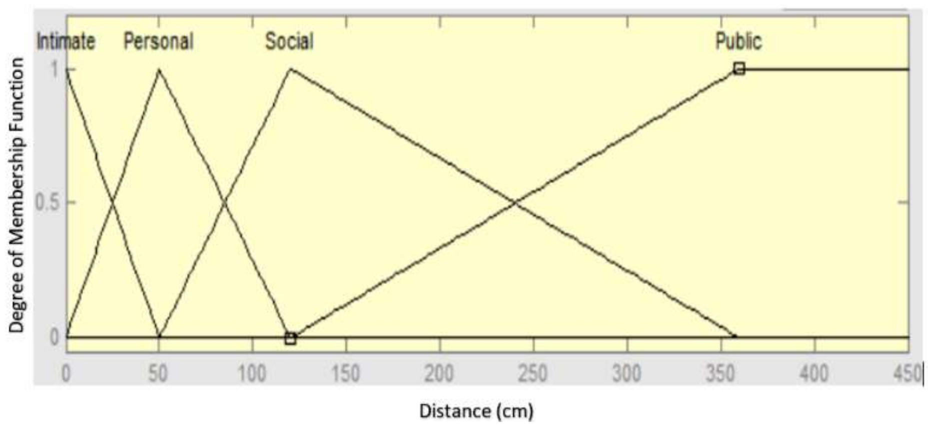


Figure 2. Mobile robot divided area



(a)



(b)

Figure 3. Fuzzy membership function of obstacle (a) angle to mobile robot (b) distance to mobile robot

The fuzzy rule was categorized into two, fuzzy rule with self-determined value and fuzzy rule value optimized with Particle Swarm Optimization (PSO). The fuzzy rule of that self-determine value is shown in Table 1.

Table 1. Fuzzy Rule

Obstacle		Distance			
		Intimate	**Personal**	**Social**	**Public**
Direction	**Front**	1000	500	500	500
	Side-Front	500	500	200	50
	Side-Back	200	200	50	50
	Back	50	50	50	25

The value of the fuzzy rule in Table 1 represents the gain value used in SFM based on information on the distance and position of the obstacle to the mobile robot. The greater the gain value, the faster the response of the mobile robot to avoid these obstacles. The value of the fuzzy rule is set with this value rule so that the robot is more reactive if the obstacle is in the forward direction with the mobile robot. In contrast, the robot is less reactive to avoiding if the obstacle is behind the robot. The closer the obstacle to the mobile robot, the greater the gain value, and vice versa.

2.2.3 Particle Swarm Optimization

In the navigation process, it is difficult to find the most effective gain factor, $\mathbf{k}$, for each force's equations in different situations. Therefore, the Fuzzy rules used in the Social Force Model need to be optimized. According to **(Abdalla & Abdulkareem, 2013)**, PSO for tuning the parameter of fuzzy results the good performance result in a shorter time rather than other optimization methods. The PSO optimized FSFM based on **(Marini & Walczak, 2015)**. The first step of PSO is determining the number of particles and sub-particles used in PSO optimization. In this research, the number of particles used is 5. Each particle represents a set of fuzzy rules, which contains 16 sub-particles of fuzzy rules. The PSO equation to update each particle's velocity and position is shown in Equation (13) and Equation (14).

$$Vel_{i,j} = Vel_{i,j} + c_1 \,.\, r_1 \,.\, \left(Pbest_{i,j} - P_{i,j}\right) + c_2 \,.\, r_2 \,.\, \left(Gbest_j - P_{i,j}\right) \tag{13}$$

$$Pos_{i,j} = Vel_{i,j} + P_{i,j} \tag{14}$$

The PSO also needs a general parameter to run the optimization phase. The parameter is shown in Table 2.

Table 2. PSO General Parameter

Parameter	Value
Particle	5
Sub-particle	16
C1	2
C2	2
Particle Max Value	1000
Particle Min Value	25
Iteration	10, 20, 50, 100

Every optimization requires an $\boldsymbol{Objective\ Function}$ to evaluate and update the optimization value to get the best value. In this case, the $\boldsymbol{Objective\ Function}$ to be used is in Equation (15).

$$\boldsymbol{Objective\ Function} = \boldsymbol{Reward} + \boldsymbol{Travel\ time} + \boldsymbol{\alpha_{Goal}} \tag{15}$$

Where $\boldsymbol{Reward}$ represents rewards for each iteration. If the robot reaches the goal, the reward is worth 100. Meanwhile, if the robot does not reach the goal, the reward is worth 1000. $\boldsymbol{Travel\ time}$ is the time it takes the robot to navigate in one iteration. This time will stop if the robot reaches the goal. $\boldsymbol{\alpha_{Goal}}$ is the difference between the direction of the goal position towards the robot and the direction of the mobile current heading. To get the $\boldsymbol{\alpha_{Goal}}$ value, the equation that will use is in Equation (16).

$$\boldsymbol{\alpha_{Goal}} = \frac{\sqrt{(\boldsymbol{Goal\ direction} - \boldsymbol{Robot\ heading})^2}\,\boldsymbol{)}}{\boldsymbol{n}} \tag{16}$$

Where $\boldsymbol{Goal\ direction}$ is the direction of the goal position towards the robot, $\boldsymbol{Robot\ heading}$ is the direction of the mobile current heading and $\boldsymbol{n}$ is total data. To illustrate to particle and sub-particle distribution to fuzzy rule shown in Figure 4.

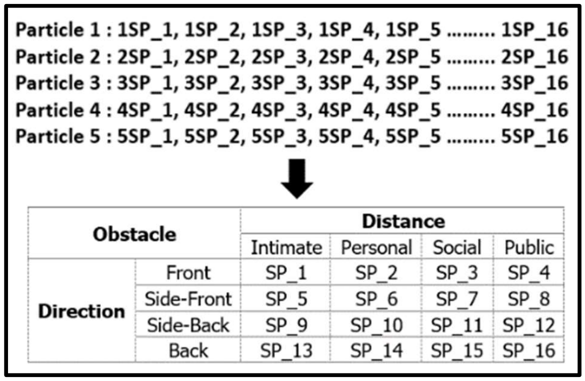


Figure 4. Particle and sub-particle distribution into fuzzy rule

The result of the objective function of each simulation is a fitness value. For each iteration, the smallest particle value will be assigned as Pbest. Meanwhile, for the five particles running in optimization, the smallest value will be taken as the Gbest value. At the end of the optimization iteration, the Gbest value is the best result of the simulation containing the optimized fuzzy rule value. The flowchart of PSO-based optimized FSFM can be shown in Figure 5.

3. RESULT AND DISCUSSION

For the experiment test, we conducted the simulation on VREP software with the mobile robot Robotino and the environment, consisting of several objects and humans. The experiment was made as realistic as possible with the natural environment imitating an indoor room. For simulation run on the laptop with specifications shown in Table 3. For the FSFM, several parameters need to be set, as shown in Table 4.

Table 3. Laptop Specification

PROCESSOR	Intel(R) Core (TM) i7-6700HQ CPU @ 2.60GHz
RAM	16 GB
OS	WINDOWS 10 HOME
Software and peripherals	Visual Studio C++ 2019 OpenCV 2.4.9 libraries VREP 3.6.2

Table 4. FSFM parameter

Parameter SFM	Value
Mass of Robot	5 kg
Maximum Velocity of Robot	0.5 m/s
Proxemics Type	Circle
Proxemics Radius	1 m
Effective Range (ψ)	1 m

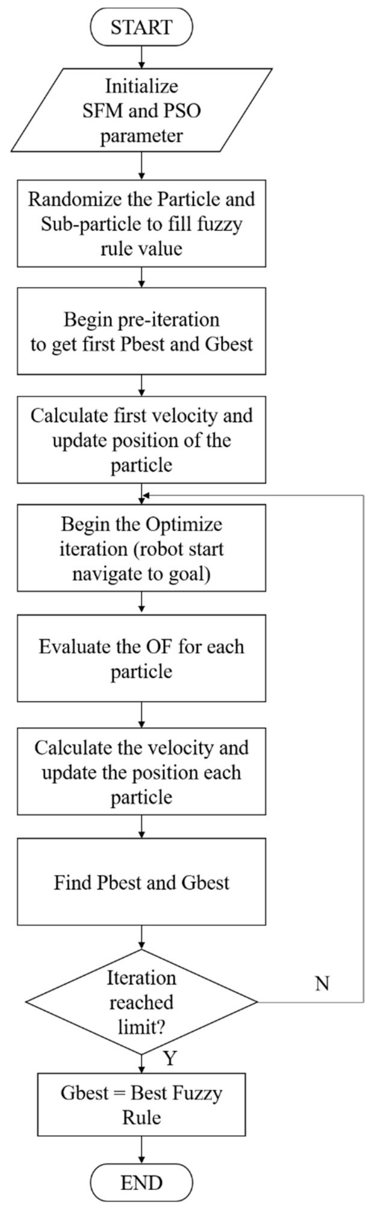


Figure 5. Flowchart of PSO-based optimized FSFM

Proxemics mentioned in Table 4 is the area used in mobile robots and dynamic obstacles based on **(Helbing & Molnár, 1995)** mimicking the pedestrian space that responds if proxemics distance each other collide. The mobile robot will navigate to avoid movement if its proxemics distance collides with the proxemics distance of the dynamic obstacle or if the static obstacle penetrates the mobile robot's proxemics distance area.

The VREP simulation software as a robot movement simulator is connected to Visual Studio C++ 2019 using API C++ connection. Through the VREP software, there are information data collected to help in working on the simulation, such as the position of the robot (x, y) in the simulator, the mobile robot heading direction, and the position of the human as a dynamic obstacle (x, y) and the position of the goal (x, y). As for the position of the static obstacle using data from LIDAR embedded in the mobile robot.

3.1 Fuzzy-Social Force Model (FSFM) testing

This test is carried out to see the performance of FSFM with the self-determined value of the fuzzy rule. The test was carried out four times, with the results of the navigation of the mobile robot shown in Figure 6. S and G in Figure 6 represent the Start and Goal of the mobile robot.

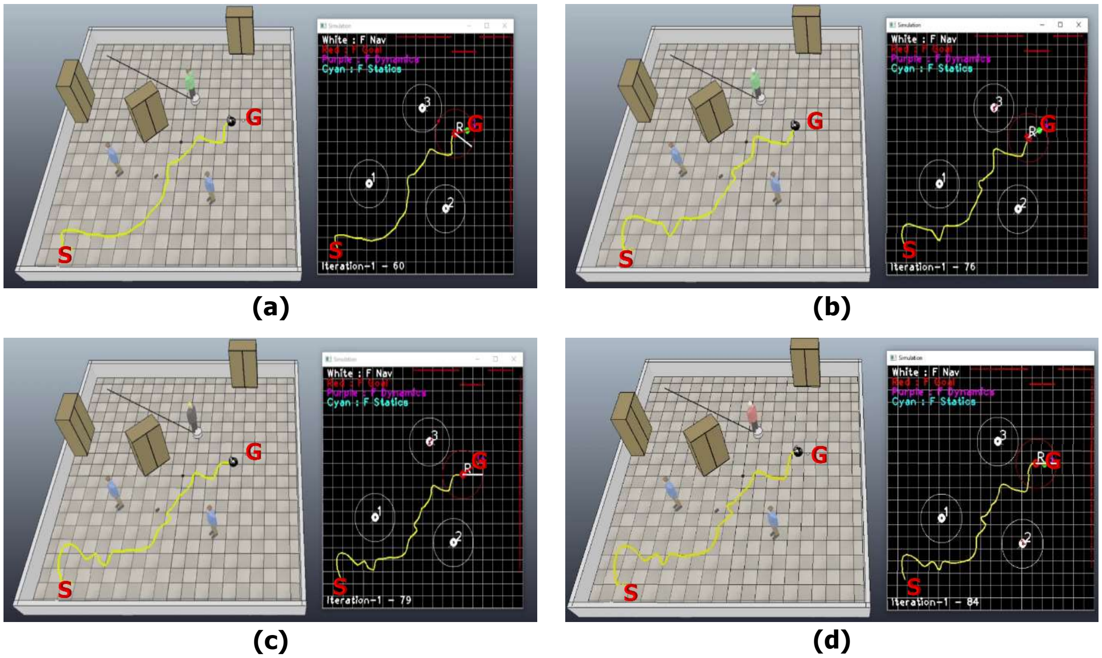


Figure 6. Fuzzy-Social Force Model Result Trial (a) First Trial (b) Second Trial (c) Third Trial (d) Fourth Trial

Each trial collected data to see the performance of the FSFM. The results of the data taken for each trial are shown in Table 5.

Table 5. Data result of FSFM Trial

Trial	Reach Goal ?	Time (s)	α_{Goal}	Step
1	Yes	27.55	1.3434	62
2	Yes	37.99	1.4942	79
3	Yes	39.42	1.4396	82
4	Yes	43.07	1.3884	85

Based on the FSFM trial result, the FSFM can navigate the robot from start to goal without hitting static and dynamic obstacles.

3.2 Fuzzy-Social Force Model (FSFM) testing with PSO optimization

Particle Swarm Optimization is used to optimize the value of the Fuzzy rule used in the Fuzzy-Social Force Model (FSFM), which previously determined the value independently. Several iterations are carried out at this testing stage to see and compare each other. For the PSO-based optimized FSFM, several iteration trials conduct to compare the best result for navigation of the mobile robot. The iteration number tests are 10, 20, 50, and 100. The mobile robot navigation movement of PSO-based optimized FSFM is shown in Figure 7.

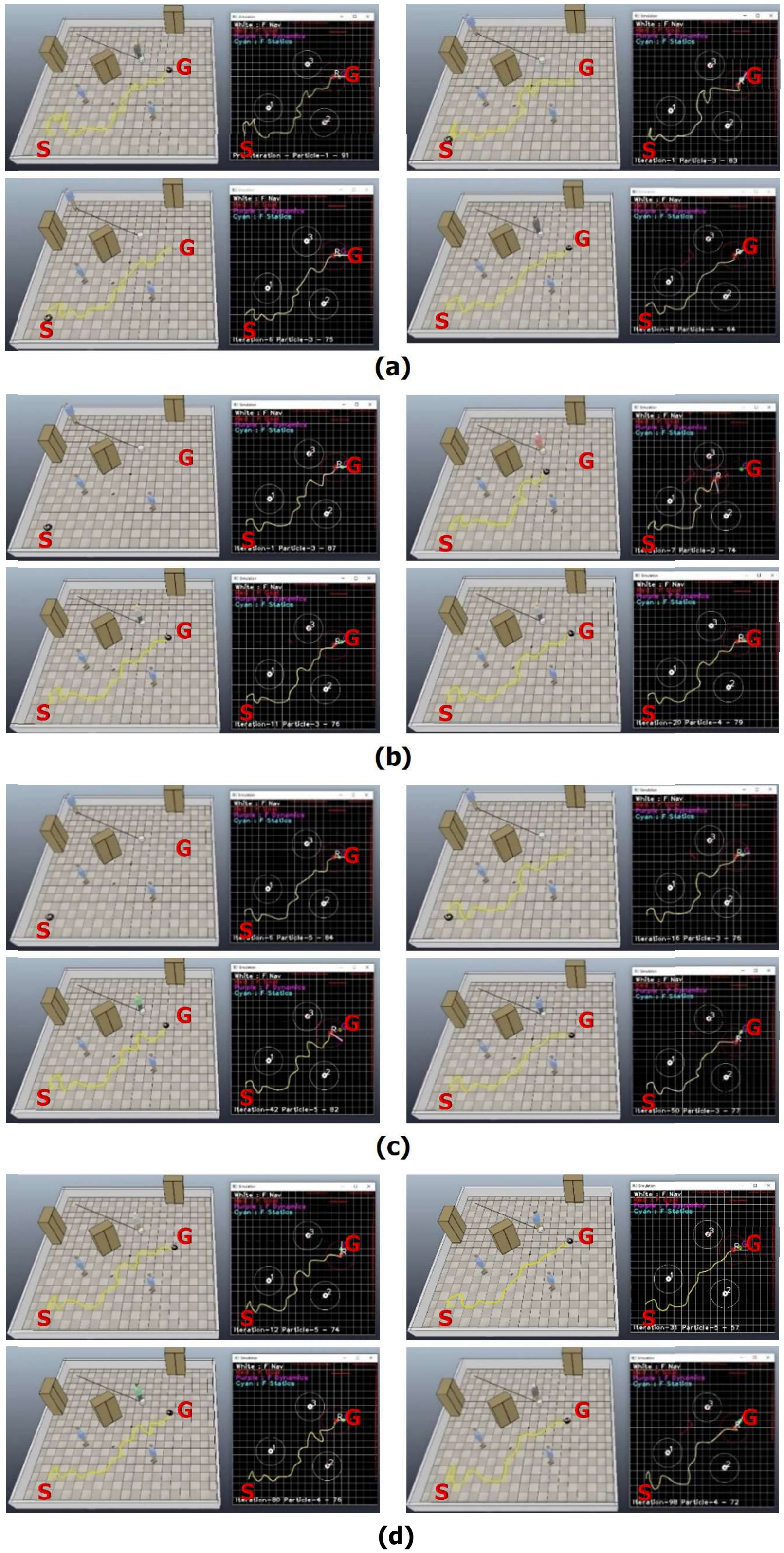


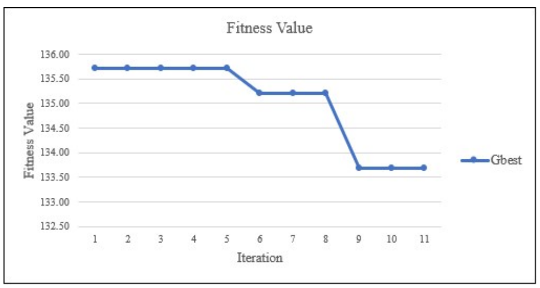
Figure 7. PSO based Optimization FSFM with (a) Iteration = 10 (b) Iteration = 20 (c) Iteration = 50 (d) Iteration = 100

S and G in Figure 7 represent the Start and Goal of the mobile robot. Each iteration will simulate the mobile robot moving from start to goal, while PSO will tune up the value of the fuzzy rule based on robot performance. The performance of PSO-based optimized FSFM in each iteration trial is shown in Table 6.

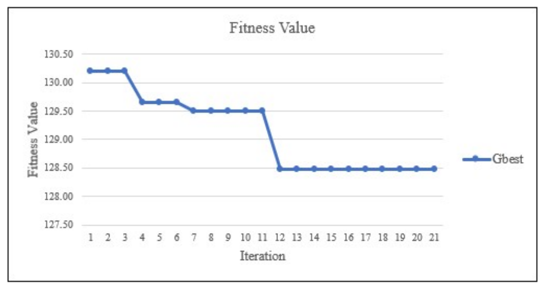
Table 6. Data result of PSO based optimized FSFM Trial

Iteration	Reach Goal ?	Time (s)	α_{Goal}	Step	Fitness Value
10	Yes	33.24	0.4442	82	133.69
20	Yes	27.92	0.5506	79	128.47
50	Yes	27.28	0.4247	77	127.71
100	Yes	25.96	0.4173	59	126.38

Each PSO-based optimized FSFM iteration will produce Pbest and Gbest values. The Pbest value is the personal best of each particle collected from iteration running, while Gbest is the best value taken from the entire Pbest. The Gbest value is called the fitness value. The evolution of the fitness value for each iteration is shown in Figure 8.



(a)



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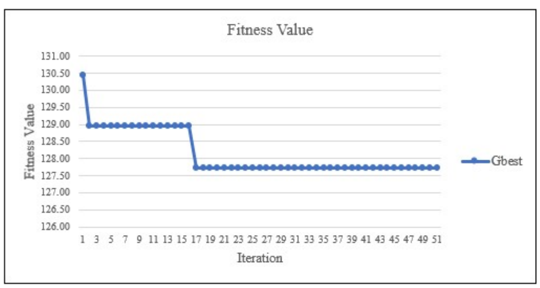

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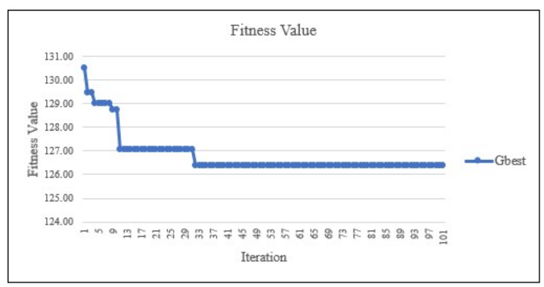

(d)

Figure 8. PSO based optimized FSFM Fitness Value Evolution (a) Iteration = 10 (b) Iteration = 20 (c) Iteration = 50 (d) Iteration = 100

After data from PSO-based optimized FSFM was collected, we tried to compare the result from both testing trials of FSFM with and without optimization. The comparing data result is shown in Table 7.

Table 7. Comparison of FSFM Data Results with and without optimizing

FSFM	Trial	Reach Goal ?	Time (s)	α_{Goal}	Step
FSFM without optimizing	1	Yes	27.55	1.3434	62
	2	Yes	37.99	1.4942	79
	3	Yes	39.42	1.4396	82
	4	Yes	43.07	1.3884	85
PSO-based optimized FSFM	**Iteration**	**Reach Goal ?**	**Time (s)**	α_{Goal}	**Step**
	10	Yes	33.24	0.4442	82
	20	Yes	27.92	0.5506	79
	50	Yes	27.28	0.4247	77
	100	**Yes**	**25.96**	**0.4173**	**59**

From the comparison data result of FSFM with and without optimization, the PSO-based optimizing FSFM resulting the best performance value in time taken to goal, $\boldsymbol{\alpha_{Goal}}$, and step value. The PSO as optimization works well to optimize the fuzzy rule based adapting the social environment simulation on the performance of the travel time to the goal, $\boldsymbol{\alpha_{Goal}}$, and the success rate of the robot's movement to the goal. The PSO-based outperforms the FSFM without optimization because the fuzzy rule FIS optimized to get the best value based on the time taken to goal, error margin of $\boldsymbol{\alpha_{Goal}}$ and success rate of mobile robot navigate to goal.

4. CONCLUSION

This research has developed a navigation system using the Fuzzy-Social Force Model (FSFM) optimized with Particle Swarm Optimization (PSO) into an Omnidirectional mobile robot. As a primary navigation algorithm, the Social Force Model (SFM) can navigate the mobile robot towards the goal position without colliding with static or dynamic obstacles. At the same time, the fuzzy generates adaptive gain value needed by SFM to perform avoidance navigation based on the distance and position of the obstacle. The fuzzy input consists of information distance and position of the obstacle. The PSO is used to optimize the fuzzy rule of FSFM so the FSFM can be more adaptable to the social environment. The results of the experiments that have been carried out have shown that FSFM can navigate the mobile robot from start to goal without hitting obstacles around it. The experimental results also show that the PSO optimized FSFM drives the mobile robot to navigate faster and more accurately to reach the goal than the FSFM without optimization. In the future, we will try to adapt more parameters at once to get better results. Additionally, we will be implementing our method combined with the Robot Operating System (ROS) into real robots to test the performance of the PSO-based FSFM in a natural social environment.

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