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Real-Time Motion Planning of Multiple Mobile Robots Using Artificial Potential Field Method

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Abstract: *This paper focuses on autonomous motion planning of multiple mobile robots in an unknown cluttered environment based on Artificial Potential Field (APF) method. The navigation technique of robot control using new artificial potential function depends on the distances between obstacle positions with respect to robots and targets and bearing angles between them, while classical approaches make use of the distances between obstacle positions with respect to the robots and targets. In this particular application, the new potential field function has been proposed to approximate the robots to the nearest targets and also each robot finds particular target assigned to them in an effective manner. The local minima problem has been solved by redefining the repulsive potential field. In order to avoid inter robot collision each robot incorporates a set of collision prevention rules implemented as a Petri Net model in its controller. The resulting navigation algorithm has been implemented on real mobile robots and tested in various environments. Experimental results presented demonstrate the effectiveness and improved performance of the developed controller navigation scheme.*

Keywords: *Multiple robots, Obstacle avoidance, Collision free, Target seeking, Petri net model, Artificial potential field*

1. INTRODUCTION

The path planning and control of mobile robots in a dynamic environment has been an area of great interest to many AI researchers. In order to navigate safely in an unknown environment, a mobile robot needs to deal with the uncertainty and imprecise or incomplete information about the environment in a timely manner. The Potential field method is commonly used for autonomous navigation in the past decade because of its elegant mathematical analysis and simplicity. The basic concept of the potential field method is to fill the robot's workspace with an artificial potential field in which the robot is attracted to its target position and is repulsed away from the obstacles (Latombe, [8]). Most of the previous studies use potential field methods to deal with single mobile robot path planning in stationary environments where target and obstacles were all stationary. However, very limited works have been reported for multiple robots motion planning in a dynamic environment with multiple targets using APF. The following research works have been reported by several investigators for navigation of mobile robot using this method.

Potential field methods, introduced by Khatib [13], are widely used for real time collision free path planning. In this technique the robot gets stuck at local minima before attaining the goal configuration. Borenstein *et al.* [7] have developed a real-time obstacle avoidance approach for mobile robots. The navigation algorithm takes into account of dynamic behavior of a mobile robot and solves the local minimum trap problem. The repulsive force is much larger than the attractive force being considered by them. In otherwords, the target position is not a global minimum of the total potential field. Therefore the robot cannot reach its goal due to the obstacle nearby. Karen *et al.* [18] have discussed about the control of a mobile robot using potential field method. They have validated their result in experimental and simulation mode. McFetridge *et al.* [9] have presented a new reliable methodology for robot navigation and obstacle avoidance based on APF. They have presented simulation results demonstrating the ability of the algorithm to perform successfully in simple environments. Veelaert *et al.* [4] have proposed a landmark-based navigation of mobile robots. They have

mapped the robot motions using potential field method. Mbede *et al.* [2] have focused on autonomous motion planning of manipulators in known environments and with unknown dynamic obstacles. They have also done stability analysis using Lyapunov theory. Tsourveloudis *et al.* [3] have discussed about electrostatic potential field (EPF) path planner in combination with a two-layered fuzzy logic inference engine. They have implemented their theory for real-time mobile robot navigation in a 2-D dynamic environment. Their proposed approach was experimentally tested using the "Nomad 200" mobile robot. Tsuji *et al.* [17] have proposed a new trajectory generation method that allows full control of transient behavior, namely, time-to-target and velocity profile based on the artificial potential field approach for a real-time motion-planning problem of robots. Ren *et al.* [14] have considered potential field-based cooperative motion planning for a distributed team of semi-autonomous robots. They have presented a navigation function by using Gaussian function to model obstacles in order to avoid undesired local minima. Their method was verified in simulations for navigation while avoiding collisions between robots and obstacles as well as collisions among team members.

Min *et al.* [12] have described a new concept of path planning scheme based on APF using virtual obstacle to escape from local minima problem. Arambula *et al.* [5] have presented a new scheme for autonomous navigation of a mobile robot, based on improved artificial potential fields in which multiple auxiliary attraction points have been used to allow the robot to avoid large or closely spaced obstacles. They have conducted the simulation experiments for verification of their theory. Huang *et al.* [6] have proposed a new approach for vision-guided local navigation, based upon a model of human navigation. Their approach for target finding uses the relative headings to the goal and to obstacles, the distance to the goal and the angular width of obstacles, to compute a potential field over the robot heading. They have implemented and tested their method in experimental mode. Ren and McIsaac *et al.* [15] have investigated the inherent oscillation problem of potential field methods (PFMs) in presence of obstacles and in narrow passages. They have used modified Newton's method which greatly improves system performance when compared to the standard gradient descent approach. They have validated their technique by comparing its performance with different potential models by changing different parameters. Pradhan *et al.* [16] proposed a modified potential field method which is suitable for navigation of several mobile robots in complex and unknown environments. Masoud [1] has explored the construction of a decentralized traffic controller for a large group of agents sharing a workspace with stationary forbidden regions using the potential field approach. They have given simulation results for verification of the theory developed. Wachter *et al.* [10] have presented a video which is the results of an effort to adopt APF methods for high-speed, dynamic, non-holonomic robots. The video describes the experimental test bed: a fleet of inexpensive 4-wheel drive skid-steered robots called "Dynabots" capable of speeds up to 10 m/s and accelerations of atleast 4 m^2/s. These robots fuse GPS and inertial measurement to estimate their own state. They communicate via wireless 802.11b.

In this paper a new potential field method for motion planning of mobile robots in presence of static and moving obstacles in a totally unknown environment has been proposed. The classical APF is dependent only on the relative distances between the robots and the surrounding obstacles. This technique also takes care the distances between the robots and bearing angles between them so that the robots do not collide among themselves. Here the new potential function and the corresponding virtual force are defined. The developed potential field has been used as a controller for navigation of multiple mobile robots. To realize the controller in real sense the program is embedded in the robot for online independent navigation. Robots know their position from movements of their respective wheels (as steering angle of robot depends on the left and right wheel velocities). Each robot has an array of ultrasonic sensors for measuring the distances of obstacles around it and an infrared sensor for detecting the bearing of the target. These techniques have been demonstrated in various exercises, which depicts that the robots are able to avoid obstacles as well as negotiate the dead ends and reach the targets efficiently. The developed navigation method can be applied suitably for autonomous cooperative task handling by mobile robots in space mission, hazardous environments and factory shop floors.

2. POTENTIAL FIELD METHOD

The motion-planning problem for multiple mobile robots in a dynamic environment is to control the robots motion from an initial position to final targets while avoiding obstacles. Three assumptions are made to simplify the analysis:

Assumption 1: The robots are of point mass.

Assumption 2: The robots moves in a two dimensional workspace. Its position in the workspace is denoted by $q = [x, y]$.

Assumption 3: At each time instant, only one front obstacle, which is perpendicular to the

robot, one left obstacle and one right obstacle, which are in co-linear with the robot, need to be avoided.

2.1 Analysis of Potential Field Method

2.1.1 Attractive Potential Function

The most common attractive potential function proposed in the literature [2] is;

$$U_{att}(q) = \frac{1}{2}\,\delta\rho^{m}\left(q, q_{Target}\right) \tag{1}$$

where δ is a positive scaling factor.

$\rho(q, q_{\text{Target}}) = \|q_{\text{Target}} - q\|$ is the distance between the robot 'q' and target, q_{Target} and $m = 1$ or 2. Depending upon the value of 'm' the shape of the attractive potential function is determined. (e.g., for $m = 1$, the shape is conical and for $m = 2$, the shape is parabolic.)

The attractive force is given by the negative gradient of the attractive potential field.

$$F_{\text{att}}(x) = -\nabla U_{\text{att}}(x) = \delta(x_{\text{Target}} - x) \quad \text{for } m = 2 \tag{2}$$

where the operator $\nabla = i\,\frac{\partial}{\partial x} + j\,\frac{\partial}{\partial y} + k\,\frac{\partial}{\partial z}$

Therefore,

$$\{U_{Total}\}_{att} = \sum_{s=1}^{r} U_{att}\left(tar_s\right) \tag{3}$$

2.1.2 Repulsive Potential Function

The commonly used repulsive function in the literature [14] is:

$$U_{rep}(obs) = \begin{cases} \frac{1}{2}\,\alpha\left(\frac{1}{\rho\,(q\,,\,q_{obs})} - \frac{1}{\rho_0}\right)^2, & if\ \rho(q\,,\,q_{obs}) \le \rho_0 \\ 0 & if\ \rho(q\,,\,q_{obs}) > \rho_0 \end{cases} \tag{4}$$

Where α is the positive scaling factor, $\rho(q, q_{obs})$ denotes the minimal distance from the robot q to the obstacle, q_{obs}, ρ_0 is the positive constant denoting the distance of influence of the obstacle. The corresponding repulsive force is given by; F_{rep} (obs) = $-\nabla U_{rep}$ (obs)

$$\begin{cases} \alpha\left(\frac{1}{\rho\,(q\,,\,q_{obs})} - \frac{1}{\rho_0}\right)\frac{1}{\rho^2\,(q\,,\,q_{obs})}\nabla\rho(q\,,\,q_{obs}) & if\ \rho\,(q\,,\,q_{obs}) \le \rho_0 \\ 0 & if\ \rho(q\,,\,q_{obs}) > \rho_0 \end{cases} \tag{5}$$

Suppose in the environment there are many obstacles surround the target and robot then, the repulsive potential can be found as follows:

For obstacle 1,

$$U_{rep}(obs_1) = \begin{cases} \frac{1}{2}\,\alpha_1\left(\frac{1}{\rho\,(q\,,\,q_{obs_1})} - \frac{1}{\rho_0}\right)^2 & if\ \rho(q\,,\,q_{obs_1}) \le \rho_0 \\ 0 & if\ \rho(q\,,\,q_{obs_1}) > \rho_0 \end{cases} \quad \text{and}$$

$$F_{rep}(obs_1) = \begin{cases} \alpha_1\left(\frac{1}{\rho\,(q\,,\,q_{obs_1})} - \frac{1}{\rho_0}\right)\frac{1}{\rho^2(q\,,\,q_{obs_1})}\nabla\rho(q\,,\,q_{obs_1}) & if\ \rho(q\,,\,q_{obs_1}) \le \rho_0 \\ 0 & if\ \rho(q\,,\,q_{obs_1}) > \rho_0 \end{cases} \tag{6}$$

For i[th] obstacle,

$$U_{rep}(obs_i) = \begin{cases} \frac{1}{2}\,\alpha_i\left(\frac{1}{\rho\,(q\,,\,q_{obs_i})} - \frac{1}{\rho_0}\right)^2 & if\ \rho(q\,,\,q_{obs_i}) \le \rho_0 \\ 0 & if\ \rho(q\,,\,q_{obs_i}) > \rho_0 \end{cases} \quad \text{and}$$

$$F_{rep}(obs_i) = \begin{cases} \alpha_i\left(\frac{1}{\rho\,(q\,,\,q_{obs_i})} - \frac{1}{\rho_0}\right)\frac{1}{\rho^2(q\,,\,q_{obs_i})}\nabla\rho(q\,,\,q_{obs_i}) & if\ \rho(q\,,\,q_{obs_i}) \le \rho_0 \\ 0 & if\ \rho(q\,,\,q_{obs_i}) > \rho_0 \end{cases} \tag{7}$$

where i is the number of obstacles and varies from 1 to n and α_1, α_2,……α_i are the positive scaling factors for the corresponding obstacles.

Therefore the total repulsive potential due to i number obstacles are,

$$(U_{rep})Total = U_{rep}(obs_1) + U_{rep}(obs_2) + \ldots\ldots\ldots\ldots + U_{rep}(obs_i)$$

$$= \sum_{i=1}^{m} U_{rep}(obs_i) \tag{8}$$

Similarly the total repulsive force due to i number obstacles are,

$$(F_{rep})_{Total} = F_{rep}(obs_1) + F_{rep}(obs_2) + \ldots\ldots\ldots + F_{rep}(obs_i)$$

$$= \sum_{i=1}^{m} F_{rep}(obs_i) \tag{9}$$

Total potential influences on the robot $\{U_{\text{Total}}\}$ = Attractive potential due to r numbers of targets $\{\sum_{s=1}^{r} U_{att}(tar_s)\}$ + Repulsive potential due to n number of obstacles $\{\sum_{i=1}^{n} U_{rep}(obs_i)\}$

Therefore, $$U_{Total} = \sum_{s=1}^{r} U_{att}\left(\text{tar}_s\right) + \sum_{i=1}^{n} U_{rep}\left(obs_i\right) \tag{10}$$

Where 's' is the numbers of targets and varies from 1 to r. Similarly the total force applied on the robot is the sum

of attractive potential forces and repulsive potential forces.

$$F_{Total} = \sum_{s=1}^{r} F_{att}\left(\text{tar}_s\right) + \sum_{i=1}^{n} F_{rep}\left(obs_i\right) \qquad (11)$$

which determines the motion of the robot.

It can be noted that, for the multiple targets case the robots are pulled towards the nearest target because the influence of attractive forces is more for the nearest target and hence the robot will not be trapped between the targets.

When the above induced force is applied for motion planning of multiple mobile robots there are four commonly referred problems [14], as follows: (1) trap situations due to local minima; (2) no passage between closely spaced obstacles; (3) oscillations in the presence of obstacles; and (4) oscillations in narrow passages. However, the above list is not complete. In fact, there is an additional problem, targets non-reachable with nearby obstacles, encountered when the target is very close to an obstacle. When the robot approaches its target, it approaches the obstacle as well. Near the obstacle repulsive force dominates attractive force. Thus, the robot will be repelled away rather than reaching the goal. This is due to the existence of local minima in the environment. This problem has been addressed in the next section.

2.2 Local Minima Problem and New Repulsive Potential Function

In an environment (shown in Fig. 1(a), where the robot position $q = [x, 0]$, target position $q_{\text{target}} = [0, 0]$, obstacle 1 ($q_{\text{obs1}}$) = [0.5, 0] on the right-hand side of the target, obstacle 2 (q_{obs2}) = [–1, 0] on the left-hand side of the target and obstacle 3 (q_{obs3}) = [–0.5, 0.5]) the robot will be trapped in a local minima by using equations mentioned by Katib [1]. Here target and robot is within the influence of obstacle because the robot is very close to the obstacles. Therefore the robot will be trapped due to presence of local minima and can not reach the target.

Case-I (Stationary Obstacles and target)

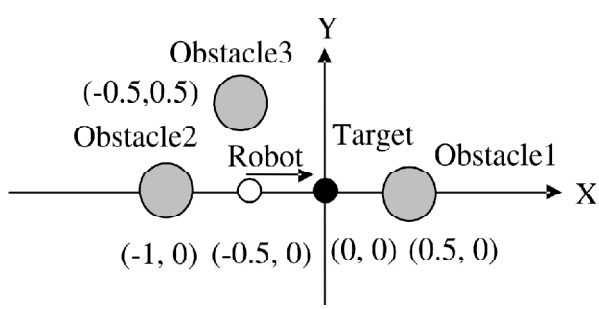

Figure 1(a): Location of Robot, Target and Obstacles for Local Minima Problem

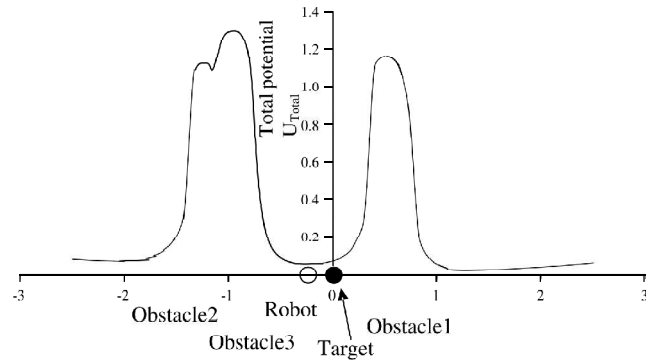

Figure 1(b): Total Potential Function for the Above Case

For the above environment a graph has been plotted between total potential (U_{Total}) verses x-axis which includes the obstacles, robot and target which is shown in Fig. 1(b). It can be observed from the graph that the robot will be trapped at $x = -0.2$. Therefore it is clear that the target is not the minimum of the total potential function. Hence the robot cannot reach the target, though there are no obstacles on its way. Thus robot stuck in local minima at $x = -0.2$. To overcome this problem, new repulsive potential functions are proposed taking into account the relative distance between the robot and the target.

2.2.1 New Repulsive Potential Function

From the above discussion we conclude that, the global minimum of the total potential field is not at the target position. This problem occurs as the robot approaches the target, the repulsive potential force increases due to presence of obstacle near the target. It is observed that if the repulsive potential force approaches zero, the robot approaches the target. To attain the global minimum at the target for the environment where three obstacles, one robot and one target present, we developed new repulsive potential functions that take the relative distance between the robot and the target is given in equation (12).

$$U_{rep(obs_i)} = \begin{cases} \frac{1}{2}\alpha_i \left(\frac{1}{\rho\left(q, q_{obs_i}\right)} - \frac{1}{\rho_0} \right)^2 \rho^n\left(q, q_{target}\right) & if\, \rho\left(q, q_{obs_i}\right) \le \rho_o \\ 0 & if\, \rho\left(q, q_{obs_i}\right) > \rho_o \end{cases} \qquad (12)$$

where $\rho(q, q_{\text{obsi}})$, is the minimum distance between robot q and obstacle i & varies from 1 to n. $\rho\,(q, q_{\text{target}})$ is the distance between the robot and the target.

The contour and surface plot are plotted for the total potential for the above case and are shown in Fig. 2 and 3.

From Fig. 2 it is obvious that, at the target i. e. at the origin, the total potential reaches its global minimum

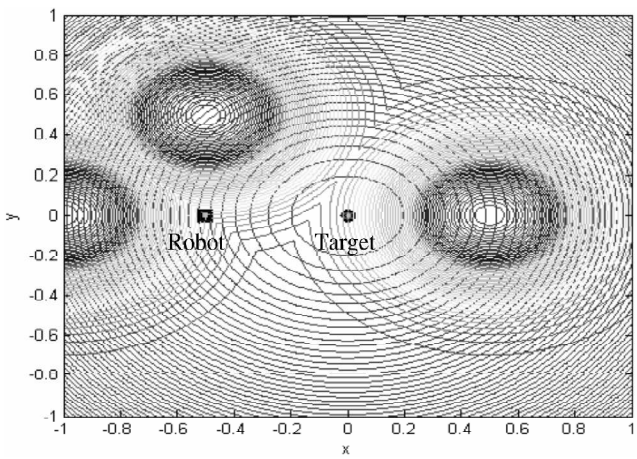

Figure 2: Contour Plot of Mobile Robots Navigation using New Repulsive Potential Function

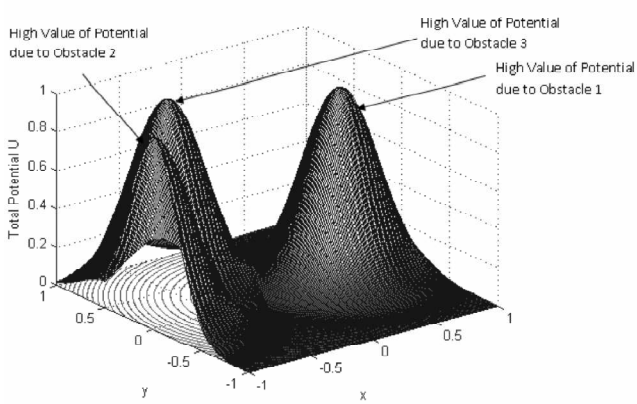

Figure 3: Total Potential Function without Local Minima

equal to zero. The equation (12) along with factor $\rho^n(q, q_{target})$ drag the robot towards the nearest target, thus ensuring the robot to be at the global minimum. The total potential $\{U_{Total}\}$ can be obtained using Eq. (10). For $n = 2$ and $\delta = \alpha_1 = \alpha_2 = \alpha_3 = 1$ we found (Fig. 2 and 3) there is only one minima exist which is at the target. The flow chart and calculation for change in steering angle (Phir [ir]) is shown in Appendix A and B.

Case-II (Dynamic obstacle and target)

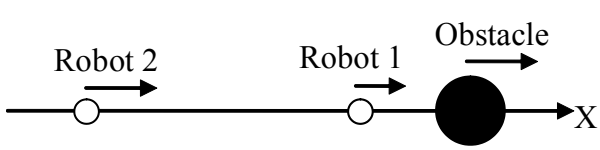

Figure 4: Line Diagram for Local Minima Program

When employing the new potential functions for dynamic motion planning, local minimum problems do exist and should be taken care of. For example, consider the case when two robots and the target move in the same direction along the same line and the robot 2 is in between, as shown in Fig. 4. Assuming that the target moves outward or synchronously with the robot (this assumption ensures that the robot2 is between the robot1 and the target all the time), the robot1 is obstructed by the robot2 because robot2 is the obstacle for the robot1 and cannot reach the target.

To solve the problem, the simplest method is to keep the robot1 moves according to the total potential force as usual and wait for the robot2 or the target to change their motion. Since the environment is highly dynamic where both the target and the obstacles are moving, the situations where the configuration of the robot2 and target keeps static are rare. Thus, the waiting method is often adopted. However, if after a certain period of waiting, the configuration of the robot2 and target is still unchanged and the robot1 is still trapped, it can then be assumed that the configuration will not change temporarily and the robot will have to take other approaches to escape from the trap situation. Since the configuration of the robot1, robot2 and target is relatively stationary, the conventional local minimum recovery approaches such as wall following method, which were designed for the stationary environment cases, can be applied.

2.3 Petri Net Modeling to Avoid Collision among the Robots

In the APF method of navigation even though robots reach the target efficiently by escaping from local minima but still there may be possibility of collision among robots. In order to avoid the inter-robot collision in multiple mobile robots system Petri Net model has been introduced. C.A. Petri [11] first developed Petri Net model. In this strategy motion generation is selected for mutual collision avoidance according to the complexity of the situation. Figure 5 depicts the Petri Net model built into each robot to enable it to avoid collision with other robots. The model comprises 6 states (or Tasks). The location of the token indicates the current state of the robot.

It is assumed that, initially, the robots are in a highly cluttered environment, without any prior knowledge of one another or of the targets and obstacles. This means the robot is in state "Task 1" ("Wait for the start signal"). In Fig. 5, the token is in place "Task 1". Once the robots have received a command to start searching for the targets, they will try to locate targets while avoiding obstacles and one another. The robot is thus in state "task2" ("Moving, avoiding obstacles and searching for targets").

During navigation, if the path of a robot is obstructed by another robot, a conflict situation is raised. (State "Task

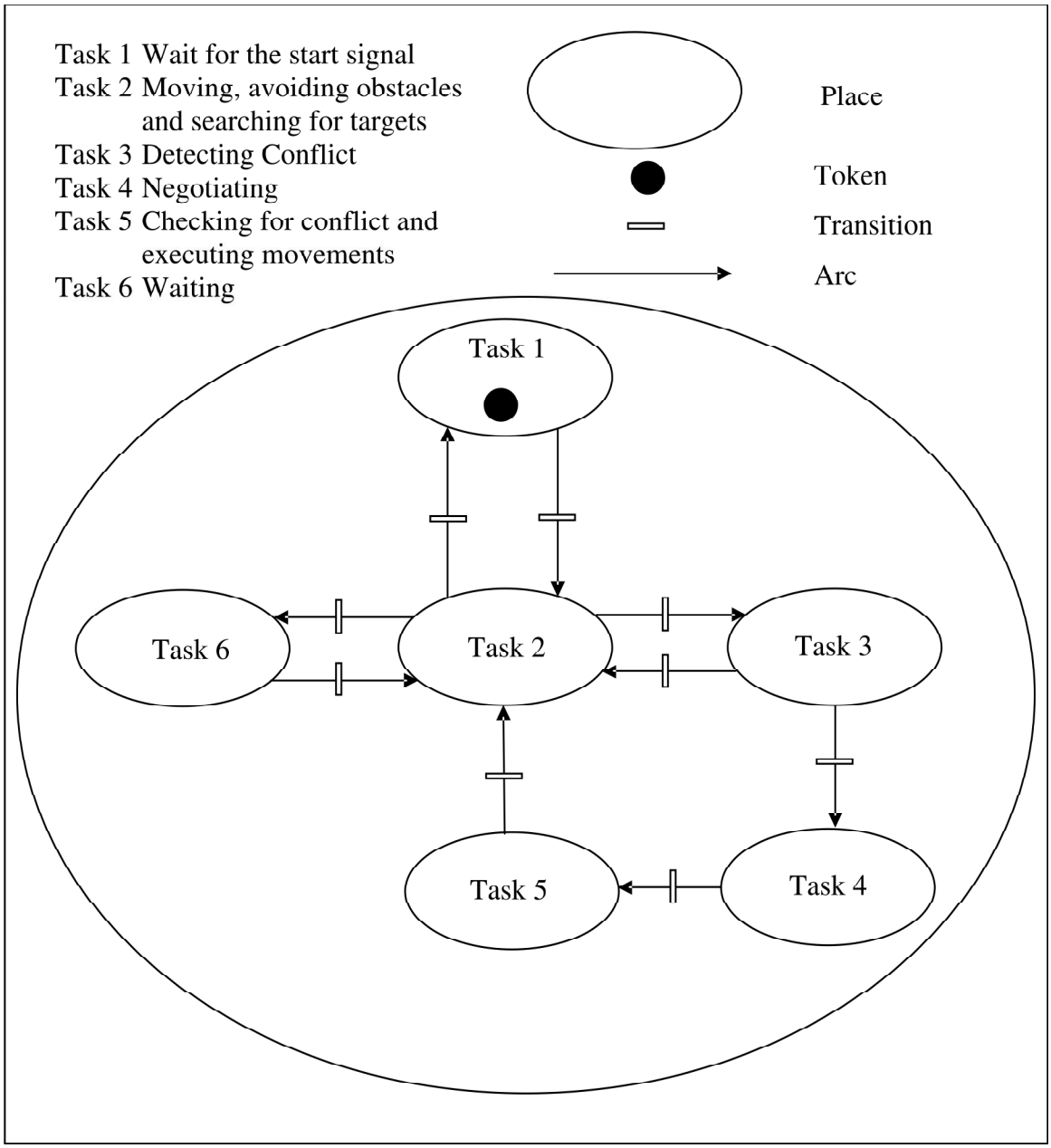

Figure 5: Petri Net Model for Avoiding inter-robot Collision

3", "Detecting Conflict"). Conflicting robots will negotiate with each other to decide which one has priority. The lower priority robot will be treated as a static obstacle and the higher priority robot as a proper mobile robot (state "Task 4", "Negotiating").

As soon as the conflict situation is resolved, the robots will look for other conflicts and if there is no other conflict they will execute their movements (state "Task 5", "Checking for conflict and executing movements").

If a robot meets two other robots already in a conflict situation, its priority will be lowest and it will be treated as a static obstacle (state "Task 6", "Waiting") until the conflict is resolved. When this is done, the robot will re-enter state "Task 2".

3. SIMULATION RESULT FOR POTENTIAL FIELD BASED NAVIGATION

This section presents exercises aimed at illustrating the ability of the proposed control scheme to manage the navigation of mobile robots in different situations. Simulations were conducted with the help of MATLAB software package developed by the author. This generalized program enables to generate any number of mobile robots, targets and obstacles and controls in an

artificial simulated environment containing multi targets and obstacles. Three exercises have been designed to show the different capabilities of the proposed control scheme.

3.1 Collision-free Movement, Obstacle Avoidance and Target Seeking

Here we consider two robots, moving in a platform with thirteen obstacles and one target (Fig. 6). This exercise designed to demonstrate that the robots reach the target without colliding with obstacles or one another and at the same time avoiding the obstacles. Robots choose their own path to reach the target by covering the shortest length. It can be noted that the robots stay well away from the obstacles.

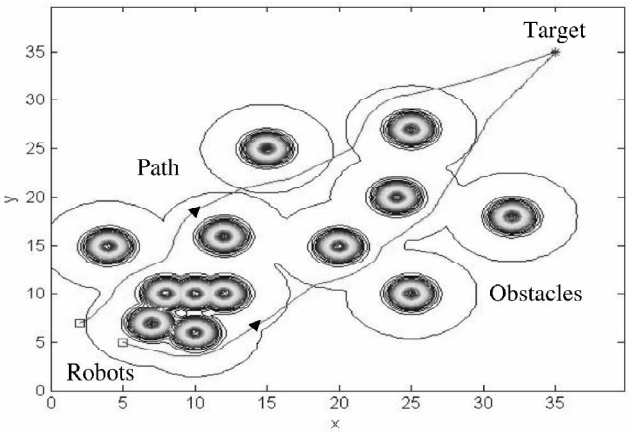

Figure 6: Navigation Environment for Two Mobile Robots for Avoiding Thirteen Obstacles

3.2 Obstacle Avoidance and Target Seeking by Multiple Robots

This exercise involves three mobile robots initially assembled in a highly cluttered environment. The Fig. 7 depicts a situation where three mobile robots and twenty obstacles and two targets. In this simulation, each robot has reached their nearest target in an efficient manner without any collision between themselves and obstacles in a highly cluttered priori unknown environment.

3.3 Wall Following and Target Seeking

The wall following and target seeking behavior has been shown in Fig. 8. This exercise involves the wall following behavior of a one mobile robot consisting of sixteen obstacles. In the present scenario the obstacles are arranged in a particular fashion so that they act like a wall between the robot and the target. As the robots search for their targets, they find the walls along which they continue to move by applying the wall following rules. Ultimately, the robots able to see the targets and proceed to reach them.

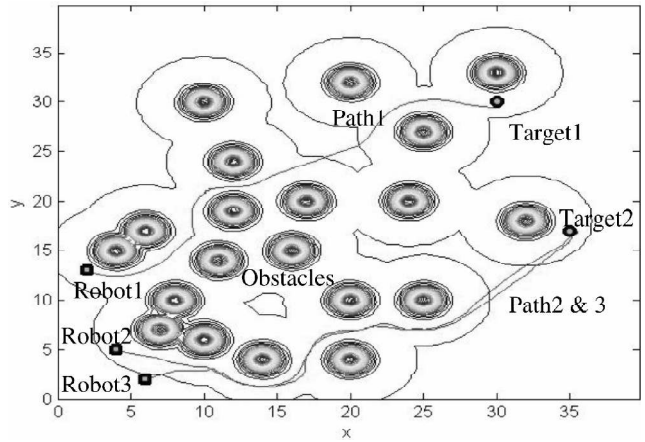

Figure 7: Navigation Environment for Three Mobile Robots and Two Targets for Avoiding Twenty Obstacles

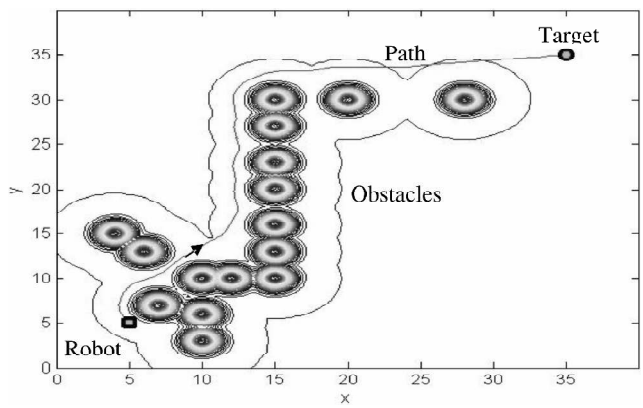

Figure 8: Navigation Environment for one Robot and One Target for Avoiding Sixteen Obstacles

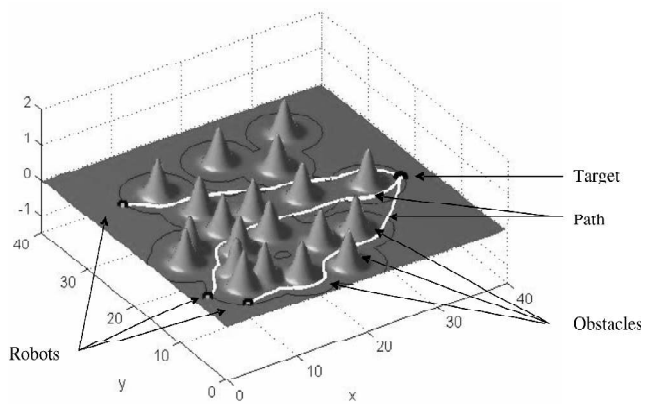

Figure 9: Three-dimensional Obstacles using APF for target-seeking along with the paths (final scenario)

In Fig. 9, shows the final scenario of the work space having three-dimensional obstacles using APF for target-seeking along with the path.

In the above simulations, the path are found by assuming that the robots moves at constant speed, and the resultant virtual force applied to it only determines the direction of its motion.

4. COMPARISON OF RESULTS

In this section a comparison has been made between Min Gyu *et al.,* [12] model and results from current control scheme in simulation and experimental mode. The performance of the two methods was mainly evaluated on following three criteria:

(i) numbers of steps required to reach the target

(ii) the path length

(iii) the smoothness of the trajectories.

The results from Min Gyu *et al.* are shown in Fig. 10(a), (c), (e) and (g) are compared with the results obtained from present investigation for similar environment [Fig. 10(b), (d), (f) and (h)].

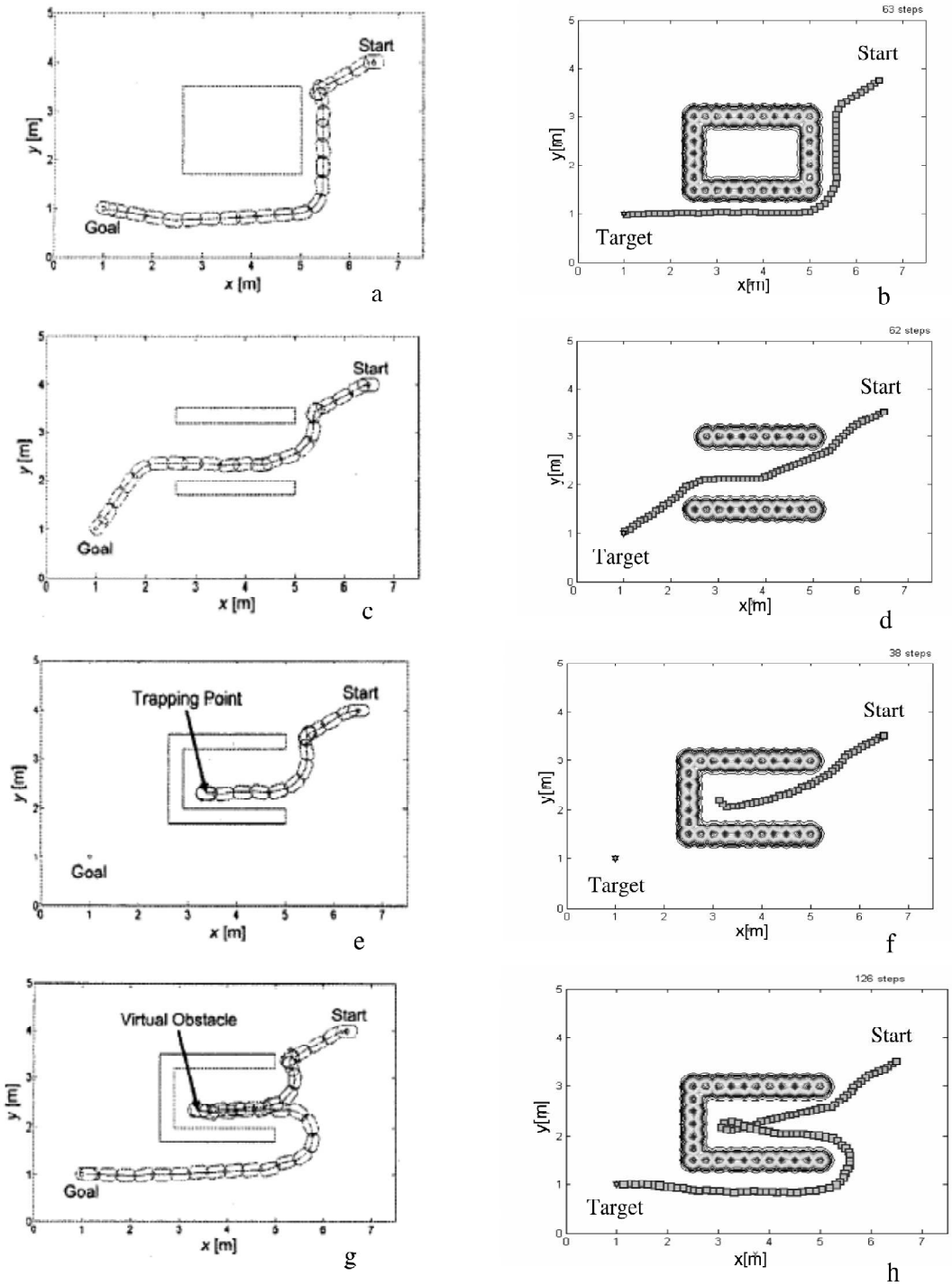

Figure 10: Comparison of Results from the Current Investigation and Min Gyu *et al.*

The simulation has been conducted in a similar environment as described by Min Gyu *et al.* [12], It has been observed in the environment shown in Fig. 10(a) and (c) presented by Min Gyu and Fig. 10(b) and (d) from current developed technique are free from any local minima problem, therefore the robot can successfully reach the goal by only the APF approach. Similarly in the Fig. 10(e) and 10(f), both the cases the robots are trapped at the closed U-shape boundary due to the existence of local minima. In Fig. 10(h) robot escape from the local minima by using new APF equation for obstacles which drags the robot near the target in a shortest path. In some scenarios, of Min Gyu *et al.* [12] it can be seen that, the path of robot has sudden change in direction with some greater steering angle and sometimes small zigzag like motion that has been taken care in the present investigation. In Fig. 10(b), (d), (f) and (h) shows the robot reach the target in shortest path with smooth trajectory by using the new potential field function. From the above simulation results it is very clear that, the developed algorithm can efficiently drive the robot in a cluttered environment.

Table 1
Comparison of Results from the Current Investigation with Min Gyu *et al.* Model

Sl No.	*Environmental types*	*Path length of Min Gyu et al. Model, in 'cm'*	*Path length from current investigation in 'cm'*
1.	Rectangular obstacle and path planning by APF method [Fig.10(a) & (b)]	71	60
2.	Open aisle and path planning by APF method [Fig.10(c) & (d)]	64	51
3.	Closed aisle and failed path planning by APF method [Fig.10(e) & (f)]	37	32
4.	Closed aisle and path planning by APF method with virtual obstacle [Fig.10(g) & (h)]	102	98

Experimental verification of the above simulation results has been shown in next section (Figs. 12- 15).

5. EXPERIMENTAL IMPLEMENTATION

5.1 Real Robot Specification

Experimental validation and verification of the proposed method has been demonstrated using the three similar prototype mobile robots developed in the laboratory. For experimental validation of simulation result three prototype mobile robots developed in the laboratory was used. The mobile robot has two active wheels and two passive wheels. Each active wheel is driven by DC gear servo motor (12V, 30 rpm) independently and a driver circuit for the motor is mounted on the dual-wheel caster assembly in the prototype robot. Passive wheels are installed on the front of the steering axis as an auxiliary wheel in order to keep the balance of the active dual-wheel caster assembly and the prototype robot. The position and posture of the prototype robot can be estimated by dead reckoning using the equations developed and information from the encoders arranged on the wheels and the steering axes. The appearance of the wheeled mobile robot assembly is presented by Fig. 11.

The approximate size of the robot is as follows:

Length : 16 cm (including sensor position)

Width : 12 cm

Height : 10 cm from ground and

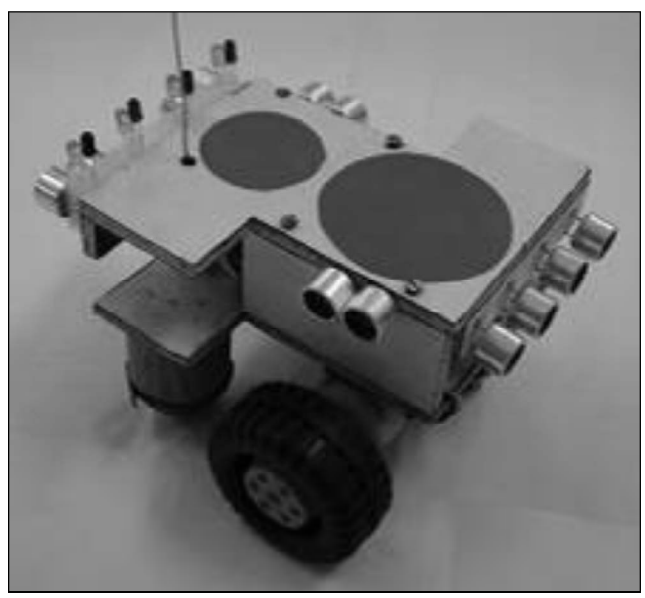

Figure 11: Appearance of the Wheeled Mobile Robot

The size of platform (test bed) used for navigation is as follows:

Length : 1.4 m

Width : 2.0 m

Height : 0.18 m

The robot considered for experiment is a differential drive robot with an on-board PC and wireless Ethernet. There are six ultrasonic and four infra red sensors mounted around the top of robot (out of which two sensors in each in front and back sides and one in each at the left and right side of the mounting) in order to sense the front, left, right, and back obstacle distance. Although the range of the above mentioned sensors are about 1m, but the robot takes a turn when the obstacle distances reaches 10cm.

5.1.1 Control System

Control commands from microprocessor are given in form of voltages through D/A converter using an interface board (RIF-01). These voltage signals drive the DC-motors via driver circuits, so that driving torque is occurred. While, pulses from the encoders are counted by UPP (Universal Pulse Processor) on the interface board. These counts are transmitted to the microprocessor for further processing.

5.2 Real-Time Experiment

In order to demonstrate the effectiveness of the above control system and the validity of the algorithm developed using new potential field function, a variety of experiments using the prototype robot were conducted. In this section we present the simulation results from our motion planner, which was operated in an environment with cylindrical target and conical obstacles ranging from 0.05 to 0.12 m base diameter. The path traced by the robot during motion was marked on the floor by means of a pen attached to the front of the robot frame.

The four different cases of similar environments as described by Min Gyu *et al.* [12], which are already verified in simulation mode have been verified experimentally [shown in Figs.12-15] to show the effectiveness of the developed controller.

In figures 12(a-f)**,** it is demonstrated a situation where robot and target are placed in opposite corner of a rectangular boundary (created by a variety of conical obstacle configurations). When robot starts motion it speeds up in straight path up to the obstacle 1 and slows down to take turn near obstacle 2, then follows a wall following rules to reach the target. The robot autonomously chooses its way in the shortest trajectory

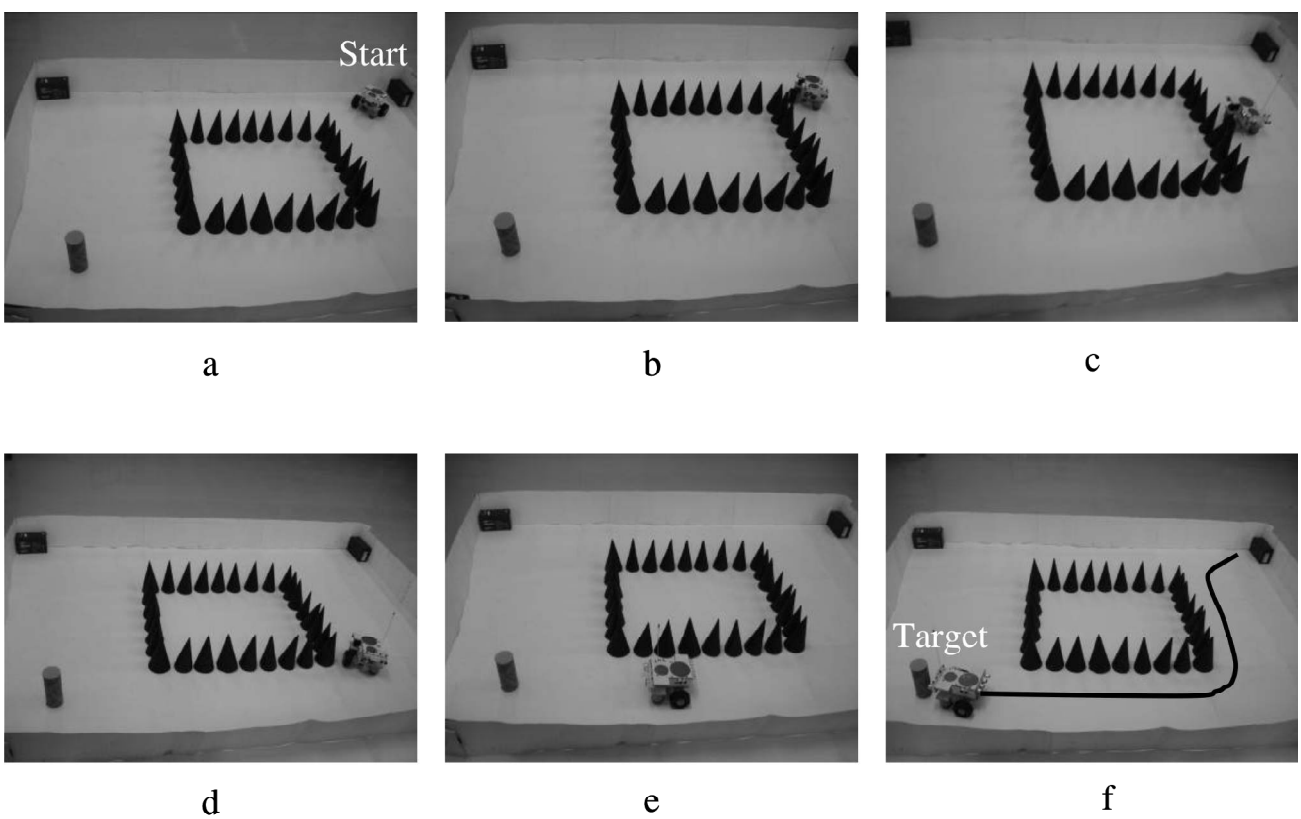

Figure 12: Experimental Set up for Navigation of Mobile Robot in the Similar Environment Shown in Fig. 11(b)

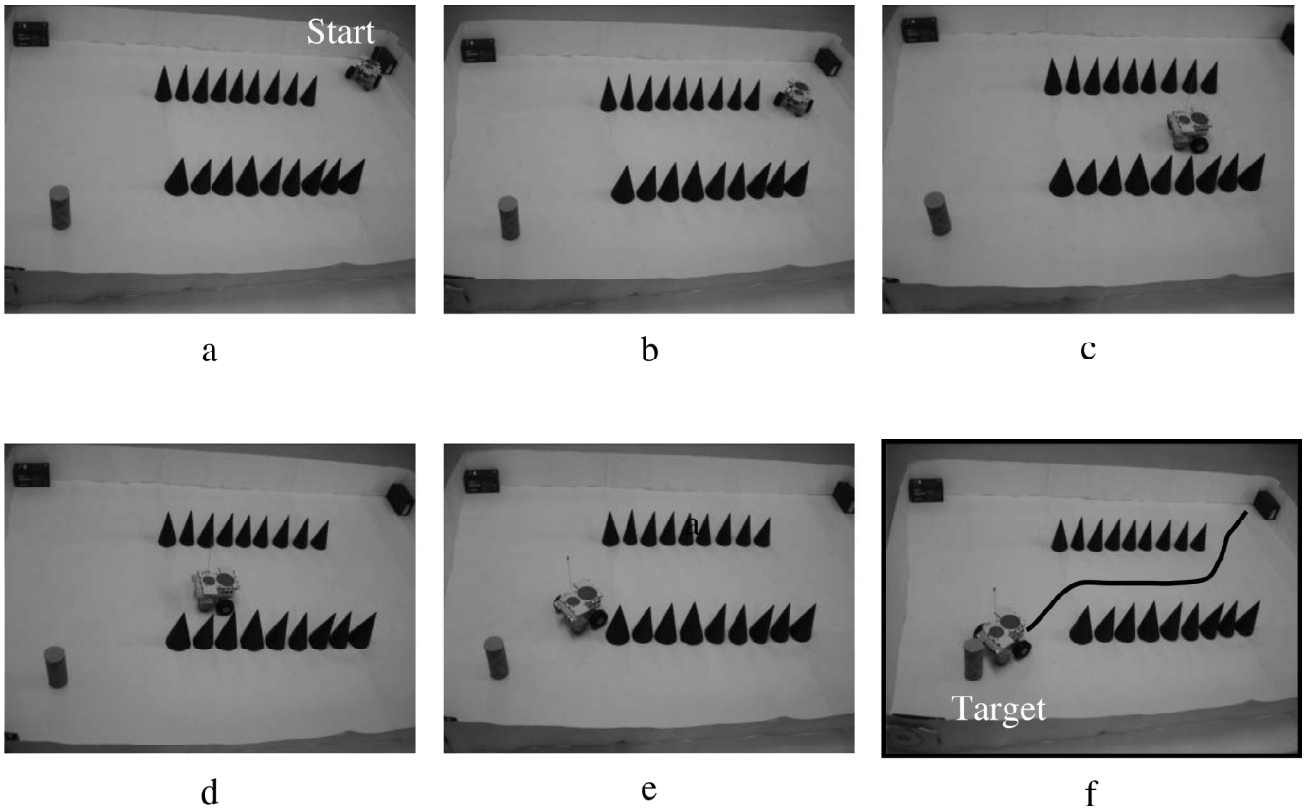

Figure 13: Experimental Set up for Navigation of Mobile Robot in the Similar Environment Shown in Fig. 11(d)

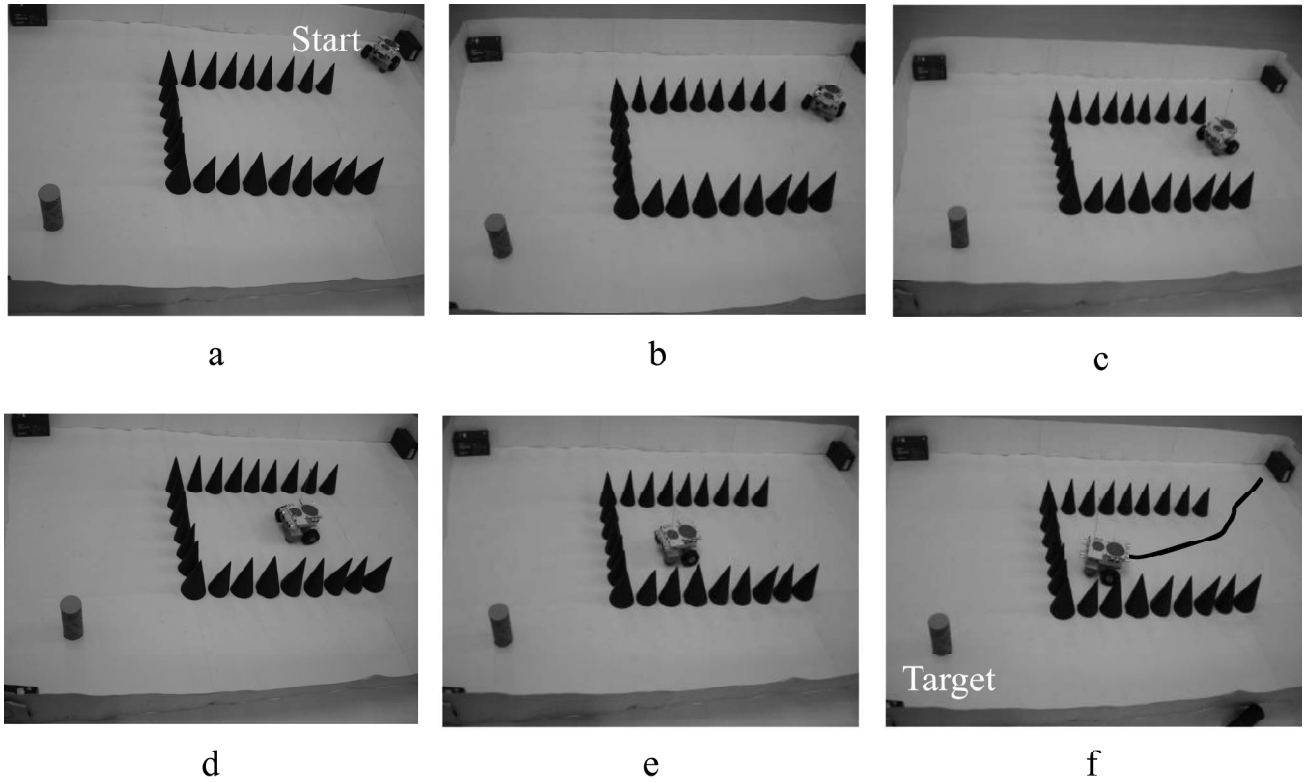

Figure 14: Experimental Set up for Navigation of Mobile Robot in the Similar Environment Shown in Fig. 11(f)

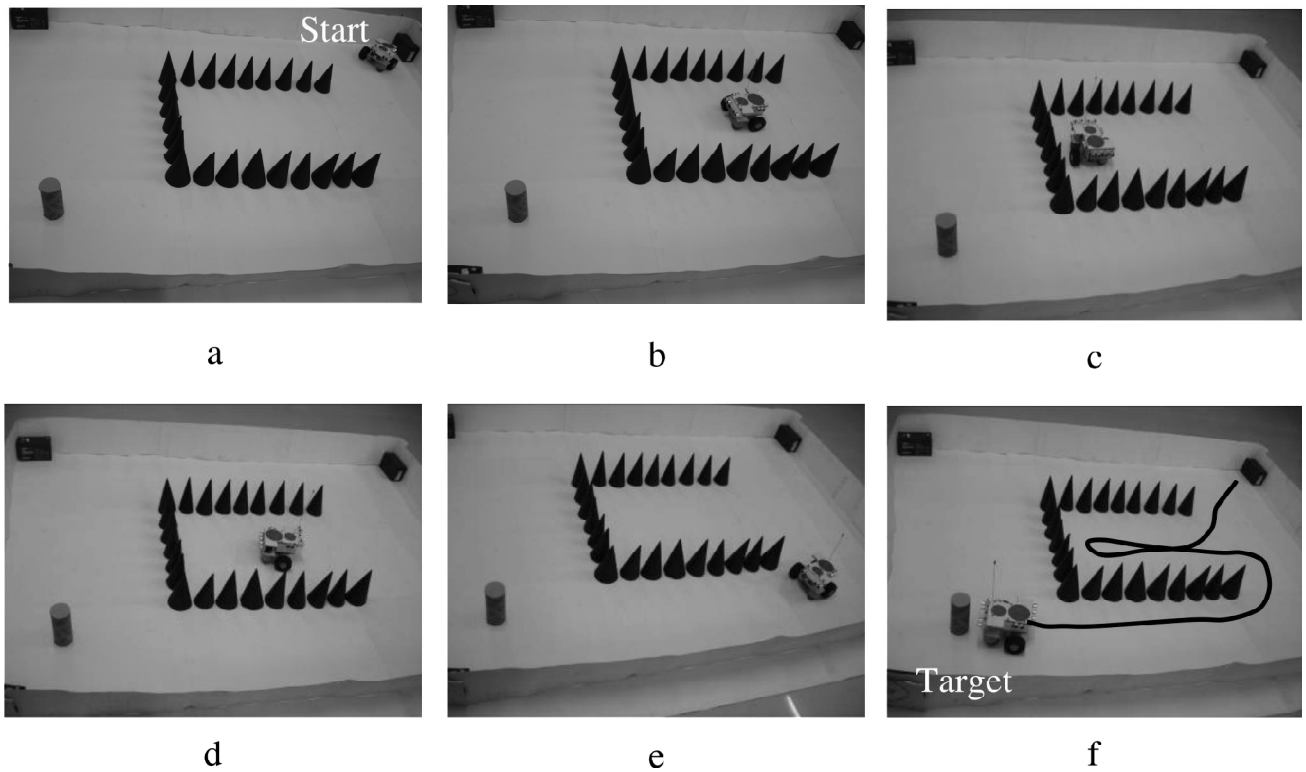

Figure 15: Experimental Set up for Navigation of Mobile Robot in the Similar Environment Shown in Fig. 11(h)

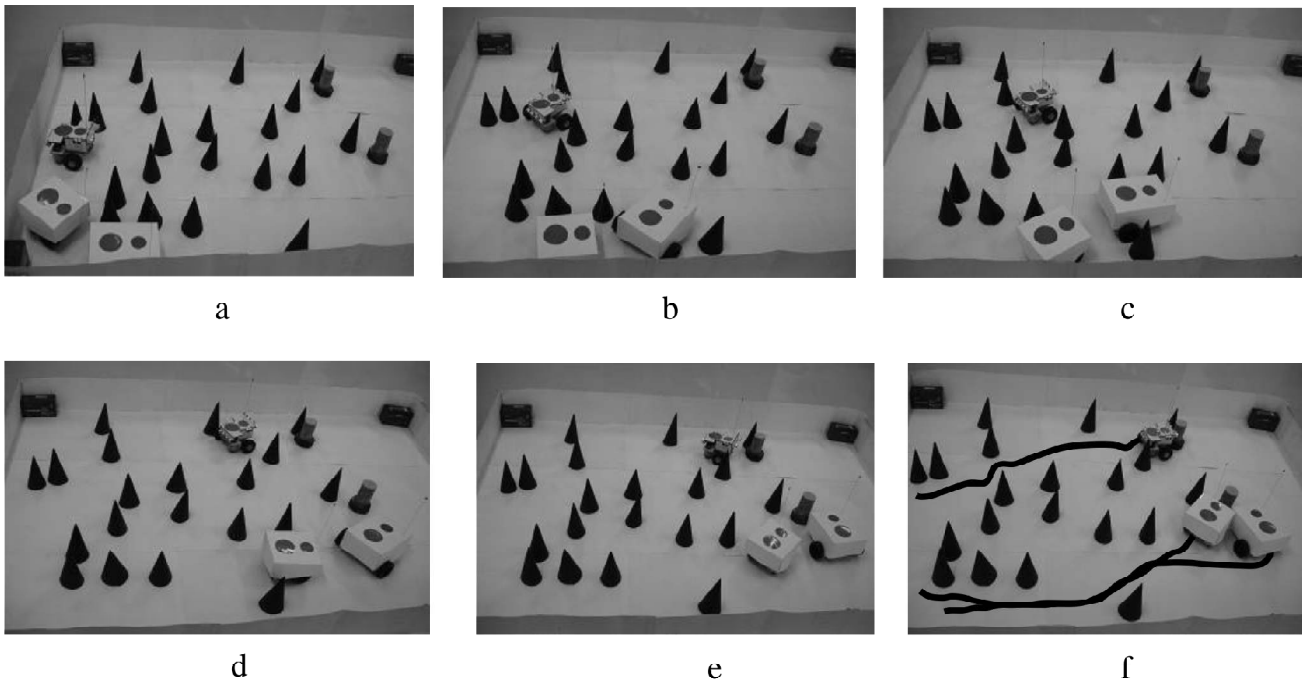

Figure 16: Experimental Set up for Navigation of Three Mobile Robots with two Different Target

to reach the desired destination. For the second robot navigation (Fig. 13), it can be observed that, the robot follows a straight path except the turning points from its start to the goal position.

There are, however, situations such as in Figs. 14(a-f), in which the robot is following a local minimum corresponding to a U-shaped boundary that prevents the robot to pass through and find the target. As the robot

approaches this situation, the level of the obstacle potential rises, causing the robot to slow down and stop before a collision occurs. In some cases the robot can rotate and move with some zigzag motion until it reaches another local minima in the potential that can lead it out of this situation. The developed potential field method takes care to invoke a new path based on available information received by the robot about the environment with heuristic recovery approach. Finally the robot ables to reach the target which is shown in Figs. 15(a-f).

Here the potential field approach has been used as a local holonomic motion planner. The new potential function is used for real time experiments with the developed robot. The experimental results of single robot and three robots are presented in Figs. 12-16 respectively. The experimentally obtained paths follow closely those traced by the robots during simulation. From these figures, it can be seen that the robots can indeed avoid obstacles and reach the targets.

It has been concluded by comparing the results from both the simulation as well as experiment that, the path followed by the robots using new potential field function can successfully arrive at the target by avoiding obstacles. The trajectories are smooth and take reasonably efficient paths as compared to Min Gyu path.

More than thirty experiments have been conducted to test the model. The maximum velocity of mobile robot used for navigation is 0.05 ms^{-1}. There are a number of trials with varying complexity to show that the model works for different sizes and numbers of obstacles. The real time simulated results show the effectiveness of the developed controller for mobile robots navigating in priori unknown cluttered environment.

6. DISCUSSION

In the above simulations different types of environmental scenarios have been presented for robots navigation. From the results it is clear that the robots reached the targets without collision among themselves while avoiding the obstacles. In Fig. 6 an environmental scenario has been presented for target seeking behavior of two mobile robots respectively for collision-free movement. Fig. 7 shows the obstacle avoidance and collision free movement by three robots and two-targets systems when they are used to roam in a highly cluttered environment. Fig. 8 shows the wall following behavior of single robot and single target. Fig. 9 exhibits a navigational environment for three-dimensional obstacles with associate Artificial Potential Field (APF) along with the paths.

The simulation results are compared with the experimental results [Figs. 12-15] being obtained by using newly developed equations. It has been observed that, the robots follow closely the simulation path. From the above results it is concluded that using new artificial potential field functions, the robots are able to navigate successfully in a cluttered environment.

7. CONCLUSIONS

In this paper, a new potential field method has been proposed for mobile robot motion planning in presence of static and dynamic obstacles in a cluttered environment. The mobile robot navigation control system described in this paper comprises of two parts. The first part is an APF based controller that combines the total attractive and repulsive forces (by taking into account the relative distances of the robots with respect to the targets and obstacles and the bearing angles between them) to direct the steering of the robot to avoid obstacles in its path and reach the target. The second part is a Petri Net model implementing crisp rules for preventing collision between different mobile robots. This division of the navigation control task is based on the rationale that information concerning moving obstacles around a robot is often not known precisely, while the simultaneous relative locations of the robots can be much better defined through communication between themselves. A comparison has been made between Min Gyu *et al.* [12] model and results from current control scheme both in simulation and experimental mode. The simulations and tests on actual robots demonstrated that the proposed system functions correctly, enabling the robots to find targets in environments cluttered with obstacles and other mobile robots without hitting the obstacles or colliding against one another.

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APPENDIX A

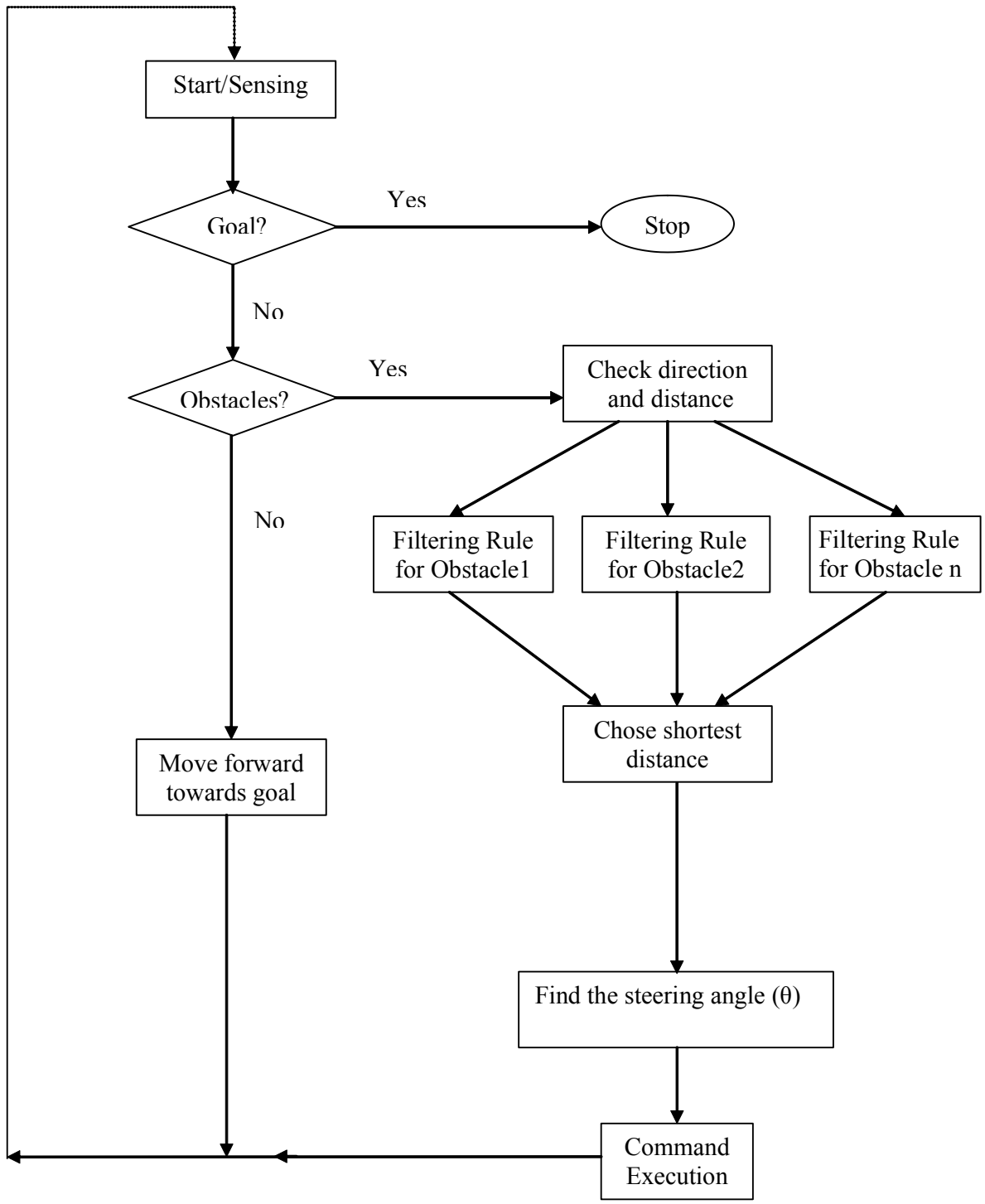

Figure 17: Flow Chart for APF Program

APPENDIX B

With the help of sensors the robot will detect obstacles around it in the environment. Accordingly the robot will calculate the repulsive navigation forces (Fig. 18).

Let $\Sigma F_{\text{Front-rear}}$ = Resultant repulsive navigation force along the direction of left-right axis of the robot due to the obstacles which influence the robot.

$\Sigma F_{\text{Left-right}}$ = Resultant repulsive navigation force along the direction of left-right axis of the robot due to the obstacles which influence the robot.

θ = Current heading angle at which the robot moving in the environment.

Change in steering angle (Phir [ir]) required for obstacle avoidance is

$$\text{Phir[ir]} = Tan^{-1}\left[\frac{F_{Front-rear}}{F_{Left-right}}\right] \quad \text{(A1)}$$

New heading angle θnew = θ + Phir[ir] (A2)

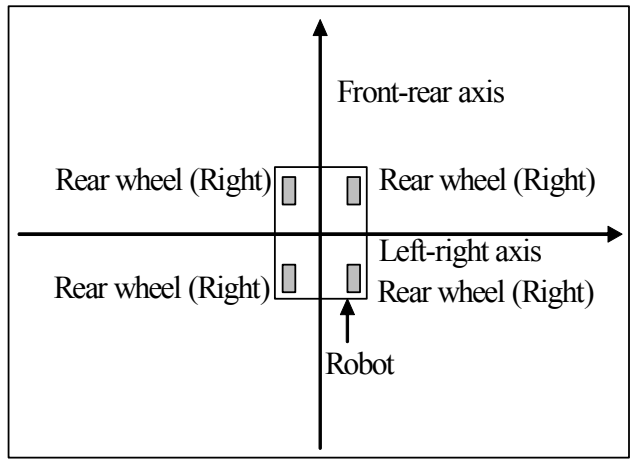

Figure 18: Front-rear Axis and Left-right Axis of the Robot