NAVIGATIONAL CONTROL OF MULTIPLE MOBILE ROBOTS IN VARIOUS ENVIRONMENTS

Jagadish Chandra Mohanta

Department of Mechanical Engineering
National Institute of Technology Rourkela

NAVIGATIONAL CONTROL OF MULTIPLE MOBILE ROBOTS IN VARIOUS ENVIRONMENTS

A thesis submitted in partial fulfilment of the requirements for the degree of

Doctor of Philosophy
in
Mechanical Engineering

by

Jagadish Chandra Mohanta
Roll No: 50603001

Under the supervision of

Prof. D. R. Parhi, Prof. S. K. Patel & Dr. I. P. S. Paul

Department of Mechanical Engineering
National Institute of Technology Rourkela

March, 2011

This thesis is dedicated

to

Bhagavan Sri Sathya Sai Baba

&

.......PARENTS.......

Declaration

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgement has been made in the text.

Date: 7th March 2011 Jagadish Chandra Mohanta
N.I.T. Rourkela

Department of Mechanical Engineering
NATIONAL INSTITUTE OF TECHNOLOGY, ROURKELA
ORISSA, INDIA – 769 008

CERTIFICATE

This is to certify that the thesis entitled "***Navigational Control of Multiple Mobile Robots in Various Environments***", being submitted by **Jagadish Chandra Mohanta**, Roll No. **50603001,** to the National Institute of Technology, Rourkela for the award of the degree of ***Doctor of Philosophy*** in Mechanical Engineering, is a bona fide record of research work carried out by him under our supervision and guidance.

The candidate has fulfilled all the prescribed requirements.

The thesis, which is based on candidate's own work, has not been submitted elsewhere for the award of a degree.

In our opinion, the thesis is of the standard required for the award of Doctor of Philosophy in Mechanical Engineering.

To the best of our knowledge, he bears a good moral character and decent behaviour.

Supervisors

Prof. (Dr.) D. R. Parhi, **(Supervisor)**
Prof. (Dr.) S. K. Patel **(Co-supervisor)**
Department of Mechanical Engineering
NATIONAL INSTITUTE OF TECHNOLOGY
Rourkela-769 008 (INDIA)

Dr. I. P. S. Paul
(External supervisor)
Ex- Additional Director (Training & HRD)
CENTRAL POWER RESEARCH INSTITUTE
Bangalore-560080 (INDIA)

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Jagadish Chandra Mohanta

Bio-Data of the Candidate

Name of the Candidate : Jagadish Chandra Mohanta

Father's Name : Rushinath Mohanta

Permanent Address : AT/PO- Angarpada
PS- Raruan, Mayurbhanj
Orissa- 757035

Email ID : jagadish_mohanta@yahoo.co.in

ACADEMIC QUALIFICATION

- Continuing **Ph. D.** in Mechanical Engineering, National Institute of Technology Rourkela, Orissa (India). Expected year of award of degree: 2010-11.

- **M. Tech.** in Mechanical Engineering (Machine Design & Analysis), National Institute of Technology Rourkela, Orissa (India).

LIST OF PUBLICATIONS BASED ON THE RESEARCH WORK

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2. **Jagadish Ch. Mohanta**, Dayal, Ramakrushna Parhia , Saroj Kr. Patel a and I.P.S. Paul, “Motion Control And Path Tracking Of Mobile Robots Using Artificial Intelligence Method”, *IEEE Sponsored Conference on Computational Intelligence, Control And Computer Vision In Robotics & Automation, IEEE CICCRA 2008.*, N.I.T., Rourkela-769008, Orissa, India, pp-158-161.

Abstract

The thesis addresses the problem of mobile robots navigation in various cluttered environments and proposes methodologies based on a soft computing approach, concerning to three main techniques: Potential Field technique, Genetic Algorithm technique and Fuzzy Logic technique. The selected techniques along with their hybrid models, based on a mathematical support, solve the three main issues of path planning of robots such as environment representation, localization and navigation.

The motivation of the thesis is based on some cutting edge issues for path planning and navigation capabilities, that retrieve the essential for various situations found in day-to-day life. For this purpose, complete algorithms are developed and analysed for standalone techniques and their hybrid models. In the potential field technique the local minima due to existence of dead cycle problem has been addressed and the possible solution for different situations has been carried out. In fuzzy logic technique the different controllers have been designed and their performance analysis has been done during their navigational control in various environments. Firstly, the fuzzy controller having all triangular members with five membership functions have been considered. Subsequently the membership functions are changed from Triangular to other functions, e.g. Trapezoidal, Gaussian functions and combinational form to have a more smooth and optimised control response. It has been found that the fuzzy controller with all Gaussian membership function works better compared to other chosen membership functions. Similarly the proposed Genetic algorithm is based on the suitable population size and fitness functions for finding out the robot steering angle in various cluttered field.

At the end hybrid approaches e.g. Potential-Fuzzy, Potential-Genetic, Fuzzy-Genetic and Potential-Fuzzy-Genetic are considered for navigation of multiple mobile robots. Initially the combination of two techniques has been selected in order to model the controllers and then all the techniques have been hybridized to get a better controller. These hybrid controllers are first designed and analysed for possible solutions for various situations provided by human intelligence. Then computer simulations have been executed extensively for various known and unknown environments. The proposed hybrid algorithms are embedded in the controllers of the

real robots and tested in realistic scenarios to demonstrate the effectiveness of the developed controllers.

Finally, the thesis concludes in a chapter describing the comparison of results acquired from various environments, showing that the developed algorithms achieve the main goals proposed by different approaches with a high level of simulations. The main contribution provided in the thesis is the definition and demonstration of the applicability of multiple mobile robots navigations with multiple targets in various environments based on the strategy of path optimisation.

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Abbreviations

F.O.D.	=	Left obstacle distance
L.O.D.	=	Left obstacle distance
R.O.D.	=	Right obstacle distance
H.A.	=	Heading angle
LV	=	Left wheel velocity of a robot
RV	=	Right wheel velocity of a robot
www	=	World Wide Web
obs	=	Obstacle
tar	=	Target
Left-obs	=	Left obstacle
Right-obs	=	Right obstacle
Front-obs	=	Front obstacle
Tar-ang	=	Target angle
Med	=	Medium
HTML	=	Hyper Text Markup Language
HTTP	=	Hyper Text Transfer Protocol
Neg	=	Negative
Pos	=	Positive
VF	=	Very Far
VN	=	Very Near
OA	=	Obstacle Avoidance
TS	=	Target seeking

List of Symbols

φ	=	Heading angle
r_v	=	Sensing range of a robot
t	=	Time taken by a robot to move from a distance from the start to the goal position
μ	=	Fuzzy membership function
$\vee$	=	Aggregate (union)
Λ	=	Minimum (min) operation
$\forall$	=	For every
α	=	Positive scaling factors
q	=	Position of robot
ρ	=	Function
θ	=	Angle between vehicle frame orientation and X-axis;
l	=	Wheel-base of mobile robot;
I_c	=	Center of curvature;
R	=	Distance from point 'I_c' to point (x_r, y_r);
v	=	Linear velocity
ω	=	Angular velocities;
V_L	=	Left wheel velocity
V_R	=	Right wheel velocity
d	=	Wheel base.

Chapter 1

Introduction

- **The background**
- **Needs statement**
- **Objectives and scope of the work**
- **Outline of the thesis**

1. Introduction

This chapter gives motivations for conducting research in the fields of mobile robot navigation, a brief overview of the problem to be tackled and its application domains. A brief summary of the thesis contributions along with the thesis structure in the form of a series of short chapter abstracts can be found at the end of this introductory chapter.

1.1. The background

The problem of motion planning in presence of obstacles has been extensively studied over the last decade. The main task of path planning for autonomous robot manipulators is to find an optimal collision-free trajectory from an initial to a final configuration. Since 1960's the research on mobile robots have been an emerging area in the field of automation and development. A vision-guided autonomous mobile machine named Shakey, is one of the earliest mobile robots designed in the year 1966 [1] at the Stanford Research Institute. Until recently, work has concentrated on the control of individual robots. From last two decades, there has been a great interest among scientific community to focus towards the co-ordination of multiple mobile robots. This interest has stemmed both from practical considerations that multiple robots are able to handle tasks that individual machines cannot, for instance carrying large, bulky and heavy loads and from a desire to create artificial systems that mimic nature in particular by exhibiting some of the primary behaviours observed in human and other animal societies. Many important contributions to this problem have been made in recent years. The design goal for path planning is to enable a mobile robot to navigate safely and efficiently without collisions to a target position in an unknown and complex environment.

The navigation strategies of mobile robots can be generally classified into two categories, global path planning and local reactive navigation. The former such as artificial potential fields by [2] connectivity graphs or cell decomposition [3] is done offline, and the robot has complete prior knowledge about the shape, location, orientation, and even the movements of the obstacles in the environment. Some important contributions for navigation of multiple mobile robots in various environments have been reported in recent years [4-8]. The dynamic analyses of flexible robotic manipulators have been reported by [9] and [10].

Many artificial intelligence (AI) techniques have been adopted to tackle this problem [11], such as fuzzy logic techniques [12-14], genetic algorithms, potential field methods [15,16], neural networks approaches [17,18] and even hybrid techniques [19,20]. Each method has its own advantage over others in certain aspects. Generally, the main difficulties for robot-path-planning problem are computational complexity, local optimum and adaptability. Researchers have always been seeking alternative and more efficient ways to solve the problem. It is obvious that path planning can be viewed as an optimization problem (e. g., shortest distance) under certain constraints (e.g., the given environment with collision-free motion). However, in all such studies, a limited effort was made to find an optimal controller for mobile robots navigation with multiple targets.

Present work introduces the algorithms which integrates the intelligent properties of potential field, genetic algorithm and fuzzy logic behaviour to develop a novel solution for multiple robots navigation for multiple targets seeking behaviour. It consisted of providing a general and well designed method for the derivation of input–output data to construct a hybrid controller that can be used by the robots to guide its navigation in presence of obstacles. The devised method has also accounted for collision-free paths and reduction of travel time while lessening the number of controller variables and hence structure. The noted superiority of the algorithm can provide a great help in building good hybrid models without the necessity of putting a great deal of effort in obtaining highly accurate and a huge number of data points. These controllers of different combinations are first designed and analyzed for possible solutions for various situations. Then computer simulations have been executed for various known and unknown environments. Finally the proposed algorithms are embedded in the controllers of the real robots to demonstrate the effectiveness of the developed controllers. The hybrid algorithm using Potential-Genetic-Fuzzy technique has been found advantageous over other chosen stand alone techniques in all these efficiency aspects and these advantages have respected well on the robot trajectories in terms of their lengths and smoothness of motion by the robot to reach destination.

1.2. Needs statement

This chapter cater to sound principles of software design, development and testing of multiple mobile robots using *the above mentioned techniques* (through window based

MATLAB software) in order to facilitate the integration of different capabilities. We have compared our simulation results with other models in similar environments and same has been implemented through real situation using prototype robots. However, the experience of simulation results and experimental exercises have led to certain key insights in research finding for the particular problem of local minima incurred during the navigation in a large-scale systems having dead end boundary, especially with respect to mixed hardware- and software-intensive simulation. Further, in order to substantiate the work in a more precise manner the same multiple robots has been studied using search optimization technique such as genetic algorithm for optimum trajectories. Initially it was tried for multiple robots with single target and subsequently the same system was used for multi-robot with multi-targets systems. The details have been briefly described in the succeeding sections.

1.3. Objectives and scope of the work

The prime objective of this research is to explore the application of artificial intelligence (AI) techniques for navigational control of multiple mobile robots. In particular, the research will seek to determine artificial intelligence techniques such as fuzzy logic, genetic algorithm (GA), artificial potential fields (APF) and hybrid techniques for implementing navigation algorithms for safe/efficient navigation of multiple mobile robots in a highly cluttered environment. In this particular application, the local minima problem due to existence of dead end cycle has been solved by redefining the repulsive potential field function. 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. This application also dealt with the multiple targets case to show the effectiveness and improved performance of the developed controller navigation scheme. This investigation is justifiable and timely, because the task of controlling the safe movements of many robots is complex and thus requires a higher degree of “intelligence”. The intelligent systems techniques can be realized efficiently in hardware and software using micro controllers, sensors and programming tools.

The methodologies followed in the research are as follows:

- To develop a fuzzy logic based navigation techniques for multiple mobile robots.

- To develop an artificial potential field based controller for controlling the movement of several robots simultaneously.
- To develop a genetic algorithm based navigation techniques for optimal or near optimal path between the start to goal configuration.
- To model hybrid potential-fuzzy technique, potential- genetic technique, genetic-fuzzy technique and potential-fuzzy-genetic techniques for realising the better navigational response.
- To verify the effectiveness and efficiency of the proposed developed techniques via simulation studies as well as real time experiment in various environments.

1.4. Outline of the thesis

The thesis is structured as follows:

- **Chapter 1** introduces mobile robot navigation and basics of literature survey based on algorithms applied to path planning problems.
- **Chapter 2** is devoted to a detailed literature survey on mobile robot navigation and intelligent systems techniques.
- **Chapter 3** introduces the analysis of potential field based techniques in context of motion planning architecture of mobile robots. The general structure of obstacle avoidance and target seeking behaviour of the above proposed control scheme along with conceptual diagram of inter-robot collision avoidance module using Petri- net modelling has been explained in this chapter.
- **Chapter 4** describes the analysis of Genetic Controller for mobile robot navigation by keeping in view of path optimisation. A novel method has been adopted for path optimisation by suitably designing the fitness function. This fitness function is being analysed and implemented in the real robot in order to get robust control architecture for mobile robot navigation.
- **Chapter 5** deals with the analysis of a proposed fuzzy logic technique for navigation of multiple mobile robots by suitably designing different membership function distributions in order to get an efficient path planning strategy. The developed strategy takes into account the reference motion, direction, distances

between the robots and obstacles, distances between the robots and targets heuristically and refined later to find the optimum steering angle.

- **Chapter 6** deals with navigation using four different hybrid techniques. They are as follows: 1) potential-fuzzy technique, 2) potential- genetic technique, 3) genetic-fuzzy technique and 4) potential-fuzzy-genetic techniques. The detail controller design, analysis and implementation with real robot to fit in various environments have been described. The simulation results have been demonstrated, analysed and compared in order to illustrate the ability of the proposed control scheme to manage the navigation of mobile robots in different situations.
- **Chapter 7** deals with the navigation of robots remotely controlled using the techniques described in the previous chapters.
- **Chapter 8 c**onclusions are drawn on the basis of analysis, simulation and experimental results and ideas for further work are suggested and some further research scopes are suggested.

Chapter 2

Literature Review

- **The background**
- **Navigation of mobile robots**
- **Different techniques used for navigation of mobile robots**
- **Different sensors used for navigation of mobile robots**
- **Summary**

2. Literature Review

This chapter provides information about the relevant work and the state-of-the-art related to the area of mobile robot navigation focussing on intelligent systems techniques. The incremental development for path planning and control of mobile robot navigation from past decades to the recent has been addressed here.

2.1. The background

The path planning and control of mobile robots in a dynamic environment has been an area of great interest to many AI researchers. In the real world of robot applications, a mobile robot should be able to operate in an unknown dynamic environment. Therefore, solving the motion planning problem is one of the vital tasks in navigation of an autonomous mobile robot. The path planning methods are based on knowing a priori complete information about the robot environment. The complete information about the robot environment is passed through the algorithm first and then, the path planner is launched to create a path or route from the robot's start to its target configuration. In fact, these methods have carried out offline in completely known environments. On the other hand, the Robot navigation algorithms tried to find a route online, without having a priori information about the robot's environment. Therefore, these kinds of algorithms that take the advantages of such information usually provided by ultrasonic, infrared, vision, laser range finder, proximity sensors and bumper switches are commonly known as Robot Navigation Algorithms.

Recently, these algorithms have become more interesting for the robot control programmers; although, they have some limitation and restrictions too. For example, it is difficult to force a robot in a completely cluttered environment that cannot be described as a mathematical model and pass these information to a Robot Navigation Algorithm. So, inspired from the human intelligence, fuzzy logic neural network, genetic algorithm and potential field approaches have been deployed in navigation of mobile robots in many recent algorithms. However, the incorporation of an integral procedure to frame the hybrid controller is becoming an increasing necessity for autonomous robots capable of moving along in the industrial environments. Each method has its own advantage over others in certain aspects. Generally, the main difficulties for robot-path-planning problem are computational complexity, local optimum, and adaptability. Researchers have always been seeking alternative and more efficient ways to solve the problem.

2.2. Navigation of mobile robots

Since last few decades, the research communities in mobile robotics have paid lot of attentions to the development of different control architectures for navigation of mobile robots. For this, mainly two principle designs have been adopted. One is called the functional or horizontal decomposition [21] and the other is the behavioural or vertical decomposition [22] as shown in Fig. 2.1 & Fig. 2.2. The former approach is sequential and involves modelling and planning. The latter approach is parallel and requires exploration and map building. Both approaches use many distinct sensory inputs and computational processes. Decisions such as turn left, turn right, run or stop are made on the basis of those inputs [23].

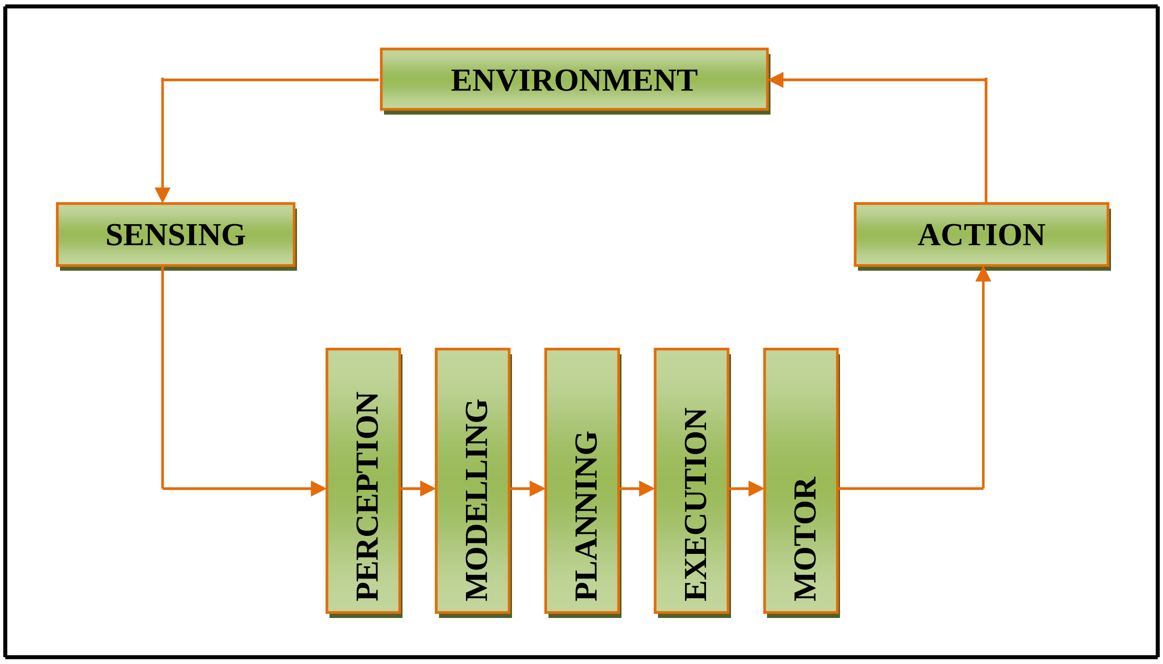

Fig. 2.1. Flow diagram of the horizontal decomposition method for navigation of mobile robot.

Navigation for mobile robots can be well defined in mathematical (geometrical) terms. It involved many distinct sensory inputs and computational processes. Thus, it is necessary first to define what navigation is and what the function of a navigation system is. Levitt and Lawton [24] tried to define the navigation by following three questions: (a)

"Where am I ?", (b) "Where are other places relative to me ? " and (c) "How do I get to other places from here ?". Underlying question (a) is the problem of recognising and identifying the particular place and questions (b) and (c) focused the point, how to get rid of the obstacle and march towards goal respectively.

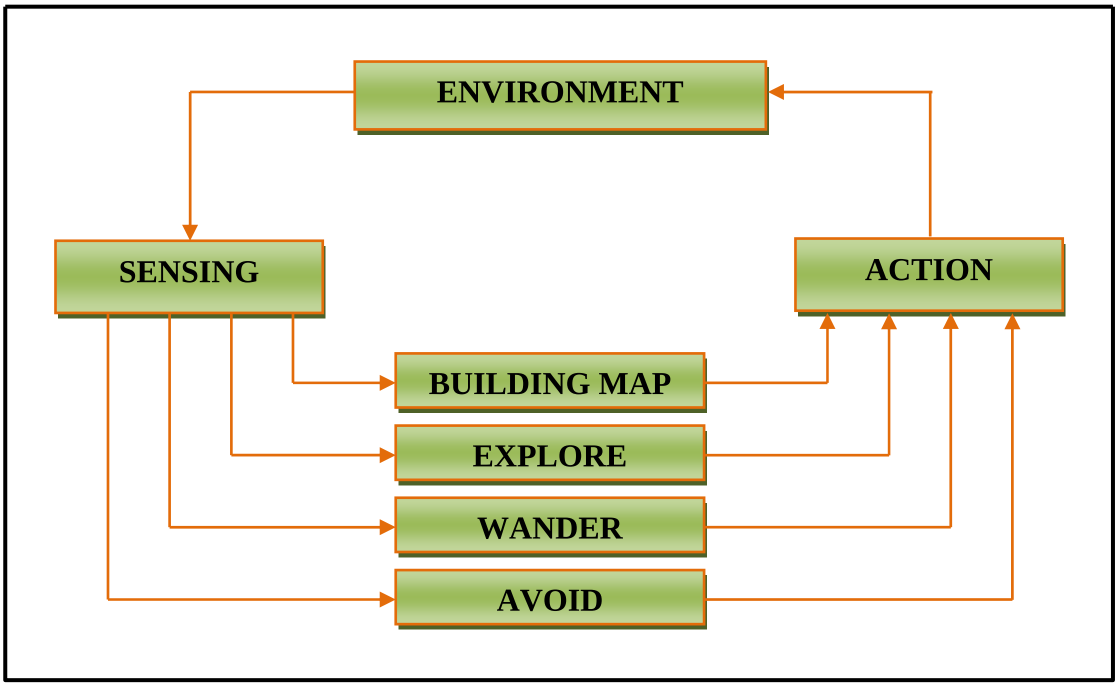

Fig. 2.2. Flow diagram of the vertical decomposition method for navigation of mobile robot.

An autonomous mobile robot is a system capable of interpreting, perceiving, executing and realising a task in an environment without any outside help. To accomplish this, the robot must first be able to interpret and perceive its environment, then analyse and model it. Next using this information, a navigation algorithm must allow the robot to determine a suitable trajectory with its available information. Finally, a control process must be able to assume that the robot moves correctly within its environment. In order to move safely in a work place and to detect the nearby object, the mobile robot must have a way to perceive its environment. Researchers mainly use devices such as laser, sonar, vision, infrared [25,26] or a heterogeneous sensor systems.

Using the environmental information perceived at each instant as well as data from previous instants, a strategy should be pursued to enable the robot to reach its target position without colliding the obstacles. Keeping in view of the various research publications in the recent years in this field, attempt has been made to explore three main techniques such as Potential Field technique, Genetic Algorithm technique, and Fuzzy Logic technique along with some other techniques viz. Neural Network technique, Grid Based technique, Heuristic technique, Adaptive Navigation technique, Virtual Impedance technique, and Divide and Conquer techniques and their hybrid models have been discussed. Those techniques together with the different sensors employed [27,28] have been reviewed below. It is realized that the research for navigation of mobile robot are not matured till date and has to be modified in many respects. Research may be done in finding out the optimal navigational technique for several mobile robots with multiple targets. Technical details may be found out to achieve various interactive perceptions between the robots and to recognise the obstacles ahead.

2.3. Different techniques used for navigation of mobile robots

Since last three decades researchers have focussed on various techniques for control of mobile robots. The different techniques incorporated for the navigation of mobile robots are summarised below.

2.4. Potential field technique

2.4.1. Introduction

The potential field approach was first introduced to the field of navigation of mobile robot by A. I. Khatib [29] around 1979. It is based on the metaphor that the goal should attract the robot towards it, and that the obstacles should repel the robot from them. The important variables in potential field navigation are the position of the robot, position of the goal point and positions of any obstacles. The total force exerted on the robot is equal to the vector sum of the attractive and repulsive forces. The attractive force is proportional to the distance from the goal point and the repulsive force is inversely proportional to the distance from the obstacle. Combining these two forces upon the robot produces a net resultant force that moves the robot towards the goal and away from obstacles simultaneously as shown in Fig. 2.3.

This technique can be used in either a continuous or discrete form and is suitable for online navigation. It is computationally cheap (both in terms of computing the function to represent the potential field, and in terms of computing the desired direction for the agent at positions on the potential field). Unfortunately, the basic technique is also incomplete and non-optimal, and in fact it is likely to fail on anything other than a trivial environment containing a few convex obstacles. Arbitrary obstacle shapes can be represented by this technique. Many researchers have used potential field techniques for navigation of the mobile robots, the incremental improvement and their look falls are highlighted below.

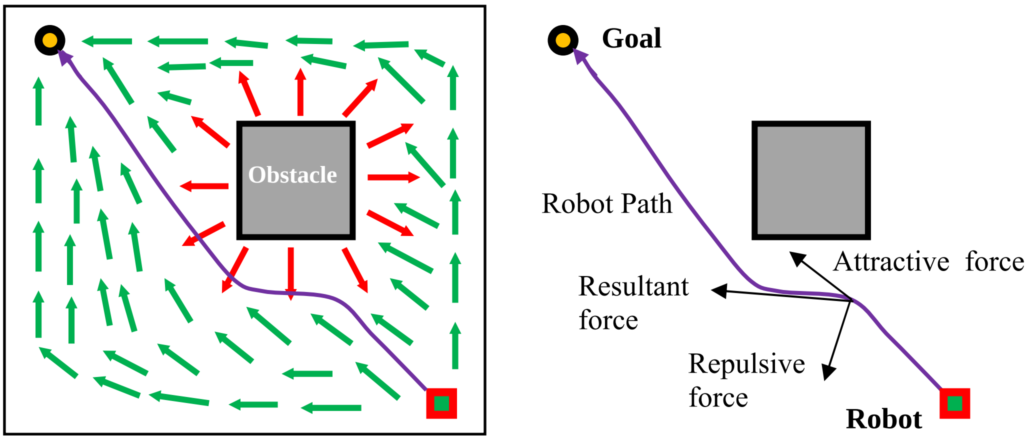

Fig. 2.3. Example of a potential field approach for mobile robot navigation.

2.4.2. Potential field technique for mobile robot navigation

Potential field technique is rapidly gaining popularity in navigation and obstacle avoidance applications for mobile robots because of its elegant mathematical analysis and simplicity. The potential field approach uses a scalar function called the potential function. It has a minimum value, when the robot is at the goal configuration and has a high value on obstacles. Anywhere else, the function slopes down towards the goal configuration, so that the robot can reach the target by following the negative gradient of the potential field. The high value of the potential field prevents the robot going near the obstacles. Potential field based navigation has been shaped by engineers for robot navigation. A chronology of important and recent publications in potential field based mobile robot navigation is given in terms of landmark papers as follows:

In 1978, Khatib published his first paper with La Maitre [30] to suggest a need for a computationally lean yet flexible control technique for robots in a cluttered environment and posits a potential fields approach. In the year 1986, Khatib published the landmark journal paper, “Real Time Obstacle Avoidance for Manipulators and Mobile Robots” [2], that is widely recognised as the start of mainstream research in this field. The approach faces several problems though, particularly the local minimum problem. A year later in 1987, Koditschek presents a landmark paper containing the minimum-free navigational potential field approach [31]. This is followed up by other papers by Koditschek et al. in 1989 and 1992 [32, 16] improving his technique. By 1990, most of the research into Khatib's original heuristic model of potential fields has stopped, with hybrid approaches and discrete potential field approaches having been the best practical efforts at overcoming local minima. Latombe [33] published the most significant work in discrete technique. In 1992 attempts were made to try and make the navigational field approach more general, by Connolly et al. [34] and Kim and Khosla [35].

As early as 1991, doubts are being expressed as to whether the potential field method can ever be made to work [36], and by 1993, most of the research into variations of the navigational potential fields approach has been stopped, without managing to overcome key problems such as computational cost, inability to cope with complex environments or the limitation to offline navigation. After 1993, there were no more major historical breakthroughs in this field, but rather there was a path of research focused on applications of potential fields in particular niches of robotics and on making small modifications to existing work to try and incrementally improve, rather than revolutionise the field. The main areas of work were: hybridising potential fields with some other mechanism with potential fields being used to provide continuous trajectories [37- 39]; slightly improving upon the computational costs of the potential field approach [40]; or re-applying potential fields to more complicated problems than basic online navigation, i.e. multiple agents [41- 43] or navigation under non-holonomic constraints [44- 46]. Since the mid 1990s, potential fields have been found in lecture notes and books about navigation, but no revolutionary work has taken place - such as novel types of approach to the basic problem of navigation, or novel approaches to overcome the local minimum problem. Instead, small revisions are being made to existing approaches that have been around since the late 1980s and early 1990s.

After that Borenstein et al. [47] and Koren et al. [36] have developed a real-time obstacle avoidance approach for mobile robots. The navigation algorithm takes into account of dynamic behaviour 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 other words, 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. Garibotto et al. [48] have proposed a potential field approach for local path planning of a mobile robot in telerobotics context, i.e. with the presence of a human operator in the control loop at a supervisory level. Kim et al. [35] have developed a new function in artificial potential field by using harmonic functions that eliminate local minima for obstacle avoidance problem of a mobile robot in a known environment. Rimon et al. [49] and Koditschek [31] have presented a new methodology for exact robot motion planning and control unifying kinematic path planning problem and the lower level feedback controller design. They validate their results in simulation mode. Guldner et al. [50] have discussed a suitable control for tracking the gradient of an artificial potential field. However such functions are usually plagued by local minima. Al-Sultan et al. [51] have introduced a new potential function for path planning that has the remarkable feature of no local minima.

Yun et al. [52] have analysed a wall following action using potential field based on motion planning method. The new algorithm switches to a wall following control mode when the robot falls into local minima. They implemented the new algorithm on a Nomad 200 mobile robot. They have demonstrated simulation and experimental results to validate the usefulness of their method. Chuang et al. [53] have presented analytical tractable potential field model of free space. They have used Newtonian potential function for collision avoidance between object and obstacle. Sekhawat et al. [54] have developed a technique based on holonomic potential field taking into account the nonholonomic constraints of the system. Liu et al. [55] have presented a navigation algorithm, which integrates virtual obstacle concept with a potential-field-based method to maneuver cylindrical mobile robots in unknown environments. Their study focuses on the real-time feature of the navigation algorithm for fast moving mobile robots. They mainly consider the potential-field method in conjunction with virtual obstacle concept as the basis of their navigation algorithm. They have presented their results in simulation and experiment modes.

Wang et al. [56] have presented a new artificial potential field method for path planning of non-spherical single-body robot. The optimal path problem is calculated as per the heat flow with minimal thermal resistance. Ren et al. [57] have investigated the inherent oscillation problem of potential field methods (PFMs) in the presence of obstacles and in narrow passages. These situations can cause slow progress and system instability in implementation. To overcome these two problems, they have proposed a modification of Newton's method. The use of the modified Newton's method greatly improves system performance when compared to the standard gradient descent approach. They have validated their technique by comparing the performance with the gradient descent method in obstacle-avoidance tasks. Xi-yong et al. [58] have presented a robot navigation algorithm with global path generation capability. Their algorithm prevents the robot from running into local minima. Simulation results show that the algorithm proposed by the author is very effective in complex obstacle environments. Chengqing et al. [59] have presented a navigation algorithm, which integrates virtual obstacle concept with a potential-field-based method to maneuver cylindrical mobile robots in unknown or unstructured environments. Simulation and experiments of their algorithm shows good performance and ability to overcome the local minimum problem associated with potential field methods.

Im et al. [60] have proposed a local navigation algorithm for mobile robots that combines rule-based and neural network approaches. First, the Extended Virtual Force Field (EVFF), an extension of the conventional Virtual Force Field (VFF), implements a rule base under the potential field concept. Second, the neural network performs fusion of the three primitive behaviours generated by EVFF. Finally, evolutionary programming is used to optimise the weights of the neural network with an arbitrary form of objective function. Furthermore, a multi network version of the fusion neural network has been proposed that lends itself to not only an efficient architecture but also a greatly enhanced generalization capability. The global path environment has been classified into a number of basic local path environments to which each module has been optimised with higher resolution and better generalization. These techniques have been verified through computer simulation under a collection of complex and varying environments.

Tsourveloudis et al. [61] have used an electrostatic potential field (EPF) path planner, which combined with a two-layered fuzzy logic inference engine and implemented for real-time mobile robot navigation in a 2-D dynamic environment. The first layer of their fuzzy logic inference engine performs sensor fusion from sensor readings into a fuzzy variable, collision, providing information about possible collisions in four directions, front, back, left, and right. The second layer guarantees collision avoidance with dynamic obstacles while following the trajectory generated by the electrostatic potential field. They have tested their proposed approach experimentally using the Nomad 200 mobile robot. The potential field approach have been used by Cosio et al. [62] which allow for avoidance of large or closely spaced obstacles, through the use of auxiliary attraction points with adjustable force strength and distance to the goal. A genetic algorithm has been used for optimisation of the force intensity parameters of the repulsion and attraction cells, as well as the position parameter of the auxiliary attraction points. Their scheme reported constitutes an effective strategy for autonomous robot navigation. McFetridge et al. [63] have presented a methodology for robot navigation and obstacle avoidance. Their approach is based on the artificial potential field (APF) method, which is used for obstacle avoidance with fuzzy logic technique. They have presented simulation results demonstrating the ability of their developed algorithm to perform successfully in simple environments.

Vadakkepat et al. [64] have proposed Evolutionary Artificial Potential Field (EAPF) for real-time robot path planning. The artificial potential field method is combined with genetic algorithms, to derive optimal potential field functions. Their proposed Evolutionary Artificial Potential Field approach is capable of navigating robot situated among moving obstacles. Fitness functions like, goal-factor, obstacle-factor, smoothness-factor and minimum-path length factor are developed for the Multi-Objective Evolutionary Algorithm (MOEA) selection criteria. Simulation results showed that their proposed methodology is efficient and robust for robot path planning with non-stationary goals and obstacles. Ratering et al. [65] have proposed hybrid potential field method to navigate a robot in which the environment is known. They have tested their techniques in real as well as simulated mode.

An algorithm based on an artificial potential field and hierarchical cell decomposition technique has been developed by Hou et al. [66] to solve the path finding problem for a mobile robot. The complete map of the workspace including obstacle locations has been assumed to be known a priori. The basic cell structure used for decomposition is a hexagon. Their artificial potential field is based on an attractive force from the goal position and repelling forces from the obstacles. They have also presented the computer simulations for various obstacles scenarios.

The local path planning by Cha et al.[67] is about directional weighting method based on configuration space method and potential approach method. Their directional weighting method decided the heading direction of the mobile robot by estimating the attractive resultant force. The heading direction enables the mobile robot to approach the goal through shortest path, without any collision with surrounding obstacles. They have estimated the effectiveness of their directional weighting method for real time mobile robot by computer simulation and experiment in a complex environment. Aisultan et al. [68] have discussed about the path planning of mobile robot by using potential function. They have presented the simulation using a point mobile robot in an environment with smooth obstacles. They have also given experimental evidence of their theory developed. Shkel et al. [69] have considered the case of a point-mass mobile robot operating in a planner environment with unknown stationary obstacles of arbitrary shapes. Based on the velocity and sensing data, the robot continuously plans its collision free motion based on canonical solutions. Each of which presents a time optimal path within the robot's sensing range. Their simulation results demonstrate the performance of the algorithm.

Pradhan et al. [70] described a modified potential field method for robots navigation. The developed potential field function takes care of both obstacles and targets. The final aim of the robots is to reach some pre-defined targets. The new potential function can configure a free space, which is free from any local minima irrespective of number of repulsive nodes (obstacles) in the configured space. There is a unique global minimum for an attractive node (target) whose region of attraction extends over the whole free space. Simulation results show that the proposed potential field method is suitable for navigation of several mobile robots in complex and unknown environments.

Jean et al. [71] have used navigation of mobile robot using potential field method. Their proposed approach contributes in eliminating the existing problems of motor schema such as trap situations due to local minima, no passage between closely spaced obstacles, oscillations in presence of obstacles and oscillations in narrow passages. Masoud [72] 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. Mbede et al. [73] have focused on autonomous motion planning of manipulators in known environments and with unknown dynamic obstacles using potential field method. Tsourveloudis et al. [61] have discussed about electrostatic potential field (EPF) path planner in combination with a two-layered fuzzy logic inference engine. Their proposed approach was experimentally tested using the "Nomad 200" mobile robot. Cosio et al. [62, 74] 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. [75] 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. Wachter et al. [76] 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. These robots fuse GPS and inertial measurement to estimate their own state. Jing et al. [77] have investigated the inherent oscillation problem of potential field methods (PFMs) in presence of obstacles and in narrow passages. They have validated their technique by comparing its performance with different potential models by changing different parameters. Tsuji et al. [78] have proposed a new trajectory generation method that allows full control of transient behaviour, namely, time-to-target and velocity profile based on the artificial potential field approach for a real-time motion-planning problem of robots. Apart from the above literature review, G. A. based navigational technique for control of mobile robots is also discussed below.

2.5. Genetic algorithm technique

2.5.1. Introduction

Motion planning is an important aspect in the field of mobile robotics. Motion planning is to find a suitable collision-free path for a mobile robot to move from a start configuration to target configuration in an environment consisting of obstacles. In course of motion planning, very often this path is highly desirable to be optimal or near-optimal with respect to time, distance, energy and smoothness. Distance is a commonly adopted criterion.

It is obvious that path planning can be viewed as an optimization problem (e. g., shortest distance) under certain constraints (e.g., the given environment with collision-free motion). Since the appearance of genetic algorithms (GA) in 1975 [79], GAs have been used in solving many optimization problems successfully. GA is stochastic search technique analogous to natural evolution based on the principle of survival of the fittest. The potential solutions of a problem are encoded as chromosomes, which form a population. Each individual of the population is evaluated by a fitness function. A selection mechanism based on the fitness is applied to the population and the individuals strive for survival. The fittest ones have more chance to be selected and to reproduce offspring by means of genetic transformations such as crossover and mutation. The process is repeated and the population is evolved generation by generation. After many generations, the population converges to solutions of good quality, and the best individual has good chance to be the optimal or near optimal solution. The feature of parallel search and the ability of quickly locating high performance region [80] contribute to the success of GAs on many applications.

2.5.2. Genetic algorithm technique for mobile robot navigation

Since last few decades robot path planning has been an emerging area, and many techniques have been adopted to tackle this problem. Researchers have always been seeking alternative and more efficient ways to solve the problem. In the recent years many researchers have used Genetic Algorithm for navigational path optimisation of mobile robots which are described below.

The article by Merchán et al. [81] is based on genetic algorithm (GA) for navigational behaviors of an autonomous robot. They presented a method to adapt basic reactive behaviors using a genetic algorithm. In order to test the rules obtained in each generation of the genetic evolution process, a real robot has been used. They have shown their results numerically. Ming et al. [82] have used genetic algorithm for path planning of mobile robot. They have used this method to adjust the membership functions associated with the linguistic labels that defined the variables of a rule based control system. Their designed control system has allowed mobile robot to avoid unexpected obstacles in an unknown environment. Noguchi et al. [83] have developed a path for agricultural mobile robot using genetic algorithm. They have optimised the time series of the steering angle and created the optimal work path for the mobile robot. Joo et al. [84] have discussed about Genetic Algorithm (GA) to produce a model for navigation control of a mobile robot. The validity of their result has been demonstrated by experiment. Genci et al. [85] have implemented an extended multi-population genetic algorithm (EMPGA), for navigation of an autonomous intelligent agent. Their algorithm tries to distribute the number of individuals among sub populations as different strategies and became successful during the course of evolution. Malrey [86] has discussed about the distributed autonomous robots (agents) systems. In his approach it is essential that each robot has both learning and evolution ability to adapt in dynamic environment. The validity of his system was verified through simulation, as shown in Fig. 2.4.

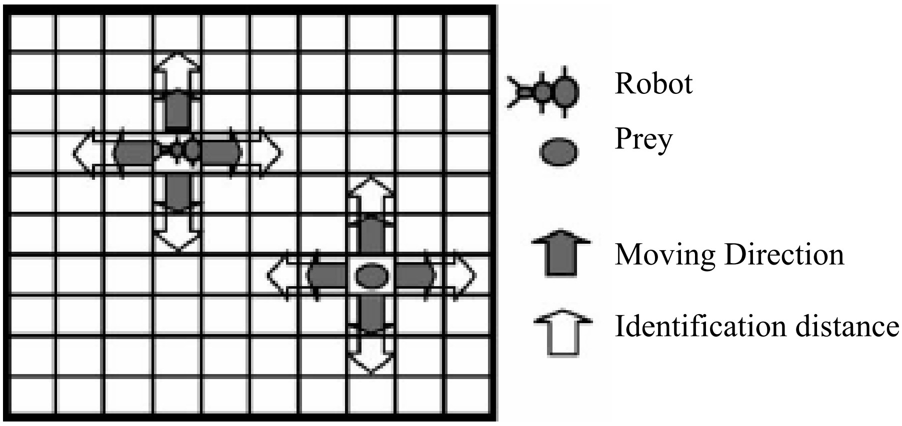

Fig. 2.4. Identification of distance and moving direction of artificial organisms.

Jeong et al. [87] have described an efficient approach for designing a multi-agent system consisting of mobile robots that co-operate to achieve specific objectives. They have implemented an evolutionary approach to design controllers for mobile robots. Experiment and simulations are performed to verify the proposed idea. Noguchi et al. [83] have developed a method that is able to create a sub optimal path of an agricultural mobile robot. Their control technique is combining a neural network (NN) and a genetic algorithm (GA). They have also shown the comparison between simulation and experimental results in Fig. 2.5.

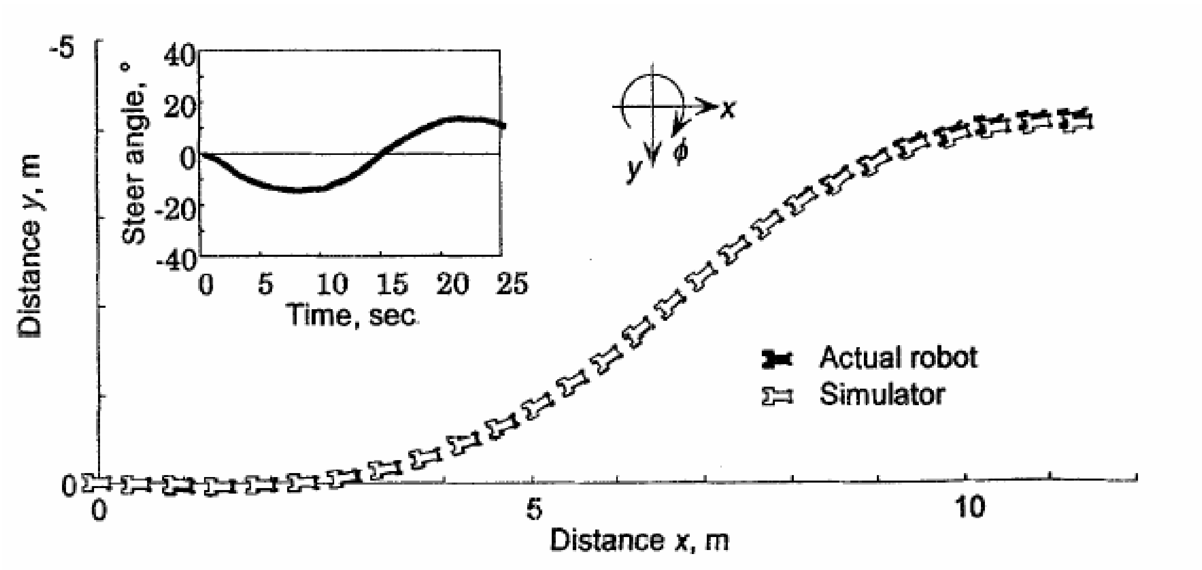

Fig. 2.5. Comparison between the trajectory of the robot simulator and that of the actual robot.

GAs has been used by several researchers for path planning of mobile robots [88,87]. However, like most early GA applications, most of those methods adopt classical GAs that use fixed-length binary strings and two basic genetic operators, and few modifications were made to the algorithms. Genetic algorithm based path planning with fix-length binary string chromosomes based on cell representation of mobile robot environment has been proposed [89]. Its binary encoding is biased and inefficient. Besides, in order to use the standard GA, the path planning solutions are restricted to X-monotone or Y-monotone. The classical GAs uses binary strings and two basic genetic operators. After encoding solutions to a problem, the classical GAs are more like "blind" search, and perform well when very little prior knowledge is available. However, GAs do not have to be "blind" search, when additional knowledge about problem is available, it can be incorporated into GAs to improve the efficiency of GA [90]. Path planning is such a problem that requires knowledge incorporation into the GAs for the problem. Graph technique is a traditional way of representing the environment where a mobile robot moves around. A genetic algorithm based on MAKLINK graph environment representation is proposed by many authors [91,92]. In this genetic algorithm, the path is represented by variable length chromosomes formed by mid-points of the free-links, which is a more natural way of encoding than binary strings. This graph based method needs to form a configuration space before applying the genetic algorithm.

A specialized genetic operators was designed [93,94] with some heuristic knowledge. A path is represented by a hierarchically ordered set of vectors that define path vertices generated by a modified Gram-Schmidt orthogonalization process [95]. An evolutionary planner was proposed using GA for both on-line and off-line planning [98]. However, both approaches are relatively complicated on problem representation, evaluation, or GA structure. A novel Genetic Algorithms (GAs) approach was proposed [96] for a near optimal path planning of a mobile robot in a greenhouse. The chromosome encoding features in inverse proportion between research spaces of GAs and complexity of obstacles. They designed the fitness evaluation for both incomplete and complete paths to guide the evolutional direction.

An improved genetic algorithm performance was developed by considering more efficient genotype structure for a known environment with static obstacles [97]. Motion was constrained to only row-wise navigation. The above work was improved and presented results of a genetic algorithm based path-planning model developed for local obstacle avoidance of a mobile robot in a given search space [98]. While a new approach based on evolutionary computations is discussed to solve constrained nonlinear programming problems [99]. Three dominant hybrid approaches to intelligent control are experimentally applied to address various robotic control issues for navigation of mobile robot [100]. The hybrid controllers consist of a hierarchical NN-fuzzy controller applied to a direct drive motor, a GA-fuzzy hierarchical controller applied to position control of a flexible robot link, and a GP-fuzzy behavior based controller applied to a mobile robot navigation task. The problem of path finding through a maze of given size has been addressed by [101]. They presented a biologically inspired solution using a two level hierarchical neural network for the mapping of the maze. In the above research a limited effort was made to find an optimal controller (instead, a GA was designed based on a particular user-defined function and rules) for mobile robots navigation with multiple targets. Moreover, in these literature no way it has been noticed the incorporation of Petri net model with GA, which is attempted in the current investigation to make an integrated effective navigational controller for path planning of mobile robots.

2.6. Fuzzy logic technique

2.6.1. Introduction

Fuzzy logic approach has a very important characteristic in the way it deals with various situations without analytical modelling of the environment. Fuzzy control concepts are useful in both global and local path planning tasks for autonomous mobile objects. Humans have a remarkable capability to perform a wide variety of physical and mental task without any explicit measurements or computations. Examples of everyday tasks are, driving in city traffic, parking a car, and cleaning of house. In performing such familiar tasks, humans use perceptions of time, distance, speed, shape, and other attributes of physical and mental objects. Perceptions are described by propositions drawn from a natural language, in which the boundaries of perceived classes are fuzzy. It is highly desirable to capture the expertise of a human mind and to utilise the knowledge to develop autonomous navigation strategies for mobile robots. Fuzzy logic provides a mean towards accomplishing this goal. Fuzzy logic provides a formal methodology for representing and implementing the human expert's heuristic knowledge and perception-base actions. Using the fuzzy logic framework, the attributes of human reasoning and decision-making can be formulated by a set of simple and intuitive IF (antecedent)–THEN (consequent) rules, coupled with easily understandable and natural linguistic representations.

2.6.2. Fuzzy logic techniques for mobile robot navigation

Fuzzy logic technique was first introduced by Lofti Zadeh [102] in 1979 and since then it has been used in many fields of engineering applications. Robot navigation control is one of the most emerging areas of fuzzy logic applications [103]. Fuzzy logic technique can efficiently be used for navigation of mobile robots. Many scientists have used this technique in the recent years for the navigation of mobile robot which are discussed below.

Martinez et al. [104] have considered a problem in which sensor based motion control of mobile robot among obstacles in structured and/or unstructured environments with collision-free motion. For this they have taken fuzzy logic based intelligent control strategy, to computationally implement the approximate reasoning necessary for handling the uncertainty inherent in the collision avoidance problem. Sensor-based navigation method, which utilised fuzzy logic and reinforcement learning for navigation of mobile robot in uncertain environments, has been proposed by Boem et al. [105]. Their proposed navigator consisted of obstacle avoidance and goal-seeking behaviours. They have designed the two behaviours independently at the design stage and then combined together by a behaviour selector at the running stage. A behaviour selector using a bi-stable switching function chooses a behaviour, at each action step so that the mobile robot can go for the goal position without colliding with obstacles. In order to know the present state of mobile robot the ultrasonic sensors are used. The effectiveness of their proposed method was verified by a series of simulations.

Ishikawa [106] has described about a sonar-based navigation method using fuzzy control. His purpose is to construct an expert knowledge for efficient and better piloting of autonomous mobile robot. His method provides two functions i.e. tracing a planned path by sensing distances of an autonomous mobile robot and other function for avoiding stationary and moving obstacles by sensing free area distances ahead of autonomous mobile robot. He has used fuzzy control to select suitable rules i.e. tracing a path/ avoiding obstacles according to a situation, which was derived from sensor information by using fuzzy control. He has established his theory by means of simulations. Maeda et al. [107] deal with the drive control of an autonomous mobile robot. The approach is based on a forecast learning fuzzy control. In their approach, the robot forecasts whether it will drive safely or not by prediction, i.e. by using their integrated control rules. Robot considers the results of the forecast, and then adjust the conclusion parts of the integrated control rules in order to drive safely in an unknown environment. They have also verified their experimental results with simulation.

Beaufrere et al. [108] have discussed about real time navigation planning through an unknown obstacle field for mobile robot. They have used a two dimensional array to rapidly model the local environment. The array is continuously updated with an on board ultrasonic sensors. The information allows the robot to immediately compute the motion applying a navigation algorithm. The algorithm composed of three modules whose functions are to avoid obstacles, to reach the target point and to manage direction change of the mobile robot during path planning. For their approach they have used the method based on fuzzy reasoning. They have tested the approach both by simulation and experiment.

Wang [109] has used fuzzy systems to model higher levels of hierarchical systems and design controllers for the hierarchical systems. He has done two case studies i.e. 1) integrated planning and 2) control of mobile robots. In control part he has designed two types of control system for hierarchical model. He has shown in both cases that the whole hierarchical control system to be stable with tracking error converging to zero. A fuzzy approach for collision avoidance of automated guided vehicle (AGV) has been discussed by Lin et al.[110]. By fuzzy inference, they have guided an AGV from the starting point, towards the target without colliding with any static as well as moving obstacles. In trap recovering of the AGV they have used fuzzy logic and crisp reasoning combinely to get rid of a trap. They have shown the simulation results to show the feasibility of their proposed approach.

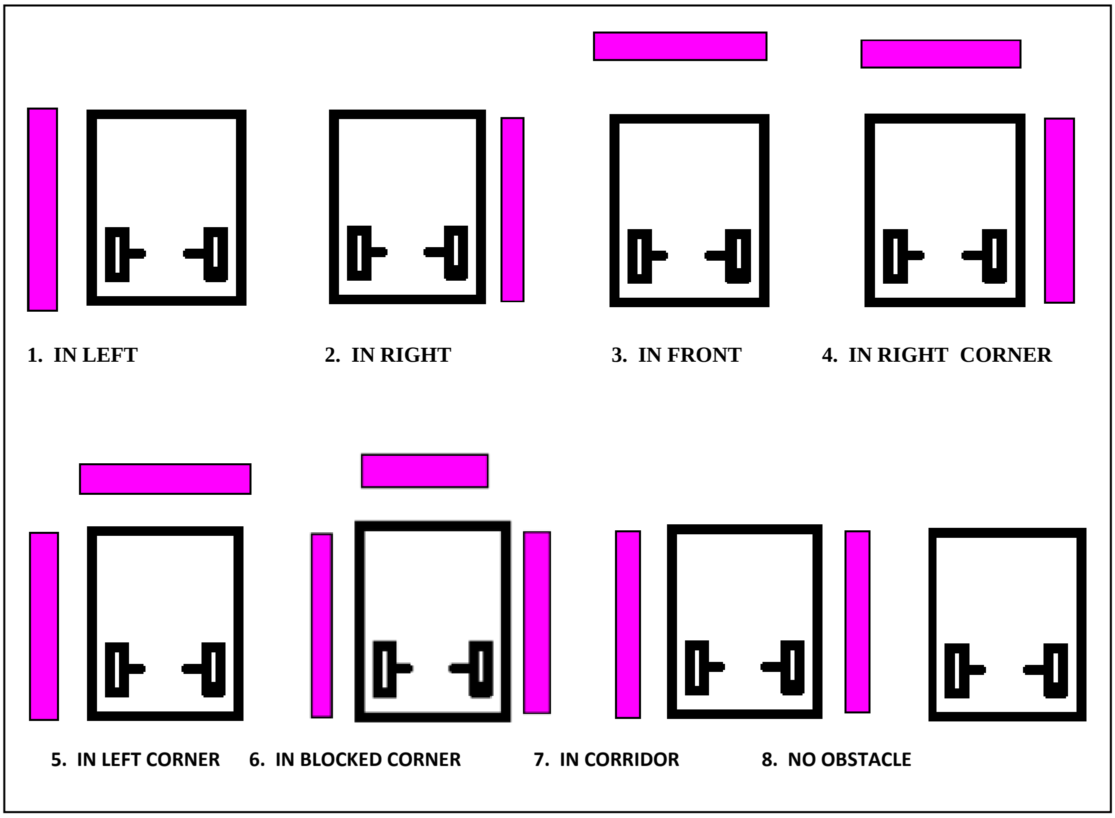

Fig. 2.6. Schematic view of the eight perpetual space categories, for fuzzy logic rules, used in navigation of mobile robot.

The paper by Zhang et al. [111] is mainly concerned with a mobile robot reactive navigation in an unknown cluttered environment based on fuzzy logic. Their reactive navigation is a mapping between sensory data and commands without planning. Their algorithm provides a steering command letting a mobile robot to avoid a collision with obstacles, shown in Fig. 2.6. They have authenticated their techniques by experimental and simulation results. Jagannathan [112] has discussed about the control of a mobile robot using fuzzy logic controller. He has shown the simulation results for his theoretical results.

Al-Khatib et al. [113] have developed a data-driven fuzzy approach for solving the motion planning problem of a mobile robot in the presence of moving obstacles. Their approach consists of devising a general method for the derivation of input–output data to construct a fuzzy logic controller (FLC). They have tested their algorithm in experimental model.

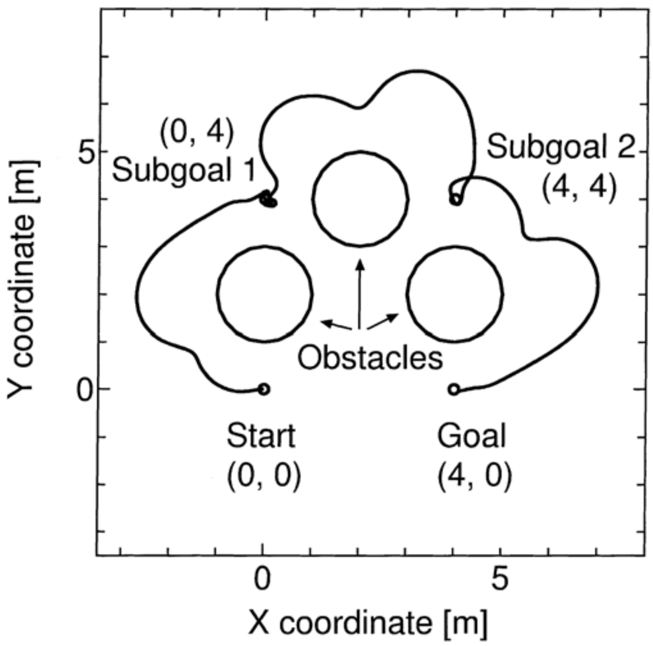

Fig. 2.7. Trajectory of the mobile robot with the scalar for the environment with three obstacles and two sub-objective points.

Izumi et al. [114] have used intelligent control techniques for robotic systems with some success in a wide variety of applications. They have presented a method for the intelligent control system of a robot using the fuzzy behavior-based control, which decomposes the control system into several elemental behaviors, and each one is realized by fuzzy reasoning. The proposed method has been applied for an obstacle-avoidance problem of a mobile robot. The effectiveness of the method is illustrated through some simulations shown in Fig. 2.7.

The article by Alfro et al. [115] has described the development and implementation of an automatic controller for path planning and navigation of an autonomous mobile robot using simulated annealing and fuzzy logic. The simulated annealing algorithm has been used to obtain a collision-free optimal trajectory among fixed polygonal obstacles. The trajectory tracking has been performed with a fuzzy logic algorithm. The objectives of the control algorithm are to track the planned trajectory and to avoid collision with moving obstacles. They have shown simulations and experimental results to validate their theory developed.

Lee et al.[116] have investigated the use of linguistic rules based on 'rules-of-thumb' experiences and engineering judgments to guide an industrial robot to follow a moving target using visual information. The problem has been formulated in the context of “Prey Capture” with the robot as a 'pursuer' and a moving object as a passive 'prey'. Such a formulation mimics the function and capable of a natural being to pursue its prey. The feasibility of the fuzzy logic control strategy has been verified experimentally.

Fuzzy logic controller for mobile robot navigation has been designed by Montaner et al. [117]. They have used their proposed technique on an experimental mobile robot which uses a set of seven ultrasonic sensors to perceive the environment. The designed fuzzy controller maps the input space (information coming from ultrasonic sensors) to a safe collision-avoidance trajectory (output space) in real time. This is accomplished by an inference process based on rules (a list of IF-THEN statements) taken from a knowledge base. Their simulation and experimental results show that the method can be used satisfactorily for navigation of mobile robots.

Hoffmann et al. [118] have presented a learning method which automatically designs fuzzy logic controllers (FLCs) by means of a genetic algorithm (GA). They have proposed a dynamically weighted objective function for control problems with multiple conflicting goals, which prevents the GA from premature convergence on FLCs that are exclusively specialized in the easier subtasks. Their robot obtains the task of reaching a target point by avoiding collisions with obstacles on its way. It perceives its environment by means of ultrasonic sensors. They have tested their results in simulation as well as in experimental mode. Mucientes et al. [119] have described a fuzzy control system for the avoidance of moving objects by a robot. A new paradigm of fuzzy temporal reasoning, which we call fuzzy temporal rules (FTRs), is used for this control task. Their control system has over 117 rules, which reflects the complexity of the problem to be tackled. They have also presented the experimental analysis for the corresponding simulation results.

Parhi [120] has described a mobile robot navigation control system based on fuzzy logic. Fuzzy rules embedded in the controller of mobile robot enables it to avoid obstacles in a cluttered environment. Each robot also incorporates a set of collision prevention rules implemented by a Petri Net model within its controller. The navigation control system has been tested in simulation and experimental modes. Therefore, in the recent approaches, many researchers proposed the navigation algorithms by using fuzzy logic [121,122]. However, in cases of operating the mobile robot in complex environments, the above methods have disadvantages of consistently constructing the navigation rules. Thus, to overcome this new problem, some other methods like Behavior Based Algorithms have also been suggested [123,124]. A considerable amount of work [125,126,127] has been carried out to develop suitable methods for motion planning of mobile robots, in presence of obstacles in an unknown environment. The automatic navigation of intelligent mobile robots in an unknown and changing environment were proposed by many authors [14, 128–131] based on fuzzy logic approach. Simulation and experimental results have presented by them to validate their approach. Huq et al. [132] have developed a novel approach to combine motor schema and fuzzy context dependent behavior modulation for mobile robot navigation. Their proposed approach contributes in eliminating the existing problems of motor schema such as trap situations due to local minima, no passage between closely spaced obstacles, oscillations in presence of obstacles and oscillations in narrow passages.

The Fuzzy controllers are mainly constructed by designing the fuzzy rules and membership functions (input and output) based on expert knowledge, modelling of processor learning [133]. To date, definition of fuzzy logic controller rules in robot obstacle avoidance are usually based on Mamdani or Takagi–Sugeno–Kang(TSK)rule base system [134–137]. However, it is difficult to maintain the correctness, consistency, and completeness of the generated fuzzy rule base. Various learning methods have been employed to design the fuzzy rule base [138, 139] and even construct fuzzy controllers [140,135]. Moreover, these methods contribute to the increasing complexity of the fuzzy controllers and could cause lost of interpretability [141]. Increasing the number of input and output variables could also contribute the lost of rule base interpretability and understanding the condition to activate the rules become more difficult [142]. The ordinal structure model of fuzzy reasoning has an advantage of an easier approach of defining rules with multiple inputs and outputs, by giving an associated weight to each rule in the defuzzification process. Feng et al. [143] have proposed an evolutionary particle swarm optimization (PSO)-learning algorithm to automatically generate fuzzy decision rules. Due to the development of the fuzzy rule-based system, it actually regulates the omni-directional vision-based mobile robot for obstacle avoidance and desired target approximation as soon as possible. Boubertakh et al. [144] proposes a new fuzzy logic-based navigation method for a mobile robot moving in an unknown environment. This method endows the robot with the capabilities of obstacles avoidance and goal seeking without being stuck in local minima. A simple Fuzzy controller is constructed based on the human sense and a reinforcement learning algorithm is used to fine tune the fuzzy rule base parameters. Apart from the above discussed techniques some other techniques are also used for navigation of mobile robots which are discussed briefly as follows.

2.7. Other techniques

2.7.1. Neural network technique

In recent years many researchers have used neural network technique for navigation of mobile robot. The works carried out by them are described below.

Tani et al. [145] have presented a novel scheme for sensory-based navigation of a mobile robot. They have shown that their scheme, which constructs a correct mapping from sensory inputs, sequences to the manoeuvring outputs through neural adaptation, such that a hypothetical vector field that achieves the goal can be generated as shown in Fig. 2.8. Their simulation results have shown that robot can learn task of homing and sequential routing successfully in the workspace of a certain geometrical complexity.

Janet et al. [146] have discussed about the neural network technique for navigation of mobile robot. They have used Kohonen and region-feature neural networks for this purpose. In both approaches they have categorised discrete region of space in a manner similar to optical character recognition. In their method, single robot can transform its knowledge of various learned regions to other mobile robots. Hui et al. [147] have used neuro-fuzzy controller for mobile robot navigation.

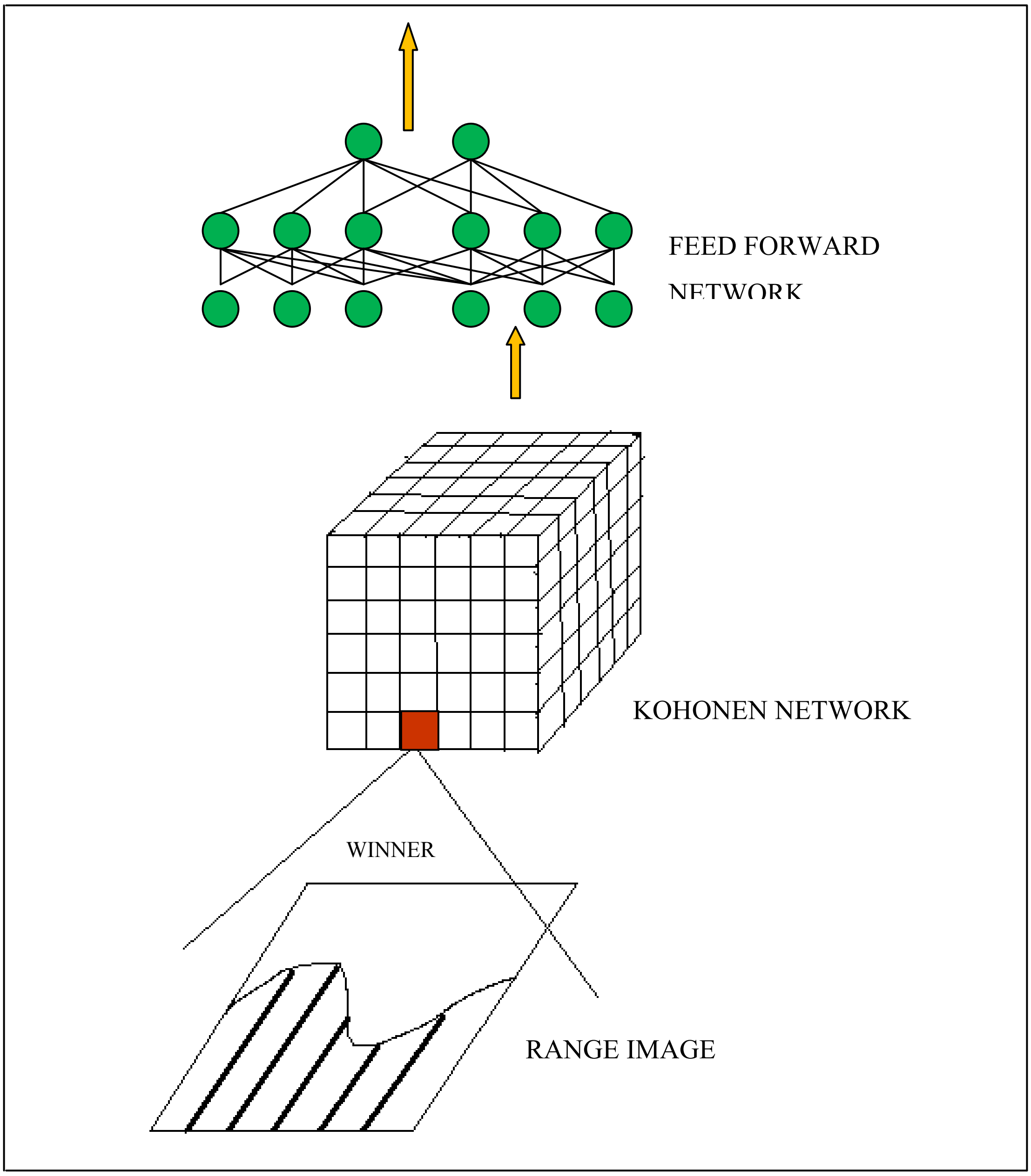

Fig. 2.8. Schematic view of the neural networks for mobile robots navigation with Kohonen network input.

The performances of these neuro-fuzzy approaches are compared with default behavior, manually-constructed FLC and potential field method, through computer simulations. They have stated that the neuro-fuzzy approach performs better than the other approaches, in most of the test scenarios. Antonini et al. [148] have proposed a real-time multiprocessor system for the solution of the tracking problem of mobile robots operating in a real context with environmental disturbances and parameter uncertainties. Their proposed control scheme utilizes multiple models of the robot for its identification in an adaptive and learning control framework. They have also shown the results experimentally for their theoretical validation.

2.7.2. Grid based technique

Many scientists map the environment into grids and use them in the navigation of the mobile robots. This method which has been used by various researchers, have been discussed below.

Lee et al. [149] adopted a methodology for global path planning for autonomous mobile robot in a grid-type world model.

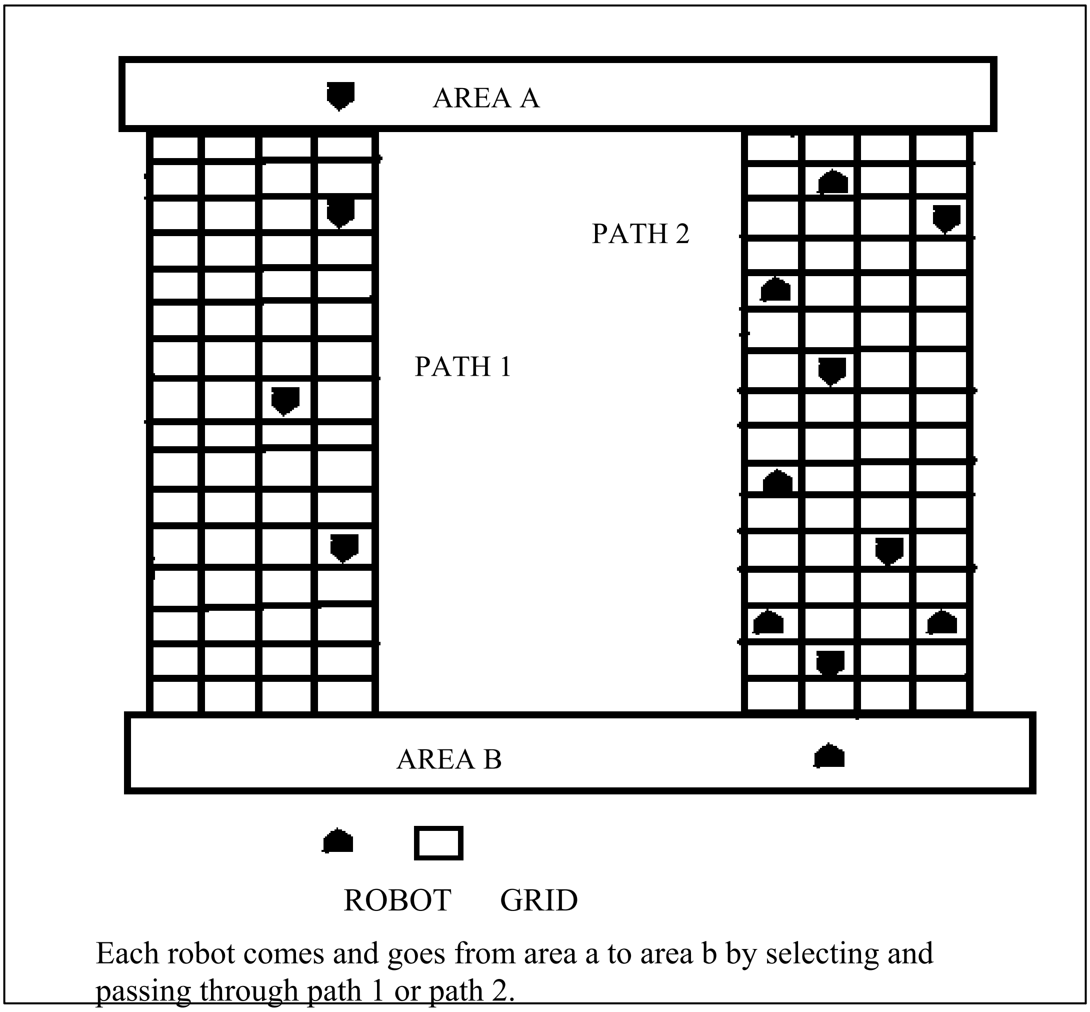

Fig. 2.9. Schematic view of the grid base representation for navigation of mobile robots.

The value of a certainty grid representing the existence of an obstacle has been calculated from reading of sonar sensors. A complete Bayesian derivation for a sensor data updating formula has been discussed and its validity is confirmed in a simulation by Cho et al. [150]. Asama et al.[151] have also discussed about the navigation of mobile robots by expressing the robot path as grid lines, Fig. 2.9.

Meyer et al.[152] have reviewed map-learning and path-planning strategies within the context of map-based navigation in mobile robots. A hierarchy of navigation strategies has been outlined in the discussion, together with the sort of adaptive capacities, each affords to cope with unexpected obstacles or dangers encountered on robot’s way to its goal. Filliat et al.[153] have presented a navigation technique for a robot, which has been used for internal representation of the spatial layout of its environment to position itself is a very complex task. The advantages and drawbacks of these strategies, notably with respect to the limitations of the sensors on which they rely.

2.7.3. Heuristic technique

Many investigators have used heuristic search method for the navigation of mobile robot. These are depicted below.

The automatic reaction of a mobile robot, computed in real time during its movement towards a target in an open field with obstacles in it has been dealt by Xu et al.[154]. They have implemented the navigation control of the robot through fuzzy reasoning by utilising the above mentioned heuristic rules. They have also shown the simulation results of mobile robot avoiding obstacles. Song et al.[155] have experimentally studied the navigation system that allows mobile robot to travel in an environment about which it has no prior knowledge. Their developed navigation system has been tested in their experimental mobile robot to demonstrate its possible application in practical situation. Meeran et al. [156] have discussed about the optimal path planning for mobile robot. For this they have presented a system which uses heuristic rules to augment the convex hull initial sub-tour created by the Graham scan algorithm. Bruske et al.[157] have discussed about reinforcement learning of reactive collision avoidance for an autonomous mobile robot. Their sensory input consists of eight unprocessed sonar readings. With the help of adaptive heuristic method, they are able to find an obstacle free path for the mobile robot.

The local path-planning algorithm using a human's heuristic method along with laser range finder for real-time navigation of a free-ranging mobile robot has been discussed by Cha [158]. Their algorithm utilises the human's heuristic by which the shortest path from various pathways to the goal can be found. He has estimated the effectiveness of the established path-planning algorithm both by computer simulation and by experiment in a complex environment.

2.7.4. Adaptive technique

Some of the scientists in recent years have used adaptive methods for the navigation of mobile robots. The research works by them are described below.

Ram et al. [159] have discussed about a continuous case-based reasoning and its application to the dynamic selection, modification and acquisition of robot behaviours in an autonomous navigation system. They have investigated about the adaptive reactive control mechanisms for autonomous intelligent agents in different environments. Pourboghrat et al. [160] have presented adaptive control rules at the dynamics level for the navigation of non-holonomic mobile robots with unknown dynamic parameters. Adaptive controls are derived for mobile robots using back stepping technique for tracking of a reference trajectory and stabilization to a fixed posture. The proposed control laws include a velocity/acceleration limiter that prevents the robot's wheels from slipping.

2.7.5. Virtual impedance technique

Virtual impedance is one of the emerging methods used by various engineers for navigation of mobile robot. The techniques are briefly discussed below.

Ota et al. [161] have discussed about the concept of "groups" in motion planning of multiple mobile robots. They have classified the groups into "static groups" and "dynamic groups". In virtual impedance method, the trajectory is determined by means of virtual forces. The virtual forces consist of three parts: that is the force generated between a reference point of the robot at the present time and the real position of the robot, the force generated between two robots and the force generated between a robot and an obstacle. The reference points for each robot as a function of time are calculated in advance.

2.7.6. Divide and conquer technique

The divide and conquer technique used for robot navigation by different investigators has been described below.

Mehta et al. [162] present a solution to the problem of constructing control programs. For their control programme they have used divide and conquer strategy for producing control laws, i.e. input-to-output map. Nagabhushan et al. [163] have proposed an algorithm based on quad tree-based method for planning the shortest path from a given source to any given destination. The algorithm uses recursive divide-and-conquer design strategy. Their proposed algorithm works in a 2D static environment with obstacles of any shape and practically unconstrained size of an autonomous vehicle. Minguez et al. [164] in their paper have addressed the reactive collision avoidance for robots that move in very dense, cluttered, and complex scenarios. They have described the design of a reactive navigation method that uses a “divide and conquer” strategy based on situations to simplify the difficulty of the navigation. They have also proposed a geometry-based implementation of the design called the *nearness diagram navigation*. The advantage of this reactive method is to successfully move robots in troublesome scenarios. They have also shown the experimental results on a real vehicle to validate their research. In the below section some more reviews are done for mobile robot navigation based on hybrid techniques.

2.8. Hybrid technique for navigation of mobile robots

In recent years, most of the researchers have used hybrid techniques for navigation of mobile robots. The related works carried out by them are briefly described below.

Kubota et al. [165] have proposed a GA based techniques for mobile robot navigation by perceiving information about the dynamic environment. They apply the proposed method for acquiring collision avoidance behaviors of a mobile robot in a dynamic environment. They conduct several computer simulations and simple experiments of a mobile robot. in changing environment. Cosio et al. [166] in their paper presented a new scheme for autonomous navigation of a mobile robot, based on improved artificial potential fields and a genetic algorithm. In their scheme multiple auxiliary attraction points have been used to allow the robot to avoid large, or closely spaced, obstacles. The configuration of the optimum potential field is automatically determined by genetic algorithm. Simulation experiments performed with three different obstacle configurations, and ten different routes, showed that the scheme reported has a good performance in environments with high obstacle densities, achieving a success rate of 93 per cent. Xin et al. [167] have proposed a method of global path planning based on neural network and genetic algorithm. They constructed the neural network model of environmental information in the workspace for a robot and used this model to establish the relationship between a collision avoidance path and the output of the model. Then the two-dimensional coding for the path via-points was converted to one-dimensional one and the fitness of both the collision avoidance path and the shortest distance are integrated into a fitness function. The simulation results showed that the proposed method is correct and effective. Wong et al. [168] proposed, a method based on Genetic Algorithms (GA) is to design a fuzzy system to control an omni-directional mobile robot so that it can move to any direction and spin at a rotating rate. In this method, an individual of the population in the GA-based method is used to automatically generate fuzzy sets of the premise and consequent parts of fuzzy system. A fitness function is proposed to guide the search procedure to select an appropriate parameter set of the fuzzy system such that the output of the fuzzy system can approach the output of data base established from the kinematics model of the three-wheeled mobile robot.

Hui et al. [169] have developed Neuro-fuzzy approaches to determine time-optimal, collision-free path of a car-like mobile robot navigating in a dynamic environment. They also compared the performances of both the genetic algorithm (GA)-optimized NN-FLC (Mamdani Approach) as well as GA-optimized NN-FLC (Takagi and Sugeno Approach). Begum et al. [170] made use of fuzzy logic for inferring the uncertainty in robot's location after motion commands, and then matching process is performed using genetic algorithms, which search the most probable map given the location information. The correspondence problem is solved exploiting the property of natural selection, which supports better performing individuals to survive in the competition. Tan et al. [171] developed a genetic algorithm (GA)-based fuzzy-interference control system with an accelerate/brake (A/B) module for a mobile robot in unknown environments with moving obstacles. The A/B module of the proposed system is to enable the mobile robot to make human-like decisions as it moves toward a target. Under the control of the proposed fuzzy inference model, the robot can perform well in avoiding both static and moving obstacles.

The GA module is employed to tune the membership functions enables the robot without suffering from local minima. The effectiveness of the proposed approach is demonstrated by simulation studies. Garcia et al. [172] have presented a novel proposal to solve the problem of path planning for mobile robots based on Simple Ant Colony Optimization Meta-Heuristic (SACO-MH). In SACOdm, the decision making process is influenced by the existing distance between the source and target nodes; moreover the ants can remember the visited nodes. The selection of the optimal path relies in the criterion of a Fuzzy Inference System, which is adjusted using a Simple Tuning Algorithm. The path planner application has two operating modes, one is for virtual environments, and the second one works with a real mobile robot using wireless communication. Both operating modes are global planners for plain terrain and support static and dynamic obstacle avoidance.

Daglarli et al. [173] present an artificial emotional-cognitive system-based autonomous robot control architecture for a four-wheel driven and four-wheel steered mobile robot. They considered discrete stochastic state-space mathematical model for behavioral and emotional transition processes of the autonomous mobile robot in the dynamic realistic environment. Deng et al. [174] explored a feedback control scheme of a two-wheeled mobile robot in dynamic environments. They discussed the existence of local minima and design of controller based on Lyapunov function candidate and considered virtual forces information including detouring force. Samsudin et al. [175] proposed a methodology to design an ordinal fuzzy logic controller with application for obstacle avoidance of Khepera mobile robot is presented. The implementation will show that ordinal structure fuzzy is easier to design with highly interpretable rules compared to conventional fuzzy controller. In order to achieve high accuracy, a specially tailored Genetic Algorithm (GA) approach for reinforcement learning has been proposed to optimize the ordinal structure fuzzy controller. They had shown the Simulation results and compared their results with conventional fuzzy controllers.

Fuzzy logic control (FLC) has been discussed by Petru et al. [176] for controlling a robot. They have divided the FLC into several smaller subsystems which reduce the negative effect that a rule-base may have on real-time performance. Learning allows autonomous robots to acquire knowledge by interacting with the environment and subsequently adapting their behavior. Behavior learning methods have been used to solve complex control problems that autonomous robots encounter in an unfamiliar real-world environment. Their paper discusses an experimental neuro-fuzzy controller for sensor-based mobile robot navigation in indoor environments. The autonomous mobile robot uses infrared and contact sensors for detecting targets and avoiding collisions.

2.9. Different sensors used for navigation of mobile robots

For navigation of mobile robot, sensors have an important role to play. There are different types of sensors used for navigation of mobile robot in the recent years. They can be classified into following categories: (i) Ultrasonic Sensor, (ii) Laser Sensor, (iii) Magnetic Compass Disk Sensor, (iv) Infrared Sensor, and (v) Vision (Camera) Sensor. Various researchers have used these sensors in navigation of mobile robots as described below.

2.9.1. Ultrasonic sensor

Ultrasonic sensors are widely used as external sensors for mobile robots, because they are simple to build and are of low cost. Generally, in the pulse-echo method the distance to the target can be accurately measured. Ultrasound signals can be induced through the piezoelectric effect or through electrostatic forces. Most sensors used in robotics are electrostatic since this mechanism is more efficient for coupling into air. It can be used to obtain distances from about 0.25m to 10m through direct time-of-flight measurement. A firing pulse triggers an ultrasound burst from the sensor and starts a counter. The counter is halted when the sensor, now acting as a receiver, detects a signal above a pre-set threshold. The counter reading thus gives the time of flight. The related researches for navigation of mobile robot using ultrasonic sensors are discussed below.

The research of Skewis et al. [177] has involved ultrasonic sensor-based motion planning for a single robot. They have used information from assumed sensor media as input to the motion-planning algorithm. A method for estimating the position and heading angle of a mobile robot moving on a flat surface has been proposed by Boem et al. [178]. Their localisation method utilises two passive beacons and a single rotating ultrasonic sensor. The passive beacons consist of two cylinders with different diameters and reflect the ultrasonic pulses from the sonar sensor mounted on the mobile robot. Their algorithm is suitable for processing sonar scan data obtained by an ultrasonic sensor with a wide beam spread. The proposed system has been implemented for a single robot in a very simple environment. Kleeman et al. [179] have established that two transmitters and two receivers are necessary and sufficient for a mobile robot to distinguish between planes, corners and edges. They have used a sonar sensor array with a minimum number of transmitters and receivers for their mobile robot. With their method, it is very difficult to navigate a single mobile robot in an unknown environment.

Mallita et al. [180] have discussed an ultrasonic imaging system for a mobile robot. Their transmitters cover a wide area and from the time-of-flight and the angle of incidence of echo pulses, their algorithm is able to detect obstacles ahead of the mobile robot. They have not implemented their method for multiple mobile robots. Hong et al. [181] have discussed the sensing of room boundaries for a mobile robot using an ultrasonic sensor array. They have implemented their algorithm with an extended Kalman Filter. Again, their technique was meant for a single mobile robot in a simple environment. Budenske et al. [182] have discussed the navigation of a robot with the help of sensory data. They have shown that their approach can be applied to guide a robot to and through an unknown and narrow doorway. Sonic range data is used to find the doorway, walls and obstacles. They have implemented their method for a single mobile robot for obstacle avoidance only.

2.9.2. Laser sensor

Laser sensor is one of the popular sensors used for navigation of mobile robot. The use of this sensor, for navigation are summarised below.

Navigation of mobile robot in cluttered room using a range-measuring laser as a sensor has been described by Forsberg et al. [183]. The robot estimates the size of the cluttered rectangle room and the position and orientation during its navigation. Failures in mobile robot navigation is due to errors in localising the robot relative to the environment could considerably reduced by path planning method proposed by Takeda et al.[184] . They introduced a method called Sensory Uncertainty Field (SUF), for every possible robot configuration '*q*'. This field estimates the distribution of possible errors in the robot configuration. They described in detail the computation of a specific SUF for a mobile robot equipped with a laser range sensor. Delaescalera et al. [185] have used an algorithm for localisation of mobile robot, which can be classified into two groups viz. 1) re-localisation through the detection of landmarks present in that environment and 2) for the map, they have used the sensors like laser diode and a CCD camera. The robot estimates its position by matching its sensorial information which is modelled as a straight line with a priori map of the environment. Their algorithm is able to work in real time. Lu et al. [25] have suggested two iterative algorithms for laser range scan so as to compute relative robot positions in an unknown environment. A solution to the problem of simultaneously extracting and tracking a piece-wise linear range representation of a mobile robot's local environment is discussed by Pears [186]. He has used optical laser sensor for the navigation control.

2.9.3. Magnetic compass disc sensor

Magnetic compass disc sensor is mainly used for navigation of mobile robot. Their use has been discussed in the following sections.

Finding the steering angle of an autonomous mobile robot by using an encoded magnetic compass disc as an orientation sensor has been discussed by Kim et al.[187]. They have done the experiments on two cases: 1) line path tracking test in a slippery environment and 2) orientation steering test in a circular path. They have also shown that the system is simple to design and applicable to mobile robot navigation.

Borenstein et al. [188] have shown that the magnetic compass is a very good sensor for finding out the location and heading angle (x, y and θ) for navigation of mobile robot. They have outlined different magnetic sensor i.e. 1) Mechanical Magnetic Compass, 2) Fluxgate Compass, 3) Hall-Effect Compass, 4) Magneto-Resistive Compass and 5) Magneto-Elastic Compass. The compass best suited for use with mobile robot applications is the Fluxgate compass. Noguchi et al. [189] have described about a mobile robot system, including a positioning system using the geomagnetic direction sensor. They have developed a control algorithm system for the mobile robot and conducted test on mobile robot in grassland. They have found the average error of the final position of each target position to be about 0.4m. Their absolute maximum error and rms errors are about 0.51m and 0.23m respectively.

2.9.4. Infrared sensor

Infrared sensor remains one of the efficient device for navigation of mobile robots. The uses of this sensor for the navigation of mobile robot in the recent years have been discussed below.

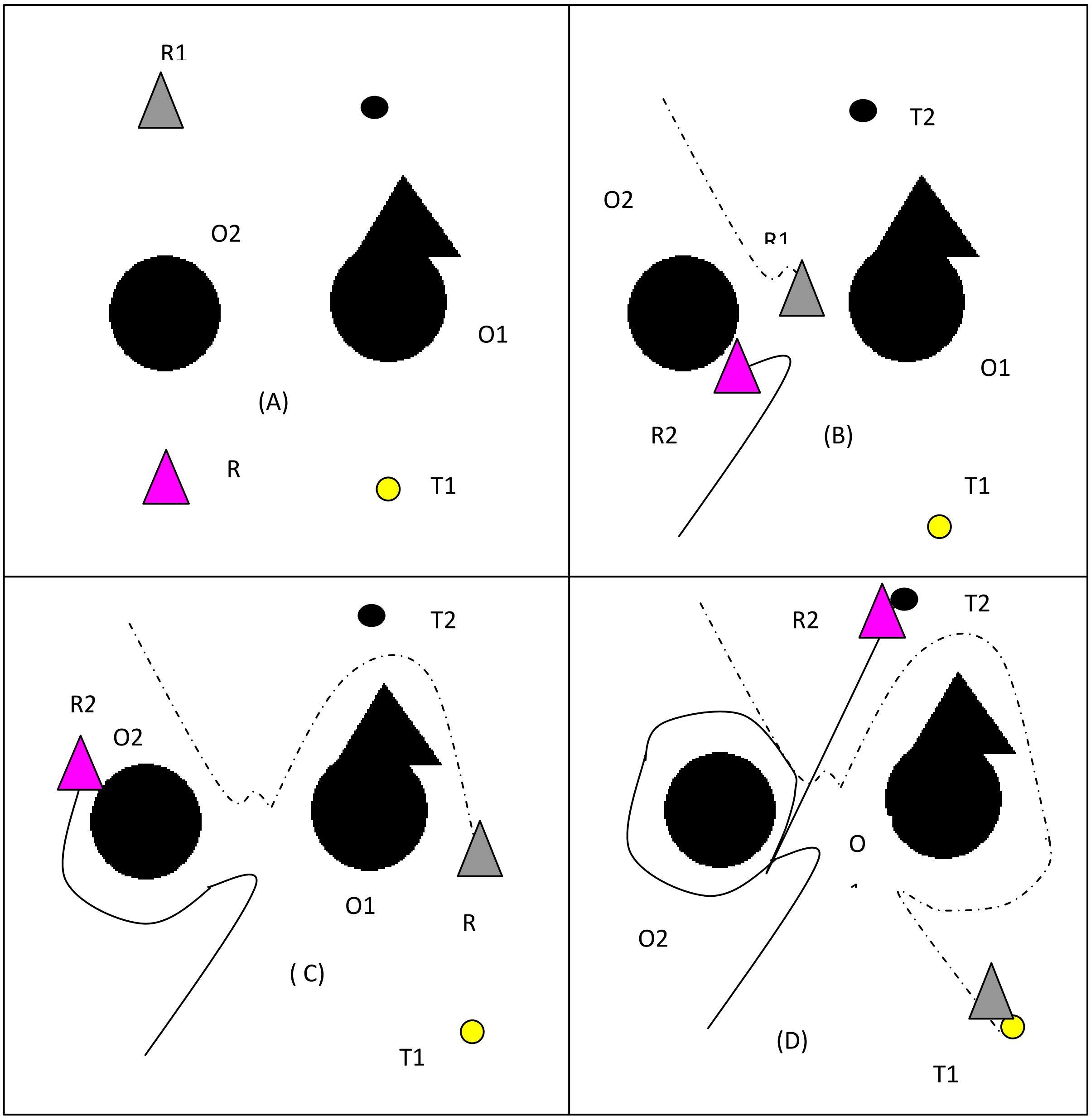

Fig. 2.10. Mobile robots navigation based on infrared sensor (where T1 and T2 are the target positions of the robots R1 and R2. O1 and O2 are the obstacles).

Aimy-an Autonomous Mobile Robot (AMR), capable of moving in an unknown environment filled with obstacles, has been developed by Yu et al. [190]. They have used infrared detector system to avoid collision with unexpected obstacles. They have also given the experimental results, which exhibit the power of developed algorithm and infrared detector system. Kube et al.[191] in their robot have used infrared sensor for obstacle avoidance. In a multi-robot scenario, their infrared obstacle sensor can detect obstacle within a five foot range.

Lumelsky et al. [192] have presented an approach for decentralised real-time motion planning for multiple mobile robots operating in unknown stationary obstacles. There robot has no knowledge about the scene or the paths and objectives of other robots. Each robot plans its path towards the target dynamically, based on the current position and sensory feedback shown in Fig. 2.10. They have used infrared sensor for their sensor feedback. Vandorpe et al. [193] have designed an autonomous mobile robot known as Leuvan Intelligent Autonomous System (LIAS). The robot is equipped with three types of sensor such as: ultrasonic sensor, tri-aural sensor and infrared sensor. Their optical infrared sensor gives a complete panoramic image of the scenario. In their robot an onboard system executes different modular navigation task.

2.9.5. Vision sensor

For object recognition by the mobile robot scientists mainly depend upon vision sensor. The use of this sensor for the navigation of mobile robot in recent years has been discussed below.

Han et al.[194] have described a navigation method of a mobile robot in which a single camera and a guide mark was used. They have instructed a travel path to the robot by means of path drawn on a monitor screen. The image of the guide mark provided information regarding the robots position and heading direction. The heading direction was adjusted while moving if any deviation from the specified path is detected. They have implemented their method in a mobile robot, which runs at a average speed of 2.5 ft/s. Yagi et al. [195] have designed a omni-directional image sensor for navigation of a mobile robot. Their robot is able to navigate by detecting the azimuth of each object in the omni-directional image as shown in Fig. 2.11. By matching the azimuth with the environmental map, the robot can precisely estimate its own location and motion.

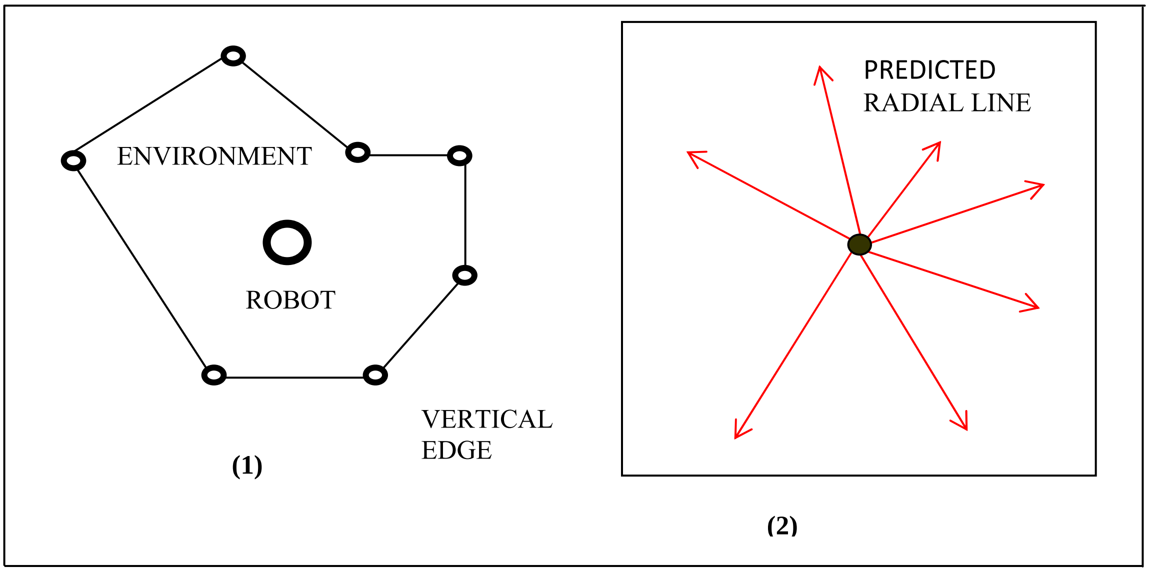

Fig. 2.11. Environmental map and prediction of the azimuth angle by vision sensor.

The robot can avoid colliding with unknown obstacles and estimate location by detecting azimuth changes, while moving about in the environment. Lin et al. [196] have described a landmark-based navigation technique for a mobile robot. They have achieved the robot position estimation by using a camera and a navigational landmark pattern.

Wichert [197] proposed a new methodology for image-based navigation using a self-organized visual representation of the environment. Self-organization leads to internal representations, which can be used by the robot but are not transparent to the user. It is shown how this conceptual gap can be bridged.

Kidono et al.[198] have proposed a navigation strategy which requires minimum user assistance using image sensors. In this strategy, the user first guides a mobile robot to a destination by remote control. During this movement, the robot observes the surrounding environment to make a map. Once the map is generated, the robot computes and follows the shortest path to the destination autonomously. They have also shown the experimental results using a real robot.

2.10. Summary

In this chapter an intensive review has been done on navigation of mobile robots. The basic problem of mobile robot navigations and some of the constraints, their limitations, merits/ demerits and successive improvement from the years together using various AI techniques, especially focussing on those utilising potential field techniques, genetic algorithm techniques, fuzzy logic techniques and their hybrid techniques have been studied. This chapter also provides an overview of characteristics and metrics of navigation solutions, along with descriptions of the various sensors used for navigation of mobile robots. A survey of the application domains of automated navigation in complex and dynamic environment has been outlined in context of intelligent control technique.

From the above literatures it have been found that most of the techniques have been implemented only in simulation and that a very limited works has been reported for controlling of multiple mobile robots with multiple targets in complex environments. Further there are no techniques which explain the inter-robot collision avoidance during navigation. This problem has been taken up in this work and addressed here for successful cognition for cooperative behaviour of multiple mobile robots in various complex environments. It is clear that it would be beneficial to have an approach to navigation that is computationally flexible, and as complete, optimal and natural as possible and that is capable of coping with a range of environments in terms of obstacle complexity and total number of obstacles. It would also be useful to have an approach that is general in nature so that it could be applied to all of the application domains and can be added to navigation problems to make them more challenging.

Chapter 3

Potential Field Technique for Navigation of Mobile Robots

- **Introduction**
- **Analysis of potential field technique for robot navigation**
- **Analysis of Petri-net model for inter robot collision avoidance**
- **Simulation results**
- **Comparison of results with other models**
- **Experimental implementation**
- **Summary**

3. Potential Field Technique for Navigation of Mobile Robots

This chapter introduces the analysis of potential field technique in context of motion planning architecture of mobile robots. The general structure of obstacle avoidance and target seeking behaviour of the proposed control scheme along with conceptual diagram for inter-robot collision avoidance module using Petri- net modelling has been explained in this chapter.

3.1. Introduction

This Chapter focuses on autonomous motion planning of multiple mobile robots in an unknown cluttered environment based on Artificial Potential Field (APF) technique. The navigation technique of robot control using modified 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 modified potential field function has been proposed to approximate the robots to the nearest targets. 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 function. 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.

3.2. Analysis of potential field technique for robot navigation

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 moves in a two dimensional workspace. Its centre position in the workspace is denoted by q = [x, y].

Assumption 2: At each time instant, only one front obstacle, which is perpendicular to the robot, one left obstacle and one right obstacle, which are nearest and co-linear with the robot, need to be avoided.

3.2.1. Attractive potential function

Potential field method is one of the most popular conventional techniques for solving the motion planning problems of mobile robot [199]. In this approach, the robot in the configuration space is represented as a particle under the influence of an artificial potential field U. The potential field function can be defined over free surface as the sum of an attractive potential, pulling the robot towards the goal configuration and a repulsive potential pushing the robot away from the obstacle [200]. The attractive potential function used for target seeking is represented as follows [94];

$$U_{att}(q) = \frac{1}{2}\delta\rho^{m}\left(q, q_{Target}\right) \tag{3.1}$$

where δ is a positive scaling factor.

$\rho\left(q, q_{Target}\right) = || q_{Target} - q ||$ denotes the Euclidean distance of the robot q from its current position to the 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 effectiveness of the potential field method mainly depends upon the chosen artificial potential function for particular application. Several potential functions, such as parabolic well, conic well, hyperbolic function, rotational field functions, quadratic potential field function, and exponential potential field function are used for various applications. However, parabolic and hyperbolic functions were mainly used for evaluating attractive and repulsive potential fields for path planning problem of robot respectively. The attractive potential field $U_{att}(x)$ can be defined as a parabolic well as follows.

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

$$F_{att}\left(x\right) = -\nabla U_{att}\left(x\right) = \delta\left(x_{Target} - x\right) \tag{3.2}$$

where, $F_{att}\left(x\right)$= attractive force between robot and the target.

$U_{att}\left(x\right)$=potential energy function of the robot due to target.

x_{Target}=position of the target.

x= position of robot and

$$\nabla = \frac{\partial}{\partial x}\hat{i} + \frac{\partial}{\partial y}\hat{j} + \frac{\partial}{\partial z}\hat{k}$$

Therefore,

$$\left\{U_{Total}\right\}_{att} = \sum_{s=1}^{r} U_{att}(tar_s) \tag{3.3}$$

where s is the numbers of targets, which varies from 1 to r

The distance between the robot and goal becomes equal to zero when there will not be any attractive force. Moreover, attractive force increases with the distance $\| q_{Target} - q \|$ in a linear fashion. Also, it is known that when the robot is far away from the obstacle, the repulsive force will be less and in such a condition, the robot's motion will not be affected due to the presence of obstacle, whereas if the obstacle is found nearer to the robot, it exerts a repulsive force.

3.2.2. *Repulsive potential function*

The commonly used repulsive function in the literature [201] is:

$$U_{rep}\left(obs\right) = \begin{cases} \frac{1}{2}\,\alpha\left(\frac{1}{\rho\left(q\,,\,q_{obs}\right)} - \frac{1}{\rho_0}\right)^2, & if\ \rho\left(q\,,\,q_{obs}\right) \le \rho_0 \\ 0 & if\ \rho\left(q\,,\,q_{obs}\right) > \rho_0 \end{cases} \tag{3.4}$$

Where α is the positive scaling factor, $\rho\left(\mathrm{q}\,,\,\mathrm{q_{obs}}\right)$ 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;

$$F_{rep}\left(obs\right) = -\nabla U_{rep}\left(obs\right)$$

$$=\begin{cases} \alpha \left(\dfrac{1}{\rho\ (q\ ,\ q_{obs})} - \dfrac{1}{\rho_0} \right) \dfrac{1}{\rho^2\ (q\ ,\ q_{obs})} \nabla\rho(q\ ,\ q_{obs}) & if\ \rho\ (q\ ,\ q_{obs}) \le \rho_0 \\ 0 & if\ \rho(q\ ,\ q_{obs}) > \rho_0 \end{cases} \tag{3.5}$$

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,

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

$$F_{rep}\ (obs_1) = \begin{cases} \alpha_1 \left(\dfrac{1}{\rho\ (q\ ,\ q_{obs_1})} - \dfrac{1}{\rho_0} \right) \dfrac{1}{\rho^2(q\ ,\ q_{obs_1})} \nabla\rho(q\ ,\ q_{obs_1}) & if\ \rho(q\ ,\ q_{obs_1}) \le \rho_0 \\ 0 & if\ \rho(q\ ,\ q_{obs_1}) > \rho_0 \end{cases} \tag{3.6}$$

For i^{th} obstacle,

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

$$F_{rep}\ (obs_i) = \begin{cases} \alpha_i \left(\dfrac{1}{\rho\ (q\ ,\ q_{obs_i})} - \dfrac{1}{\rho_0} \right) \dfrac{1}{\rho^2(q\ ,\ q_{obs_i})} \nabla\rho(q\ ,\ q_{obs_i}) & if\ \rho(q\ ,\ q_{obs_i}) \le \rho_0 \\ 0 & if\ \rho(q\ ,\ q_{obs_i}) > \rho_0 \end{cases} \tag{3.7}$$

where i is the number of obstacles and it varies from 1 to h, and $\alpha_1\ ,\ \alpha_2\ ,\ldots\ldots\ldots\ldots\alpha_i$ are the positive scaling factors for the corresponding obstacles.

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

$$\left(U_{rep}\right)_{Total} = U_{rep}\left(obs_1\right) + U_{rep}\left(obs_2\right) + \ldots\ldots.. + U_{rep}\left(obs_i\right) + \ldots\ldots.. + U_{rep}\left(obs_h\right) \tag{3.8}$$

$$= \sum_{i=1}^{h} U_{rep}\ (obs_i)$$

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

$$\left(F_{rep}\right)_{Total} = F_{rep}\left(obs_1\right) + F_{rep}\left(obs_2\right) + ... + F_{rep}\left(obs_i\right) + ... + F_{rep}\left(obs_h\right) \tag{3.9}$$
$$= \sum_{i=1}^{h} F_{rep}\ \left(obs_i\right)$$

The magnitude of the repulsive force will increase as the distance between the robot and the obstacle decreases. Then, the resultant force F_{Total} can be calculated by adding $F_{att}\ \left(tar_s\right)$ with $U_{rep}\left(obs_i\right)$ vectorically.

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

$$U_{Total} = \sum_{s=1}^{r} U_{att}\ \left(tar_s\right) + \sum_{i=1}^{h} U_{rep}\ \left(obs_i\right) \tag{3.10}$$

Similarly the total force applied on the robot is the sum of attractive potential forces and repulsive potential forces.

$$F_{Total} = \sum_{s=1}^{r} F_{att}\ \left(tar_s\right) + \sum_{i=1}^{h} F_{rep}\ \left(obs_i\right) \tag{3.11}$$

which determines the motion of the robot as per the robot Kinematics (Appendix A).

When the above induced force is applied for motion planning of multiple mobile robots there are four commonly referred problems [201], 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.

3.2.3. Local minima problem and new repulsive potential function

In an environment shown in Fig. 3.1(a), where the robot position $q = [x, 0]$, target position $q_{target} = [0, 0]$, obstacle 1 (q_{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 Khatib [2]. 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 cannot reach the target.

Case-I (Stationary obstacles and target)

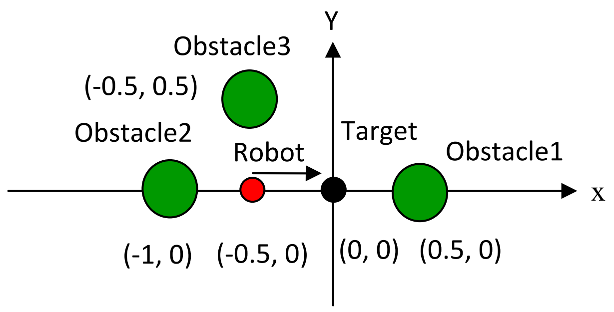

Fig. 3.1(a). Location of robot, target and obstacles for local minima problem.

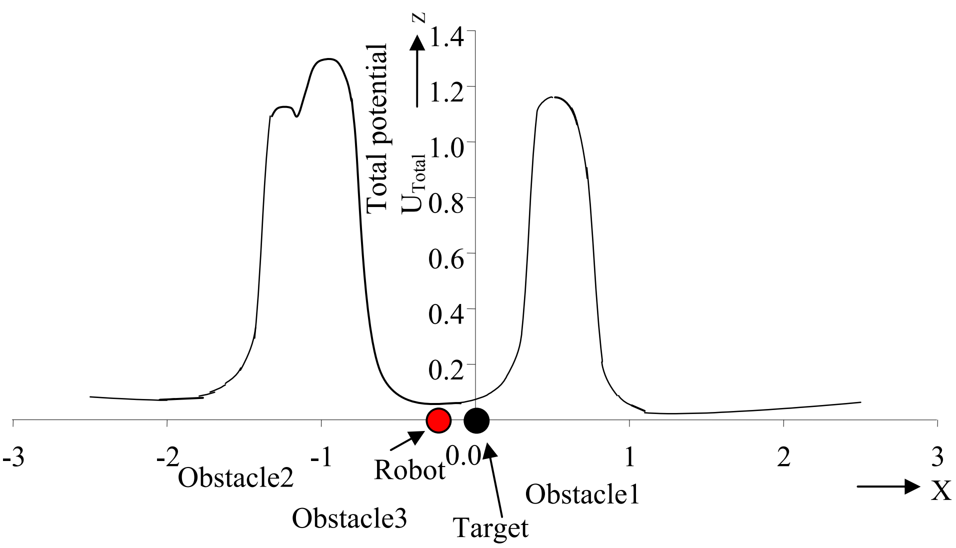

Fig. 3.1(b). The corresponding potential function (U_{Total}).

For the above environment a graph has been plotted between total potential (U_{Total}) verses x-axis which includes the obstacles, robot and target (Fig. 3.1b). 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.

3.2.4. Modified repulsive potential function

From the above discussion it has been concluded 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 shown in Fig. 3.2, a modified repulsive potential function has been developed that takes the relative distance between the robot and the target is given in Eq. (3.12).

$$U_{rep}\left(Obs_i\right) = \begin{cases} \frac{1}{2}\alpha_i\left(\frac{1}{\rho\left(q,q_{obs_i}\right)} - \frac{1}{\rho_0}\right)^2 \rho^n\left(q,q_{target}\right) & \text{if } \rho\left(q,q_{obs_i}\right) \le \rho_0 \\ 0 & \text{if } \rho\left(q,q_{obs_i}\right) > \rho_0 \end{cases} \tag{3.12}$$

where $\rho(q, q_{obsi})$ is the minimum distance between robot q and obstacle i & varies from 1 to h, and $\rho\,(q, q_{target})$ is the distance between the robot and the target. The value of $n = 2$.

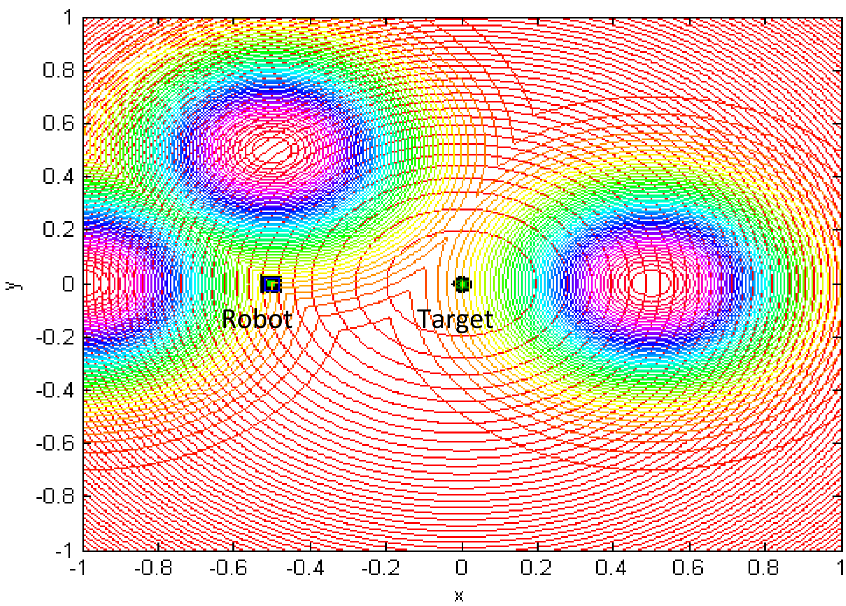

Fig. 3.2. Contour plot of mobile robots navigation using new repulsive potential function.

The contour and surface plot are plotted for the total potential for the above case and are shown in Figs. 3.2 and 3.3.

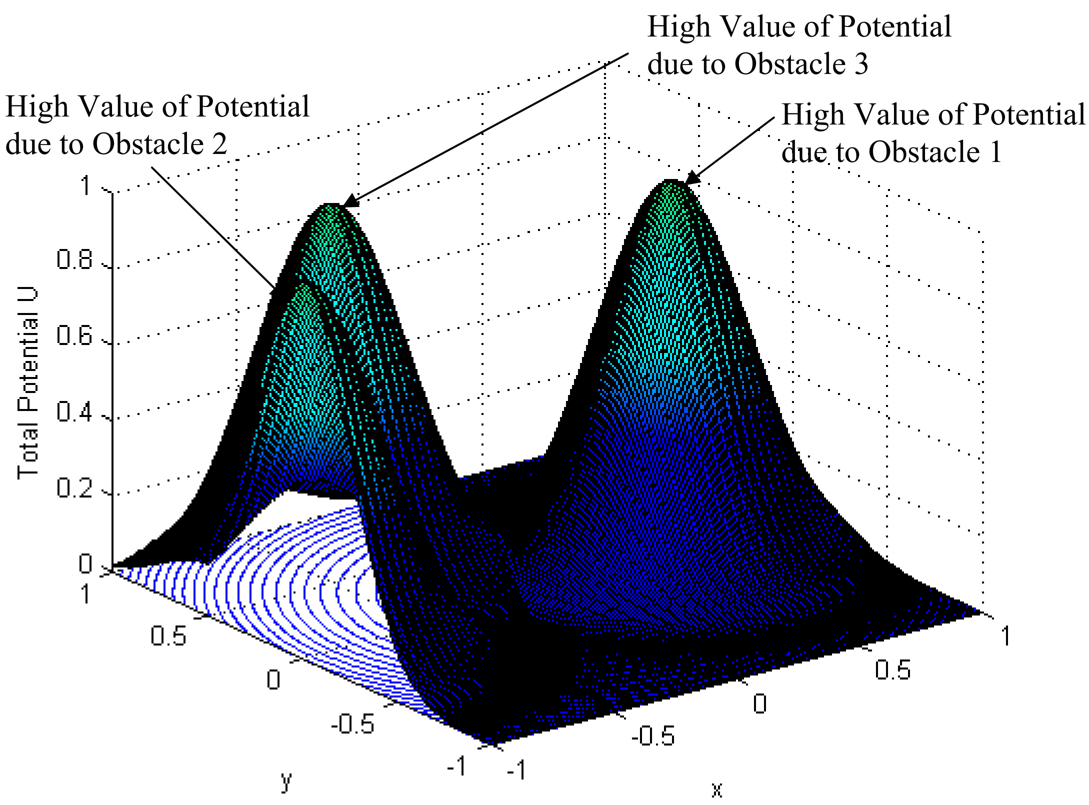

Fig. 3.3. Total Potential function without local minima.

From Fig. 3.2 it is obvious that, at the target i. e. at the origin, the total potential reaches its global minimum equal to zero. The Eq. (3.12) 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. (3.10). For n =2 and $\delta = \alpha_1 = \alpha_2 = \alpha_3 = 1$, it is found that in Fig. 3.2 there is only one minima exist which is at the target. The flow chart and detail calculation for change in steering angle (Phir [ir]) is shown in Appendix B and C respectively.

Case-II (Dynamic obstacle and target)

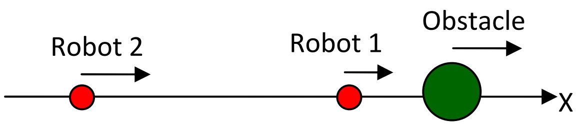

Fig. 3.4. Line diagram for local minima program.

While 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. 3.4. 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 movement of robot1 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, then it can be assumed that the configuration will not change temporarily and the robot will 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 are designed for the stationary environment cases, can be applied.

3.3. Analysis of Petri net model for inter robot collision avoidance

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. J. L. Peterson [202] first developed Petri Net model. In this strategy motion generation is selected for mutual collision avoidance according to the complexity of the situation. Fig. 3.5 depicts the Petri Net model built into each robot to enable it to avoid collision with other robots. The model comprises 7 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. 3.5, 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 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").

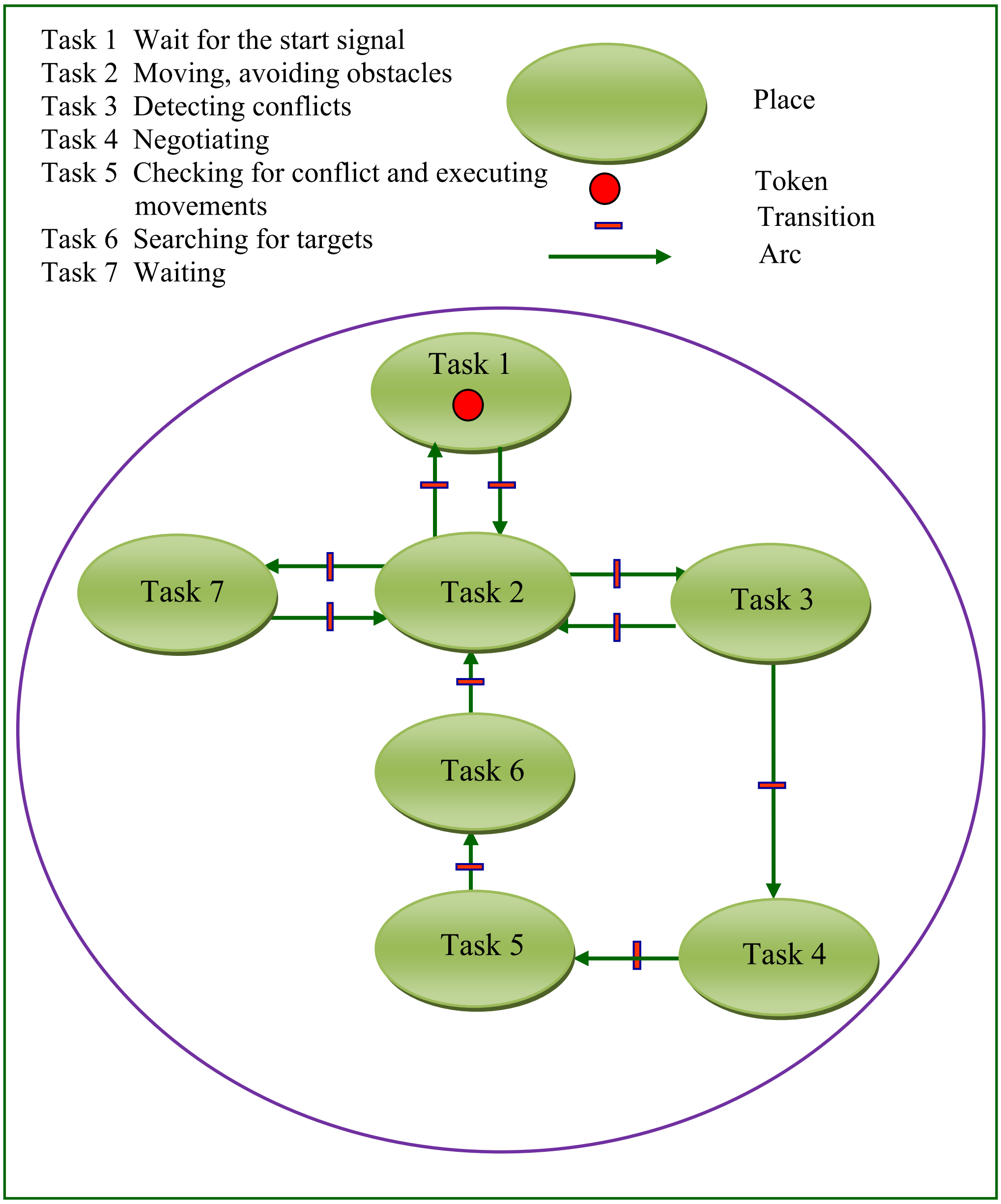

Fig. 3.5. Petri Net Model for avoiding inter-robot collision.

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".

3.4. Simulation results

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.

3.4.1. Collision-free movement, obstacle avoidance and target seeking

The current tasks comprises of two robots, moving in a platform with thirteen obstacles and one target (Fig. 3.6).

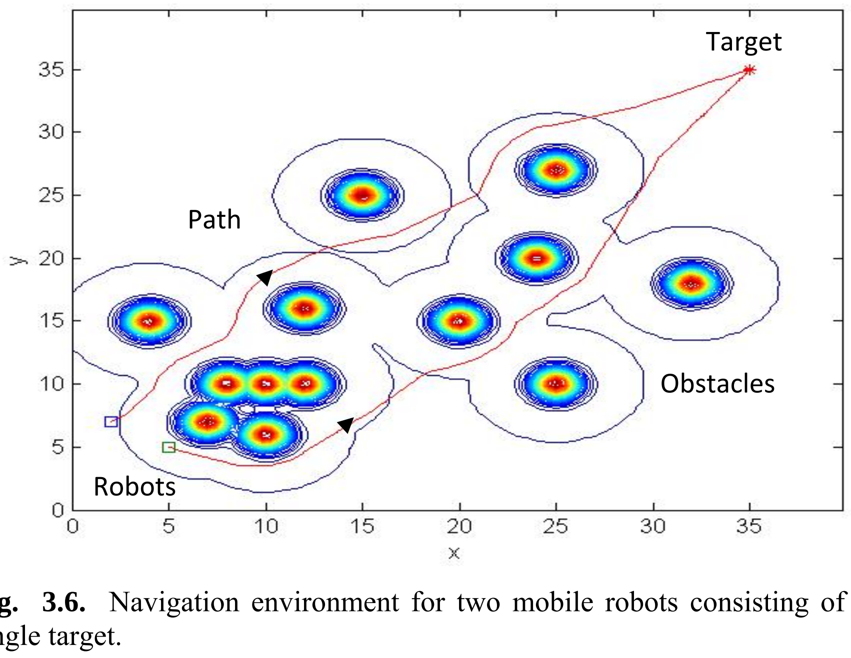

Fig. 3.6. Navigation environment for two mobile robots consisting of multiple obstacles and single target.

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.

3.4.2. Obstacle avoidance and target seeking by multiple robots

This exercise involves three mobile robots initially assembled in a highly cluttered environment. The Fig. 3.7 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.

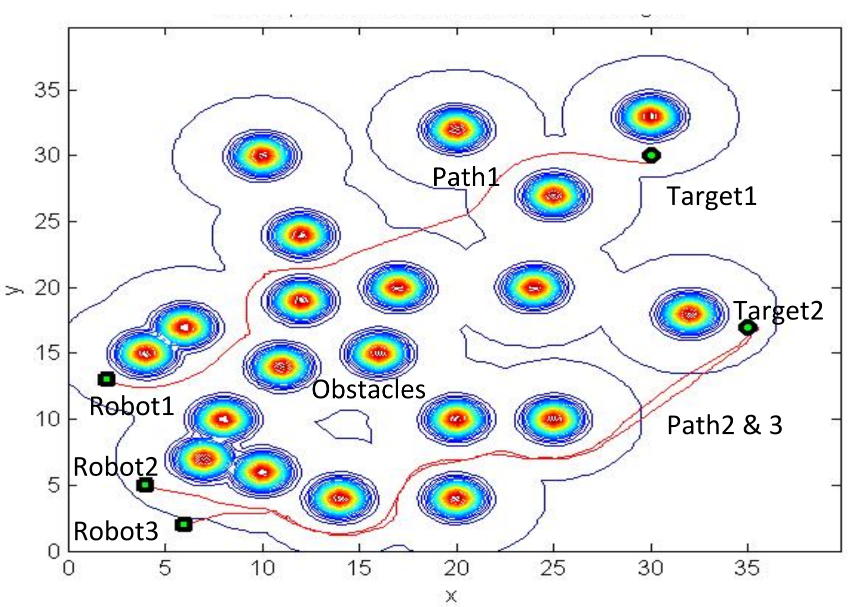

Fig. 3.7. Navigation of three mobile robots with two targets in a high density obstacle environment.

3.4.3. Wall following and target seeking

The wall following and target seeking behavior has been shown in Fig. 3.8. This exercise involves the wall following behavior of single mobile robot in an environment 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 and finally reached the target.

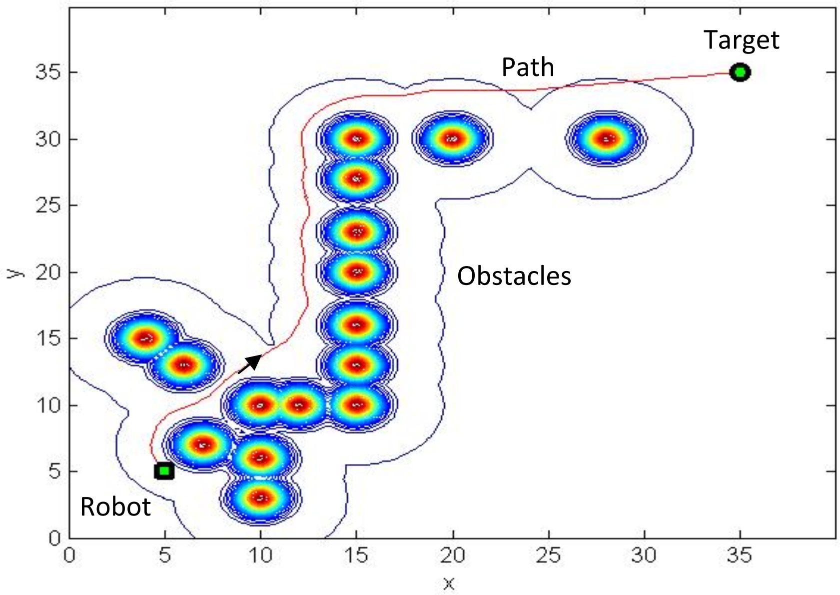

Fig. 3.8. Navigation environment for wall following behavior consists of one robot, one target and multiple obstacles.

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

3.5. Comparison of results with other models

In this section a comparison has been made between Park and Lee [203] model and results from current control scheme in simulation and experimental mode. The performance of the two methods was mainly evaluated on the basis of path length. The results from Park and Lee [203] are shown in Figs. 3.9(a), (c), (e) and (g) are compared with the results obtained from present investigation for similar environments [Figs. 3.9(b), (d), (f) and (h)] and tabulated in Table 3.1.

The simulation has been conducted in a similar environment as described by Park and Lee [203]. It has been observed in the environment shown in Fig. 3.9(a) and (c) presented by Park and Lee and Fig. 3.9(b) and (d) from current developed technique are free from any local minima problem. Therefore the robot can successfully reach the goal with the APF approach. Similarly in the Fig 3.9(e) and 3.9(f), both the cases the robots are trapped at the closed U-shape boundary due to the existence of local minima.

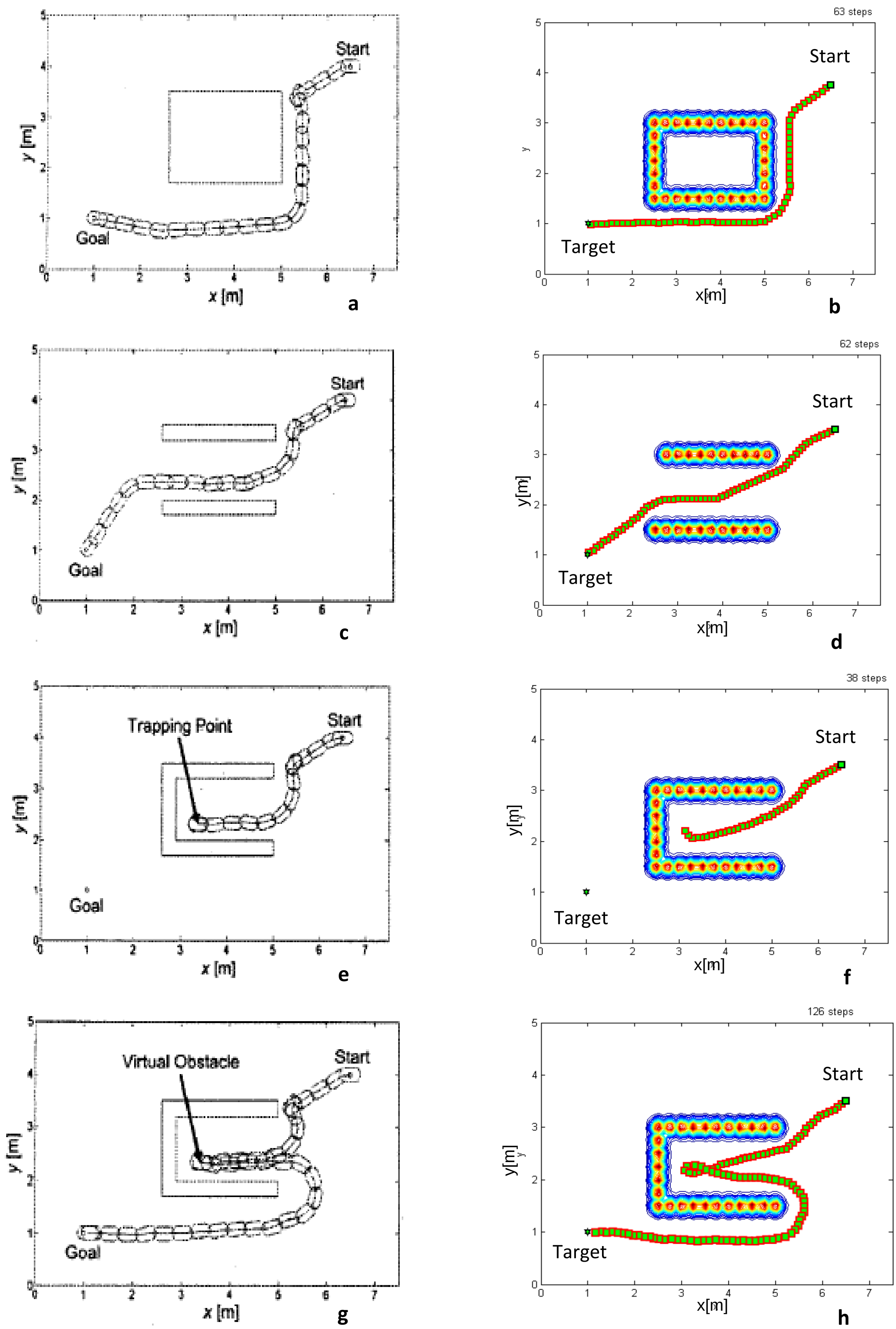

Fig. 3.9. Comparison of results from Park and Lee [203] model and current investigation.

In Fig. 3.9(h) robot escape from the local minima by using new APF function for obstacles which drag the robot near the target in a shortest path. In some scenarios, of Park and Lee [203], it can be seen that, the path of robot has sharp change in direction with large steering angle and sometimes zigzag like motion, which is taken care in the present investigation. In Fig. 3.9(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 3.1
Comparison of results from the current investigation with Park and Lee [203] model.

Sl. No.	Environmental types	Path length of Park and Lee [203] Model, in 'cm'	Path length from current investigation in 'cm'
1.	Rectangular obstacle and path planning by APF method [Fig. 3.9(a) & (b)].	7.1	6.0
2.	Open aisle and path planning by APF method [Fig. 3.9(c) & (d)].	6.4	5.1
3.	Closed aisle and failed path planning by APF method [Fig. 3.9(e) & (f)].	3.7	3.2
4.	Closed aisle and path planning by APF method with virtual obstacle [Fig. 3.9(g) & (h)].	10.2	9.8

Experimental verification of the above simulation results has been shown in next section.

3.6. Experimental implementation

3.6.1. Specification of real robot

Experimental validation and verification of the proposed method has been demonstrated using the three similar prototype mobile robots developed in the laboratory. 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 both side 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 path traced by the robot during motion was marked on the floor by means of a pen attached to the back of the robot frame. 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 shown in Appendix D.

3.6.2. 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.

3.6.3. Real-time experiment

In order to demonstrate the effectiveness of the above control system and the validity of the algorithm developed using modified potential field function, a variety of experiments using developed robot are conducted. The robot has operated in an environment with cylindrical target and conical obstacles ranging from 0.08 to 0.10 m base diameter.

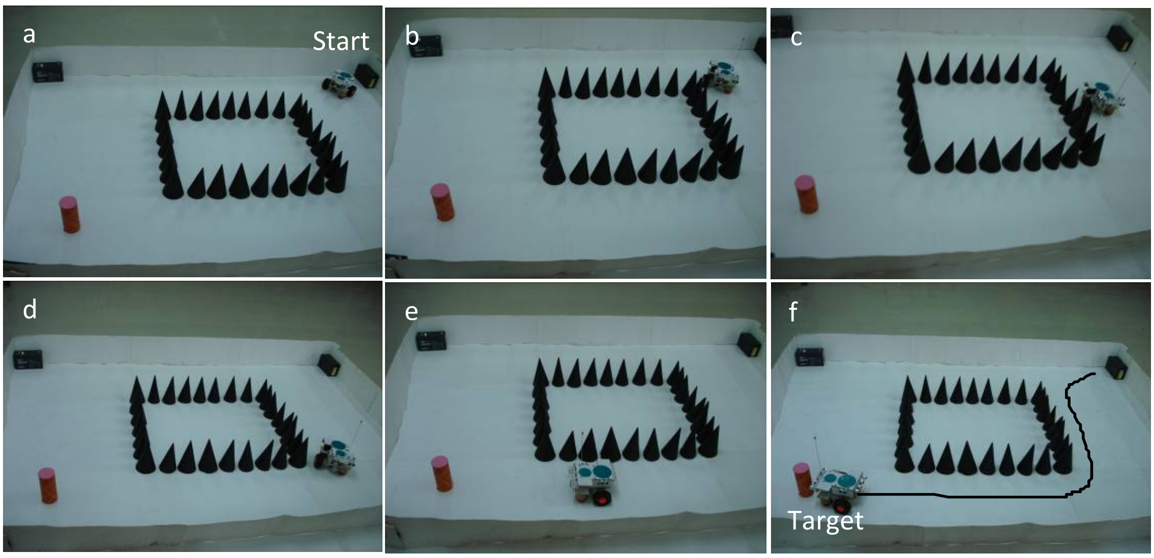

Fig. 3.10. Experimental set up for navigation of mobile robot in the similar environment shown in Fig. 3.9(b).

The four different cases of similar environments as described by Park and Lee [203], which are already verified in simulation mode have been verified experimentally [shown in Figs.3.10-3.13] to show the effectiveness of the developed controller.

Figs. 3.10(a-f) have 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 wall and slows down to take a turn near the wall, then moves according to wall following rules to reach the target. The robot autonomously chooses its way in the shortest trajectory to reach the desired destination.

For the second robot navigation (Fig. 3.11), 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. 3.12(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 able to reach the target which is shown in Figs. 3.13(a-f) sequentially.

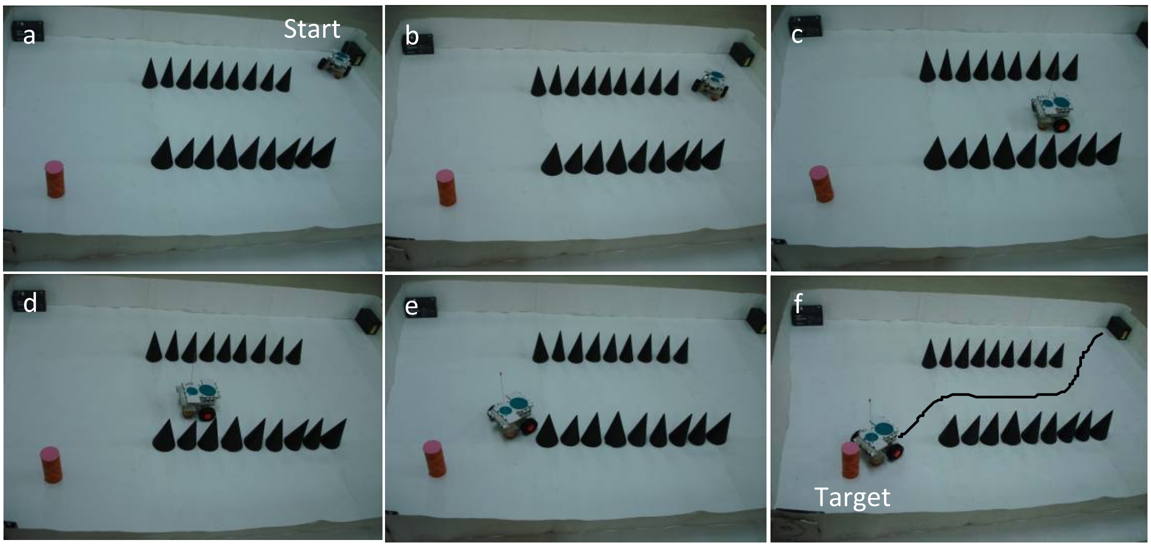

Fig. 3.11. Experimental set up for navigation of mobile robot in the similar environment shown in Fig. 3.9(d).

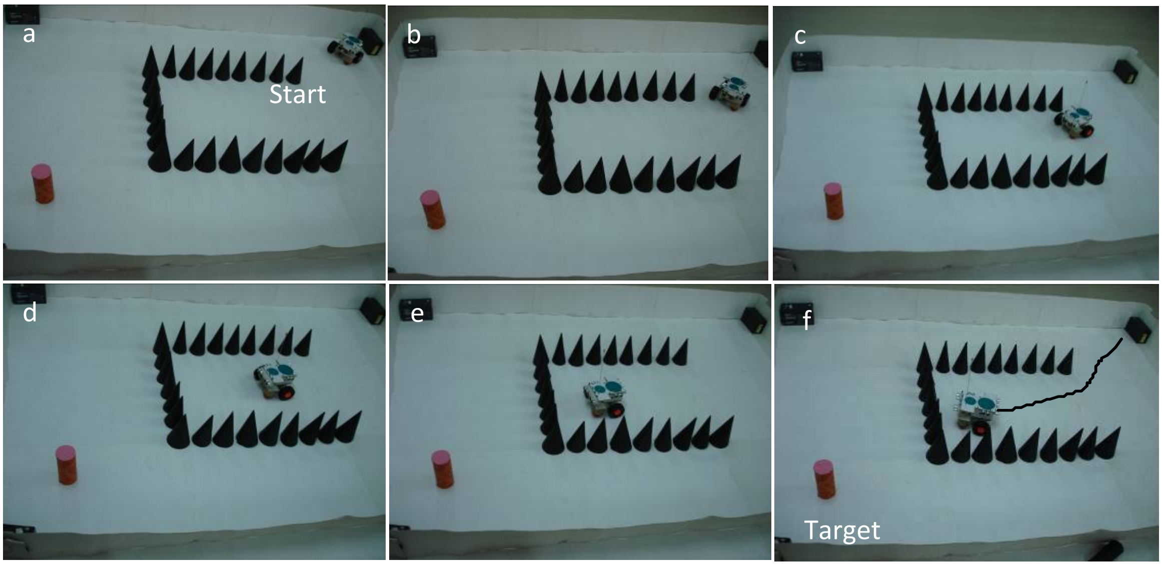

Fig. 3.12. Experimental set up for navigation of mobile robot in the similar environment shown in Fig. 3.9(f) using classical APF.

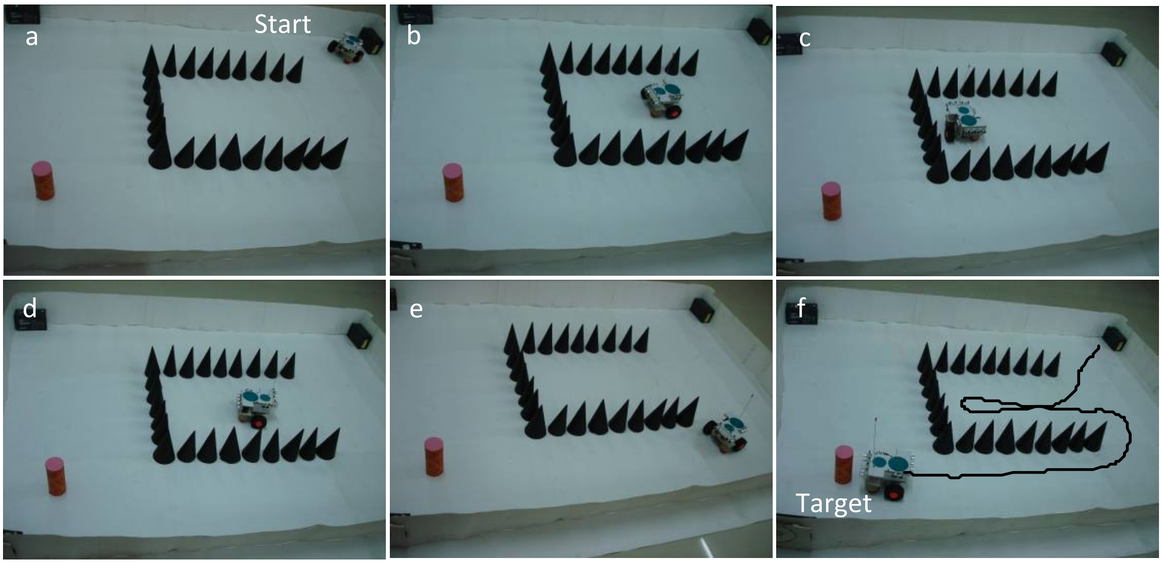

Fig. 3.13. Experimental set up for navigation of mobile robot in the similar environment shown in Fig. 3.9(h) using modified APF.

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 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 is found that 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 path. More than thirty experiments have been conducted to test the model. The maximum velocity of mobile robot used for navigation is 0.05 m s−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.

3.7. Summary

In this chapter, a modified 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 chapter 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. Various exercises have been carried out by considering the different navigational scenarios such as (i) collision-free movement, obstacle avoidance and target seeking by single robot, (ii) obstacle avoidance and target seeking by multiple robots and (iii) wall following and target seeking behavior etc. It is found that the robots stay well and able to reach their targets efficiently. A comparison has been made between Park and Lee [203] model and results from current control scheme both in simulation and experimental modes. 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.

In the subsequent chapters genetic algorithm and fuzzy-logic have been explored and analyzed as standalone techniques. These techniques are then combined and hybridized to develop better controller for path planning of mobile robots.

Chapter 4

Genetic Algorithm Technique for Navigation of Mobile Robots

- **Introduction**
- **Design of mobile controller using GA**
- **Simulation results**
- **Approach for design validation with other models**
- **Experimental results and discussions**
- **Summary**

4. Genetic Algorithm Technique for Navigation of Mobile Robots

This chapter describes the analysis of Genetic Controller for mobile robot navigation by keeping in view of path optimisation. A novel method has been adopted for path optimisation by suitably designing the fitness function. This fitness function is being analysed and implemented in the real robot in order to get robust control architecture for mobile robot navigation.

4.1. Introduction

In the past three decades, genetic algorithms have been widely used for optimisation of various engineering applications. In the current chapter genetic algorithm has been explored for analysis and optimization of path for mobile robot navigation. It is desirable that a robot can navigate safely in an unknown environment in a specified path plan, and that the motion controller has to follow the plan as closely as possible. Robot has become a prominent tools that it has increasingly taken a more important role in many different industries. As such, it has to operate with great efficiency and accuracy. In an environment including obstacles, motion planning is to find a suitable collision-free path for a mobile robot to move from a start configuration to target configuration. In course motion planning very often this path depends upon the parameters such as time, distance, energy and smoothness. Distance is a commonly adopted criterion. GAs can optimise many such parameters encountered by the robot during navigation.

4.1.1. Overview

Genetic algorithms (GAs) are introduced as a computational analogy of adaptive systems. A typical genetic algorithm requires a genetic representation of the solution domain and a fitness function to evaluate the solution domain. A standard representation of the solution is as an array of bits. The main property that makes these genetic representations convenient is that their parts are easily aligned due to their fixed size, which facilitates simple crossover operations during child formation. Variable length representations may also be used, but crossover implementation is more complex in this case. Tree-like representations are explored in genetic programming and graph-form representations are explored in evolutionary programming.

The fitness function is defined over the genetic representation and measures the quality of the represented solution. The fitness function is always unique and problem dependent. Once the genetic representation and the fitness functions are defined, GA proceeds to initialize a population of solutions randomly, then improve it through repetitive application of mutation, crossover, inversion and selection operators.

4.1.2. Problem formulation

In this chapter, a novel knowledge based genetic algorithm for path planning of multiple robots for multiple targets seeking behaviour in presence of obstacles is proposed. The proposed algorithm based upon an iterative non-linear search, which utilizes matches between observed geometry of the environment and a map of position locations from sensors data to estimate a suitable heading angle, there by correcting the position and orientation of the robots to find targets. This knowledge based GA is capable of finding an optimal or near-optimal robot path in complex environments. The resulting navigation algorithm has been implemented on real mobile robots and tested in various environments for comparison.

4.2. Design of mobile controller using GA

4.2.1. Basic approach for obstacle avoidance

As specified earlier a genetic algorithm (GA) based obstacle avoidance scheme has been used here for path planning of multiple robots with multiple targets in presence of obstacles. Genetic algorithms are heuristic optimization methods whose mechanisms are analogous to biological evolution. The evolutionary procedure employed in the simulations consists of a standard GA program. The speed of genetic algorithm depends heavily on the encoding scheme of the chromosomes and on the genetic operators that work on these chromosomes [204, 93]. In order to speed up a GA, the chromosome’s and gene’s structures need to be as simple as possible. In addition, only a few, but very effective, reproduction operators should be applied on the chromosomes. A GA operates on a population of chromosomes, which represent possible solutions for a given problem. This implementation is a new approach to the path-planning and obstacle avoidance problem, representing each chromosome as a group of basic elements. These elements define the robot's movements in agreement with the feedback generated by its environment. Each feedback, which is used as input to the system, is based on the sensors reading and on the robot's direction to its goal location. The sensors reading are presented to the GA system in a simplified form. The proposed simulator provides 6 sets of ultrasonic and 4 sets of IR sensors for detecting the obstacles and bearing of the targets. However, the distances are calculated at each instantaneous position of the robots. These distances are calculated based on the position and orientation of the obstacles with respect to robots instantaneous position.

The basic inputs to the genetic controller are front obstacle distance (FOD), left obstacle distance (LOD) and right obstacle distance (ROD) to all the GAC and output is heading angle (H.A.). These inputs and outputs are expressed in terms of encoded generation function distributions by crisp values. Then, these crisps values are converted to binary values in order to facilitate the interface with machine language for further processing of the controller. To visualise the above genetic controller in real sense the problem has been addressed in different stages. The stages are analysed below:

Stage 1: Formation of pool set for obstacle avoidance

From the sensors outputs (F.O.D., L.O.D. and R.O.D.) distances an initial population pool is created with a predefined population size. The population contains number of individuals (i.e., chromosomes). Each individual represents a solution for the problem under study. In our case, each solution is in terms of a heading angle between the current directions of the robots' steering with respect to targets' directions from its start to end point in the search space. The initial population with size n can be presented as follows:

Initial Population = $<P_1, P_2, \ldots, P_n>$

Each structure have the elements $p_{(i,i)}$ which are simply an integer string of length L, in general. Each population have 5-sets of chromosomes which are represented by Element numbers 1 to 5.

	Element: 1	Element: 2	Element: 3	Element: 4	Element: 5
$P_1 = \{$	$p_{1,1}$	$p_{1,2}$	$p_{1,3}$	$p_{1,4}$	$p_{1,5}\}$
$P_2 = \{$	$p_{2,1}$	$p_{2,2}$	$p_{2,3}$	$p_{2,4}$	$p_{2,5}\}$

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$P_n = \{\ p_{n,1},\quad p_{n,2},\quad p_{n,3},\quad p_{n,4},\quad p_{n,5}\}$

where,

Element No. 1 ($p_{1,1}$ to $p_{n,1}$) represents the left obstacle distance (F.O.D.).

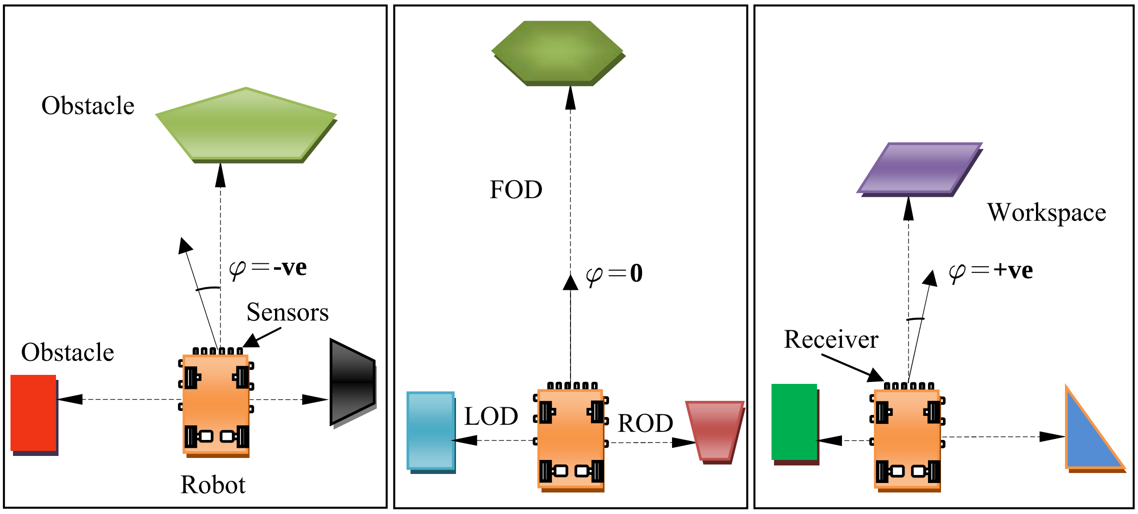
Element No. 2 ($p_{1,2}$ to $p_{n,2}$) represents the front obstacle distance (L.O.D.).

Element No. 3 ($p_{1,3}$ to $p_{n,3}$) represents the front obstacle distance (R.O.D.).

Element No. 4 ($p_{1,4}$ to $p_{n,4}$) represents the instantaneous heading angle (H.A) with respect to target position.

Element No. 5 ($p_{1,5}$ to $p_{n,5}$) represents the sign conversion ('+ve', 'zero' and '–ve') for clockwise, straight and anti clockwise based on the direction of HA (φ) respectively which is shown in Fig. 4.1.

Distances beyond 511 mm radius the region is treated as obstacle free and in this case robot considered that, there is no obstacle in the particular direction and starts moving towards target till find any obstacle on the way within the range. In this case heading angle will be zero (Case 5 in Table 4.1). In case 2 left obstacle distance is medium, front obstacle distance is near and right obstacle distance is near, so robot will take a left turn of 12degree (-ve) in order to avoid obstacle.



Scenario 1
(Case: close right obstacle)

Scenario 2
(Case: obstacles far around)

Scenario 3
(Case: close left obstacle)

Fig. 4.1. Sign convention of GA output in terms of heading angle (HA) with respect to obstacle position.

Similarly in case 8, left obstacle distance is near, front obstacle distance is very near and right obstacle distance is medium, so robot will take a right turn of 12degree (+ve) in order to avoid obstacle. For the heading angle each degree of rotation is taken as $(511/180)^{th}$ part for both clockwise and anti clockwise movement of robot. For simplicity a set of 10 populations has been shown in tabular form (Table 4.1).

Table 4.1.

Heading angle (H.A.) with respect to different obstacle positions.

Case	FOD (mm)	LOD (mm)	ROD (mm)	HA(φ) (Degree)	Direction (+/-)ve
1	250	200	150	18	-ve
2	300	340	260	12	-ve
3	400	300	150	10	-ve
4	270	280	160	15	-ve
5	600	100	120	0	straight
6	505	400	280	5	-ve
7	480	220	450	14	+ve
8	120	200	360	12	+ve
9	500	100	450	16	+ve
10	320	450	180	10	-ve

Stage 2: Analysis of fitness function for obstacle avoidance

Fitness function represents an important part of any evolutionary process using GAs. Appropriate selection of the fitness function will lead the search towards the optimal solution. The optimal obstacle avoidance, in our case, is the possible collision free motion of robot with optimum heading angle (HA) with respect to target location, thereby optimising the trajectory between the start and end point in the environment. Thus, the fitness function is responsible for optimal obstacle avoidance. The proposed GA knowledge based controller helps computing the total number of steps the mobile robot need during navigation to reach the end point. Consequently, the fitness value for a complete solution is computed as:

$$f_{Total} = 0.4(f_1) + 0.15(f_2) + 0.15(f_3) + 0.15(f_4) + 0.15(f_5) \qquad (4.1)$$

where,

$$f_1 = \sqrt{\left\{\left(C_{FOD} - p_{ci,1}\right)^2 + \left(C_{LOD} - p_{ci,2}\right)^2 + \left(C_{ROD} - p_{ci,3}\right)^2\right\}} \tag{4.2}$$

$$f_2 = \left|C_{FOD} - p_{ci,1}\right| \tag{4.3}$$

$$f_3 = \left|C_{LOD} - p_{ci,2}\right| \tag{4.4}$$

$$f_4 = \left|C_{ROD} - p_{ci,3}\right| \tag{4.5}$$

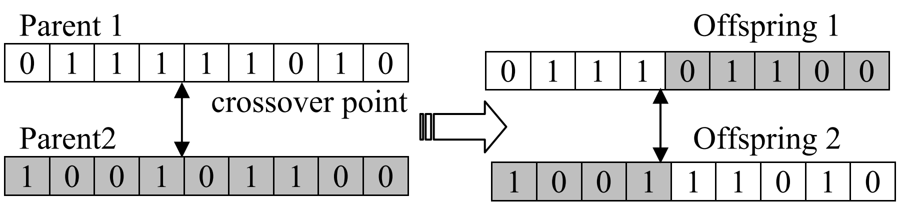
$$f_5 = \left|TA - HD\right| \tag{4.6}$$

and $(C_{FOD} - P_{ci,1})$, $(C_{LOD} - P_{ci,2})$ *and* $(C_{ROD} - P_{ci,3})$ are the best distances (child) obtained from the given pool set of front, left and right obstacles distances from instantaneous obstacle position with respect to initial position. TA and HD are the target angle and heading direction respectively. The coefficients of the fitness function are computed statistically using fuzzy inference technique and are cited in Appendix E.

Stage 3: Crossover of parameters and its analysis

During the operation of reproduction crossover is applied on the chosen parent chromosomes only within a certain probability, the crossover probability. In the chosen crossover operator, two parent chromosomes are combined applying a single-cross-point, value encoding crossover. The crossover operator has been modified to produce two offspring chromosomes with each crossover operation. This is achieved by using the gene information, which are not used to build offspring one, in order to build a second chromosome. In the proposed controller the crossover operators has been used for front, left and right obstacle distances as well as for the heading angle. The function of crossover operator for first two pool set cases are shown in Table 1 and illustrated in Fig. 4.2.

Cross over for "F.O.D."



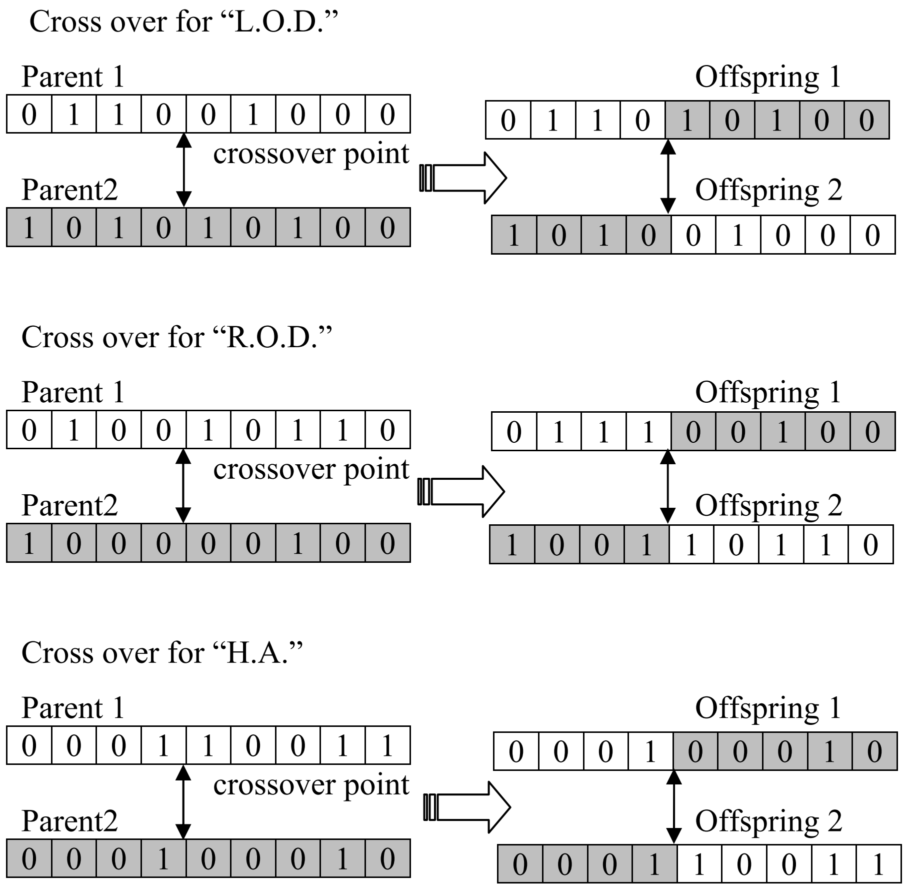


Fig. 4.2. Single-Cross-Point, value-encoding crossover for F.O.D., L.O.D., R.O.D. and H.A.

Stage 4: Mutation

For mutation, almost every operation that changes the order of genes within a chromosome or that changes a gene's value (such as location or direction) is a valid mutation operator. The mutation operator has been designed according to the addressed obstacle avoidance problem. The chosen mutation operator checks with a mutation probability for every single gene whether it should be mutated or not. If a gene is to be mutated, a random number between 1 and the total number of population in the search space is assigned to location and a random direction, either clock wise, anticlockwise or straight, is based on reference direction. This mutation variant has the advantage that it gives the opportunity for a chromosome to become significantly altered. That means that the complete search space will be explored and it therefore prevents the GA from getting stuck in a local optimum. The fitness of all affected genes (steps) is re-evaluated and stored immediately after the changes in location and direction are made. Each step's fitness is therefore always up to date with every instantaneous position of robot.

Stage 5: Evaluation of fittest child according to fitness function

The evaluation of fittest child is computed as per the fitness function described in stage 2. The outline of the schematic diagram showing the flowchart for the proposed knowledge based genetic algorithm is given in Fig. 4.3 and the detailed working principle is highlighted below.

The GA controller begins its search by randomly creating a number of solutions (equals to the population size) represented by the binary strings and are evaluated by the fitness function derived in Eq. (4.1). Two parents for FOD, LOD and ROD are selected from the pool set according to fitness function. Once the parents are chosen from the population, they are modified by using three operators: reproduction, crossover and bit-wise mutation. The iteration process involving these three operators followed by the fitness evaluation is called a generation. The generations proceed until a termination criterion is satisfied. In the current approach, the termination criterion can either be that the preset maximum generation is exceeded, or that the best solution remains unchanged for certain generations. Accordingly the best heading angle (φ) will be decided and command execution starts to move the robot towards the target.

The proposed algorithm can also be suitably applied for dynamic environment. During navigation it checks sensing about the environment periodically. If the environment is changed, the algorithm will re-evaluate the current population according to the new environment and starts the process to get a new solution. In such cases, in order to increase the diversity of the population mutation with higher probability is applied to the current population. According to the fittest child, the heading angle of the robot will be decided. The obstacle avoidance behaviour of the robot using genetic algorithm will be incorporated in the Petri-net model for successful navigation of the mobile robot. The working principle of the proposed Petri-net model for inter-robot collision avoidance has been discussed in the previous section. The task used for the Petri-net model using GA has been outlined below.

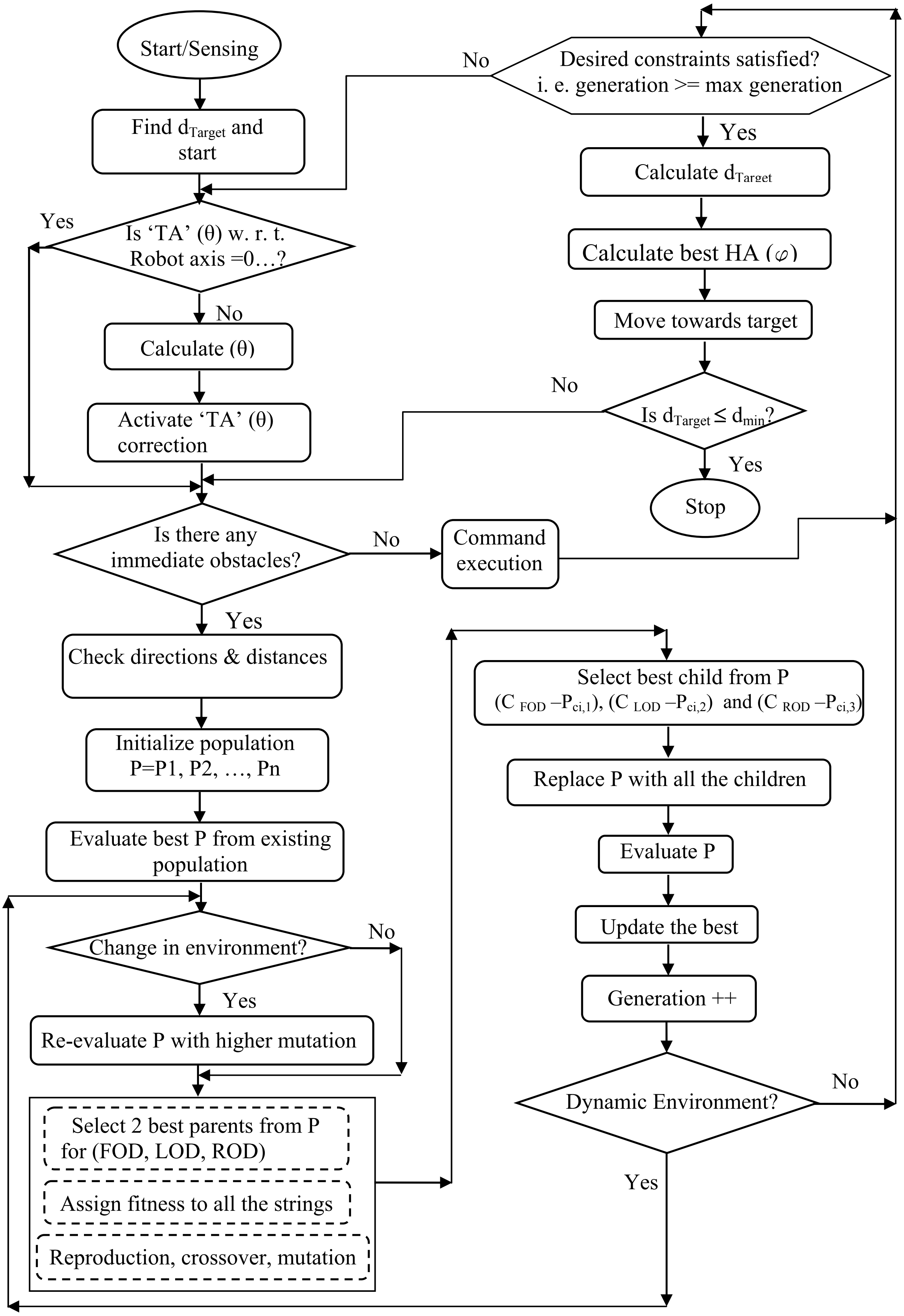


Fig. 4.3. The outline of schematic diagram showing the flowchart for the proposed motion planning scheme.

Task 1 Wait for the start signal

Task 2 Moving, avoiding obstacles using GA

Task 3 Detecting conflicts with the help of GA

Task 4 Negotiating

Task 5 Checking for conflict and executing movements

Task 6 Searching for targets using GA

Task 7 Waiting

4.3. Simulation results

This section presents exercises aimed at illustrating the ability of the proposed control scheme to manage the navigation of mobile robots in different situations. MATLAB software package has been developed and used for conducting simulation. 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 by arranging obstacles in different fashions to create different environment for the GA based controllers to show the capabilities of the proposed control scheme.

4.3.1. Collision-free movement, obstacle avoidance and target seeking in highly clutter environment

The navigation environment for collision free motion and obstacle avoidance for three robots with three targets in a highly cluttered environment has been shown in Fig. 4.4. This exercise is designed to demonstrate that each robot reach their targets without colliding with other robots while avoiding the obstacles. Robots choose their path by its own to reach the target by following the shortest trajectories.

It can be noted that the robots stay well away from the obstacles and move in smooth path from its start locations to end locations and found their targets efficiently.

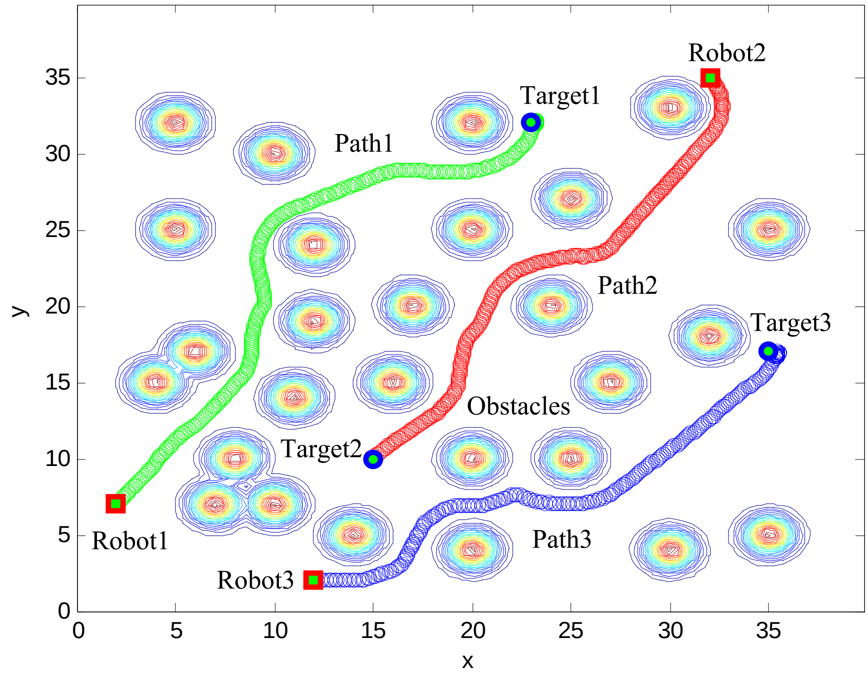


Fig. 4.4. A view of navigational environment for collision avoidance by three robots and three targets in a highly cluttered environment.

4.3.2. Obstacle avoidance and target seeking by several robots

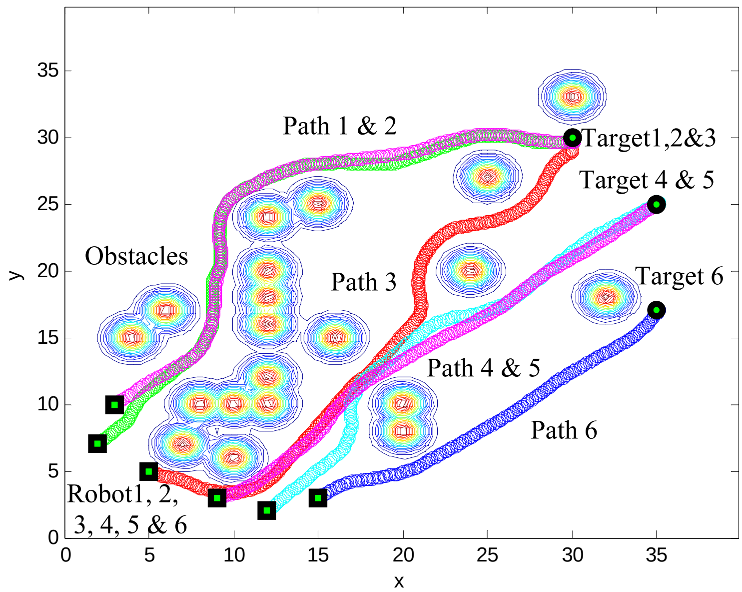


Fig. 4.5. Navigation environment for target seeking behaviour for collision free motion and obstacle avoidance by multiple robots with multiple targets.

This exercise (Fig. 4.5) involves six mobile robots assembled in a cluttered environment for navigation. In this simulation, each robot has reached their nearest target in an efficient manner without any collision between themselves and obstacles in a cluttered unknown environment using GA technique.

4.3.3. Wall following and target seeking behavior

The wall following and target seeking behavior has been shown in Fig. 4.6. This exercise involves the wall following behavior of four robots consisting of two targets. In the present scenario the obstacles are arranged in a particular fashion so that they represent like a wall between the robots and the targets. As the robots search for their targets, they find the walls along which they continue to move by applying the wall following rules. In the initial position the robots are heading towards the dead-end. Due to the additional context information provided by the proposed controller robots can able to perceive the dead ends. The controllers initiate the turning manoeuvre, which last until the robots are heading away from the dead-ends. Afterwards, the normal wall-following behaviour guides the robots to exit from the corridor by keeping a safe distance from the wall. Fig. 4.6 shows the robots trajectories from start positions to targets without suffering from ‘‘dead cycle” problems.

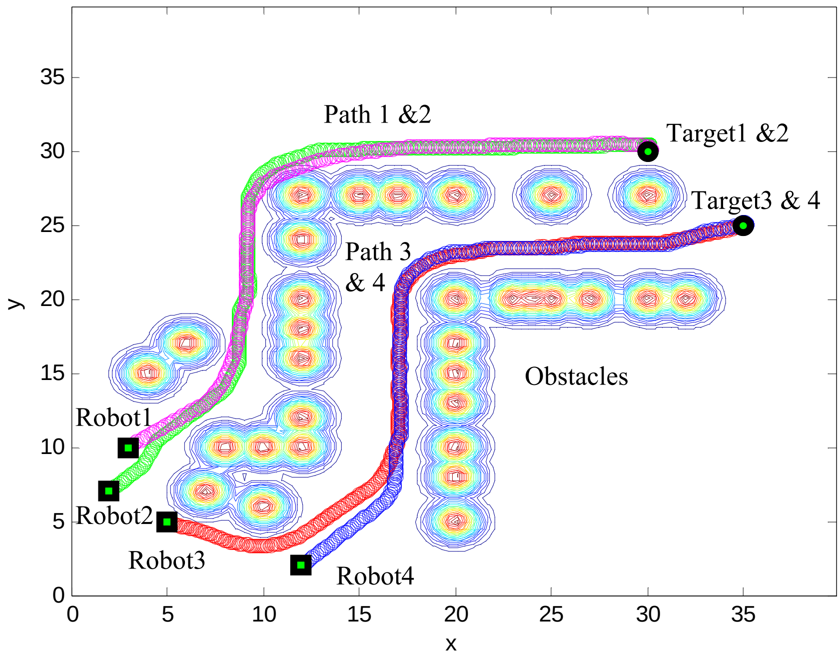


Fig. 4.6. Navigation environment for wall following and target seeking behaviour of multiple robots.

In the above simulation, it can be seen that each robot has reached their nearest target in an efficient manner without any collision between themselves and obstacles in a dynamic environment. Further the robots have well compromised between themselves in the cluttered environment in order to avoid collision among themselves as well as with other obstacles. The same controller has been demonstrated for other cases of simulation in the succeeding sections.

4.4. Approach for design validation with other models

In this section a comparison has been made between Gemeinder and Gerke [205] model and results from current control scheme in simulation and experimental mode. The performance of the two methods is mainly evaluated on the basis of the path length. The results from Gemeinder and Gerke [205] shown in Fig. 4.7(a) and Fig. 4.8(a) are compared with the results obtained from current investigation [Fig. 4.7(b) and 4.8(b)] for similar environments. The comparisons of results for both the methods are given in Table 2.

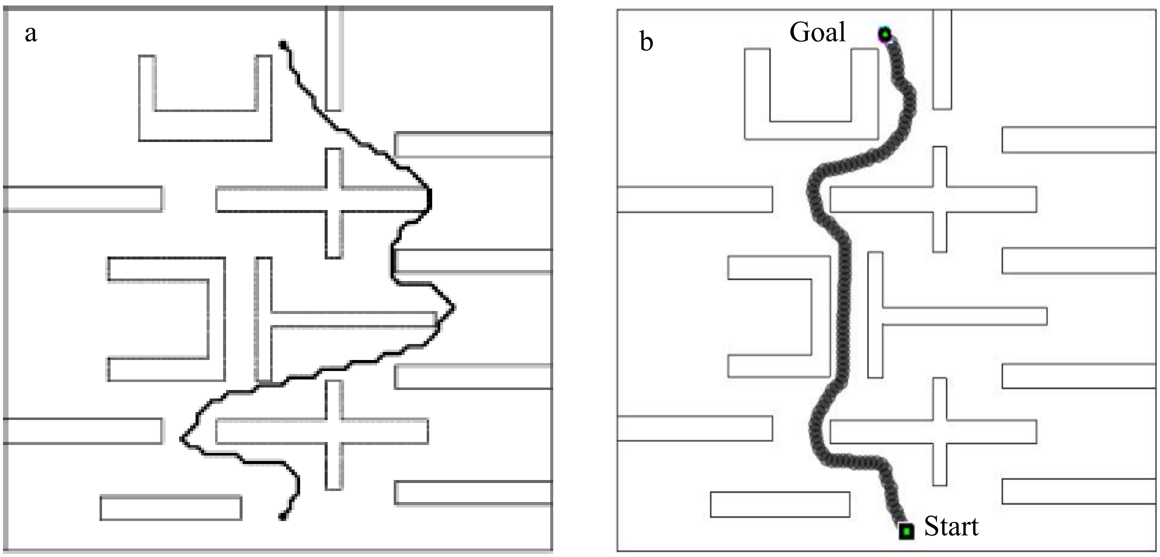


Fig. 4.7. Comparison of results from the current investigation and Gemeinder and Gerke [205] (Scenario 1).

In the first case, both the controllers are applied to a situation with complex maze with different shapes of boundary that would cause the existence of ‘‘dead cycle” problems. In this case the robot cannot see the target directly due to the wall in between them. It can be observed in the environment (Gemeinder and Gerke [205] model), shown in Fig. 4.7(a) that the robot is trapped at each steps throughout the maze due to the existence of local minima and finally able to find their target after a long exercise by following a longer trajectory. In Fig. 4.7(b) the robot can avoid the maze made with similar boundary found on its way towards the target efficiently by the proposed GA model. In this case robot will first takes left turn due to the obstacle (boundary) in front of it, then sense the target and finally follows the walls in order to reach the target successfully by receiving systematic information from the sensors through the state memory strategy.

In the second case, the robot supposed to find the target approximately in a complex situation like closed aisle for a dead cycle problem. In Fig. 4.8(a) proposed by Gemeinder and Gerke [205] model the robot got trapped in the U-shaped area first, and then it has escaped from the trap by taking a loop and eventually reaches the target by following a zigzag motion. Fig. 4.8(b) shows a simulation result of the robot behavior adapted by means of the proposed method. In the initial position the robot is heading towards the dead-end. Due to the additional context information provided by the proposed controller robot can able to perceive the dead-end. The controller initiates a turning manoeuvre, which lasts until the robot is heading away from the dead-end. Afterwards, the normal wall-following behaviour guides the robot to the exit of the corridor by keeping a safe distance from the wall.

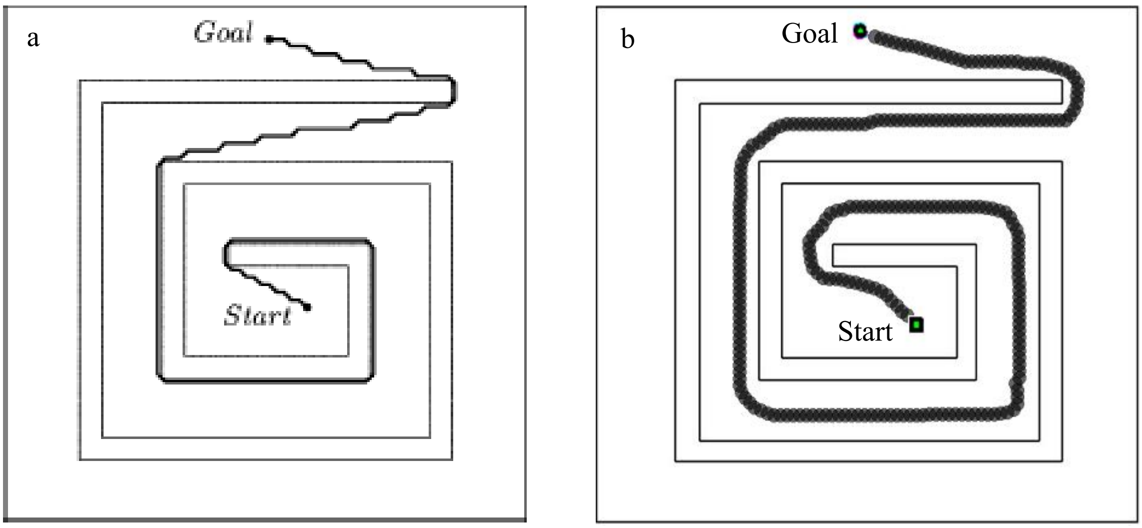


Fig. 4.8. Comparison of results from the current investigation and Gemeinder and Gerke [205] (Scenario 2).

Table 4.2

Comparison of results from the current investigation with Gemeinder and Gerke [205] model

Sl No.	Environmental types	Path length of Gemeinder Model, in 'cm'	Path length from current investigation in 'cm'
1.	Complex maze with different shape of Rectangular obstacles and path planning using GA [Fig. 7(a) & (b)]	11.6	8.8
2.	Closed aisle and path planning using GA [Fig. 8(a) & (b)]	17.2	20.4

In some scenarios of Gemeinder and Gerke [205] model it can be seen that the path of robot has sharp change in direction with some greater steering angle and sometimes small zigzag like motion that has been taken care in the present investigation. Fig. 4.7(b) and 4.8(b) show that the robot reaches their target in a smooth motion with the proposed approach. The performance of the two models was mainly evaluated on the basis of path length and smoothness of trajectory which is shown in Table 4.2. From the above simulation results it is clear that, the developed algorithm can efficiently drive the robot in a cluttered environment. The above simulation results has been verified experimentally and shown in next sections (Figs. 4.9- 4.10).

4.5. Experimental results and discussion

The effectiveness of the proposed systems has been demonstrated by analysing the experimental results. In this section the experimental results from developed motion planner has been demonstrated for its operation in an environment with rectangular aisle of different shapes. Two different cases of similar environments as described by Gemeinder and Gerke [205] model, which are already verified in simulation mode, have been verified experimentally (Figs. 4.9- 4.10) using the robot developed in the laboratory.

Figs. 4.9(a-f), demonstrate a situation where robot and target are placed in opposite corner of the complex maze (created by a variety of rectangular obstacle configurations). Initially robot cannot see the target directly because of the obstacles between robot and target. When robot starts motion it senses the target and speeds up in straight path towards the targets up to the U-shaped wall and slows down to take right turn to avoid obstacle, then follows a wall following rules to reach the target.

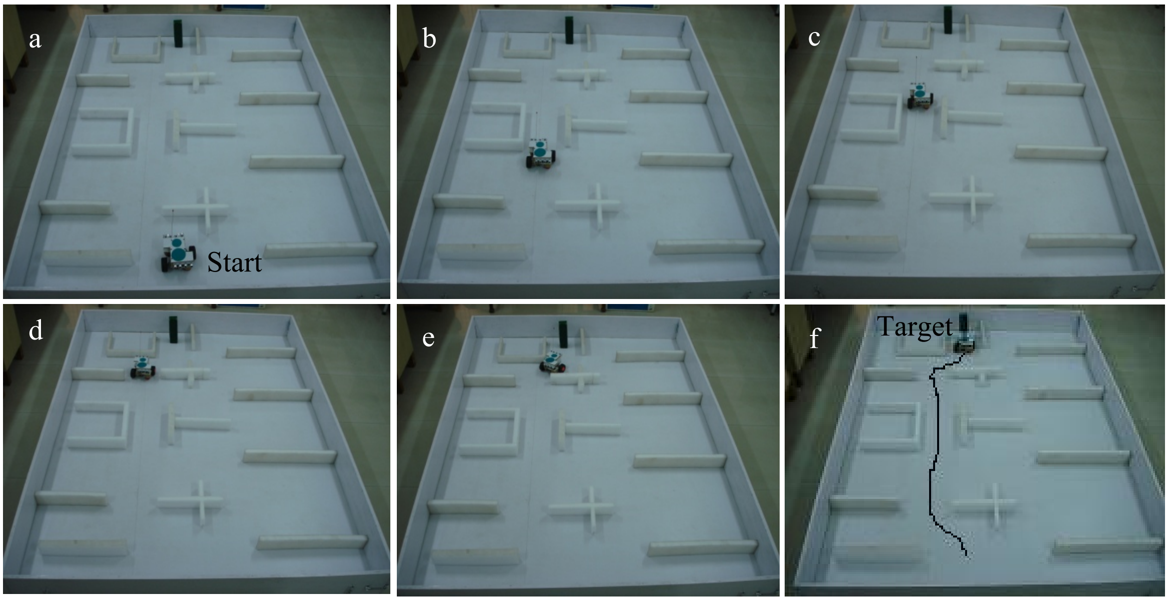


Fig. 4.9. Experimental results for navigation of mobile robot in the similar environment shown in Fig. 4.7(b)

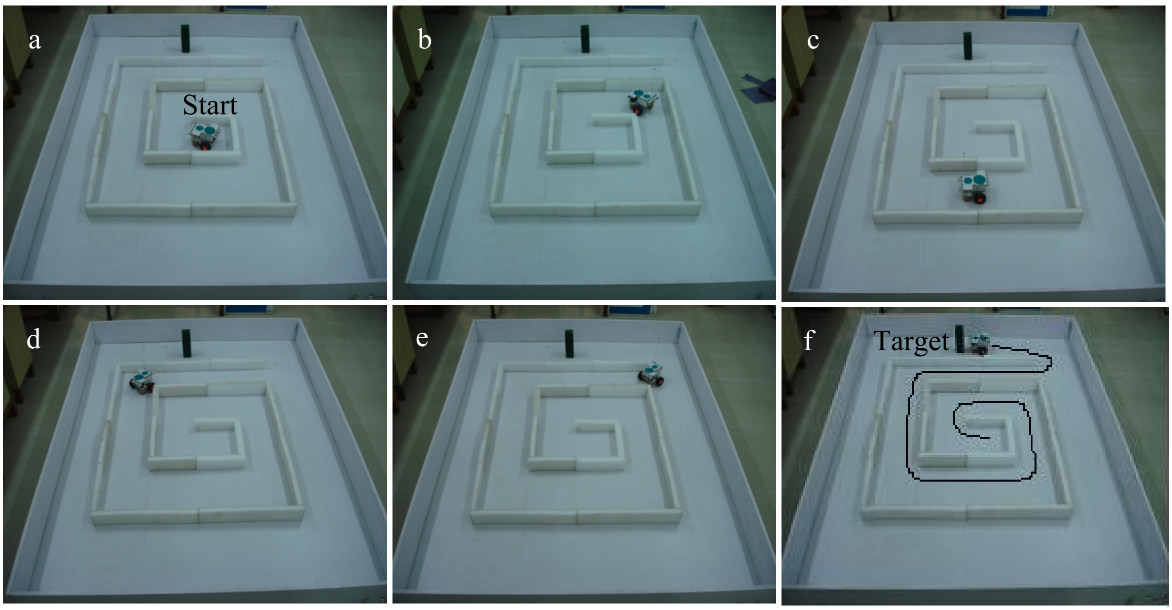


Fig. 4.10. Experimental results for navigation of mobile robot in the similar environment shown in Fig. 4.8(b).

The robot autonomously chooses its way in the shortest trajectory to reach the desired destination by getting the optimised heading angle obtained from knowledge based GA controller. For the second case of navigation (Fig. 4.10(f)), it can be observed that, the robot follows a straight path except the turning points from its start to the goal position inside the closed aisle. In some cases the robot can rotate and move with some zigzag motion until it reaches target. The developed controller takes care to invoke a new path based on available information received by the robot about the environment with ruled based heuristic recovery GA approach.

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 the proposed controller can successfully arrive at the target by avoiding obstacles. The trajectories are smooth and take reasonably efficient paths as compared to Gemeinder and Gerke [205] paths. More than thirty experiments have been conducted to test the model. The maximum velocity of mobile robot used for navigation is 0.05 m s^{-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.

4.6. Summary

In this study, the prime objective was to construct the framework of some hierarchical or procedural control structures to implement basic navigation problems for multiple robots based on GA. Firstly, we have proposed a method for adjustment of fitness values to avoid statistical variation due to randomness in initial positions and orientations of obstacles. Then the distances of obstacles from three directions (viz. front, left and right) were evaluated by using suitable fitness function and optimised by the proposed algorithm based upon an iterative non-linear search, which utilizes matches between observed geometry of the environment and a-priori map of position locations, there by correcting the position and orientation of the robot to find targets. During navigation of several robots there could be the chances for conflict situations and inter robot collision among them. This has been taken care in the present study by suitably designing of a general-purpose conflict avoidance module based on Petri-net model and embedded in the controllers of each robot in order to navigate safely in the environment. The developed strategies have been checked via simulations as well as experiments, which show the ability of proposed controller to solve the multiple robot navigation tasks in an optimised way and to obtain a strategy for this purpose.

Chapter 5

Fuzzy Logic Technique for Navigation of Mobile Robots

- **Introduction**
- **Control architecture**
- **Simulation results**
- **Experimental result and discussions**
- **Summary**

5. Fuzzy Logic Technique for Navigation of Mobile Robots

This chapter deals with the analysis of proposed fuzzy logic technique for navigation of multiple mobile robots by suitably designing different membership function distributions in order to get an efficient path planning strategy. The developed strategy takes into account the reference motion, direction, distances between the robots and obstacles, distances between the robots and targets heuristically and refined later to find the optimum steering angle.

5.1. Introduction

The development of Artificial Intelligence (AI) techniques for autonomous navigation in real-world environments constitutes one of the major trends in the current research on robotics. An important problem in autonomous navigation is the need to cope with the large amount of uncertainties and ambiguities that are inherent of natural environments. Fuzzy logic has features that make it an adequate tool to address this problem. This chapter interprets a method for controlling multiple mobile robots with multiple targets in various (known and unknown) environments using fuzzy rule based on heuristic knowledge. The focus has been made to design robust behavior path planning modules for mobile agents to coordinate in a highly cluttered environment. Several such modules by using sensory information from instantaneous position of obstacles and bearing of targets have been integrated to obtain an intelligent controller for high-level reasoning and low-level execution strategy. For such issue, a thorough review has been done in the literature survey search. The pros and cons of fuzzy logic solutions for navigation of several mobile robotic agents have also been discussed.

5.1.1. Overview

Fuzzy logic technique plays an important role to design the intelligent controller for mobile robot. Fuzzy set theory provides a mathematical framework for representing and treating uncertainties in the sense of vagueness, imprecision, lack of information and partial truth. Fuzzy control systems employ a mode of approximate reasoning that resembles the decision-making process of human's knowledge. A fuzzy system is usually designed by interviewing an expert and formulating the implicit knowledge of the underlying process into a set of linguistic variables and fuzzy rules. In particular for complex control tasks, obtaining the fuzzy knowledge base from an expert is often based on a tedious and unreliable trial and error approach [140]. Fuzzy set theory was first introduced by Lofti Zadeh [102] in the mid sixties and since then fuzzy logic has been applied to many diverse fields, from control theory to artificial intelligence. This section presents a variety of fuzzy logic models, combining the different membership functions to find an efficient controller which addresses an optimal or near optimal path for the challenges posed by autonomous robot navigation.

5.1.2. Problem formulation

In this chapter, a novel real-time fuzzy navigation algorithm for multiple mobile robots operating in unknown cluttered environments is presented. The final aim of the robots is to reach some pre-defined goals in shortest trajectories without collision between themselves, while avoiding obstacles. Based upon reference motion, direction, distances between the robots and obstacles, distances between the robots and targets, different types of fuzzy rules are taken (by selecting different combinations of membership functions) heuristically and refined later to find the steering angle. In order to get the requisite information between robots, targets and obstacles each robot is equipped with an array of on board ultrasonic sensors for measuring the distances of obstacles and other robots around it and series of infrared sensors for detecting the bearing of target. 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). 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. It has been found that the best path optimization takes place when the fuzzy logic controller (FLC) having Gaussian membership function is used. The resulting navigation algorithm has been implemented on real mobile robots and tested in various environments. The experimental results presented demonstrate the effectiveness and improved performance of the developed controller navigation scheme.

5.2. Control architecture

5.2.1. Analysis of obstacle avoidance and target seeking behavior

The robots considered here are of differential wheel drive type and can readily move in each direction (limited to a predefined value) and can similarly rotate in any arbitrary degree (limited to another predefined value). The Ultrasonic and Infrared Sensors used in the robots to sense the obstacles from left, right and front of the robot with acceptable tolerance in their measured value. In the proposed algorithm, the robot's environment is considered with smooth floor and the obstacles are assumed as vertical substances with rigid bodies enough to reflect the ultrasonic beams. At the end, supporting the above consideration, the aim is to design and implement an appropriate algorithm that can guide the robot from any arbitrary position in the work space as the start point, to another arbitrary location as the target. The path should be free from any collision and the robots should never hit any obstacles or the walls of the work space considered for experiment. The line diagram of general structure for a basic fuzzy controller is given in Fig. 5.1.

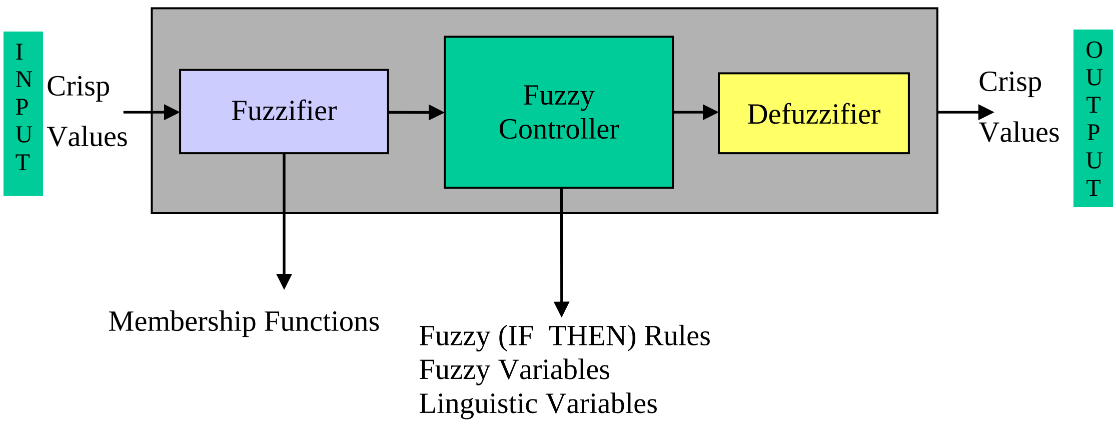


Fig. 5.1. Line diagram of a basic Fuzzy controller.

Three types of membership functions having five membership functions in each, i.e. all triangular members, combinations of trapezoidal and triangular members and all Gaussian members are considered. Linguistic variables such as ''very near'' (VN), ''near'', ''medium'', ''far'' and ''very far'' (VF) for obstacle distances have been considered for navigation of multiple mobile robots.

Some of the fuzzy control rules are activated according to the information acquired by the robots using their sensors. The outputs of the activated rules are weighted by fuzzy reasoning and the velocities of the driving wheels of the robots are calculated. Left wheel velocity and right wheel velocity are denoted as 'leftvelo' (LV) and 'rightvelo' (RV) respectively. Similarly 'leftdist', 'rightdist', and 'frontdist' are defined for the distances left obstacle distance (L.O.D.), right obstacle distance (R.O.D.) and front obstacle distance (F.O.D.) respectively.

Table 5.1
Input parameters to the fuzzy controller.

(a) Parameters for Obstacle Distances

Linguistic Variables	Very Near (m)	Near (m)	Medium (m)	Far (m)	Very Far (m)
LOD	0.0	0.2	0.4	0.6	0.8
ROD	0.2	0.4	0.6	0.8	1.0
FOD	0.4	0.6	0.8	1.0	1.2

(b) Parameters for Target Heading Angle

Linguistic Variables	''More neg'' (deg.)	''Neg'' (deg.)	Zero(deg.)	''Pos'' (deg.)	''More pos'' (deg.)
Target Heading Angle(φ)	-180	-120	-10	10	60
	-120	-60	0.0	60	120
	-60	0	10	120	180

Table 5.2
Output parameters of the fuzzy controller.

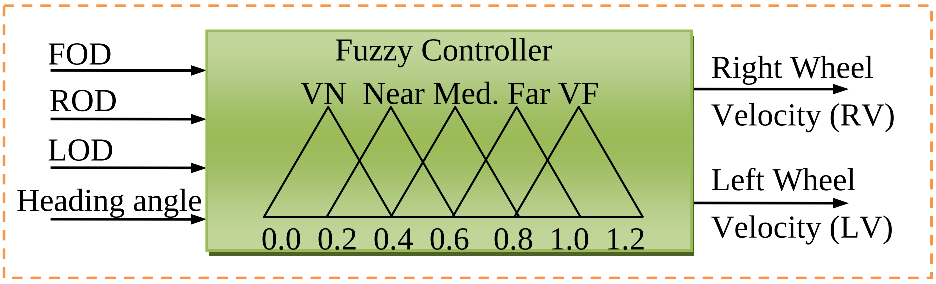
(a) Parameters for Wheel Velocity

Linguistic Variables	Very Slow (m/s)	Slow (m/s)	Medium (m/s)	Fast (m/s)	Very Fast (m/s)
LV & RV	0.01	0.02	0.03	0.04	0.05
	0.02	0.03	0.04	0.05	0.06
	0.03	0.04	0.05	0.06	0.07

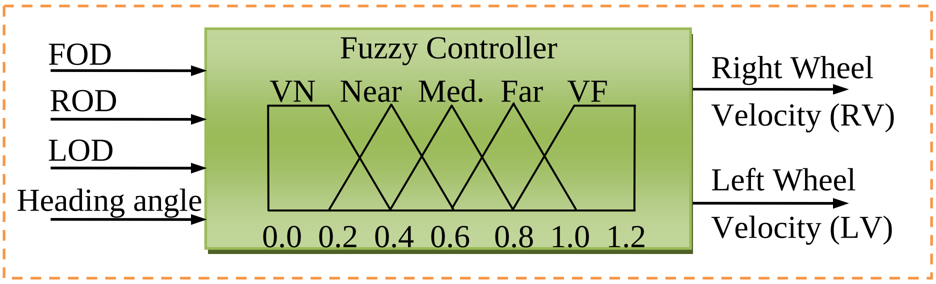
The parameters defining the input and output functions are listed in Table 5.1(a, b) and Table 5.2 respectively. The values of the parameters are decided empirically by considering sensing distance of the used sensors and speed of driving wheels.

Terms like 'very slow' (VS), 'slow', 'medium' (med.), 'fast', and 'very fast'(VF) are considered for left wheel velocity and right wheel velocity for five-membership functions. Similarly linguistic variables such as 'more pos' (more positive), 'pos' (positive), 'zero', 'neg' (negative) and 'more neg' (more negative) are defined for the bearing of heading angle (HA) with respect to target.

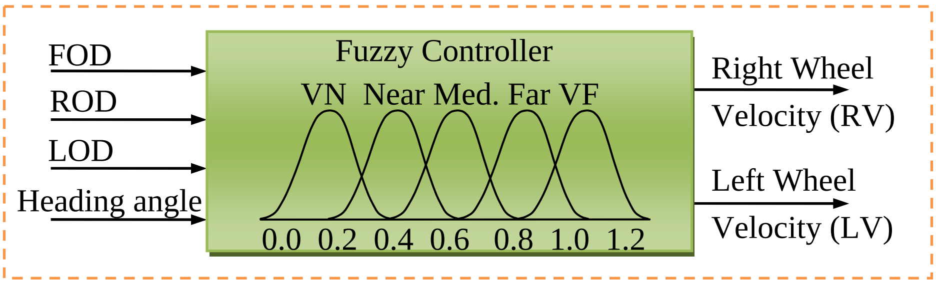
The term 'notargetconsider' is used if there is no target in the environment. The membership functions described above are shown in Fig. 5.2.



Five membership Fuzzy controller with all triangular members for mobile robot navigation



Five membership Fuzzy controller with triangular and trapezoidal members for mobile robot navigation



Five membership Fuzzy controller with all Gaussian members for mobile robot navigation

Fig. 5.2. Fuzzy Controllers for mobile robot navigation.

5.2.2. The fuzzy mechanism for mobile robot navigation

Based on the subsets, the fuzzy control rules are defined as follows:

If LD is $LD_i \Lambda$ FD is $FD_j \Lambda$ RD is $RD_k \Lambda$ HA is HA_l

Then LV is LV_{ijkl} Λ RV is RV_{ijkl} (5.1) where i = 1–5, j = 1–5, k = 1–5 and l = 1–5 because LD, FD, RD and HA have five-membership functions each.

From expression (1) two rules can be written:

$$\left.\begin{array}{l}\text{If (LD is LD}_i\text{ and FD is FD}_j\text{ and RD is RD}_k\text{ and HA is HA}_l\text{)}\\ \text{Then LV = LV}_{ijkl}\\ \text{And}\\ \text{If LD is LD}_i\text{ and FD is FD}_j\text{ and RD is RD}_k\text{ and HA is HA}_l\\ \text{Then RV = RV}_{ijkl}\end{array}\right\} \tag{5.2}$$

A factor W_{ijkl} is defined for the rules as follows:

$$W_{ijkl} = \mu_{\mathrm{LD}i}\,(\mathrm{dis}_i) L \mu_{\mathrm{FD}j}\,(\mathrm{dis}_j) L \mu_{\mathrm{RD}k}\,(\mathrm{dis}_k) L \mu_{\mathrm{HA}l}\,(\mathrm{ang}_l) \tag{5.3}$$

where dis_i, dis_j and dis_k are the measured distances and ang_l is the value of the heading angle.

The membership values of the left wheel and right wheel velocities $\mathrm{vel}_{\mathrm{LV}}$ and $\mathrm{vel}_{\mathrm{RV}}$ are given by:

$$\left.\begin{array}{l}\mu_{LV'_{ijkl}}(vel) = W_{ijkl} \wedge \mu_{LV_{ijkl}}(vel_{LV}) \quad \forall_{vel} \in LV\\ \mu_{RV'_{ijkl}}(vel) = W_{ijkl} \wedge \mu_{RV_{ijkl}}(vel_{RV}) \quad \forall_{vel} \in RV\end{array}\right\} \tag{5.4}$$

The overall conclusion by combining the outputs of all the fuzzy rules for five-membership function can be written as follows:

$$\left.\begin{array}{l}\mu_{LV}(vel) = \mu_{LV'_{1111}}(vel_{LV}) \vee \ldots \vee \mu_{LV'_{ijkl}}(vel_{LV}) \vee \ldots \vee \mu_{LV'_{5555}}(vel_{LV})\\ \mu_{RV}(vel) = \mu_{RV'_{1111}}(vel_{RV}) \vee \ldots \vee \mu_{RV'_{ijkl}}(vel_{RV}) \vee \ldots \vee \mu_{RV'_{5555}}(vel_{RV})\end{array}\right\} \tag{5.5}$$

The crisp values of Left Velocity and Right Velocity are computed using center of gravity method is:

$$\left.\begin{array}{l}\text{Left Wheel Velocity} = LV = \dfrac{\int vel.\mu_{LV}(vel).d(vel)}{\int \mu_{LV}(vel).d(vel)}\\ \text{Right Wheel Velocity} = RV = \dfrac{\int vel.\mu_{RV}(vel).d(vel)}{\int \mu_{LV}(vel).d(vel)}\end{array}\right\} \tag{5.6}$$

5.2.3. Analysis of obstacle avoidance

When the robot is very close to the target, the attractive force between the robot and the target causes the robot seeking towards the target. Similarly when the robot is very close to an obstacle, because of repulsive force developed between the robot and the obstacle the robot must change its speed and heading angle to avoid the obstacle. In order to demonstrate the control architecture for obstacle avoidance and target seeking behaviour an example has been explained using the proposed fuzzy mechanism. Here five membership functions with all Gaussian members have been considered for distances, heading angle and wheel velocities as the crisp values for inputs and outputs. Referring to Figs. 5.3 & 5.4, it has been seen in the environment that the front obstacle distance is 0.43m, left obstacle distance is 0.22m and right obstacle distance is 0.96m respectively.

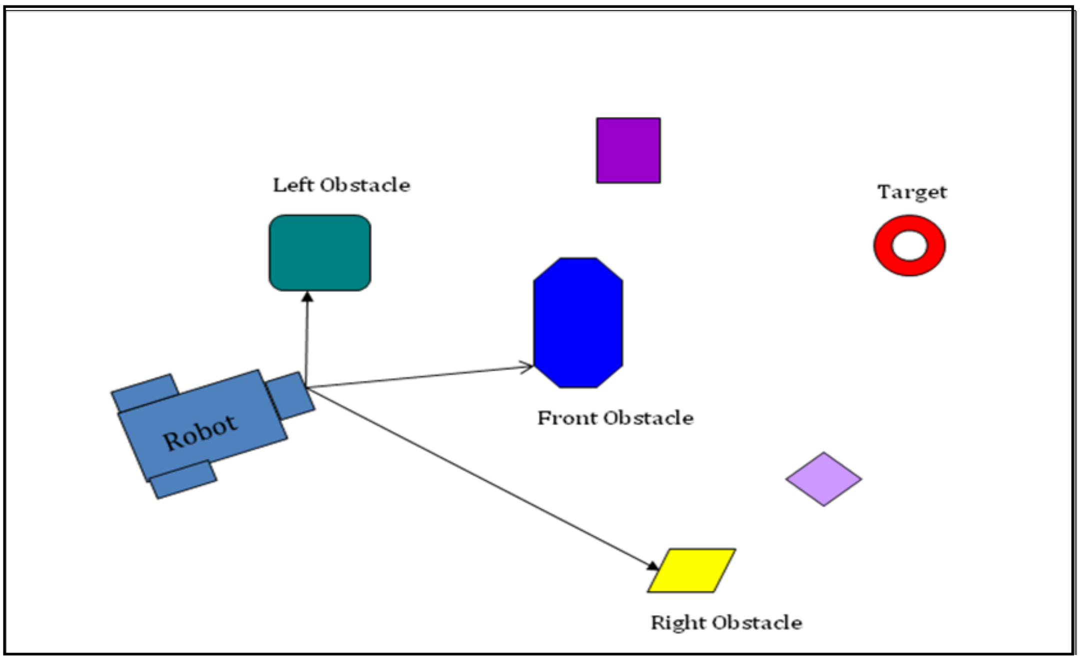


Fig. 5.3. Initial position of the robot in an unknown environment.

Some of the fuzzy rules used for obstacle avoidance by robots are listed in Table 5.3. All the rules in that table have been obtained heuristically using human intelligence.

Some of the fuzzy rules using five-membership function mentioned in Table 5.3 cater for extreme conditions when the obstacles have to be avoided as quickly as possible. For example in rule 2 (Table 5.3), the left obstacle distance is ‘‘very far’’, front obstacle distance is ‘‘very near’’, right obstacle distance is ‘‘near’’ and no target is located around the robot, then the robot should turn to left side to avoid collision with the obstacle in front and towards right of it. For the above condition the right wheel velocity should increase very fast and left wheel velocity should decrease very slowly. In this manner the robots avoid the obstacles by activating the rules applicable for the particular situation.

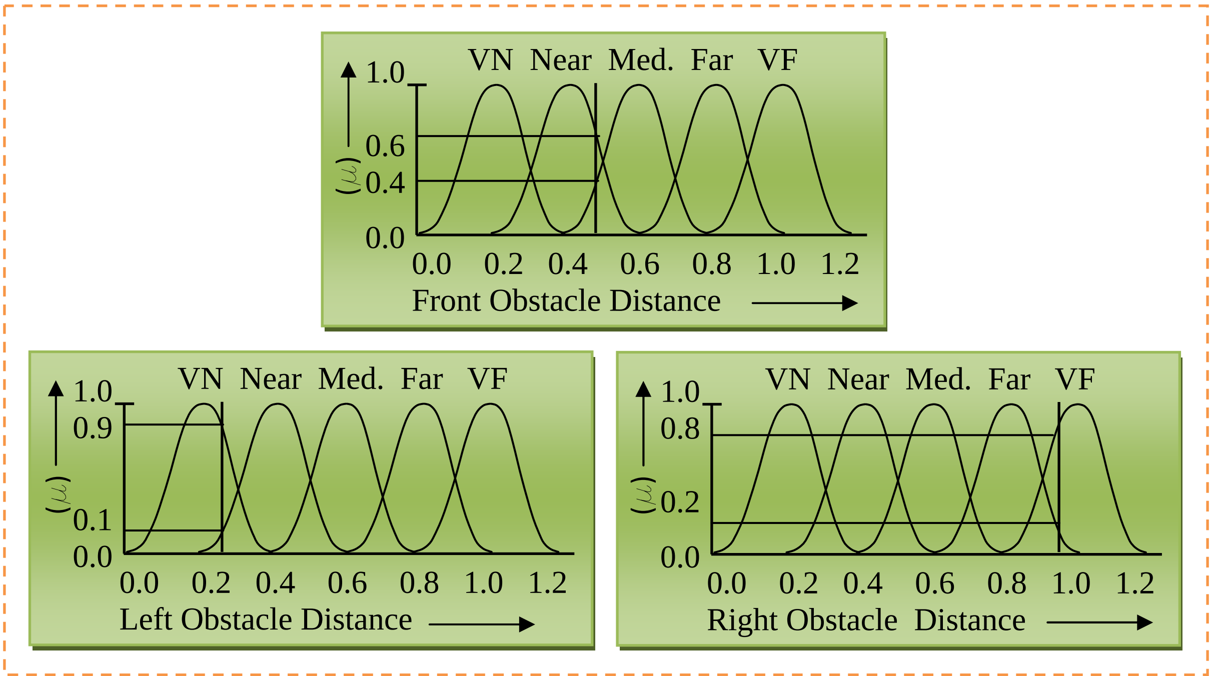


Fig. 5.4. Left, front and right obstacle distances.

Table 5.3

Obstacle avoidance rules for five-membership function.

Fuzzy rule no.	Action	leftdist	frontdist	rightdist	Heading angle(φ)	leftvelo	rightvelo
1	OA	VN	VN	VN	Notargetconsidered	VS	Slow
2	OA	VF	VN	Near	Notargetconsidered	VS	VF
3	OA	VN	VN	Med.	Notargetconsidered	Fast	Slow
4	OA	VN	VN	Far	Notargetconsidered	Fast	Slow
5	OA	VN	VN	Very Far	Notargetconsidered	VF	Med.
6	OA	VN	Near	VN	Notargetconsidered	Slow	Slow
7	OA	VN	Near	Near	Notargetconsidered	Slow	Slow
8	OA	VN	Near	Med.	Notargetconsidered	Fast	Med.
9	OA	VN	Near	Far	Notargetconsidered	Fast	Slow
10	OA	VN	Near	Very Far	Notargetconsidered	VF	Fast

Note: Where (μ) = Degree of membership function, OA: obstacle avoidance, TS: target seeking, Positive: right turn, Negative: left turn, VF: very far (for Obstacle distances), VF: very fast (for wheel velocity).

5.2.4. Control steering action for target acquisition

The prime objective of the robots is to reach the target safely and efficiently in a shortest trajectory. If any one of the robots senses a target, it will decide whether it can reach the target or there is any obstacle that will obstruct the path. If there is no obstacle on the path leading to the target, the robot will find its desired path and proceed towards it. Table 5.4 describes some of the rules for five-membership function to locate the target. The above fuzzy rules for control strategy are obtained heuristically.

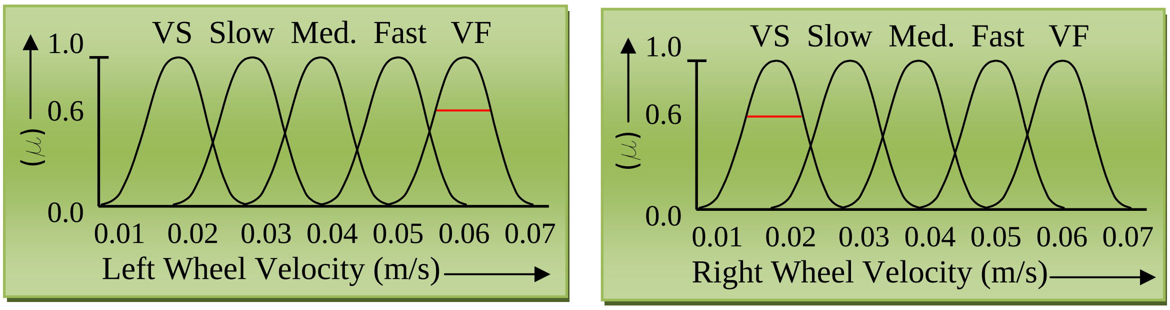
Table 5.4

Target seeking rules for five-membership function.

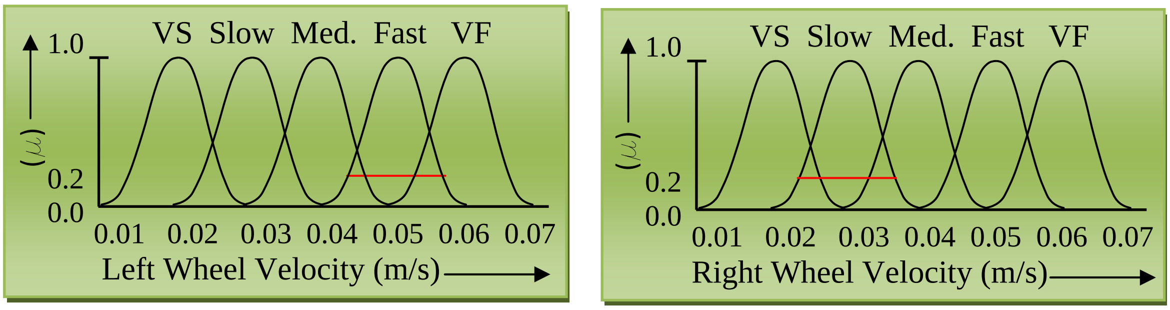
Fuzzy rule no.	Action	leftdist	frontdist	rightdist	Heading angle(φ)	leftvelo	rightvelo
11	TS	VN	Far	Near	Positive	Slow	VS
12	TS	VN	Med.	Very Far	Positive	VF	VS
13	TS	Near	Far	Far	Positive	Fast	Slow
14	TS	Med.	Far	Near	Negative	Slow	Med.
15	TS	Far	Med.	Near	Negative	Med.	Fast
16	TS	Far	Very Far	Near	Negative	Med.	VF

Rule number 12 (Table 5.4) states that if the left obstacle distance is ‘‘very near’’, front obstacle distance is ‘‘medium’’ and right obstacle distance is ‘‘very far’’ and the robot detects a target located on the right side (positive), then the robot should turn right as soon as possible. To do this, the left wheel velocity of the robot should increase very fast and the right wheel velocity should decrease very slowly.

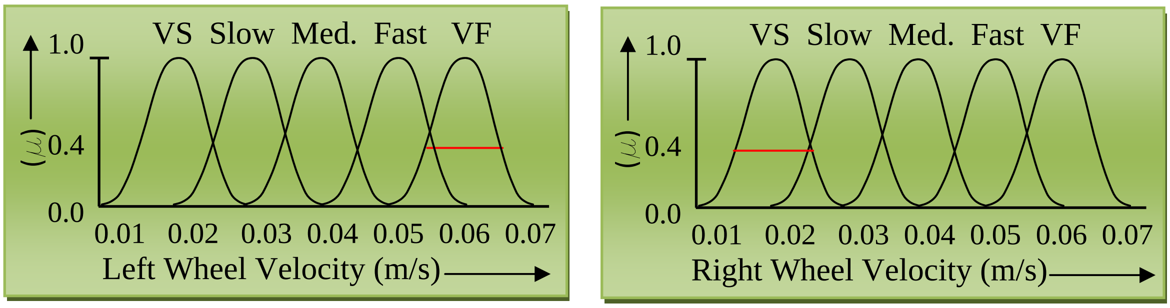
Considering the same situation as described in Fig. 5.4 for target seeking behaviour, the corresponding velocities are found from the fuzzy rules described in Table 5.4. For the mentioned obstacles, there will be 2 ×2 ×2 = 8 fuzzy rules activated to control the left wheel velocity and right wheel velocity of the robot which are tabulated in Table 5.5. The resultant velocities are given in Fig. 5.5, from which the crisp values can be determined and the realization of target tracking behaviour can be achieved.



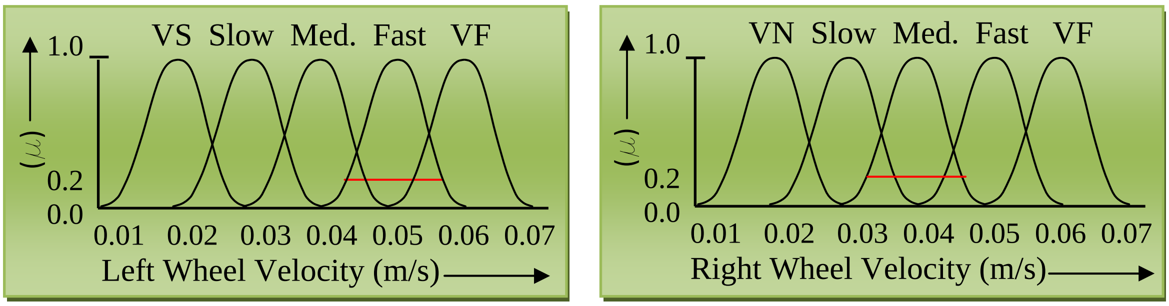
Fuzzy rule for first combination is activated



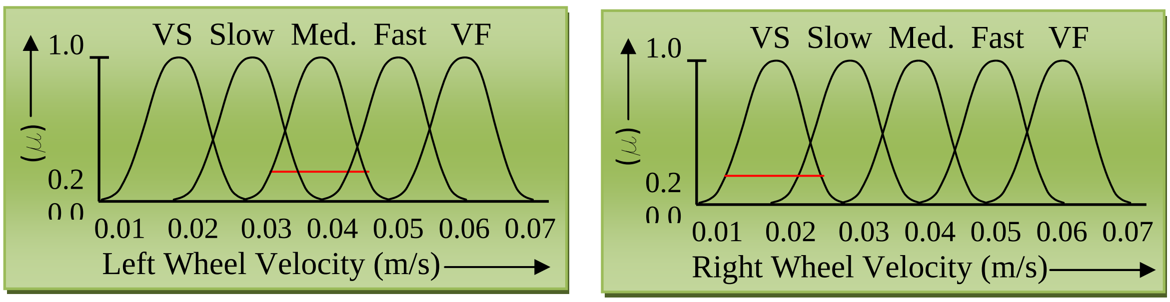
Fuzzy rule for second combination is activated



Fuzzy rule for third combination is activated



Fuzzy rule for fourth combination is activated



Fuzzy rule for fifth combination is activated

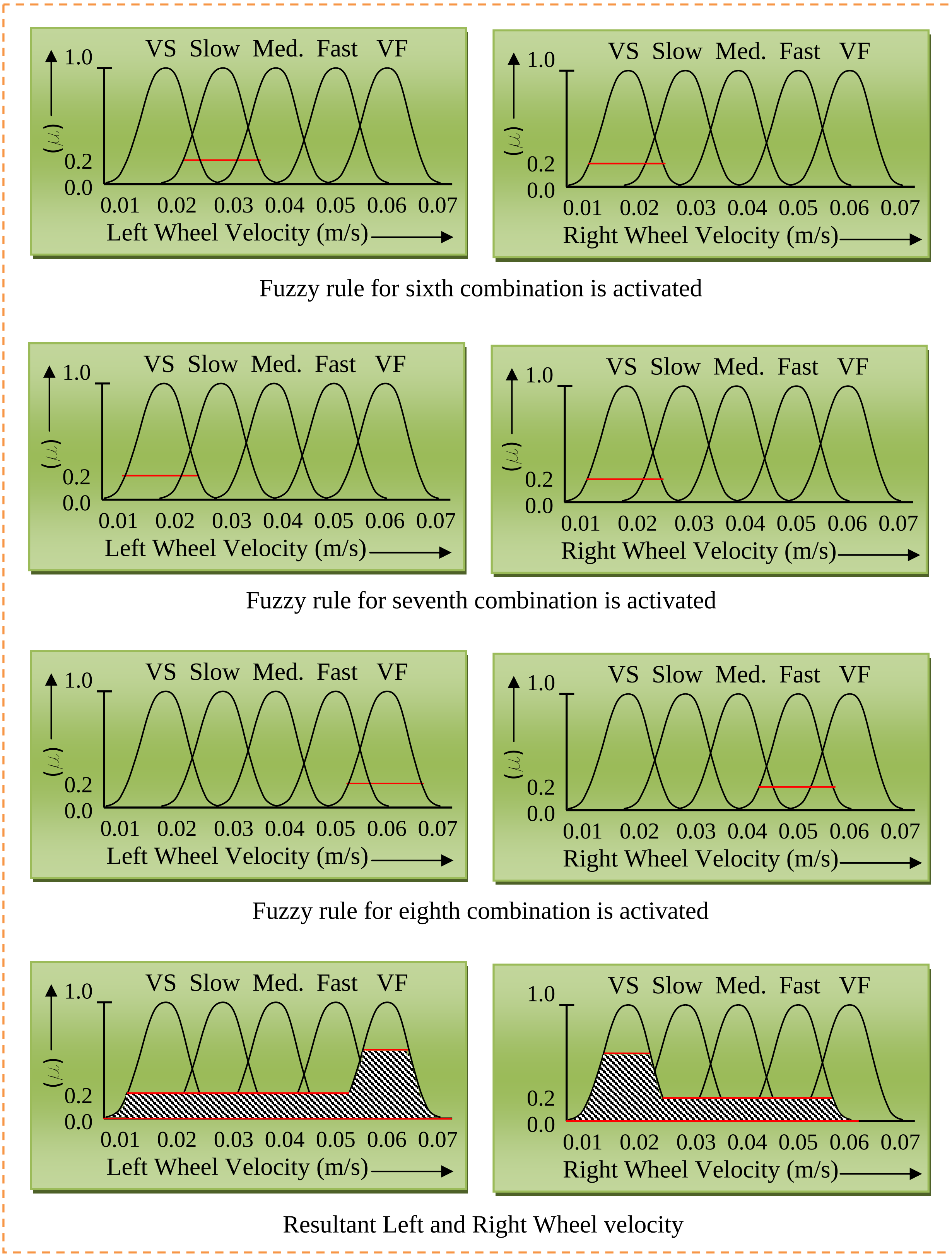


Fig. 5.5. Resultant left and right wheel velocity obtained as output from the proposed fuzzy controller.

Table 5.5

Robot wheel velocities according to different combinations of obstacle distances.

Sl. No.	Different combinations of obstacle distances	Wheel velocities according to fuzzy rules
1.	Left obstacle: very near, front obstacle: near and right obstacle: very far	Left wheel velocity: *very fast* and right wheel velocity: *very slow*
2.	Left obstacle: very near, front obstacle: near and right obstacle: far	Left wheel velocity: *fast* and right wheel velocity: *slow*
3.	Left obstacle: very near, front obstacle: medium and right obstacle: very far	Left wheel velocity: *very fast* and right wheel velocity: very *slow*
4.	Left obstacle: very near, front obstacle: medium and right obstacle: far	Left wheel velocity: *fast* and right wheel velocity: *medium*
5.	Left obstacle: near, front obstacle: near and right obstacle: very far	Left wheel velocity: *medium* and right wheel velocity: *very slow*
6.	Left obstacle: near, front obstacle: near and right obstacle: far	Left wheel velocity: *slow* and right wheel velocity: *very slow*
7.	Left obstacle: near, front obstacle: medium and left wheel velocity: very fast	Right obstacle: *very far* and right wheel velocity: *very slow*
8.	Left obstacle: near, front obstacle: medium and right obstacle: far	Left wheel velocity: *fast* and right wheel velocity: *slow*

In all the rules heading angle is taken as zero.

While navigation of multiple robots there could be the chances for conflict situations and inter robot collision among them. This has been taken care in the present study by suitably designing a general-purpose conflict module based on Petri Net model discussed in chapter 3 and embedded in the controllers of each robot in order to navigate safely in the environment.

The various tasks of the Petri-Fuzzy embedded module are outlined below.

Task 1 Wait for the start signal

Task 2 Moving, avoiding obstacles using fuzzy inference

Task 3 Detecting conflicts using fuzzy inference

Task 4 Negotiating

Task 5 Checking for conflict and executing movements

Task 6 Searching for targets using fuzzy inference

Task 7 Waiting

5.3. Simulation results

In the current section various simulation results are exhibited for navigation of mobile robots using fuzzy inference techniques for a typical situation by considering three robots and two targets. Three exercises have been designed for different combinations of five-membership fuzzy controllers to show the capabilities of the proposed control scheme. The effectiveness of various fuzzy controllers are analysed, discussed and compared for path optimization.

5.3.1. Comparison between different types of fuzzy controller

In order to compare the performances of different combinations of fuzzy controllers simulation has been carried out in a similar environment using five-membership functions. Figs. 5.6–5.8 represent the path traced by the robots using five-membership triangular function, five-membership triangular and trapezoidal function and Gaussian membership function respectively. Total path lengths for different fuzzy controllers are measured (in pixels) for three mobile robots. The comparison of results in terms path lengths, time taken to reach the targets and performance evaluations (%) for different cases are given in Table 5.6.

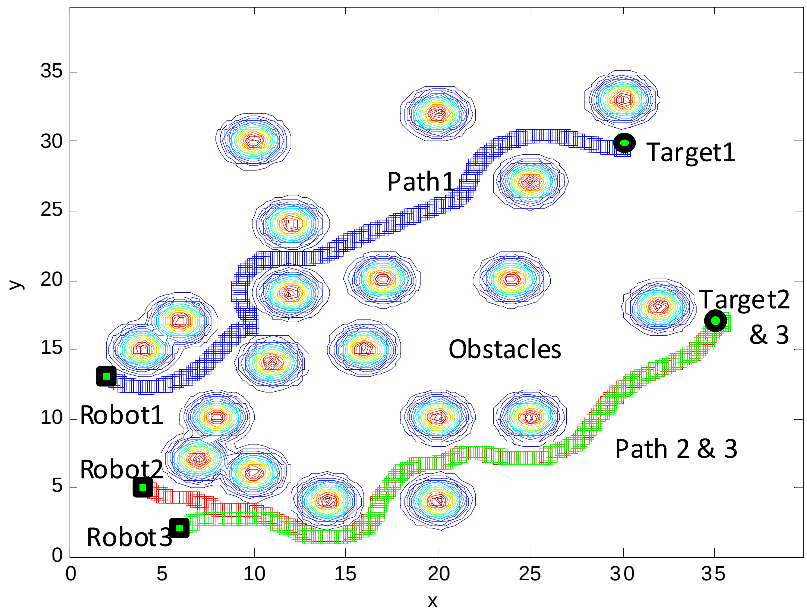


Fig. 5.6 Collision avoidance by three mobile robots with two targets using five-membership fuzzy controller with all triangular members.

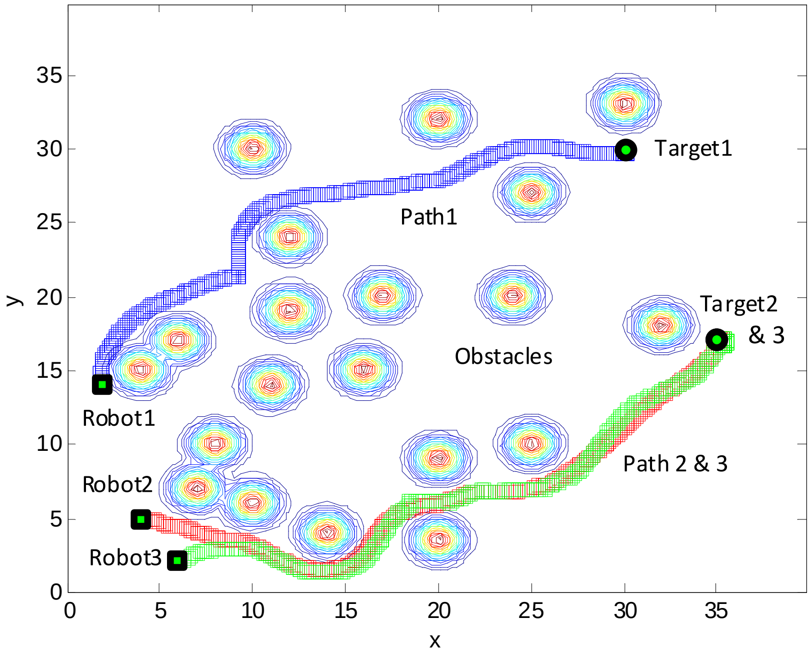


Fig. 5.7 Collision avoidance by three mobile robots with two targets using five-membership fuzzy controller with combination of triangular and trapezoidal members.

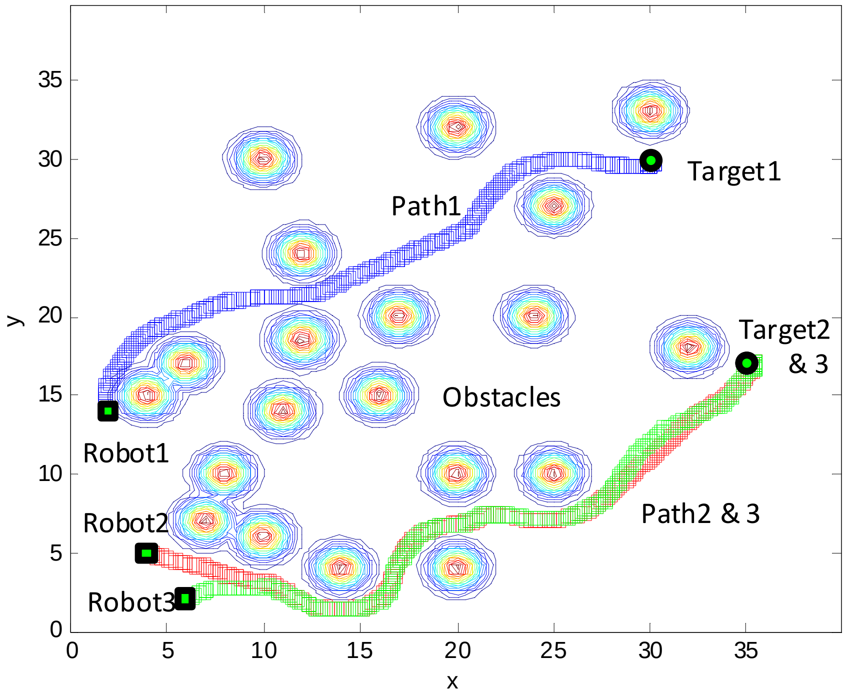


Fig. 5.8. Collision avoidance by three mobile robots with two targets using five-membership fuzzy controller with all Gaussian members.

Table 5.6

Performance evaluation from five-membership triangular FLC with other FLCs for navigation of three mobile robots in a similar environment.

Sl. No.	Different techniques	Robot number	Path length in pixels	Time taken to reach the targets in sec.	Performance evaluation (%)
1.	Five-membership triangular FLC	1	324	33.1	-
		2	342	34.8	-
		3	335	34.0	-
2.	Five-membership triangular & trapezoidal combination FLC	1	312	31.7	4.41
		2	336	34.2	1.75
		3	330	33.5	1.50
3.	Five-membership Gaussian FLC	1	295	29.9	10.73
		2	332	33.6	3.57
		3	325	32.8	3.65

In the above simulation, it can be seen that each robot has reached their nearest target in an efficient manner without any collision between themselves and obstacles in a highly cluttered environment. But still there are some differences in the path length, smoothness of trajectories and time frame to reach the targets. It can be seen from the above simulations that, in Fig. 5.6 (considering all five triangular membership functions) the paths of all the robots are not smooth and the robots followed a longer trajectories to reach the goal. In Fig. 5.7 (considering combinations of triangular-trapezoidal membership functions) the paths followed by all three robots are smoother as well as lesser in lengths as compared to the environment with all five triangular membership functions. Similarly in Fig. 5.8 (considering all five Gaussian membership functions) all the robots reached their nearest targets efficiently in shortest trajectories with comparatively smoother motion. Further the robots well compromised between themselves in the cluttered environment in order to avoid collision among themselves as well as with other obstacles. From the above simulation it can be concluded that the controller with all Gaussian membership functions was found to be most efficient among the other controllers for chosen simulations. Hence the same fuzzy controller using Gaussian membership functions has been demonstrated for other cases of simulation in the succeeding sections.

5.3.2. Approach for design validation with other models

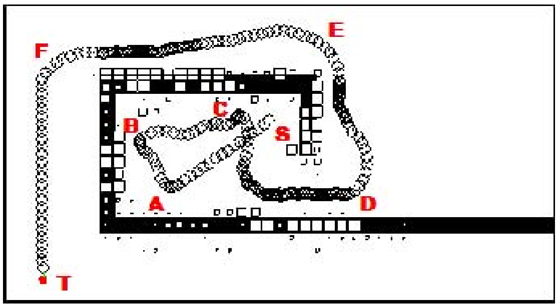
In this section a comparison has been made between Wang and James [206] model and results from current control scheme in simulation and experimental mode. The performance of the two methods was mainly evaluated on following two criteria;

i. the path length
ii. the smoothness of the trajectories.

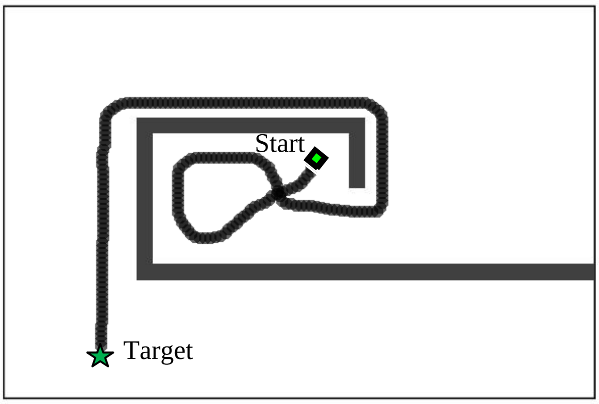
The results from Wang model are shown in Fig. 5.9(a), (c) and (e) are compared with the results obtained from present study for similar environments [Fig. 5.9(b), (d) and (f)] has been tabulated in Table 5.7.

In the first case, both the controllers are applied to a situation with U-shape boundary that would cause the existence of ‘‘dead cycle” problems. In this case the robot cannot see the target directly due to the wall in between them. It can be observed in the environment shown in Fig. 5.9(a) presented by Wang and James [206] that the robot is trapped at the closed U-shape boundary due to the existence of local minima and finally able to find their target after a long exercise by following a longer trajectory.

In Fig. 5.9(b) the robot can avoid the U-shaped boundary found on its way towards the target efficiently by the proposed fuzzy logic model. In this case robot will first follow the wall following rules in order to escape from dead end and successfully found its targets by receiving systematic information from the sensors through the state memory strategy. This shows the robot trajectory from start position to target without suffering from the “symmetric indecision” and ‘‘dead cycle” problems.



a



b

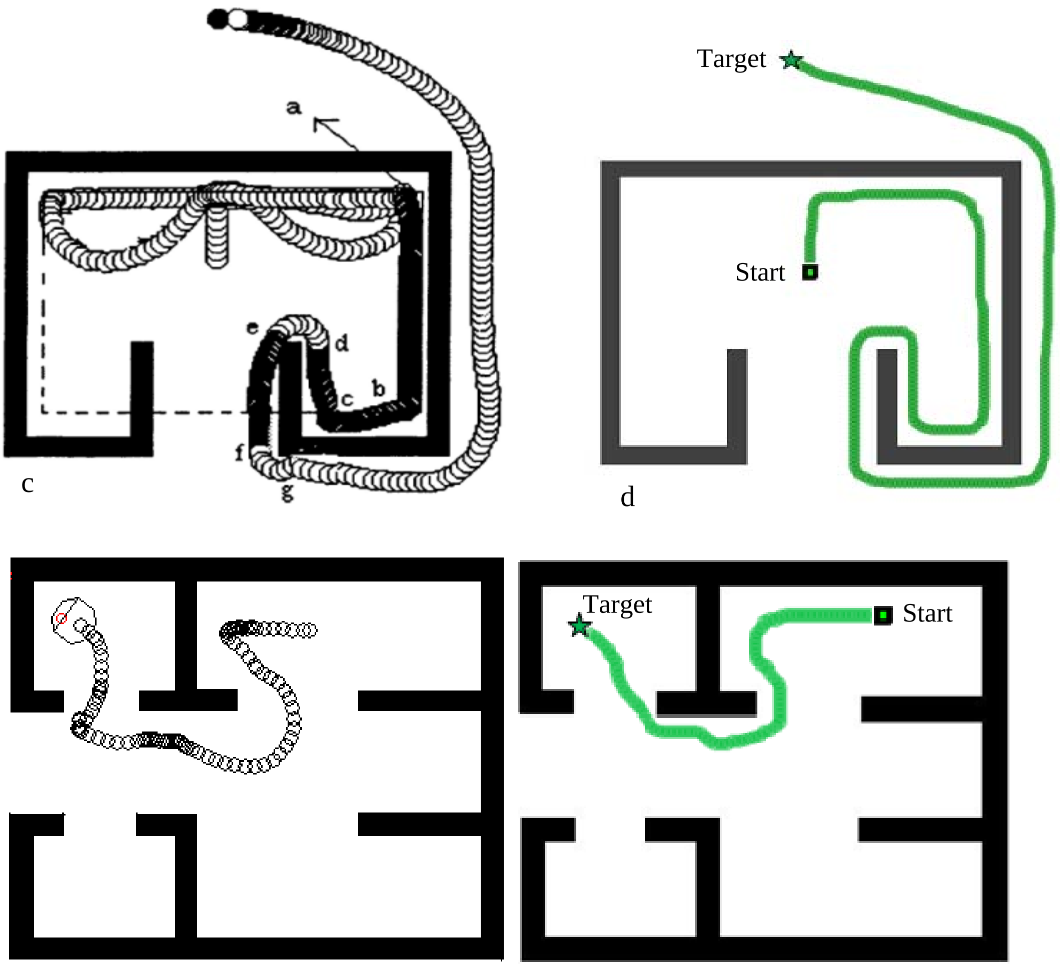


Fig. 5.9. Comparison of results from the current investigation and Wang and James [206].

In the second case, the robot supposed to find the target approximately in a similar situation as described in first case. In Fig. 5.9(c) proposed by Wang and James [206] the robot got trapped in the U-shaped area first, then it was escaped from the trap by taking a loop and eventually reaches the target. Fig. 5.9(d) shows a simulation of the robot behavior adapted by means of the proposed method. In the initial position the robot is heading towards the dead-end. Due to the additional context information provided by the proposed controller robot can able to perceive the dead-end. The controller initiates a turning manoeuvre, which lasts until the robot is heading away from the dead-end. Afterwards, the normal wall-following behaviour guides the robot to the exit of the corridor by keeping a safe distance to the left wall. Similarly in third case the robot from current developed technique found the goal in shortest trajectories with a smoother motion as compared to Wang and James [206] model [Fig. 5.9(e) and 5.9(f)].

Table 5.7

Comparison of results from the current investigation with Wang and James [206] simulation.

Sl No.	Environmental types	Path length of Wang and James [206] model, in ‘cm’	Path length from current investigation in ‘cm’
1.	Rectangular obstacle and path planning by FLC [Fig. 5.9(a) and (b)].	15.6	13.5
2.	U-shaped aisle and path planning by FLC [Fig. 5.9(c) and (d)].	33.2	21.5
3.	Closed aisle and path planning by FLC [Fig. 5.9(e) and (f)].	7.0	6.2

In some scenarios, of Wang and James [206] simulation 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. Fig. 5.9(b), (d) and (f) show that the robot reaches their target in a shortest path with smooth motion by using the present fuzzy logic approach. The performance of the two models was mainly evaluated on the basis of path length and smoothness of trajectory which is shown in Table 5.7. From the above simulation results it is clear that, the developed algorithm can efficiently drive the robot in a cluttered environment. Experimental verification of the above simulation results has been shown in next sections (Fig. 5.10- 5.12).

5.4. Experimental result and discussions

To demonstrate the effectiveness of the above control system and validity of the algorithm developed using Gaussian membership FLCs, a variety of experiments using prototype robots are conducted. In this section the simulation results from currently developed motion planner has been presented for experiments, which was operated in an environment with rectangular aisle of different shapes. The detail specification of the developed robot is given in Chapter 3 (Section 3.6.1).

Three different cases of similar environments as described by Wang and James [206], which are already verified in simulation mode have been verified experimentally [Fig. 5.10- 5.12] to show the effectiveness of the developed controller. In Figs. 5.10(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 rectangular obstacle configurations). When robot starts motion it senses the target and speeds up in straight path towards the targets up to the bottom left corner of the rectangular wall and slows down to take right turn to avoid obstacle, then follows a wall following rules to reach the target.

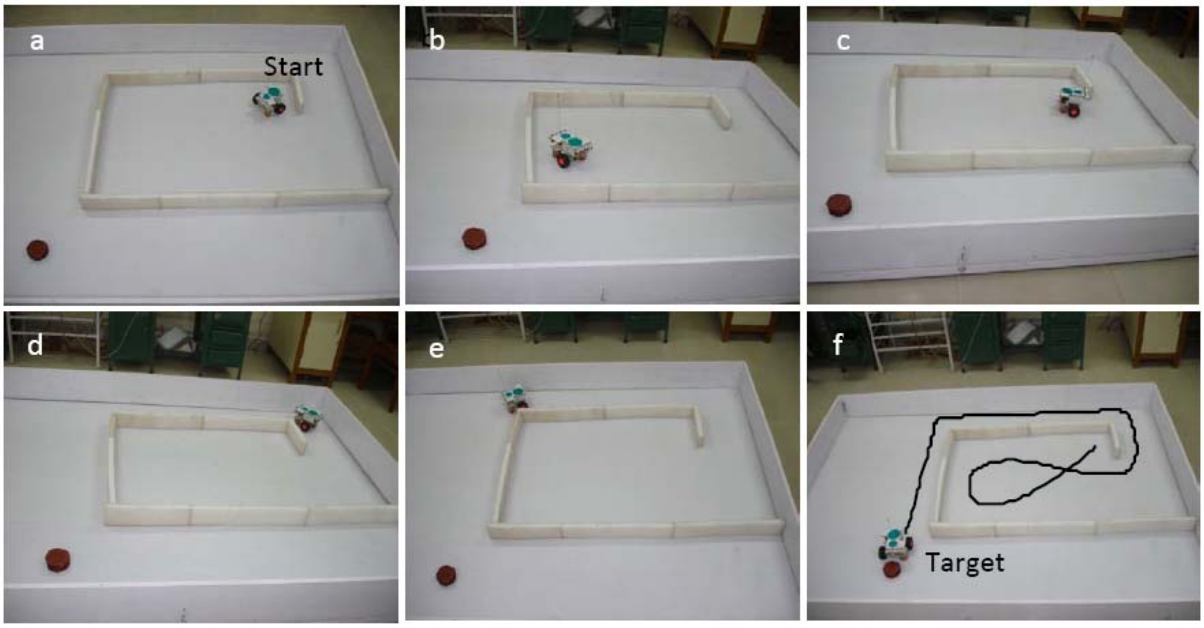


Fig. 5.10. Experimental set up for navigation of mobile robot in the similar environment as shown in Fig. 5.9(b).

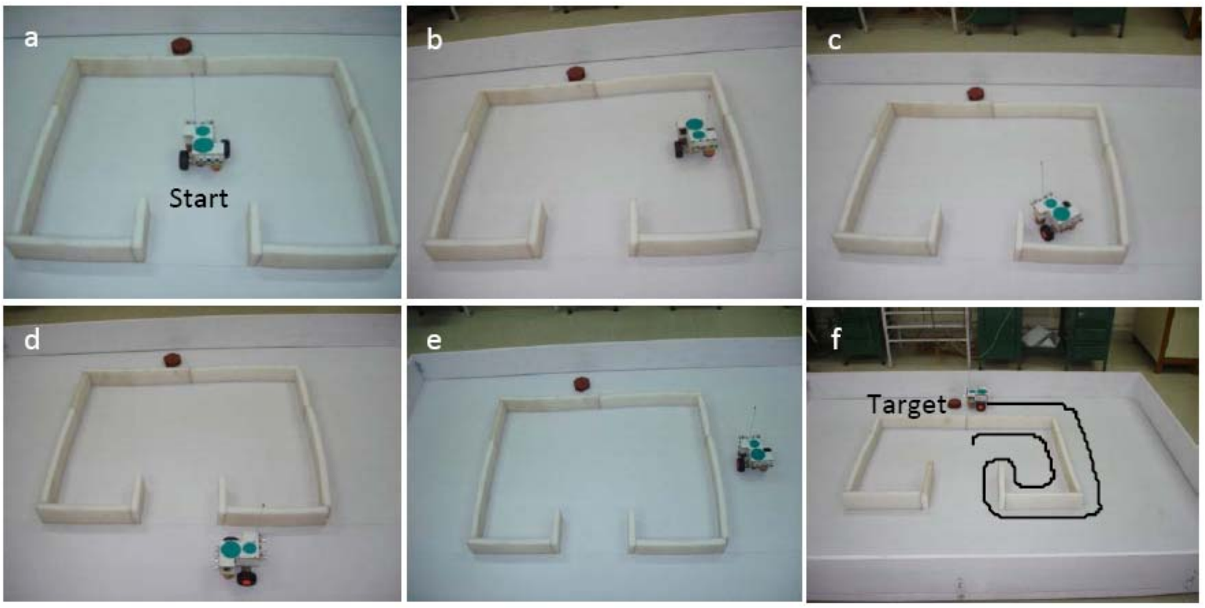


Fig. 5.11. Experimental set up for navigation of mobile robot in the similar environment as shown in Fig. 5.9(d).

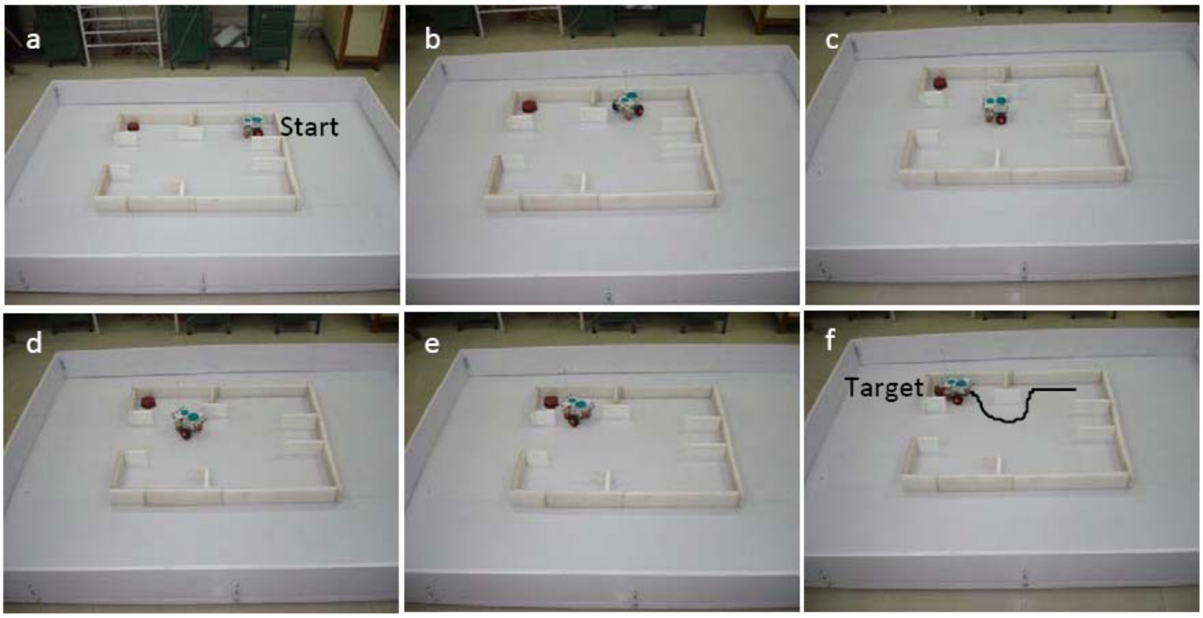


Fig. 5.12. Experimental set up for navigation of mobile robot in the similar environment as shown in Fig. 5.9(f).

For the second robot navigation (Fig. 5.11f), 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 Fig. 5.12(f), in which the robot is following a U-shaped path to find the target. In some cases the robot can rotate and move with some zigzag motion until it reaches target. The developed fuzzy logic controller takes care to invoke a new path based on available information received by the robot about the environment with ruled based heuristic recovery approach.

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 Gaussian function can successfully arrive at the target by avoiding obstacles. The trajectories are smooth and take reasonably lesser paths as compared to Wang and James [206] paths.

5.5. Summary

In this chapter different fuzzy logic controllers have been designed and analysed their performance to control the motion of multiple mobile robots in various environments. First the triangular members with five membership functions have been considered and subsequently the membership functions are changed from triangular to other functions and combinations to have a more smooth control response. The robot navigation control system described in this chapter takes 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. In order to navigate safely and avoid inter robot collision each robot incorporates a set of collision prevention rules implemented as a Petri Net model in its controller. It is seen that the fuzzy controller with Gaussian membership function works better and safely navigate the robots from start to goal position in a precise manner with smooth trajectory. The developed strategies have been checked via simulations as well as experiments, which show the ability of proposed controller to solve the multiple robot navigation tasks in an optimised way to obtain a strategy for the purpose. It has been observed that, the robots follow closely the simulation path by the developed motion planning approach and able to navigate successfully in a cluttered environment.

It is observed that hybridisation of techniques improve the effectiveness/performance and hence increases the robustness of the controller. In the next chapter different developed hybrid techniques are analysed and discussed by taking into account the strategy developed in Chapter-3, 4 and 5.

Chapter 6

Hybrid Techniques for Navigation of Mobile Robots

- **The background**
- **Analysis of Potential-Fuzzy hybrid controller for mobile robot navigation**
- **Analysis of GA-Fuzzy hybrid controller for mobile robot navigation**
- **Analysis of Potential-GA Hybrid Controller for mobile robot navigation**
- **Analysis of Potential-Fuzzy-Genetic Hybrid Controller for mobile robot navigation**
- **Summary**

6. Hybrid Techniques for Navigation of Mobile Robots

This chapter deals with navigation using four different hybrid techniques. They are as follows: 1) potential-fuzzy technique, 2) potential- genetic technique, 3) genetic-fuzzy technique and 4) potential-fuzzy-genetic techniques. The detail controller design, analysis and implementation with real robot to fit in various environments have been described. The simulation results have been demonstrated, analysed and compared in order to illustrate the ability of the proposed control scheme to manage the navigation of mobile robots in different situations.

6.1. The background

In previous chapters the navigation of mobile robots has been widely demonstrated in various known and unknown environments by using standalone potential, genetic and fuzzy logic techniques. These techniques are not always the best choice for some tasks that can be effectively produced a robust performance in dynamic and complex environments. Sometimes the task to be performed needs the robot to make some intelligent decision to reach the destination in an optimal or near optimal path while avoiding collision among themselves and obstacles. This leads a platform to try the similar situations with various combinations of hybrid controllers for the purpose. In these hybrid approaches firstly, the combinations of two techniques has been selected in order to model the controllers and secondly, all the techniques have been hybridized to get a better controller. These hybrid controllers are first designed and analysed for possible solutions for various situations. Then computer simulations have been executed for various known and unknown environments. Finally the proposed hybrid algorithms are embedded in the controllers of the real robots to demonstrate the effectiveness of the developed control scheme.

This chapter gives navigational analysis of different models, their advantages and disadvantages for following four main approaches; i.e. Potential-Fuzzy technique, Genetic-Fuzzy technique, Potential-Genetic technique and Potential-Fuzzy-Genetic hybrid technique. A thorough comparison was carried out for various situations and examples of such hybrid architectures among themselves and others AI techniques are presented in this chapter.

6.2. Analysis of Potential-Fuzzy hybrid controller for mobile robot navigation

6.2.1. Introduction

In this chapter the motion planning of multiple mobile robots with multiple targets in presence of obstacles in a priori unknown cluttered environment using Potential-Fuzzy Hybrid Controller (PFHC) is discussed. Based upon a reference motion, direction; distances between the robots and obstacles; distances between the robots and targets are given as inputs to the Potential-Fuzzy controller (Fig. 6.1). A combination of multiple sensors is equipped on the prototype robot to sense the obstacles near the robot, the targets location and the current robot speed. The hybrid controller takes the control decision on the basis of signals received from sensors mounted around the robot. To realize the controller in real sense the program is embedded in the robot for online independent navigation. The Petri net model discussed in chapter 3 has also been simultaneously integrated with the hybrid technique for inter robot collision avoidance and obstacle avoidance during navigation. The "symmetric indecision" problem is resolved by several mandatory-turn rules, while the "dead cycle" problem is resolved by a state memory strategy. Under the control of the proposed Petri-Potential-Fuzzy model, the mobile robot can preferably "see" the environment around and avoid static and moving obstacles automatically. The robot can generate reasonable trajectories towards the target in various situations without suffering from the "symmetric indecision" and the "dead cycle" problems. The effectiveness and efficiency of the proposed approach are demonstrated through simulation studies as well as experimental implementation in various environments.

6.2.2. Control architecture

To carry out the above procedures two techniques such as potential field method and fuzzy inference technique have been studied and analysed in previous sections are combined to generate the Potential-Fuzzy hybrid techniques. The details inputs to the potential segments are obstacle position and target position around. Based on the obstacle and target positions the resultant repulsive and attractive potential forces are calculated as follows;

Let $\sum F_{Front}$ = Resultant repulsive potential force along the direction of rear-front axis of the robot due to the obstacles which influence the robot.

$\sum F_{Along}$ = Resultant repulsive potential force along the direction of left-right axis of the robot due to the obstacles which influence the robot.

The output from the potential field method is First Heading Angle (F.H.A.) can is calculated as follows;

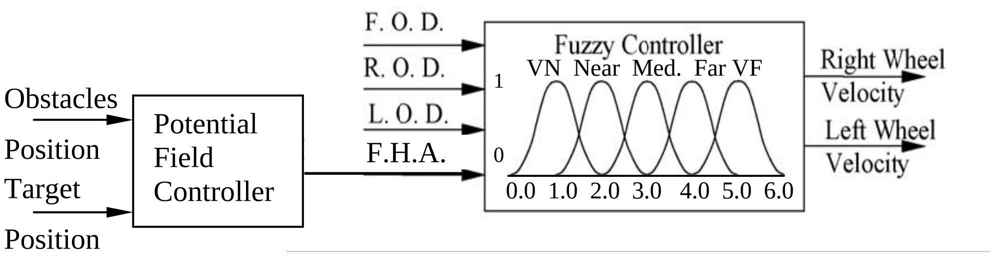
θ = Current heading angle at which the robot moving in the environment.

Change in steering angle required for obstacle avoidance is

$$Phif\left[ir\right] = Tan^{-1}\left[\frac{F_{Front}}{F_{Along}}\right] \tag{6.1}$$

First heading angle $\theta_{first} = \theta + Phir\ [ir]$ (6.2)

The intermediate analysis and mathematical steps for calculating the attractive and repulsive forces are explained extensively in Chapter 3. The inputs and outputs of potential segment have been given pictorially in Fig. 6.1. The other part of the potential-fuzzy hybrid techniques consists of the fuzzy inference techniques having several inputs and outputs. The inputs are F.O.D., L.O.D., R.O.D. and F.H.A (that have been obtained from potential segment of the hybrid controller) as shown in Fig. 6.1. The overall outputs of the potential fuzzy hybrid technique are LV and RV. These two velocities ultimately give the heading angle (φ) according to the flow diagram shown in Fig. 6.2. The Gaussian membership functions are used in fuzzy inference technique to get the optimum results as discussed in Chapter 5.



Note: VN: Very Near, Med.: Medium and VF: Very Fast.

Fig. 6.1. Five membership Potential-Fuzzy hybrid controller with all Gaussian members for mobile robot navigation.

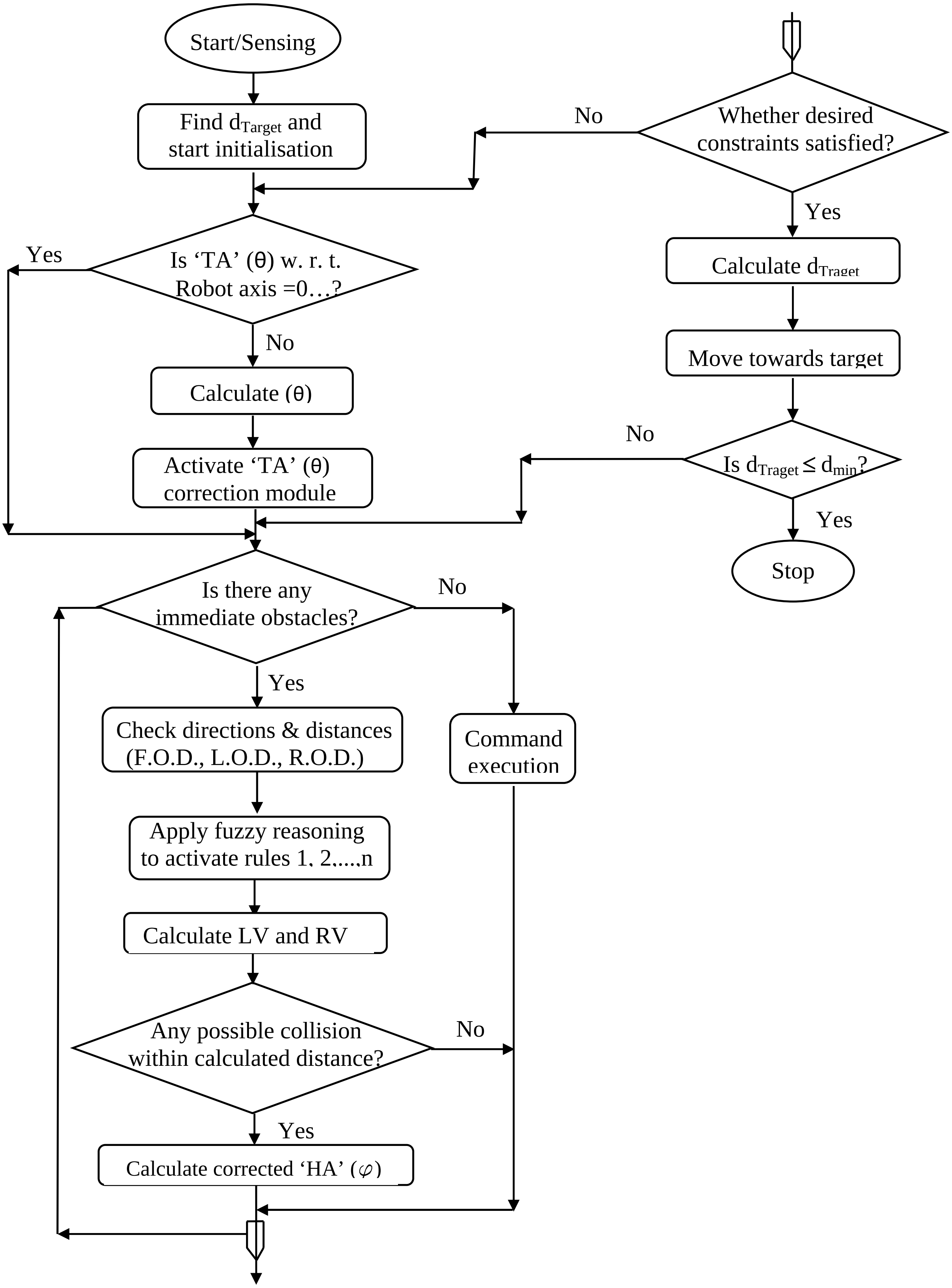


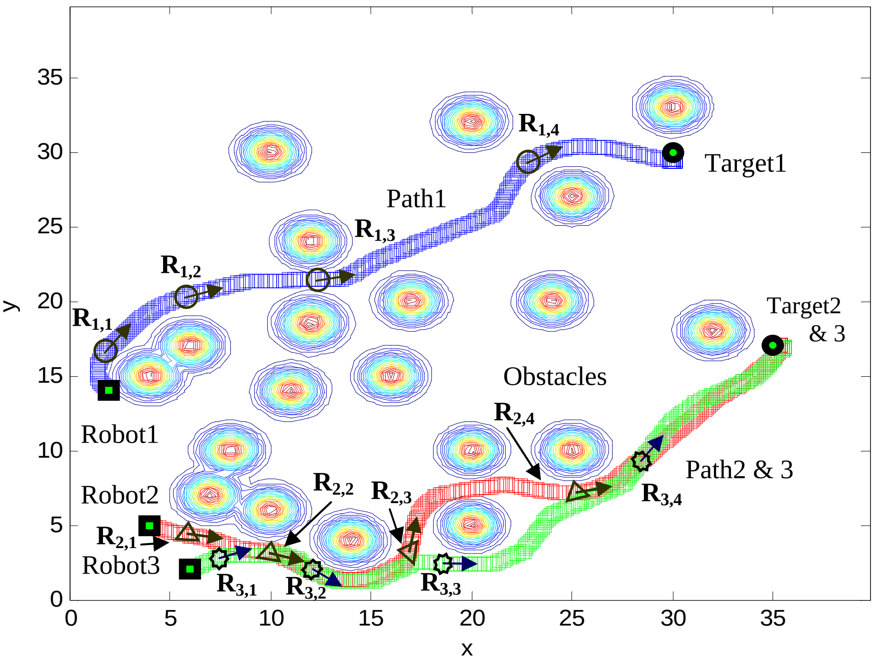
Fig. 6.2. A schematic diagram showing flowchart for step by step algorithm of the proposed motion planning scheme.

The overall flow chart of the potential-fuzzy hybrid controller is given Fig. 6.2. For navigational control of the robot, an incremental approach is adopted, where the robot's movement is a collection of small steps combining both straight and non linear curved paths. In the beginning of navigation, the axis correction module is activated by considering the obstacle's and target's positions if the robot's main axis does not coincide with the target direction. This is done by getting systematic sensory information from the targets and obstacles and accordingly the corresponding attractive/ repulsive forces generated using the potential segment of the hybrid controller. After that, the robot search for existence of any critical obstacle ahead of it, in the predicted distance step. If it finds any critical obstacle, the motion planner is to be activated; otherwise the robot moves with the maximum possible speed in the direction of target with zero deviation of HA in the next step. The outputs of the motion planner are nothing but the left wheel velocity and right wheel velocity of the robot and the corresponding deviation necessary to avoid collision with the most critical obstacle. Moreover, if required, the motion planner's deviation output is to be corrected by using the collision avoidance scheme implemented in the form of Petrinet Model which is shown in Chapter 3 (Section 3.3). If the robot's future direction of movement differs from the existing one, then all the constraints are to be satisfied, else it starts from step one. This process will continue, till the robot reaches its target location (Fig. 6.2). The simulation results based on Potential-Fuzzy controller obtained during navigation of mobile robots are analysed and discussed below.

6.2.3. Simulation results

This section presents exercises aimed at illustrating the ability of the proposed hybrid control scheme to manage the navigation of mobile robots in different situations. Simulations are conducted from the computer program being developed by the author. Two case studies have been designed by considering multiple robots and multiple targets using Potential-Fuzzy hybrid controller (PFHC) with five member ship Gaussian functions to show the capabilities of the proposed control scheme. In the first navigational scenario the three robots with two targets in a highly cluttered environment are considered. In the second navigational scenario the three robots with three targets in a quite different environment of highly cluttered type is taken to demonstrate the results. These two environmental scenarios will be discussed for other hybrid approaches in the forth coming sections and results are compared to find an optimal controller for the purpose.

Scenario 1



Note: $R_{(1,1)}$…… $R_{(1,4)}$, $R_{(2,1)}$…… $R_{(2,4)}$ and $R_{(3,1)}$…… $R_{(3,4)}$ are different instantaneous positions at time (*t*) of robot1, 2 and 3 respectively.

Fig. 6.3(a). Collision avoidance by three mobile robots with two targets using Potential-Fuzzy hybrid controller (2-D workspace and obstacles).

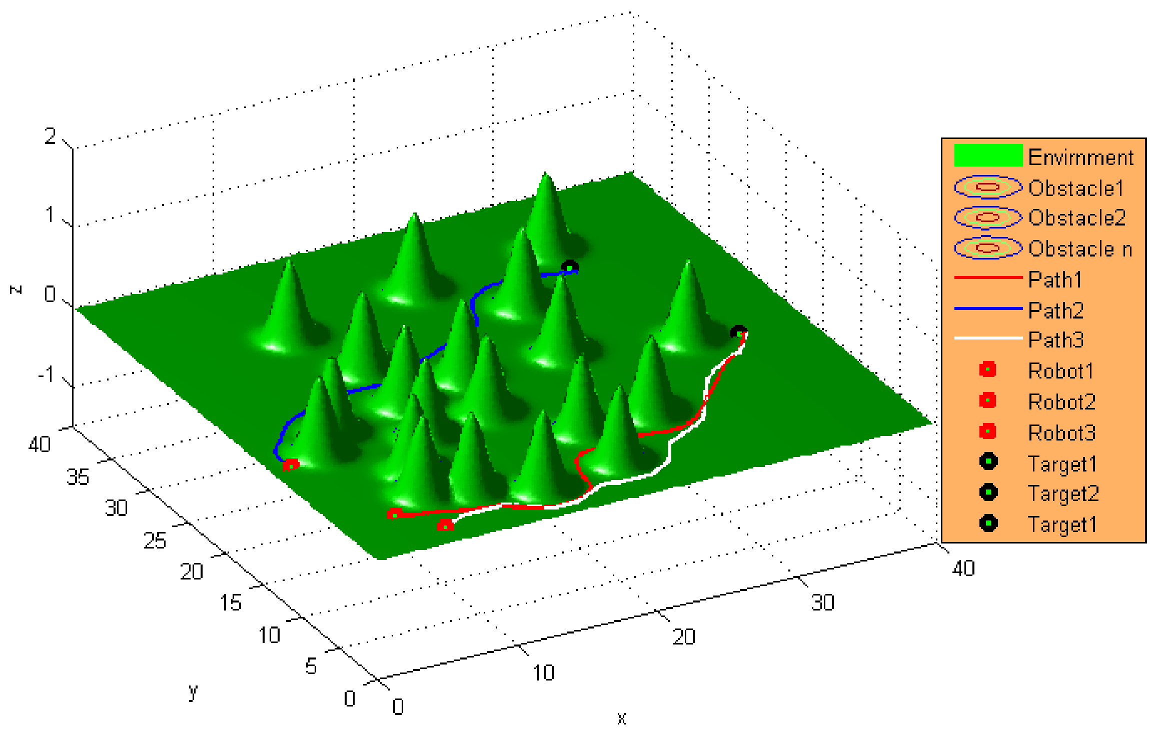


Fig. 6.3(b). Collision avoidance by three mobile robots with two targets using Potential-Fuzzy hybrid controller (3-D work space and obstacles).

Scenario 2

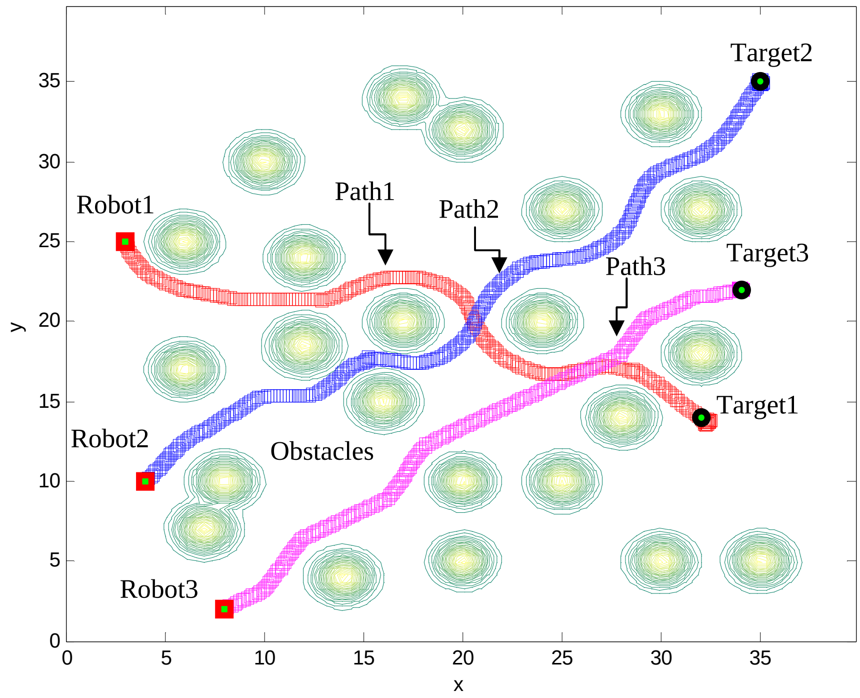


Fig. 6.4(a). Collision avoidance by three mobile robots with three targets using Potential-Fuzzy hybrid controller (2-D work space and obstacles).

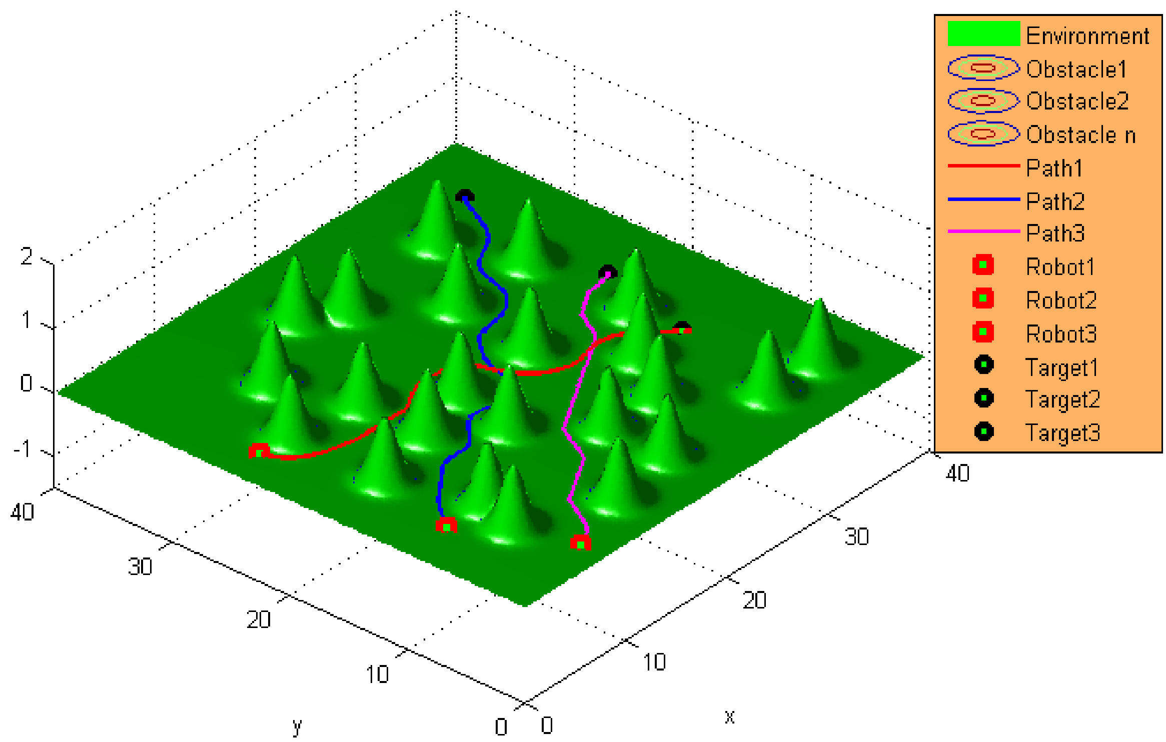


Fig. 6.4(b). Collision avoidance by three mobile robots with three targets using Potential-Fuzzy hybrid controller (3-D work space and obstacles).

The 2-D and 3-D view of scenario 1 and 2 are presented in Figs. 6.3(a, b) and Figs. 6.4(a, b). Path traced by three robots in environmental scenario 1 & 2 using the proposed hybrid model are given in Table 6.1. From the above simulations it can be seen that each robot has reached their nearest target in an efficient manner without any collision between themselves and obstacles in a cluttered environment. The details of computational steps at different instantaneous positions for scenario 1 are shown in Appendix F.

Table 6.1

Path obtained from scenario 1 & 2 using Potential-Fuzzy hybrid controller for multiple robots navigation.

Sl. No.	Scenario Type	Robot number	Path length in 'pixels'	Time taken to reach the targets in 'sec'.
1.	Scenario 1	1	290	29.3
		2	311	33.0
		3	295	32.0
2.	Scenario 2	1	228	27.0
		2	283	29.6
		3	232	27.2

6.2.4. Comparison of results with other models

In this section a comparison has been made between Wang and James [206] model as discussed in Chapter 5 (section 5.3.2), results using stand alone fuzzy logic techniques and results from current hybrid control scheme in simulation and experimental mode are presented. This scenario considered for the comparison focuses on navigation with dead end problem escape from U-shape and corridor navigation. The simulation results obtained for the above discussed environment using Potential-Fuzzy Hybrid Controller (PFHC) and Wang and James [206] model are shown in Figs. 6.5(a-f). The comparison of results for two methodologies is given in Table 6.2.

In the first case (i.e. navigation with dead end) the robot navigates in the environment searching for the target. During navigation the robot confronts with dead end, negotiate and finally come out from the dead end during target searching [Figs. 6.5(a, b)]. At the end robot reached the target. It has been observed that the current controller gives optimum and smoother trajectories by Parhi and Mohanta [207] compared to Wang and James [206] trajectories and Fuzzy Gaussian trajectories as discussed in chapter 5.

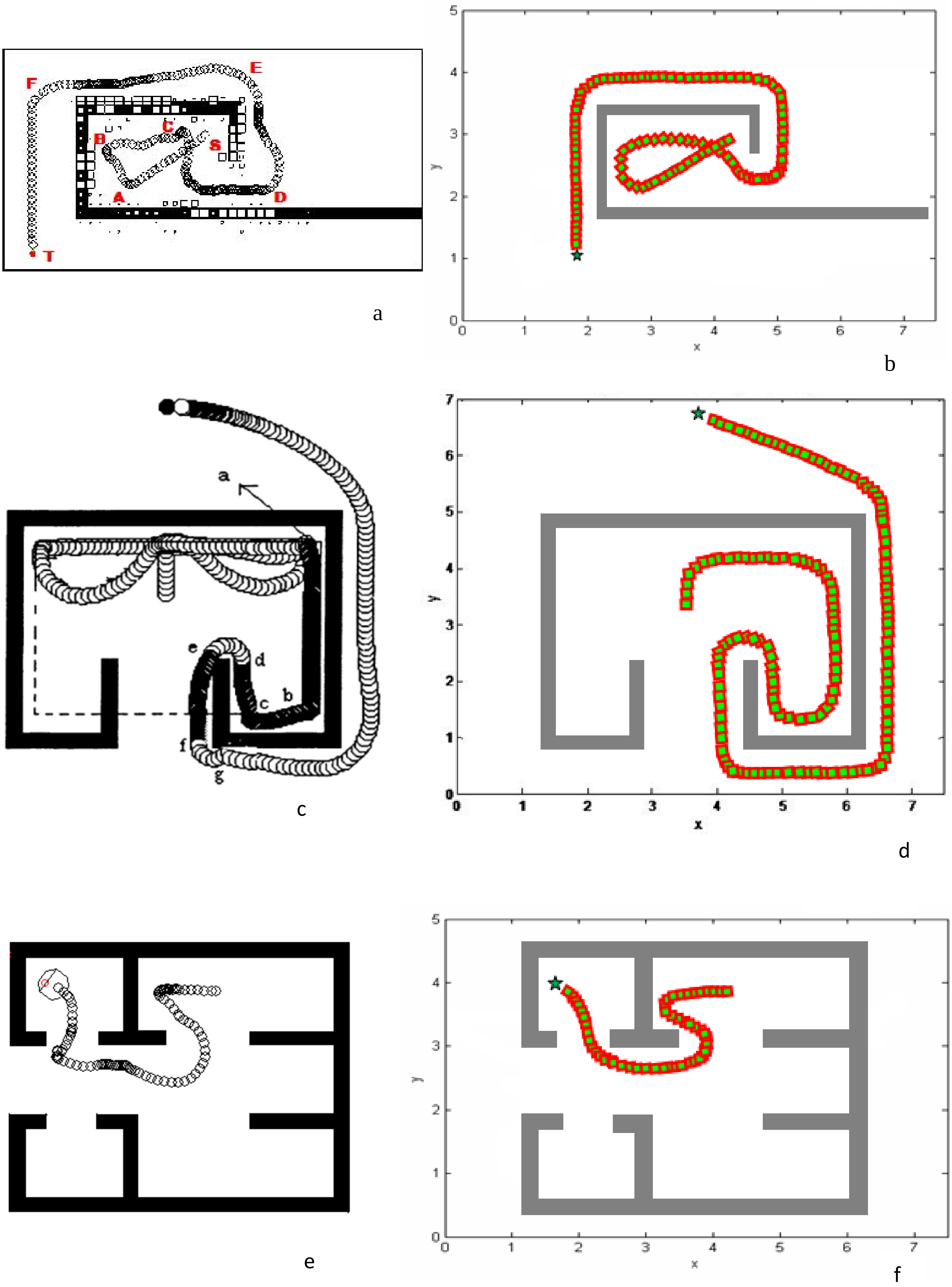


Fig. 6.5. Comparison of results from the current investigation and Wang and James [206].

Similarly in case two it has been observed that robot trapped by Wang and James [206] model and afterwards escaped from the U-shaped obstacles. During comparison between

Fuzzy-Gaussian technique (discussed in Chapter 5), Wang and James [206] technique and Potential-Fuzzy technique, the results of the current hybrid technique are optimum [207]. Also a better result is obtained using current hybrid technique by Parhi and Mohanta [207] for the above simulation.

Table 6.2
Comparison of results between Wang and James [206] model, Stand alone fuzzy logic technique and Potential-Fuzzy hybrid techniques in similar environment.

Sl No.	Environmental types	Path length of different techniques in 'cm'		
		Wang and James [206] Model	Gaussian-Fuzzy Logic Technique	Potential-Fuzzy hybrid Technique [207]
1.	Rectangular aisle	15.6	13.5	12.6
2.	U-shaped aisle	33.2	21.5	20.7
3.	Closed aisle	7.0	6.2	5.4

6.2.5. Real-time experiment

Experimental verifications are also carried out using prototype robot developed in the laboratory for the similar situations such as Rectangular aisle, escape from U-shape obstacles and closed aisle which are shown in Figs. 6.6, 6.7 and 6.8. The robot navigates in the above outline environment using the hybrid potential-fuzzy controller. A very good agreement is observed between the simulation and experimental results of the hybrid potential-fuzzy controller.

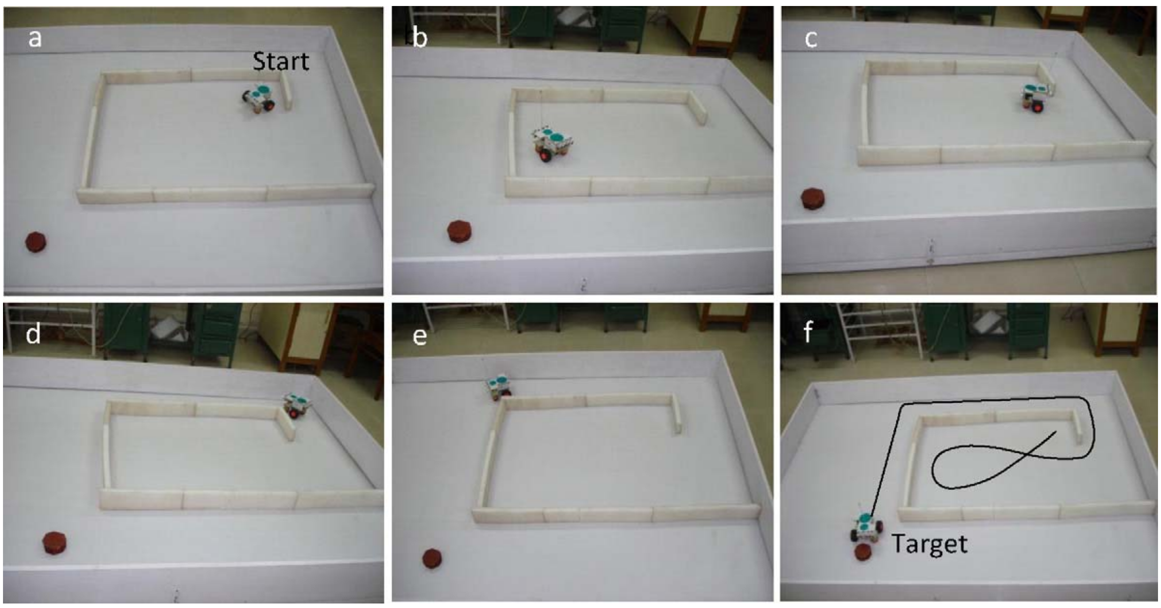


Fig. 6.6. Experimental set up for navigation of mobile robot in the similar environment shown in Fig. 6.5(b)

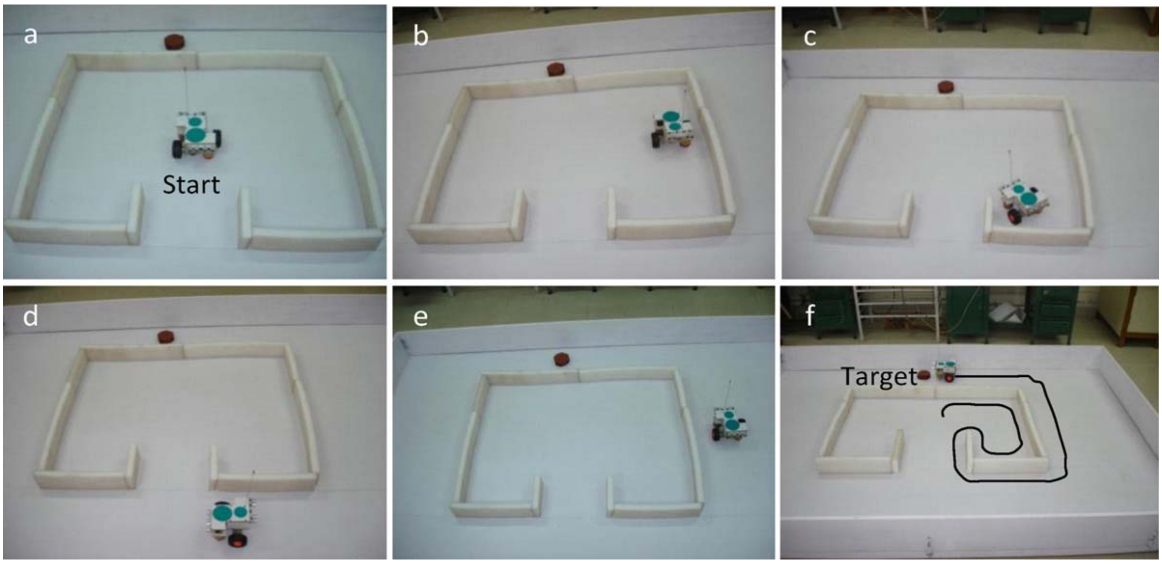


Fig. 6.7. Experimental set up for navigation of mobile robot in the similar environment shown in Fig. 6.5(d).

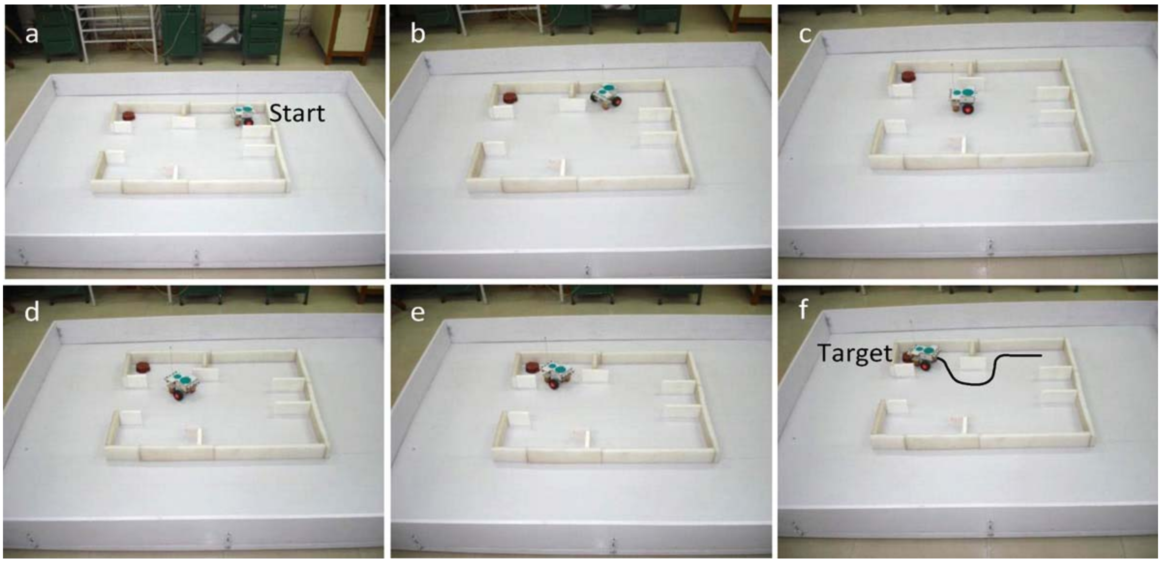


Fig. 6.8. Experimental set up for navigation of mobile robot in the similar environment shown in Fig. 6.5(f).

6.3. Analysis of GA-Fuzzy hybrid controller for mobile robot navigation

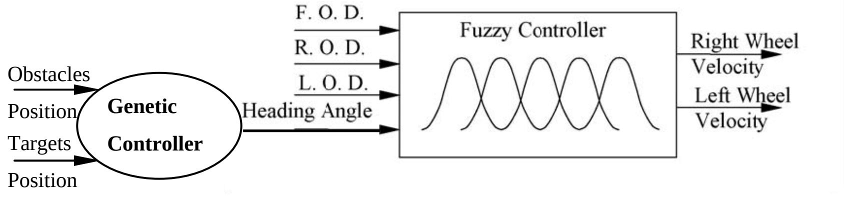
6.3.1. Introduction

This chapter presents an approach to build a hybrid Petri-Genetic-Fuzzy Controller (PGFC) for navigational behaviour of multi-robotic agents. The incorporation of an integration procedure to frame a hybrid controller is becoming an increasing necessity for autonomous robotic vehicles capable of moving along in the industrial environment. To find a suitable collision-free path for multiple mobile robots navigation in real world environment is extremely necessity for cooperative tasks. In this section genetic algorithm technique is integrated with Fuzzy logic technique to find an efficient controller for the purpose mentioned. In the fuzzy inference system five membership functions with all Gaussian members has been considered. The direction and motion control of the robots based on the final output of the Genetic-Fuzzy hybrid controller. The Petri-net model (already discussed in Chapter 3) which is integrated with Genetic-Fuzzy controller to avoid inter robot collision during navigation. The proposed approach has also been applied for achieving multi-target systems.

6.3.2. Design of mobile controller using GA-Fuzzy Hybrid approach

As specified earlier a genetic algorithm (GA) and fuzzy logic based obstacle avoidance scheme has been used here for path planning of multiple robots with multiple targets in presence of obstacles. Problem-specific genetic fuzzy operators are not only designed with domain knowledge, but also incorporate small-scale local search that improves efficiency of the operators. This task could be carried out by specifying a set of GA-Fuzzy rules by taking into account the different situations found by the mobile robots. The schematic diagram for the proposed Genetic-Fuzzy hybrid controller is shown in Fig. 6.9.

For this purpose the basic inputs to the genetic segment of Genetic-Fuzzy controller (FGC) are obstacles position and targets position and output is heading angle (H.A.). This output is again passed through the fuzzy segment of hybrid controller in addition to the other parameters such as front obstacle distances (FOD), right obstacle distances (ROD) and left obstacle distances (LOD) to get the requisite left and right wheel velocity which controls the motion of the robot.



Five membership genetic- fuzzy controller with all Gaussian members for mobile robot navigation

Fig. 6.9. Genetic-fuzzy hybrid controllers for mobile robot navigation.

The detail mathematical analysis and step by algorithm are discussed in corresponding chapters. The proposed hybrid Genetic-fuzzy controller is suitable for both static and dynamic environments. The effectiveness and efficiency of the proposed approach are exhibited through simulation and experimental results.

6.3.3. Simulation results

In this section the two environmental scenarios which are already discussed in previous sections using Potential-fuzzy hybrid technique are taken for simulation using the proposed Genetic-fuzzy hybrid controller.

The first scenario consists of 3-robots and two targets. During navigation it can be observed that, the robots follow different path with respect to the robots controlled by the Potential-fuzzy technique. It has been noticed that, the robot can successfully reach the target by avoiding the obstacles using the proposed Genetic-fuzzy technique. The corresponding 2-D & 3-D simulations for two discussed scenarios are shown in Figs. 6.10(a, b) and 6.11(a, b). Total path traced by three mobile robots for two different scenarios are measured (in pixels) and tabulated in Table 6.3.

Scenario 1

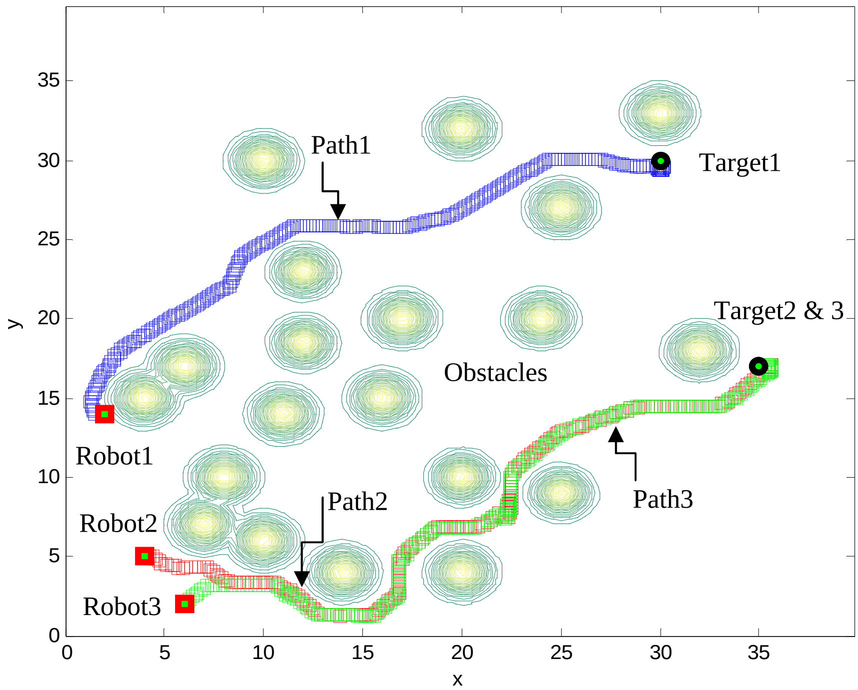


Fig. 6.10(a). Collision avoidance by three mobile robots with two targets using Genetic-Fuzzy hybrid controller (2-D workspace and obstacles).

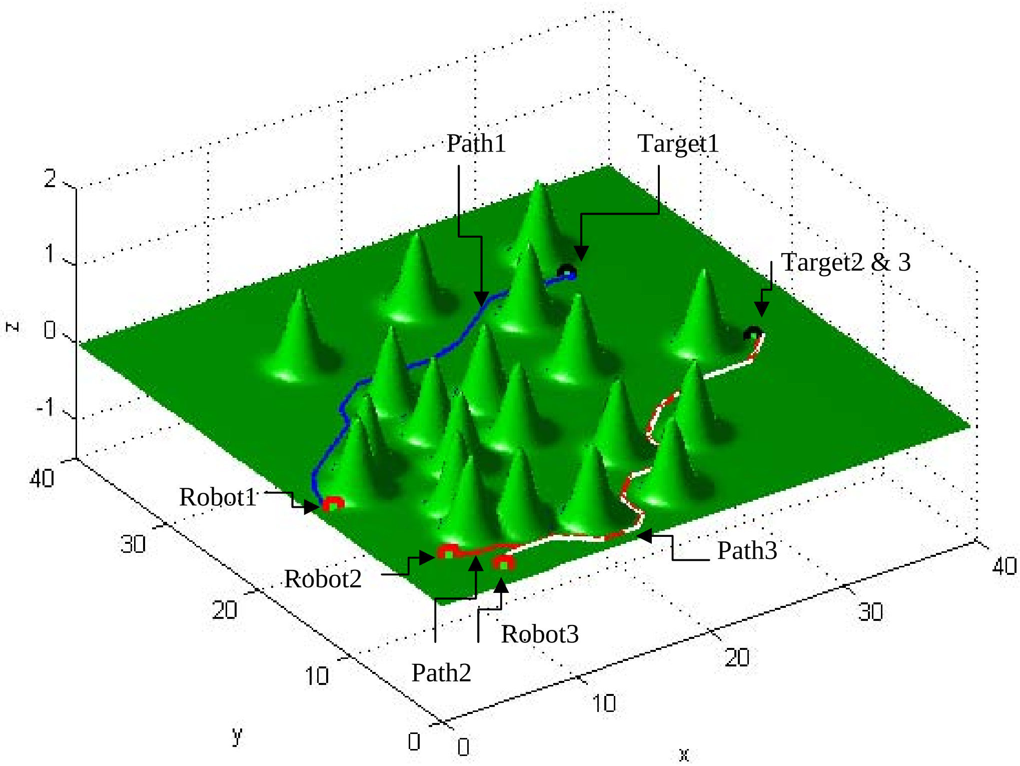


Fig. 6.10(b). Collision avoidance by three mobile robots with two targets using Genetic-Fuzzy hybrid controller (3-D workspace and obstacles).

Scenario 2

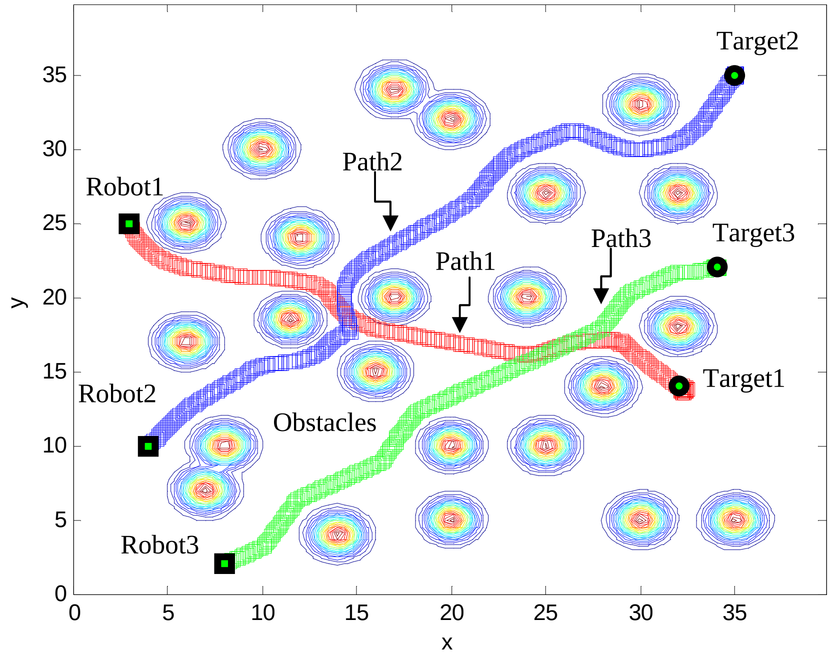


Fig. 6.11(a). Collision avoidance by three mobile robots with three targets using Genetic-Fuzzy hybrid controller (2-D workspace and obstacles).

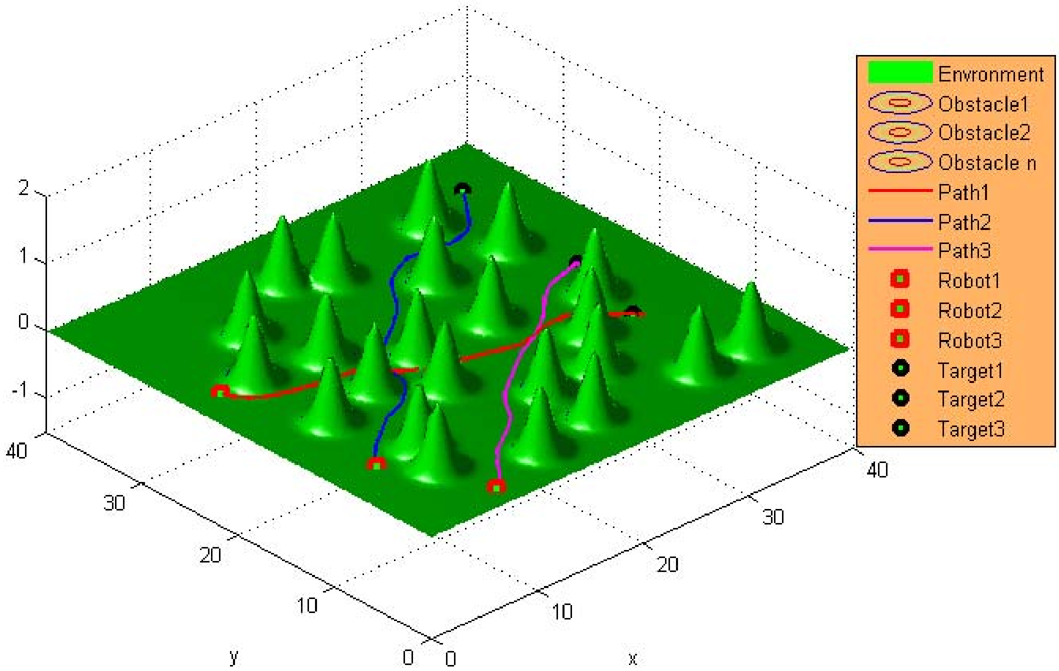


Fig. 6.11(b). Collision avoidance by three mobile robots with three targets using Genetic-Fuzzy hybrid controller (3-D workspace and obstacles).

Table 6.3

Path obtained from scenario 1 & 2 using Genetic-Fuzzy hybrid controller for multiple robots navigation.

Sl. No.	Scenario Type	Robot number	Path length in 'pixels'	Time taken to reach the targets in 'sec'.
1.	Scenario 1	1	283	28.7
		2	298	32.2
		3	292	31.8
2.	Scenario 2	1	220	26.5
		2	276	28.6
		3	216	27.0

6.3.4. Comparison of results with other model

A comparison has been made between Luh and Liu [208] model and results from hybrid Genetic-Fuzzy control scheme in simulation and experimental mode. The performance of the two methods is mainly evaluated keeping in view the following parameters.

i. the path length
ii. the smoothness of the trajectories.

The results of three different cases obtained by Luh and Liu [208] shown in Fig. 6.12 (a, c, e) are compared with the results obtained from present investigation for similar environment [Fig. 6.12(b, d, f)].

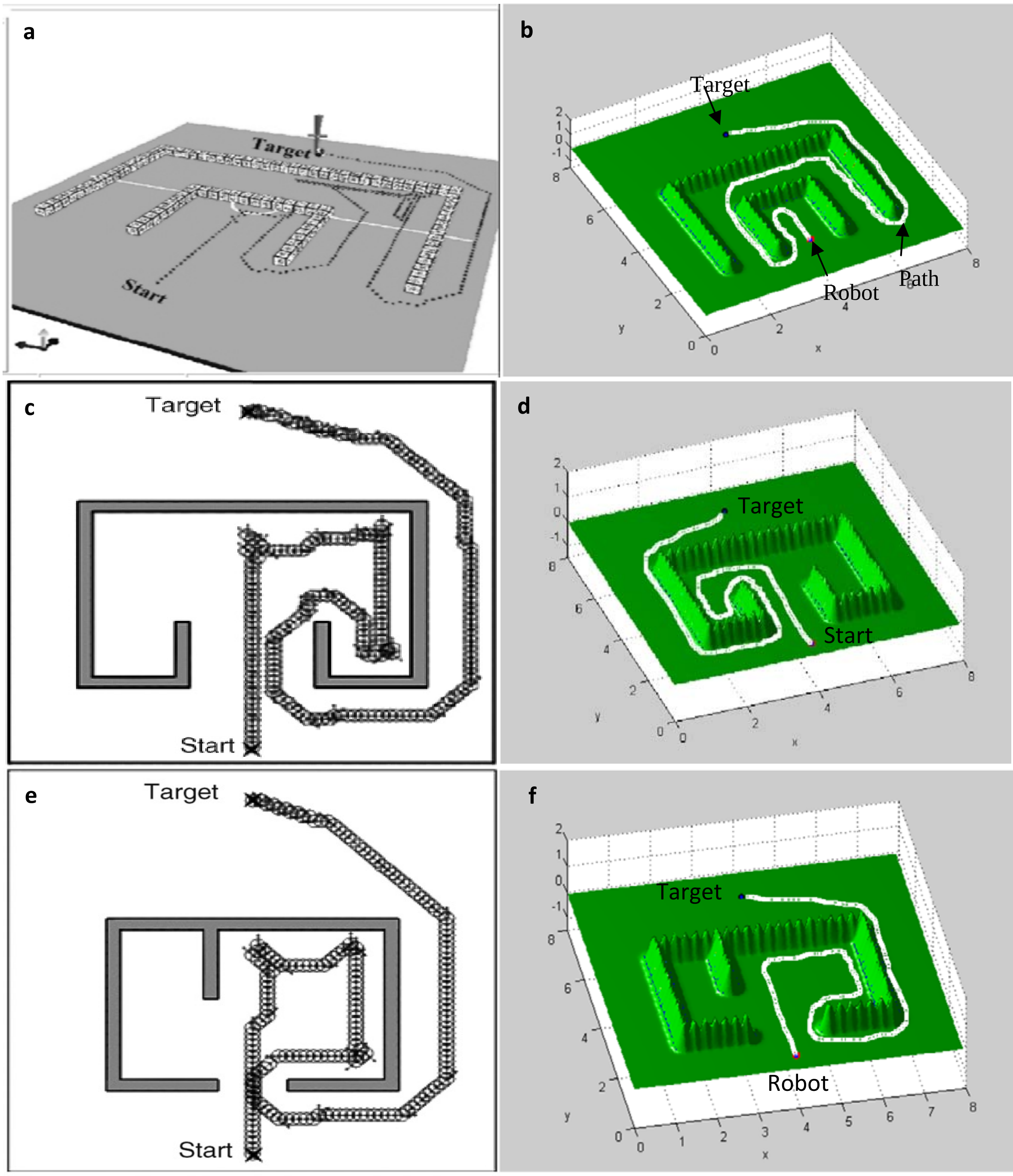


Fig. 6.12. Comparison of results from the current investigation and Luh and Liu [208].

The simulation has been conducted in a similar environment as described by Luh and Liu [208]. The first case has shown a situation for path planning in which robot is enclosed by double U-shaped boundary, and target is placed just opposite side of robot.

During navigation it has been observed that robot first move towards target location by straight path take a turning manoeuvre due to the presence of wall between them and able to reach the target after long exercise. The same situation has been tested via simulation using genetic-fuzzy hybrid controller. The path covered by the robot is found to be smooth and shortest as compared to the Luh and Liu [208] path described in Fig. 6.12(b). In the second environment robot is placed in a closed U-shaped boundary and target is in the opposite corner of robot. In this case robot was first trapped near the corner and finally able to reach the target by taking a longer trajectory shown in Fig. 6.12(c). Similarly in the Figs. 6.12(e, f), for both the cases the robots trapped at the complex U-shaped boundary due to the existence of local minima. In Fig. 6.12(f) robot escaped from the local minima exits due the wall between them by using new control scheme which drags the robot near the target in a shortest path. The detail comparison of results has been given in Table 6.4.

Table 6.4

Comparison of results from the current investigation with Luh and Liu [208] model.

Sl No.	Environmental types	Path length of Luh and Liu [208]. in 'cm'	Path length from current investigation in 'cm'
1.	U-shaped boundary, [Fig. 6.12(a, b)].	17.4	14.6
2	Closed U-shaped boundary, [Fig. 6.12(c, d)].	21.2	15.4
2	Complex U-shaped boundary, [Fig. 6.12 (e, f)].	19.6	14.8

From the above simulation results it is clear that, the developed algorithm can efficiently drive the robot in a cluttered environment. Experimental verification of the above simulation results have been shown in next section (Fig. 6.13- 6.15).

6.3.5. Real-time experimental results

To realize the effectiveness of Genetic-Fuzzy hybrid controller a variety of experiments using Khepera II robots are conducted. The position and posture of the prototype robot can be estimated by dead reckoning using the hybrid control technique and information from the encoders arranged on the wheels and the steering axes. The robot considered for experiment is a differential drive robot with an on-board PC and wireless Ethernet. A series of distance measuring sensors are mounted around the top of robot in order to sense the front, left, right, and back obstacle distances. The signals received from different sensors according to obstacle distances decides the speed at DC-motors via driver circuits, so that driving torque occurs by the robot for its movement.

The three different cases of similar environments as described by Luh and Liu [208], which are already verified in simulation mode have been verified experimentally (Fig. 6.13- 6.15) to show the effectiveness of the developed controller.

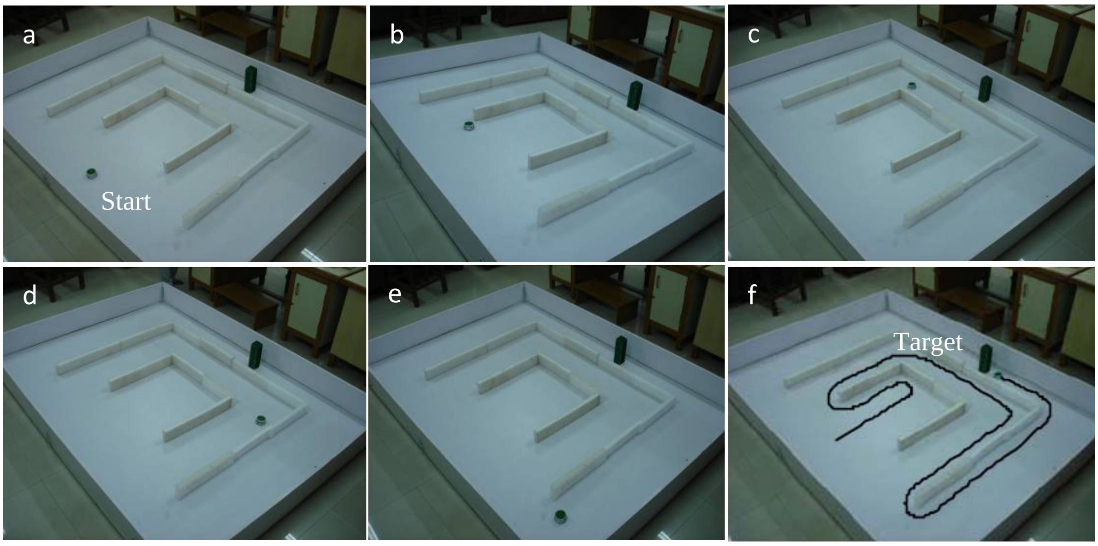


Fig. 6.13. Experimental set up for navigation of Khepera II mobile robot in the similar environment shown in Fig. 6.12(b).

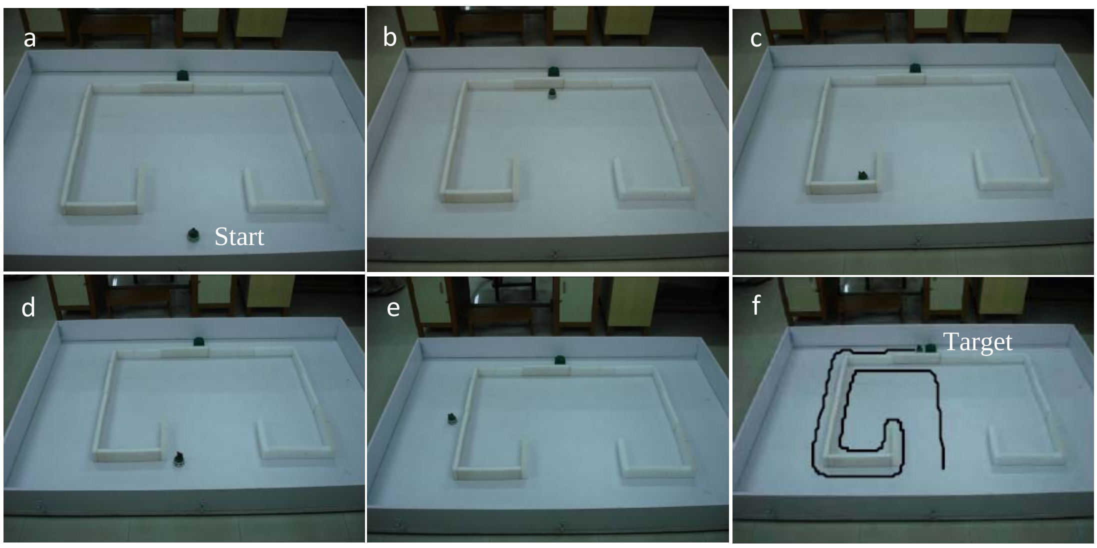


Fig. 6.14. Experimental set up for navigation of Khepera II mobile robot in the similar environment shown in Fig. 6.12(d).

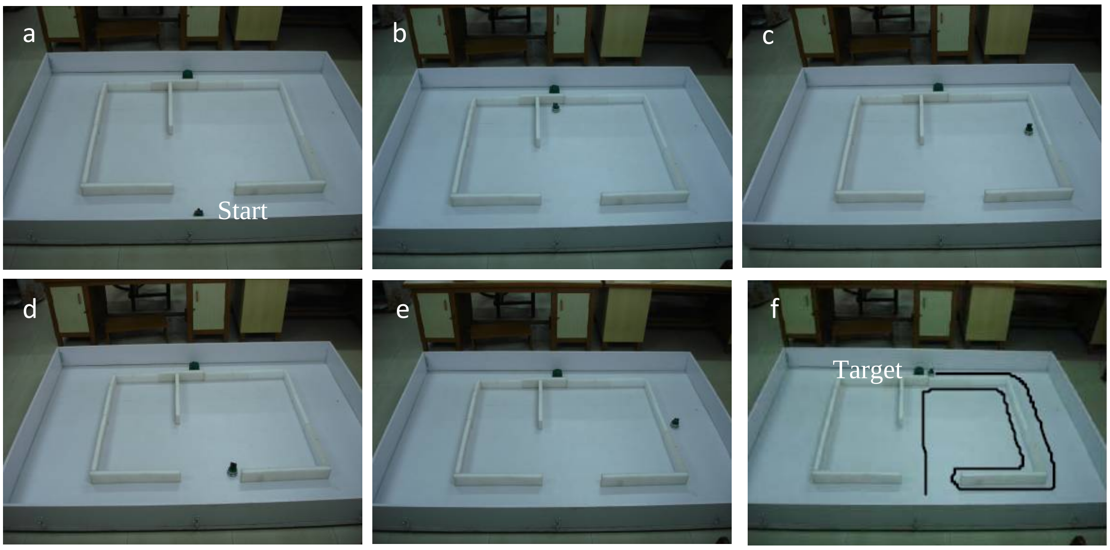


Fig. 6.15. Experimental set up for navigation of Khepera II mobile robot in the similar environment shown in Fig. 6.12(f).

Fig. 6.13(a-f), demonstrated a situation where robot and target are placed in opposite side of double U-shaped boundary. When robot starts motion it senses the target and speeds up in straight path towards the targets up to the bottom corner of the wall and slows down to take right turn to avoid collision, then follows a wall (wall following behaviour) to reach the target. The robot autonomously chooses its way in the shortest trajectory to reach the desired destination. For the second robot navigation [Fig. 6.14(f)], it can be observed that, the robot follows a straight path except the turning points from its start to the goal position. Figs. 6.14(a-f) explain a situation in which the robot is trapped in a local minimum (corresponding to a closed 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. The developed algorithm takes care to invoke a new path based on available information received by the robot about the environment with heuristic recovery approach, which has been shown in Fig. 6.14(a-f). In Fig. 6.15(f) robot successfully reach the target from the trap situation by taking a turning manoeuvre and then wall following rules to reach the goal by systematic information received from the proposed hybrid controller. The comparison of simulation and experimental results from the current investigation are shown in Table 6.5.

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.

Table 6.5

Comparison of simulation and experimental results from the current investigation.

Sl No.	Environmental types	Simulation Results		Experimental Results	
		Path length (cm)	Time taken(Sec)	Path length (cm) in 1/10th scale	Time taken (Sec) in 1/10th scale
1.	U-shaped boundary [Fig. 6.12(b) & Fig. 6.13]	12.1	24.52	14.8	34.24
2.	Closed U-shaped boundary [Fig. 6.12(d) & Fig. 6.14]	10.0	20.86	11.4	23.20
3.	Complex U-shaped boundary[Fig. 6.12(f) & Fig. 6.15]	9.8	18.65	10.6	22.42

It has been concluded by comparing the results from both the simulation as well as experiment that, the path followed by the robots using Petri-Genetic-fuzzy controller can successfully arrive at the target by avoiding obstacles. The trajectories are smooth and take reasonably efficient paths as compared to Luh and Liu [208] path.

6.4. Analysis of Potential-GA Hybrid Controller for mobile robot navigation

6.4.1. Introduction

This chapter proposes a new approach for the design and development of intelligent mobile robot based on Potential-Genetic hybrid controller. It discusses the complex functional structure of such systems, providing solutions to some typical design problems. The system, on the one hand, offers some solutions for the problems related to the hybrid potential field building (like dead lock and local minima problem), and on the other hand, looks for the problem-solutions connected with self organization of the mobile robots during navigation. It is decentralized and behaviour-oriented, because the agents sharing the basic information about the positions and orientations between each other, and on the basis of these information they define the next possible position and orientation. It is evolutionary self-organized, because the moving strategies are defined by a genetic algorithm and with the specified policies the near-optimal next possible move can be determined. To realize the controller in real sense the program is embedded in the robot for online independent navigation. 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 (already discussed in chapter 3). Numerical examples as well as simulation results are provided to evaluate the feasibility of the proposed approach. The current research involves the design, development, systems integration, simulation and experimental testing of the intelligent mobile robot in various environments for validity of the proposed control scheme.

In this section the motion planning of multiple mobile robots with multiple targets in presence of obstacles in a priori unknown environment using modified knowledge based potential-GA controller is discussed. The inputs to the controller are obstacles positions and target positions and output heading angles (H.A.) are expressed in terms of encoded generation function distributions by crisp values. This output is again passes through the hybrid potential controller in addition to the other parameters such as left obstacle distances (L.O.D.), front obstacle distances (F.O.D.) and right obstacle distances (R.O.D.) to get the requisite final wheel velocities which controls the motion of the robot. The proposed potential-GA controller is suitable for both static and dynamic environments. The effectiveness and efficiency of the proposed approach are demonstrated through simulation studies as well as experimental implementation in various environments.

6.4.2. Control architecture

Chapter 3 discusses about the total attractive force and repulsive force using the potential field function taking into the consideration the inputs such as obstacle and target positions around the robot and detail analysis is done in chapter 3. The F.H.A. can be calculated from the following equation.

The change in steering angle required for obstacle avoidance is;

$$Phif\left[ir\right] = Tan^{-1}\left[\frac{\sum F_{Front}}{\sum F_{Along}}\right] \tag{6.3}$$

The corresponding First heading angle (F. H. A.) = θ + Phir [ir] (6.4)

It determines the motion of the robot.

Where,

$\sum F_{Front}$ = Resultant repulsive potential force along the direction of rear-front axis of the robot due to the obstacles which influence the robot.

$\sum F_{Along}$ = Resultant repulsive potential 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.

This First heading angle (F. H. A.) along with the instantaneous obstacles distances i. e. F.O.D., L.O.D. and R.O.D. are again input to the genetic segment of the potential-genetic controller. From the sensors outputs of the instantaneous distances (F.O.D., L.O.D. and R.O.D.) an initial population pool is created with a predefined population size. The population contains number of individuals (i.e., chromosomes). Each individual represents a solution for the problem under study. In our case, each solution is in terms of a second heading angle (S.H.A.) between the current directions of the robots' steering with respect to targets' directions from its start to end point in the search space. The evaluation of fittest child is computed as per the fitness function described in stage 2 (Chapter. 4, Section.4.2). According to the fittest child, the heading angle of the robot will be decided. The output of the genetic segment is expressed in terms of 'Second heading angle' (S. H. A.), which is the final output of hybrid controller for robot navigation. This optimised S.H.A. drag the robots near the target in a shortest path as compared to potential controller alone. The schematic diagram for the hybrid controller is shown in Fig. 6.16.

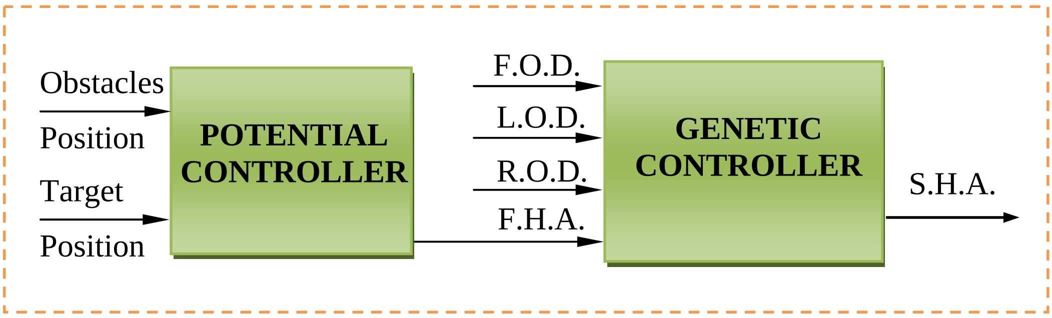


Fig. 6.16. Potential-GA hybrid controllers for mobile robot navigation

The obstacle avoidance behaviour of the robot using hybrid potential genetic algorithm has been incorporated in the Petri-net model for successful navigation of the mobile robot. The detail of the proposed Petri-net model is discussed in Chapter 3.

6.4.3. Simulation results

This section presents tasks aimed at illustrating the ability of the proposed control scheme to manage the navigation of mobile robots in different situations. Firstly, windows based simulations of the mechanical, electronic and software systems are carried out. These tests are conducted in accordance with the proposed working principle of Potential-GA hybrid systems. The two scenarios recorded for mobile robot navigation using potential genetic hybrid controller consists of multiple robots, targets and obstacles as described earlier. The simulation results show the initial scenario, intermediate scenario and final scenario in both 2-D and 3-D environment (Figs. 6.17-6.22).

Scenario 1

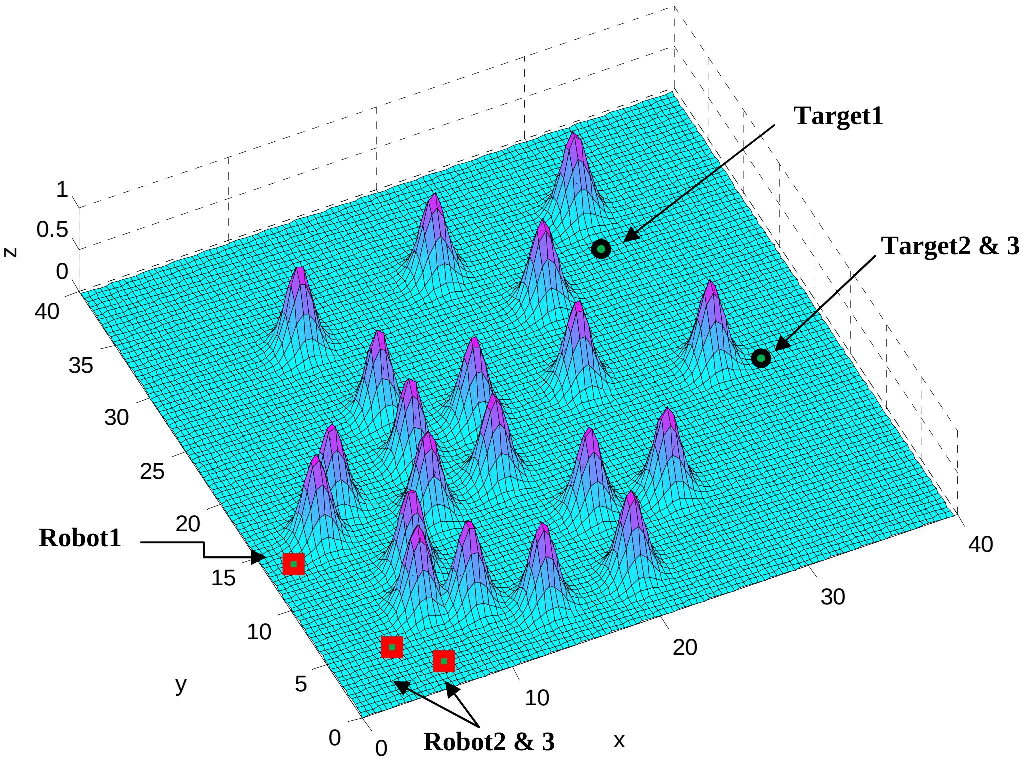


Fig. 6.17. Collision avoidance by three mobile robots with two targets using Potential-Genetic hybrid controller (3-D workspace and obstacles: Initial scenario).

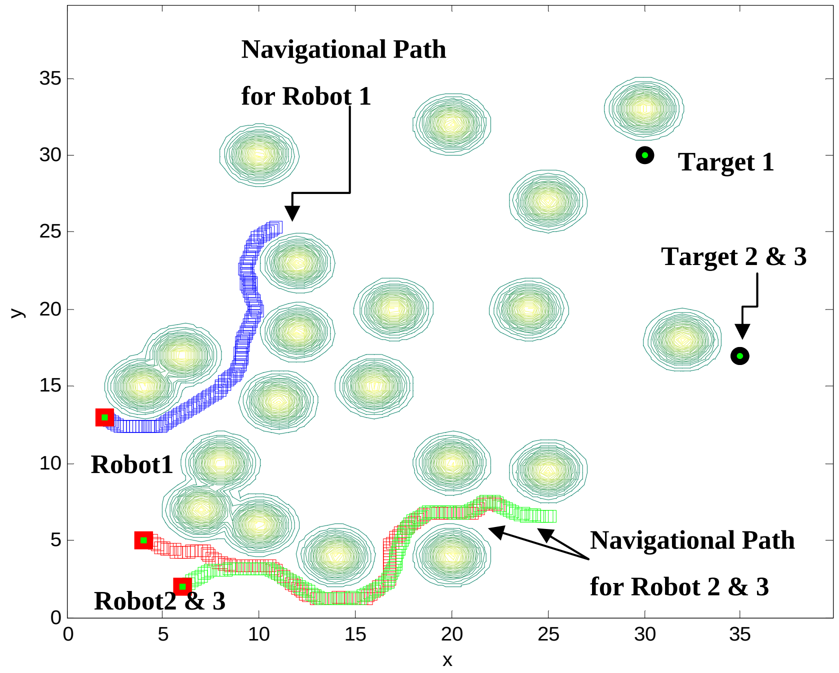


Fig. 6.18(a). Collision avoidance by three mobile robots with two targets using Potential-Genetic hybrid controller (2-D workspace and obstacles: Intermediate scenario).

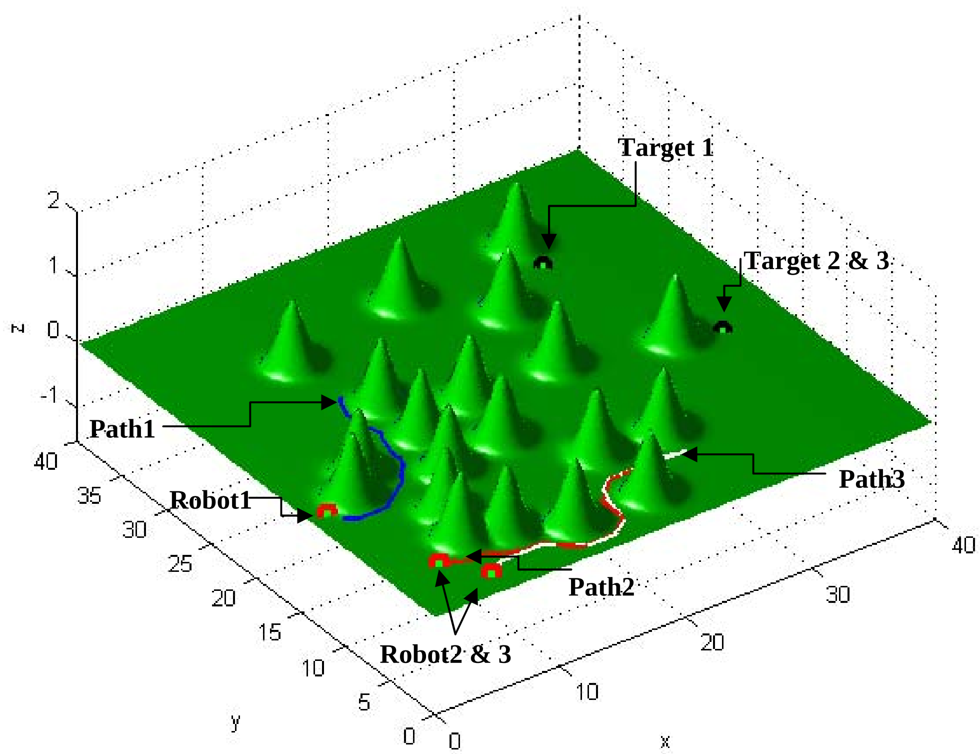


Fig. 6.18(b). Collision avoidance by three mobile robots with two targets using Potential-Genetic hybrid controller (3-D workspace and obstacles: Intermediate scenario).

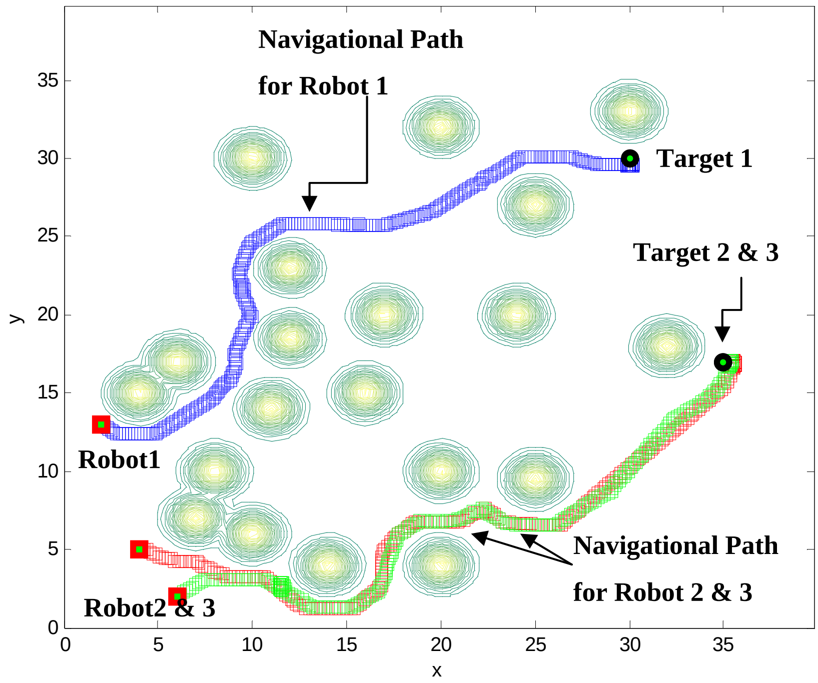


Fig. 6.19(a). Collision avoidance by three mobile robots with two targets using Potential-Genetic hybrid controller (2-D workspace and obstacles: Final scenario).

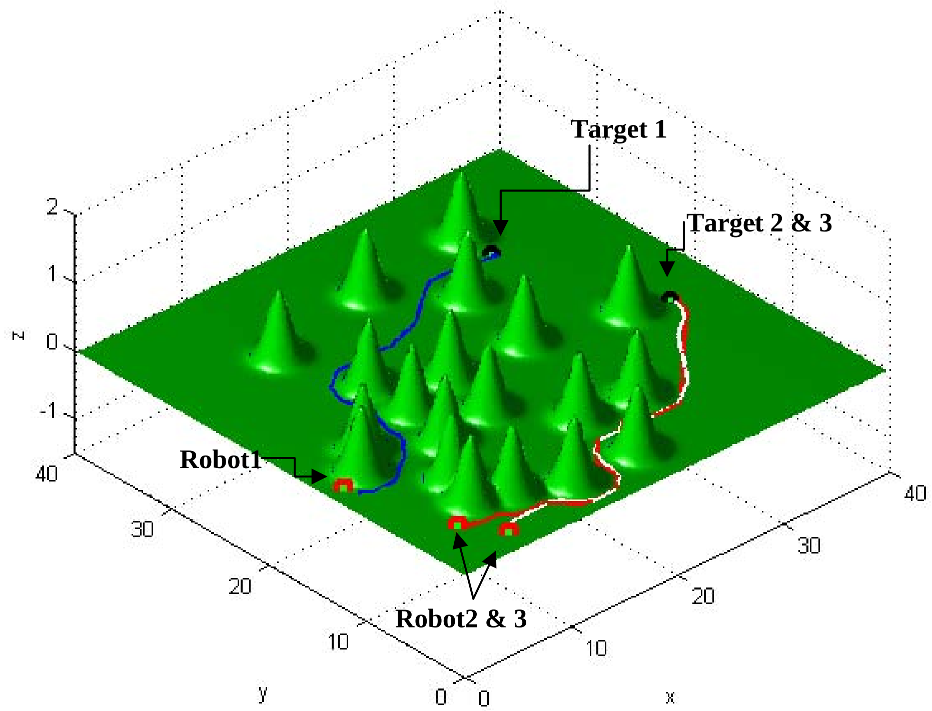


Fig. 6.19(b). Collision avoidance by three mobile robots with two targets using Potential-Genetic hybrid controller (3-D workspace and obstacles: Final scenario).

Scenario: 2

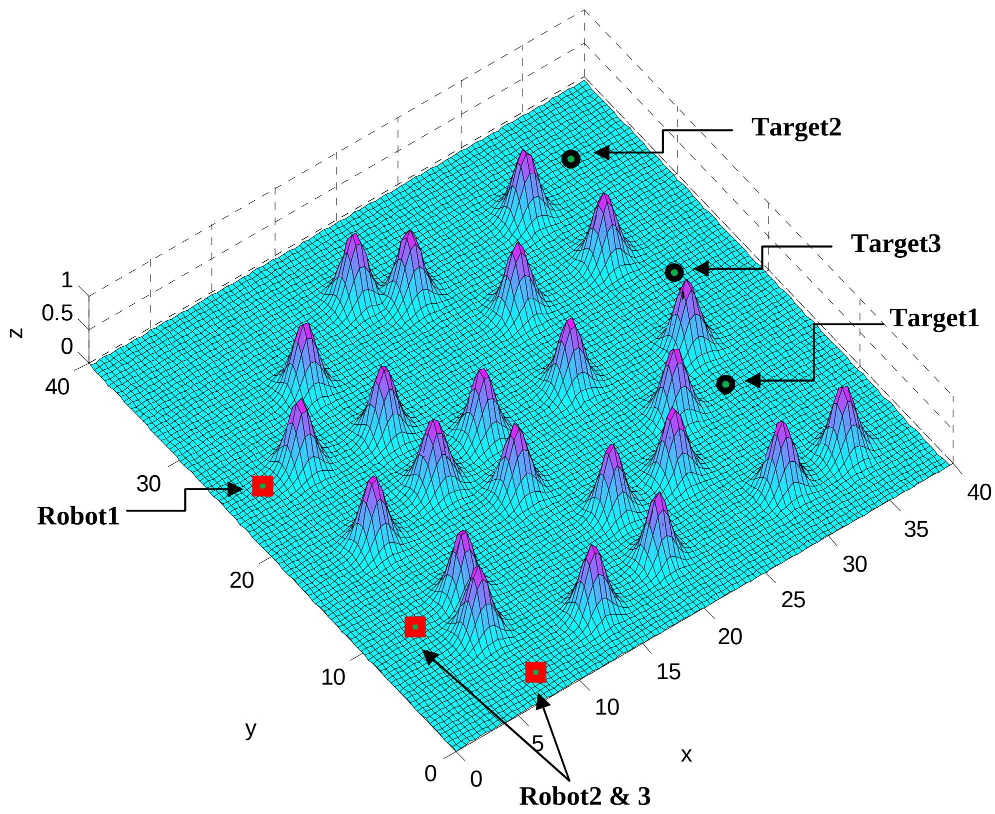


Fig. 6.20. Collision avoidance by three mobile robots with three targets using Potential-Genetic hybrid controller (3-D workspace and obstacles: Initial scenario).

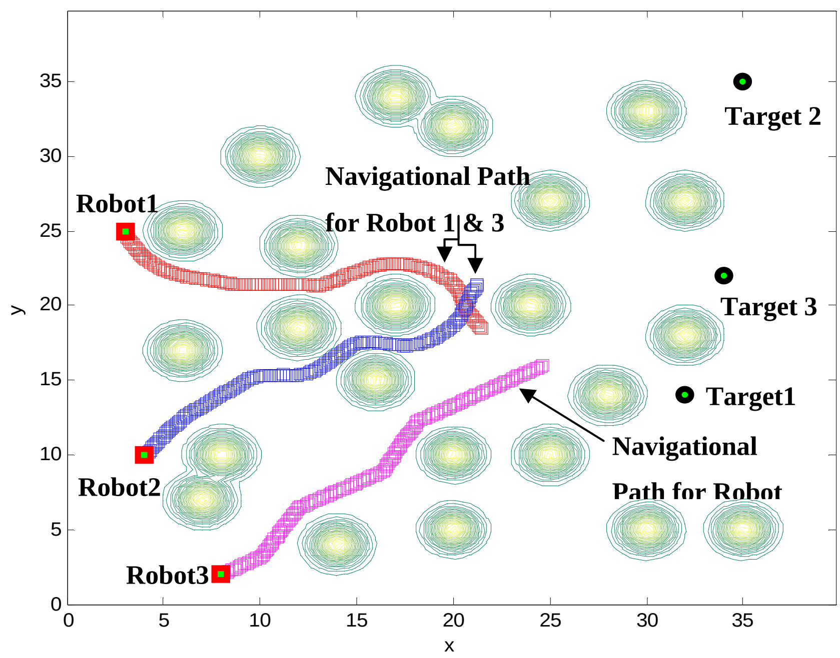


Fig. 6.21(a). Collision avoidance by three mobile robots with three targets using Potential-Genetic hybrid controller (2-D workspace and obstacles: Intermediate scenario).

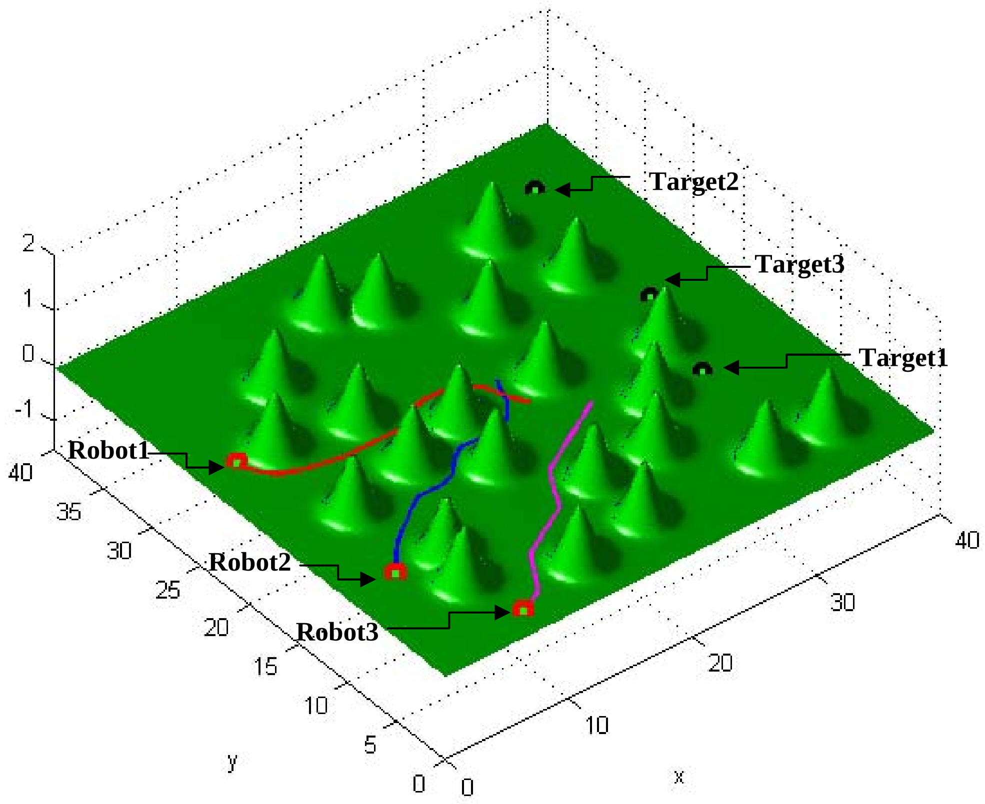


Fig. 6.21(b). Collision avoidance by three mobile robots with three targets using Potential-Genetic hybrid controller (3-D workspace and obstacles: Intermediate scenario).

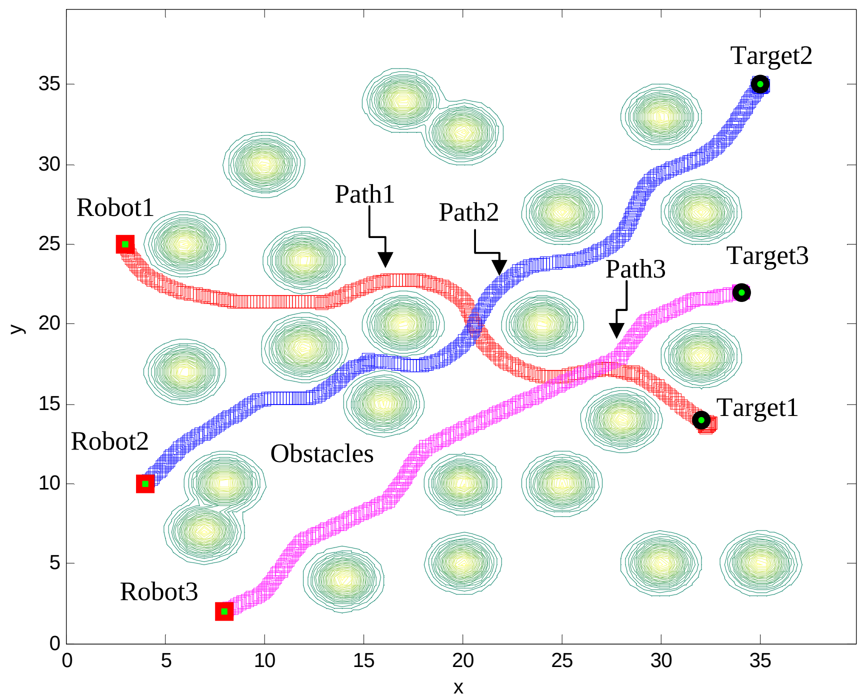


Fig. 6.22(a). Collision avoidance by three mobile robots with three targets using Potential-Genetic hybrid controller (2-D workspace and obstacles: Final scenario).

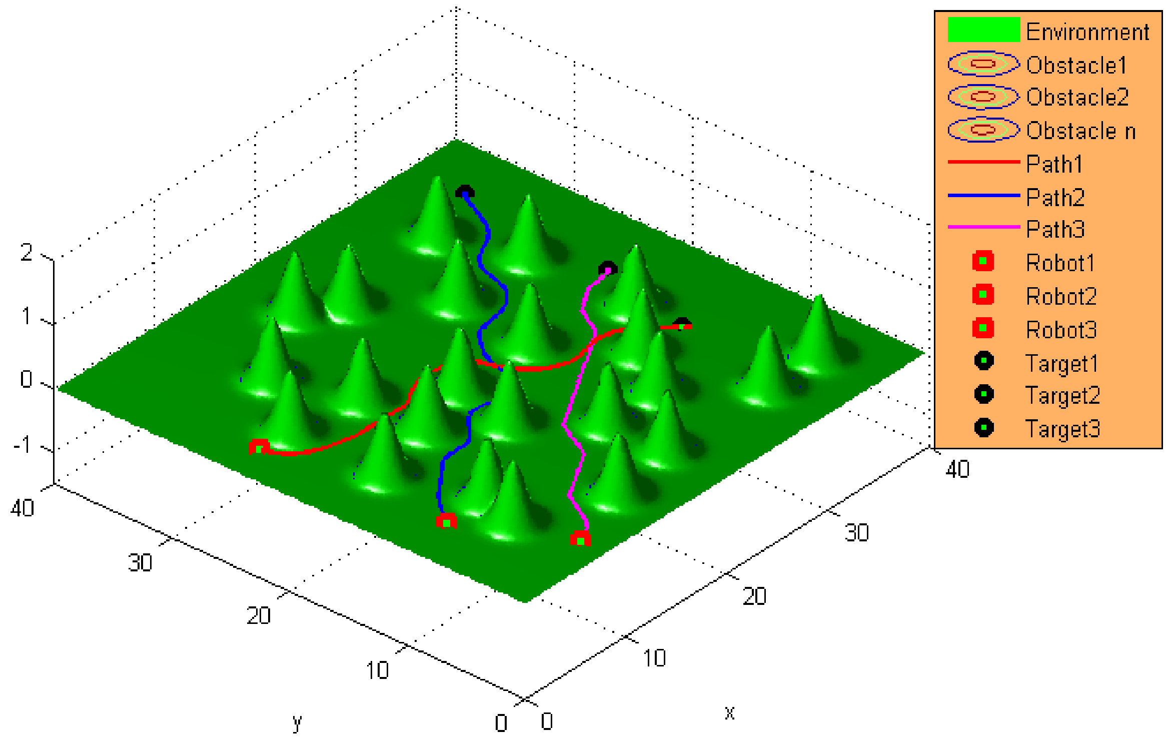


Fig. 6.22(b). Collision avoidance by three mobile robots with three targets using Potential-Genetic hybrid controller (3-D workspace and obstacles: Final scenario).

It has been observed that mobile robot can navigate successfully in a cluttered environment and at the end able to reach the targets. Robots choose their path by its own to reach the target by following the shortest trajectories. It can be noted that the robots stay well away from the obstacles and move in smooth path from its start location to end location.

The aim of these simulations is to ensure that the robot can cope with different working environments. In these simulations, the environment outline is modified by repositioning obstacles in different fashion and to get optimal navigational path. The same controller has been demonstrated for other cases of simulation in the succeeding sections.

6.4.4. Approach for design validation with other models

The validation of the proposed techniques has been made with Krishna and Kalra [209] model. The validated results are shown both in simulation and experimental modes.

The results from Krishna and Kalra [209] shown in Fig. 6.23(a) and Fig. 6.24(a) are compared with the results obtained from present study in similar environments [Fig. 6.23(b) and Fig. 6.24(b)]. The results are also given in tabular form in Table 6.6.

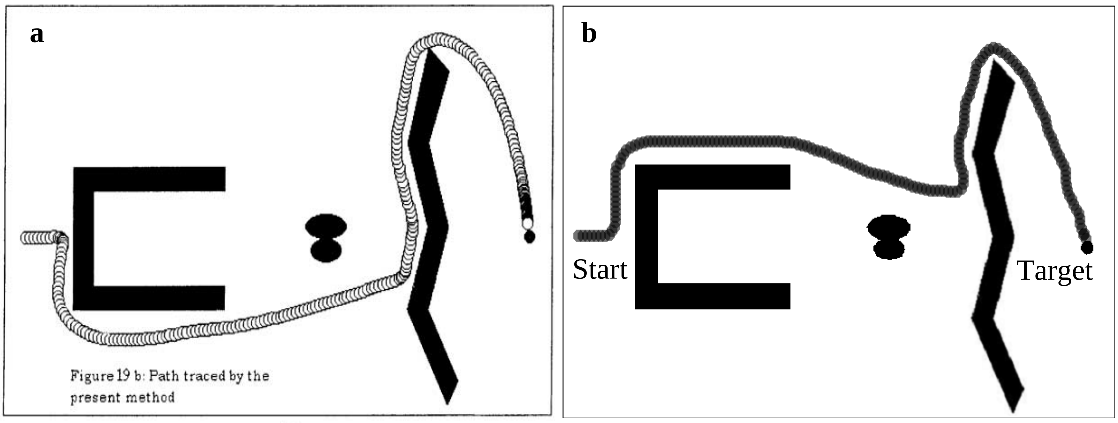


Fig. 6.23. Comparison of results from the current investigation and Krishna and Kalra [209].

In the first case, both the controllers are applied to a situation with complex maze with different shapes of boundary that would cause the existence of ‘‘dead cycle” problems. In this case the robot cannot see the target directly due to the wall in between them. It can be observed in the environment shown in Fig. 6.23(a) presented by Krishna and Kalra [209] model that the robot is trapped at each steps throughout the maze due to the existence of local minima and finally able to find their target after a long exercise by following a longer trajectory. In Fig. 6.23(b) the robot can avoid the maze made with similar boundary found on its way towards the target efficiently by the proposed GA model. In this case robot will first takes left turn due to the obstacle (U- shaped boundary) in front of it, then sense the target and finally follows the walls in order to reach the target successfully by receiving systematic information from the sensors through the state memory strategy.

In the second case, the robot supposed to find the target approximately in an complex situation like closed aisle for a dead cycle problem. In Fig. 6.24(a) proposed by Krishna and Kalra [209] model the robot got trapped in the T-shaped area first, and then it was escaped from the trap by taking a long loop through the entire boundary and eventually reaches the target by following a zigzag motion. Fig. 6.24(b) shows a simulation of the robot behaviour adapted by means of the proposed method.

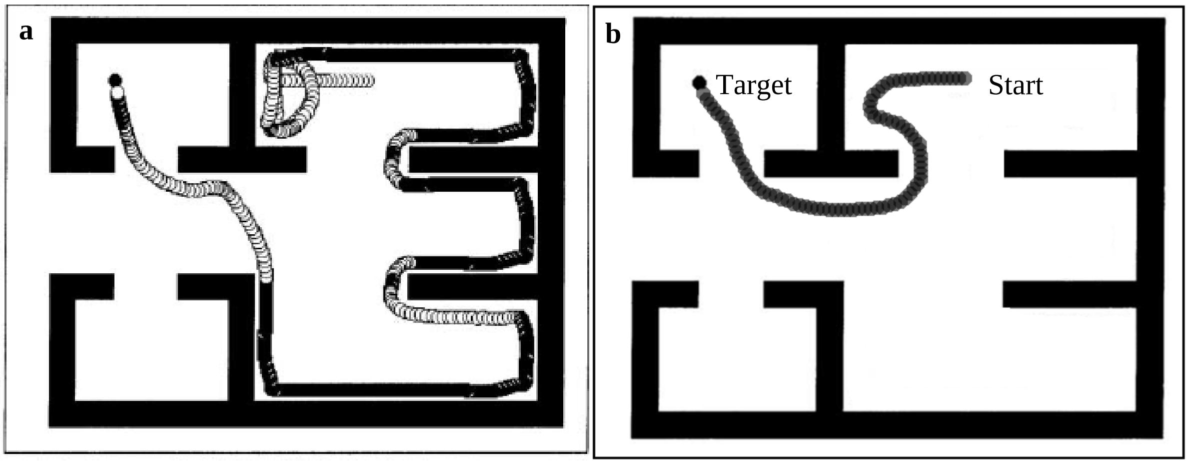


Fig. 6.24. Comparison of results from the current investigation and Krishna and Kalra [209].

In the initial position the robot is heading towards the dead-end. Due to the additional context information provided by the proposed controller robot can able to perceive the dead-end. The controller initiates a turning manoeuvre, which lasts until the robot is heading away from the dead-end. Afterwards, the normal wall-following behaviour guides the robot to the exit of the corridor by keeping a safe distance to the left wall.

Table 6.6
Comparison of results from the current investigation with Krishna and Kalra [209] model

Sl No.	Environmental types	Path length of Krishna and Kalra [209], in 'cm'	Path length from current investigation in 'cm'
1.	Maze with U-shape and oval shaped obstacles [Fig. 6.23(a) & (b)]	12.2	10.5
2.	Complex closed aisle [Fig. 6.24(a) & (b)]	28.4	6.8

The performances of the two models are mainly evaluated on the basis of path length (Table 6.6). From the above simulation results it is clear that, the developed algorithm can efficiently drive the robot in a cluttered environment. Experimental verification of the above simulation results has been shown in next sections.

6.4.5. Real-time experimental results

Figs. 6.23 & 6.24, show the experimental result scenario in stepwise for the problems defined in preceding Section.6.4.4. Two different cases of similar environments as described by Krishna and Kalra [209] model (verified in simulation mode) have been verified experimentally (Figs. 6.25- 6.26) to show the effectiveness of the developed controller. Khepera mobile robots are used for carrying out the experimentation. The detail specifications and hardwares of Khepera II robots are given in Appendix G. During experimentation it is seen that the robot follows closely the simulation using the proposed hybrid potential GA controller. In the next section a more complex potential genetic fuzzy controller is discussed.

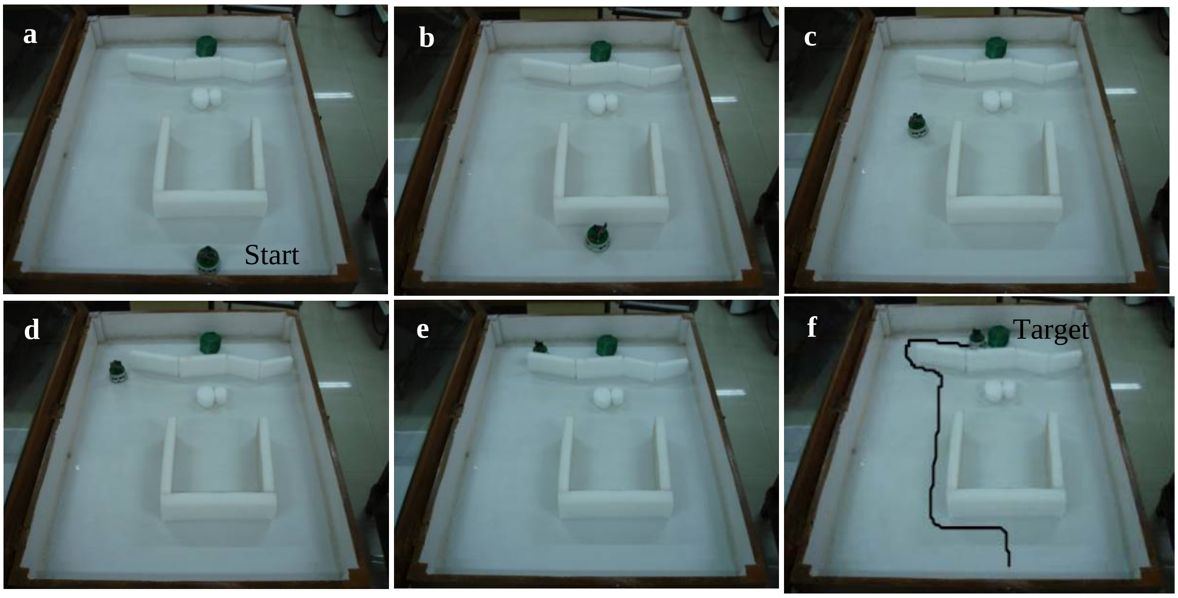


Fig. 6.25. Experimental results for navigation of mobile robot in the similar environment shown in Fig. 6.23(b).

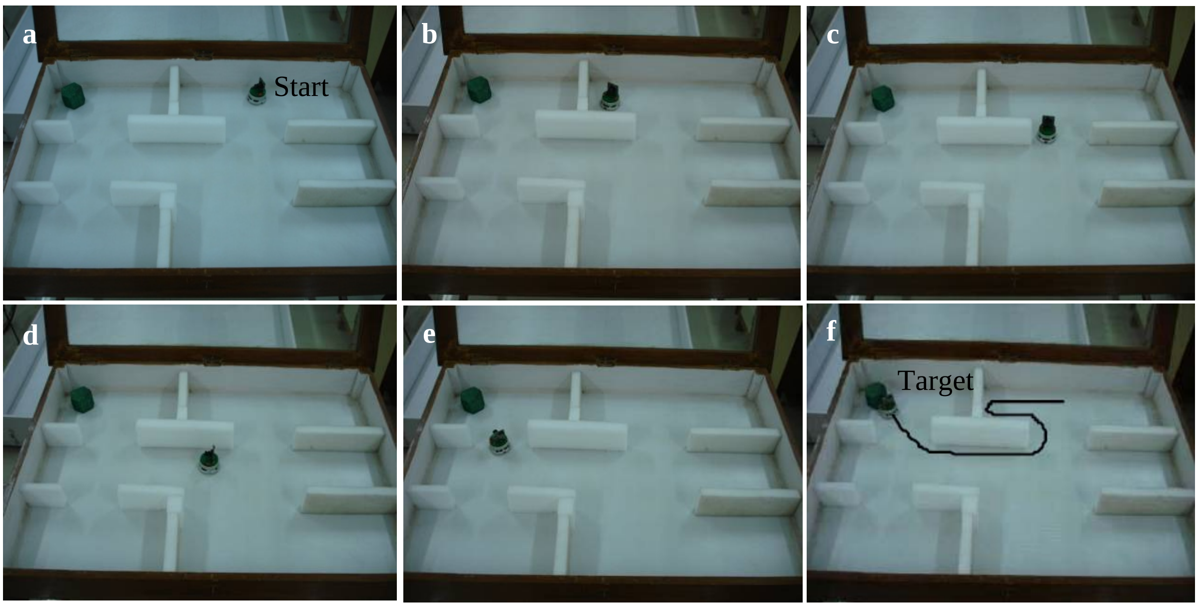


Fig. 6.26. Experimental results for navigation of mobile robot in the similar environment shown in Fig. 6.24(b).

Figs. 6.25(a-f), have demonstrated a situation where robot and target are placed in opposite side of the complex maze (created by a variety of obstacle configurations). Initially robot cannot see the target directly because of the obstacles between robot and target. When robot starts motion it senses the target and speeds up in straight path towards the targets up to the U-shaped wall and slows down to take left turn to avoid obstacle, then follows a wall following rules to reach the target.

Similarly for the second case of robot navigation it can be observed that, the robot follows a straight path except the turning points from its start to the goal position inside the closed aisle (Fig.6.26f). The experimentally obtained paths follow closely those traced by the robots during simulation. The trajectories are smooth and take reasonably efficient paths as compared to Krishna and Kalra [209] paths. The real time simulated results show the effectiveness of the developed controller for mobile robots navigating in priori unknown cluttered environment.

6.5. Analysis of Potential-Fuzzy-Genetic Hybrid Controller for mobile robot navigation

6.5.1. Introduction

This chapter presents an approach for building multi-input and single-output hybrid models. Such a model is composed of a learning method which automatically designs fuzzy logic controllers (FLCs) by means of a potential-genetic algorithm (PGA). The fuzzy membership functions that define these variables have been optimised through potential-genetic operators by receiving systematic information from the targets and obstacles position. Simulation examples are provided to evaluate the feasibility of the proposed approach. Comparison shows that the suggested approach can produce a hybrid model with higher accuracy. The validity of the resultant model is demonstrated by simulation and experiment.

In this chapter the motion planning of multiple mobile robots with multiple targets in presence of obstacles in a priori unknown environment using modified Potential Field based Genetic-fuzzy hybrid Controller is discussed. This task could be carried out by specifying a set of potential GA-fuzzy rules by taking into account the different situations found by the mobile robots. The approach is to extract a set of potential GA-fuzzy rules from a set of trajectories provided by human intelligence. Problem specific potential GA-fuzzy operators are not only designed with domain knowledge, but also incorporate small-scale local search that improves efficiency of the operators. A relatively simple but effective evaluation method is applied to both feasible and infeasible solutions. For this purpose inputs are obstacles position and target position to all the controllers and output heading angles (HA) are expressed in terms of encoded generation function distributions by crisp values. The outputs of the hybrid controller are the requisite wheel velocity i.e. LV and RV, which controls the motion of the robot.

6.5.2. Design and analysis of hybrid Potential-GA-Fuzzy controller

The hybrid controller (shown in Fig. 6.27) has three segments, i.e. potential controller, genetic controller and fuzzy controller. The inputs to the potential controller are obstacle position and target position, and output is the first heading angle (F.H.A.). The F.H.A. is computed on the basis of the total attractive and repulsive forces as shown in Chapter 3. The output of potential controller, in addition to obstacle distances i.e. F.O.D., L.O.D., R.O.D. are passed through the genetic controller to get a quite better heading angle i. e. Second Heading Angle (S.H.A.). The second heading angle is computed by carrying out the steps as describe in chapter 4. The output of genetic controller, in addition to obstacle distances i.e. F.O.D., L.O.D., R.O.D. are again passed through the fuzzy controller to get a optimal response in terms of left wheel and right wheel velocity, which are the overall output of the Hybrid Potential-GA-fuzzy Controller. The filtered fuzzy rules are embedded in the controller by providing a set of fuzzy rules from a set of trajectories which are extracted by human intelligence. The outputs from the fuzzy controller are LV and RV. The velocities are computed from fuzzy inference technique and subsequently by defuzzification method as discussed in chapter 5. These defuzzified velocities can produce the optimal or near optimal trajectory by optimizing the heading angle. The obstacle avoidance behaviour of the robot using hybrid potential-GA-fuzzy Controller has been incorporated in the Petri-net model for successful navigation of the mobile robot. The detail of the proposed Petri-net model is discussed in section 3. The validity of the resultant model is demonstrated through simulation studies as well as experimentation in various situations.

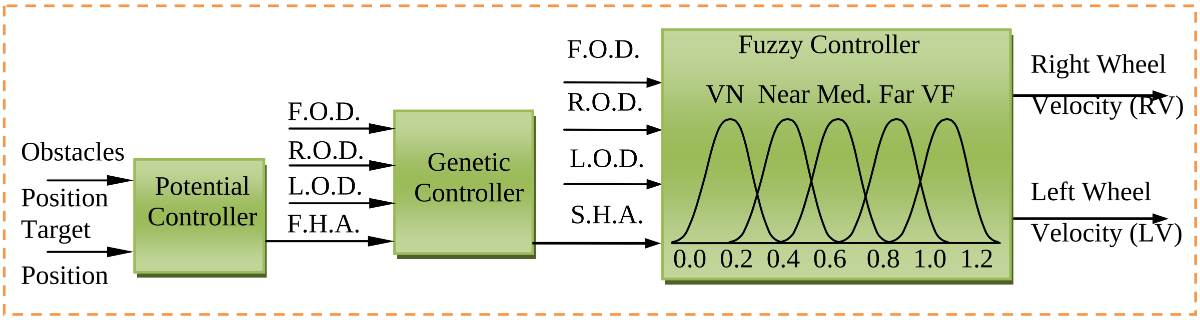


Fig. 6.27. Potential-GA-fuzzy hybrid controller with Gussian fuzzy membership functions for mobile robot navigation

6.5.3. Simulation results

Using potential-GA-Fuzzy controller two specific tasks has been carried out. These tasks resemble the environment given in previous section of this chapter (section 2-4). Four figures are outlined for carrying out the task. Out of which two figures are dedicated for 2D environmental situation and another two figures are showing the 3D representation of 2D environment. In this task multiple numbers of robots, targets and obstacles are involved.

Scenario 1

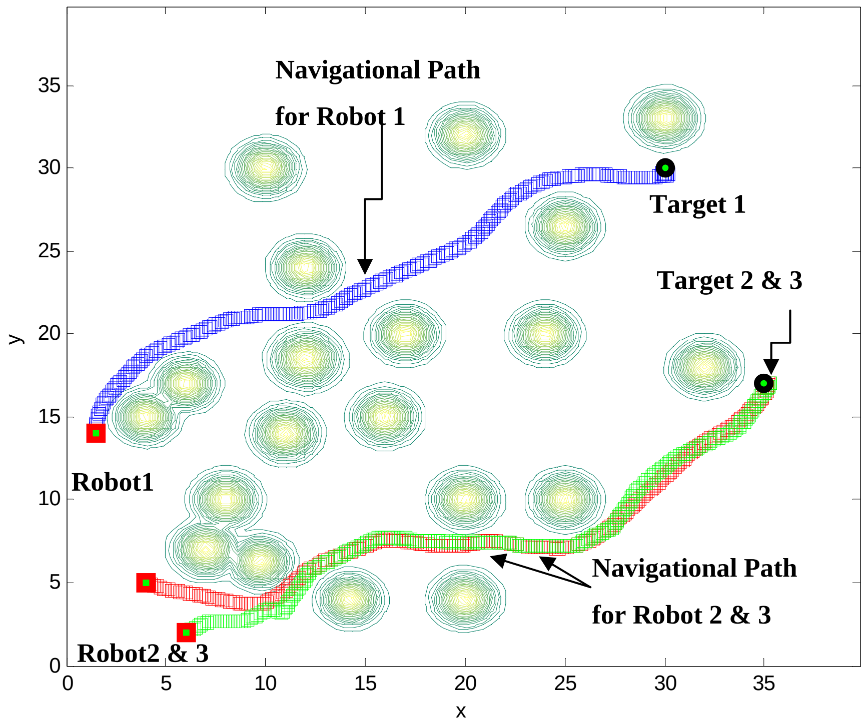


Fig. 6.28(a). Collision avoidance by three mobile robots with two targets using Potential-Genetic-Fuzzy hybrid controller (2-D work space and obstacles).

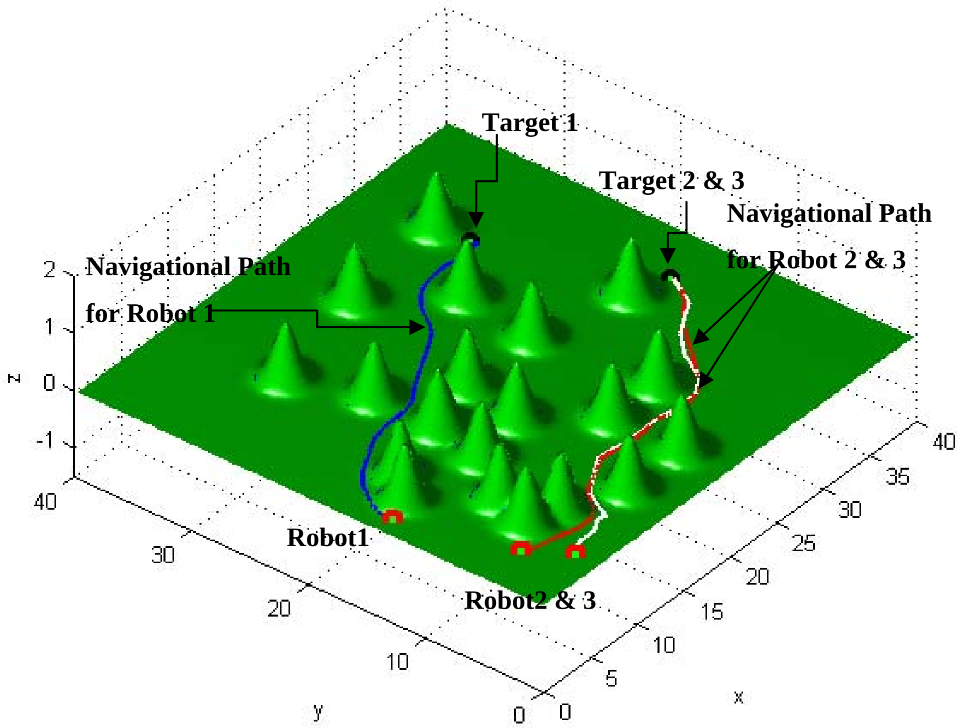


Fig. 6.28(b). Collision avoidance by three mobile robots with two targets using Potential-Genetic-Fuzzy hybrid controller (3-D work space and obstacles).

Scenario 2

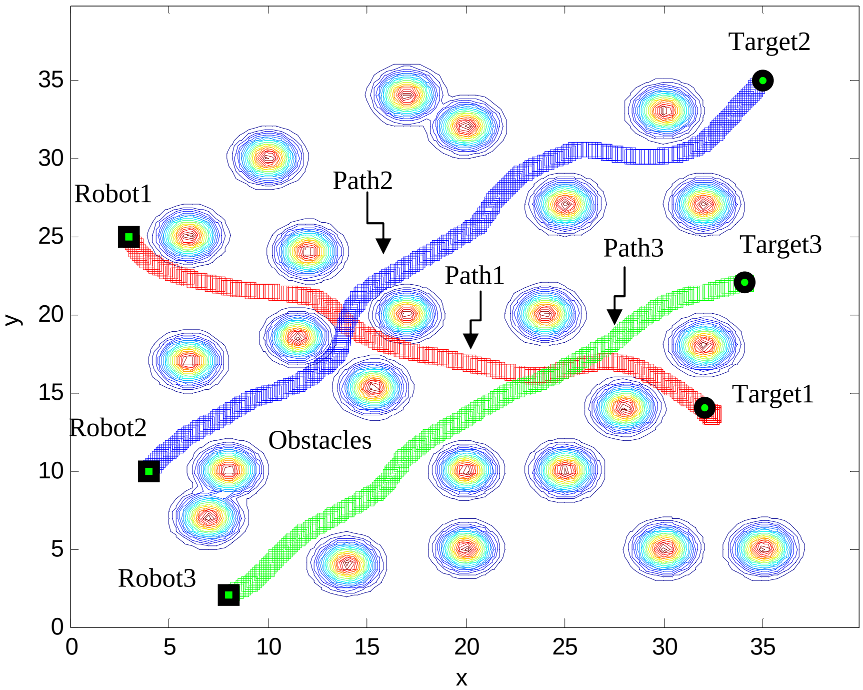


Fig. 6.29(a). Collision avoidance by three mobile robots with three targets using Potential-Genetic-Fuzzy hybrid controller (2-D work space and obstacles).

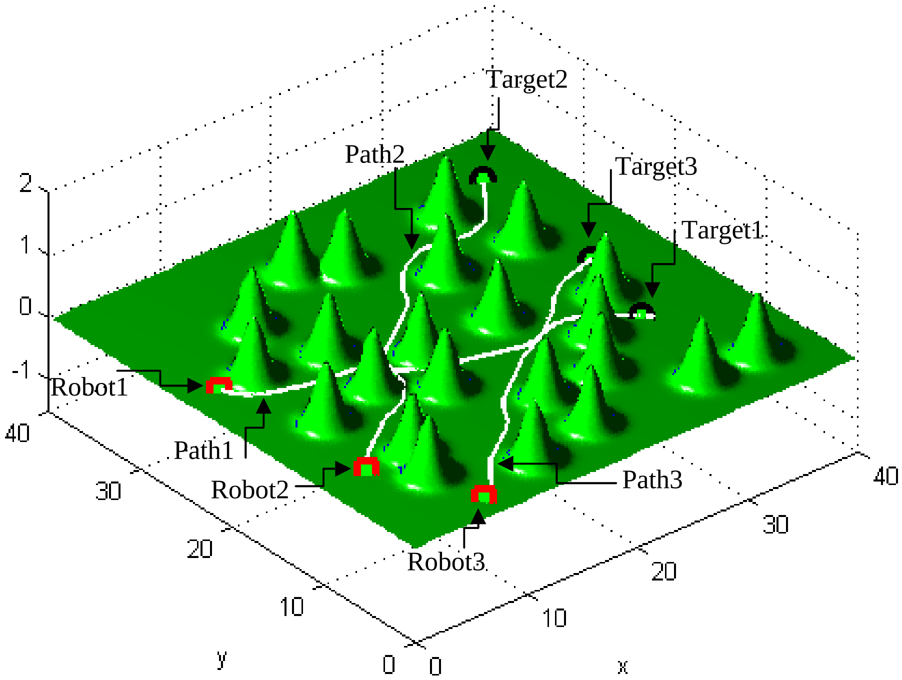


Fig. 6.29(b). Collision avoidance by three mobile robots with three targets using Potential-Genetic-Fuzzy hybrid controller (3-D work space and obstacles).

6.5.4. Overall comparison of results with different hybrid models

It can be observed that at the end of this task the robots able to reach their defined targets in most efficient manner as compared to the results obtained from Potential-Fuzzy, Potential-Genetic and Genetic-Fuzzy systems. An overall comparison has been drawn on the basis of path lengths for both the cases and respective results are given in Table 6.7.

Table 6.7

Path lengths (in 'Pixel') of three robots for the environments shown using different hybrid techniques.

Sl. No.	Environment types	Robot No	Potential-Fuzzy	Potential-GA	GA-Fuzzy	Potential GA-Fuzzy
1.	Environment 1	1	290	267	283	253
		2	311	295	298	293
		3	295	293	291	281
2.	Environment 2	1	228	223	220	211
		2	283	274	276	265
		3	232	211	216	202

Other tasks such as navigation in a highly cluttered environment (Fig. 6.30) and corridor navigation (Fig. 6.31) are also shown using the Potential-GA-Fuzzy controller. Fig.6.30 shows the navigational scenarios for single robot in a highly cluttered environment with different obstacle size. The target is placed on the opposite corner of the robot and robot has to move in a very close passage between different obstacle configurations. Using the developed hybrid technique i.e. Potential-GA-Fuzzy controller, the robot finally able to reach the target efficiently in a shortest trajectory.

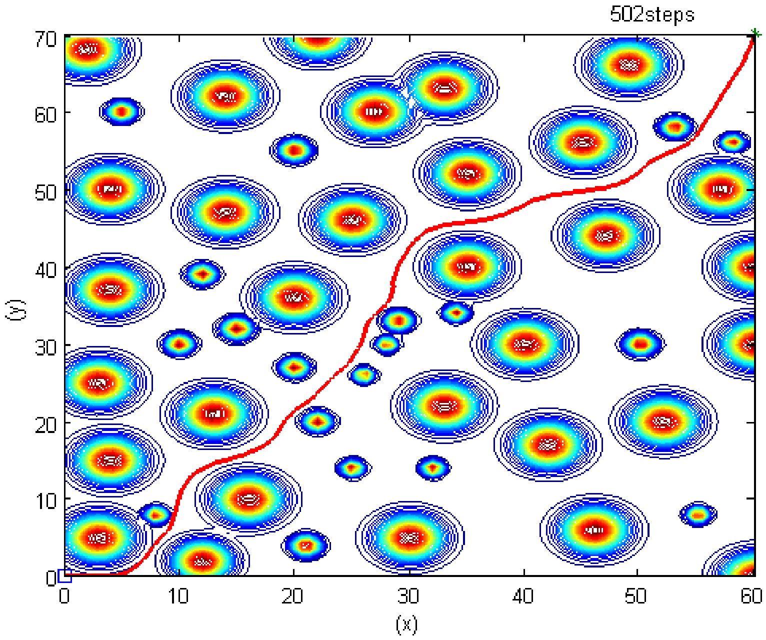


Fig. 6.30. Collision-free movement, obstacle avoidance and target seeking behaviour in a highly cluttered environment by single robot with single target.

The second exercise involves the wall following behaviour of single robot with single target. 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 robot search for the target, it finds the wall along which it continues to move by applying the wall following rules. In the initial position the robot is heading towards the dead-end. Due to the additional context information provided by the proposed controller robot can able to perceive the dead end. The controller initiates a turning manoeuvre, which lasts until the robot is heading away from the dead-end. Afterwards, the normal wall-following behaviour guides the robot to the exit of the corridor by keeping a safe distance to the left wall. Fig. 6.31 shows the robot trajectory from start position to target without suffering from ‘‘dead cycle” problems.

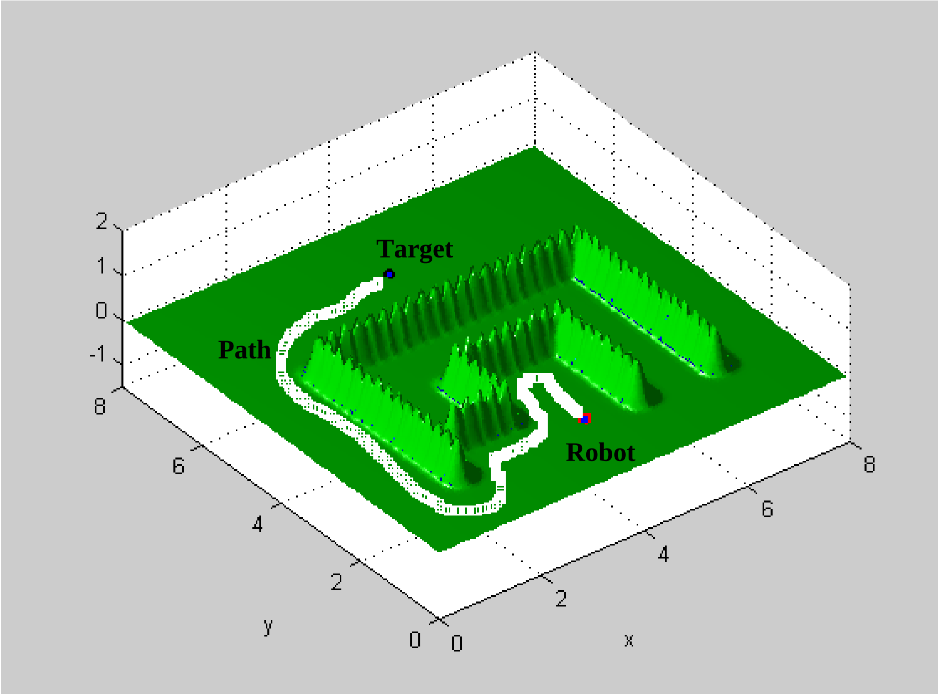


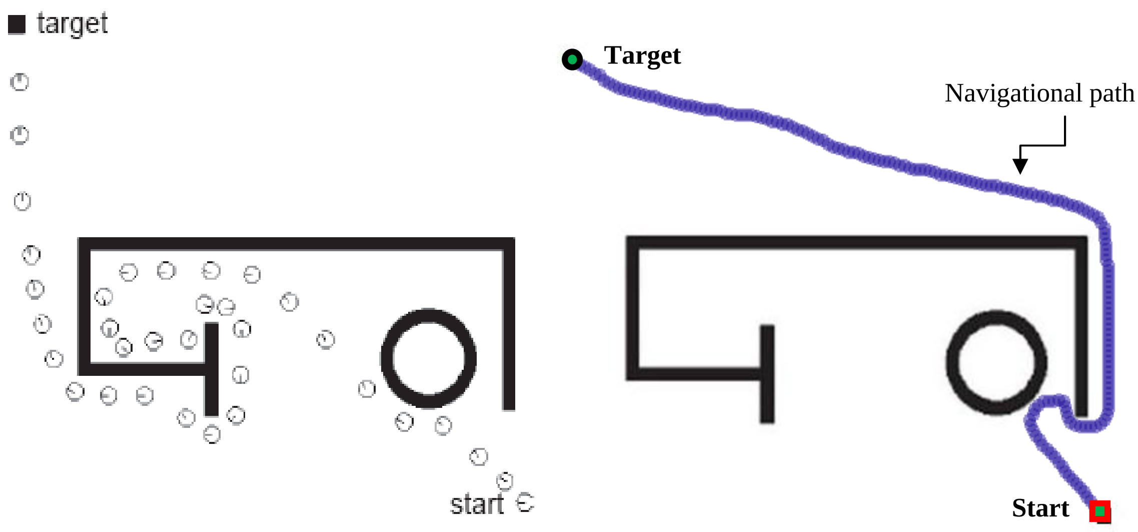
Fig. 6.31. Navigation environment for wall following and target seeking behaviour of single robot.

The results of the simulations showed that all robots are stayed away from each other and each robot has reached their nearest target in an efficient manner without any collision between themselves and obstacles in different environments. Further the robots well compromised between themselves in the environment in order to avoid collision among themselves as well as with other obstacles. The aim of these simulations is to ensure that the robot can cope with different working environments. In these simulations, the room outline is modified by repositioning obstacles in different fashion. The same controller has been demonstrated for other cases of simulation in the succeeding sections.

6.5.5. Approach for design validation with other models

In the current section a comparison has been carried out between the results among the proposed model and the Reza et al. [210] model. The complete detail of the comparison is explained below.

In this section a comparison has been made between Reza et al. [210] model and results from current control scheme in simulation and experimental mode. The performance of the two methods was mainly evaluated on following the path length. The results from Reza et al. [210] are shown in Fig. 6.32(a) and Fig. 6.33(a) are compared with the results obtained from present study for similar environments [Fig. 6.32(b) and 6.33(b)] as has been tabulated in table 6.8.

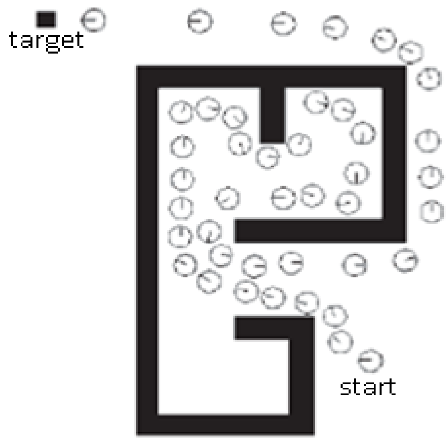


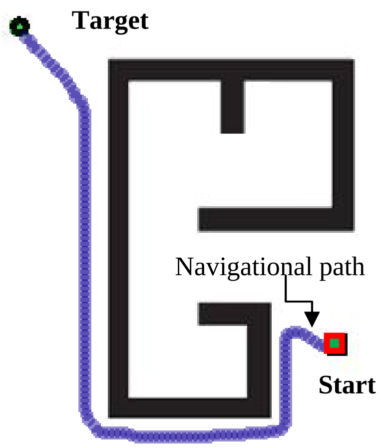
(a) Simulation results of Reza et al. [210] model (b) Simulation results from current investigation

Fig. 6.32. Comparison of results from Reza et al. [210] model the current investigation (Scenario 1).

In the first case, both the controllers are applied to a situation with complex maze with different shapes of boundary that would cause the existence of ‘‘dead cycle” problems. In this case the robot cannot see the target directly due to the wall in between them. It can be observed in the environment shown in Fig. 6.32(a) presented by Reza et al. [210] model that the robot is trapped at each steps throughout the maze due to the existence of local minima and finally able to find the target after a long exercise by following a longer trajectory. In Fig. 6.32(b) the robot can avoid the maze made with similar boundary found on its way towards the target efficiently by the proposed GA model. In this case robot first takes right turn due to the obstacle (circular- shaped boundary) in front of it, then senses the target and finally follows the walls in order to reach the target successfully by receiving systematic information from the sensors through the state memory strategy.

In the second case, the robot supposed to find the target approximately in a complex situation like closed aisle for a dead cycle problem. In Fig. 6.33(a) proposed by Reza et al. [210] model the robot got trapped in the T-shaped area first, and then it was escaped from the trap by taking a long loop through the entire boundary and eventually reached the target by following a zigzag motion. Fig. 6.33(b) shows a simulation of the robot behaviour adapted by means of the proposed method.





(a) Simulation results of Reza et al. [210] model

(b) Simulation results from current investigation

Fig. 6.33. Comparison of results from Reza et al. [210] model the current investigation (Scenario 2).

In the initial position the robot is heading towards the dead-end. Due to the additional context information provided by the proposed controller robot can able to perceive the dead-end. The controller initiates a turning manoeuvre, which lasts until the robot is heading away from the dead-end. Afterwards, the normal wall-following behaviour guides the robot to the exit of the corridor by keeping a safe distance to the left wall.

Table 6.8 Comparison of results from the current investigation with Reza et al. [210] model

Sl No.	Environmental types	Path length of Reza et al. [210] Model, in 'cm'	Path length from current investigation in 'cm'
1.	Maze with U-shape and oval shaped obstacle [Fig. 6.32(a) & (b)].	17.5	12.4
2.	Complex closed aisle [Fig. 6.33(a) & (b)].	20.8	10.2

In some scenarios of Reza et al. [210] model 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. Fig. 6.32(b) and Fig.

6.33(b) show that the robot reaches their target in a smooth motion with the proposed approach. The performance of the two models was mainly evaluated on the basis of path length and smoothness of trajectory which is shown in Table 6.8. From the above simulation results it is clear that, the developed algorithm can efficiently drive the robot in a cluttered environment. Experimental verification of the above simulation results has been shown in next sections.

6.5.6. Experimental validations and discussions

The current section discusses about the experimental details for carrying out the tasks of the simulation environment shown in Fig. 6.32 & Fig. 6.33. During experimentation Khepera II robot is used. The detailed hardware specification of the Khepera II mobile robot are given in Appendix G. the discussion about the experimental procedure for carrying out the task is given below.

Two different cases of similar environments as described by Reza et al. [210] model, have been verified experimentally (Figs. 6.34- 6.35) to show the effectiveness of the developed controller.

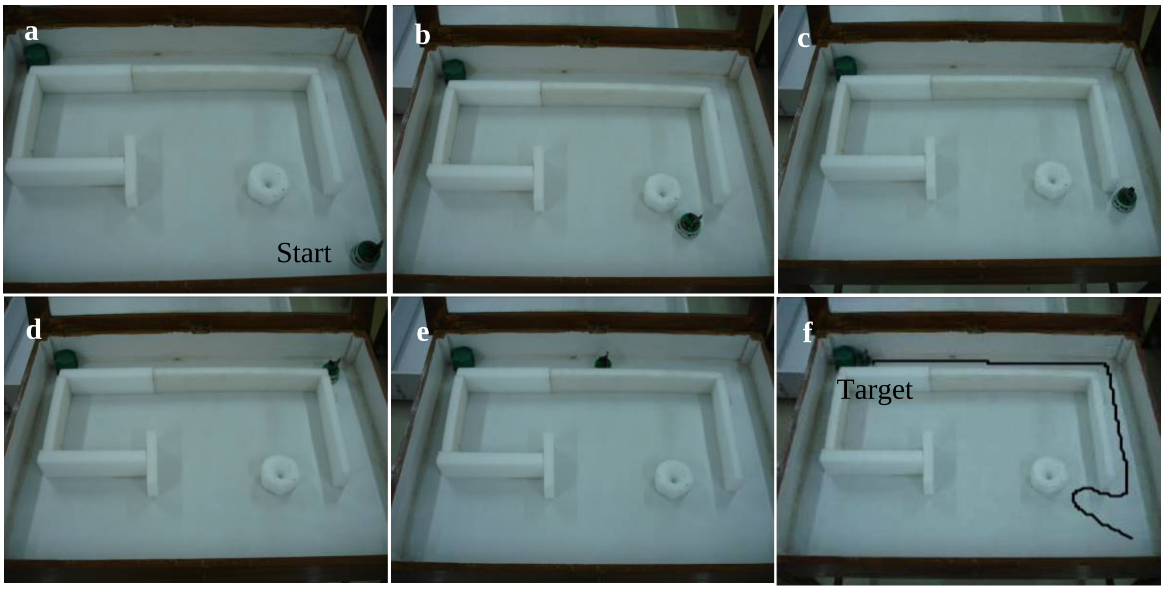


Fig. 6.34 Experimental results for navigation of mobile robot in the similar environment shown in Fig. 6.32(b)

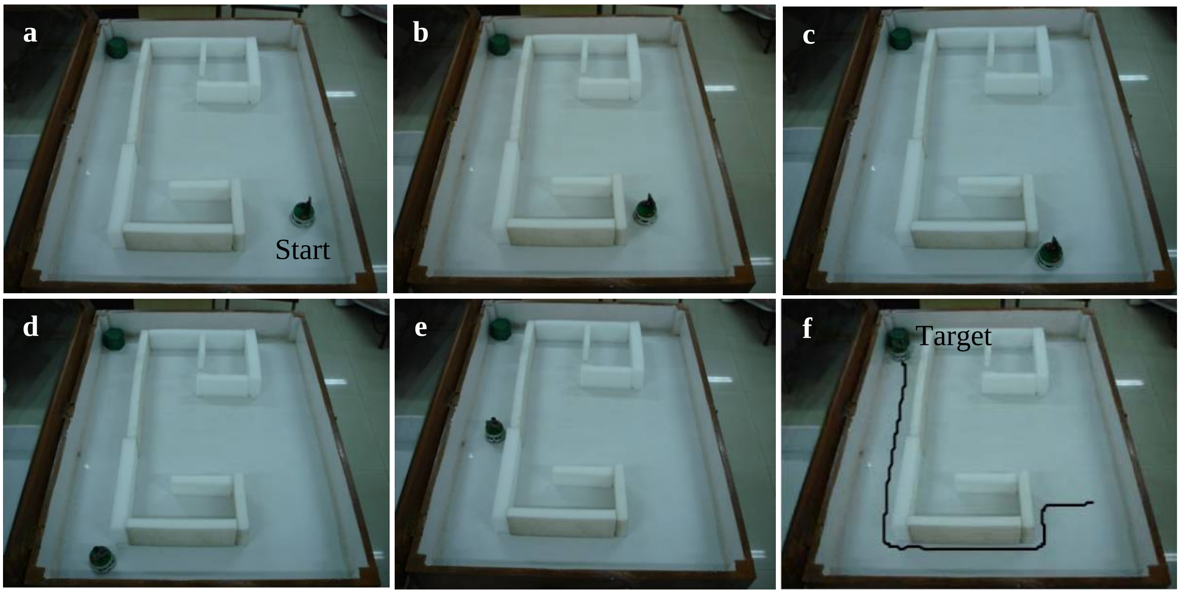


Fig. 6.35 Experimental results for navigation of mobile robot in the similar environment shown in Fig. 6.33(b).

In Figs. 6.34(a-f) a situation is demonstrated where robot and target are placed in opposite side of the complex maze (created by wall type obstacle configuration). Initially robot cannot see the target directly because of the wall between robot and target. When robot starts motion it senses the target and speeds up in straight path towards the targets up to the U-shaped wall and slows down to take left turn to avoid obstacle, then follows a wall following rules to reach the target. The robot autonomously chooses its way in the shortest trajectory to reach the desired destination by getting the optimised heading angle obtained from hybrid controller. For the second robot navigation case (Fig. 6.35f), it can be observed that, the robot follows a straight path except the turning points from its start to the goal position inside the closed aisle.

Table 6.9
Comparison of simulation and experimental results from the current investigation.

Sl No.	Environmental types	Simulation Results		Experimental Results	
		Path length (cm)	Time taken (Sec)	Path length (cm) in 1/10th scale	Time taken (Sec in 1/10th scale
1.	Maze with U-shape and oval shaped obstacle [Fig. 6.32(b) & Fig. 6.34]	12.4	24.12	14.2	32.36
2.	Complex closed aisle [Fig. 6.33(b) & Fig. 6.35]	10.2	20.16	11.0	22.15

The developed controller takes care to invoke a new path based on available information received by the robot about the environment with ruled based heuristic recovery GA approach. The experimental and simulation results for both the environments are given in Table. 6.9. From these results it can be noticed that the experimentally obtained paths follow closely those traced by the robots during simulation.

6.5.7. Real-time experiment for multiple robots navigation

In order to demonstrate the effectiveness and improved performance of the developed hybrid navigation scheme (i. e. Potential-Genetic-Fuzzy controller) the experiment using Khepera II robots has been carried out. The four Khepera II robots are taken for experiment in an abundant maze with single target. The three stages of navigation scenario have been shown in Figs. (6.36-6.38).

Fig. 6.36. Navigation of four real robots (Khepera II) in a cluttered environment (Initial scenario).

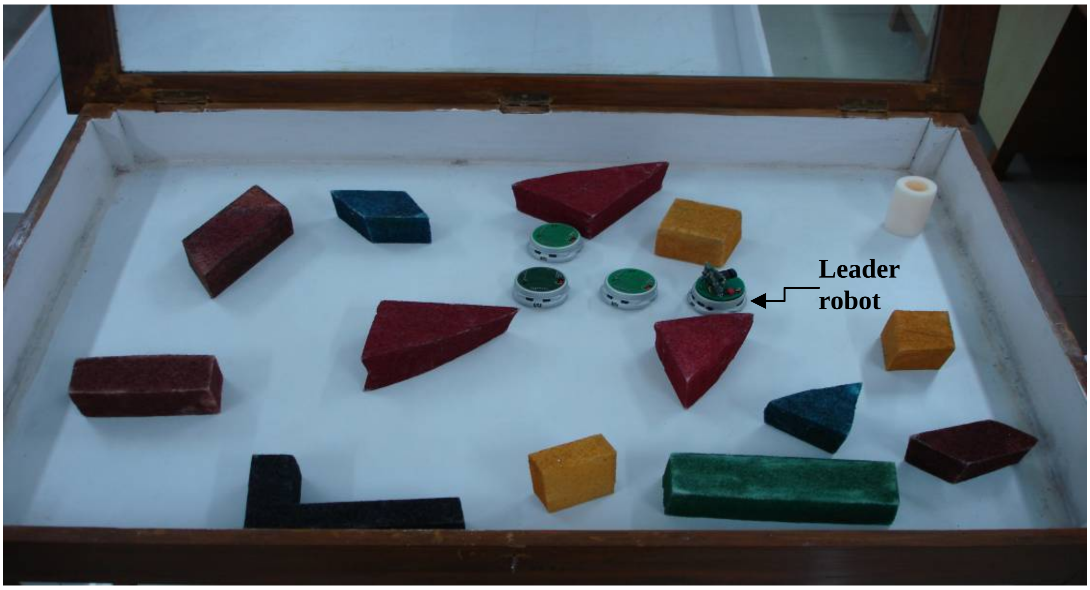


Fig. 6.37. Navigation of four real robots (Khepera II) in a cluttered environment (Intermediate scenario).

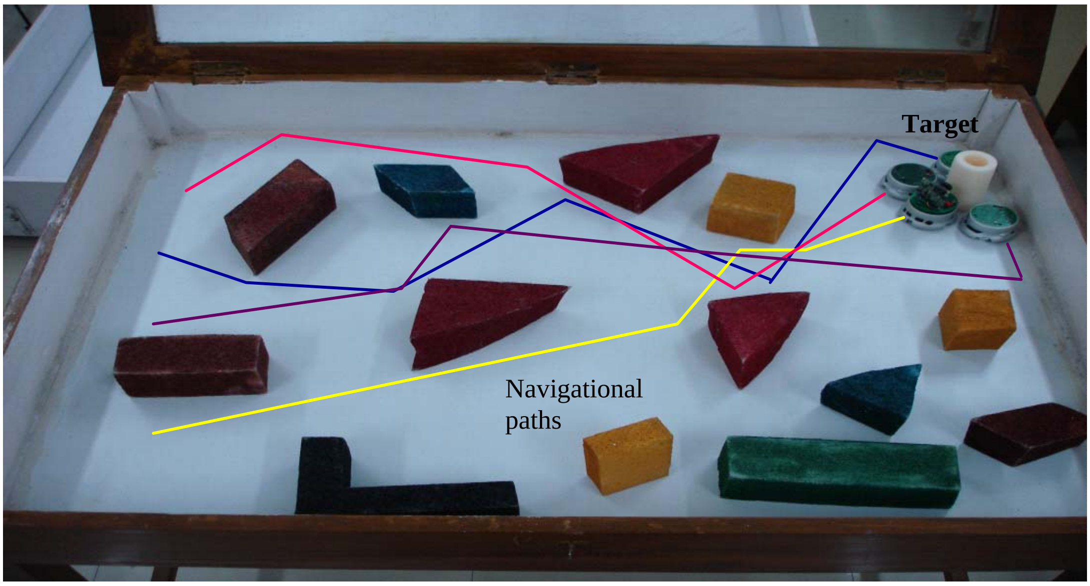


Fig. 6.38. Navigation of four real robots (Khepera II) in a cluttered environment (Final scenario).

From the experimental results it can be seen that the robots can indeed avoid obstacles and reached the target. It is concluded from the above real-time experimental results that the proposed hybrid algorithm can also be works satisfactorily for multiple robots navigation. 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.

6.6. Summary

In the present chapter four types of hybrid techniques such as Potential-fuzzy, Potential-Genetic, Genetic Fuzzy and potential fuzzy genetic has been analysed. For carrying the analysis two types of scenarios have been taken into account. While studying the scenarios it has been observed that potential-genetic-fuzzy technique gives smoothes and best trajectories compared to other three developed hybrid model. It has been also noticed that using the first three hybrid models robots are able to reach the target while negotiating with the obstacles. A comparison is also made between the potential fuzzy techniques and Wang and James [206] technique, potential genetic technique with Krishna and Kalra [209] and genetic +fuzzy technique and Luh and Liu [208] technique last potential fuzzy genetic and Reza et al. [210] techniques. During the comparison it has been observed that using the developed hybrid techniques the robots follow the path in an optimum way in comparison to other technique. Experimental verifications are also carried out for different scenarios for different hybrid controller to collaborate their respective working model in reality. During experimental comparison it is found that the robot follows closely the simulation path. Other tasks such as corridor navigation in highly cluttered environment and multiple robot seeking for multiple target scenarios are given for potential fuzzy genetic controller. It is observed that the robot successfully navigate in the environment while achieving the goal. In the next chapter an overview of online navigation is given.

Chapter 7

Control of Multiple Mobile Robots using Remote Connection

- **Robot Navigation through WWW implementation**
- **Demonstrations**
- **Summary**

7. Control of Multiple Mobile Robots using Remote Connection

In this chapter remote control of multiple mobile robots has been discussed. The rapidly growing standard means of communication, (i.e. World Wide Web, www) is adopted in this work as the medium for transmitting control information between the different robots. Although control of robots has been demonstrated in obstacle avoidance exercises, such a form of control can be regarded as reactive. Some evidences of controlling multiple robots remotely are also provided in this chapter.

7.1. Introduction

The Remote Control has been discussed in this chapter. With the help of World Wide Web (www) the remote methodology has been implemented for realising the task in real form. In the current study potential- - genetic -fuzzy technique has been implemented for verifying the remote methodology used in the current chapter.

7.2. Robot Navigation through www implementation

7.2.1. Data transfer between Computers through the www

A schematic view of the connection between two computers: Computer A (client) and Computer B (server) is shown in Fig. 7.1, which is divided into three parts: Client, Middle Tier and Backend.

(a) Client

Clients are common users who can access web pages in a computer connected to the Internet (e.g. Computer A). The web pages that the client access are Hyper Text Markup Language (HTML) or Script pages. The HTML or script page are used for sending data consist of buttons and tabs which clients select according to their needs.

For example, clients can choose one of the techniques for robot navigation. There is also a provision for starting or stopping the navigation as desired by selecting the respective buttons. The “Send” tab is used for sending the chosen technique command and the “start” or “stop” command to Computer B. The “Reset” tab gives an option to clients for initialising a different set of commands. The commands are sent in accordance with the Hyper Text Transfer Protocol (HTTP) or Script page from Computer A to Computer B.

(b) Middle Tier

The Middle Tier consists of a Web Server and a software application (script page), both of which reside in Computer B (Fig. 7.1). The script page writes data (received by the server from clients) into the memory (hard disk) of Computer B.

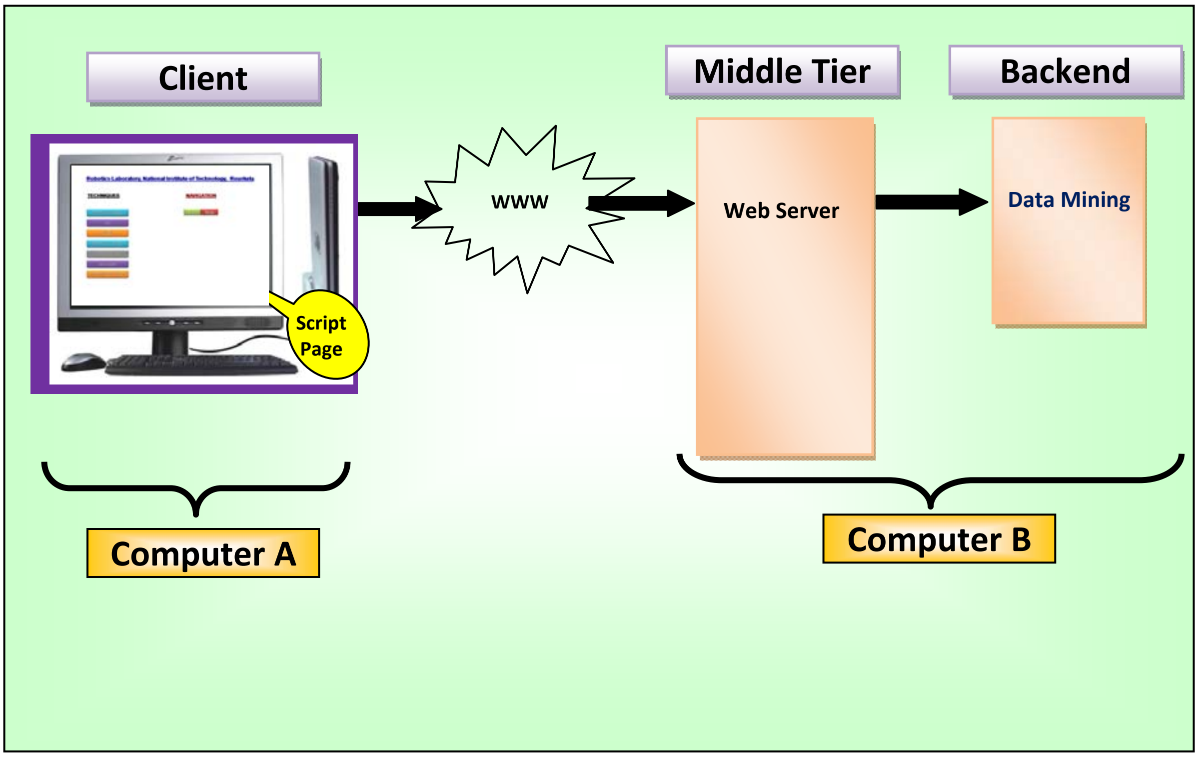


Fig. 7.1. Schematic view of 3-tier combination for remote control (through www) of mobile robots

(c) Backend

The Backend consists of data files which reside in Computer B (Fig. 7.1). These data files are created and updated by the script pages using the data supplied by clients.

7.2.2. Connection between Robot Software and Data Files

The robot simulation and control software resides in Computer B. The control software reads data from the data files stored in Computer B every second and takes action accordingly. The sequence of stages from clients to robots is shown in Fig. 7.2.

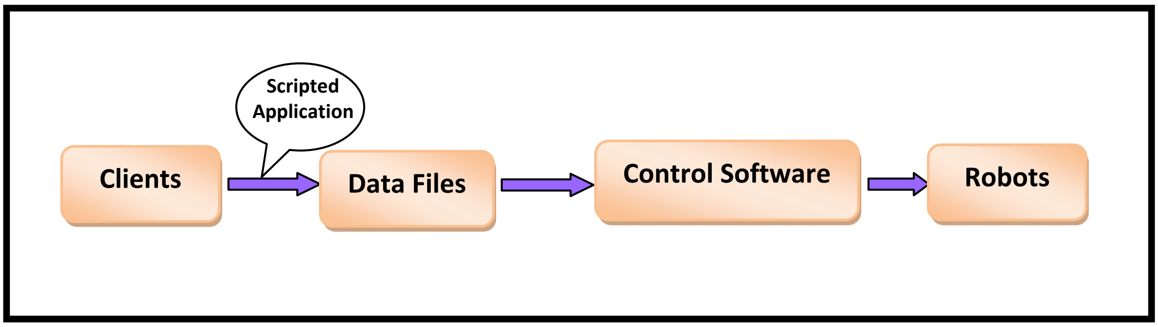


Fig. 7.2. Stages in robot control by clients.

7.2.3. Updated Images of Robot Workspace

Pictures of the robot workspace are captured at regular intervals of one second using the "SnagIt" window screen capture software. The captured images are stored in the Graphics Interchange Format (GIF) in Computer B. As soon as the client clicks the “Send” tab, Computer A connects to another script page, which displays images of the robot workspace.

7.3. Demonstrations

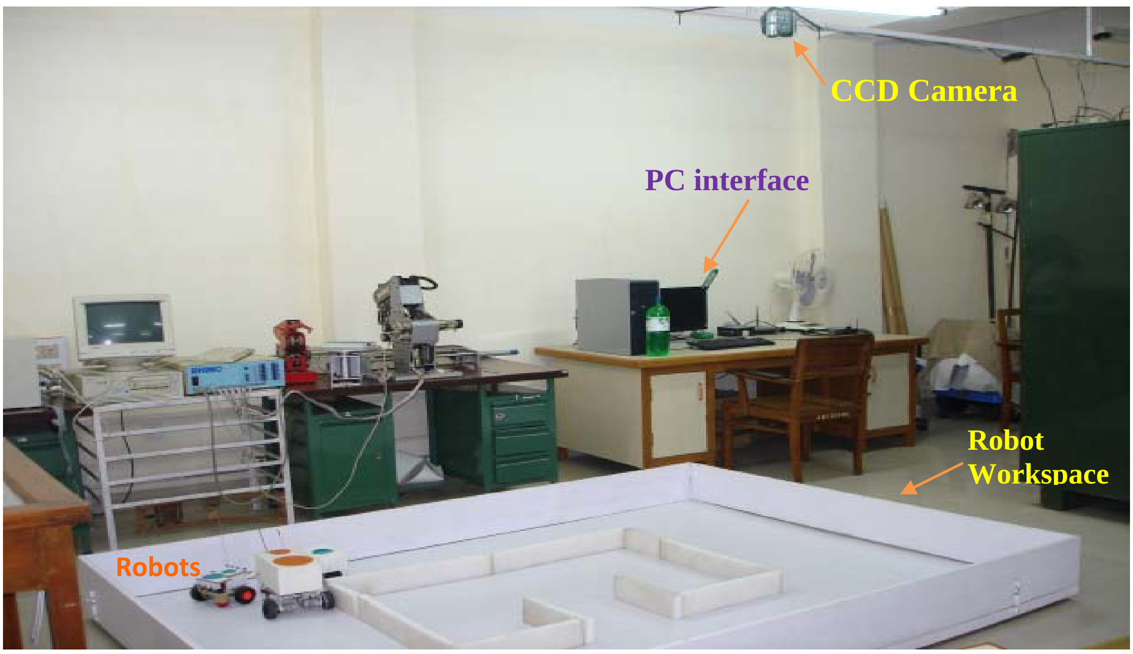


Fig. 7.3(a). Detailed remote experimental set up for navigation of three mobile robots.

Figures 7.3(a-d) depict the navigation of three mobile robots controlled via the www using Potential-Genetic-Fuzzy techniques. In these scenarios the robot negotiate with U-shaped objects, while avoiding obstacles and reaching the targets. This technique has been chosen for demonstration as it is found to be the best among those developed in this work. Fig. 7.3 (b, c & d) present the real navigation results for the developed technique.

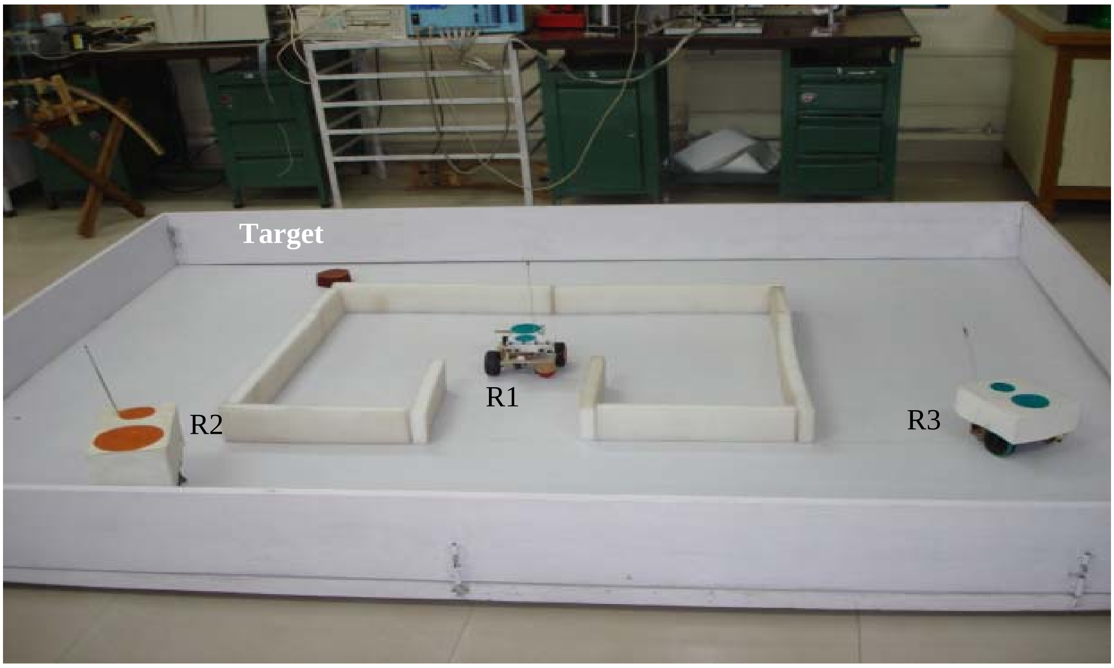


Fig. 7.3(b). Navigation of multiple mobile robots using WWW (Initial scenario).

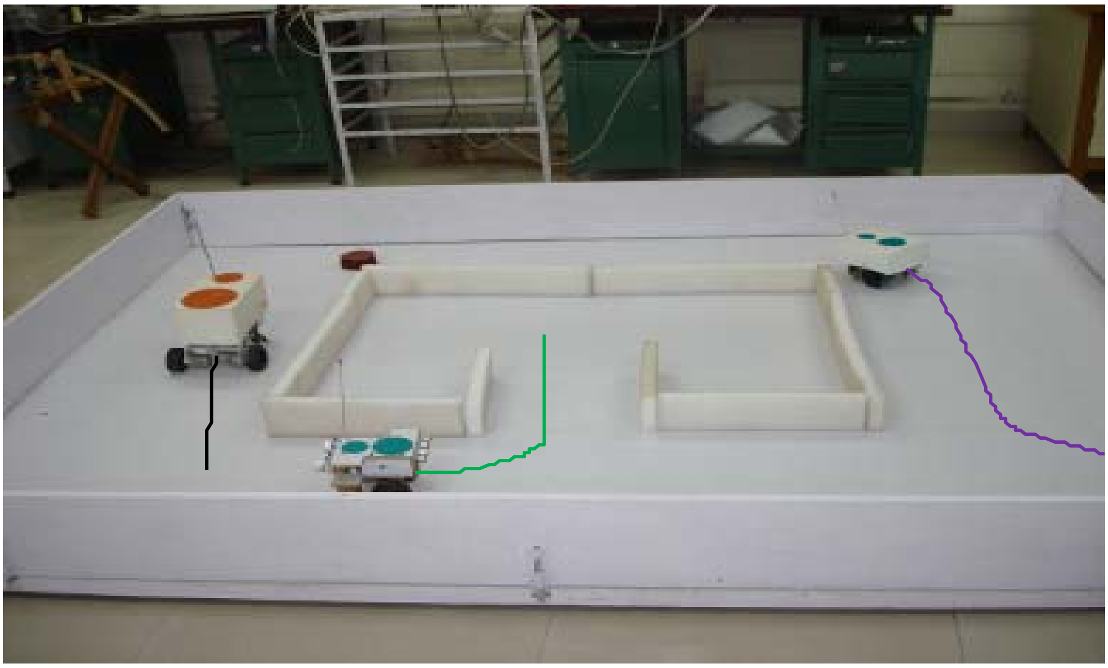


Fig. 7.3(c). Navigation of multiple mobile robots using WWW (Intermediate scenario).

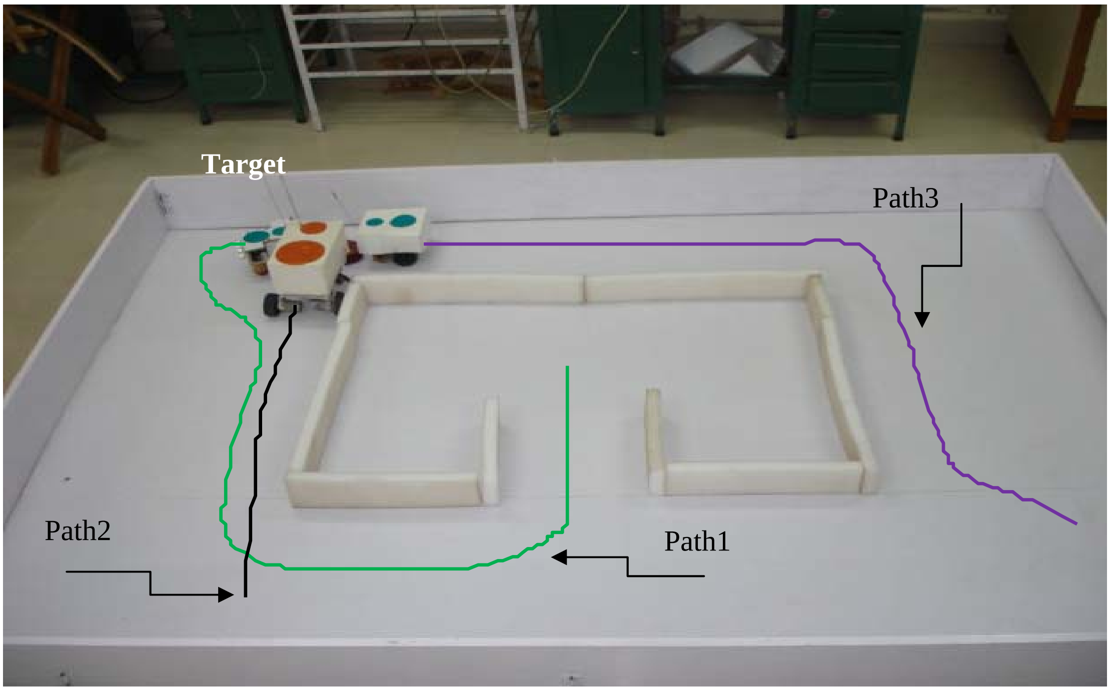


Fig. 7.3(d). Navigation of multiple mobile robots using WWW (Final scenario).

7.4. Summary

This chapter has described the implementation of different techniques for remote robot navigation. The medium for transmitting control commands is the World Wide Web because of its almost universal acceptance as a means for asynchronous communication. Script pages are used for transmitting and receiving the data between the front end and backend. Robots can be used for navigational application in hazardous environment remotely using the current methodology.

Chapter 8

Conclusion and Future Directions

- **Important contributions**
- **Conclusions**
- **Future directions**

8. Conclusion and Future Directions

The previous chapters discuss the background, need statement, problem formulation and approach for navigation of mobile robot navigation in various environments. Different techniques have been used; their capabilities and fit for several situations are studied in detail via simulation and real time experiments. This chapter summarises the main contributions and conclusions of the research and proposes ideas for further work.

8.1. Important contributions

The core objective of this research is to develop some effective methodology by exploring the AI techniques for safe and efficient path planning strategy techniques for cooperative locomotion of mobile robot in various environments. In the present work different controllers with stand alone AI techniques as well as hybrid techniques have been designed and their performance analysis is studied during their navigational control in various environments. The major contributions and findings are summarised below.

Firstly, a novel, straight forward and purely Potential field based navigation technique was considered. The new potential functions take into account the relative distances and bearing between obstacles and the targets with respect to the robots. It has been seen that by using new potential field function the robots are able to avoid efficiently any obstacles, escape from dead ends and find targets without collision. The robots also follow the wall and reach the target effectively.

Secondly, genetic algorithm techniques was considered to construct the framework of some hierarchical or procedural control structures to implement basic navigation problems for multiple robots based on GA. Firstly, a method has been proposed for adjustment of fitness values to avoid statistical variation due to randomness in initial positions and orientations of obstacles. Then the distances of obstacles from three directions (viz. front, left and right) were evaluated by using suitable fitness function and optimised by the proposed algorithm based upon an iterative non-linear search, which utilizes matches between observed geometry of the environment and a-priori map of position locations, there by correcting the position and orientation of the robot to find targets.

Thirdly, the fuzzy logic techniques with all five triangular membership functions have been considered. Subsequently the membership functions are changed from triangular to other functions, e.g. trapezoidal, Gaussian functions and combinational form to have a more smooth control response. It has been found that the fuzzy controller with Gaussian membership function works better and it is observed that robots able to navigate safely from start to goal position in an unknown cluttered environment.

Finally, hybrid techniques were analysed by considering different combination of techniques. The devised method has also accounted for collision-free paths and reduction of travel time while lessening the number of controller variables and hence structure. It is seen that hybrid techniques performs well compared to stand alone techniques and best results observed with the potential-genetic-fuzzy hybrid controller among the chosen techniques. The developed strategies have been checked via simulations as well as experiments, which show the evidence of the capabilities of proposed controller to solve the multiple robot navigation tasks with multiple targets in an optimised way and to obtain a strategy for this purpose.

8.2. Conclusions

From the simulation and experimental results, it is concluded that the developed simple fuzzy controller with all Gaussian membership is able to control the navigation of multiple mobile robots in an unknown cluttered workspace.

The potential-fuzzy technique has increased the performance compared to both the stand alone potential and fuzzy logic techniques. Similarly the potential-genetic technique performs better than the simple genetic technique.

The best performing techniques are based on potential-Genetic-Fuzzy technique, which gives robust navigation results in an unknown environment. This technique provides better result than other hybrid techniques developed, namely the potential-fuzzy and potential-genetic and genetic-fuzzy technique.

Further the technique demonstrates that it is possible to provide a navigation technique that can overcome a number of surface problems including the local minimum problem. The Proposed techniques also allow the approach to operate in 3D environments including obstacle which shows novelty of the techniques used for the navigation of mobile robots. The navigational techniques developed in this research have been successfully applied in controlling the mobile robots remotely (through the WWW) and on-site, with the help of developed software. This provides a user-friendly and flexible way of controlling the mobile robots using different navigational techniques.

8.3. Future directions

Though much work have been conducted in this field, the tasks are not yet completed for navigational solutions of all possible situations found in day to day life. There is still an open area of research for autonomous navigation. There are a number of interesting directions to pursue as future work by improving the state of the art through an entirely new type of navigational approach.

The following are suggestions for further investigation:

- In the current research work, the techniques developed for multiple mobile robot navigation enable the robots to avoid each other and static obstacles. However, further development of the techniques may be required for the avoidance of moving obstacles other than the robots. These obstacles (e.g. animals, moving equipments etc.) may or may not have sensors mounted on them that are able to communicate with robots.
- Co-ordination between the robots for co-operative task with static as well as moving obstacles.
- The navigational techniques developed in this research work are capable of detecting and reaching static targets. Further modifications in these navigational techniques may be carried out so that the robots can not only detect dynamic targets but also reach them.
- When several robots are involved in a co-operative task using the techniques developed in this research, such as moving objects from one position to another

and avoiding obstacles, sentinel robots are required for co-ordination. Modification of the navigational techniques is required to carry out sentinel-free co-operation in an environment having obstacles.

- Further work needs to be undertaken in the area of optimising the number of robots reaching and handling a particular object according to its weight and volume. This will optimise the process of co-operation by controlling the number of robots required for each task. The navigational techniques developed in this research could be extended to incorporate this feature.

- Further work with respect to the use of visual sensing may be undertaken to improve the environmental perception of mobile robots. This may help to facilitate co-operation between the robots in a more intelligent manner (by providing additional, improved sensory data). It may also be used in the context of robot control through the WWW by presenting on-line pictures of the robot's work area. Digital cameras (e.g. web cams) with a suitable computer interface may be employed for this purpose.

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Appendix A

Kinematic Analysis of differential drive Robot:

The motion of the wheeled mobile robot is discussed in this section.

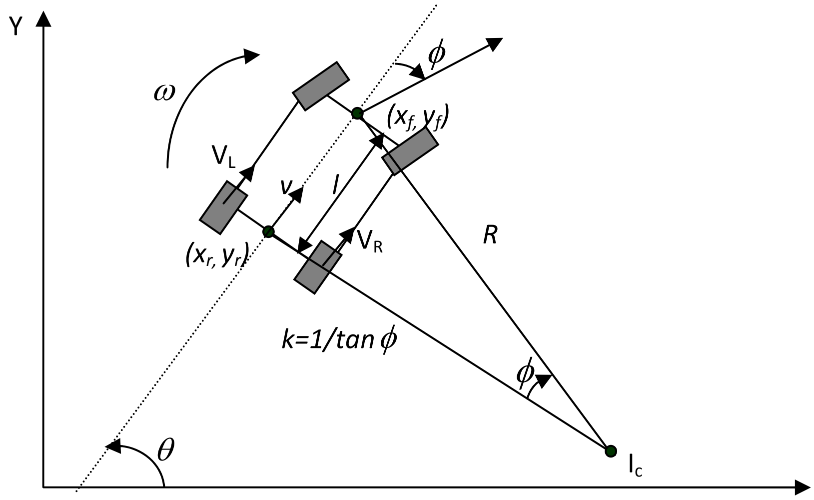


Fig. A1. Kinematic model of a four wheeled mobile robot.

A kinematic model of a wheeled mobile robot has been considered in Fig. A1. The rear wheels are fixed parallel to robot body and allowed to roll or spin but not slip. The front wheels can turn to left or right, but the left and right front wheels must be parallel. All the corresponding parameters of the wheeled mobile robot are depicted in Fig.A1 and defined as follows.

$\left(x_f, y_f\right)$ Position of the front wheel center of wheeled mobile robot

$\left(x_r, y_r\right)$ Position of the rear wheel center of wheeled mobile robot

The configuration of the robot moving on a plane surface at every instant is defined by the parameter *(x, y, θ)*. The rear wheel is always tangent to the orientation of the vehicle. The no-slipping condition mentioned previously requires that the robot navigate in the direction of its wheels. Thus, we have

$$\dot{x}_r \sin\theta - \dot{y}_r \cos\theta = 0 \tag{A1}$$

This is nonholonomic constraint. The front of the wheeled mobile robot is fixed relative to the rear, thus the coordinate $\left(x_r, y_r\right)$ is related to $\left(x_f, y_f\right)$

$$\left.\begin{aligned} x_r &= x_f - l\cos\theta \\ y_r &= y_f - l\sin\theta \end{aligned}\right\} \tag{A2}$$

Thus, differentiating (2) with respect to time gives

$$\left.\begin{aligned} \dot{x}_r &= \dot{x}_f + \dot{\theta} l \sin\theta \\ \dot{y}_r &= \dot{y}_f - \dot{\theta} l \cos\theta \end{aligned}\right\} \tag{A3}$$

Substituting (A3) to (A1), we can get

$$\dot{x}_f \sin\theta - \dot{y}_f \cos\theta + \dot{\theta} l = 0 \tag{A4}$$

From Fig. A1, we have

$$\left.\begin{aligned} \dot{x}_f &= v\cos(\theta - \phi) \\ \dot{y}_f &= v\sin(\theta - \phi) \end{aligned}\right\} \tag{A5}$$

Substituting (A5) to (A4), we can derive

$$\dot{\theta} = v\frac{\sin\phi}{l} \tag{A6}$$

Equations (A5) and (A6) are the kinematic equations of wheeled mobile robot with respect to the axle center of the front wheels and are used to generate the next forward state position of the vehicle when the present states and control input are given. Then using equations (A3) to (A6), the kinematics of wheeled mobile robot with respect to the axle center of the rear wheels is described as,

$$\left.\begin{aligned} \dot{x}_r &= v\cos\theta\cos\phi \\ \dot{y}_r &= v\sin\theta\cos\phi \\ \dot{\theta} &= v\frac{\sin\phi}{l} \end{aligned}\right\} \tag{A7}$$

Equations (A7) is used to generate the next backward state position of the vehicle when the present state and control input are given.

From equation (A7) we have,

$$v = \dot{\theta} l \frac{1}{\sin\phi}$$

$$\omega R = \dot{\theta} l \frac{1}{\sin\phi} \qquad \text{as } (v = \omega R)$$

$$\left.\begin{aligned} \omega\left(R + \frac{d}{2}\right) &= \left(\dot{\theta} l \frac{1}{\sin\phi}\right) + \omega\frac{d}{2} = V_R \\ \omega\left(R - \frac{d}{2}\right) &= \left(\dot{\theta} l \frac{1}{\sin\phi}\right) - \omega\frac{d}{2} = V_L \end{aligned}\right\} \tag{A8}$$

Where V_{L} and V_{R} are the left and right wheel velocity of the rear wheels.

By changing the velocities of the two wheels, the instantaneous center (I_c) of rotation will move and different trajectories will be followed (Fig. A2).

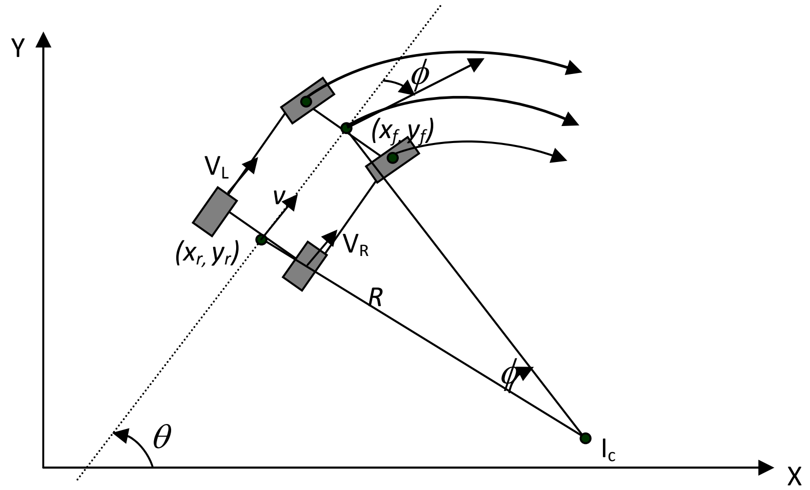


Fig. A2. The differential drive motion of wheeled mobile robot.

At each moment in time the left and right wheels follow a path (Fig. A2) that moves around the I_c with the same angular rate *dt*.

Therefore,

$$R = \left(\frac{V_L + V_R}{V_L - V_R}\right)\frac{d}{2}$$
$$\omega = \frac{V_L - V_R}{d} \qquad \text{(A9)}$$

The velocity of the centre point, which is the midpoint between the two wheels, can be calculated as the average of the velocities V_L and V_R.

Thus, $$v = \frac{V_L + V_R}{2} \qquad \text{(A10)}$$

If $V_L = V_R$ then the radius *k* is infinite and the robot moves in a straight line. For different values of V_L and V_R, the mobile robot does not move in a straight line but rather follows a curved trajectory around a point located at a distance *R* from Centre point. If $V_L = -V_R$, then the radius *R* is zero and the robot rotates around one wheel. For any real value of the velocity, *r* must be real, to get a real curved path. Thus, 'θ' has to lie within 0^0 and 90^0, i.e., $0^0 < \theta < 90^0$, for a non-holonomic robot.

Appendix B

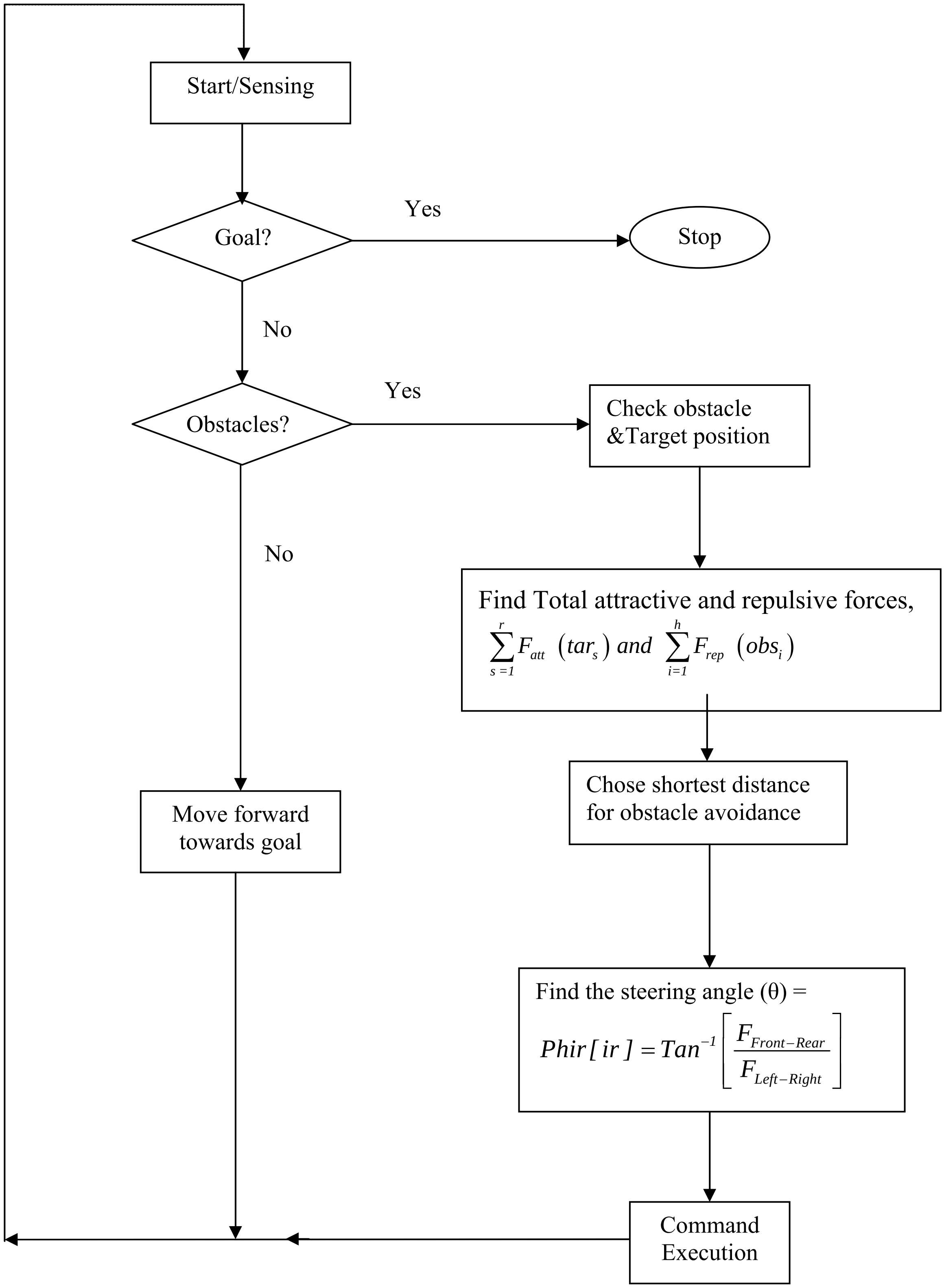


Fig. A3. Flow Chart for developed APF Program.

Appendix C

Calculation of steering angle:

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. A4).

Let,

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

$\sum F_{Left-Right}$ = 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

$$Phir[ir] = Tan^{-1}\left[\frac{F_{Front-Rear}}{F_{Left-Right}}\right] \tag{A11}$$

New heading angle (θ) new $= (\theta) + Phir[ir]$ (A12)

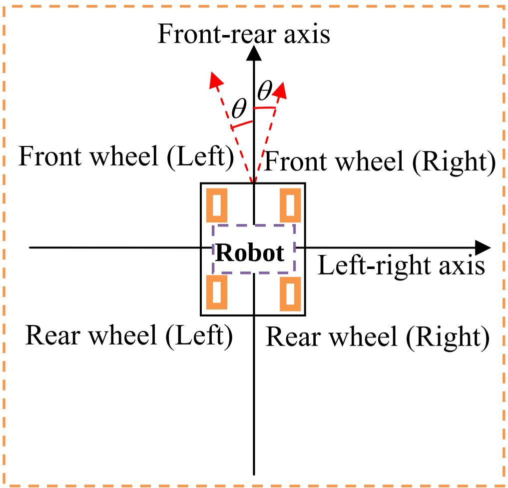


Fig. A4. Robot heading angle with respect to different obstacle positions.

Appendix D

Specification of N.I.T. Robot

The approximate size of the robot is as follows:

Length	:	16 cm (including sensor position)
Width	:	12 cm
Height	:	10 cm from ground and

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

Length	:	1.4 m
Width	:	2.0 m
Height	:	0.18 m

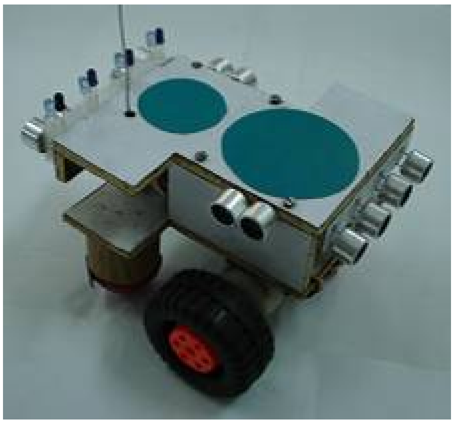
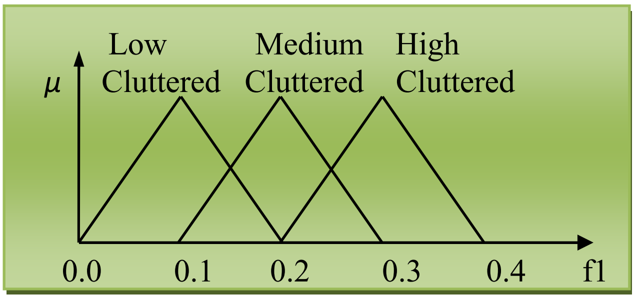


Fig. A5. Appearance of the wheeled mobile robot used for experiment.

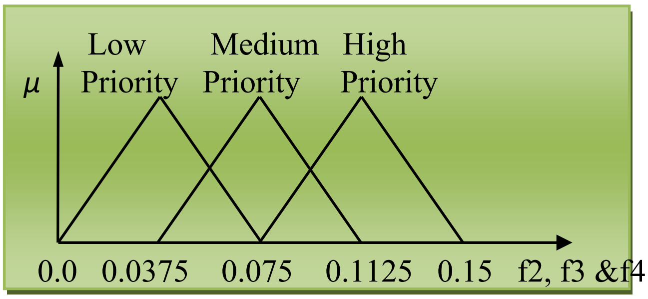
The robot considered for experiment is a differential drive robot with an on-board PC and wireless Ethernet. There are six ultrasonic and four infra red sensors mounted around the top of robot (out of which two sensors in each in front and back sides and one in each at the left and right side of the mounting) in order to sense the front, left, right, and back obstacle distances.

Appendix E

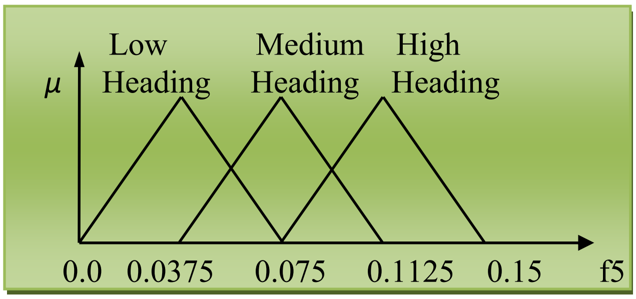
The Fuzzy membership functions for different coefficients are shown in Fig. A6. The coefficients for the sub-fitness functions f1, f2,…., f5 are calculated using fuzzy inference technique and statistical analysis. The degree of membership functions are detailed as follows.



(a) Fuzzy membership function for coefficient 'f1'



(b) Fuzzy membership function for coefficients 'f2, f3 & f4'



(c) Fuzzy membership function for coefficient 'f5'

Fig. A6. Fuzzy membership function used for evaluation of different fitness function coefficient using proposed motion planning scheme.

The maximum values are estimated statistically from the membership functions distribution. In the current case the high intensity factors are considered for navigation of mobile robots. However, the other values of coefficient can be tried in future for alternative navigational performance. It may be noted that the fuzzy inference technique is only used for calculation of the sub coefficients for the fitness function described in Eq. (4.1).

Appendix F

Computational example for different steps of the proposed hybrid controller

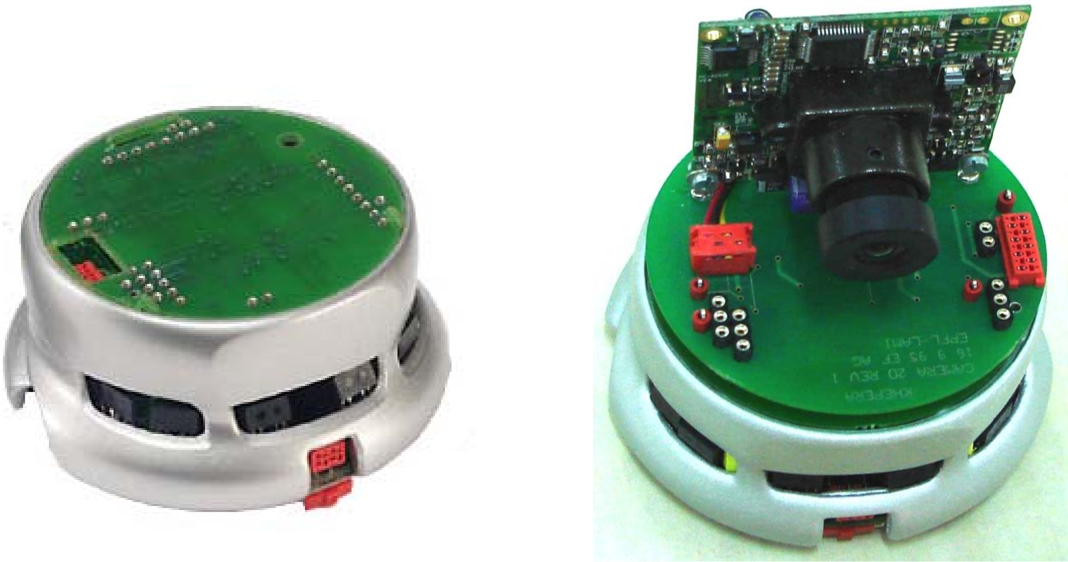
In the current paper hybrid Petri-potential fuzzy controller has been developed and used for mobile robot navigation. During navigation from start location to target location different positions of the robots at a particular time (t) are estimated step wise. The complete details are given in tabular form [Table A1] and are discussed below. Based on the sensory information the front, left, right obstacle distances and targets location for different robots are evaluated. These distances are the input to the hybrid controller. The computational results of hybrid controller of five membership function having all Gaussian members [Refer Fig. 6.3(a, b)] are considered to show the Computational steps at different instantaneous positions. Table A1 shows the computational results in four steps (i.e. [$R_{(1,1)}$, $R_{(2,1)}$), $R_{(3,1)}$], [$R_{(1,2)}$, $R_{(2,2)}$), $R_{(3,2)}$], [$R_{(1,3)}$, $R_{(2,3)}$), $R_{(3,3)}$] and [$R_{(1,4)}$, $R_{(2,4)}$), $R_{(3,4)}$] for three mobile robots.

Table A1
Example of some of the rules of Potential-Fuzzy Hybrid Controller to show the Computational steps at different instantaneous positions based on the proposed algorithm.

No. of Robot.	Position	Co-ordinates In 'pixels'	Input to the Hybrid Controller FOD in 'pixels'	LOD in 'pixels'	ROD in 'pixels'	LV	RV
Robot1	$R_{(1,1)}$	(2, 17)	46	14	2	Slow	Very Fast
	$R_{(1,2)}$	(6, 22)	22	74	4	Slow	Fast
	$R_{(1,3)}$	(12, 22)	32	2	2	Fast	Fast
	$R_{(1,4)}$	(23, 30)	30	10	6	Fast	Fast
Robot2	$R_{(2,1)}$	(6, 5)	14	3	20	Slow	Very Slow
	$R_{(2,2)}$	(10, 3)	18	4	10	Slow	Very Slow
	$R_{(2,3)}$	(17, 3)	22	4	20	Slow	Very Slow
	$R_{(2,4)}$	(25, 7)	66	4	24	Very Fast	Slow
Robot3	$R_{(3,1)}$	(8, 3)	24	10	10	Slow	Slow
	$R_{(3,2)}$	(14, 2)	26	4	4	Slow	Slow
	$R_{(3,3)}$	(19, 3)	90	4	10	Very Fast	Fast
	$R_{(3,4)}$	(28, 10)	76	6	20	Very Fast	Fast

Appendix G

Specifications of Khepera-II

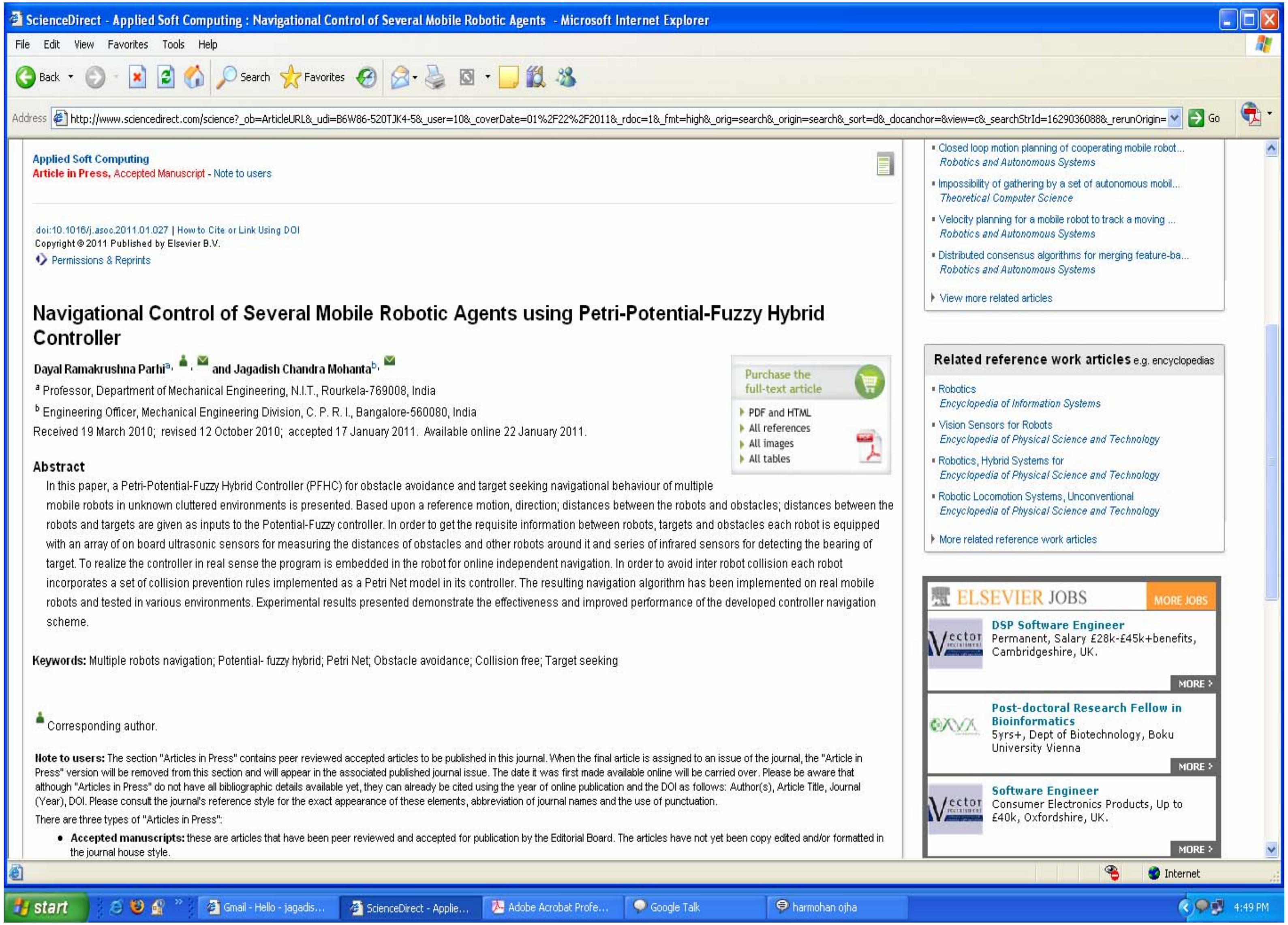


(a) (b)

Fig. A7. Khepera II Robot with and without camera.

Elements	Technical Information
Processor	Motorola 68331, 25MHz IMPROVED
RAM	512 Kbytes IMPROVED
Flash	512 Kbytes Programmable via serial port NEW
Motion	2 DC brushed servo motors with incremental encoders (roughly 12 pulses per mm of robot motion)
Speed	Max: 0.5 m/s, Min: 0.02 m/s
Sensors	8 Infra-red proximity and ambient light sensors with up to 100mm range IMPROVED AND Power Consumption NEW
I/O	3 Analog Inputs (0-4.3V, 8bit)
Power	Power Adapater OR

	Rechargeable NiMH Batteries IMPROVED
Autonomy	1 hour, moving continuously IMPROVED. Additional turrets will reduce battery life.
Communication	Standard Serial Port, up to 115kbps IMPROVED
Extension Bus	Expansion modules can be added to the robot using the K-Extension bus.
Size	Diameter: 70 mm Height: 30 mm
Weight	Approx 80 g
Payload	Approx 250 g
Simulators	WEBOTS, Realistic 3D Simulator and robot programming (Windows & Linux) BotController. 2D simulation and robot programming
Development Environment for Autonomous Application	KTProject, graphical interface for GNU C Cross-Compiler (Windows) GNU C Cross-Compiler, for native on-board applications (Windows, Linux & Sun) Freeware
Remote control Software via tether or radio	LabVIEW® (on PC, MAC or SUN) using RS232 MATLAB® (on PC, MAC, Linux or SUN) using RS232 SysQuake® (on PC, MAC, Linux or SUN) using RS232 Freeware Any other software capable of RS232 communication



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Navigational Control of Several Mobile Robotic Agents using Petri-Potential-Fuzzy Hybrid Controller

Dayal Ramakrushna Parhi[a], and Jagadish Chandra Mohanta[b],

[a] Professor, Department of Mechanical Engineering, N.I.T., Rourkela-769008, India

[b] Engineering Officer, Mechanical Engineering Division, C. P. R. I., Bangalore-560080, India

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Abstract

In this paper, a Petri-Potential-Fuzzy Hybrid Controller (PFHC) for obstacle avoidance and target seeking navigational behaviour of multiple mobile robots in unknown cluttered environments is presented. Based upon a reference motion, direction; distances between the robots and obstacles; distances between the robots and targets are given as inputs to the Potential-Fuzzy controller. In order to get the requisite information between robots, targets and obstacles each robot is equipped with an array of on board ultrasonic sensors for measuring the distances of obstacles and other robots around it and series of infrared sensors for detecting the bearing of target. To realize the controller in real sense the program is embedded in the robot for online independent navigation. 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 navigation; Potential- fuzzy hybrid; Petri Net; Obstacle avoidance; Collision free; Target seeking

Corresponding author.

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AN INTELLIGENT MOTION PLANNING APPROACH FOR MULTIPLE MOBILE ROBOTS USING ARTIFICIAL POTENTIAL FIELD METHOD

Dayal Ramakrushna Parhi*, Jagadish Chandra Mohanta Saroj Kumar Patel* and I. P. S. Paul****

Abstract: This paper deals with the motion planning problem for wheeled mobile robots in a cluttered environment. In this paper, we proposed a new scheme for autonomous navigation of multiple mobile robots based on improved APF method. The developed technique introduces a variable, which takes care of the obstacles' and targets' influences on path of the robots. The control system integrates repelling influences related to the distances between robots and nearby obstacles and with attracting influences between the robots and targets. The developed APF technique depends on the distances between obstacles positions with respect to robots and targets. This technique also takes care the distances between the robots so that the robots do not collide among themselves. Local minima problems for static and dynamic environments have been considered in this work. Simulation results show the effectiveness of the developed algorithm to avoid the local minima completely. Experimental results are presented to verify the developed algorithm in a similar environment. The result obtained shows that by using improved APF method robots are able to navigate successfully in a highly cluttered environment.

Keywords: Mobile robots: Obstacle avoidance: Collision free: Target seeking: Artificial potential field

1. INTRODUCTION

Potential field method is rapidly gaining popularity in obstacle avoidance applications for mobile robots. This method is particularly attractive because of its elegance and simplicity. The following research works have been reported by several investigators for navigation of mobile robot using this method.

Potential field navigation has been introduced by Khatib [1] and since then many efforts have been made for navigation of mobile robot in an efficient manner. Borenstein *et al.* [2] have developed a real-time obstacle avoidance approach for mobile robots. Their navigation algorithm takes into account of dynamic behavior of a mobile robot and solves the local minimum trap problem. Karen *et al.* [3] 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.* [4] have presented a summary of the research aimed at developing a new reliable methodology for robot navigation and obstacle avoidance. Their new approach was based on the artificial potential field (APF) method, which was used extensively for obstacle avoidance. Simulation results are presented demonstrating the ability of the algorithm to perform successfully in simple environments. Veelaert *et al.* [5] have proposed a landmark based navigation of mobile robots. They have mapped the robot motions using potential field method. Mbede *et al.* [6] have focused on autonomous motion planning of manipulators in known environments and with unknown dynamic obstacles. The navigation technique of robot control is based on artificial potential functions. They have also done stability analysis using Lyapunov theory. Tsourveloudis *et al.* [7] 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.* [8] have proposed a new trajectory generation method that allows full

* Department of Mechanical Engineering, N. I. T., Rourkela-769008, Orissa, India, *E-mail: dayalparhi@yahoo.com*

** Central Power Research Institute, Bangalore-560080, India

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ANALYSIS OF HYBRID GENETIC TECHNIQUE FOR NAVIGATION OF INTELLIGENT AUTONOMOUS MOBILE ROBOTS

Dayal Ramakrushna Parhi*, Jagadish Chandra Mohanta, B. B. V. L. Deepak* and Saroj Kumar Patel***

Abstract: Hybrid Petri-potential-genetic controller has been discussed in this paper for navigation of intelligent mobile robots. The inputs to the controller are obstacle position and target angle. The interim output is First heading angle and is a input to the fuzzy controller. The other inputs to the fuzzy controller are left, right and front obstacle positions. The output from the hybrid controller is heading angle. In the real robot intelligent program codes are embedded for online independent navigation. Petri Net model has been used for inter robot collision avoidance during navigation.

Keywords: Robots; Navigation; Potential; Genetic

1. INTRODUCTION

Many Researcher have used artificial intelligence for navigation of mobile robots in the last few decades. Mainly the work done are focused on the analysis for navigation of single mobile robot. The relevant work are discussed below.

Potential field approach has been used by Masoud [1] for the construction of a decentralized traffic controller for a large group of agents sharing a workspace with stationary forbidden regions. Simulation results are given by them for verification of the theory developed. Autonomous navigation of a mobile robot have presented by Cosio *et al.* [2]. This method is 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. Simulation experiments are done by them for verification of their theory. Many authors [3-5] have described genetic algorithm based on MAKLINK graph environment representation. In their genetic algorithm, the path is represented by variable length chromosomes formed by mid-points of the free-links. They claim that this is a more natural way of encoding than binary strings. This graph based method needs to form a configuration space before applying the genetic algorithm. Rresearchers have used GAs for path planning of mobile robots [6-8]. GAs use binary strings and two basic genetic operators. After encoding solutions to a problem, the GAs are more like "blind" search, and perform well when very little prior knowledge is available. However, improved GAs do not have to be "blind" search, when additional knowledge about problem is available, it can be incorporated into GAs to improve the efficiency of GA[9-10]. Genetic algorithm based path-planning model has been used by Sedighi *et al.* [11] for local obstacle avoidance of a mobile robot in an environment. A new method has been proposed by Huang *et al.* [12] for vision-guided navigation, based upon a model of human navigation. They use the relative headings to the goal and to obstacles for target finding. The distance to the goal and the angular width of obstacles are used to compute the robot heading angle.

This paper discusses the navigational path planning of mobile robots with surrounded by obstacles and targets. The path planning method is based on potential-GA controller . The inputs to the controller are obstacles position and target position and output is heading angles (HA). This out put is one of the inputs to hybrid potential controller.

* Department of Mechanical Engineering, N.I. T., Rourkela-769008, India

** Mechanical Engineering Division, C. P. R. I., Bangalore-560080, India

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

Jagadish Chandra Mohanta
Engineering Officer, Mechanical Engineering Division, C. P. R. I, Bangalore-560080, India
E-mail: jagadish_mohanta@yahoo.co.in

Dayal Ramakrushna Parhi & Saroj Kumar Patel
Professor, Department of Mechanical Engineering, N.I.T., Rourkela-769008, Orissa, India

Saroj Kumar Pradhan
Sr. Lect. Department of Mechanical Engineering, N.I.T., Hamirpur-177005, HP, India

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

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Mobile Robot Path Planning and Tracking using AI Techniques

Dayal R. Parhi, Jagadish Chandra Mohanta
Department of Mechanical Engineering, N.I.T., Rourkela, Orissa, 769008, India
E-mail: dayalparhi@yahoo.com, jagadish_mohanta@yahoo.co.in.

Abstract: *In this paper an intensive study has been carried out to find the various techniques and sensors being used for navigation of mobile robots in recent years. Keeping in view of the above objectives, this paper has been divided into two main parts. In the first part effort has been made to find out the techniques used for navigation of mobile robots. These techniques are classified as follows; (i) Fuzzy Logic technique, (ii) Neural Network technique, (iii) Genetic Algorithm technique, (iv) Potential Field technique, (v) Grid Based technique, (vi) Heuristic technique, (vii) Adaptive Navigation technique, (viii) Virtual Impedance technique and (ix) Divide and Conquer technique. The second part basically describes the sensors being used for navigation of mobile robots. These sensors are categorised into five types, i.e. (i) Ultrasonic Sensor, (ii) Laser Sensor, (iii) Magnetic Compass Disk Sensor, (iv) Infrared Sensor and (v) Vision (Camera) Sensor. Keeping in view of the recent research investigations, in the above areas a consolidated review has been presented to find out the optimal navigation methodology for several mobile robots.*

Keywords: *fuzzy logic, neural network, genetic algorithm, potential field, grid, heuristic, adaptive, virtual impedance, sensors.*

1. INTRODUCTION

During the last decade, the research communities in mobile robotics have paid lot of attentions towards the development of different control architectures for navigation of mobile robots. For this, mainly two principal designs have been adopted. One is called the functional or horizontal decomposition [116], shown in Fig. 1(a) and the other is the behavioral or vertical decomposition [103], which is shown in Fig. 1(b).

Navigation for mobile robots can be well defined in mathematical (geometrical) terms. It involved many

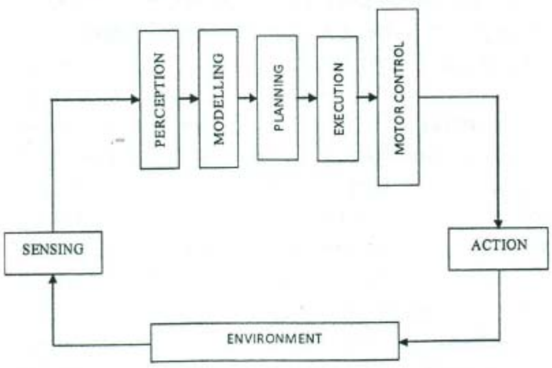

Fig. 1(a): Flow Diagram of the Horizontal Decomposition Method for Navigation of Mobile Robot.

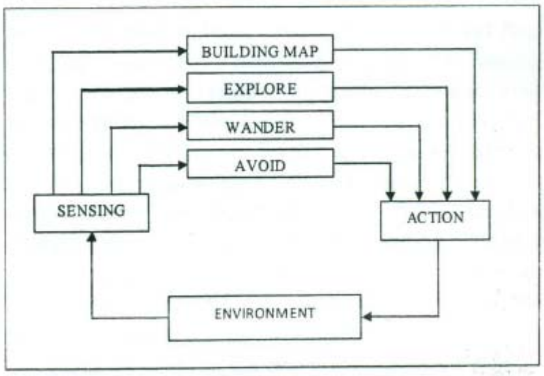

Fig. 1(b): Flow Diagram of the Vertical Decomposition Method for Navigation of Mobile Robot.

distinct sensory inputs and computational processes. Elementary decisions like turn left, or turn right, or run or stop, are made on the basis of thousands of incoming signals [121]. Thus it is necessary first to define what navigation is and what the function of a navigation system is. Levitt and Lawton [122] tried to define the navigation by following three questions: (a) "Where am I ?", (b) "Where are other places relative to me ? ", and (c) "How do I get to other places from here ?". Underlying question (a) is the problem of recognising and identifying the particular place and question (b) and (c) focused the point,

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Title: Path planning strategy for autonomous mobile robot navigation using Petri-GA optimization

Article Type: Research Paper

Keywords: Path Planning; Multiple robots; GA Based controller; Obstacle avoidance; Multiple target seeking

Corresponding Author: Dr. Jagadish Chandra Mohanta,

Corresponding Author's Institution: Mechanical Engineering Division, C. P. R. I., Bangalore-560080, India

First Author: Jagadish Chandra Mohanta

Order of Authors: Jagadish Chandra Mohanta; Dayal Ramakrushna Parhi; Saroj Kumar Patel

Abstract: In this paper, a novel knowledge based genetic algorithm (GA) for path planning of multiple robots for multiple targets seeking behaviour in presence of obstacles is proposed. GA technique has been incorporated in Petri net model to make an integrated navigational controller. The proposed algorithm based upon an iterative non-linear search, which utilizes matches between observed geometry of the environment and a priori map of position locations, to estimate a suitable heading angle, there by correcting the position and orientation of the robots to find targets. This knowledge based GA is capable of finding an optimal or near optimal robot path in complex environments. The Petri-GA model can handle inter robot collision avoidance effectively than the stand alone GA. The resulting navigation algorithm has been implemented on real mobile robots and tested in various environments to validate the developed control scheme.

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Motion Control And Path Tracking Of Mobile Robots Using Artificial Intelligence Method

Jagadish Ch. Mohanta[a], Dayal, Ramakrushna Parhi[a] , Saroj Kr. Patel[a] and I.P.S. Paul[b]
[a] *Department of Mechanical Engineering, N.I.T., Rourkela-769008, Orissa, India;*
[b] *HRD, Central Power Research Institute, Bangalore-560080, India;*

***Abstract*--The investigation presented in the paper aims at developing a new reliable methodology for robot navigation and obstacle avoidance in an unknown cluttered environment using Artificial Potential Field (APF) method. This method is used extensively for obstacles avoidance and target seeking. The classical APF is dependent only on the relative distances between the robots and the surrounding obstacles. The new scheme introduces a variable, which takes care of the obstacles' and target's influences on the path of the robot. The control system combines a repelling influence related to the distances between robots and nearby obstacles and with an attracting influence between the robots and target. The variable is dependent on the obstacles positions, both angle and distance, with respect to the robots. Simulation results are presented demonstrating the ability of the algorithm. These results exhibit that the robots navigate successfully in a cluttered unknown environment.**

***Keywords*: Mobile robots; Obstacle avoidance; Navigation; Artificial potential field.**

I. INTRODUCTION

Potential field methods are rapidly gaining popularity in obstacle avoidance applications for mobile robots. The potential field principle is attractive because of its elegance and simplicity. The research works being conducted in recent years for navigation of mobile robot using potential field method are depicted below.

Potential field navigation has been introduced in 1986 by Khatib [1] and since then many efforts has been made for navigation of mobile robot in an efficient manner. Borenstein et al. [2] 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. Arambula et al. [3] have presented a new scheme for autonomous navigation of a mobile robot, based on improved artificial potential fields and genetic algorithm. In their paper 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. Huanga et al. [4] have proposed a new approach to vision-guided local navigation, based upon a model of human navigation. Their approach 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. Mbede et al. [5] have focused on autonomous motion planning of manipulators in known environments and with unknown dynamic obstacles. The navigation technique of robot control is based on artificial potential functions and done stability analysis using Lyapunov theory. Tsourveloudis et al. [6] have discussed about electrostatic potential field (EPF) path planner in combination with a two-layered fuzzy logic inference engine. They have verified their theory experimentally in a 2-D dynamic environment using *Nomad 200* mobile robot.

Toshio et al. [7] 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. Masoud et al. [8] have explored the construction of a decentralized traffic controller for a large group of agents sharing a workspace with stationary forbidden regions. The controller is realized using the potential field approach. They have given simulation results for verification of the theory developed. Veelaert et al. [9] have proposed a landmark based navigation of mobile robots. They have defined mapped the robot motions using potential field method. Mc Fetridge et al. [10] have presented a summary of the research aimed at developing a new reliable methodology for robot navigation and obstacle avoidance. This new approach is based on the artificial potential field (APF) method, which is used extensively for obstacle avoidance. Simulation results are presented demonstrating the ability of the algorithm to perform successfully in simple environments. Koren et al. [11] have discussed about the control of a mobile root using potential field method. They have validated their result in experimental and simulation mode.

This paper proposes an efficient potential field method for motion planning of mobile robots in a cluttered environment. Firstly, the new potential function and the corresponding virtual force are defined. This method enables the multiple robots to find the target in an unknown cluttered environment. Finally, computer simulation is used to demonstrate the effectiveness of the dynamic motion planning scheme based on the new potential field method.

II. 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. Two assumptions are made to simplify the analysis:

Assumption 1: The robots are of point mass.

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Mobile robot motion planning using improved artificial potential field method

J. C. Mohanta[1]*, D. R. Parhi[2], S. K. Patel[2], S. K. Pradhan[3]
[1]Research Scholar, NIT, Hamirpur, India;
jagadish_mohanta@yahoo.co.in
[2]Department of Mechanical Engineering, N.I.T., Rourkela-769008, Orissa, India;
[3]Department of Mechanical Engineering, N.I.T., Hamirpur-177005, HP, India;

Abstract

In this paper a new technique is proposed for autonomous navigation of multiple mobile robots based on improved Artificial Potential Field (APF) method. The developed technique introduces a variable, which takes care of the obstacles' and targets' influences on path of the robots. The control system integrates repelling influences related to the distances between robots and nearby obstacles and with attracting influences between the robots and targets. The developed APF technique depends on the distances between obstacle positions with respect to robots and targets. This technique also takes care the distances between the robots so that the robots do not collide among themselves. Local minima problems for static and dynamic environments have been considered in this work. Simulation results show the effectiveness of the developed algorithm to avoid the local minima completely. Experimental results are presented to verify the developed algorithm in a similar environment. The result obtained shows that by using improved APF method robots are able to navigate successfully in a highly cluttered environment.

Key words: Mobile robots, Obstacle avoidance, Collision free, Target seeking, Artificial potential field

1. Introduction

Potential field method is rapidly gaining popularity in obstacle avoidance applications for mobile robots. This method is particularly attractive because of its elegance and simplicity. The following research works have been reported by several investigators for navigation of mobile robot using this method.

Potential field navigation has been introduced by Khatib [1] and since then many efforts have been made for navigation of mobile robot in an efficient manner. Borenstein et al. [2] have developed a real-time obstacle avoidance approach for mobile robots. Their navigation algorithm takes into account of dynamic behavior of a mobile robot and solves the local minimum trap problem. Karen et al. [3] 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. [4] have presented a summary of the research aimed at developing a new reliable methodology for robot navigation and obstacle avoidance. Their new approach was based on the artificial potential field (APF) method, which was used extensively for obstacle avoidance. Simulation results are presented demonstrating the ability of the algorithm to perform successfully in simple environments.

Min et al. [5] have described a new concept of path planning scheme based on APF using virtual obstacle to escape from local minima problem. Arambula et al. [6] have presented a new scheme for autonomous navigation of a mobile robot, based on improved artificial potential fields and a genetic algorithm. In their paper 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. Ren and McIsaac et al. [7] have investigated the inherent oscillation problem of potential field methods (PFMs) in presence of obstacles and in narrow passages. They