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Review

Controlling the Motion of an Autonomous Mobile Robot Using Various Techniques: a Review

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Abstract

Autonomous navigation of mobile robots in an uncertain and complex environment is a broad and complicated issue due to a variety of obstacles that mobile robots have to detect and represent in their maps to navigate safely. The objective of the navigation-mobile robot is to obtain an optimum path, meaning that the robot should plan a reliable path between the source point and the target point without colliding with the static and dynamic obstacles found in an uncertain and complex environment. Several efficient techniques have been developed by researchers in the motion planning of mobile robots. This paper presents detailed analysis of various techniques used in the autonomous navigation of mobile robot.

Keywords: Mobile Robot; Navigation; Obstacle avoidance

1. Introduction

In developed engineering and technology, the concept of autonomy of mobile robots encompasses many areas of knowledge, methodologies, and ultimately algorithms designed for trajectory control, obstacle avoidance, localization, map building, and so on. Practically, the success of a path planning and navigation mission of an autonomous mobile robot depends on the availability of an accurate representation of the navigation environment.

Global path planning requires a completely known environment and a static terrain. In this approach, the algorithm develops a complete path from the source point to the target point before the robot starts its motion. On the other hand, local path planning means the environment is completely unknown to the mobile robot; in other words, the algorithm is capable of developing a new path to reach at the destination point. We discuss path planning methodologies for autonomous mobile robots in this literature review.

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2. Classical Methods

2.1 Roadmap Methodology

In the roadmap approach, the mobile robot connects the source point to the target point by curved or straight lines. Once a roadmap is created, it is used as a network of roads (path) for mobile robot motion planning. Path planning is thus reduced to connecting the starting and final positions of the robot to the road network, then finding a series of roads from the starting robot position to its destination. Here we discuss two roadmap approaches, the visibility graph and Voronoi diagram. In the visibility graph, the path of the mobile robot is very close to the obstacle and resulting minimum path distance solutions, whereas in the Voronoi Diagram path, the mobile robot stays away from the obstacle as much as possible.

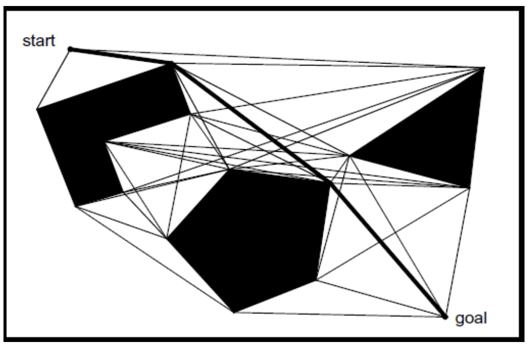

Fig 1. Visibility graph

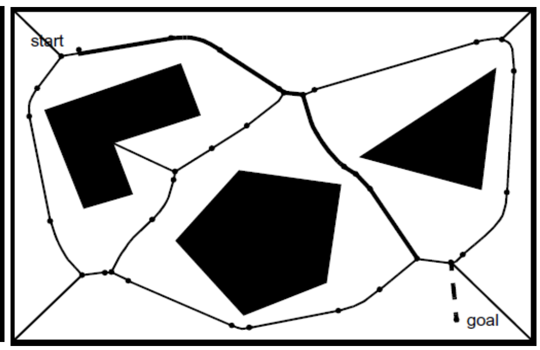

Fig 2. Voronoi Diagram

In the roadmap approach, the nodes of the graph are the start and destination points whereas the vertices of the configuration space are obstacles (polygons). All nodes which are visible from each other are connected by straight-line segments, defining the roadmap (path). Bacaa et al. (2011) have proposed an indoor appearance-based mapping and a localization approach for mobile robots based on the human knowledge model, which was used to construct a Feature Stability Histogram (FSH) at each node in the robot topological map. In another study, Amigoni and Caglioti (2010) presented a mapping system utilizing an information-based exploration strategy that allows a mobile robot equipped with a laser range scanner to efficiently build the map of an unknown environment. Remazeilleshas and Chaumette (2007) developed a new control method for robot navigation, in which an image path is first extracted from visual memory describing the environment. Then this image path defines the visual features that the camera should observe during the motion. Kim and Cho (2006) have investigated a new 3D sensor system for environment recognition needed for mobile robots with less scanning time using multi-stripe laser pattern projection, composed of the laser pattern projector of generating multiple line stripes and two cameras with laser band-pass filters.

2.2 Cell Decomposition Method

The basic idea behind cell decomposition is to discriminate between geometric areas or cells that are free and areas that are occupied by obstacles. An important aspect of the cell decomposition method is the placement of boundaries between cells. If boundaries are placed as a function of the structure of the environment, such that the decomposition is loss-less, then the method is termed exact cell decomposition. If decomposition results in an approximation of the actual map, the system is called as approximate cell decomposition method.

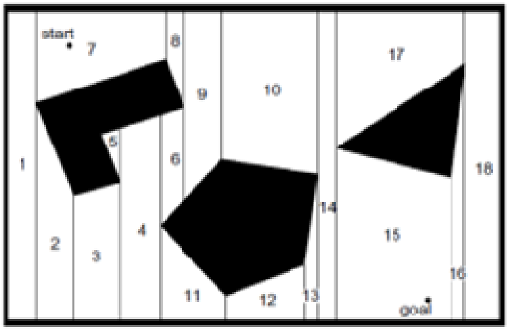

Fig 3. Exact cell decomposition

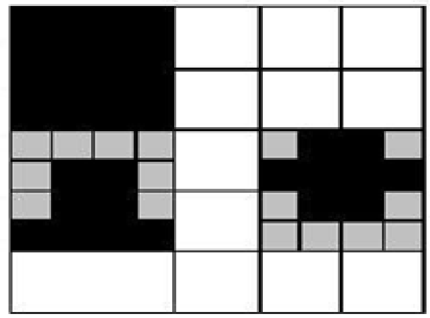

Fig 4. Approximate Cell decomposition

Shojaeipour et al. (2010) presented a novel method for mobile robot navigation by visual environments. This approach implemented on motion robots verifies the shortest path via the Quad-tree Decomposition method (QD). Rekleitis et al. (2002) presented an algorithm on a team of mobile robots for the complete coverage of free space. They developed a new multi-robot coverage algorithm similar to single robot planar cell-based decomposition. This method permits planning to occur for a team of robots in a 2D configuration field.

2.3 Artificial Potential Field Method

The application of artificial potential fields to obstacle avoidance was first developed by Khatib (1985). The concept is that artificial forces generated by the obstacles and target, are applied to the robot in order to move about the environment collision-free. The obstacles and goal position are assigned repulsive and attractive forces respectively. This motivates the robot to move towards the goal while being 'pushed' away from the obstacles. The main disadvantages of the potential field methodology are that trap situations can occur due to the presence of local minima.

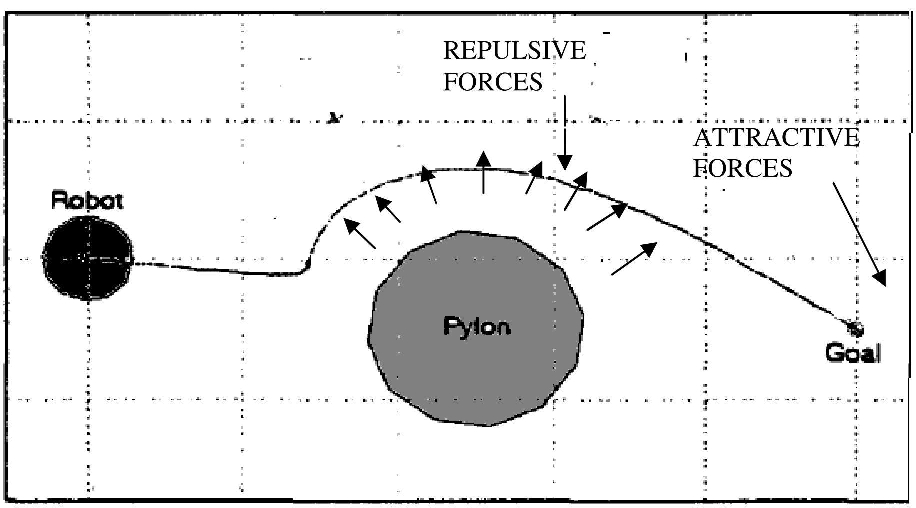

Fig 5. Artificial Potential Field Method

A new form of repelling potential was proposed by Sfeir et al. (2011) in order to reduce oscillations and avoid conflicts when the target is close to obstacles. According to them, a rotational force is integrated as well, allowing for a smoother trajectory around the obstacles which leads to safe robot navigation. Instead of a single mobile robot, Kang et al. (2011) presented multi mobile robots that can perform complex tasks using a simple robot system and algorithm. In this study, based on the energy method, a driving algorithm is applied to the individual robot in a group. This makes a cluster form automatically and suggests a cluster as the automatic driving method for stably reaching the target point. A modified potential field method for robot navigation was described by Pradhan et al. (2006). They formulated a new potential function that configures a free space, which is free from any local minima irrespective of the number of repulsive points (obstacles) in the configured space. The main disadvantages of the APF approach are that:

- Trap situations occur due to local minima.
- No passage between closely spaced obstacles.
- A local minimum in narrow passages as robot experiences forces from both sides.

3. Heuristic Methods

3.1 Fuzzy logic controller technique

Fuzzy logic provides a formal technique representing and implementing human experts' heuristic knowledge and perception-base actions, and was developed by Prof. Zadeh in1965. In fuzzy logic controller behavior based navigation, the problem is broken down into simpler tasks (independent behaviors) and each behavior is composed of a set of fuzzy logic rule statements intended at achieving a well-defined set of objectives. Pradhan et al. (2009) have used different fuzzy controllers to control the motion of multiple mobile robots in a highly cluttered environment. They have given right obstacle distance, left obstacle distance; front obstacle distance and heading angle input to the controller, and the output the from controller are left wheel velocity and right wheel velocity of mobile robot.

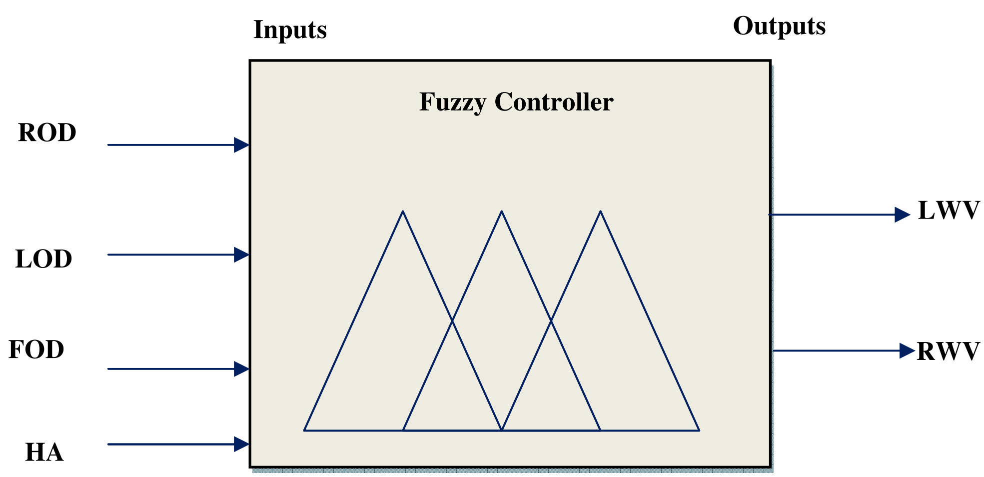

Fig 6. Fuzzy controller developed by Pradhan et al. (2009)

Based on the fuzzy mechanism, the fuzzy control rules are defined in general form as follows Pradhan et al. (2009)

If (LD is LD_i and FD is FD_j and RD is RD_k and HA is HA_m) then LV is LV_{ijkm} and RV is RV is RV_{ijkm} (1)

Where i=1 to 3, j= 1 to 3, k= 1 to 3 and m=1to3 because LD, FD, RD and HA have three membership functions each.

Finally, they concluded that the fuzzy logic controller utilizing Gaussian membership is best among techniques for navigation of multiple mobile robots. The development of a computer simulation program based on fuzzy logic for navigation of mobile robots in the presence of obstacles was described by Abiyev et al. (2010). They found that both traditional and fuzzy logic-based algorithms gave good obstacle-avoiding results, although their implementation details varied greatly. The mobile robot navigation control system using fuzzy logic was presented by Parhi et al. (2005), with two parts. The first part is a fuzzy logic controller that combines fuzzy rules to direct robot steering to avoid obstacles in its path and the second part is a Petri Net model implementing crisp rules for preventing collision between different mobile robots. In this research, issues of individual behavior design and action coordination of the behaviors of mobile robot using fuzzy logic were addressed by Fatmi et al. (2006). A layered approach is employed in this work in which a supervision layer based on context makes a decision as to which behavior(s) to process (activate) rather than processing all behavior(s) and then blending the appropriate ones, as a result saving time and computational resources. Fuzzy logic-based real-time robot navigation in an unknown environment with dead ends was presented by Wang and Liu (2008). Fuzzy logic is used here to implement behavior design and coordination, which indeed is a good tool to model human expertise and effectively handle errors derived from sensor data and self-localization.

3.2 Neural Network technique

Robot motion in the real-world environment was planned through the dynamic activity landscape of the artificial neural network without explicitly searching free space or collision-free paths, without explicitly optimizing any cost function, without any prior knowledge of the dynamic environment, without any learning process, and without any local collision checking procedures. Developing autonomously an ideal control action arrangement for the Autonomous Guided Vehicle (AGV) system based on Artificial Neural Networks was discussed by Patiln and Carelli (2004). The principal objective in this paper is to autonomously design an optimal controller that can control the center of the vehicle through a number of via nodes in a particular sequence using a minimum amount of time. Engedy and Horvath (2009) described a dynamic artificial neural network based on the mobile robot motion and path planning system. According to them, the motion controlling ANN is trained online with an extended back propagation through time algorithm, which uses potential fields for obstacle avoidance and the paths of moving obstacles predicted by other ANNs for better obstacle avoidance. The Intelligent Neuro-Controller for Navigation of Mobile Robot was presented by Singh and Parhi (2009). They gave right obstacle distance, left obstacle distance, front obstacle distance and target angle input to the neural controller, and the output from the controller was the steering angle of mobile robot. They also used a four layer neural network to design and develop the neuro-controller to solve navigation problems of mobile robots. Xiao et al. (2007) considered a multi-layer feed forward artificial neural network (ANN) to construct a path planning controller by its powerful nonlinear functional approximation.

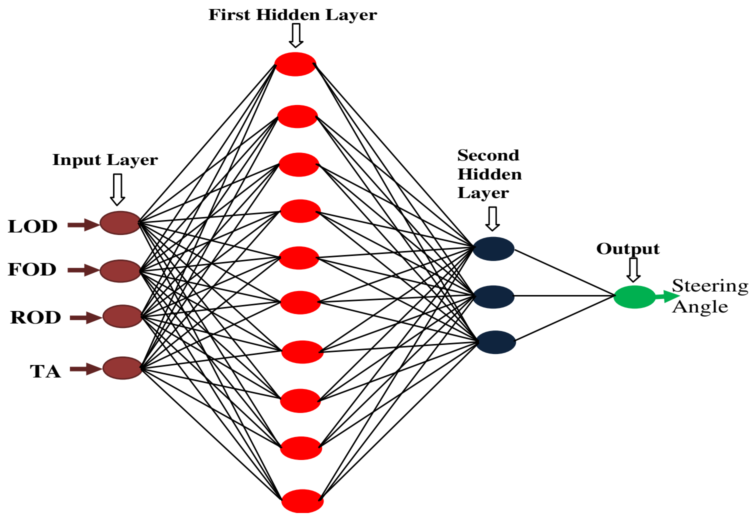

Fig 7. Neural controller developed by Singh et al.(2009**)**

3.3 Neuro- Fuzzy technique

Humans are remarkably competent in implementing a wide variety of physical and mental tasks without any explicit measurements or computations. Fuzzy logic and neural networks provide a means to accomplishing this target. Fuzzy logic delivers a proper methodology for representing and implementing human expert heuristic knowledge and perception-based 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-THEN rules, coupled with easily understandable and natural linguistic representations. Neural networks can be trained using different patterns as required. The trained neural network can be efficiently used for problem-solving for different field configurations. Neuro-fuzzy techniques for navigation of multiple mobile robots was employed by Parhi et al. (2006). Their neuro-fuzzy technique comprises a neural network, performing as a preprocessor for a fuzzy logic controller. They also showed how this could be achieved using a controller based on the Takagi-Sugeno design and a radial basis function neural network for its implementation.

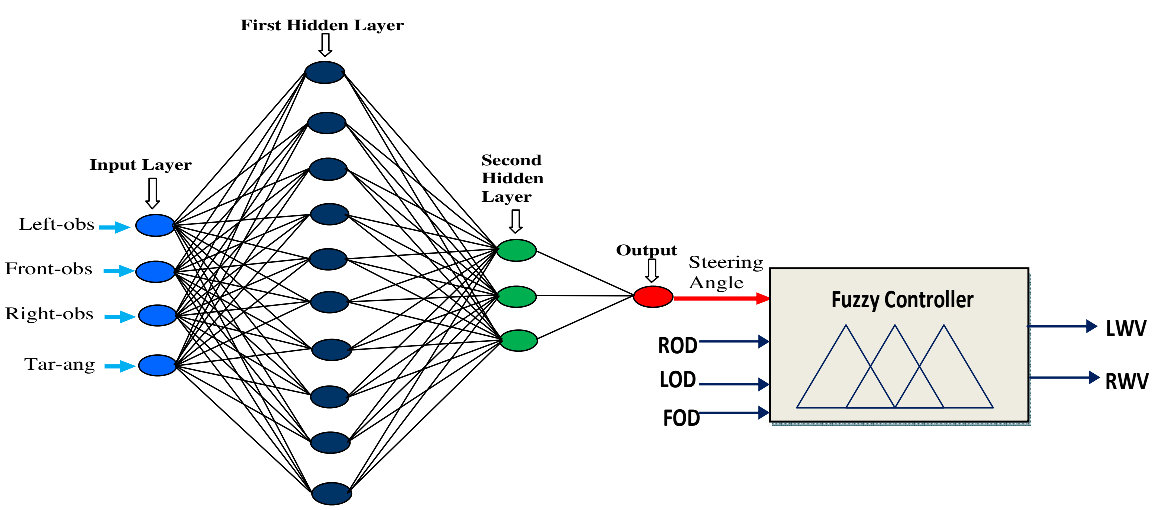

Fig 8. Neuro-Fuzzy controller developed by Parhi et al. (2006)

The inputs to the hidden neurons which generates outputs given by Parhi et al. (2006);

$$y_j^{[lay]} = f(V_j^{[lay]}) \tag{2}$$

Where
$$V_j^{[lay]} = \sum_i W_{ji}^{[lay]} \cdot y_i^{[lay-1]}$$
Lay=2, 3
j= label for jth neuron in hidden layer 'layer'
i= label for ith neuron in hidden layer 'lay-1'
$W_{ji}^{[lay]}$-Weight of the connection from neuron I in layer 'lay-1' to neuron in layer 'lay'

In their review, Singh et al. (2009) discussed navigation control of mobile robots using adaptive neuro-fuzzy inference system (ANFIS) in a real-world dynamic environment. A learning algorithm based on neural network technique was developed to tune the parameters of fuzzy membership functions, which smooth the trajectory generated by the fuzzy logic system.

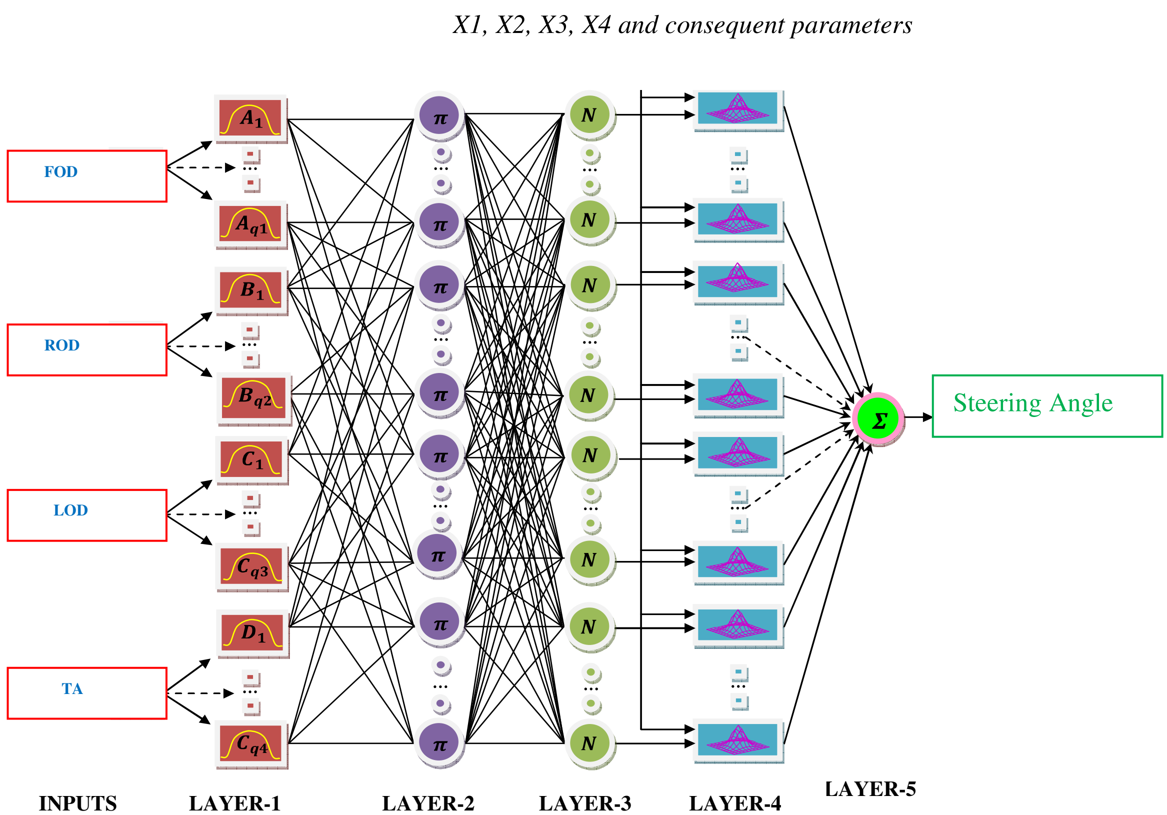

Fig 9. ANFIS architecture for robot navigation by Singh et al. (2009)

A fuzzy-neural network-based intelligent task planning and selection mechanism for a mobile robot in a soccers system was presented by Jolly et al. (2010). In this system a five layer fuzzy neural network system is trained through error back propagation learning algorithm to impart a strategy based on action selection. Wang et al. (2004) considered a neuro-fuzzy technique to produce autonomous navigation of a mobile robot in an unknown environment. The distance information obtained from the sensors is processed by the proposed neuro-fuzzy controller to adjust the velocities of the differential-drive system of the mobile robot.

3.4 Genetic Algorithm technique

The implementation of Genetic Algorithm to the mobile robot path planning problem needs the development of an appropriate 'chromosome' for the robot path, a path direction mechanism, a methodology to cater for obstacle avoidance and an appropriate constraint definition providing mechanisms to minimize path length as well as provide collision-free paths. The use of genetic algorithms (GA) allows the minimization of a nonlinear cost function in real time, avoiding the complex training process of the neural networks and fuzzy algorithms. The determination function of a chromosome measures the objective cost function. The distance of a path indicated by the chromosome is used to find its fitness, since fitness should increase as distance decreases. Thus, the fitness function (F) of a feasible path is evaluated (Nagib and Gharieb, 2004).

$$F = \begin{cases} \dfrac{1}{\sum_{i=1}^{m+1} d(P_i, P_{i+1})} & \text{Feasible path} \\ 0 & \text{Infeasible path} \end{cases} \tag{3}$$

where d (P_i,P_{i+1}) is the segment length between a point P_i and P_{i+1} in chromosome of length m+2 points. m is the number of static obstacles.

Yun et al. (2010) have proposed an improved genetic algorithm of optimum path planning for mobile robot navigation. They introduced an obstacle avoidance algorithm and a Distinguish Algorithm (DA) to generate the initial population in order to improve the collision-free path planning efficiency and to select only the feasible paths during the development of the genetic algorithm. Aiming at the existent problem of global path planning for mobile robots, a path planning based on chaos genetic algorithm was developed by Gao et al.(2008). First, they designed a fitness function and the chaos operation was added to the genetic algorithm to improve the efficiency of the genetic algorithm optimization. It also avoided trapping in local optima. Castillo et al. (2007) described the use of a genetic algorithm (GA) for the problem of offline point-to-point autonomous mobile robot path planning. They also discussed useful performance measures and simulation results of the conventional GA and of the MOGA (multi-objective genetic algorithm). Algorithms for global path planning to a target for a mobile robot in a known environment have been presented by Kang et al. (1995). The algorithm uses the modified quadtree data structure to make a database of the environment and utilizes a genetic algorithm to generate an optimal path for the mobile robot to move in various configuration fields.

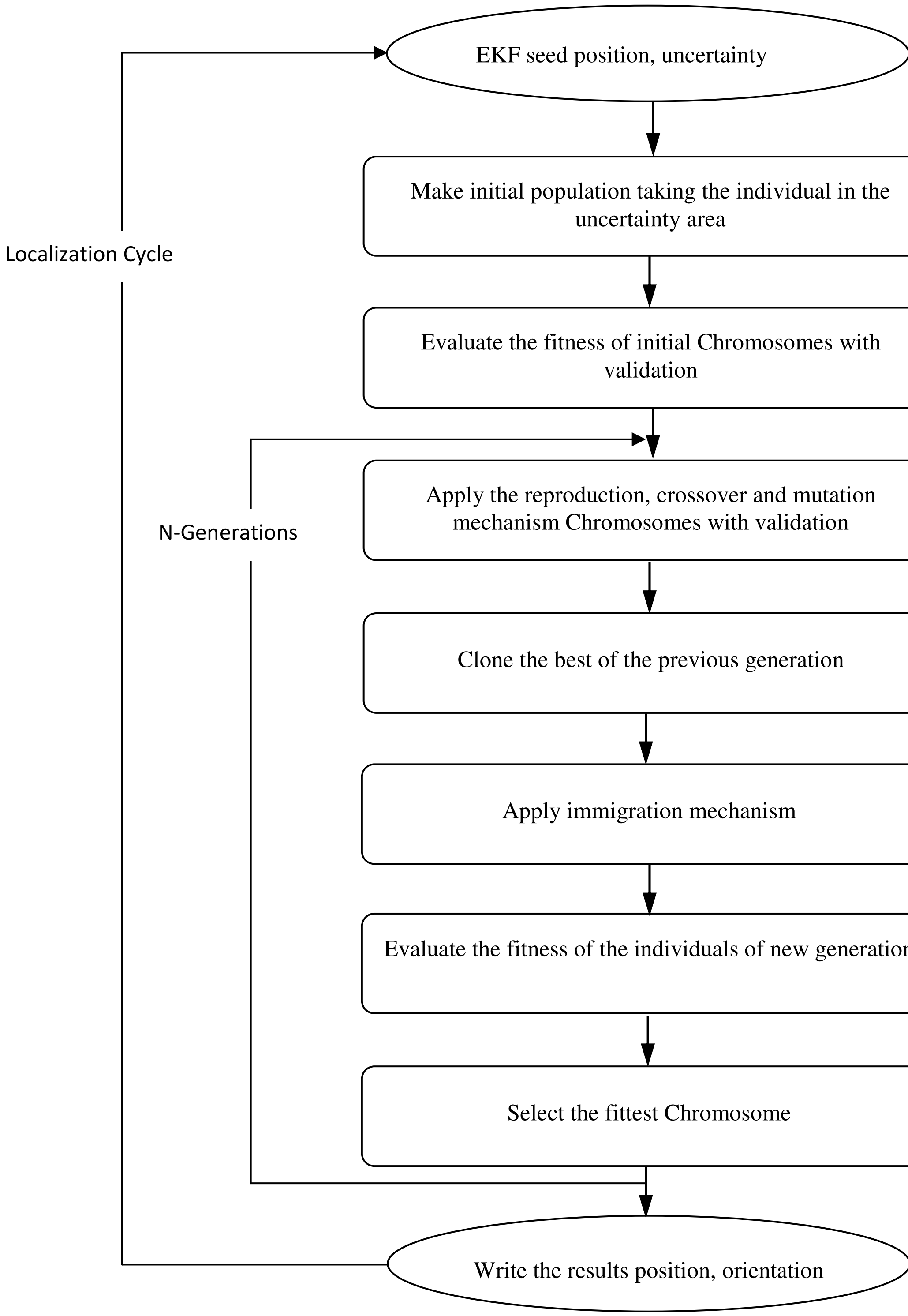

Fig 10. Genetic optimization flowchart

3.5 Ant Colony Optimization technique

The objective of the Ant Colony Optimization (ACO) algorithm is to search for an optimal path in a field, to solve many combinatorial optimization problems. In case of any obstacles present in their way, ants move along the contour of the obstacle on either sides and find their path to the food source. An artificial ant makes movements based on the attraction of pheromone. As the concentration of pheromones are more along the shorter path, ants accumulate more pheromone in a given time interval along the shorter path. The direction of the mobile robot has eight selections shown in Fig. 11--forward, backward, right, left, right-up, right-down, left-up and left down. The mobile robot must avoid obstacles to select an optimization motion path moving to the target position in the unknown environment.

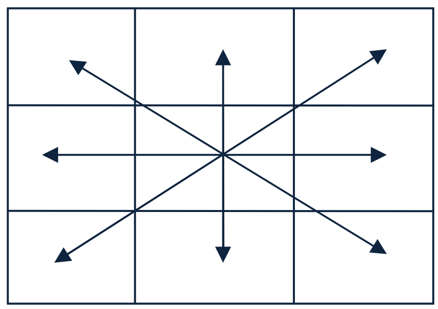

Fig 11. Different motion of Ant motion direction

In this article, the aim is to find the optimum path of a mobile robot between source and target using the Ant Colony Optimization algorithm. At time t, the transition probability of moving from node i to j for ant k is (Chen et al. 2011)

$$p_{ij}^{k} = \frac{\tau_{ij}^{a}\eta_{ij}^{\beta}}{\sum_{l\in\psi}\tau_{ij}^{\alpha}\eta_{ij}^{\beta}}, \quad j \in \psi \tag{4}$$

In this function, ψ is the set of accessible neighbor nodes of i, η is the local visibility, τ is the pheromone intensity, and α and β are the constant parameters that find the relative ant. After the ants in the algorithm end their tours, the pheromone trail amount will update according to the following formula:

$$\tau_{ij}(t+h) = \rho\tau_{ij}(t) + \sum_{k=1}^{w}\Delta\tau_{ij}^{k} \tag{5}$$

Where ρ is the pheromone evaporation rate, and

$$\tau_{ij}^{k} = \begin{cases} \dfrac{Q}{L_k} & \text{if } k^{\text{th}} \text{ ant use edge (i, j) in its travelling} \\ 0 & \text{otherwise } 0 \end{cases} \tag{6}$$

In (6), q is a constant and L_k is the length of path found by the k-th ant.

The Path Planning Method for Mobile Robot Based on Ant Colony Optimization algorithm was presented by Cen et al. (2011). Here environment constraints and path length were integrated in the fitness function which was developed by neural network and the path nodes were viewed as an ant, so with the quality of ACO algorithm, the best path was found. In this study, Zeng Bi et al. (2009) proposed a new method of robot planning navigation using an improved Ant Colony Optimization algorithm. This method first utilizes the fuzzy logistic knowledge base description to establish the fuzzy environment model of robot local area, and then adopts the improved ACO algorithm to rapidly search each local optimal path. Yang et al. (2010) designed an improved globally optimal path planning method for mobile robots based on the Ant Colony System algorithm (angle priority strategy). They present an ACO algorithm based on dynamic partitioning and new heuristic function involved in angle to optimize the sub-optimal path obtained by Dijkstra algorithm. Optimal path planning of mobile robots using the ant colony optimization (ACO) algorithm was developed by Chia et al. (2010). They implemented four variety type obstacles to program the motion path using the ant colony optimization algorithm, and search the optimization path of the mobile robot moving to the goal position.

3.6 Particle Swarm Optimization technique

The main aim of the PSO algorithms is to determine the solution of an optimization problem in the search configuration field. Path planning for each robot has to be determined in order to avoid collisions between the robots while they are in motion. Several undesirable situations like congestion and deadlocks may obstruct the progress path for the robots. In such conditions, use of the particle swarm optimization algorithm can be beneficial for efficient path planning and avoiding undesirable situations in the real world environment. The mathematic description of PSO is as follows (Qi et al.2008)

Suppose the dimension of the searching area is D, the number of the particles is n. Vector $X_i = (x_{i1}, x_{i2}, x_{i3} \ldots\ldots\ldots x_{iD})$ notates the position of the i^{th} particle and $pBest_i=(p_{i1}, p_{i2}, p_{i3} \ldots\ldots p_{iD})$ is its best position searched by now, and the whole particle swarm's best position is represented as gBest=($g_l, g_2, \ldots, g_D$).Vector $V_i=(v_{i1}, v_{i2}, v_{i3} \ldots\ldots\ldots v_{iD})$ is the position change rate of the i^{th} particle. Each particle updates its position according to the following formulas:

$$v_{id}(t+1) = wv_{id}(t) + c_1 rand().[p_{id}(t) - x_{id}(t)] + c_2 rand()[g_d(t) - x_{id}(t)] \quad (7)$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1), \quad 1 \le i \le n \quad 1 \le d \le D \quad (8)$$

where c_1 and c_2 are positive constant parameters called acceleration coefficients. Rand() is a random function with range [0, 1]. The inertia weight, w is a user-specified parameters that controls, with c_1 and c_2 the impact of previous historical values of particle velocities on its current one.

Tang and Eberhard (2011) investigated the concept of collective coordinated movement under constraints and obstacles in the real-world environment. They have used a particle swarm optimization (PSO)-based algorithm to optimize the motion planning for swarm mobile robots in various fields. Li and Chen (2005) presented a novel design for mobile robot path planning using particle swarm optimization (PSO). It shows that path planning generated with this algorithm is smooth with low computational cost to avoid obstacles, so that mobile robots can use a smooth control strategy to track the trajectory. Chen and Yangmin (2010) presented an improved path planning technique named stochastic particle swarm optimization (S-PSO) for a mobile robot with obstacle avoidance. They developed a combined fitness function for evaluating the route length of a path and the performance of obstacle avoidance. A modified PSO algorithm based on a danger degree map (DDM) was presented by Yinghua and Hongpeng (2011) to solve the static path planning problem for the mobile robot. They designed a non-equidistant distributed PSO method based on the change rate of the barrier, which can improve the adaptability of the path planning to the environment.

3.7 Artificial Immune Network technique

We now discuss reactive immune networks inspired by the biological immune system for robot navigation (target-reaching and obstacle-avoidance) in stationary environments. An antigen here is the environment perceived by the robot's sensors and camera at any given time and condition. Antigen presentation proceeds from information extraction to the perception translation and then the antigen deliver the reports about the current location and position of the mobile robot and obstacles. As the antigen is a combination of various environment situations, it can interact with various antibodies (obstacle) but only one antibody can bind to the antigen. Farmer et al. (1986) proposed that Jerne's hypothesis be modeled as a differential equation simulating the changing concentrations of antibodies with respect to the stimulatory and suppressive effects and the natural death rate. Their model supposes that in a system with N antibodies $[x_1,x_2,x_3\ldots\ldots x_N]$ and L antigens $[y_1,y_2,y_3,\ldots\ldots y_L]$, the differential equation governing rate of change in concentration C of antibody x_i is given by

$$\dot{C}(x_i) = b[\sum_{j=1}^{L} U_{ij} C(x_i) C(y_j) - k_1 \sum_{m=1}^{N} V_{im} C(x_i) C(x_m) + \sum_{p=1}^{N} W_{ip} C(x_i) C(x_p)] - k_2 C(x_1) \qquad (9)$$

The first sum in the square bracket shows the stimulation of antibody x_i in response to all antigens. Here, U represents a matching function between antibodies and antigens and the $C(x_i)C(y_j)$ terms model that the probability of a collision between them is dependent on their relative concentrations. The second sum states dominance of antibody x_i in response to all other antibodies. V is a function that models the degree of recognition for conquest and $C(x_i)C(x_m)$ is the collision factor. The third sum models the stimulation of antibody x_i in response to the other antibodies. The function W represents the degree of recognition for stimulation and $C(x_i)C(x_p)$ models the collisions. The variable k_1 allows possible inequalities between inter-antibody stimulation and suppression, but if k_1 = 1 these forces are equal. The k_2 term outside the brackets is a damping factor, which denotes the tendency of antibodies to die in the absence of interactions, with constant rate. Variable b is a rate constant that simulates both the number of collisions per unit time and the rate of antibody production when a collision occurs.

Mobile robot path planning based on artificial immune network (AIN) was proposed by Xuanzi Hu and Qingui Xu (2007). In their proposed method, they employed a mobile robot environment in the U-shape obstacle and an environment with seven obstacles, respectively. A reactive immune network (RIN) was employed by Luh and Cheng (2002) for mobile robot navigation within unknown environments. In this study they tried to explore the principle of an immune network focusing on self-organization, adaptive learning capability, and immune feedback. Singh and Maulik (2008) described a learning process of a mobile robot which takes speech as input commands and performs navigation tasks through a distinct man-machine interaction with the application of learning based on the AIS. To solve the path planning in complicated environments, improved artificial immune network strategies for mobile robot path planning was presented by Yuan et al. (2010). They took the environment surrounding the robot and robot action as antigen and antibody respectively. An artificial immune network was constructed through the simulation, and finally the results concluded that an optimal path is found by AIS system.

4. Concluding Remarks

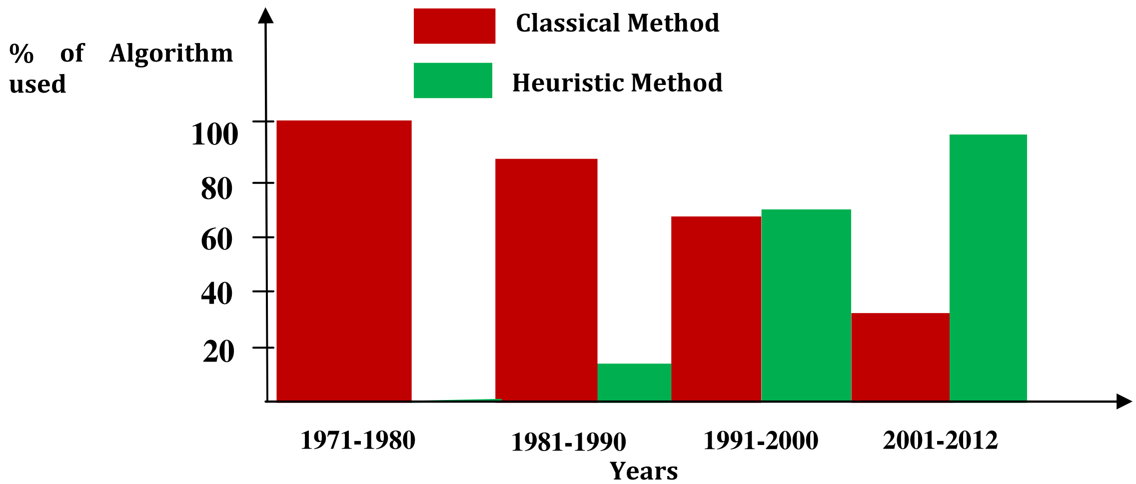

Fig 12. Application of classical and heuristic Algorithms

This review paper describes the various techniques applied for navigation of an intelligent mobile robot. After surveying about 1000 papers of current research it was found that the heuristic approaches (Fuzzy logic, Neural Network, Neuro-Fuzzy, Genetic Algorithm, Particle Swam Optimization, Ant Colony Optimization and Artificial Immune System) specially hybridized technique (Neuro-Fuzzy) gave suitable and effective results for mobile robot navigation (target-reaching and obstacle-avoidance) in an unknown and dynamic environment compared to classical techniques. Using the heuristic approach, the mobile robot can navigate safely among the obstacles without hitting them and reach the predefined target point. These techniques are also helpful for the solution of the local minima problem. Future work is needed to survey other heuristic techniques used for path planning for a single mobile robot as well as for multiple robots.

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