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Path Planning Techniques for Navigation of Mobile Robot: A survey

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Abstract: *In this survey we have presented the detailed survey of path planning algorithms and techniques available so far. All the available methods and techniques are systematically understand and presented in the proper manner in order to make a research gap in the available techniques. The path planning algorithms are applied on static as well as in the dynamic environment. We also present the techniques based on these environments. The Approaches are classified into classical and reactive approaches. The classical approaches such as cell decomposition (CD), roadmap approach (RA), artificial potential field (APF); reactive approaches such as genetic algorithm (GA), fuzzy logic (FL), neural network (NN), firefly algorithm (FA), particle swarm optimization (PSO), ant colony optimization (ACO), bacterial foraging optimization (BFO), artificial bee colony (ABC), cuckoo search (CS), shuffled frog leaping algorithm (SFLA) and other miscellaneous algorithms (OMA) are considered for study. The navigational algorithms are applied on static as well as in the dynamic environment for analysis and it has been conclude that the reactive methods are more suitable for path planning and navigation of mobile robot.*

I. Introduction:

Initially, the application of a mobile robot was limited tomanufacturing industries only. But nowadays, it is commonly usedin the fields of entertainment, medicine, mining, rescuing, education,military, space, agriculture and many more. While performingthe task of navigation, the robot is equipped with many intelligentequipment's which are required to model the environment andlocalize its position, control the motion, detect obstacles, and avoidobstacles by using navigational techniques. Safe path planning (bydetecting and avoiding the obstacles) from the initial position tothe target position is the most important function of any navigational

technique. Therefore, the proper selection of the navigationaltechnique is the most important step in the path planning of a robotwhen working in a simple and complex environment. At present,many techniques have been developed by various researchers inthe field of mobile robot navigation and it is the most researchedtopic of today. Mobile robot navigation is classified into three categories:global navigation, local navigation and personal navigation.The capability to define the position of elements in theenvironment with respect to the reference axis, and to stir towardsthe pre-decided goal, is global navigation. Local navigation dealswith the identification of the dynamic conditions of the environmentand the establishment of positional relationships amongvarious elements. To handle the various elements of the environmentrelative to each other, by considering their position, is personalnavigation. The basic steps involved in the functioning of therobot [1] are presented in Fig. 1.

In this paper, the navigation strategy has been classified basedon the prior information of the environment required for pathplanning. It is broadly classified as global navigation and local

navigation. In global navigation, the mobile robot must require theprior information of the environment, obstacle position and goalposition whereas in local navigation the mobile robot does notrequire the prior information of the environment. Global navigation strategy deals with a completely known environment.Local navigation strategy deals with the unknown and partiallyknown environment. The path planning algorithm for a knownenvironment is based on a classical approach such as CD, RA, andAPF. These algorithms are traditional and have limited intelligence.Local navigational approaches are known as reactive approaches asthey are more intelligent and able to control and execute a planautonomously.

II. Navigational techniques used for mobile robot navigation

2.1 Traditional approaches:

Initially, classical approaches were very popular for solvingrobot navigational problems because in those days artificiallyintelligent techniques had not been developed. By using classicalapproaches for performing a task, it is observed that either a result would be obtained, or it would be confirmed that a result does notexist. The major drawback of this approach is high computationalcost and failure to respond to the uncertainty present in the environment;therefore, it is less preferred for real-time implementation.CD, RA, and APF are some of the classical approaches which arereviewed here.

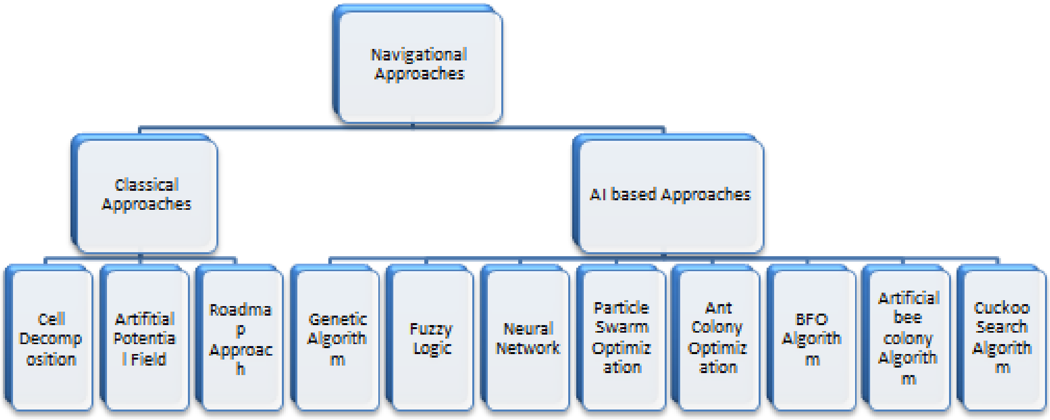

Figure-1: Mobile robot Navigational Approaches

2.1.1 Cell decomposition (CD) approach

This approach divides the region into non-overlapping grids(cells) and uses connectivity graphs for traversing from one cell toanother to achieve the goal. During traversing, pure cells (cellswithout obstacles) are considered to achieve path planning fromthe initial position to the target position. Corrupted cells (cellscontaining obstacles) present in the path are further divided intotwo new cells to get a pure cell and this pure cell gets added to thesequence while determining the optimal path from the initial positionto the target position. In the CD approach, the initial positionand target position are represented by the start and end cells. The CD approach is classified as adaptive, approximateand exact.

2.1.2. Roadmap approach (RA)

The RA is also known as the highway approach. It is the way toget from one place to another and the connection among the freespaces is represented by a set of one-dimensional curves [22].When the roadmap is built, then it is utilized as an arrangement ofhomogeneous ways where the planner will seek to discover theideal arrangement. Here, nodes play an important role in gettingthe desired path for the robot. The RA is used to find the shortest path from the robot's initial position to its target position; Voronoiand visibility graphs are used to develop the roadmap. The visibilitygraph method connects the initial and the goal position with nodesfrom the map. This methodis also used for an environment with polygonal obstacles in whichthe vertices of the polygon are represented by the nodes and edgesas a connector between the nodes [24]. The Voronoi diagram is another roadmap algorithm used for the path planning of therobot. This method divides the region into sub-regions where alledges of the figure are constructed using equidistant points fromthe adjacent two points on the obstacle's boundaries. The application of theVoronoi diagram in the field of mobile robot navigation aroundobstacles is presented.

2.1.3 Artificial potential field (APF) approach

In APF approach, the goal and obstacles act likecharged surfaces and the total potential creates the imaginary forceon the robot. This imaginary force attracts the robot towards thegoal and keeps it away from an obstacle. Here, therobot follows the negative gradient to avoid the obstacle and reachthe target point. Application of this method for mobile robot navigationis presented by Garibotto et al. [39]. A new obstacleavoidance strategy in an unknown environment is discussed byKim et al. [40] by using APF. They used a harmonic function to avoida local minimum problem. Borenstein et al. [41] have also presenteda solution to the problem of the local minima conditions. Inthis research, they have considered the dynamic properties of robotnavigation.

2.2 Artificial Intelligence based Approaches: AI based approaches are more popular as they havethe ability to deal an uncertain environment quickly with lesscomputational effort.

2.2.1 Genetic algorithm (GA)

This is a popular search-based optimization tool which followsthe principle of genetics and natural selection. Its application to the field of computerscience was presented first by Holland [56] in 1975. Nowadays, ithas wide application in all areas of science and technologyincluding robot navigation. Inthis approach, the population (different individuals characterizedby genes) must be allotted for the given problem and every memberof the population is assigned with a fitness value depending uponthe objective function. These individuals are selected as per theirfitness value and allowed to pass their genes to a new generation bycrossover. The mutation maintains the diversity in population andprevents premature convergence. Finally, the algorithm is terminatedif the population has converged. Although the GA is randomizedin nature to some extent, its performance is better as theycan exploit historical information as well when compared to arandom local search.

2.2.2Fuzzy logic (FL)

The concept of FL was given first by Zadeh [77] in 1965 and waslater on used in all the fields of research and development. It is usedin situations where there is a high degree of uncertainty,complexity, and nonlinearity. Pattern recognition, automatic control,decision making, data classification are a few of them. Thehypothesis of the FL framework is encouraged by the noteworthyhuman ability to process perception-based information. It uses thehuman-supplied rules (If-Then) and converts these rules to theirmathematical equivalents. This streamlines the job of the systemdesigner and computer for getting more correct information aboutthe way systems perform in the real world and hence it is used forpath planning of a mobile robot.

2.2.3Neural network (NN)

Artificial NN is an intelligent system which consists of manysimple and highly interconnected processing elements. These elementstransfer the information by their capability of dynamic stateresponse to external inputs. The NN is basically shown by wellorganizedlayers of interconnected nodes. The nodes consist of anactivation function. The input layer of the NN mechanism recognizesthe patterns. These patterns thencommunicate to hidden layers for actual processing via a system ofweighted connections. The hidden layers connect with the outputlayer to give the required answer. NN characteristics such asgeneralization ability, massive parallelism, distributed representation,learning ability and fault tolerance make it useful in the field ofmobile robot navigation.

2.2.4 Particle swarm optimization (PSO)

This is a nature-based metaheuristic algorithm which adopts thesocial behavior of creatures such as fish schools and bird flocks. It isdeveloped by Eberhart and Kennedy [117] in 1995 and it is a rapidlygrowing optimization tool for solving the various problems of engineeringand science. The PSO mimics the behavior of the socialanimal but does not require any leader within the group to reachthe target. When the flock of birds goes to find food, they do notrequire any leaders; they go with one of the members who is at thenearest position to the food (Fig. 15). In this way, the flock of birdsreaches their required solution by proper communication with themembers of the population. The PSO algorithm consists of a groupof particles where each particle represents a potential solution.Nowadays, PSO is widely used in the field of mobile robot navigation.

2.2.5 Ant colony optimization (ACO)

This is a swarm intelligence algorithm which is a population-basedapproach used to solve the combinatorial optimization problem.The ACO algorithm originated from the behavior of ants and itsability to find the shortest path from their nest to a food source. The ACO algorithm is already applied to various fields ofscience and engineering such as job-shop scheduling, vehiclerouting, quadratic assignment problem, travelling salesman problems,graph coloring and many more. Nowadays, the ACO is used tohandle the mobile robot navigation problem for obstacle avoidanceand effective path planning.

2.2.6 Bacterial foraging optimization (BFO) algorithm

Passino [123] in 2002 presented the new nature-inspired optimizationalgorithm which is originated from the behavior of anE. coli and M. Xanthus bacteria. These bacteria search for nutrientsby making the best use of energy achieved per unit time. The BFOalgorithm is featured by chemotaxis that perceives chemical gradientsby which bacteria communicate specific signals with eachother. It has four basic principles such as chemotaxis, swarming,reproduction and elimination, and dispersal. The behavior of thebacteria [124] for searching the nutrient region is presented asbelow and explained in Fig. 19.

_ Bacteria always travel in search of more nutrient regions on themap. Bacteria with sufficient food have a longer life and splitinto two equal parts whereas bacteria in the lesser nutrientregion will disperse and die.

_ Bacteria present in the more nutrient region are attracted toothers by chemical phenomenon and those who are in the lessernutrient region give a warning signal to other bacteria using aspecific signal.

_ Bacteria get a highly nutrient region on the map.

_ Bacteria are dispersed again in the map for a new region ofnutrients.

2.2.7 Artificial bee colony (ABC) algorithm

The ABC algorithm is a swarm-based intelligent approachinspired by the activities of honey bees in search of foodand is proposed by Kharaboga [125]. The ABC algorithm is apopulation-based strategy consisting of a population of inherentsolutions (food source for bees). It is relatively simple in use, fast inprocessing and is a population-based stochastic search approach inthe field of swarm algorithms.

2.2.8 Cuckoo search (CS) algorithm

The CS algorithm is a metaheuristic algorithm presented byYang and Deb [136] in 2009. The algorithm is based on the lazybehavior of some cuckoos for laying their own eggs in the nests ofother host birds. According to Yang, the algorithm follows threebasic rules for an optimization problem as follows.

_ Each cuckoo lays one egg at a time in a randomly chosen nest.

_ The best nests with high-quality eggs will be carried over to thenext generation.

_ The number of available host nests is fixed, and the egg laid by acuckoo may be discovered by the host bird with a probability pa2(0, 1).

In this case, the host bird can either get rid of the egg orsimply abandon the nest and build a completely new nest.The CS algorithm is an improved method because it increasesthe convergence rate and efficiency hence it is widely accepted invarious engineering optimization problem; mobile robot navigationis one area where performance and computational time is to beoptimized.

III. Conclusion:

After systematicall presenting the survey on mobile robot navigation methodologies, all the methods are classified into two categories. They are Traditional and Artificial Intelligence based approaches. The key points ofthe study are as follows.

_ Artificial based approaches perform better than classical approachesbecause they have a higher capability to handle uncertaintypresent in the environment.

_ Artificial based approaches are most preferably used for real-timenavigation problems.

_ Very few research papers are published based on a dynamicenvironment compared with a static environment.

_ In a dynamic environment, there are many fewer papers onnavigation of a robot for a moving goal problem compared witha moving obstacle problem.

_ To date, most papers demonstrate only a simulation analysis;papers on the real-time application are much fewer.

_ Papers on the navigation of multiple mobile robot systems arefew compared with the single mobile robot system.

_ There are many fewer papers on hybrid algorithms comparedwith those on standalone algorithms.

_ There is great scope in applying newly developed algorithmssuch as SFLA, CS, IWO, BA, HS, DE, BFO, ABC and FA for navigationin an unknown complex environment in the presence ofmaximum uncertainty and these can be used to develop newkinds of hybrid approaches.

_ The performance of classical approaches can be improved byhybridizing with Artificial basedapproaches.

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