International Journal of Physical Sciences Vol. 7(9), pp. 1314 - 1320, 23 February, 2012
Available online at http://www.academicjournals.org/IJPS
DOI: 10.5897/IJPS11.1745
ISSN 1992 - 1950 ©2012 Academic Journals

Review

Optimal path planning of mobile robots: A review

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Accepted 30 January, 2012

Mobile robots are increasingly used in automated industrial environments. There are also other applications like planet exploration, surveillance, landmine detection, etc. In all these applications, in order that the mobile robots perform their tasks, collision-free path planning is a prerequisite. This article provides an overview of the research progress in path planning of a mobile robot for off-line as well as on-line environments. Commonly used classic and evolutionary approaches of path planning of mobile robots have been addressed. Review shows that evolutionary optimization algorithms are computationally efficient and hence are increasingly being used in tandem with classic approaches while handling Non-deterministic Polynomial time hard (NP-hard) problems. Also, challenges involved in developing a computationally efficient path planning algorithm are addressed.

Key words: Path planning, mobile robot, off-line environment, on-line environment, classic, evolutionary algorithms.

INTRODUCTION

Mobile robots are increasingly being employed in many automated environments. Potential applications of mobile robots include a wide range such as service robots for elderly persons, automated guided vehicles for transferring goods in a factory, unmanned bomb disposal robots and planet exploration robots. In all these applications, the mobile robots perform their navigation tasks using the building blocks (Siegwart and Nourbakhsh, 2004) as shown in Figure 1.

Navigation of a mobile robot involves perception of environment, localization and map building, cognition and path planning and motion control. While perception refers to understanding its sensory data, finding its pose or configuration in the surroundings is localization and map building. Planning the path in accordance with the task by using cognitive decision making is an essential phase before actually accomplishing the preferred trajectory by controlling the motion. As each of the building blocks is by itself a vast research field, this paper reviews path planning approaches.

Apart from robotic applications, path planning finds use in planning the routes on circuit boards, obtaining the hierarchical routes for networks in wireless mobile communication (Manousakis et al., 2005), planning the path for digital artists in computer graphics and in computational biology to understand probable protein folding paths (Choset et al., 2005).

The objective of this paper is to provide an overview of path planning algorithms used in mobile robots. This article provides an overview of the research progress in path planning of a mobile robot for off-line as well as on-line environments. Commonly used classic and evolutionary approaches of path planning of mobile robots have been addressed. Further scope and challenges involved in developing computationally efficient path planning algorithms are also identified.

CATEGORIES OF PATH PLANNING ALGORITHMS

Path planning of a mobile robot is to determine a collision-free path from a starting point to a goal point optimizing a performance criterion such as distance, time or energy, distance being the most commonly adopted criterion. Based on the availability of information about environment, there are two categories of path planning algorithms, namely off-line and on-line. Off-line path planning of robots in environments where complete information about stationary obstacles and trajectory of

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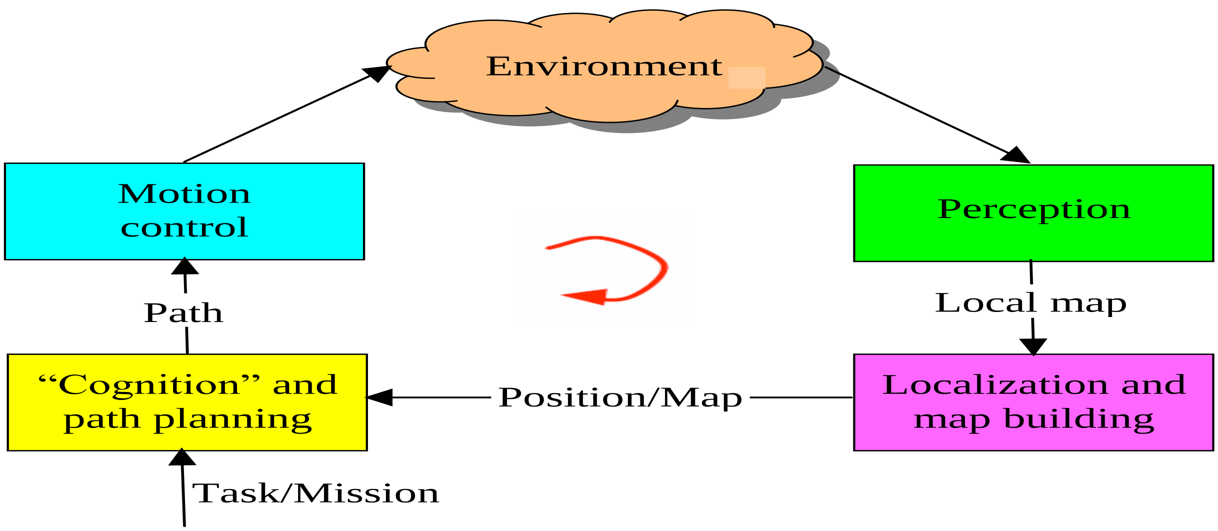

Figure 1. Building blocks of mobile robot navigation.

moving obstacles are known in advance is also known as global path planning. When complete information about environment is not available in advance, mobile robot gets information through sensors, as it moves through the environment. This is known as on-line or local path planning. Essentially, on-line path planning begins its initial path off-line but switches to on-line mode when it discovers new changes in obstacle scenario.

OFF-LINE PATH PLANNING ALGORITHMS

Examples of path planning in off-line environments are service robots operating during maintenance period of a nuclear power plant, automated guided vehicles in a factory, etc. where there may not be any change in the captured environment map.

Classic approaches

A fundamental approach for formulating and solving the path planning problem is the configuration space (C-space) approach (Lozano-Perez and Wesley, 1979). Though the idea was also exercised by Udupa (1977) in his doctoral thesis, it was Lozano-Perez who extensively used this in the perspective of path planning. The central idea of this approach is the representation of the robot as a single point. Thus, the C-space of the mobile robot path planning problem is reduced to a 2-dimensional problem. As robot is reduced to a point, each obstacle is enlarged by the size of the robot to compensate. The path planning literature was united around this approach by Latombe's book (1991). Using C-space as the fundamental concept, there are many classic path planning approaches like roadmap approach, cell decomposition approach, etc. In roadmap approach, networks of collision-free paths are constructed connecting start and target points. The well known roadmap methods are visibility graph and Voronoi diagram.

Visibility graph (Lozano-Perez and Wesley, 1979) is drawn by joining two vertices of mutually visible polygonal obstacles that are present between start and target points. The shortest path is then identified through the roads obtained from the visibility graph. The method is efficient in sparse environments as the number of roads is dependent on the number of polygonal obstacles and their edges (Li et al., 2002; Siegwart and Nourbakhsh, 2004). Another roadmap approach, the Voronoi diagram (Dunlaing and Yap, 1985) is constructed using via points which are equidistant from two or more obstacles. As a result, the obtained path is safer but normally not shorter (Masehian and Amin-Naseri, 2007; Garrido et al., 2011).

The cell decomposition approach (Lozano-Perez, 1983) computes the C-space of the mobile robot decomposes the resulting space into cells and then searches for a route in the free space cell graph. Grid method (Brooks and Lozano-Perez, 1983; Zhu and Latombe, 1989; Payton et al., 1993; Likhachev et al., 2005; Hachour, 2008a, b) is a popular cell decomposition approach where grids are used to generate the map of the environment. The main difficulty is how to find the size of the grids, the lesser the size of grids, the more accurate will be the representation of the environment. However, using lesser grids will result in exponential rise in memory space and search range (Zheng et al., 2007).

Evolutionary approaches

Classic approaches though found to be effective, take more time in the determination of feasible collision-free path. Also, classic approaches tend to get locked in local optimal solution which may be far inferior to the global optimal solution. Moreover, path planning of a mobile robot in the presence of multiple obstacles is found to be non-deterministic polynomial time hard (NP-hard) problem (Canny and Reif, 1987). It becomes even more complicated when the environment is dynamic. These drawbacks make the classic approaches to be incompetent in complex environments (Sugihara and Smith, 1997). Hence, evolutionary approaches such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), etc. Similarly, Ant Colony Optimization (ACO) and Simulated Annealing (SA) are employed to solve the path planning problem quickly.

GA is an optimization tool based on the mechanics of natural genetics and selection (Holland, 1975; Goldberg, 2000). The first step in path planning using GA is random generation of population containing alternative paths. Dozier et al. (1997) from NASA presented a hybrid planner which makes use of visibility-based repair approach and evolutionary technique. The visibility-based repair approach is used to quickly transform the ones which interfere with the obstacles (invalid paths) into valid paths and then subject to binary coded GA. GA with binary string is computationally costly for the reason that before each evaluation of function, chromosomes are transformed to phenotypes (Ripon et al., 2007). Xiao et al. (1997) proposed an evolutionary planner for path planning. This planner has comparatively simple genotype structures that can represent valid paths, but necessitates complex decoders and fitness functions to obtain the optimal path. Moreover, there may be loss of accuracy in transforming to binary mode.

Further, Sugihara and Smith (1997), Gallardo et al. (1998), Nagib and Gharieb (2004) and Al-Taharwa et al. (2008) used fixed-length path consisting of binary strings. A fixed-length path gives a quick solution for environments with few obstacles and it takes hours to evolve a solution for a complex environment. In order to reach the target in a complex environment, variable length chromosomes are needed. Tu and Yang (2003) presented variable length binary coded GA in which gene indicates the subsequent movement direction and distance. The main limitation of such algorithms is that they direct to some invalid results like paths that may not reach to the target point at all (Shahidi et al., 2004).

Wang et al. (2006) presented a genetic based path planning algorithm, in which populations are generated including the ones which interfere with the obstacles (invalid paths also). Later such invalid path sequences are subjected to penalty function evaluation. This increases computation load resulting in higher execution time (Raja and Pugazhenthi, 2008, 2009a, b, 2011).

PSO is another very widely used evolutionary algorithm in path planning. It is an evolutionary computation technique inspired by social behavior of bird flocking or fish schooling. Years of study on the dynamics of bird and fish resulted in the possibilities of utilizing this behavior as an optimization tool. Compared to GA, the advantages of PSO are that PSO is easier to implement and there are fewer parameters to be adjusted (Kennedy and Eberhart, 1995). Qin et al. (2004) proposed an algorithm which finds out shortest path using graph based approach and PSO. They used graph based approach to obtain the collision–free paths in static environments and then PSO along with mutation operator to arrive at the shortest path.

Zhang and Gu (2008) used variable path length which depends upon number of vertices of polygonal obstacles. Binary PSO along with genetic like mutation operator is used to optimize the path. Nasrollahy and Javadi (2009) presented a PSO based planner for dynamic environments in which populations are generated containing invalid paths and then they are subjected to penalty function evaluation. Recently, Gong et al. (2011) proposed a model which uses a multi objective PSO and genetic like mutation operator. The multi objectives are shortest distance and danger of path from the obstacles. The mutation operator is used to repair the invalid paths.

The other optimization algorithms which have been used in path planning to a smaller percentage are ant colony optimization (ACO) and simulated annealing (SA) algorithms (Masehian and Sedighizadeh, 2007). ACO is inspired by the foraging behavior of ants for finding the shortest path to the food source. A method for optimal path planning based on improved Dijkstra algorithm and ACO is proposed by Guan-zheng et al. (2006). The improved Dijkstra algorithm consists of the standard Dijkstra algorithm and removal of unnecessary path nodes algorithm to get the sub-optimal paths. ACO is used to obtain the global optimal path from the sub-optimal paths. Garcia et al. (2009) presented simple ACO – distance memory (SACO-dm) algorithm for global path planning among static and moving obstacles. In SACO-dm, optimal path is influenced by current distance between robot and target nodes and the memory capability of ants remembering the visited nodes. Results show that optimal paths are achieved with lesser computation time compared to SACO.

SA is a type of heuristic random search method and it resembles the cooling process of molten metals through annealing. A method employing SA for collision-free path amid static polygonal obstacles in C-space setting is presented in Martinez-Alfaro and Gomez-Garcia (1998). Binary setting is used which may result in non-optimal path when shorter computation time is desired. Miao and Tian (2008) developed SA algorithm based approach for dynamic environments. Their approach uses vertices of the static and dynamic obstacles as search space. Then the SA algorithm is used to find the optimal path.

ON-LINE PATH PLANNING ALGORITHMS

In recent times, on-line path planning has received more attention from researchers (Masehian and Katebi, 2007) since autonomous mobile robots must be capable of operating in dynamic environments. Applications of path planning in on-line environments include planet exploration, mine industry, reconnaissance robots, etc. (Hachour, 2008a). On-line path planning approaches like potential field approach and collision-cone approach have been traditionally followed. Nowadays, evolutionary approaches are increasingly being used along with classic approaches.

Classic approaches

Pioneering works have been initiated by Khatib (1986) who proposed Artificial Potential Field (APF) approach which is popular in mobile robotics. By this approach, a point robot in C-space moves under the influence of an APF in which obstacles are assumed to generate repulsive forces and the target is assumed to generate attractive forces. The robot moves as per the resultant of these forces. This approach is known for its mathematical elegance and simplicity as path is found with very little computation. However, the drawback of this algorithm is that robot may become stagnant or trapped when there is a cancellation of equal magnitudes of attractive and repulsive forces. One solution to overcome this problem is to complement with influential algorithms to escape from trap (Latombe, 1991) and till date many variants of potential field approach like escape-force algorithm (Vadakkepat et al., 2000, 2001), trap recovery model used by Lv and Feng (2006), adaptive virtual target algorithm (Luh and Liu, 2007, 2008), etc. have been proposed.

Path planning problem can also be solved by vector field histogram approach (Borenstein and Koren, 1991). At every instant, a polar histogram is generated to represent the polar density of obstacles around a robot. The robot's steering direction is chosen based on the least polar density and closeness to the goal. In a given environment, the polar histogram must be regularly regenerated for every instant and hence the method is suited for environments with sparse moving obstacles.

Another commonly used on-line approach is based on collision cone concept (Chakravarthy and Ghose, 1998; Qu et al., 2004). Collision of robot can be averted if the relative velocity of robot with regard to a particular obstacle falls exterior to the collision cone. Fiorini and Shiller (1998) proposed a velocity obstacle approach, which is in resemblance to collision cone approach. It consists of choosing avoidance maneuvers to avoid static and moving obstacles in the velocity space. They used basic heuristic strategy for prioritizing objectives such as averting collisions, attaining the goal or accomplishing trajectories with preferred topologies.

Another on-line approach for obstacle avoidance is dynamic windows approach (Fox et al., 1997; Brock and Khatib, 1999). The dynamic window contains the feasible linear and angular velocities taking into consideration acceleration capability of robot. Then the velocity at the next instant is optimized for obstacle avoidance, subject to vehicle dynamics.

Evolutionary approaches

Although classic approaches are found to be effective, computation time is crucial for the success of any on-line path planning algorithms. But, with classic approaches, optimum result can hardly be achieved in quick computation time owing to incomplete information of the environment. Further, due to NP-hard complexity of path planning problem, classic approaches are often combined with evolutionary approaches like GA, PSO, etc. to overcome their drawbacks.

Vadakkepat et al. (2000, 2001) proposed evolutionary APF (EAPF) algorithm to derive optimal potential field functions using GA. When the robot is trapped, a separate algorithm named escape-force is introduced to recover from trap. Potential field immune network proposed by Luh and Liu (2008) used velocity obstacle method to identify the most imminent collision of the obstacle. Potential field approach coupled with biologically inspired immune network is used to avoid the most imminent obstacle. The overall response of the immune network is calculated using GA. Adaptive virtual target algorithm is proposed to direct the robot out of the trap. It was assumed that robot is being trapped if it moves beyond 90° off-target.

Min et al. (2005) employed a mathematical model using collision cone approach and PSO for on-line path planning. To facilitate reduction of computational burden, they ignored instantaneous changes in obstacle velocities in the motion model. Therefore, their algorithm is suited to sparse environments having obstacles with slow velocities. Also, PSO in combination with binary coded genetic operators is used as optimization tool without considering dynamic constraints. Nevertheless, recent studies show that real coded evolutionary algorithms execute better than the binary coded.

Hu et al. (2007) addressed an approach to steer the mobile robot in static or dynamic environments based on PSO and stream functions (or potential flows). Stream functions, derived from hydrodynamics, are engaged to steer an autonomous robot to avoid the obstacles. However, their model also does not consider instantaneous changes in obstacle velocities. Park and Kim (2008) proposed a PSO algorithm based on the potential field approach. The potential field is mathematically modeled by particles' fitness value. The PSO particles are designed to move with Newtonian dynamics. Lu and Gong (2008) proposed an on-line path planning algorithm using PSO technique for unknown environments. Their algorithm is entirely based on distance information of the environment without any mathematical model featuring velocity of nearing obstacle. Recently, Hong et al. (2011) presented a model using classic APF considering dynamic model of velocity potential field obtained by a variant of PSO called quantum PSO. Inspired by the nature of motion of microscopic particles (quantum mechanics), quantum PSO updates state of a particle by wave function instead of position and velocity.

Mei et al. (2006) proposed a hybrid algorithm which combines APF and ACO for dynamic environments. ACO is applied to plan the global path and then APF is employed to guide the robot for local route. Lv and Feng (2006) proposed numerical potential field to model the environment and applied ACO to search for optimal path. A trap recovery solution was also discussed by them. The main problem of ACO is difficulty in obtaining the quick solution convergence. Lee et al. (2008) presented improved ACO using potential field approach to get quick solution convergence by tuning the control parameters of ACO. Improved ACO makes use of altered pheromone (a substance secreted by ants) to update the position vector.

Zhang et al. (2004) proposed an APF approach in combination with SA which considers the problems of goal non-reachable with obstacles nearby (GNRON) and local minima in soccer robots. New potential functions have been derived by considering the distance information of start and target points for GNRON problem. Miao (2010) presented a multi operator based SA approach for path planning. Switching, deleting, mutating and repairing operators are introduced along with SA. The parameters of SA are fine tuned for moving obstacles also.

SCOPE AND CHALLENGES

In the domain of path planning, evolutionary methods have proved to yield better results than pure classical approaches (Garcia MAP et al., 2009). Several algorithms have been proposed to overcome the complex nature of NP-hard path planning problem as efficient functioning of mobile robot is influenced by better quality of paths. The review of literature shows that there is still scope for developing more efficient off-line path planning algorithms that will yield better quality paths by addressing some of the issues as follows:

1) Valid paths which do not interfere with the obstacles should alone be considered in the initial generation of population eliminating the use of penalty function evaluation.
2) Optimization techniques with real strings are computationally less expensive because before the evaluation of objective function, details of alternative paths need not be expressed in binary codes.
3) Path containing variable number of segments can be used in generation of population considering the complexity (number of vertices) of environment.
4) Simple decoders and fitness functions can be used to decrease the computational time of algorithms.

Compared to off-line, developing a computationally efficient on-line algorithm is more challenging. One of the difficulties in working with incomplete information of environment is that the path cannot be pre-planned and therefore global optimum solutions can hardly be achieved. However, better quality paths can be achieved by addressing the challenges as follows:

1) More accurate mathematical models can be developed which feature instantaneous velocity of robot as well as nearing obstacles to tackle even cluttered moving obstacles.
2) The influence of other constraining obstacles while negotiating the most imminent obstacle can yield overall better result. Therefore, mathematical model should simultaneously consider the effect of constraining obstacles which may cause further deviation more than avoiding the imminent threat.
3) Avoiding trap of a robot when there exists a path is another vital issue in obstacle avoidance. The need for trap recovery can be eliminated.
4) Any on-line path planning algorithm becomes truly successful if the next instant of the robot is planned within the bounds of the kinematic and dynamic constraints of the mobile robot. So the mathematical models should incorporate the upper bounds for the dynamic constraints in tough time varying environments.

Further, multiple optimization objectives, multiple robot coordination, uncertainties in sensing, prediction, motion control, etc. pose many other challenges in mobile robotics.

CONCLUSION

At present, development in path planning is progressively more inspired by new applications such as circuit board designs, network routings, computer animations, pharmaceutical drug designs, computational biology, etc. The research community puts forward many approaches for solving the path planning problem. This article reflects the research progress that has taken place in path planning of mobile robots, including on-line planning. Although many efficient algorithms have been developed, the diversity of path planning problems has been constantly increasing. Up to 90s, determination of collision-free path remained the main objective. Currently, though collision-free path is a necessary condition, other significant issues such as modeling of dynamic environment, multiple optimal functions, dynamic constraints, etc. are also to be addressed. These constraints craft path planning problems to be more challenging and necessitate more robust and efficient algorithms.

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