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ROBOT PATH PLANNING USING OPTIMIZATION TECHNIQUES

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Abstract

Robotics accommodates the enormous uncertainty that exist in the physical world. The level of uncertainty depends on the application realm. In the area of robotics applications, such as assembly lines, humans can cleverly engineer the system so that uncertainty is only an insignificant factor. In disparity, robots operating in residential homes, military operate or on other planets will have to cope with substantial uncertainty. The most important step towards full-bodied real-world robot system is probably by managing uncertainty. Path planning problem is a demanding topic in robotics. Indeed, a significant amount of research has been devoted to this problem in recent years. Optimization principles have become a dominating approach in the fields of machine learning and computer vision. The paper describes the various optimization techniques for the robot path planning.

***Key Words*:**Robotics, Path Planning, Machine Learning Techniques, Artificial Intelligence, Optimization Techniques.

1 INTRODUCTION

Robotics is making progress in huge strides, some people say. Others disagree and believe robotics has not been able to establish itself as a discipline distinct from control, mechanical engineering, and computer science. This disagreement should be reason enough for the robotics community to ask some questions. A curious look over to some other rather young disciplines may prove helpful. Take machine learning, for example. Originally a part of computer science and AI (Artificial Intelligence), it now has established itself as a new discipline with whole university departments dedicated to it. One of the catalysts of progress in machine learning has been the extensive use of optimization to formalize problems. In fact, large parts of modern machine learning are covered when referring to one of the many supervised or unsupervised learning objectives (losses, regularizations, embedding costs, KL-minimization, etc).A similar situation is found in the field of modern computer vision, which largely builds on rigorous mathematical programming formulations. Optimization techniques find a solution to an optimization problem so that a given quantity is optimized subject to a set of constraints. Recent optimization techniques deal with hard optimization problems and automation like robot motion planning, manufacturing cells formation, vehicle routing problem, worker scheduling, cell assignment, assembly line balancing, shortest sequence planning, sensor placement, UAV (unmanned-aerial vehicles) communication relaying and multi-robot coordination to name just a few. The main propose of path planning is find a specific route in order to reach the target destination.

Development of an optimization model can be divided into five major phases.

1. Collection of data.
2. Problem definition and formulation.
3. Model development.
4. Model validation and evaluation or performance.
5. Model application and interpretation of results.

Figure 1: Classification of the Robot Path Planning Methods

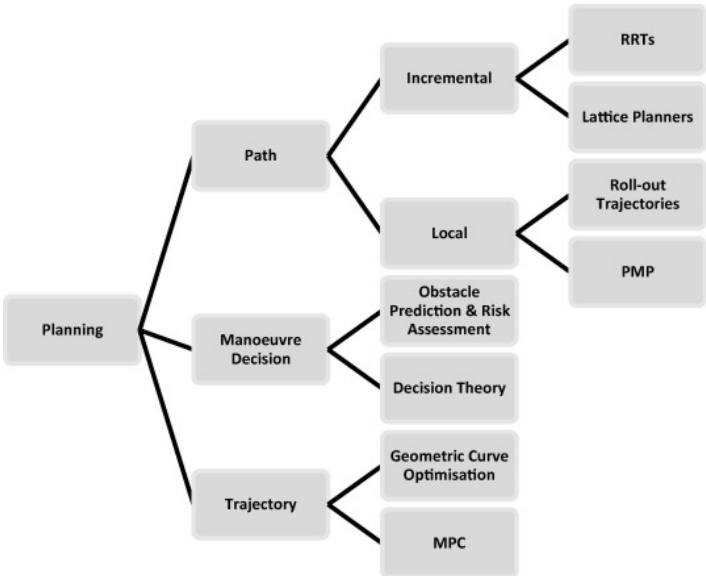

Figure 1: Classification of the robot path planning methods
Source: Compiled

2 REVIEW OF LITERATURE

Usage of algorithm for collision avoidance using backtracking and the ACA (ant colony algorithm) to find the optimum path to reach the destination (Yogita Gigras, Kusum Gupta, 2012). Buniyamin N., Sariff N., Wan Ngah W.A.J., Mohammad Z. solved the RPP (Robot Path Planning) problem and proposed the precise depiction of heuristic and visibility equations of state transition rules. The proposed algorithm was applied within a global static map having feasible free space nodes. The application of Ant Colony Optimization (ACO) to robot path planning in a dynamic environment (Michael Brand, Michael Masuda, Nicole Wehner, Xiao-Hua Yu, 2010). O. Hachour proposed algorithm for path planning of autonomous mobile robot in an unknown environment. The robot travels within the environment sensing and avoiding obstacles that come across its way to the target station. Daniel Angus modified the existing Ant System Meta heuristic by including 3 (three) parameters such as cost, visibility and pheromone. Based on this a new algorithm for the Shortest Path Ant Colony Optimization (SPACO) was developed. The most important parameter included in this algorithm to solve shortest path problem is visibility.

Path planning is an essential task navigation and motion control of autonomous robot. This problem in mobile robotic is not simple, and the same is attached by two distinct approaches. Raja et al. (2012) opined that in the classical approaches, the C-space is the representation of the robot as a simple point. The same approach is described by Latombe (1991) . Under concept of C-space, are developed path planning approaches with roadmap and visibility graph was introduced. Sparce environments considering to polygonal obstacles and their edges. The Voroni diagram was introduced. A related problem is when both, the map and the vehicle position are not known. This problem is usually known as Simultaneous Localization and Map Building (SLAM), and was originally introduced. Until recently, have been significant advances in the solution of the SLAM problem. The potential problems with SLAM algorithm have been the computational requirements. The complexity of original algorithm is of O (N3) but, can be reduced to O (N2) where, N will be the number of landmarks in the map. In computational complexity theory, path planning is classified as an NP (non-deterministic polynomial time) complete problem. Evolutionary approaches provide these solutions.

3 Existing Optimality Approaches in Robotics

The whole field of control theory (Markov Decision Processes and Reinforcement Learning approaches with this) lays one of the most important foundations of robotics. Each of these can concisely be described in terms of optimality principles but also just in terms of their laws, of course. However it seems without doubt that in the area of control (and learning/adaptive control) the optimality approach was very successful as a method to develop a large variety of efficient solutions. Optimization principles have also become a main-stay of robot path generation, a very extensive area of research. While sampling-based approaches, such as Rapidly Exploring Random Trees and Probabilistic Road Maps are the dominant method of choice, the optimization view more recently led to a series of methods (Ratliff et al., 2009; Toussaint, 2014) that are strong in terms of speed in high-dimensional settings, but weak in terms of global completeness, and therefore complementary to sampling-based methods.

4 PATH PLANNING TECHNIQUES

Path planning can be achieved through various different methods. In this section we describe the various techniques for path planning.

A. Particle swarm optimization (PSO): PSO method is new population-based intelligence algorithms that display better performance. In the optimization process, the particles become more and more similar, and gather into the neighborhood of the best particle in the swarm, which makes the swarm prematurely converged possibly around the local solution. PSO do not guarantee an optimal solution and does not use the gradient of the problem being optimized.

B. Genetic algorithm (GA): GA is a part of evolutionary algorithms (EA) that produces solutions to the optimization problems by using techniques that are inspired by natural evolution, such as mutation, selection, inheritance, and crossover. In a

GA, a population of strings called chromosomes or the genotype of the genome, which encodes candidate solutions called individuals, creatures, or phenotypes to an optimization problem, evolves toward better solutions.

C. Tabu Search (TS): Tabu search, a new approach for allowing hill climbing to overcome local optima (Fred Glover, 1986).The basic principle is to pursue the search whenever a local optimum is encountered by allowing non-improving moves; cycling back to previously visited solutions is prevented by the use of memories, called tabu lists, which record the recent history of the search. TS is based on the foundation that problem solving must incorporate adaptive memory and responsive exploration, in order to qualify as an intelligent system.

D. Simulated Annealing (SA): SA was developed in 1983 to deal with highly nonlinear problems. The global maximization problem similarly to using a bouncing ball that can bounce over mountains from valley to valley is dependent on the Simulated Annealing approach.

E. Reactive Search Optimization (RSO): RSO backs the integration of MLT (Machine Learning Techniques) into search heuristics for solving complex optimization problems. It also addresses a scientific issues relating to the reproducibility of results and to the objective evaluation of methods. Reactive Search is a methodology for solving hard optimization problems, both in the discrete and continuous domain, based on the integration of machine learning and optimization in an online manner.

F. Ant Colony Optimization Algorithms (ACOA): The ACOA is a relatively recent approach to solving optimization problems by simulating the behavior of real ant colonies. The Ant Colony System (ACS) models the behavior of ants, which are known to be able to find the shortest path from their nest to a food source and they accomplish this by depositing a substance called a pheromone as they move. This chemical trail can be detected by other ants that are more likely to follow a path rich in pheromone. This trail information can be utilized to adapt to sudden unexpected changes to the terrain, such as when an obstruction blocks a previously used part of the path.

5 CURRENT OPTIMIZATION TECHNIQUES

A significant part of research on ACO is still concerned with applications. However, increasing attention is and will be given to even more challenging problems that, for example, involve multiple objectives, dynamic modifications of the data, and the stochastic nature of the objective function and of the constraints.

A. Dynamic optimization problems: Dynamic problems are characterized by the fact that the search space changes during time. Hence, while searching, the conditions of the search, the definition of the problem instance and, thus, the quality of the solutions already found may change. For this problem, ACO algorithms belong to the state-of-the-art techniques. An ACS (Ant Colony System) algorithm has also been applied to dynamic vehicle routing problems, showing good behavior on randomly generated as well as real-world instances.

B. Stochastic optimization problems: Some variables have a stochastic nature. The probabilistic traveling salesman problem (PTSP) was the first stochastic problem tackled by ACO algorithms. The first ACO algorithm for this problem was proposed by Bianchi et al. (2002). Further ACO algorithms for the PTSP have been proposed by Branke and Guntsch (2003), Gutjahr (2003), and Birattari et al (2005).

C. Multi-objective optimization : Multiple objectives can often be handled by ordering or weighting them according to their relative importance. In the two-colony ACS algorithm for the vehicle routing problem with time window constraints and in the MMAS (Mathematical Methods in the Applied Sciences) for the bi-objective two-machine permutation flow shop problem , the multi-objective optimization problem is handled by ordering the objectives; differently.

D. Continuous optimization: ACO algorithms have been applied to continuous optimization. When an algorithm designed for combinatorial optimization is used to tackle a continuous problem, the simplest approach would be to divide the domain of each variable into a set of intervals. Research in this direction is currently ongoing.

6 CONCLUSION

This paper implicates a wide range of applications that establishes most successful optimization technique. This knowledge will be applied in optimizing a simulation model for Robotics operations. Due to its application nature, the optimization methodology has to meet certain requirements, must be able to provide a 95 (ninety-five) % confidence level for its estimates of the global optimum. Second, it must be tolerant for faults and must be able to produce realistic results despite minor inconsistencies. Third at a minimum, it should be able to come up with a good approximation of, the local minima when constrained to execute in a given time frame. Fourth, it should be robust enough. Finally, implementing at ease, a highly secure version is most desirable and such implementation must not compromise the security of the underlying hardware and software systems.

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