Robotics and Computer-Integrated Manufacturing 27 (2011) 135–149

Contents lists available at ScienceDirect

Robotics and Computer-Integrated Manufacturing

journal homepage: www.elsevier.com/locate/rcim

Reinforcement based mobile robot navigation in dynamic environment

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ARTICLE INFO

Article history:
Received 9 April 2009
Received in revised form
22 June 2010
Accepted 24 June 2010

Keywords:
Robot navigation
Q-learning
Unsupervised learning
Potential filed force
Path planning
Mobile target

ABSTRACT

In this paper, a new approach is developed for solving the problem of mobile robot path planning in an unknown dynamic environment based on Q-learning. Q-learning algorithms have been used widely for solving real world problems, especially in robotics since it has been proved to give reliable and efficient solutions due to its simple and well developed theory. However, most of the researchers who tried to use Q-learning for solving the mobile robot navigation problem dealt with static environments; they avoided using it for dynamic environments because it is a more complex problem that has infinite number of states. This great number of states makes the training for the intelligent agent very difficult. In this paper, the Q-learning algorithm was applied for solving the mobile robot navigation in dynamic environment problem by limiting the number of states based on a new definition for the states space. This has the effect of reducing the size of the Q-table and hence, increasing the speed of the navigation algorithm. The conducted experimental simulation scenarios indicate the strength of the new proposed approach for mobile robot navigation in dynamic environment. The results show that the new approach has a high Hit rate and that the robot succeeded to reach its target in a collision free path in most cases which is the most desirable feature in any navigation algorithm.

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1. Introduction

In the recent years, research and industrial interests are focused on developing smart machines such as robots that are able to work under certain conditions for a very long time and without any human intervention. This includes doing specific tasks in hazardous and hostile environments. Mobile robots are smart machines that can do such tedious tasks. These robots are used in the areas where the robot navigates and carries a certain task at the same time such as, service robots, surveillance and explorations [1].

Mobile robot navigation in an unknown environment has two main problems: localization and path planning [5,6]. Localization is the process of determining the position and orientation of the robot with respect to its surrounding. The robot needs to recognize the objects around it. It needs to recognize each object as a target or as an obstacle. Many techniques deal with this localization problem using laser range finders, sonar range finders, ultrasonic sensors, infrared sensors, vision sensors and GPS that have been developed on-board or off-board. When a larger view of the environment is necessary, a network of cameras has been used.

The other problem is the path planning in which the robot needs to find a collision free path from its starting point to its end point. In order to be able to find that path, the robot needs to run a suitable path planning algorithm, to compute the path between any two points [7].

Many researchers studied the problem of robot path planning with obstacle avoidance and many solutions were proposed to deal with the problem [8,9]. Since the robot motion in dynamic field has a certain amount of randomness due to the nature of the real world, these solutions did not give accurate results under all conditions. In the recent years there was a drift toward artificial intelligent approaches to improve the robot autonomous ability based on accumulated experiences. In general, artificial intelligent methods can be computationally less expensive and easier than classical methods.

This research focuses on mobile robot path planning moving in a dynamic environment, where a new approach is proposed to solve this problem based on Q-learning algorithm. Q-learning algorithm has many features that make it suitable for solving the mobile robot navigation problem in dynamic environment. First, the Q-learning agent is a reinforcement learning [29] agent that has no previous knowledge about its working environment. It learns about the environment through interacting with it. This type of learning agents is called unsupervised learning agent. Since it was assumed that the mobile robot has no previous knowledge about its working environment a Q-learning agent is a

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doi:10.1016/j.rcim.2010.06.019

good alternative for solving the mobile robot navigation problem in dynamic environment. Secondly, Q-learning agent is an on-line learning agent. It learns the best action to take at each state by trial and error. It chooses actions randomly and calculates the value for taking an action at a specific state. Through evaluating every state and action pair it can build a policy for working in the environment. In the mobile robot navigation problem in order to find a collision free path, the robot needs to find the best action to take at each state. It needs to learn this knowledge on line, while navigating its environment. Because Q-learning is very simple, it is a very appealing alternative [10].

2. Literature review

In the last decade many classical solutions tried to address the robot path planning problem. The most commonly used solution is the potential field method [22] and its variants [12,14]. This method has been studied extensively by scholars. It was introduced in its most common form by Borenstein and Koren [11]. The basic idea behind this method is to fill the robot environment with a potential field in which the robot is attracted to the target position and is repulsive away from obstacles. At any position, the robot calculates the position that has the global minimum repulsive force and moves toward this position, and repeats this method as much as it is required until it reaches its target. Many variations appeared to this method like the ones introduced by Ge and Cui [12,13] to solve the problems of non-reachable targets when the target is very close to the obstacle [12] and to propose a solution for robot path planning in dynamic field when both the target and the obstacles are moving [13]. The potential field method is a good method for robot navigation, but it suffers from the local minima problem. When the net of the attractive and repulsive forces on the robot is zero, the robot stops moving. Unless a change occurs in the environment of the robot the robot will never be able to reach the target.

Since the robot navigation in dynamic environment is considered a very complex problem because the environment is difficult to be modeled the classical solutions worked under certain conditions but failed in the presence of sudden events or changes in the environment. Therefore, there was a drift toward artificial intelligent solutions to solve the robot path planning problems. Many artificial intelligent techniques were used by scholars to solve the problem, like fuzzy logic, neural networks and genetic algorithms. In 1999 a new method was introduced by Pratihar et al. [9] to solve the problem using a genetic-fuzzy approach. In this solution the robot field was assumed to be dynamic but the target was assumed to be static. In this approach the robot acts according to the location of the moving obstacle in the immediate past. This may lead to inadequate actions under some conditions. In 2001 Mucientes et al. [4] came up with a new fuzzy control system for avoiding the moving object by the robots. In this system the robot applied fuzzy temporal rules to estimate the movement trend of the obstacles. In 2005 Meng Joo and Chang Deng [15], proposed a new hybrid learning approach and a neuro-fuzzy controller was developed based on supervised learning in a simulation environment. All the previous methods deal with environments where the obstacles are moving, but the target is static.

Some other methods tried to deal with the robot navigation problem in dynamic environment, but they were adapted to the robot soccer environments. The limit cycle method is one of those methods [16], which is a reactive method that relies on the sense-plan-act cycle. This method assumes that the target trajectories are known in advance, so the environment is not completely unknown to the robot. This assumption makes it suitable for robot soccer. Another approach for developing a self-learning agent using the adaptive Q-learning algorithm was proposed in [17] and it was adapted to robot soccer only. These methods cannot be applied to arbitrary environment because they use the rules of the soccer game in their implementation for the navigation algorithm.

3. Mobile robot path planning using Reinforcement Learning in literature

In the proposed approach the robot path planning is solved using Q-learning. This method was first introduced by Watkins [18] for learning from delayed rewards and punishments. In literature there were many attempts to solve the mobile robot path planning problem using Reinforcement Learning algorithms. These methods learn the optimal policy for navigation to select the action that produces maximum cumulative reward.

Smart and Kaelbling [23,24] used the Q-learning for mobile robot navigation and obstacle avoidance. The used reward function assigns a value of 1 to the goal state, a value of -1 for the collision state and a value of 0 to all other states. The perceptions to the system from the environment are the distance between the robot and the target and the distances between the robot and all other obstacles in the environment. The conducted experiments trained the robot for several times then evaluated the learned information by exposing the robot to an environment that contains one static target and one static obstacle. The achieved hit rate was considered small and the navigation time to the target was considered long using their method. However, the conducted experiments showed the promise in using Reinforcement Learning for controlling the robot to accomplish different tasks.

Aranibar and Alsina [19], used Reinforcement Learning to solve the mobile robot path planning in three dimensional environment. They used Q-learning, and neural Q-learning and they compared it to the dynamic programming using the greedy search algorithm. The reward function that has been used is the same reward function used by Smart and Kaelbling [23] but with the addition of the definition of invalid states which are states outside the working environment and giving them reward value of 0. They found that the dynamic programming is better to be used for small-state spaces. Q-learning is better for medium-size spaces and neural Q-learning works best for large-size spaces, but they worked on static three dimensional environments only.

Some algorithms tried to combine the unsupervised Reinforcement Learning with other learning techniques like Fuzzy Logic and Neural Networks. Boem and Cho [25] proposed a hybrid approach using Fuzzy Logic and Reinforcement Learning. The proposed method is an Environment Exploration Method (EEM). The navigation algorithm consists of two basic modules: avoidance behavior and goal-seeking behavior. Each behavior is designed independently in the design state and they were combined into behavior selection in the running state. Both the avoidance behavior and the goal seeking behavior are fuzzy engines that map the input state of the environment supplied by the sensor readings to fuzzy output which is the desirable action. The fuzzy rules bases are built using reinforcement learning which requires simple evaluation data rather than thousands of training data.

Yung and Ye [26] presents another hybrid learning approach for mobile robot navigation using Fuzzy Logic and Reinforcement Learning. The navigator consists of three basic modules: obstacle avoidance, move-to-goal and a fuzzy behavior supervisor. The obstacle avoidance module learns the avoidance fuzzy rules using reinforcement learning. It perceives sensory inputs that are fuzzified then the rules are constructed using reinforcement

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