2.5D Multi-Objective Path Planning for Ground Vehicles

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Due to the vastly different energy consumption between up-slope and down-slope, a path with the shortest length in a complex off-road terrain environment (2.5D map) is not always the path with the least energy consumption. For any energy-sensitive vehicle, realizing a good trade-off between distance and energy consumption in 2.5D path planning is significantly meaningful.

1. Introduction

The use of energy is a important topic of interest in the field of ground vehicles (GVs) [1]. GVs such as exploration robots and space probes mostly operate in the complex off-road terrain environment (2.5D environment), and energy consumption can become a problem that restricts their working range and time. So far, scholars have studied battery technology [2], motor control technology [3], and gas engine technology [4] in order to improve energy efficiency.

An energy-saving method from the perspective of path planning for GVs is studied. A GV going uphill always consumes a lot of energy to overcome its gravity, which means a path with less up-slope but a bit longer may save more energy than that of the shortest path, which covers many up-slopes. Hence, there will always be some energy-saving paths on the 2.5D map. Meanwhile, some of these paths with longer distances may significantly increase the traveling time, which is also unacceptable. Overall, this yields a multi-objective path planning problem: to find paths on a terrain environment with a good trade-off between energy consumption and distance.

The traditional methods such as violent search [5], heuristic-based search [6] and probabilistic search [7], etc., can solve this multi-objective path planning problem to some extent. However, all of them encounter some shortcomings on this task. The violent search methods have to search a large area with low efficiency. The heuristic-based methods suffer the difficulty of modeling the heuristic function for 2.5D path planning (it is hard to estimate the cost of a path on the terrain map). The probabilistic search methods show unstable performance in the off-road environment.

Lately, deep reinforcement learning (DRL) has emerged as a highly promising approach for tackling path planning problems [8]. Therefore, researchers employ DRL to establish a multi-objective 2.5D path planning method (DMOP) that focuses on improving planning efficiency while ensuring a good balance between energy consumption and the distance of the planned path.

2. 2.5D Multi-Objective Path Planning for Ground Vehicles

Path planning methods that consider slope (on 2.5D map) have been studied for years, and researchers are concentrating on finding suitable paths for GVs in complex terrain environments [9][10][11]. In early research, most studies focused on single-object optimization problems, such as traversability or avoiding obstacles. Therefore, scholars are concerned about vehicle dynamics to ensure motion stability [7][12][13]. For instance, a probabilistic road map (PRM)-based path planning method considering traversability is proposed for extreme-terrain rappelling rovers [7]. Linhui et al. [12] present an obstacle avoidance path-planning algorithm based on a stereo vision system for intelligent vehicles; such an algorithm uses stereo matching techniques to recognize obstacles. Shin et al. [13] propose a path planning method for autonomous ground vehicles (AGVs) operating in rough terrain dynamic environments, employing a passivity-based model predictive control. Obviously, these planning methods place less emphasis on the global nature of the path.

As research on 2.5D path planning deepens, scholars are prone to create multi-objective path planning methods that take complex characteristics of 2.5D terrain into account, especially the issues of operational efficiency, energy consumption, and the difficulty of mechanical operation. These works aim to find paths that are energy efficient and easy to pass [14][15]. Ma et al. [16] propose an energy-efficient path planning method built upon an enhanced A* algorithm and a particle swarm

algorithm for ground robots in complex outdoor scenarios. This method considers the slope parameter and friction coefficient, which can effectively assist ground robots in traversing areas with various terrain features and landcover types. Based on the hybrid A* method, Ganganath et al. [17] present a algorithm by incorporating a heuristic energy-cost function, which enables the robots to find energy-efficient paths in steep terrains. Even though A*-based methods are likely to find the optimal or near-optimal path, their performance in terms of search time tends to be poor due to the search mechanism. Moreover, Jiang et al. [18] investigate a reliable and robust rapidly exploring random tree (R2-RRT*) algorithm for the multi-objective planning mission of AGVs under uncertain terrain environment. However, this kind of method has an unavoidable weaknesses, local minimum, which means it cannot guarantee the quality of the path. Despite the fact that existing research has made notable achievements, the 2.5D path planning method considering energy consumption and the distance of the global path has not been widely studied.

Regarding this topic, the team has previously proposed a heuristic-based method (H3DM) [19]. In this method, a novel weight decay model is introduced to solve the modeling problem of the heuristic function, and then the path planning with a better trade-off of distance and energy consumption is realized. Nonetheless, the solutions obtained by this method are not good enough regarding the path's global nature and the search efficiency. Thus, the multi-objective path planning method, which considers the path's global nature and time efficiency, should be further researched.

With the merit of solving complex programming problems, DRL has achieved much success in Go [20], video games [21], internet recommendation systems [22], etc. Scholars have also proved that DRL has the potential to solve N-P hard problems [23], such as the traveling salesman problem (TSP) [24] and the postman problem [25]. Since the path planning problem is also a kind of N-P hard problem [26][27], researchers have begun to apply DRL theory to solve path planning problems. Ren et al. [28] create a two-stage DRL method, which enables the mobile robot to navigate from any initial point in the continuous workspace to a specific goal location along an optimal path. Based on the double deep Q network, Chu et al. [29] propose a path planning method for autonomous underwater vehicles under unknown environments with disturbances from ocean currents. These methods have powerful reasoning capabilities and show the great potential of DRL in the field of path planning.

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