Modified Artificial Potential Field Method for Online Path Planning Applications

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***Abstract*—This paper presents a modified potential field method for robot navigation. The approach overcomes the well-known artificial potential field (APF) method issue, which is due to local minima that induce the standard APF method to trap in. Thus, the standard APF method is no longer useful in such case. The advantage of the new proposed method, as opposed to those that resort to the global optimization methods, is the low computing time that lines up with the standard A-Star (A*) method. The strategy consists of looking for a practical path in the potential field—according to the potential gradient descent algorithm (PGDA)—and adding a repulsive potential to the current state, in case of blocking configuration, a local minimum. When the PGDA reaches the global minimum, a new potential field will be constructed with only one minimum that matches the final destination of the robot, the global minimum. Finally, to determine the achievable trajectory, a second iteration is performed by the PGDA.**

***Keywords*—Path Planning; Artificial Potential Field Method; Potential Gradient Descent Algorithm; A* algorithm.**

I Introduction

One of the most important branches of artificial intelligence is trajectory planning, which is applied to robotic navigation and self-driving vehicles. It consists of finding a set of sequences that allows a robot to travel from an initial to a global state [1]. It could also be defined as moving furniture in a house without colliding with or touching walls and the other objects [1]. In the early work, the robots' operational environment is considered to be deterministic or inert, especially deployed in and for industrial environment [2]. Gradually, developments in technology enabled the new robotic generations to become partially autonomous. Therefore, the robot must be suitably equipped with the perception, localization, data fusion, decision making, and control abilities. If the first generation of robots were equipped with simple integrated circuits for fixed-control programs—relying on basic intelligence to repeat a series of actions in a static environment—the coming generations will require a significantly more sophisticated artificial intelligence [2]. In fact, these needs are a consequence of the increase in the number of degrees of freedom (DOF) of self-governing robots. The new generation, so-called third generation, must be able to map their trajectories and react instantaneously to their surroundings [1]. Another aspect of artificial intelligence, which characterizes a smart robot, is traveling from its current position to its destination by determining a feasible path autonomously [3], without involving humans. In other words, the robot moves on its own. Most of the decisions are made fully autonomously: meaning that itinerary (the planned route), obstacle detection and avoidance, the robots' dynamic control, and communication with its environment (other robots, infrastructure, etc.) will be made autonomously. As a consequence, the requirements for a self-driving robot result in the development of a new robotics field on a large scale, and in an uncertain environment. Therefore, artificial intelligence is definitely changing the operating mode of the existing robots and will certainly continue towards making them completely autonomous. Furthermore, intelligent robots are influencing manufacturers and their vision of their interaction with humans. This is mainly due to the improvement in semiconductors technologies that provide computers with high computing abilities, enabling complex operations, such as data processing, control, planning, etc., and with sufficient memory to store all incoming and outgoing data to and from the robots' environment (which is needed for decision making algorithms and robot control).

This paper describes a new approach for robot real-time navigation in static and highly dynamic environments. The strategy is based on a modified potential field method (MPFM). The proposed MPFM eliminates local minima (which are due to the robots environment configuration), and find a practical trajectory for robot path planning. The paper incorporates a total of six parts: The first part is a short introduction to autonomous robot evolution in static and non-deterministic environment that requires some basic abilities, and artificial intelligence, that are based on the robot-sensing equipment. The second part mainly presents some related work on trajectory planning algorithms based on artificial potential field method, or combined with other path planning methods. The third part describes two classical trajectory planning algorithms: A* and artificial potential field methods, according to literature, that highlights some of their advantages and drawbacks. In the fourth part, the major problem of the potential field method

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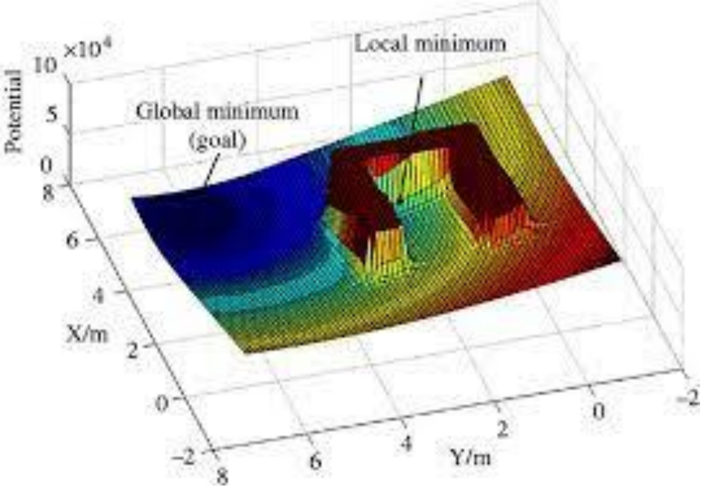
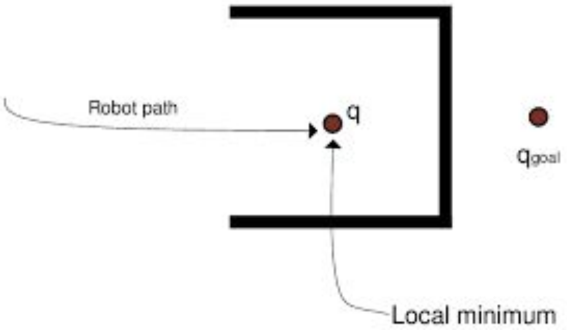
Main Idea

- Online Path Planning for autonomous driving using Potential Field Method
- **Issue** : Online evasion of Local Minima due to other cars
- Solutions :
    - **A*** - Computationally expensive
    - **Modified Artificial Potential Field** (MAPF) - Computationally inexpensive
- Main results compare **A*** and **MAPF** trajectories and time required

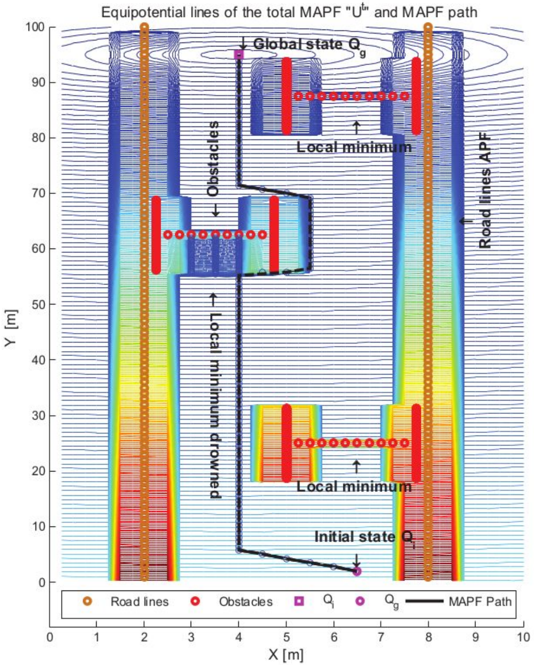


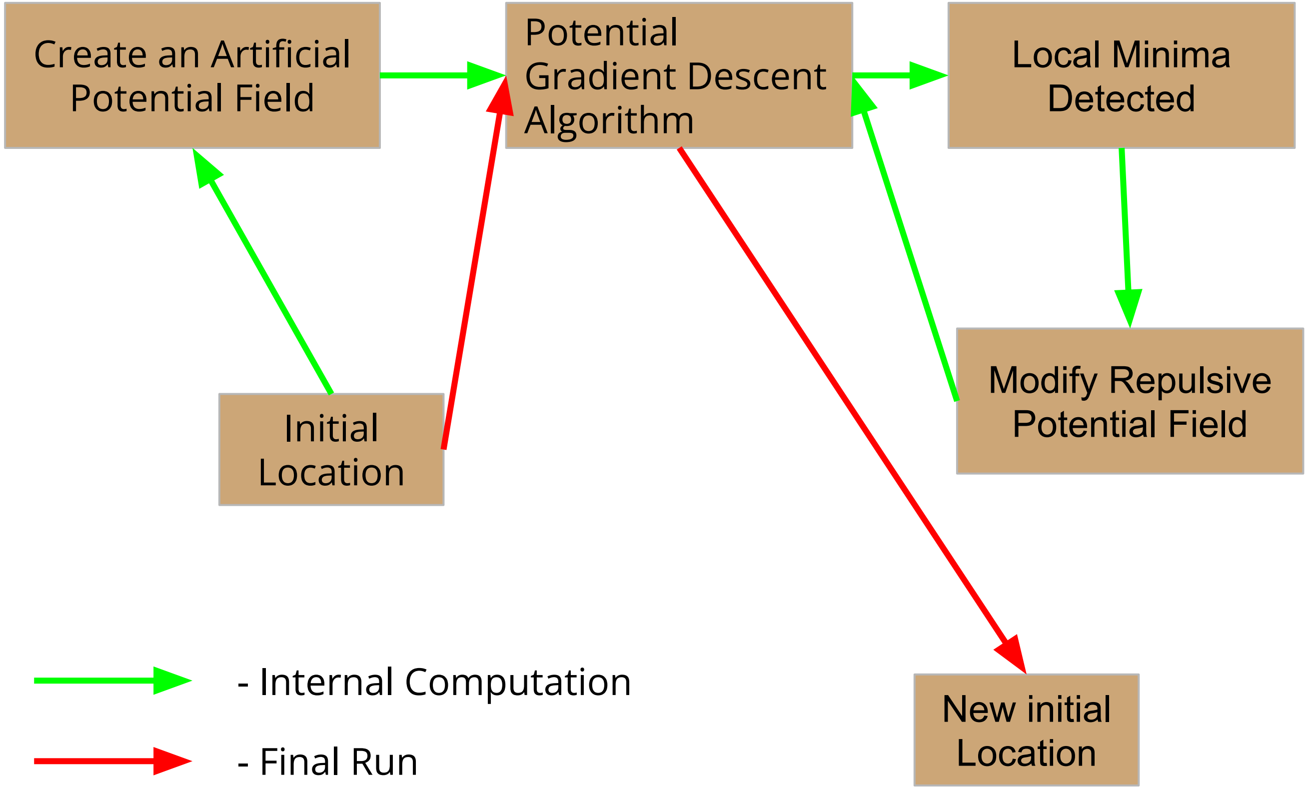


Reference -

- https://www.researchgate.net/publication/316507090/figure/fig2/AS:571505505300480@1513268938509/Total-potential-when-a-the-local-minima-exist-b-the-local-minima-moving-from-the_Q320.jpg
- https://i.stack.imgur.com/l9RZi.png

Problem Formulation





Problem Formulation

Suggested Modification to Repulsive Potential Field :

$$U^{a_c}(Q) = \frac{1}{2} k^a d(Q)$$

$$U_i^r(Q) = \begin{cases} \frac{1}{2} k_i^r d_i(Q) \left(\frac{1}{d_i(Q)} + \frac{1}{d_i^o} \right)^2 & \text{if } d(Q) \le d_i^o \\ 0 & \text{otherwise} \end{cases}$$

$$U^t(Q) = U^a(Q) + U^r(Q) = U^a(Q) + \sum_{i=1}^{n} U_i^r(Q)$$

Initial Potential Field

+

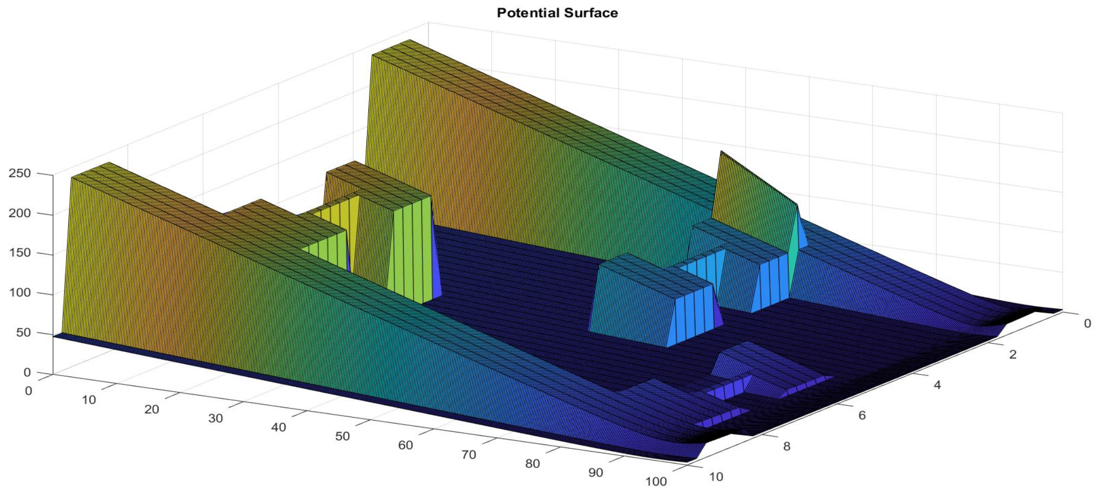
$$U_i^r(Q) = \begin{cases} \frac{1}{2} k_i^r \left(\frac{1}{d_i(Q)} - \frac{1}{d_i^o} \right)^2 \\ 0 \end{cases}$$

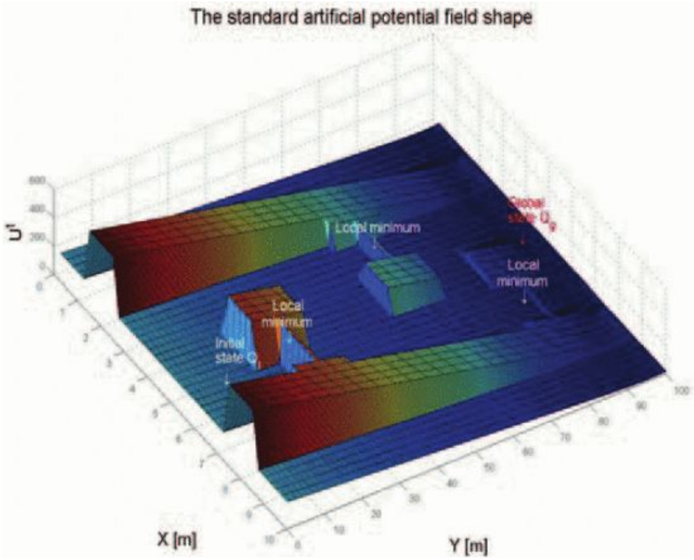
Repulsive potential to existing potential field at the location of local Minima

=

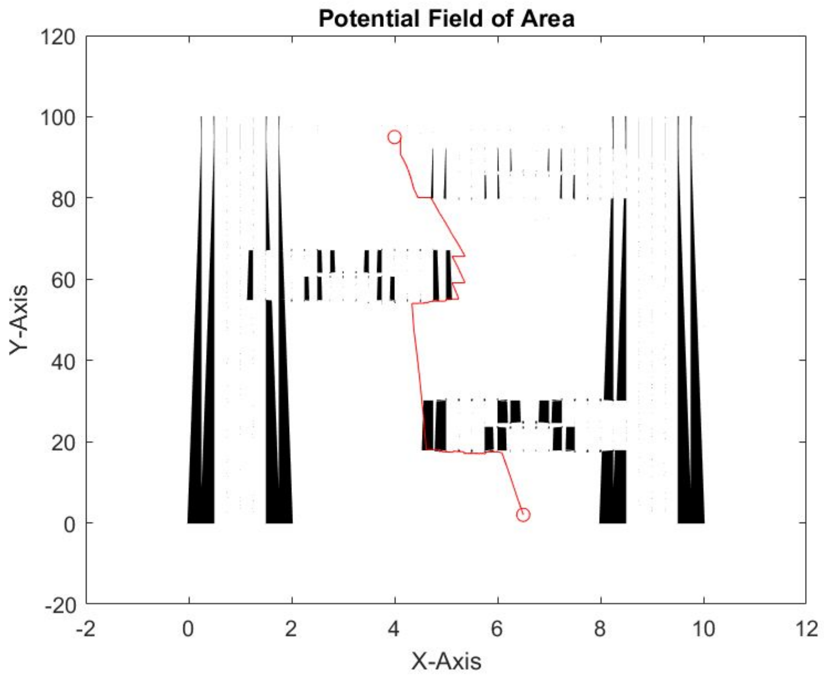
Modified Potential Field for Gradient Descent

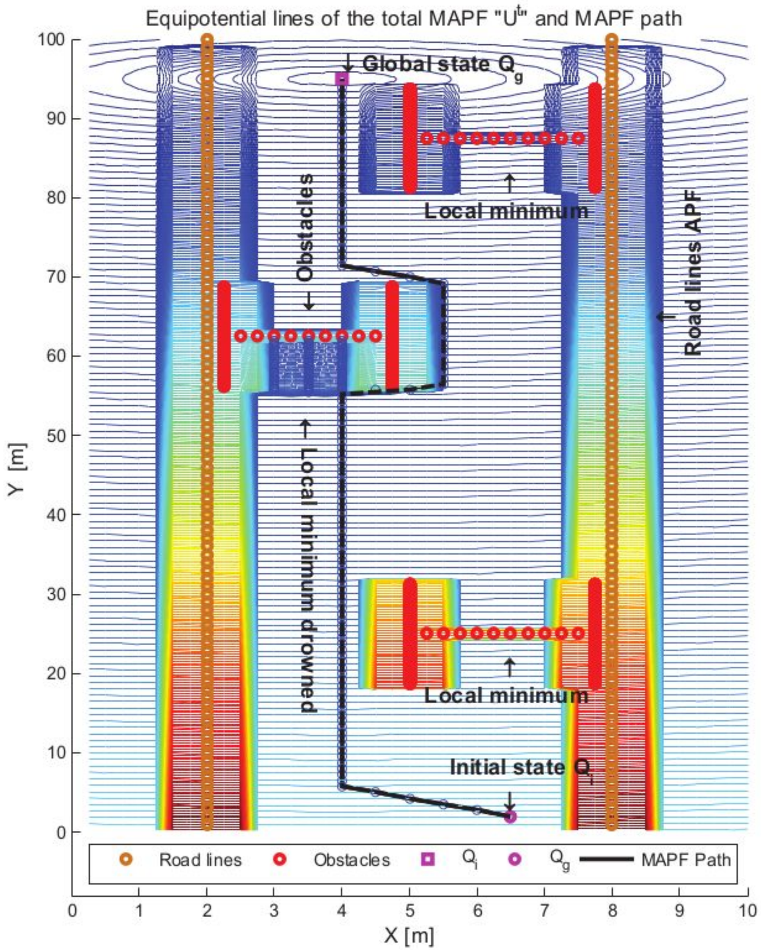
Simulation Results



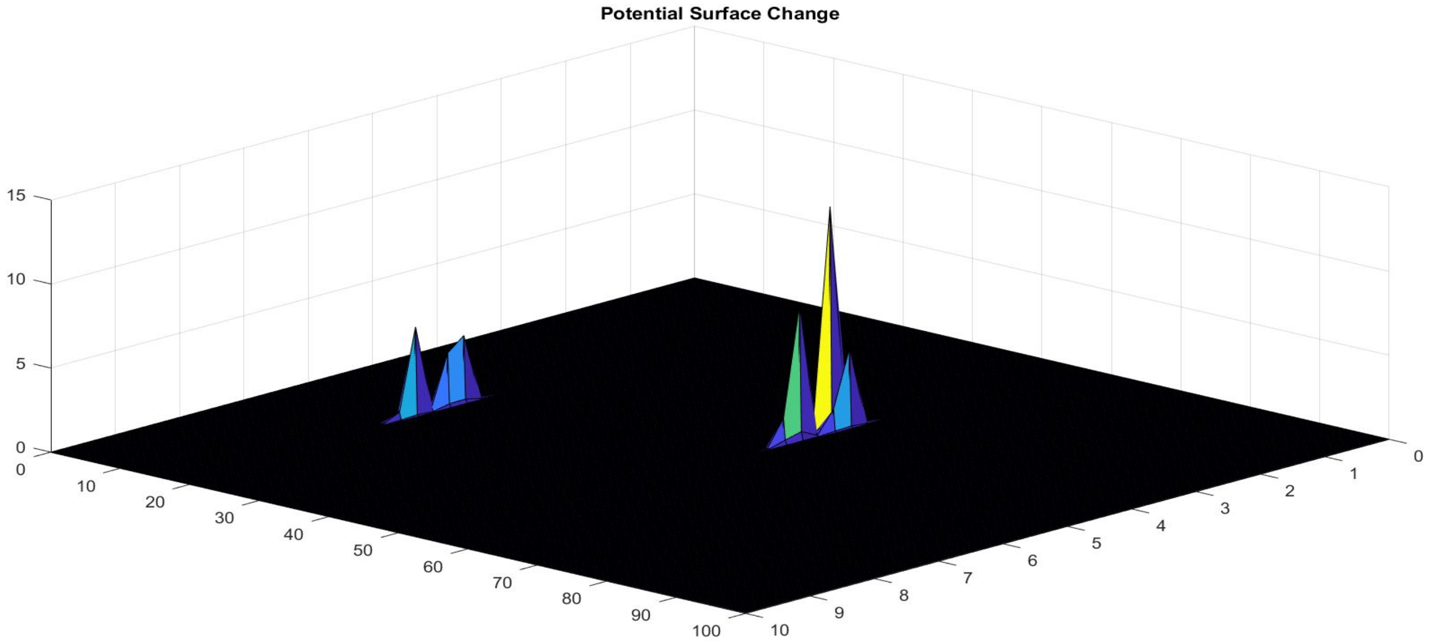


Simulation results



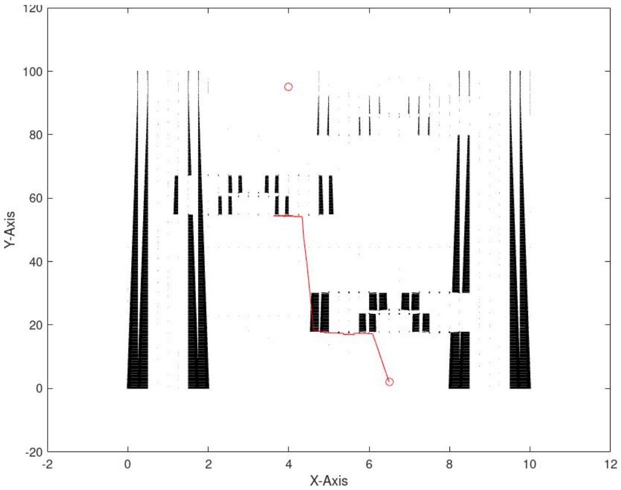


Simulation Results

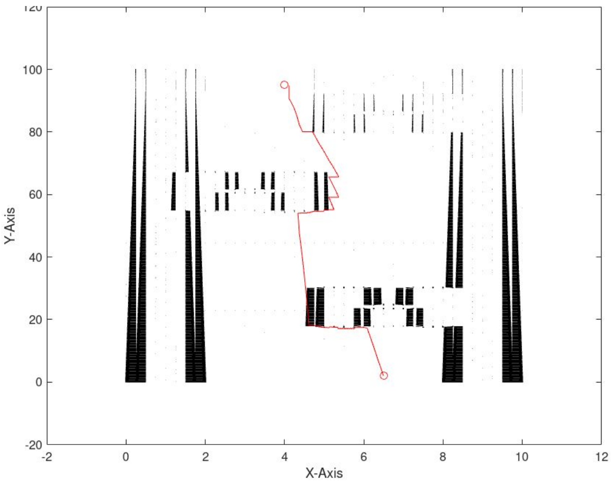


Observations and Comments

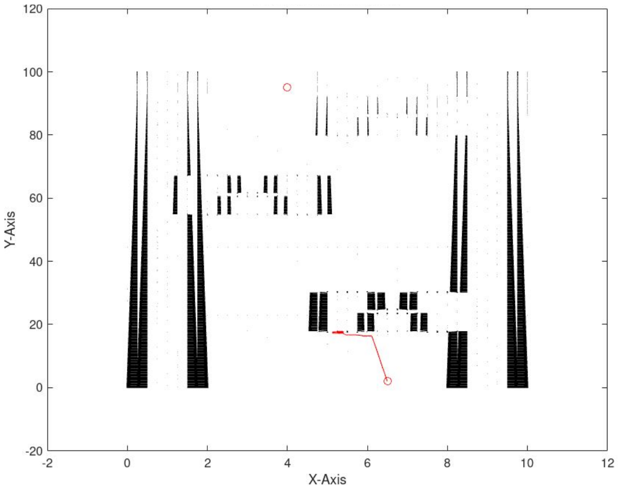
- Repeatability issues : values of proportionality constants depend upon shape, size and location of obstacles.



$K^r = 0.3$



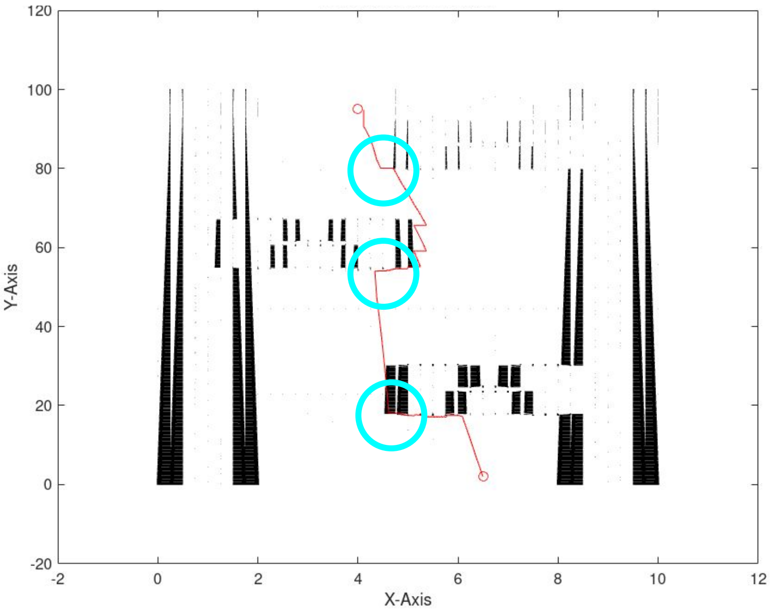
$K^r = 0.2$



$K^r = 0.1$

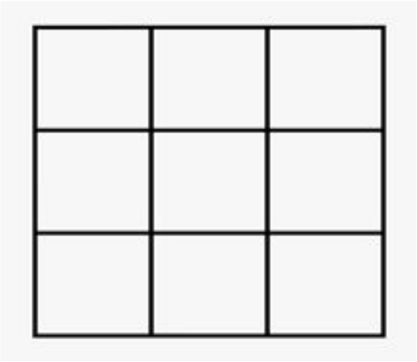
Observations and Comments

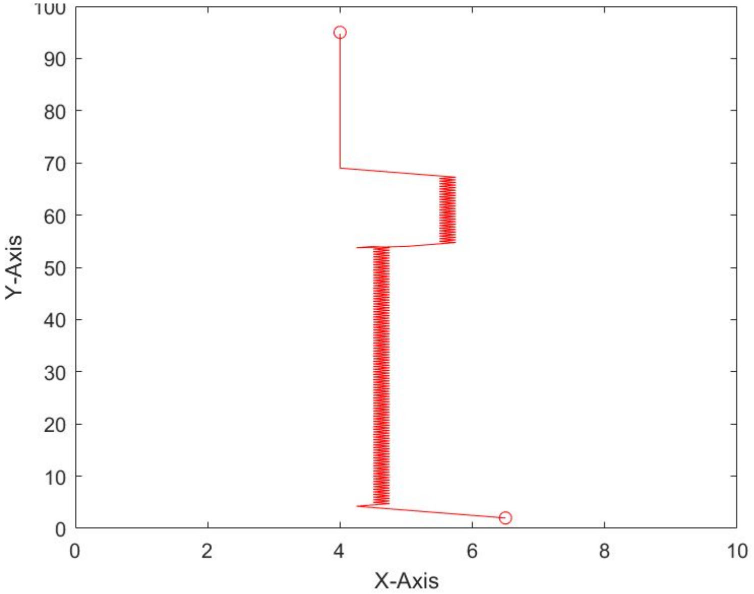
- Trajectory with sharp turns : Difficult for robot with non-holonomic constraints to follow the generated trajectory.

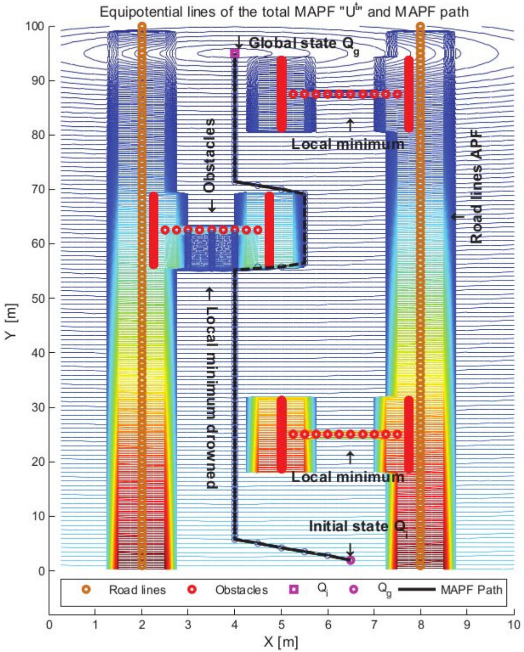


Observations and Comments

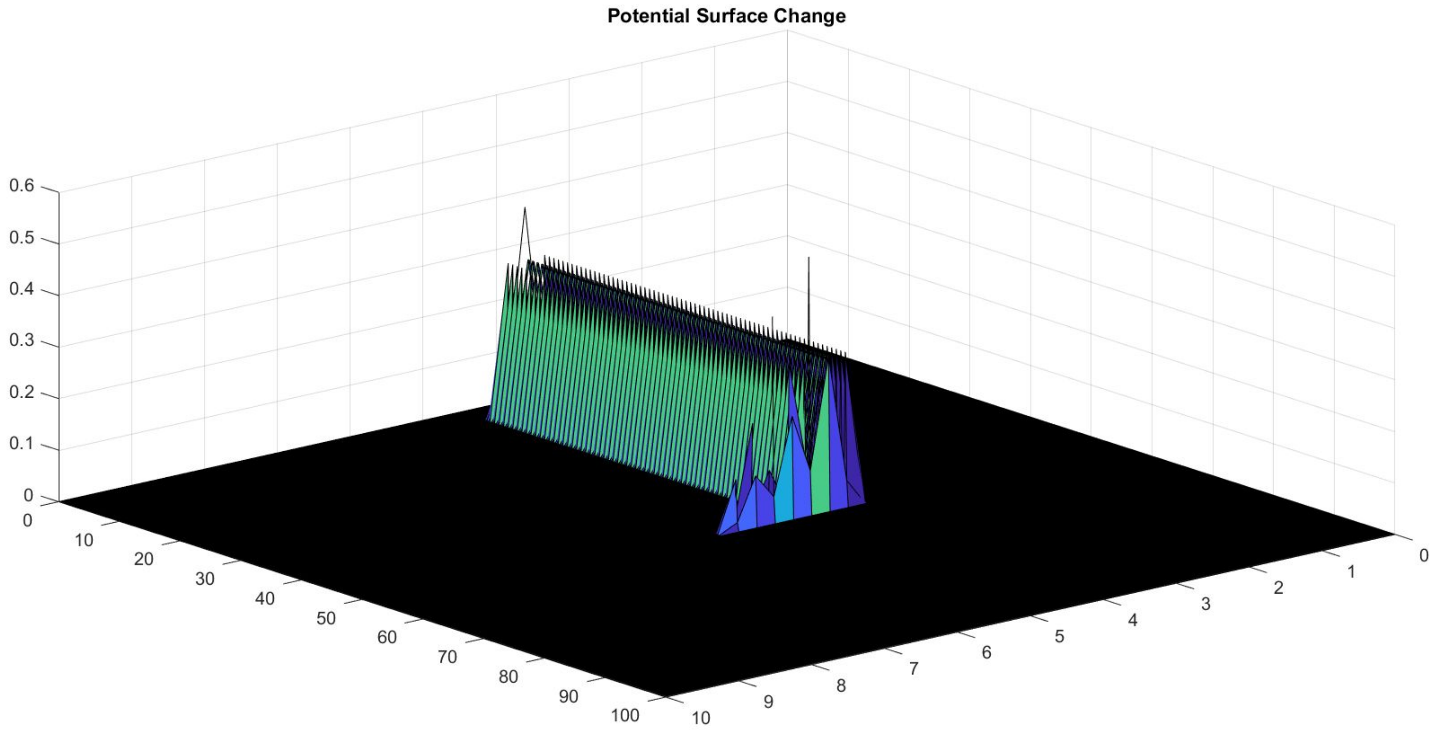
- The results heavily depend on the step size in gradient descent and the criteria for detecting local minima.







Observations and Comments



Questions ?

Appendix

Code : https://github.com/wakodeashay/Modified-Artificial-Potential-Field