Evaluation and Enhancement of Artificial Potential Fields for Path Planning in Dynamic Environments

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Auswertung und Verbesserung des Artificial Potential Field Algorithmus für die Pfadplanung in einer dynamischen Umgebung

Abstract

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Contents

1 Introduction

Nowadays, more and more machines are expected to be able to work autonomously, i.e. without additional human influence. Be it in the virtual world to fend off cyber attacks, answer questions of any kind, or in the real world to transport people or to explore foreign planets. Autonomous driving, such as is already possible in some vehicles, must of course solve many technical problems as well as ethical issues. The detection of obstacles such as pedestrians or other cars, the calculation and implementing goal-oriented evasive maneuvers, or generally approaching a specific destination. These are only a few of such problems, but they quickly show how complex a seemingly simple task like "driving from A to B through an unknown area" can be.

Path planning is therefore about maneuvering the robot safely to the target without causing collisions or detecting and preventing them at an early stage. In an unknown environment, the robot must constantly update its route and adapt to the new conditions detected by its sensors. In this case, it is usually not given that the robot runs along an optimal path. With previous knowledge of the initial situation, however, this can be achieved. This is called local and global path planning. Local calculations are however for real time applications rather suitable, since it is with applications rarely the case that the entire environment is known and it is likewise difficult on unexpected events to be able to react.

In the following work, a very popular model in path planning called "artificial potential fields" (APF) will be presented and analysed. It stands out from other models because of its simplicity and robustness and can also be used for real time applications. This model delivers good results especially in a static environment, i.e. an environment where the obstacles do not move. However, the classic model is not designed for moving obstacles, which is why it performs rather poorly in dynamic environments. This issue will be investigated, adding several possible extensions to the APF and analyzing its usefulness.

1.0.1. Related Work

Path planning is a very complex topic with a wide variety of approaches that cannot be discussed further in this paper. These can be roughly divided into two types: model-based and learning-based.

In the former, a search space for the planning is built, for example a two or three dimensional one to describe the environment. In the case of a dynamic environment, a four dimensional one can be used, where time is added as an additional dimension. Now a path through this environment must be found by means of mathematical analysis [1] [2] [3].

Another approach that has become increasingly popular in recent years is the use of machine learning. Mostly, neural networks are trained using raw sensor data, such as camera images or lidar sensors. Supervised learning-based approaches or reinforcement learning-based approaches are just some of the examples. But they are all based on a high amount of data, which is needed to learn. With enough different data sets, the method can abstract well enough and work reliably even in previously unknown areas. It can operate in a static as well as in a dynamic environment [4].

1.0.2. Thesis outline

The following work is structured as follows:

- Chapter 2 provides background to the APF algoritmn
- Chapter 3 presents the various extensions of the model
- Chapter 4 examines the extensions using simulation results
- Chapter 5 contains the final conclusion and gives an outlook for further improvements

2 Background

2.1. Potential Field

The Artificial Potential Field (APF) was firstly introduced 1985 by O. Khatib [5]. He described a method for path planning where the robot is under the influences of two different types of constructed fields generated by the destination point and obstacles nearby. One to move the robot to the target and the other to keep it away from hindrances. This approach for navigating a robot thru an environment later became important for path planning, not only because of its ease of implementation, but also because of its good mathematical analysis capabilities. Its simplicity also allows it to work in real time.

You can use different types of forces here. However, the most common ones are presented below. The first constructed field is determined by the target point and the position of the robot. The field is created so that the robot can 'roll down' the field similar to a marble and thus reach the target. This becomes clearer by having a closer look at figures 2.1 and 2.3 below.

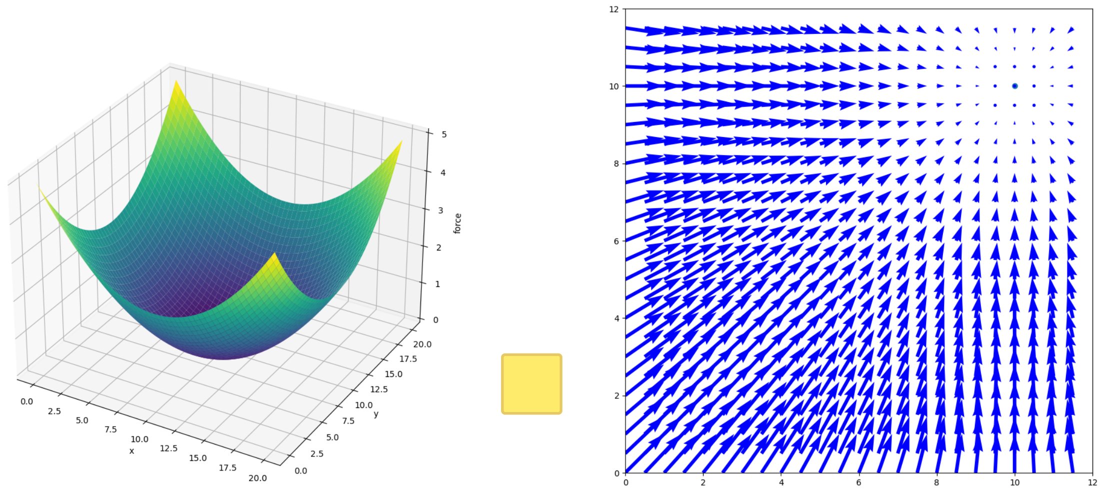
Definition 2.1.1 (Attraction Field)
Let $p \in R^n$ be a point in the environment representing the position of the robot on a two dimensional map. Let $g \in R^n$ be the goal of the path planning. The attraction field at p can be represented as:

$$U_{att}(p) = \frac{1}{2} * k_a * ||p - g||^2$$

where k_a is a positive scaling constant and $||.||$ is the Euclidean distance.

The force acting through the field is calculated by taking the negative gradient.

$$\begin{aligned} F_{att}(p) &= -\nabla U_{att}(p) \\ &= -\frac{1}{2} k_a * 2 * (p - g) \\ &= k_a * (g - p) \end{aligned}$$



(a) Attraction field

(b) Force acting on the robot

Figure 2.1.: Attraction field and resulting forces

Another field is generated by the obstacles of the environment and generates repulsive forces from them. Here, too, different variants can be used, but the most common one is based on the gravitational force.

Definition 2.1.2 (Repulsive Field)
Let $p \in R^n$ be a point in the environment representing the position of the robot on a two dimensional map. Let O$\subset R^n$ be a set representing the position of k obstacles.
For each obstacle position $o_i \in O$ (i = 1,...,k) the repulsive Field is calculated as:

$$U_i(p) = \begin{cases} \frac{1}{2} * k_r * (\frac{1}{d} - \frac{1}{d_0}) & , d \leq d_0 \\ 0 & , d \geq d_0 \end{cases}$$

where k_r is a positive scaling constant, d_0 the distance of the obstacle repulsive force field and d being the Euclidean distance between o_i and the robot position p.

The force acting through each obstacle is calculated by taking the negative gradient.

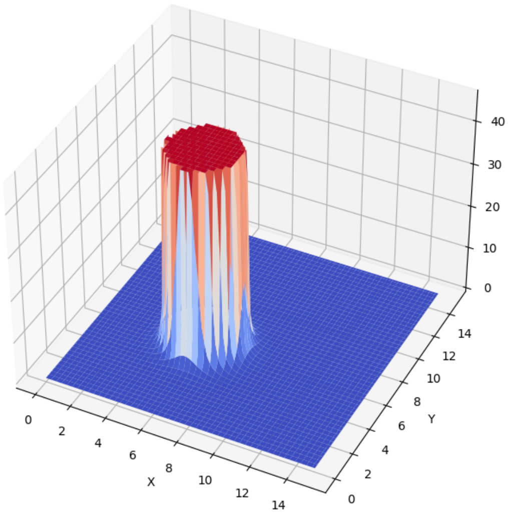
$$F_i(p) = \begin{cases} -\nabla U_i(p) & , d_0 \leq 0 \\ 0 & , d_0 \geq 0 \end{cases}$$
$$= \begin{cases} k_r * (\frac{1}{d} - \frac{1}{d_0}) * (p - o_i) * \frac{1}{d^3} & , d \leq d_0 \\ 0 & , d \geq d_0 \end{cases}$$

The total repulsive field is the combination of each obstacle field:

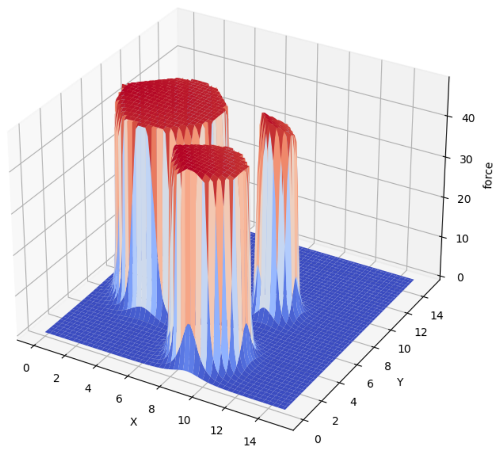
$$U_{rep}(p) = \sum_{i=0}^{k} U_i$$

This results in the total repulsive force acting on the robot as:

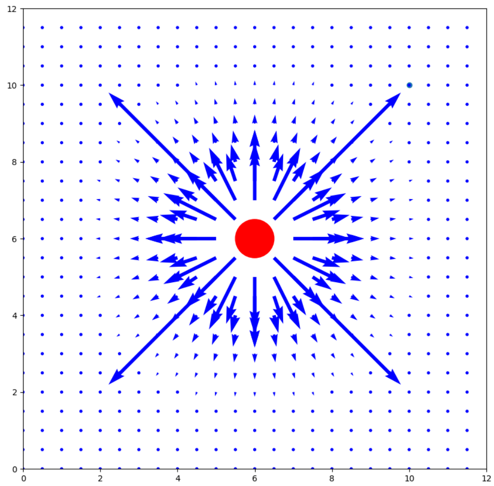
$$F_{rep}(p) = \sum_{i=0}^{k} F_i$$



(a) Repulsive field



(b) Repulsive field with 3 obstacles



(c) Force acting on the robot with one obstacle

Figure 2.2.: Repulsive field and resulting forces

The combination of the two fields now results in the potential field of the environment as shown in figure 2.3 below.

Definition 2.1.3 (Potential Field)
Let $p \in R^n$ be a point in the environment representing the position of the robot on a two dimensional map. Let O$\subset R^n$ be a set representing the position of k obstacles. Let $g \in R^n$ be the goal of the path planning.

The APF function can be represented as:

$$U(p) = U_{att}(p) + U_{rep}(p)$$

and this gives the forces acting on the robot:

$$\begin{aligned} F(p) &= -\nabla U(p) \\ &= F_{att}(p) + F_{rep}(p) \end{aligned}$$

Having a priori knowledge about the whole environment makes it possible to generate the potential field offline, to further decrease the computation.

2.1.1. Limitations

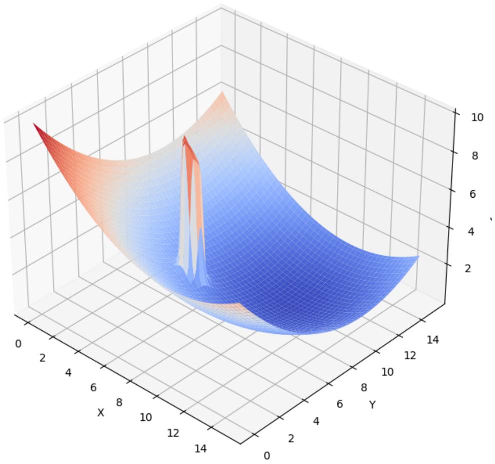
However, this classic model also had its flaws. The first one being that the goal is not reachable because an obstacle is too narrow resulting in the repulsive force being significantly higher then the attraction.

However the most common problem is the so called local minimum, also resulting in a not reachable goal situation. It can occur for example when a passage created by two or more obstacles is too narrow, not specifically for the physical robot itself, rather the fact that the forces resulting from the hindrances are one more time significantly higher then the attraction by the goal. The robot is now trapped in a loop right in front of these obstacles or does not move it all.

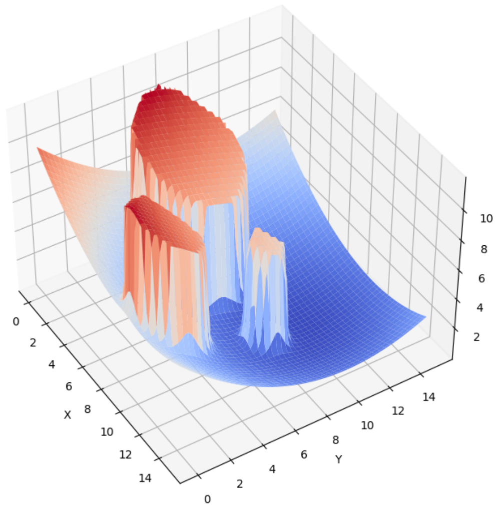
Figure 2.4 illustrates these two problems. How these problems can be solved and others can be found in [6].

2.2. Robot Controls

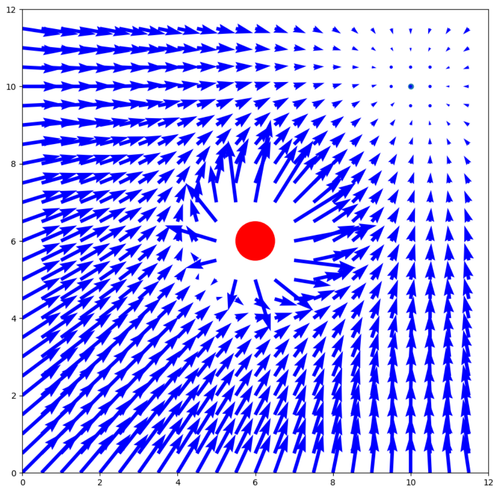
[TODO: Aus Vektor Robot Bewegung erklären]



(a) Potential field

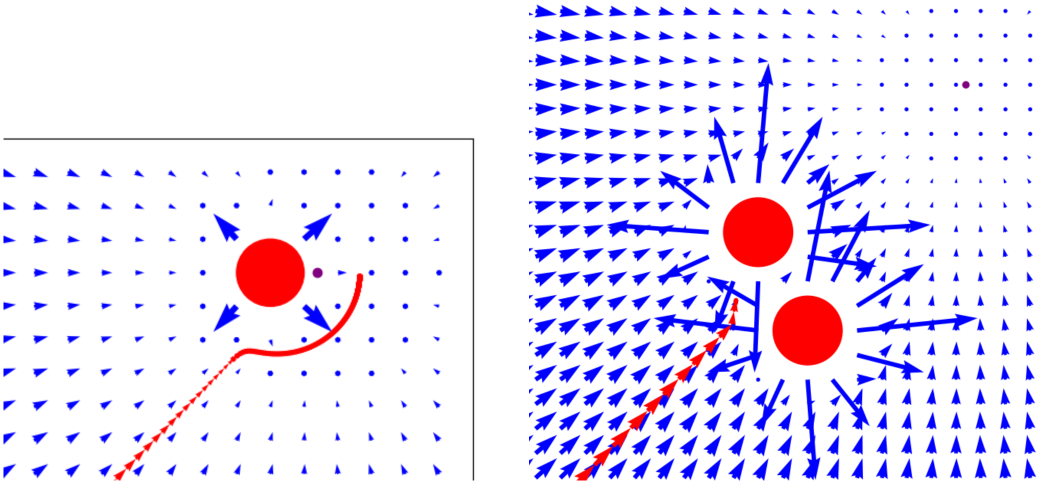


(b) Potential field with 3 obstacles



(c) Force acting on the robot with one obstacle

Figure 2.3.: Potential field and resulting forces



(a) Goal not reachable example

(b) locale minima example

Figure 2.4.: Limitation examples

3 Method

3.1. Settings

[Aufbau und Umgebung erklären, Hindernisse als Zylinder approx, 5x5 Feld]

3.2. Models

3.2.1. Forward Projection

3.2.2. Rotational APF

3.2.3. (Improved APF)

4 Simulation

4.1. Settings

[Gazebo/Ros, Turtlebot]

4.2. Models

4.2.1. Forward Projection

4.2.2. Rotational APF

4.2.3. (Improved APF)

5 Conclusion and Outlook

A | Some Appendix Chapter

List of Figures

List of Tables

Bibliography

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Declaration of Academic Integrity

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Niklas Hellmann, Münster, August 29, 2023