CS365: Group 25
Dynamic Motion Planning using Fuzzy potential fields

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Abstract

The aim of the project is to ensure the soft landing of the robot on the mobile target while avoiding nearby moving or stationary obstacles with the help of potential fields. Instead of using the traditional methods we model obstacles and targets using fuzzy inference systems. Attractive potential of the target is modeled using Mamdani Inference system. For obstacle(s) we use TSK inference system in which the parameters are learned through Adaptive Neuron Fuzzy Inference System (ANFIS).The dataset for ANFIS is generated by implementing a conventional potential field method and by considering various possible scenarios.

1 Introduction

The field of motion planning is crucial to the evolution and integration of robots in the mainstream. Potential fields have been historically popular as means to modeling mobile or static obstacles and targets to a good accuracy. However caveats such as Local Minima Problem and high computation costs have hindered practical application.
We combine the elegance of potential fields with Fuzzy Logic Inference Systems to tone down the computational costs using the methods provided by Jaradat[3]. Mamdani Inference System[4] is used to model the attractive force while TSK Inference System[2] is used to model the repulsive forces.The method proposed by Ge and Cui[1] is also implemented and used to train the parameters of TSK Inference system by using Adaptive Neuron Fuzzy Inference System(ANFIS) algorithm.
For simplicity ,we model both the obstacles and target as well as the robot as point objects. The attractive and repulsive force potentials are assumed to be entirely dependent on the relative velocity and relative position.

1.1 Related Work

Extensive research has occurred in the field of motion planning using potential fields since CW Warren[5] proposed their use. This approach was widely received because of its elegant mathematical analysis and simplicity. Much of the initial work was focused on path planning in static environments but progress for dynamic environment was eventually made. Ge and Cui [1] came up with a very elegant model to model moving obstacles based on their relative positions and relative velocities.

2 Attractive Potential

The attractive force as mentioned earlier is modeled by Mamdani fuzzy Inference system. It is basically an IF THEN expert system with the rules and input values being specified by using the concept of fuzzy logic. Intuitively the magnitude of the attractive force of the target on the robot(object) depends on its relative velocity and relative position from the target. To simplify the analysis we chose to work with orthogonal components i.e X and Y. This means that we have 4 independent input variables i.e Δx , Δy , Δvx and Δvy and 2 independent output variables Fx and Fy.

2.1 Membership functions

Each of the 6 variables are represented by 5 triangular membership functions. The membership functions are named as {-large,-small,zero,+small,+large}. As can be inferred from the names, each membership function represents a certain range of the possible values of the input variables. Instead of choosing 5 membership functions we could use a larger number of membership functions which will lead to a more finer division of the input space . However this complicates the analysis and also leads to a significant increase in computation cost.
The parameters of the membership functions are determined manually based on the prior knowledge or on vague predictions of the future motion. For example , If a target is moving with a speed of 10 m/s and is expected to remain in that range , then 40 m/s and 60 m/s can be chosen as the corners of the +large membership function for say Δvx.The parameters for Δx and Δy are chosen to be identical as is the case for Δvx and Δvy and also Fx and Fy.

2.2 Rules

The principles followed while determining the rules are very intuitive. For large values of say dx the attractive force Fx should be large to attain the soft landing in a realistically minimal time.Similarly if their is no relative velocity then the value of attractive force should approach zero.This leads to a total of 20 rules all of which follow either of the below enlisted forms:

1. If Δx is * then Fx is *
2. If Δy is * then Fy is *
3. If Δvx is * then Fx is *

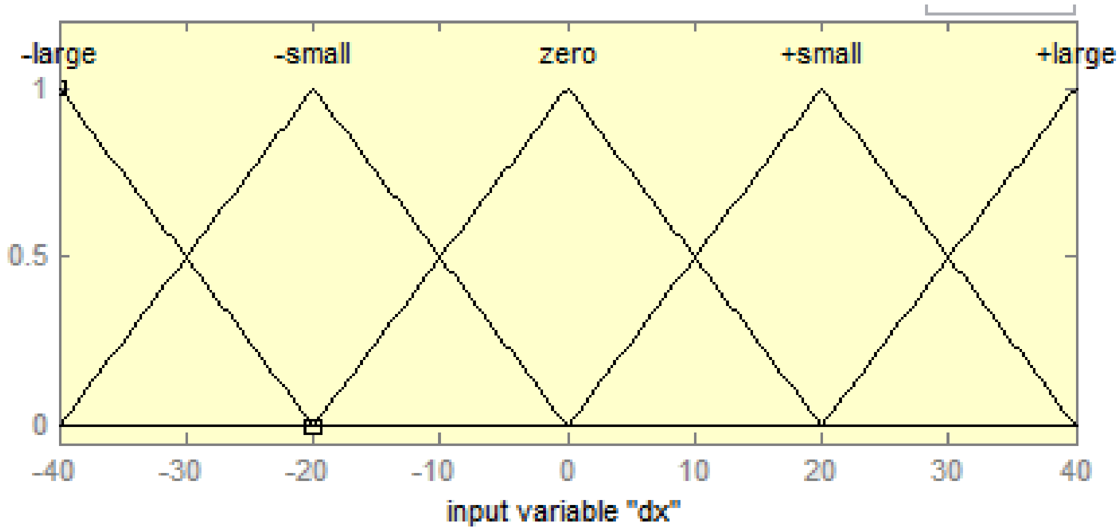


Figure 1: Triangular Membership functions

4. If Δvy is * then Fy is *

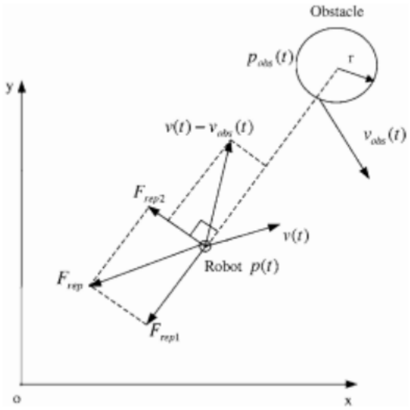
The inference output from these rules is computed by Mamdani (maxmin) operator for composition and minimum operation for implication,The centroid of the output area is used to report the final crisp output value.
The Mamdani Inference system was implemented by using the fuzzy logic Toolbox provided in Matlab. The Inference system was exported as a .fis file which was then used to calculate attractive force in various dynamic scenarios.

3 Repulsive Potential

The approach to calculate the repulsive force method is different to the calculation of attractive force. As again, the obstacle is modeled using a point and the repulsive force is said to be dependent on the relative position and velocity between the object(robot) and the obstacle.The sensing has to be done individually for all the obstacles present in the range of the robot to obtain the required input values for all obstacles. Each obstacle is considered independently and the total repulsive force is calculated by adding all the individual contributions.

3.1 Ge and Cui

First we consider the approach of repulsive potential fields discussed in [1]. Let $P_{obs}(t)$ and $V_{obs}(t)$ be the position and velocity of the robot respectively. The sensing system of the robot is assumed to provide these values instantaneously.Let $V_{ro}(t)$ be the relative velocity of robot with respect to the obstacle. $\rho_s(P_{obs}(t), P_r(t))$ denote the distance between the two.
For each obstacle a *sphere of influence* denoted by ρ_o is defined as the region in which the repulsive force is significant to have any impact on the motion of the robot. Outside it the repulsive force is small and is ignored.Again if $V_{ro}(t)$ is such that the object is moving away from the obstacle then again no repulsive force calculations are required.Let a_{Max} be the maximum possible acceleration for the robot, constrained by the design or some other reason.Then



$$\mathbf{F}_{rep1} = \frac{-\eta}{(\rho_s(\mathbf{p}, \mathbf{p}_{obs}) - \rho_m(v_{RO}))^2}\left(1 + \frac{v_{RO}}{a_{\max}}\right)\mathbf{n}_{RO}$$

$$\mathbf{F}_{rep2} = \frac{\eta v_{RO} v_{RO\perp}}{\rho_s(\mathbf{p}, \mathbf{p}_{obs}) a_{\max}(\rho_s(\mathbf{p}, \mathbf{p}_{obs}) - \rho_m(v_{RO}))^2}\mathbf{n}_{RO\perp}$$

Figure 2: Calculation of repulsive force

a certain region exists such that if the robot enters that region then it is impossible to avoid collision. This is denoted by by $\rho_m(v_{ro})$ .The equations for calculating the repulsive force due to an obstacle are shown in Fig2.

3.2 TSK Inference System

This approach is discussed in [3] and is actually an application of fuzzy inference systems on the methods provided by [1]. TSK inference system is a Type II fuzzy logic system in which the ouput membership function is either linear (in input variables)or constant.For this inference model we chose only Δx and Δy as the input variables ignoring the dependency of repulsive force on the obstacle velocities.For each input 11 input membership functions were considered. The shape of these membership functions was chosen to be Gaussian - Bell. Each gaussian bell membership function had 3 modifiable parameters.
The IF THEN rules for TSK inference system are of the form IF Δx is * Δy is * then $F_x = a_i\Delta x + b_i\Delta y + c_i$ where a_i, b_i, c_i are output parameters which vary according to the rules.11 membership functions correspond to 121 rules.
The Inference system is then trained on the data obtained by the implementation of previous algorithm to tune the membership functions as well as the rule strengths by the Adaptive Neuron Fuzzy Inference System(ANFIS) [2].

4 Results

The two Fuzzy Inference Systems were implemented in MATLAB using the Fuzzy Logic Toolbox provided.The more classic approach of [1] was also implemented in MATLAB assuming Newtonian equations of Motion.
While running simulations the time-step for re-computation of force i.e refresh rate was set in the range of 0.1s to 1s.The simulations were run for variety of scenarios as :

- Figure 5 shoes a moving target(red line) and a robot(blue line) initially starting from (0,0)

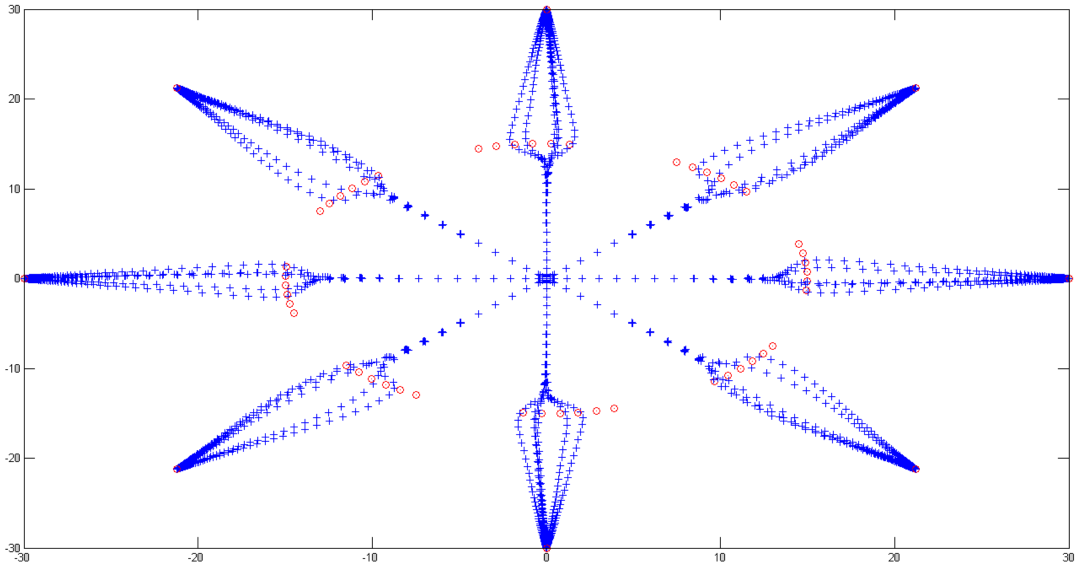


Figure 3: 48 scenarios considered to train TSK Inference system

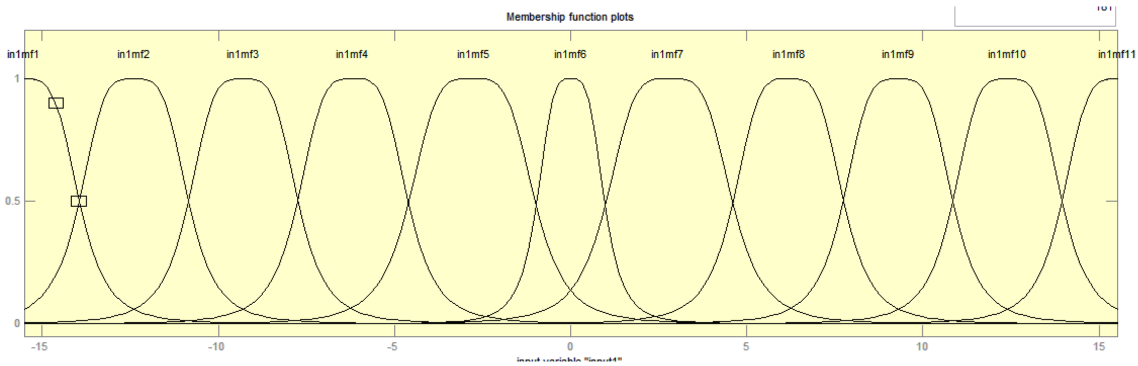


Figure 4: Shape of tuned Membership functions

softly landing on the target and following it afterwards.

- Figure 6 and 7 showcase the Local Minima Problem in dynamic and static conditions.The robot starts off from (0,0) while the target is initially located at (30,30). The obstacle(red) lies on the line joining the two. For 6 the target is moving with a constant velocity along the initial line of view. As is evident from the figures the force model is able to avoid the Local Minima Problem.

- Figure 8 has two obstacles lying on the way to target located at (30,0).

- Figure 9 shows the canceling out of the repulsive forces by two obstacles. However there still remains substantial force along the perpendicular bisector of the two obstacles. Once the target crosses the line it starts receiving the combined outward push along its line of the motion due to the two earlier bypassed robots. However it still manages to evade the 3rd robot placed just after theses two robots.

- Figure 10 displays the correct decision making of robot. After displaced by the 1st robot from its path towards the target , robot can choose to go either outside both the next 2

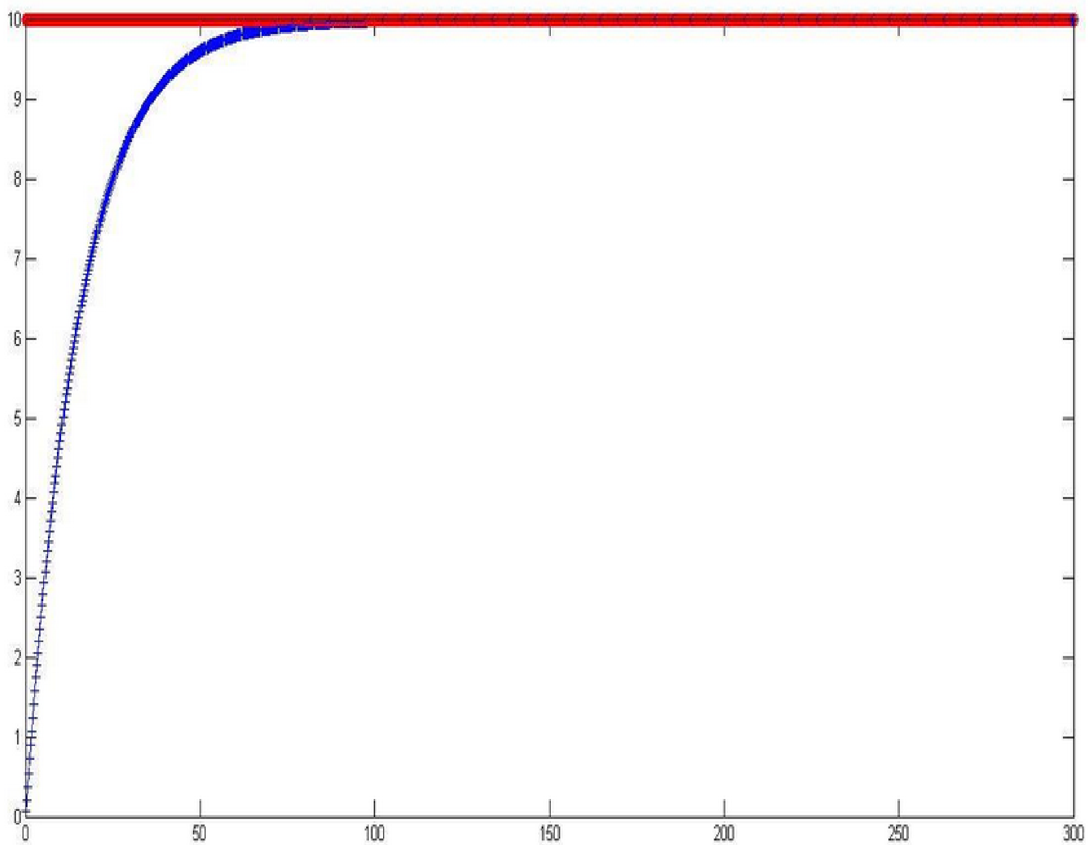


Figure 5: Soft Landing and eternal chase

robots or between them. The attractive force function guides the robot towards 2 while still being able to negotiate the obstacles.

- Figure 11 is a curious scenario in which the obstacle invades the target displacing the robot in the meanwhile. However as the distance and relative velocity between the robot and target increases the attractive force becomes dominant again and the robot is forced back again on the target while making sure no contact with the obstacle is made.
  Note the continuous red line is the path traced by the obstacle which passes through (30,30) i.e the target only after the robot had reached their first. If the robot doesn't reach there first then there won't be significant change in path of robot in comparison to earlier similar examples.

References

[1] Shuzhi S. Ge and Yun J Cui. Dynamic motion planning for mobile robots using potential field method. *Autonomous Robots*, 13(3):207–222, 2002.

[2] J-SR Jang. Anfis: adaptive-network-based fuzzy inference system. *Systems, Man and Cybernetics, IEEE Transactions on*, 23(3):665–685, 1993.

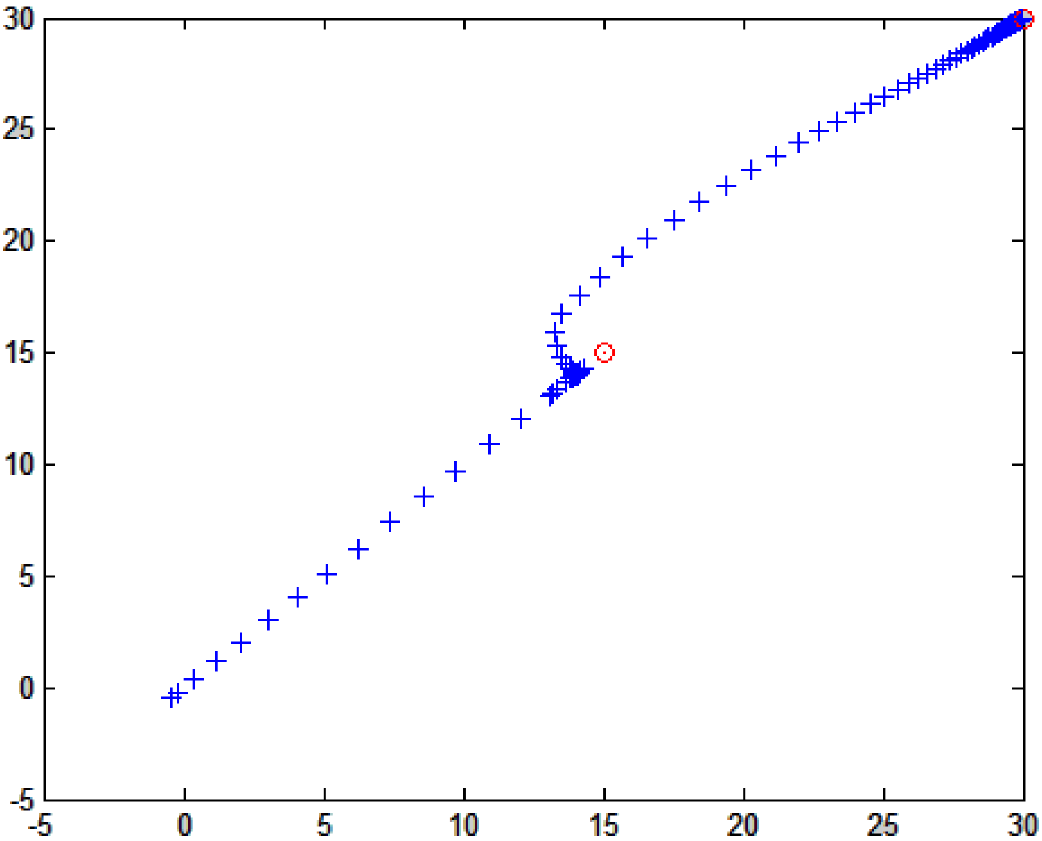


Figure 6: No Local Minima Problem in static environment

[3] Mohammad Abdel Kareem Jaradat, Mohammad H Garibeh, and Eyad A Feilat. Autonomous mobile robot dynamic motion planning using hybrid fuzzy potential field. *Soft Computing*, 16(1):153–164, 2012.

[4] Peter J King and Ehmat H Mamdani. The application of fuzzy control systems to industrial processes. *Automatica*, 13(3):235–242, 1977.

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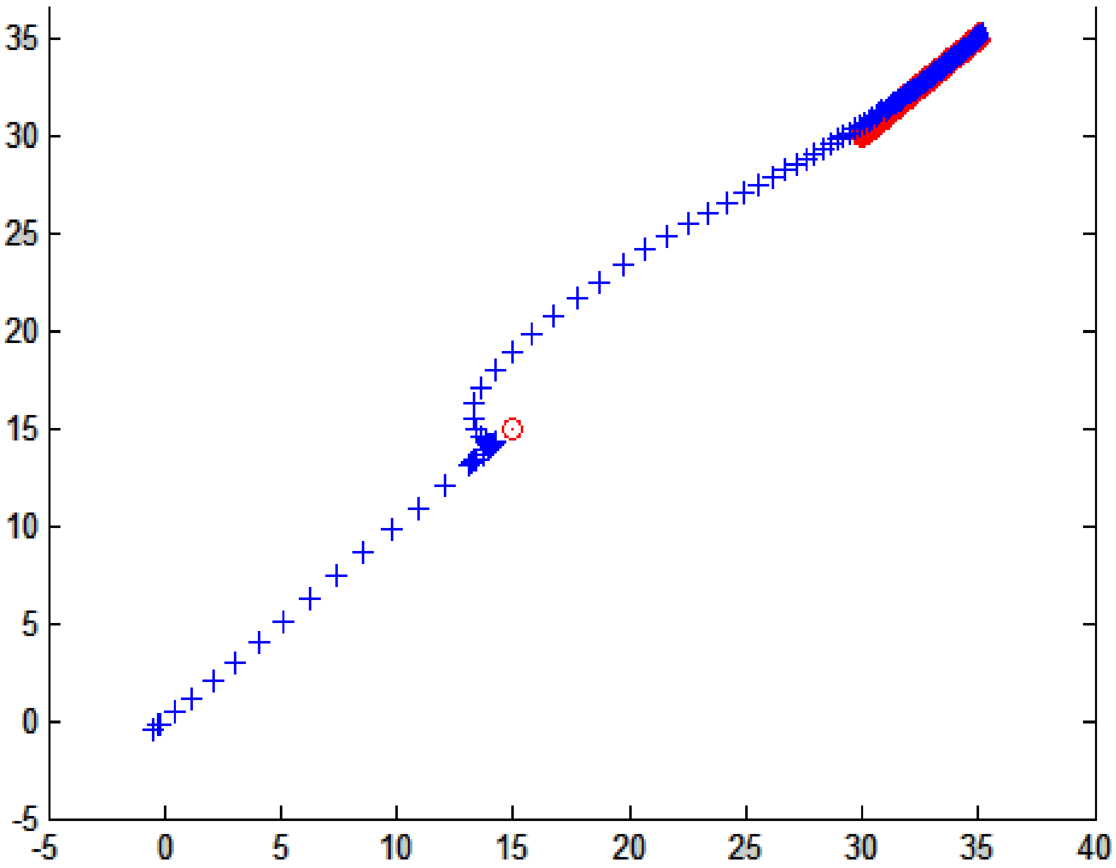

Figure 7: No Local Minima Problem in dynamic environment

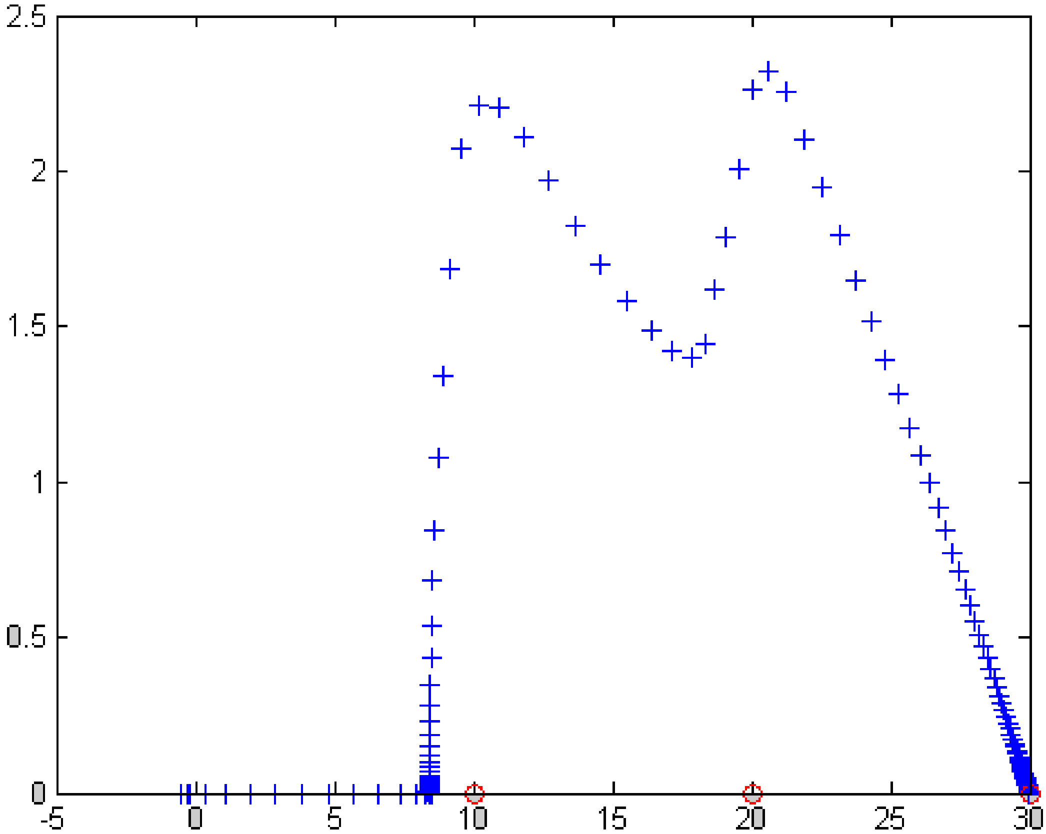

Figure 8: Two on a roll(the extra bulge is due to different scales on X and Y)

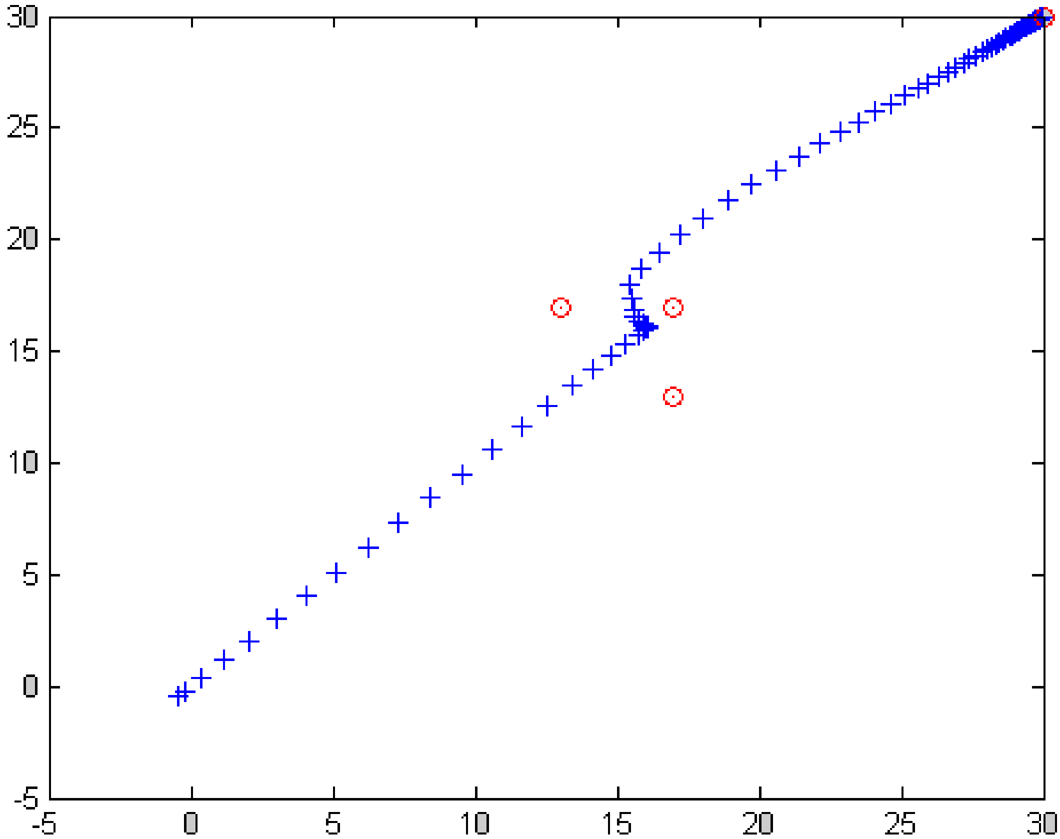

Figure 9: Cancelling effect of two Obstacles

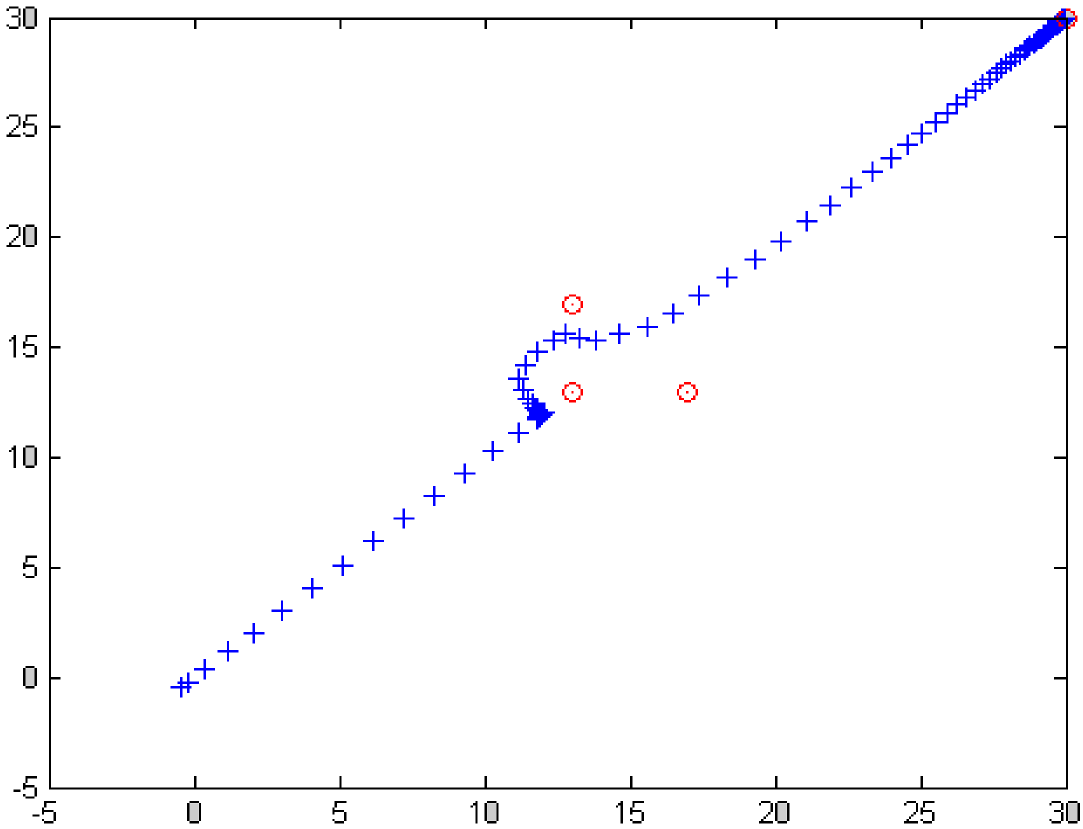

Figure 10: Working in tight spaces

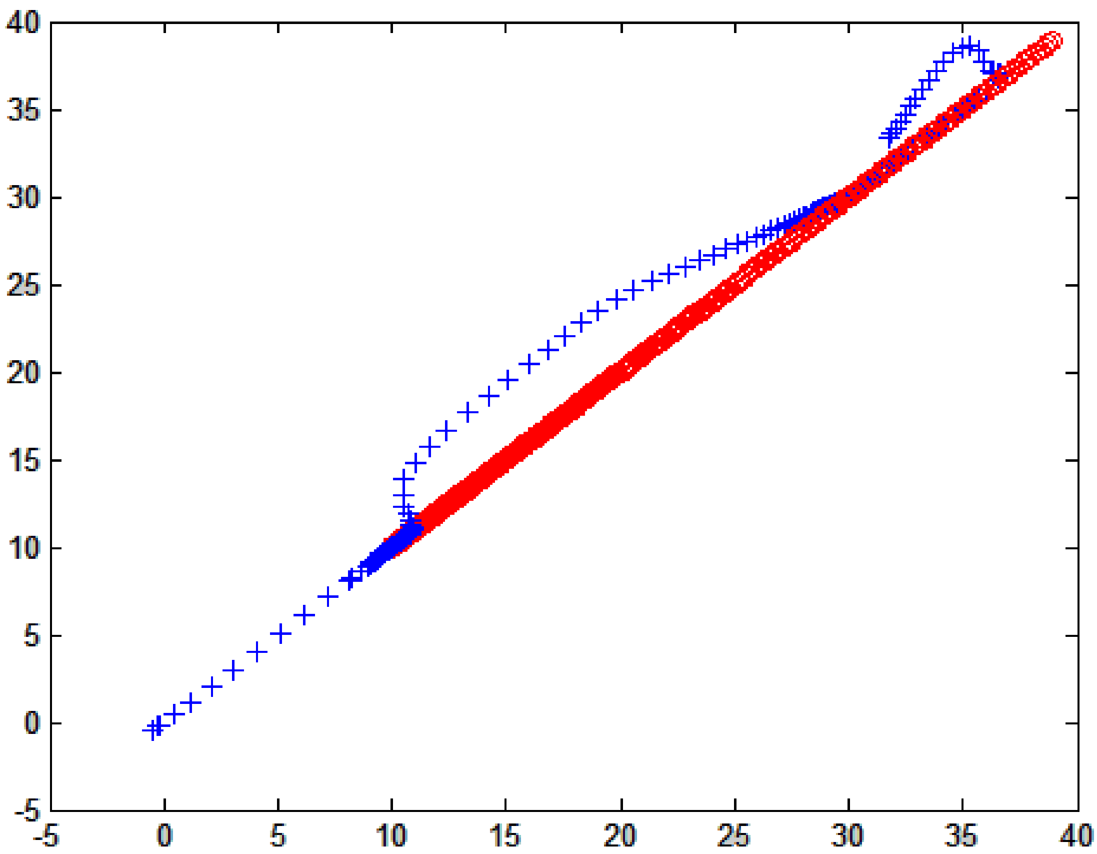

Figure 11: Obstacle invading Target