

Robot Navigation using Velocity Potential Fields and Particle Filters for Obstacle Avoidance

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Abstract: Autonomous robots are required to avoid the obstacles during navigation. For this purpose unknown and unexpected obstacles have to be detected during motion. The proposed approach uses particle filters to process sensors data and estimate relative position of the robot with regard to the obstacles and to the goal. These relative position estimations are inputs to the velocity potential field approach for obtaining time varying velocity commands for the robot to avoid all obstacles and reach the goal.

1 INTRODUCTION

Robot motion control needs data about the absolute position of the goal and the relative positions of the unexpected obstacles with regards to the robot. Often, a map of the surrounding area is needed. A solution to the simultaneous localization and map building, presented by Dissanayake et al, 2001, permits an autonomous vehicle to start in an unknown location in an unknown environment and, using relative observations only, incrementally build a map of the world and to compute an estimate of vehicle location. Montemerlo et al, 2001, paper presents FastSLAM, an algorithm that recursively estimates the full posterior distribution over robot pose and landmark locations which scales logarithmically with the number of landmarks in the map. Doucet et al, 2001, proposed sequential Monte Carlo methods for the case that prior knowledge about the phenomenon being modelled is available. This knowledge allows to formulate Bayesian models, relating prior knowledge with current observations, often done on-line. Particle filters offer a very interesting approach for obtaining such a local map from range sensing (Rekleitis, 2004), (Arulampalam, 2002, Svensson, 2014). Based on such maps, robot controllers have to provide commands for moving toward the goal while avoiding obstacles. Wang, 2009 proposed a generic force field method for robot real-time motion planning based on location, orientation, travel speed, priority, size, and the robot's environment. A dynamic variable speed force field method was designed for applications in partially known and

dynamically changing environments.

An efficient approach for robot motion control without the risk of local minima is provided by velocity potential field approach, (Masoud, 2007). A fuzzy logic navigation and obstacle avoidance by a mobile robot in an unknown dynamic environment is proposed by Faisal et al, 2013.

In this paper a robot motion controller for obstacles avoidance using particle filter method is proposed. When the robot detects the obstacles, a map of local environment can be re-built based on data received from the sensors of the robot. A novel approach for robot navigation is achieved using the integration of particle filter method with velocity potential field approach.

2 SYSTEM MODEL

The robot we use and its sensing range is shown in Figure 1, in which we can see that this sensing range of the robot is divided into three sections, i.e. left (yellow), right (green) and back (white). Local map is built with regard to front, left and right sections which sense obstacles. Since the robot will not move backwards in our experiments, we do not use back sections for detecting obstacles. The inner circle is the safety range; if obstacles lie in this area, the robot has to turn away in order to avoid them. The outer circle is the searching range, which shows the maximum range robot can detect. The blue ellipse in Figure 1 illustrates the obstacle. θ_k is the angle between the heading of the robot and the positive direction of x axis. β_k denotes the angle between the

straight line from the robot pointing to the goal and the positive direction of x axis.

Robots can find the minimum distance to obstacles with one specific beam. The coordinates of the intersection point of that beam with obstacles could be obtained. Based on knowing the position of the intersection point, two measurements with regard to that intersection point are enough to determine the position of the robot accurately; one is the distance d_{\min} from the robot to the intersection point and the other is the angle α between the chosen beam and the positive direction of x axis, both shown in Figure 1,

We choose these two measurements for the output vector

$$y_k = [d_{\min,k}, \alpha_k]^T \quad (1)$$

where k indicates the measurements taken at time k . The detected obstacle is treated as a landmark or beacon in order to get the measurements.

We use the coordinate (at time k) of the robot as hidden states

$$X_k = [x_k, y_k]^T \quad (2)$$

The state space model is

$$\begin{cases} x_{k+1} = f_k(x_k, u_k, \omega_k) \\ y_k = h_k(x_k, u_k, v_k) \end{cases} \quad (3)$$

where u_k is the control vector of the system and the noise sequences ω_k and v_k are assumed as independent white noise processes with known probability density function (pdf). We indicate the intersection point of the chosen beam and the obstacle as

$$p_k = [x_k^*, y_k^*]^T \quad (4)$$

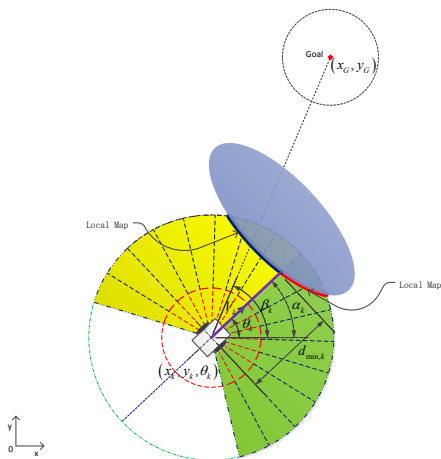


Figure 1: Local map built when sensing obstacles.

Based on the algorithm of obstacle avoidance using velocity potential field approach (Necsulescu, 2014, Nie, 2014), we can expand Equation (3) as

$$\begin{cases} x_{k+1} = x_k + T * \left[\begin{array}{l} k_a v_{\max} \left(1 - e^{-\frac{\sqrt{(x_G - x_k)^2 + (y_G - y_k)^2}}{R_{\text{goal}}}} \right) \cos(\theta_k \pm \omega_{\max} * T) + \dots \\ k_a v_{\max} \left(1 - e^{-\frac{\sqrt{(x_G - x_k)^2 + (y_G - y_k)^2}}{R_{\text{goal}}}} \right) \sin(\theta_k \pm \omega_{\max} * T) + \dots \end{array} \right] + \omega_k \\ y_k = \left[\begin{array}{l} k_n \frac{1}{d_{\min}} * e^{-\frac{d_{\min}}{R_{\text{safe}}}} * \cos(\alpha_k + \pi) + k_t \frac{1}{d_{\min}} * e^{-\frac{d_{\min}}{R_{\text{safe}}}} * \cos\left(\alpha_k + \pi \pm \frac{\pi}{2}\right) \\ k_n \frac{1}{d_{\min}} * e^{-\frac{d_{\min}}{R_{\text{safe}}}} * \sin(\alpha_k + \pi) + k_t \frac{1}{d_{\min}} * e^{-\frac{d_{\min}}{R_{\text{safe}}}} * \sin\left(\alpha_k + \pi \pm \frac{\pi}{2}\right) \end{array} \right] + v_k \\ y_k = \left[\begin{array}{l} \sqrt{(x_k - x_k^*)^2 + (y_k - y_k^*)^2} \\ \arctan\left(\frac{y_k^* - y_k}{x_k^* - x_k}\right) \end{array} \right] + v_k \end{cases} \quad (5)$$

In equation (5), T is the time step for robot control. k_a, k_n, k_t are gains for attractive, normal repulsive and tangential repulsive velocity, respectively. d_{\min} is the minimum detected distance from the robot to obstacles. R_{goal} is the radius of a region around the goal; when robot enters that region it will decrease the speed. R_{safe} is the radius with reference to the obstacles, such that when the distance d_{\min} from robot to obstacles is less than that radius, the robot will activate obstacles avoidance algorithm. v_{\max} and ω_{\max} are the maximum velocity and angular velocity of the robot. Equation (5) is applied for two situations. First, when d_{\min} is larger than R_{safe} and, second, when d_{\min} is less than or equals to R_{safe} . In the first case, Equation (5) is adapted such that the robot has applied only the attractive velocity command. In the second case, the robot is also subject to the repulsive velocity command.

For the first case, when obstacles are not present any more, equation (5) is reduced to which gives the trajectories of the robot to the goal.

$$\begin{cases} x_{k+1} = x_k + T * \left[\begin{array}{l} k_a v_{\max} \left(1 - e^{-\frac{\sqrt{(x_G - x_k)^2 + (y_G - y_k)^2}}{R_{\text{goal}}}} \right) \cos(\theta_k \pm \omega_{\max} * T) \\ k_a v_{\max} \left(1 - e^{-\frac{\sqrt{(x_G - x_k)^2 + (y_G - y_k)^2}}{R_{\text{goal}}}} \right) \sin(\theta_k \pm \omega_{\max} * T) \end{array} \right] + \omega_k \\ y_k = \left[\begin{array}{l} \sqrt{(x_k - x_k^*)^2 + (y_k - y_k^*)^2} \\ \arctan\left(\frac{y_k^* - y_k}{x_k^* - x_k}\right) \end{array} \right] + v_k \end{cases} \quad (6)$$

For the second case, when obstacles are present, equation (5) is modified into the following equation (7).

$$\left\{ \begin{array}{l} x_{k+1} = x_k + T * \left[\begin{array}{l} k_n \frac{1}{d_{\min}} * e^{-\frac{d_{\min}}{R_{\text{safte}}}} * \cos(\alpha_k + \pi) + \dots \\ k_n \frac{1}{d_{\min}} * e^{-\frac{d_{\min}}{R_{\text{safte}}}} * \sin(\alpha_k + \pi) + \dots \end{array} \right] \\ k_t \frac{1}{d_{\min}} * e^{-\frac{d_{\min}}{R_{\text{safte}}}} * \cos\left(\alpha_k + \pi \pm \frac{\pi}{2}\right) \\ k_t \frac{1}{d_{\min}} * e^{-\frac{d_{\min}}{R_{\text{safte}}}} * \sin\left(\alpha_k + \pi \pm \frac{\pi}{2}\right) \end{array} \right\} + \omega_k \\ y_k = \left[\begin{array}{l} \sqrt{(x_k - x_k^*)^2 + (y_k - y_k^*)^2} \\ \arctan\left(\frac{y_k^* - y_k}{x_k^* - x_k}\right) \end{array} \right] + v_k \quad (7)$$

Equation (7) contains a command for the robot to avoid obstacles with the attractive term of Equation (5) removed as obstacles appear. When dimensions of left obstacles are larger than right ones, the robot will turn right in order to save energy and time in avoiding obstacles, and vice versa. We gauge the size of obstacles based on the number of intersecting points of sensor beams and obstacles.

3 PARTICLE FILTERING TO TRACK THE ROBOT

After modeling the system, next step in simulation is to produce N initial particles $x_{0,i}^+$ ($i=1, \dots, N$) based on the pdf $p(x_0)$. Since we already know the initial pose of the robot, we will produce particles right in the initial position of the robot.

Then, based on the dynamics equation of equation set (5), we generate time propagation values for all particles

$$x_{k,i}^- = f_{k-1}(x_{k-1,i}^+, u_{k-1,i}^+, \omega_{k-1,i}^+) \quad (i=1, \dots, N) \quad (8)$$

to obtain a new set of a priori particles.

Then we compare $h_k(x_{k,i}^-, u_{k,i}^-, v_k^i)$ with y_k , i.e. we evaluate $p(y_k | x_{k,i}^-)$, and obtain corresponding W_k^i . It should be observed that since we have two measurements, the weight W_k^i is composed of the product of two other weights as follows

$$W_k^i = W_{k,d}^i * W_{k,\alpha}^i \quad (9)$$

where $W_{k,d}^i$ is the weight obtained based on $p(y_k | x_{k,i}^-)$. We use the normal distribution pdf to evaluate the weights comparing $h_k(x_{k,i}^-, u_{k,i}^-, v_k^i)$ with

the measured distance $d_{\min,k}$, i.e. y_k . The more $h_k(x_{k,i}^-, u_{k,i}^-, v_k^i)$ is closer to $d_{\min,k}$, the bigger the weight of that particle is. Likewise, $W_{k,\alpha}^i$ is the weight related to $p(y_k | x_{k,i}^-)$, $h_k(x_{k,i}^-, u_{k,i}^-, v_k^i)$ close to α_k will have allocated a higher weight based on the pdf of normal distribution. We prefer particles whose $h_k(x_{k,i}^-, u_{k,i}^-, v_k^i)$ is close to $d_{\min,k}$ and α_k , respectively, which result in larger W_k^i because of larger $W_{k,d}^i$ and larger $W_{k,\alpha}^i$. Larger $W_{k,d}^i$ or larger $W_{k,\alpha}^i$ only cannot produce larger W_k^i , since accurate tracking of the robot needs to combine two parameters (the distance and the angle) together. Equation (9) results from the need that the particles satisfy both the required distance and the required angle.

After obtaining the weights W_k^i for all particles $x_{k,i}^-$ ($i=1, \dots, N$), they are normalized to obtain a set of normalized weight sw_k^i ($i=1, \dots, N$). Until now we formed a first set of particles $\{x_{k,i}^-, w_k^i\}$ ($i=1, \dots, N$) in preparation for the next step resampling.

There are lots of resampling methods introduced in the literature. In this paper we use the method in Svensson, 2014. These particles $x_{k,i}^+$ after resampling with the same weight w are going to be propagated in time based on Equation (8) to arrive to the next iteration. The same process will be applied to the particles in next iteration.

The particle filtering for robot path estimation is applied until there are no measurements left, since without measurements we cannot get the weight for each particle. Likewise, if the robot cannot detect an obstacle in the beginning, the particle filter is still not able to work because of no measurements. It would also be possible that the robot can find obstacles in the beginning, whereas during its navigation process to the goal there may be some time when the robot finds no obstacles. At that time the particle filter is not going to be active until robot can find obstacles again.

After obtaining a new set of *a posteriori* particles through resampling, we can compute any desired statistical measure of this set of particles. Typically most interest is in evaluating the mean and the covariance for all these particles.

When the estimation of robot path is already known, the estimation of landmark positions conditioned on the estimated robot path based on the measurements can be obtained. For each of the robot's estimated position, the measurement without noise is considered, then the estimation of landmark from the corresponding measurements is obtained. Each measurement consists of the true measurement

and the noise and we use the true measurement without noise to better estimate the position of landmark. If there are several measurements of one landmark, Kalman filter has to be applied to get optimal estimation of that landmark based on all related measurements (Simon, 2006). In our experiments we assume that each landmark is reflected in one measurement only in the whole process, and we do not apply Kalman filter to landmark estimation.

4 SIMULATION RESULTS FOR ROBOT NAVIGATION WITH OBSTACLE AVOIDANCE

In the simulations, we consider robot navigation in the case of two obstacles with different dimensions to illustrate the performance of the proposed algorithm. Our simulation is conducted by using a switching controller such that the robot will choose proper turning direction based on the local map it created.

In the simulation, one can see that the robot successfully chose a direction that resulted in a higher efficiency and saved more time in avoiding obstacles while finally reaching the goal. In the process, while the robot was travelling towards the goal, estimations of robot path and positions of landmarks (obstacles) were obtained.

Figure 2 shows robot navigation toward the goal while avoiding two obstacles of different dimensions and too close to permit passing in-between. FastSLAM approach is used to obtain the estimations of robot path and positions of obstacles. In this simulation, the robot built a local map finding that O_2 has larger dimension than O_1 , so that it turned left when close to the obstacles. At the same time, the red dotted line indicates the ideal robot path based on our controller, and the blue square illustrates the estimated robot path; asterisk signs around the obstacles indicate the estimated positions of obstacles. The obstacle avoidance algorithm is based on the proposed velocity potential fields approach, and the estimations with regard to robot path and obstacles are performed by using the FastSLAM approach.

In Figure 2 several snapshots of robot navigation are shown. When the robot detected obstacles, estimations of the robot path used the measurements with regard to the obstacles. However, when robot bypassed obstacles and sensed the goal, the estimation of the robot path is based on

measurements with regard to the goal only. The estimated robot path and the real robot path converge finally when robot reaches the goal.

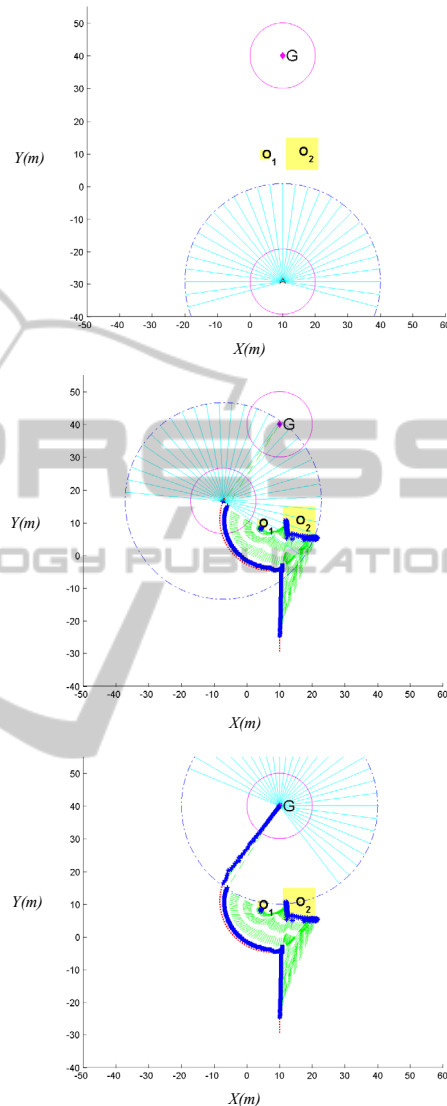


Figure 2: Robot travelling around two obstacles with the FastSLAM approach.

Symbols used are:
 magenta diamond= Goal,
 yellow square= Obstacle,
 red dotted line= Ideal robot path,
 blue square= Estimated robot position wrt obstacles,
 blue asterisk= Estimated obstacle position,
 blue pentagram= Estimated robot position wrt the goal,
 green dashed line= Estimated measurement line.

5 EXPERIMENTAL RESULTS – TWO DIFFERENT OBSTACLES

The experiments were performed using LabVIEW™ and MATLAB™. LabVIEW is used to control the robot reaching the goal without obstacles collision, and collect data regarding the measurements about obstacles and the goal. The measurement data is composed of distance measurement between the robot and obstacles/the goal and angle measurement between the chosen beam and the positive direction of x axis. After getting the measurement data, we utilized MATLAB to build the estimated map and the estimated robot path based on data we collected.

In the experiment, we consider the same scenario used in the simulation, in which the robot has to avoid two obstacles with different dimensions. The experiments with a robot travelling around two obstacles will be illustrated in two parts. The first part is related to robot navigation with two obstacles avoidance using the velocity potential field approach. During this navigation process, we collected sensor data for each robot moving step and recorded them. Robot trajectory is composed of a large number of small steps. Due to the accuracy of the rotation sensor imbedded in the servo motor, we recorded the sensor data every $\pi/8$ of sensor rotation.

In the second part of our experiment the estimations of robot path and obstacles are obtained based on the sensor data collected in order to build the local map, obtained using MATLAB. In Figure 3, the grey cylinder in the left top corner of the snapshot indicates the robot goal. Between the robot and the goal are two obstacles, a blue trash bin with a bigger size than the small obstacle, a wood block..

Several snapshots are shown in Figure 3. The robot controller chooses proper direction to turn in order to save time and energy. We can see that the controller successfully drove the robot while avoiding obstacles to reach the goal. The results in Figure 3 also show the choice of turning left, a proper turning direction given obstacles dimensions.

Sensor data were collected in the robot navigation process. Based on the data collected, a map was built using the estimations of robot positions and the local map robot sensed, as shown in Figure 4.

In Figure 4, the magenta circle indicates the goal. The red solid line indicates the ideal robot path to the goal without obstacles collision, the green square denotes the estimation with regard to obstacles sensed by the robot, and the green diamond illustrates the estimation with regard to the goal. The

green asterisk sign refers to the local map robot built based on the sensor data. We can see that, when robot detects the goal, the estimation of robot position performs better than that based on the measurements with regard to obstacles given the absolute position of the goal in the global map is known. Given that obstacle O_2 is bigger than O_1 the robot controller chose to turn left to avoid collision. The particle clouds representation of Figure 4 is shown in Figure 5.

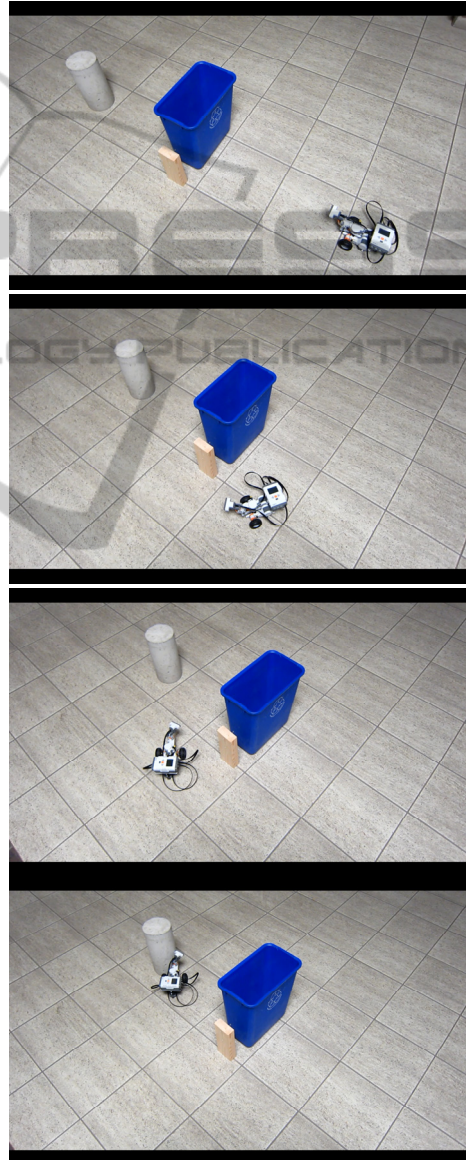


Figure 3: Robot navigation with two obstacles avoidance reaching the goal.

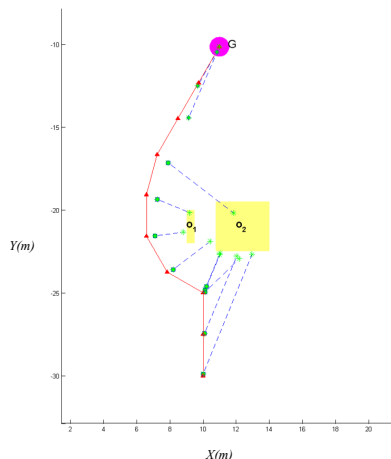


Figure 4: Estimations of robot positions and two obstacles.

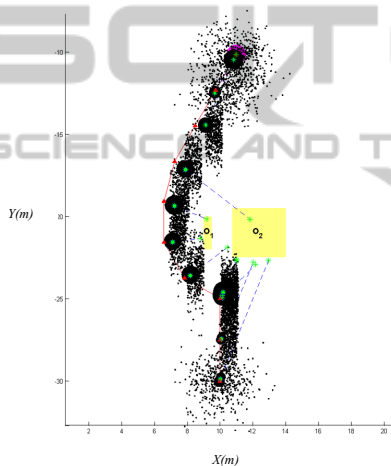


Figure 5: Particle clouds representation of Figure 4.

6 CONCLUSIONS

A novel combination of velocity potential field approach for motion control with a particle filter for unknown obstacles localization proved a good solution for obstacle avoidance without reaching a local minimum. An improvement of the velocity potential field approach is included to select proper direction of robot turning in front of obstacles. Simulation and experimental results verified the proposed approach for the case of obstacles positioned in-between initial robot position and goal position. For future, much more complex scenarios could be investigated, such as moving obstacles or humans, in order to test the validity of the proposed approach.

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