

## Project 6 : Kidnapped Vehicle localization using a Particle Filter

**Localization** is the problem of an autonomous vehicle identifying its position with-in a map. Once localized, the robot may be able to plan its motion towards its destination. Commonly used Global Positioning System(GPS) measurements are not accurate enough for a self-driving car and are also unreliable.

**Particle filter** is a type of Bayesian filter used for localization of a robot within a known map; The map is assumed to be fixed in this project. The localization is achieved by the robot sensing landmarks in the map. Bayesian filters are iterative techniques i.e they have repeated operations: prediction and update.

Following table gives a comparison of filters studied in the course

	State space	Belief	Efficiency (growth w.r.t dimensions)	Nature
<b>Histogram/Monte carlo</b>	Discrete	Multimodal	Exponential	Approx
<b>Kalman Filter</b>	Continuous	Unimodal (Gaussian)	Quadratic	Approx (works for linear systems)
<b>Particle Filter (Markov process)</b>	Continuous	Multimodal	Depends on the case	Approx

**The iterative structure** is achieved by incorporating Markov assumptions which simplifies prediction of future state by solely basing it on the current state without the need for information of any other previous states. The knowledge of the robot's position at the start of an iteration is called a priori and the estimations made after are called posterior.

**The prediction step** uses a motion model to calculate the probabilities of being at a future state from the current state. In this project for the autonomous vehicle, we are using a 'Bicycle model' of the car. The equations of motion in a bicycle model are given by

$$x_f = x_0 + \frac{v}{\theta_{dot}} (\sin(\theta_f) - \sin(\theta_0))$$

$$y_f = y_0 + \frac{v}{\theta_{dot}} (\cos(\theta_0) - \cos(\theta_f))$$

$$\theta_f = \theta_0 + \theta_{dot} * dt$$

$\theta_{dot}$  is the yaw rate,  $dt$  is the time interval,  $v$  is the velocity of the car

When  $\dot{\theta} = 0$ , EOM are updated to

$$x_f = x_0 + v(\sin(\theta_0)) \cdot dt$$

$$y_f = y_0 + v(\cos(\theta_0)) \cdot dt$$

$$\theta_f = \theta_0$$

**The update step** involves taking in sensor measurements and adjusting the predictions.

A general form of equation for posterior estimation in Bayesian filters is

$$bel(x_t) = \eta * P(z_t | x_t, m) * \widehat{bel}(x_t)$$

Where  $bel(x_t)$  is the posterior belief,  $\widehat{bel}(x_t)$  is the predicted probability,  $\eta$  is the normalizing factor,  $P(z_t | x_t, m)$  is the likelihood of observations from the position  $x_t$ .

Particle filter utilizes particles representing a hypothetical car. Initially, the particles are spread out, by iterating through the update and prediction steps, the particles converge to the real car position. Steps for implementing a particle filter in this project

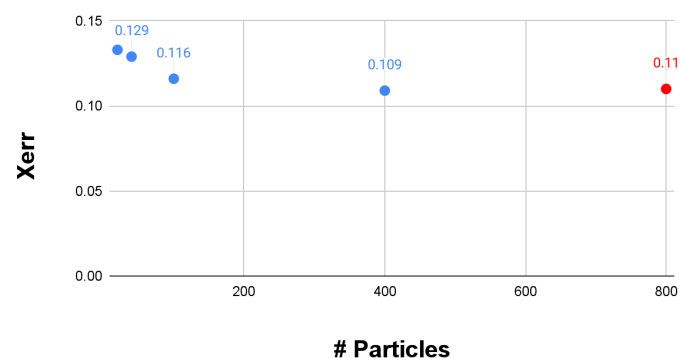
1. Initialize 'n' particles based on the GPS information and noises
2. Predict the next position of the particle using the motion model with noises added
3. Calculate a weight for each particle
  - a. Transform the observations from vehicle coordinates to map coordinates
  - b. Find the closest landmark for each observation
  - c. Weight = Prob of landmark position in a multivariate normal distribution with mean as the observation.
4. Sample 'n' particles by replacement from the current pool based on their weights
5. Go to step 2

Implementation details

- Number of particles = 400
- Error : Xerr = 0.109, Yerr = 0.101, Yawerr = 0.004

I tested the program for a different number of particles. The following chart shows the decrease

Xerr vs. # Particles



in the error with increasing number of particles. For 800 particles, however, the program failed to reach the goal within the time limit. There are no significant gains in increasing the number of particles beyond 400.

