Multi-robot Target Tracking

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I. Introduction

Robot target tracking is the task of localizing the target position by the use of a mobile robot. As the observations of the target are taken as range measurements, the task is to generate an optimal robot trajectory which minimizes the uncertainty in the target position.

Given the initial position of the target with some uncertainty, we use two approaches to model the uncertainty in target position, namely, Extended Kalman Filter and Bayesian Histograms, which will be used as an input to the greedy algorithm. The greedy algorithm will be used to generate the robot trajectory to minimize the uncertainty in the target position.

II. Method

A heatmap is the probability map, where the brighter region would denote higher chances of the region belonging to the target while the dark region would mean otherwise. The task is to reduce the bright region as much as possible so that there can be certainty in the target position. In Figure 1, we have provided a sample heatmap.

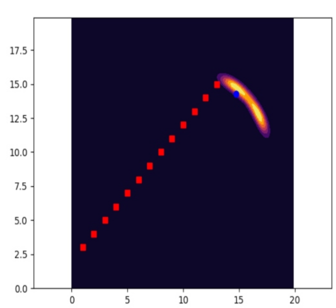

Fig. 1. Sample Heatmap, where the red squares denote the robot trajectory, blue dot is the true target position and bright region is the estimated target position

There were two approaches followed for generating the heatmap, given the robot position and the true target position at time *t*.

a. Bayesian Histograms

In this approach, we discretize the environment into a grid, where each grid cell denotes the probability of the cell belonging to the target. In our case, the environment was assumed to be 20m x 20m grid. All grid cells were initialized with probability of 1, meaning that each grid cell had equal probability of being a target position. Since the measurement model assumes zero-mean normal distribution for the sensor noise, the probability of a grid cell *v* being the true target position q^* given a relative measurement $\widehat{z}$ as:

$$\mathbb{P}(v = q^*|p, \widehat{z}) = f(z_v|\widehat{z}, \sigma_s^2) = \frac{1}{\sqrt{2\pi\sigma_s^2}} exp(\frac{-1}{2\sigma_s^2}(z_v - \widehat{z})^2)$$

where, z_v is the distance between the point *v* and the robot position *p*. As the robot plans its trajectory, the probability of the grid cell belonging to the target is updated as:

$$\mathbb{P}(v = q^*|P_{1:T}, \widehat{z}_{1:T}) = \prod f(z(p_k, v)|\widehat{z}_k, \sigma_s^2)$$

b. Extended Kalman Filter

In this approach, we use Extended Kalman Filter for predicting the targets' mean and covariance at the next time step. Extended Kalman Filter is the non-linear version of Kalman Filter which linearizes about an estimate of current mean and covariance. In the Extended Kalman Filter, the state transition and observation models dont need to be linear functions of the state but can be differentiable functions.

$$x_k = f(x_{k-1}, u_k) + w_k$$
$$z_k = h(x_k) + v_k$$

where, w_k and v_k are the process and observation noises which are assumed to be zero-mean multivariate gaussian noises with covariance Q_k and R_k respectively. u_k is the control vector. It involves two steps, namely, prediction step and update step. In the prediction step, the state and covariance are estimated, while in the update step, the measurement residual, covariance, kalman gain, state estimate and covariance estimate are calculated. The equations for prediction and update steps are given below.

Prediction:

$$\hat{o}^-(k) = \hat{o}(k-1),$$

$$\hat{\Sigma}^-(k) = \hat{\Sigma}(k-1) + R(k).$$

Update:

$$K(k) = \hat{\Sigma}^{-}(k)H^{T}(k)(H(k)\hat{\Sigma}^{-}(k)H^{T}(k) + Q(k))^{-1},$$

$$\hat{o}(k) = \hat{o}^{-}(k) + K(k)(z(k) - h(\hat{o}^{-}(k)))$$

$$\hat{\Sigma}(k) = (I - K(k)H(k))\hat{\Sigma}(k)^{-}$$

where $R(k)$ and $Q(k)$ are the covariance matrices of the noise from target's motion model and robot's measurement, respectively. $h(\hat{o}^{-}(k)) := \|p(k) - \hat{o}^{-}(k)\|_2$. $z(k)$ denotes the noisy distance measurement from the robot. $H(k)$ is the Jacobean of $h(\hat{o}^{-}(k))$.

c. Greedy Algorithm

After generating the uncertainty map of the target position, the next step was determining the robot trajectory at the next time step. The greedy algorithm consisted of two steps, determining the action set of the robot and then using a condition on the actions from the action set to find the most optimal action to be taken by the robot.

Given the robot position at time t as (r_x, r_y) and the target position at time t as (t_x, t_y), the action set was generated by defining the radius around the robot and then taking actions from the defined circular region. The radius was taken as 2 and the number of actions were 12. After generating the action set, the next step was finding the most optimal action given the current robot position and the target position. This was done by selecting the action that gave the least determinant of the covariance matrix as that action would give us a more certainty in the target position.

$$\min_{a_k \in \mathcal{A}_k} \ \text{logdet} \ (\Sigma_k)$$

or

$$\min_{a_k \in \mathcal{A}_k} \ \text{trace} \ (\Sigma_k)$$

III. Analysis

In this section we evaluate our methods for generating the heatmap and then using the heatmap as an input to the greedy algorithm. The number of robots are taken as 1 and the number of targets are 1. The target can be either moving slowly or moving in a relatively fast circular motion. We present our findings for two cases, target moving slowly and target moving fast in a circular motion.

a. Target moving slowly, Bayesian Histogram method for measuring uncertainty in target position

In this setup, the target was made to move in a circular motion with omega equal to 100. For estimating the uncertainty in target position, Bayesian Histograms were used. The analysis is shown in Figure 2.

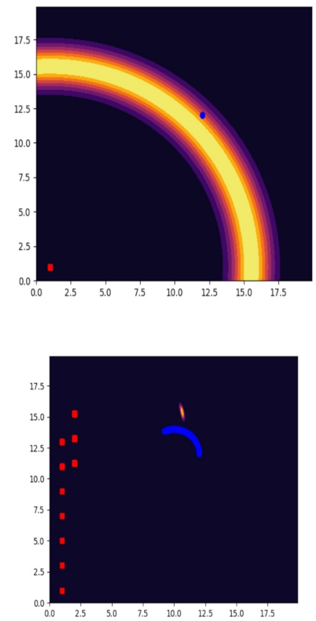

Fig. 2. Red squares denote the robot trajectory, blue dot denote the true target motion and bright region denotes the estimated target position

b. Target moving fast, Bayesian Histogram method for measuring uncertainty in target position

In this setup, the target was made to move in a circular motion with omega equal to 33. For estimating the uncertainty in target position, Bayesian Histograms were used. The analysis is shown in Figure 3.

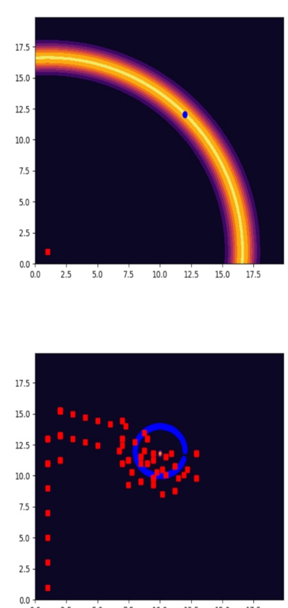

Fig. 3. Red squares denote the robot trajectory, blue dot denote the true target motion and bright region denotes the estimated target position

c. Target moving slowly, EKF method for measuring uncertainty in target position

In this setup, the target was made to move in a circular motion with omega equal to 100. For estimating the uncertainty in target position, Extended Kalman Filters were used. The analysis is shown in Figure 4.

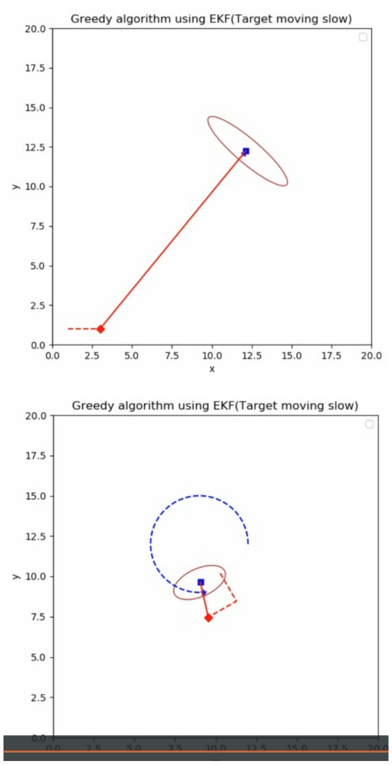

Fig. 4. Red squares denote the robot trajectory, blue dot denote the true target motion and bright region denotes the estimated target position

d. Target moving fast, EKF method for measuring uncertainty in target position

In this setup, the target was made to move in a circular motion with omega equal to 33. For estimating the uncertainty in target position, Extended Kalman Filters were used. The analysis is shown in Figure 5.

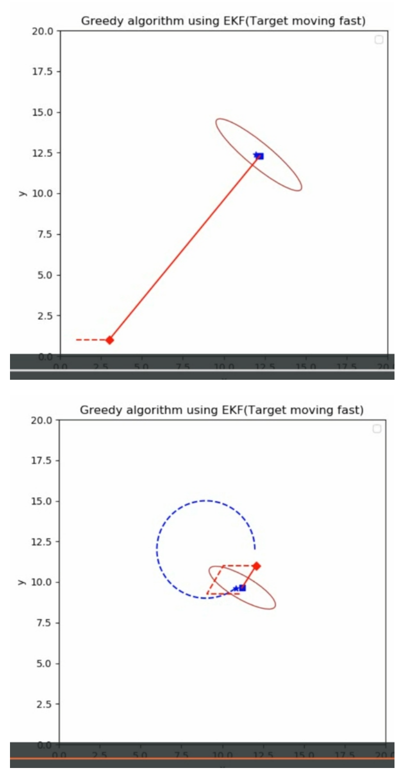

Fig. 5. Red squares denote the robot trajectory, blue dot denote the true target motion and bright region denotes the estimated target position

References

[1] E. Selim, I. Volkan, "Active localization of multiple targets from noisy relative measurements,"