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INDEX

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Research Paper Engineering

Advances In Derivative Free Mobile Robot Position Determination

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ABSTRACT

Although Kalman filters have been used for decades for navigation and system integration, almost all the EKF-like methods failed in some state estimation problems with strong non-linearity. Here in this paper we shall discuss the applicability of Unscented Kalman Filtering, as a derivative free alternative for mobile robot localization. However, there is a parameter adjustment problem associated with them, which hinders accurate localization. In the paper, we have discussed the technique to relieve mobile robot developers of the tedious task of adjusting several parameters by hand.

Keywords : Mobile Robot Localization , Unscented Kalman filtering, Parameter learning.

1. INTRODUCTION:

The applicability of various algorithms of Kalman filter as a mathematical tool to estimate the variables of a wide range of processes has been very well established since its evolution in the year 1959. Mobile robot localization has been a task, which these filters have tried to simplify, and take to new heights ever since the trials of making completely autonomous robots has been a research topic. The KF has many limitations 1[C.Suliman and F.Moldoveanu]. So many authors proposed various fixes and modifications to better estimate the process Variables.

One of the many variations of the Kalman filter is the unscented Kalman filter (UKF). This filter is based on the unscented transform (UT). UT is a method for calculating the statistics of a random variable that undergoes a nonlinear transformation. UKF has two advantages as compared to EKF. The first is that UKF can estimate accurately a probability even if model's nonlinearity is strong. The second one is that derivation of Jacobian matrices is not needed. Because UKF uses UT instead of Jacobian matrices in the approximation process, UKF can estimate a probability accurately and easily as compared to EKF [2][Nasser Houshangi and Farouk Azizi].

However, EKF and UKF have a mutual and fundamental problem for mobile robot developing. This is the estimating noise terms, in other words, determining covariance matrixes of input and observation in KFs. One of the straight forward solutions is to refer to sensor specifications. However, in practice, it will work very poorly if the specification values are used as covariance values in KF. Because, actual noise terms are often correlated each other over time 3[P. Abbeel (2005)]. Thus, users of KFs have to hand-tune these noise parameters for accurate localization. However, this handtuning process needs significant engineering cost and turning time, and it is difficult to obtain the true optimal parameters by the hand tuning.

2. UNSCENTED KALMAN FILTER

This section describes the basics of Unscented Kalman Filter (UKF) for dynamic and sequential state estimation. UKF estimates the state of a dynamic system based on a sequence of observation and control information. In this paper, we denote the true state by xt, where t is the time index. UKF assumes that the state transition is as follows:

$$x_t = f(x_t\text{-}1, u_t) + Є_t \qquad (1)$$

where, f is the nonlinear state transition function, ut is a control input, and Єt is additive and zero-mean Gaussian noise with covariance Qt. Similarly, UKF assumes that the observation is as follows:

$$z_t = h(x_t) + \delta_t \qquad (2)$$

where, zt is the observation vector, h is a nonlinear observation function, and dt is additive and zero-mean Gaussian noise with covariance R_t. In general, the functions f and h are not linear. As a result, the estimation after passing these functions is no longer Gaussian. Extended Kalman Filter (EKF) linearizes the functions to solve the problem. On the other hand, UKF applies a more accurate stochastic approximation technique called Unscented Transform (UT). Fig. 1 shows examples of UT and the linearization approach for mean and covariance propagation on two-dimensional.

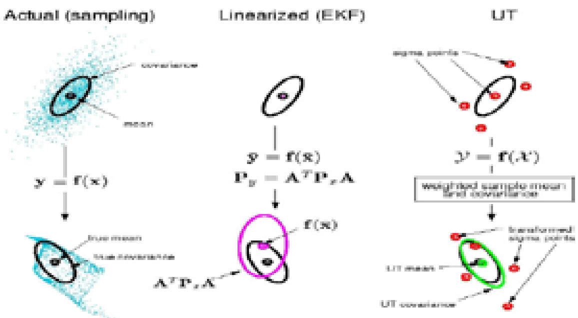

Fig 1: Examples of the UT and the linearization approach for the two-dimensional mean and covariance propagation.

The UT performs the approximation with extracted points called "Sigma points χ ". In the general case, these sigma points are chosen at the mean μ and symmetrically along the main axes of the covariance ∑ according to the following rules:

$$\chi^{[0]} = \mu$$

$$\chi^{[i]} = \mu + \left(\sqrt{(n+\lambda)\Sigma}\right)_i \qquad i=1,\ldots,n \quad (3)$$

$$\chi^{[i]} = \mu - \left(\sqrt{(n+\lambda)\Sigma}\right)_{i-n} \qquad i=n+1,\ldots,2n$$

where, n is the dimension of the state, $\sqrt{(n+\lambda)\Sigma)_i}$ is the i-th column of the matrix square root, and λ is computed by , $\lambda = \alpha^2(n+\kappa) - n$ with α and κ as scaling parameters. And then, the sigma points are passed through a nonlinear function q:

$$\bar{\chi}^{[i]} = q(\chi^{[i]}) \quad i=1,\ldots,2n$$

Here $\bar{\chi}^{[i]}$ are transformed sigma points. Finally the objective parameters μ' and ∑' of resultant Gaussian are calculated by the transformed sigma points:

$$\mu' = \sum_{i=0}^{2n} \omega_g^{[i]} \chi^{[i]} \qquad (5)$$

$$\Sigma' = \sum_{i=0}^{2n} \omega_c^{[i]} (\bar{\chi}^{[i]} - \mu')(\bar{\chi}^{[i]} - \mu')^T \qquad (6)$$

Where $\omega_g^{[i]}$ are weights used when the mean is computed, $\omega_c^{[i]}$ are weights used when the covariance of the Gaussian is recovered. These weights are calculated by the following rule :

$$\omega_g^{[0]} = \frac{\lambda}{n+\lambda}$$

$$\omega_c^{[0]} = \frac{\lambda}{n+\lambda} + (1-\alpha^2+\beta) \qquad (7)$$

$$\omega_g^{[i]} = \omega_c^{[i]} = \frac{1}{2(n+\lambda)} \qquad i=1,\ldots,2n$$

where β is the scaling parameter.

Algorithm 1 Unscented Kalman Filter

Require:
- x_{t-1}, the previous state vector
- P_{t-1}, the previous covariance
- u_t, the input
- z_t, the observation
- $\mathbf{f}$, the process model
- $\mathbf{h}$, the observation model
- Q, the covariance matrix of input
- R, the covariance matrix of observation
- n, the dimension number of state
- $\gamma = n+\lambda$, the scaling parameter of sigma point
- $\omega_g^{[i]}$, $\omega_c^{[i]}$, the weights of Gaussian recover

Ensure:

$\chi_t = (x_{t-1} \quad x_{t-1}+\sqrt{\gamma P_{t-1}} \quad x_{t-1}-\sqrt{\gamma P_{t-1}})$
for $i=0$ to $2n$ **do**
  $\bar{\chi}_t^{[i]} = \mathbf{f}(\chi_t^{[i]}, u_t)$
end for
$\hat{x}_t = \sum_{i=0}^{2n} \omega_g^{[i]} \bar{\chi}_t^{[i]}$
$\hat{P}_t = \sum_{i=0}^{2n} \omega_c^{[i]} (\bar{\chi}_t^{[i]} - \hat{x}_t)(\bar{\chi}_t^{[i]} - \hat{x}_t)^T + Q$
for $i=0$ to $2n$ **do**
  $\bar{n}_t^{[i]} = \mathbf{h}(\bar{\chi}_t)$
end for
$\hat{n}_t = \sum_{i=0}^{2n} \omega_g^{[i]} \bar{n}_t^{[i]}$
$S_t = \sum_{i=0}^{2n} \omega_c^{[i]} (\bar{n}_t^{[i]} - \hat{n}_t)(\bar{N}_t^{[i]} - \hat{n}_t)^T + R$
$\Sigma_t^{x,n} = \sum_{i=0}^{2n} \omega_c^{[i]} (\bar{\chi}_t^{[i]} - x_{t|t-1})(\bar{N}_t^{[i]} - \hat{n}_t)^T$
$K_t = \Sigma_t^{x,n}(S_t)^{-1}$
$x_t = \hat{x}_t + K_t(z_t - \hat{n}_t)$
$P_t = \hat{P}_t - K_t S_t (K_t)^T$
return x_t, P_t

Algorithm 1 4[R. van der Merwe (2004)], shows the standard UKF algorithm.

3. PARAMETER LEARNING OF UNSCENTED KALMAN FILTER

Of the different parameter learning methods, Discriminative learning is the method that we are going to discuss over here. This technique is a type of machine learning technique. The focus of this parameter is not to evaluate the intermediate parameters, but to improve the ultimate performance. Important here is that, we should have vast amount of training data, in presence of which, the discriminative learning becomes much more effective then the generative learning 1[P. Abbeel et al. (2005)], which focuses upon the learning of intermediate parameters. By this technique, the optical covariance of the input noise Rop, observation noise Qop, and the optimal Hyper-parameter vector of UKF wop can be estimated. The requirement for the technique is a highly accurate instrument (eg. A high end GPS) which can measure either all or a subset of variables of the state xt. The measurement of the sensor is used for training data and not for localization. We assume that the observation model of the highly accurate instrument is as follows:

$$y_t = g(x_t) + g_t \qquad (9)$$

where, y_t is an observation from the highly accurate instrument, g is the observation model and gt is additive and zero-mean Gaussian noise with covariance S.

In this paper $x_{0:T}$ is denoted by the entire state sequence $x_0, x_1, \ldots x_T$ and $u_{0:T}$, $z_{0:T}$, $y_{0:T}$ are denoted as well respectively. The joint probability distribution on $x_{0:T}$, $u_{0:T}$, $z_{0:T}$ and $y_{0:T}$ is defined as follows:

$$P(x_{0:T}, y_{0:T}, z_{0:T} \| u_{0:T})$$

$$= p(x_0) \prod_{t=1}^{T} p(x_t \| x_{t-1}, u_t)$$

$$\prod_{t=0}^{T} p(y_t \| x_t), p(z_t \| x_t) \qquad (10)$$

Where,

$$p(x_t \| x_{t-1}, u_t) = N(x_t; f(x_{t-1}, u_t), R, \Omega) \qquad (11)$$

$$p(y_t \| x_t) = N(y_t; g(x_t), S) \qquad (12)$$

$$p(z_t \| x_t) = N(z_t; h(x_t), R, \Omega) \qquad (13)$$

We assume that the initial robot's position is known. In order to obtain optimal parameters, the prediction likelihood objectives are maximized with Eq. (10) to (13) as follows.

$$\begin{aligned}[R_{op}, Q_{op}, \Omega_{op}] &= \arg\max_{R,Q,\Omega} \sum_{t=0}^{T} \log p(y_t | z_{0:t}, u_{1:t}) \\ &= \arg\max_{R,Q,\Omega} \sum_{t=0}^{T} -\log|2\pi\Xi_t| \qquad (14) \\ &\quad -(y_t - g(\mu_t))^T \Xi_t^{-1} (y_t - g(\mu_t))\end{aligned}$$

Where,

$$\Xi_t = H_t P_t H_t^T + S \qquad (15)$$

Here, μt is the result of running UKF algorithm, Ht is the Jacobian matrix of the function g, and Pt is the covariance matrix estimated by UKF.In this paper, to simple the learning system, we only minimizes the prediction error for the values of yt. Therefore, Eq. 14 can be modified as follows:

$$[R_{op}, Q_{op}, \Omega_{op}] = \arg\min_{RQ\Omega}$$

$$\sum_{t=0}^{T} (y_t - g(\mu_t))^T S^{-1} (y_t - g(\mu_t)) \qquad (16)$$

If P is any multiple of identity matrix, this simplifies to : $[R_{op}, Q_{op}, \Omega_{op}] =$

$$= \arg\min_{RQ\Omega} \sum_{t=0}^{T} (y_t - g(\mu_t))^2 \qquad (17)$$

Even if the simplifying the learning criterion is executed, it is known that the discriminative learning performance is sufficient for accurate localization [P. Abbeel (2005)]. Using the discriminative training method, the learning criterion can evaluate the actual performance of UKF instead of its individual components. However, it is difficult to compute the gradient for solving Eq. (16)(17) to minimize the learning criterion. Because, the learning criterion includes the UKF formulas, which are too complicated to differentiate, we suggest a coordinate ascent algorithm to solve these equations. To evaluate estimation accuracy, we use RMS error in the estimate of the robot's position:

$$RMS= \sqrt{\frac{1}{T}\sum_{t=1}^{T} \| y_t - g(\mu_t) \|^2} \quad (18)$$

Here, g(μt) is the UKF estimation of the robot's 2D position.

4. RESULTS AND CONCLUSION

Based on the above results, various simulations were performed by 5Atsushi Sakai, Yoji Kuroda. The experiments performed very well confirm the validity of the proposed method.

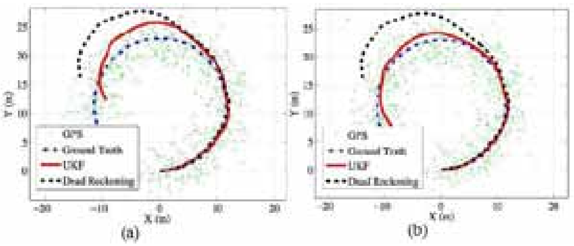

Figure 2. Simulation Results (a) Before Learning

(b) Covariance Learning.

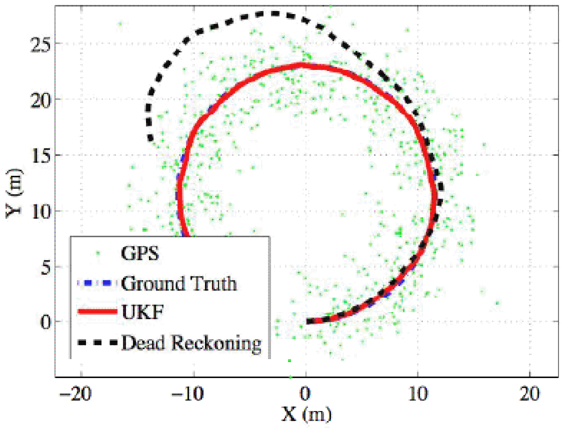

Figure 3. After discriminative learning.

These results show that the covariance learning improves the localization accuracy; however estimation error remains due to inadequate Hyper-parameters. On the other hand, the discussed method significantly improved the accuracy because to learning both covariance matrixes and Hyper-parameters.

To conclude, in this paper, a learning technique to solve parameter adjustment problems of Unscented Kalman Filter (UKF) for accurate localization has been discussed. The parameter adjustment process of Kalman filters is very cumbersome for mobile robot developers and needs significant engineering cost and time. The parameters of UKF consist of three kinds of parameters as follows: I) the covariance matrix of input noise, II) the covariance matrix of measurement noise, III) Hyper-parameter of UKF. Using the simulation result, it was shown that UKF localization performance critically depends on these parameters. One of discriminative training methods is adopted to obtain the optimal parameters. What is important to note is that the learning technique needs a highly accurate instrument for evaluating the filtering performance. A coordinate ascent algorithm [M. Jordan et al. (1998)] is used as a training algorithm to optimize these parameters included in complicated functions. The technique promises to relieve mobile robot developers of the tedious task of adjusting several parameters by hand. The effectiveness of the proposed learning method for localization has been established. However advance research possibilities still lies in the field of suggesting optimal values to Hyper-parameters, while here only the adjustment problem has been discussed using already suggested values.

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