# Unscented FastSLAM for UAV

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*Abstract*—**Simultaneous localization and mapping (SLAM) is a necessary prerequisite to make mobile vehicle truly autonomous, which is a hot research topic today. FastSLAM as a successful SLAM method abstracts many researchers' attentions. FastSLAM factors the SLAM problem into a localization problem and a mapping problem in which the landmark position is estimated by EKF. A modified FastSLAM is presented for uninhabited aerial vehicle (UAV), using UKF to replace the EKF to estimate the landmark position. So we can improve the estimation precision, at the same time no need to linearize the sensor observation model and to compute its Jacobian matrix.**

***Keywords-simultaneous localization and mapping (SLAM); unscented Kalman filter (UKF); extend Kalman filter (EKF); FastSLAM; uninhabited aerial vehicle***

## I. INTRODUCTION

The simultaneous localization and mapping (SLAM)[1] is the problem to determine the position, velocity and attitude of uninhabited aerial vehicle (UAV) moving through an unknown environment and, simultaneously, to estimate features of the environment. In the past decade, a lot of researchers focused on this problem.

Recently, the estimation algorithms can be roughly classified according to their underlying basic principle. The most popular approaches to SLAM problem are the extended Kalman filter (EKF-SLAM) and the Rao-Blackwellized Particle filter (FastSLAM)[2]. The effectiveness of the EKF approach comes from the fact that they estimate a fully correlated posterior over feature maps and UAV poses. However, the EKF-SLAM[3,4] assumes linearization of the motion and measurement models. Montemerlo[5] developed a framework called the FastSLAM for landmark based maps.

In the process of FastSLAM, particle filter is applied to estimate UAV poses and EKF is used to estimate the landmark position. But EKF has following limitations. First, it estimates highly nonlinear movement model and measurement model, likely causing estimation divergence; on the other hand, EKF needs computing Jacobian matrix. Therefore, unscented Kalman filter (UKF)[6-8] is used to replace EKF to escape the computation of Jacobian matrix, reducing the computation time and improving algorithm effectiveness.

In the next section, INS error model is used as the UAV SLAM mathematic model. Then unscented FastSLAM idea is proposed in detail. At last simulation test is carried out in UAV simulation environment and result shows this algorithm is effective and available.

## II. UAV SLAM ALGORITHM MATHEMATIC MODELS

In essence, SLAM is an estimation problem. Given UAV kinematics equation and measurement, estimate UAV pose and feature states.

UAV movement used by INS formulation:

$$x_v(k) = f_v(x_v(k-1), u(k)) + w(k)$$

In which, $w(k)$ is zero mean white noise and covariance $Q(k)$.

INS position, velocity and attitude equations are respectively:

$$P^n(k) = P^n(k-1) + v^n(k)\Delta t$$

$$v^n(k) = v^n(k-1) + (C_b^n(k) f^b(k) + g^n)\Delta t$$

$$\Psi^n(k) = \Psi^n(k-1) + E_b^n(k)\omega^b(k)\Delta t$$

INS states:

$x_v = \begin{pmatrix} X & Y & Z & V_x & V_y & V_z & \gamma & \theta & \psi \end{pmatrix}^T$, in which, $P^n = \begin{bmatrix} X & Y & Z \end{bmatrix}^T$ and $V^n = \begin{bmatrix} V_x & V_y & V_z \end{bmatrix}^T$ are the position and velocity in the coordinate of N-E-D geographical reference frame, $\Psi^n = \begin{bmatrix} \gamma & \theta & \psi \end{bmatrix}^T$ are three attitude angles; control: $u = \begin{bmatrix} a_x & a_y & a_z & b_x & b_y & b_z \end{bmatrix}^T$, $f^b = \begin{bmatrix} a_x & a_y & a_z \end{bmatrix}^T$ are outputs of accelerator, $\omega^b = \begin{bmatrix} b_x & b_y & b_z \end{bmatrix}^T$ are outputs of gyroscope. $C_b^n$ is the direction cosine matrix from body coordinate $b$ to navigation coordinate $n$, $E_b^n$ is the rotation change rate of attitude angles:

$$E_b^n = \begin{bmatrix} 1 & \sin\gamma\tan\theta & \cos\gamma\tan\theta \\ 0 & \cos\gamma & -\sin\gamma \\ 0 & \sin\gamma\sec\theta & \cos\gamma\sec\theta \end{bmatrix}$$

Feature is still and $m_i = \begin{pmatrix} X_i & Y_i & Z_i \end{pmatrix}^T$ is the state of $i$ th feature location.

Measurement equations:

$$z_i(k) = H_i(x_v(k), m_i(k)) + v_i(k)$$

In which, $v_i$ is zero mean white noise with covariance $R$

Because state equation and measurement equation of SLAM are nonlinear highly, EKF is often used to solve the problem. But when there are thousands of features in the map, EKF method is unavailable obvious with great computation burden. Then FastSLAM algorithm is proposed to solve the problem with real time.

## III. FUNDAMENTAL IDEAS OF UNSCENTED FASTSLAM

The features are described by mean $\mu$ and covariance $\Sigma$. Instead of approximating the measurement nonlinear function by Taylor series expansion, UKF deterministically extracts so-called sigma points from the Gaussian and passed these through the nonlinear function, that is unscented transform. These sigma points are defined using previous mean and covariance of features by use of symmetric sampling.

$$\chi^{[0][m]} = \mu_n^{[m]}$$

$$\chi^{[i][m]} = \mu_n^{[m]} + (\sqrt{(n+\lambda)\Sigma_n^{[m]}})_i, (i = 1, \cdots, n)$$

$$\chi^{[i][m]} = \mu_n^{[m]} - (\sqrt{(n+\lambda)\Sigma_n^{[m]}})_i, (i = n+1, \cdots, 2n)$$

Here $n$ is the dimension of feature state $(n = 3)$. $\lambda = \alpha^2(n+\kappa) - n$, with $\alpha = 0.01$ and $\kappa = 0$ being scaling parameters that determine how far the sigma points are separated from the mean. $\mu_n^{[m]}$ and $\Sigma_n^{[m]}$ are separately the mean and covariance of the $n$ th feature. [m] means an index of particles. $\chi^{[i][m]}$ is the sigma points on Cartesian coordinate.

The UKF requires computation of a matrix square root which can be implemented directly using the Cholesky factorization. However, the covariance matrices have low dimensions and can be expressed recursively. So, not only does the UKF outperform the EKF in accuracy and robustness, it does so at no extra computational cost.

A weight $\omega_g^{[i]}$ is used when computing the mean and the weight $\omega_c^{[i]}$ is used when recovering the covariance of the Gaussian. These weight are calculated by

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

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

The parameter $\beta = 2$ can be chosen to encode additional knowledge about the distribution underlying the Gaussian representation. The predicted measurement $\hat{z}_t^{[m]}$ and the Kalman gain $K_t^{[m]}$ is calculate as follows

$$\overline{Z}_t^{[i][m]} = h(\chi^{[i][m]}, x_t^{[m]})(i = 0, \ldots, 2n)$$

$$\hat{z}_t^{[m]} = \sum_{i=0}^{2n} \omega_g^{[i]} \overline{Z}_t^{[i][m]}$$

$$S_t^{[m]} = \sum_{i=0}^{2n} \omega_c^{[i]} (\overline{Z}_t^{[i][m]} \quad \hat{z}_t^{[m]})(\overline{Z}_t^{[i][m]} \quad \hat{z}_t^{[m]})^T + R_t$$

$$\overline{\Sigma}_t^{[m]} = \sum_{i=0}^{2n} \omega_c^{[i]} (\chi^{[i][m]} \quad \mu_n^{[m]})(\overline{Z}_t^{[i][m]} \quad \hat{z}_t^{[m]})^T$$

$$K_t^{[m]} = \overline{\Sigma}_t^{[m]} (S_t^{[m]})^{-1}$$

Here, $h$ is the observation model. $\overline{Z}_t^{[i][m]}$ is the sigma points on the polar coordinate made by unscented transform. $x_t^{[m]}$ denotes the state of $m$-th particle. $K_t^{[m]}$ is the Kalman gain calculated from pure nonlinear transformation. Finally, the mean $\mu_n^{[m]}$ and the covariance $\Sigma_n^{[m]}$ of the feature is updated by:

$$\mu_{n,t}^{[m]} = \mu_{n,t-1}^{[m]} + K_t^{[m]} (z_t - \hat{z}_t^{[m]})$$

$$\Sigma_{n,t}^{[m]} = \Sigma_{n,t-1}^{[m]} \quad K_t^{[m]} S_t^{[m]} (K_t^{[m]})^T$$

$z_t$ is the true measurement. We can use the Cholesky factorization in this feature update to make the algorithm more stable numerically.

## IV. Simulation Test

In simulation test, UAV circles 20m in the air and select random 12 features around UAV. UAV initial position is used as the initials:

$$x_0 = \begin{bmatrix} 0 & 0 & -30 & 10 & 0 & 0 & -7^\circ & 5^\circ & 10^\circ \end{bmatrix}^T$$

System noise and measurement noise are separately:

$$Q \quad diag([0\ 0\ 0\ 0.1\ 0.1\ 0.10.0001\ 0.0001\ 0.0001])$$

$$R = \mathrm{diag}([1^2, (1/315)^2, (1/315)^2])$$

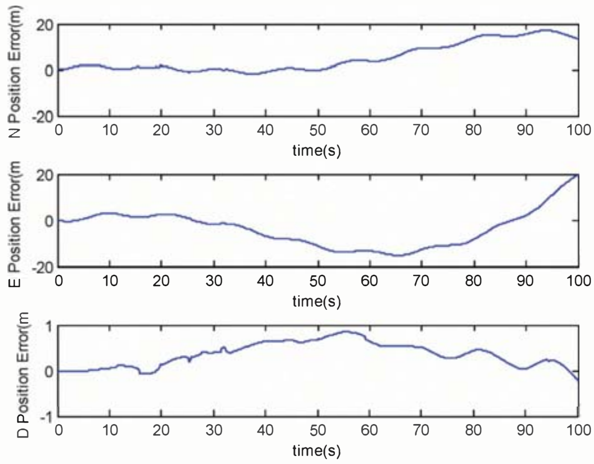


Figure 1. Unscented FastSLAM estimated UAV position error

environment. Result shows that this algorithm is effective.

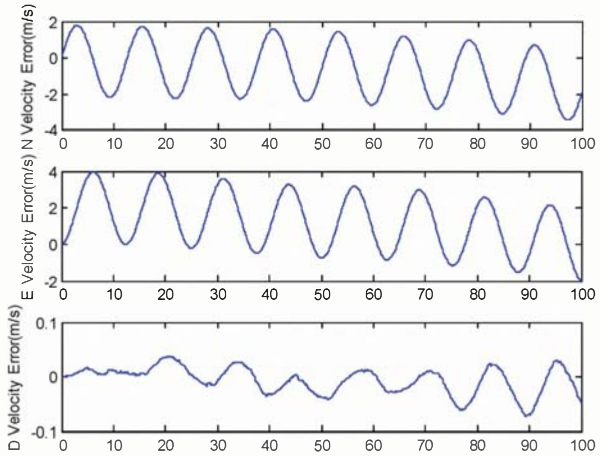


Figure 2. Unscented FastSLAM estimated UAV velocity error

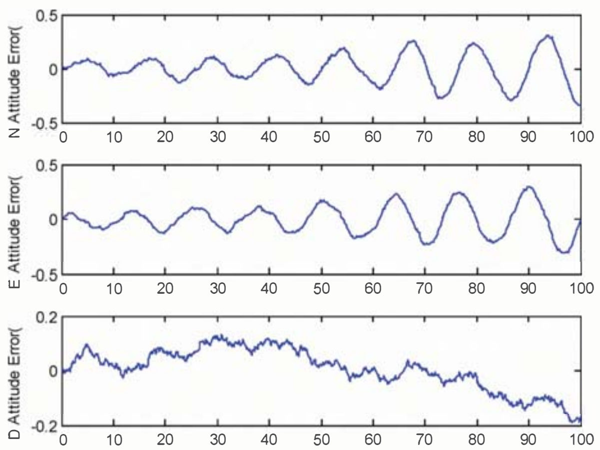


Figure 3. Unscented FastSLAM estimated UAV attitude error

Figure 1-3 separately give the FastSLAM estimated UAV position, velocity and attitude error. From the result, FastSLAM algorithm gets satisfactory result and achieves better effect.

## V. CONCLUSIONS

This paper researches unscented FastSLAM algorithm for UAV, an efficient new solution to the concurrent mapping and localization problem. UKF is used to estimate landmark position, escaping linearizing motion model and measurement model and the computation of Jacobian matrix. With no addition of computation complexity, algorithm gets better estimation precision. Proposed method is tested in UAV environment. Result shows that this algorithm is effective.

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