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Research on Navigation Algorithms Under the Adaptive Interactive Multiple Kalman Filter Architecture

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Abstract. In integrated navigation systems, information fusion and positioning accuracy depend on the characteristics of inertial systems and sensors, yet obtaining prior knowledge remains challenging in practice. To address issues of varying satellite signal quality and system nonlinearities degrading navigation performance, this paper proposes a Fuzzy Adaptive Interacting Multiple Model with Multiple Kalman Filters (FAIMM-MKF) algorithm. It combines a Fuzzy Controller based on satellite signal quality with an Adaptive Interacting Multiple Model (AIMM), integrating Unscented Kalman Filter (UKF), Iterated Extended Kalman Filter (IEKF), and Square-Root Cubature Kalman Filter (SRCKF) to match vehicle dynamics models. The performance is validated through hardware-in-the-loop experiments. Results show that compared to traditional IMM algorithms, this method significantly improves positioning accuracy in complex environments when satellite signal quality changes.

Keywords: Combination navigation, Interactive multi-model, Kalman filter, Fuzzy controller

1. Introduction

To improve state estimation and trajectory tracking accuracy under limited prior knowledge, this paper improves the traditional IMM algorithm and proposes a Multi Kalman Filter (MKF) vehicle integrated navigation method under a Fuzzy Adaptive Interactive Multi-Modeling (FAIMM) framework. This method is based on vehicle running state and satellite signal quality, and through calculating residuals it adaptively adjusts model observation likelihood so that state estimation performance can be improved [1]. Meanwhile, UKF, IEKF and SRCKF based on integrated navigation error models and measurement models are introduced for handling multi-model states, which aims to improve system stability and accuracy.

2. Fuzzy control algorithm based on satellite signal quality

Horizontal Dilution of Precision (HDOP) is one key index for measuring satellite positioning accuracy, and it shows how satellite geometry distribution affects positioning accuracy. Lower HDOP values mean satellite geometry distribution is more helpful for improving positioning accuracy, which is usually seen as good signal quality performance. Its expression is:

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$$\mathrm{HOOP}=\sqrt{q_{xx}+q_{yy}} \tag{1}$$

where q_{xx} and q_{yy} are the diagonal elements related to x-direction and y-direction position errors in the geometric dilution matrix of satellite position error state vector.The state equation and measurement equation of the integrated navigation system are discretized, and the additive noise filtering model is obtained as follows:

$$\begin{cases} x_k=f(x_{k-1})+\Gamma_{k-1}W_{k-1} \\ z_k=h(x_k)+V_k \end{cases} \tag{2}$$

The IMM algorithm has good ability for multi-model switching and state estimation, but it lacks quick response when satellite signal quality changes fast. Fuzzy controllers work very well for systems with nonlinearity and time-varying features [2, 3]. So this paper combines fuzzy control with the IMM algorithm, brings in the idea of model weight adjustment factor, and designs a fuzzy controller that judges satellite signal quality based on HDOP values and adaptively adjusts model weights. As shown in Figure 1.

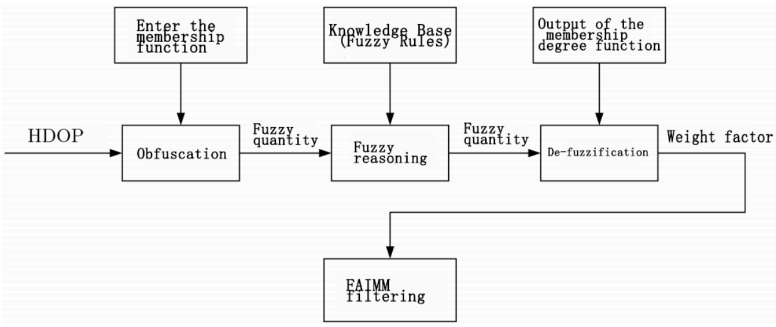

Figure 1. Fuzzy inference systems

3. A combined navigation algorithm based on FAIMM-MKF

Assume the model set is $N = \{n^1, n^2, ..., n^r\}$ with r models, and model switching follows a Markov process. Let the Markov model probability transition matrix be

$$p=\begin{bmatrix} p_{11} & \cdots & p_{1r} \\ \vdots & \ddots & \vdots \\ p_{r1} & \cdots & p_{rr} \end{bmatrix} \tag{3}$$

Let p_{ij} denote the Markov transition probability from model n^i at the previous time to model n^j,where p is usually given by prior knowledge and satisfies that the row sum equals 1,and the main diagonal is dominant.The probability that model matches model at time k-1 is denoted as μ_{k-1}^{i} . For

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the given r models with input interaction,the initial state estimation and covariance of the carrier can be described as:

$$X_{k-1}^{0j} = \sum_{i=1}^{n} X_{k-1}^{i} \mathrm{\mu}_{\mathrm{k-1}}^{\mathrm{ij}} \tag{4}$$

$$P_{k-1}^{0j} = \sum_{i=1}^{n} \mathrm{\mu}_{\mathrm{k-1}}^{\mathrm{ij}} \left[P_{k-1}^{i} + \left(X_{k-1}^{i} - X_{k-1}^{0i} \right) \bullet \left(X_{k-1}^{i} - X_{k-1}^{0i} \right)^{T} \right] \tag{5}$$

where is the state estimate of filter i at time k-1, $\mathrm{P}_{\mathrm{k-1i}}$ is the corresponding mean square error matrix of filter i at time k-1, and is the mixing probability from model i to model j at time k-1, which can be expressed by Equation (6)

$$\mathrm{\mu}_{\mathrm{k-1}}^{\mathrm{ij}} = \frac{\mathrm{p_{ij}} \mathrm{\mu}_{\mathrm{k-1}}^{\mathrm{i}}}{\sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{p_{ij}} \mathrm{\mu}_{\mathrm{k-1}}^{\mathrm{i}}} \tag{6}$$

It adaptively and dynamically adjusts the model based on current system state and observation information, concentrates the weights and parameters of each model, and finally obtains the system's final estimate by probability-weighted fusion of each filter's estimation results [4].

4. Model probability update

In the FAIMM algorithm, model updating directly affects how well the algorithm works. Based on the Bayes hypothesis testing principle, each filter's residuals are tested to update the models, and the innovation and innovation covariance after state filtering are:

$$\mathrm{S_k^j} = \mathrm{H_k^j} \mathrm{P_{k,k-1}^j} \mathrm{H_k^{jT}} + \mathrm{R_k^j} \tag{7}$$

The model weight adjustment factor output from the fuzzy controller based on HDOP values is introduced ω_e^j . The maximum likelihood function that best matches model j at time k is:

$$\Lambda_{\mathrm{k}}^{\mathrm{j}} = \frac{\omega_{\mathrm{e}}^{\mathrm{j}}}{\sqrt{2\pi \left| \mathrm{S_k^j} \right|}} \exp \left\{ -\frac{1}{2} \left(\mathrm{Z_k^j} \right)^{\mathrm{T}} \left(\mathrm{S_k^j} \right)^{-1} \mathrm{Z_k^j} \right\} \tag{8}$$

The model probabilities are updated using the Bayes hypothesis testing method.

$$\mathrm{\mu}_{\mathrm{k}}^{\mathrm{j}} = \frac{\Lambda_{\mathrm{k}}^{\mathrm{j}} \sum_{\mathrm{i=1}}^{\mathrm{r}} p_j^{\mathrm{j}} \mathrm{\mu}_{\mathrm{k-1}}^{\mathrm{j}}}{\sum_{\mathrm{i=1}}^{\mathrm{r}} \left(\Lambda_{\mathrm{k}}^{\mathrm{j}} \sum_{\mathrm{j=1}}^{\mathrm{r}} p_j^{\mathrm{j}} \mathrm{\mu}_{\mathrm{k-1}}^{\mathrm{j}} \right)} \tag{9}$$

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The state estimates and covariances of each filtering model are combined through probability-weighted fusion, and the output combined state estimate and corresponding covariance are:

$$X_k = \sum_{j=1}^{r} X_k^j \mu_k^j \tag{10}$$

$$P_k = \sum_{j=1}^{r} [P_k^j + (X_k^j - X_k) - (X_k^j - X_k)^T \mu_k^j] \tag{11}$$

The above describes one filtering recursive process of the FAIMM-MKF algorithm [5].After that, each time the previous interaction output is used as the interaction input for the next recursion, thus completing the cycle of the entire navigation tracking process.

5. Combined system vehicle onboard testing

Vehicle integrated navigation data is used to verify the algorithm's ability to suppress error divergence [6, 7]. The simulation error parameters for the inertial navigation system gyroscope and accelerometer refer to the MEMS inertial measurement unit STM300, with specific parameters shown in Table 1.

Table 1. Sensor error parameter

Performance index	Gyroscope		Accelerometer		
	Zero offset	Random walk	Zero offset	Random walk	Update Frequency
Parameter	5°/h	5°/ $\sqrt{h}$	0.2mg	800ug/ $\sqrt{Hz}$	125Hz

To verify the filtering effects of standard UKF and CKF algorithms, traditional IMM-UKF and IMM-CKF algorithms, and the improved FAIMM-MKF algorithm, three test tracks are established under good, poor, and denied satellite signal conditions. The trajectory starting point is set at longitude 103.7088°E, latitude 36.1164°N, altitude 1505.5422 m, with initial motion state at rest. The error convergence of IMM-UKF, IMM-SRCKF, IMM-MKF, and improved FAIMM-MKF algorithms under these three conditions is observed. The initial model probabilities of the algorithm are $\mu = 1/3 \;\; 1/3 \;\; 1/3$,The initial probability transition matrix is

$$\Pi_0 = \begin{matrix} 0.8 & 0.1 & 0.1 \\ 0.1 & 0.8 & 0.1 \\ 0.1 & 0.1 & 0.8 \end{matrix} \tag{12}$$

Considering the influence of satellite lever arm error in the carrier coordinate system on velocity and position, the measurement equations and corresponding measurement matrices of the two systems are:

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$$\begin{cases} Z_{SINS/OPD}=[p_{SINS}-p_{OPD}] \\ H_{SINS/OPD}=[O_{3x15}\ I_{3x3}] \end{cases} \tag{13}$$

This paper uses filters to estimate system states when prior knowledge of state covariance and noise characteristics is limited. The GNSS/SINS/ODO integrated navigation system structure is shown in Figure 2.

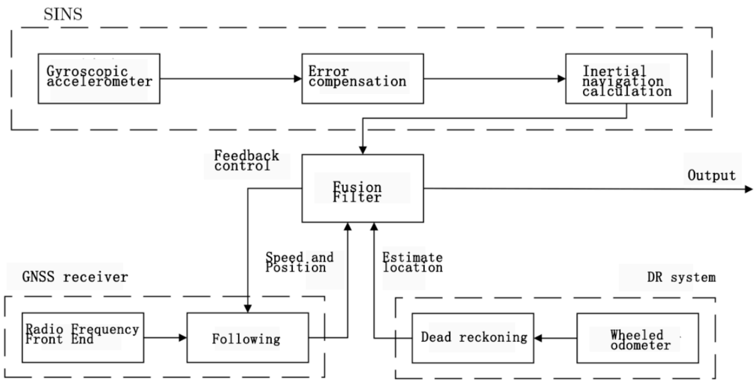

Figure 2. Structure of the GNSS/SINS/ODO integrated navigation system

6. Conclusion

This paper proposes a fuzzy adaptive interacting multiple model algorithm based on multiple Kalman filters. This method uses a fuzzy controller based on satellite signal quality to improve the IMM algorithm. According to different satellite signal quality, it adaptively adjusts model probabilities, breaks through the limitation of single filter in traditional interacting multiple model algorithm, and establishes an integrated navigation system model based on fuzzy adaptive interacting multiple Kalman filters.Future research could consider improving models and simplifying algorithms, such as introducing sequential filtering, to improve computational efficiency with little accuracy loss and ensure long-term stability of integrated navigation performance.

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