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机载激光通信终端的模糊变结构跟踪方法研究

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摘 要:为避免经典固定模型集合中多模型算法造成的模型间竞争并减小计算量,基于有向图切换的变结构方法,建立有向图切换规则和较完备的模型集合.通过模糊逻辑推理得到模型集合中各模型的匹配度,以此代替传统多模型算法中的模式概率来计算,降低了计算的复杂度.采用核粒子滤波克服了标准粒子滤波没有考虑到的量测信息问题,即粒子能够通过核密度估计后朝着状态的后验概率密度的模型移动,使真实和估计模型之间的均方误差最小.仿真结果表明,基于模糊理论的变结构核粒子滤波算法能较大地提高跟踪准确度和减少计算量.

关键词:机载激光通信;跟踪;交结构多模型;有向图切换;核粒子滤波

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Fuzzy Variable Structure Multiple-model Tracking for Airborne Laser Communication System

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Abstract: High precision tracking system for airborne laser communication is usual to adopt multiple models algorithm with a fixed structure, which brings about unnecessary inter-competition among the amount of models and calculation burden. In order to resolve this problem, variable structure multiple-Model based on digraph switching and fuzzy inference was presented, graph switching rule and complete model set were established, the fuzzy inference mechanism was introduced to get matched degree for each filtering, the calculation complexity was decreased obviously. The Kernel particle Filter can move particles toward the posterior, root mean squared error between estimated and true model is minimum, the method could be introduced into fuzzy VSMM framework. Simulation results show that the algorithm improves the accuracy of tracking by reducing the competition of the models as well as reducing the computation burden.

Key words: Airborne laser communication; Tracking; Variable Structure Multiple-Model (VSMM); Digraph switching; Kernel Particle Filter(KPF)

OCIS Codes: 060.2605; 060.4510; 100.4999

0 Introduction

Free space laser communications technology has been developed for decades. The technology promises high capacity, low power consumption, light weight, small sizes and low cost for communication terminals crosslinks[1-2]. The maturation of the physical components for optical communication has reached the

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stage where it is feasible to consider free space laser communications from airborne platforms, the main developed countries and organizations, such as the United States, Japan and the European Space Agency (ESA) have carried out airborne laser communications[3,4]. Due to diversity of maneuvering forms for the airborne platform, it is the huge challenge for airborne platform communication terminals to establish stable optical communication link[5].

It is impossible to accurately describe the movement of airborne platform with the simple model[5-6]. In recent years, the region of maneuvering communication usually adopts the Interacting Multiple Model (IMM) estimation algorithm, which is notable that IMM algorithm solves the tracking problem with a fixed model set. Once the maneuvering forms beyond the fixing model set, it will cause model mismatch and affect estimation accuracy. In order to solve the problem, one method is to expand the model set requiring a large number of models, a large model set not only brings about a great amount of calculation, but also cause model completion to reduce the performance of the algorithm, another method is to select suitable model set according to the current state of communication terminals, which is the idea of Variable Structure Multiple-Model (VSMM) algorithm[7-8], among these algorithms, the Extended Kalman Filter (EKF) and improved EKF are the classical algorithm that solves the tracking problem of airborne platform, EKF applies Taylor approximation to handle nonlinear estimation problem, which often leads to filter divergence and low accuracy due to linearization error. As particle filter algorithm could process nonlinear and non-Gaussian problems well, particle filter is a sequential Monte Carlo filters, Kernel Particle Filter (KPF) algorithm can be used to get a more effective posterior probability distribution.

Recursive Adaptive Model Set (RAMS) is the most important and natural method to realize VSMM, it consists of two parts: model set adaptation and model set sequence estimation. The paper proposes a kind of model set adaptation method with Digraph Switching VSMM (DSVSMM)[10]. In view of the above problems, VSMM combining with KPF is proposed in this paper, the new algorithm is shown to possess a good performance through computer simulation.

1 Motion and measurement model

State space dynamic equation in MM algorithm can be expressed as follows

$$\begin{aligned}\boldsymbol{X}_i(k)&=F_i(X_i(k-1))+G_i(\boldsymbol{v}_i(k-1))\\ \boldsymbol{Z}_i(k)&=H(X_i(k))+\boldsymbol{r}(k)\end{aligned}\tag{1}$$

where $\boldsymbol{X}_i(k)$ represents state vector of the model i ($i=1,2,\cdots,M$), $\boldsymbol{v}_i(k)$ is the corresponding non-Gaussian process noise vector, $\boldsymbol{r}(k)$ is the noise of the observation vector, Q and R is the covariance of $\boldsymbol{v}_i(k)$ and $\boldsymbol{r}(k)$, $\boldsymbol{Z}_i(k)$ represents measurement vector $[\theta(k)\ \beta(k)]^{\mathrm{T}}$, which are azimuth and pitch from CCD. σ_θ and σ_β is standard deviation of measurement error of azimuth and pitch respectively, meanwhile, R can be replaced with diag $(\sigma_\theta^2, \sigma_\beta^2)$.

Assume moving communication terminal position is $(x_s(k), y_s(k), z_s(k))$ at time t_k, fixed communication terminal position is (x_0, y_0, z_0), then

$$r(k)=\sqrt{(x_o(k)-x_s(k))^2+(y_0(k)-y_s(k))^2+(z_0(k)-z_s(k))^2}\tag{2}$$

$$\theta(k)=arctan\frac{y_0(k)-y_s(k)}{x_0(k)-x_s(k)}\tag{3}$$

$$\beta(k)=\frac{z_s(k)-z_0(k)}{r(k)}\tag{4}$$

It should be noted that airborne tracking of communication platform actually is angle tracking, and also is a typical nonlinear tracking problem. For the stochastic characteristics of PF, model information can be introduced in particles sampling process to realize joint estimation for state and model. Model transition probability with Markov chain can be given by

$$P(m(k+1)=j\,|\,m(k)=i)=p_{ij}\quad i,j=1,2,K\cdots M\tag{5}$$

2 KPF

The core idea of particle filter is to apply weighted average of a series of random samples to express posterior probability density. Here, $x_{0:k}=\{x_j\}_{j=0}^{k}$ is a set of sate vectors up to time t_k, $x_{0:k}=\{x_j, \omega_k^i\}_{i=1}^{N_s}$ are the random particles on behalf of posterior probability density $p(x_{0:k}\,|\,z_{1:k})$, N_s is the number of sampling points, and ω_k^i are normalized weights of $x_{0:k}^i$

$$\omega_k^i=\omega_{k-1}^i\frac{p(z_k\,|\,x_k^i)\,p(x_k^i\,|\,x_{k-1}^i)}{q(x_k^i\,|\,x_{0:k-1}^{\ i}, z_k)}\tag{6}$$

where $q(x_k^i\,|\,x_{0:k-1}^i, z_k)$ is importance density function, which is an alternative distribution function. It is easy to sample from this function and distribution. At time t_k, posterior probability density $p(x_{0:k}\,|\,z_{1:k})$ can be approximated as

$$p(x_{0:k}\,|\,z_{1:k})\approx\sum_{i=1}^{N_s}\omega_k^i.\,\delta(x_{0:k}-x_{0:k}^i)\tag{7}$$

Tradition particle filtering continually gets more accurate parameter of importance function, which plays an importance role on estimation of posterior probability density, kernel density estimation isn't strict with important function, and can directly sample particle from dynamic equation, it makes particles to move awards the high likelihood region of maximum posterior probability density, idea of estimation is shown in Fig. 1.

Kernel density estimation can accurately estimate the status of parameter, it can be shown as

$$\hat{g}(x) = \frac{1}{N_S}\sum_{i=1}^{N_s} K_h(X_K - x_k^i)\omega_k^i \tag{8}$$

$$K_h(X_k - x_k^i) = \frac{1}{h}K\left(\frac{X_k - x_k^i}{h}\right) \tag{9}$$

where $K(.)$ is kernel function with bandwidth h, it is

$$K(x) = (2\pi)^{-n/2}\exp\left(-x^{\mathrm{T}}x/2\right) \tag{10}$$

Weights of particles are required to be recalculated as the distribution of particles, new weights are

$$\omega_k^{i,m} = \frac{p(x_k^{i,m} \mid Z_k)}{\sum_{j=1}^{N_s} K_h(x_k^{i,m} - x_k^{j,m})} \tag{11}$$

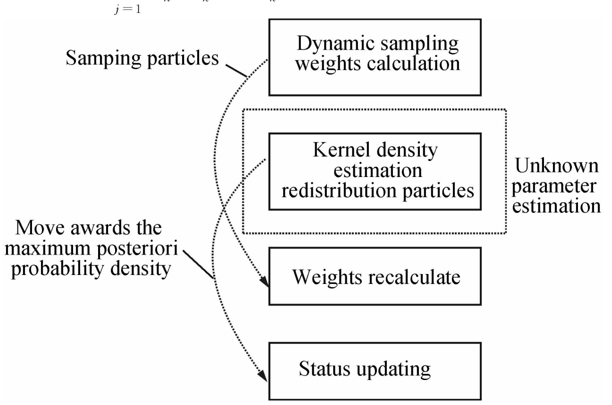

Fig. 1 Idea of kernel density

3 VSMM based on digraph switching and fuzzy inference

3.1 Digraph switching

VSMM algorithm adapts digraph switching with a certain number of model set. Due to maneuvering of platform, it can describe with different model, such as Constant Velocity (CV), Constant Acceleration velocity (CA) and constant angular velocity (CT). Workflow t of the VSMM algorithm is shown as Fig. 2.

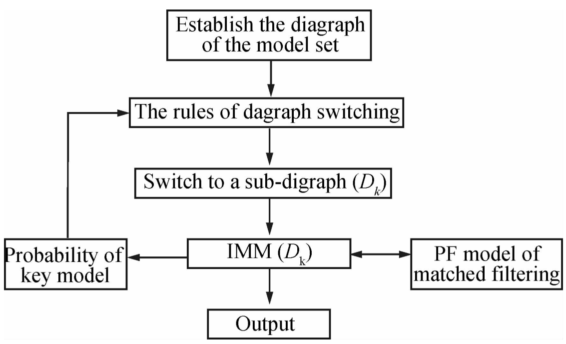

Fig. 2 Workflow of digraph switching

VSMM algorithm includes the following steps

1) According to the a priori information about the moving platform, it is possible to build a complete model set D, which constitutes digraph switching to form the full coverage.

2) According to the probability of the key model, probability is allocated to new activation mode, switching rules of digraph switching are shown as Fig. 3: Model set comprises five models, the center of Model set D_2 is initial digraph; Model set is switched according the probability of adjacent sets, suppose probability of M_2 is greater than M_3, Model set D_2 is switched to D_1.

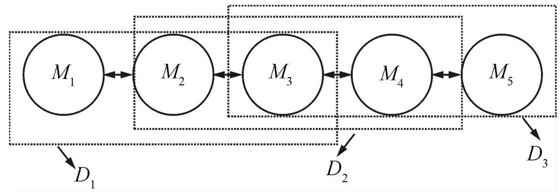

Fig. 3 Digraph switching

3) Filtering estimation: supposed the given model transition probability is p_{ij}, model probability is $\{\mu_i(0)\}_{i=1}^{M}$, state value is $\{\hat{X}_i(k-1/k-1)\}_{i=1}^{M}$, and covariance is $\{\hat{P}_i(k-1/k-1)\}_{i=1}^{M}$, where $j=1,2\cdots M$. Finally, the system state estimators are computed by

$$\hat{X}(k/k) = \sum_{i=1}^{M}\mu_i(k)\hat{X}_i(k/k) \quad i=1,2,K\cdots M \tag{12}$$

3.2 Model probability with fuzzy inference

According to the current measuring input $Z(k)$, conditional filtering of the j sub model can be shown as

$$\begin{cases} \overline{X}^j = E[X_k \mid m_k^j, Z^{k-1}] = F_{k-1}^j\hat{X}(k-1|k-1) + G_{k-1}^j\overline{W}_{k-1}^j \\ \overline{P}^j = F_{k-1}^j P(k-1|k-1)(F_{k-1}^j)^{\mathrm{T}} + G_{k-1}^j Q_{k-1}^j (G_{k-1}^j)^{\mathrm{T}} \\ \tilde{Z}^j = Z_k - H_k^j\overline{X}^j - \overline{V}_k^j \\ S^j = H_k^j\overline{P}^j(H_k^j)^{\mathrm{T}} + R_k^j \\ K^j = \overline{P}^j(H_k^j)^{\mathrm{T}}(S^j)^{-1} \\ \hat{X}_{k|k}^j = \overline{X}^j + K^j\tilde{Z}^j \\ P_{k|k}^j = \overline{P}^j - K^j S^j (K^j)^{\mathrm{T}} \end{cases} \tag{13}$$

where $\tilde{Z}^j$ is the innovation at time k, S^j is the variance of innovation, K^j is the gain of sub model filter j; $\hat{X}_{k|k}^j$ is the state predictive at time k, $P_{k|k}^j$ is covariance estimation[11].

The input index D_j in fuzzy inference system can be shown as

$$D_j = (\tilde{Z}^j)^{\mathrm{T}} \cdot (S^j)^{-1} \cdot \tilde{Z} \quad j \in M \tag{14}$$

A_j is thedomain space of D_j, $\tilde{D}_j$ is fuzzy value of input index D_j. It is assumed that different models have the same domain space ($A_i = A_j, i, j \in M$), fuzzy input set is divided into three fuzzy subset: small(S), middle (M), big (B). Membership function is assumed as Gauss function according to fuzzy input $\tilde{D}_j$, Gauss function is defined as

$$\mu(x) = \exp\left(\frac{-(x-c)^2}{2\sigma^2}\right) \tag{15}$$

where c and σ are distributed parameters of fuzzy inference system. Output space range of fuzzy inference system is [0, 1], membership function adopts the trigonometric function, fuzzy output set is divided into three fuzzy subset: small(S), middle (M), big (B). The fuzzy output adopts the IF $\cdots$THEN rule, the rules can be defined as followed

Rule-1 IF $\widetilde{D}_1=M$ and $\widetilde{D}_2=M\cdots$and $\widetilde{D}_j=S$

THEN $\tilde{\mu}_1=S$ and $\tilde{\mu}_2=S\cdots$and $\tilde{\mu}_2=B\cdots$

Rule-2 IF $\widetilde{D}_1=B$ and $\widetilde{D}_2=B\cdots$and $\widetilde{D}_j=S$

THEN $\tilde{\mu}_1=S$ and $\tilde{\mu}_2=S\cdots$and $\tilde{\mu}_2=B\cdots$

According to the fuzzy language rule, fuzzy matching degree $\tilde{\mu}_j$ of model j can be obtained through fuzzy inference, model matching Probability can be get as followed

$$\begin{cases}\mu_j=\dfrac{\tilde{\mu}_j}{\sum\limits_M \tilde{\mu}_j}\\ \sum\limits_M \tilde{\mu}_j=1\end{cases} \tag{16}$$

4 Simulation experiment

In order to simplify the problem, it is assumed that one of the two communication terminals is fixed, the other is equipped on the airborne platform, the communication terminal moves in a horizontal plane, airborne platform flies at the altitude of 5 km, where initial location at [530 m, 800 m], two kinds of moving scene is set to verify the algorithm in simulation.

In scene. 1, during the time of 0～30 s, 31～50 s, 51～80s, and 81～100 s, communication platform respectively maintains turn rate －0.05 rad/s, 0.1 rad/s, －0.07 rad/s, and 20 m/s (CV), airborne platform trajectory is shown as Fig. 4.

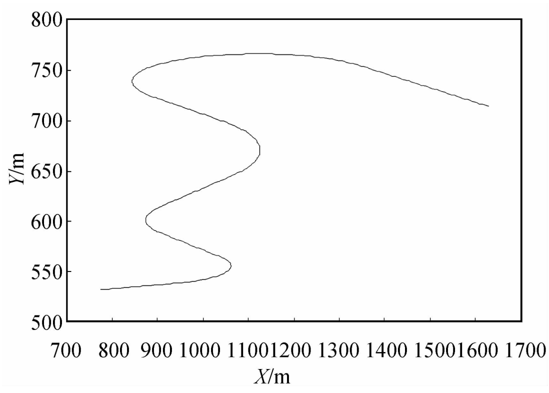

Fig. 4 Airborne platform trajectory in scene 1

Variable structure model set consist of five subsets, which include the following: M_1 (CT, 0.2 rad/s), M_2 (CT, 0.03 rad/s), M_3 (CV), M_4 (CT, －0.2 rad/s), M_5 (CT, －0.03).

The transfer matrix of model CT can be denoted as following

$$\boldsymbol{F}_{1-2,4-5}(\boldsymbol{X}_K)=\begin{vmatrix}1 & \dfrac{\sin(\omega)}{\omega} & 0 & \dfrac{\cos(\omega)-\cos(\omega)}{\omega}\\ 0 & \cos(\omega) & 0 & -\sin(\omega)\\ 0 & \dfrac{1-\cos(\omega)}{\omega} & 1 & \dfrac{\sin(\omega)}{\omega}\\ 0 & \sin(\omega) & 0 & \cos(\omega)\end{vmatrix}\boldsymbol{X}_k \tag{17}$$

The transfer matrix of model CV can be denoted as following

$$\boldsymbol{F}_3(\boldsymbol{X}_k)=\begin{vmatrix}1 & 1 & 0 & 0\\ 0 & 1 & 0 & 0\\ 0 & 0 & 1 & 1\\ 0 & 0 & 0 & 1\end{vmatrix}\boldsymbol{X}_k \tag{18}$$

Compared with the IMMPF algorithm, experimental computer adapts 2 GHz CPU Q9300 and 4 GB memory. Assume angle standard deviation of sensor is 0.1 mrad, the simulation results are shown in Fig. 2 and Fig. 3.

As can be seen from the Fig. (2)-(3), the tracking error of FVSMMKPF algorithm is always less than IMMPF in the entire tracking process. Because PF adopts transition probability of the system state as the importance density function, PF can′t use the latest observation information, however, KPF moves particles toward real posterior probability distribution, so filtering accuracy of KPF is higher than PF. Once airborne platform maneuvers, the tracking error of IMMPF algorithm increases rapidly, and reaches 1mrad almost.

One hundred experiments (N_{MC}) with Monte-Carlo method is applied to verify the FVSMMKPF algorithm, the Root Mean Square Errors (RMSE) in azimuth θ is defined by

$$\mathrm{RMSE}_\theta=\sqrt{\frac{1}{N_{\mathrm{MC}}}\sum_{m=1}^{N_{\mathrm{MC}}}(\hat{\theta}_k^m-\theta_k^{\mathrm{true}})} \tag{19}$$

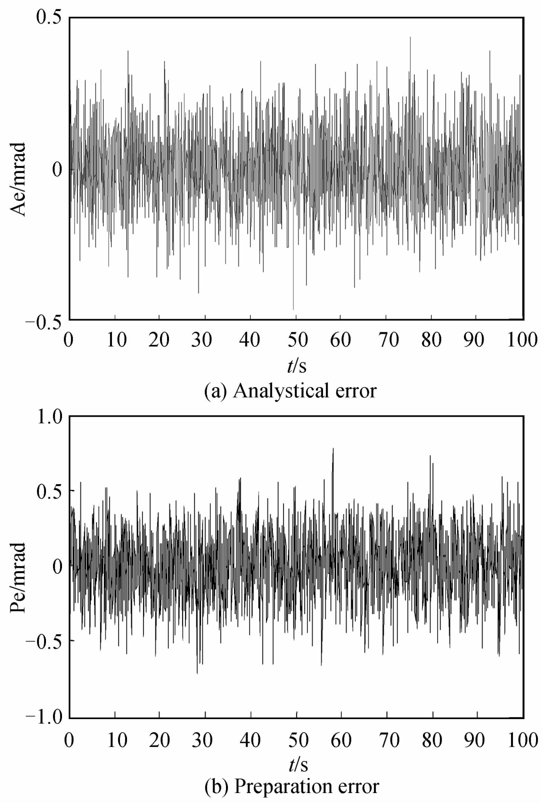

Fig. 5 Tracking error with FVSMMKPF algorithm

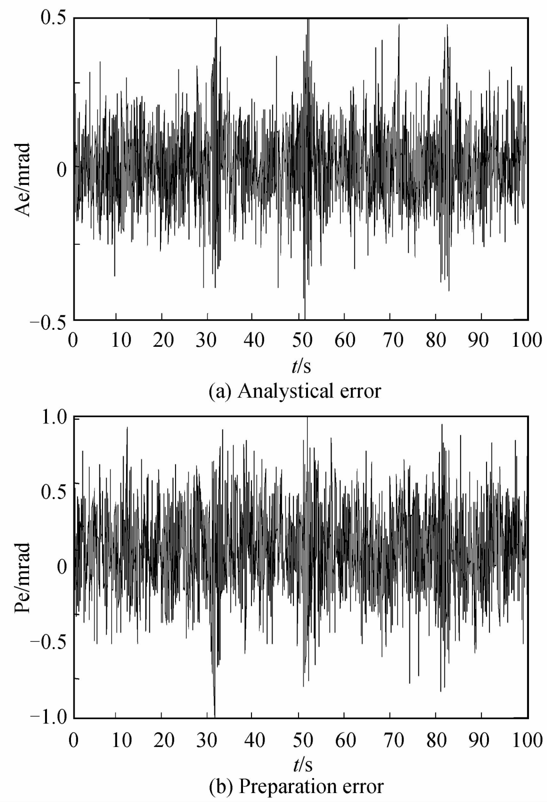

Fig. 6 Tracking error with IMMPF algorithm

where N_{MC} is the Monte Carlo number (100), θ_k^{true} is the true state vector, $\hat{\theta}_k^m$ is the estimated value.

In order to verify the above algorithms, it is important for different σ_θ to test tracking effect and times cost, the simulation results with formula 19 are shown as table (1)-(2) (assume fine tracking field 3 mrad).

Table 1 Tracking effect in different σ_θ

σ_θ/mrad	Algorithms	Error/mrad Amplitude	Error/mrad RMSE	Lost tracking time/s
0.1	FVSMMKPF	0.27	0.29	0
	IMMPF	0.52	0.67	0
0.2	FVSMMKPF	0.38	0.47	0
	IMMPF	1.2	0.75	4.7
0.4	FVSMMKPF	0.61	0.71	0
	IMMPF	1.8	0.92	8.3

Table 2 Time cost of algorithms

Algorithms	Time cost/ms
FVSMMKPF	36
IMMPF	62

As can be seen from the Table 1, with the increase of azimuth standard deviation, the tracking performance of the above algorithms all decline, but RSME of FVSMMKPF is obviously less than IMMPF. In two hundred experiments, the number and time that communication terminal loses tracking platform based on IMMPF all gradually increase with growth standard deviation, then FVSMMKPF always maintains the tracking state. In Table 2, average run time of the proposed algorithm is significantly less than IMMPF, fuzzy inference mechanism can obviously decrease, KPF can use fewer particles to approximate the posterior distribution, meanwhile fewer particles decrease computation and improve real time of algorithm.

In scene. 2, during the time of 0～20 s, 21～40 s, and 41 ～ 60 s, communication platform maintains moving in circle, in the time of 61 ～ 100s, communication platform moves in constant speed, airborne platform trajectory is shown as Fig. 7.

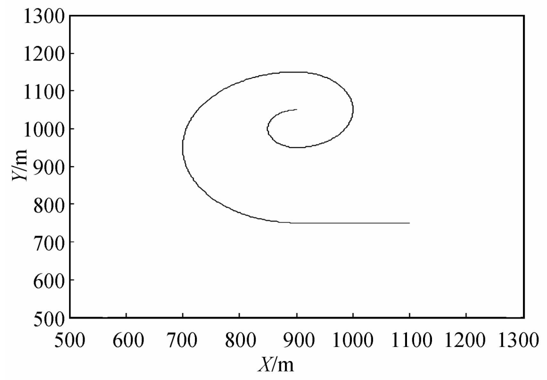

Fig. 7 Airborne platform trajectory in scene 2

With respect to the scene 1, communication platform shows the stronger maneuverability, the tracking error in IMMPF algorithm is generally more than 2 mard, equally, when the motion form changes, IMMPF algorithm increases rapidly to reaches 3 mrad, the tracking algorithm with FVSMMKPF always keeps the better stability, the tracking error maintains within 1 mrad.

From the perspective of theoretic and data analysis in two scenes, tracking effect based on FVSMMKPF includes the following several aspects: 1) variable structure multiple-model algorithm based on digraph switching and kernel particle filter is presented, and improves the accuracy of tracking by reducing the competition of the models as well as reducing the computation burden; 2) kernel density estimation can directly sample particle from dynamic equation, it make particles to move awards the high likelihood region of maximum posteriori probability density and improve filtering accuracy; 3) quadratic function of the filtering measurement innovation weighted with the inverse of its covariance matrix is considered as the input of the fuzzy inference mechanism to get the matched degree for each filtering model in the designed model set, by which model probability in the existing multiple model algorithm is replaced, and the calculation complexity is decreased obviously; 4) the uncertainty of measurement space is mapped into the fuzzy space, and the uncertainty of measurement space is resolved via the fuzzy inference mechanism.

5 Conclusions

Fuzzy VSMM-DS with KPF used in airborne laser communications is proposed in this paper, particles obtained from KPF are moved towards the maximal posterior probability density through Kernel density estimation, adaptive model set can decrease computation, and contradiction of models competition. Simulation results verify that tracking RMSE error is within the range of 0.32 mrad, FVSMMKPF method has better tracking performance and robustness.

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