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Research Article

Improved IMMPF Tracking Methods for Airborne Laser Communication

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Abstract: Tracking system offers the prerequisite and guarantee for airborne laser communication, it is vital for tracking methods to determine the tracking accuracy. Because of diversity of maneuvering forms and high nonlinear problem, it is impossible to accurately describe the movement of airborne platform with the simple model and the traditional filtering method, it is necessary to adopt Interacting Multiple Model (IMM) methods for tracking system. The Particle Filter (PF) can deal with nonlinear/non-Gaussian problems, it can be introduced into IMM framework. However, the realization of PF have a larger amount of computation, in order to solve computational complexity, the parallel structure of data processing is proposed. Through theoretical analysis and computer simulation, improved PF effectively reduces the workload; the performance of improved IMMPF is much superior to other methods.

Keywords: Airborne laser communication, IMMPF, tracking

INTRODUCTION

In the recent years free, space laser communication based on airborne platforms has become a hot research, the main developed countries and organizations, such as the United States, Japan and ESA have carried out airborne laser communications (Toni and Opperhaeuser, 2002; Vladimir *et al*., 2008; Mariusz *et al*., 2010). Because of the typical nonlinear/non-Gaussian problem in the tracking of the airborne platform (Tian *et al*., 2009), it is the huge challenge for airborne platform communication terminals to establish stable optical communication link (Young and Bullock, 2003).

Due to diversity of maneuvering forms, it is impossible to accurately describe the movement of airborne communication platform with the simple model, it is necessary to adopt the Interacting Multiple Model (IMM) methods for airborne platform tracking system; the basic idea of the multiple model estimation approach is to assume a set of models M for the hybrid system (Leitgeb *et al*., 2007; Fidler *et al*., 2010). Particle Filter (PF) algorithm can be used to estimate any state and measurement of nonlinear/non-Gaussian system, the theoretical basis of PF is the Monte Carlo simulation based on sequential importance sampling; PF has a broader scope of application and better filtering performance than series of EKF algorithm (Farrell, 2008; Koichi and Tsujimural, 2006).

In this study, we proposed IMM methods, combining with PF algorithm. The proposed improved IMMPF not only can deal with typical nonlinear estimation problem and maneuvering forms in the tracking of the airborne platform, but also can decrease heavy computational load (George and Zakharov, 2007). In several typical airborne platform environment, experimental results demontrate that the improved methods have a better performance than other methods.

TRACKING STATE SPACE MODEL

State space dynamic equation in IMM algorithm can be expressed by the formula as follows:

$$X_i(k) = F_i(X_i(k-1)) + G_i(v_i(k-1)) \tag{1}$$

$$Y_i(k) = H(X_i(k)) + r(k) \tag{2}$$

where, $X_i(k)$ represents state vector of the model i (i = 1,2, ..., M), $v_i(k)$ is the corresponding non-Gaussian process noise vector, $r(k)$ is the observation vector of the noise, Q and R is the covariance of $v_i(k)$ and $r(k)$.

It should be noted that airborne tracking of communication platform is actually angle tracking, and 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:

$$P(m(k+1) = j \mid m(k) = i) = p_{ij} \quad i, j = 1, 2, ...M \tag{3}$$

In general, the model transition probability p_{ij} is assumed to be constant in the entire tracking process.

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Initial model probability $X(0)$, initial state probability $\{\mu_i(0)\}_{i=1}^{M}$ and the observation vector $Y_i(k)$ have been known, eventually the state $X_i(k)$ can be estimated.

IMPROVED IMMPF METHODS

On the basis of Interactive operation result and the observables Y(k), state $\widehat{X}_i(k/k)$ and covariance $P_i(k/k)$ are estimated via matched filter. PF with importance resampling strategy is summarized as follows:

- **Particles initialize:** Particle swarm $\{x_i^j(0)\}_{j=1}^{N}$ is generated by the a priori probability; all particle weights are $1/N$
- At time k, the particle weights are updated to:

$$\begin{aligned}\omega_i^j(k) &= \omega_i^j(k-1)p(y_i(k)/x_i^j(k)) \\ &= \omega_i^j(k-1)p_{e(k)}(y_i(k)-H(x_i^j(k)))\end{aligned} \quad (4)$$

- Normalized particle weights are computed by:

$$\tilde{\omega}_i^j(k) = \omega_i^j(k) \Big/ \sum_{i=1}^{N} \omega_i^j(k) \quad (5)$$

- The predicted state is:

$$\hat{x}_i(k) \approx \sum_{j=1}^{N} \tilde{\omega}_i^j(k) x_i^j(k) \quad (6)$$

According to real-time requirement, some numbers of particles are divided into a collection, which is defined as a processing (PE). The work of PE is constituted by three parts, such as sampling, the weight calculation and resampling. It is the easiest parallelism strategy of *PF* that a large number of particles in a collection are divided into a number of PE consisting of small capacity particle. The parallelism strategy is depicted in Fig. 1.

From Fig. 1, it can be observed that the entire parallel system is constituted by N/M PE with M particles; the final result needs to be averaged according to the each PE output. By such decomposition, the entire operation time will be reduced to K times; it is effective to improve the computational efficiency of the algorithm. In order to improve the speed of filtering, the number of child nodes and communication load in nodes are needed to comprehensively considered, when amount of sampling particles is small, the total particles are divided into less numbers of PE, otherwise, communication time of adjacent PE is similar to computation time, it is possible to increase communication conflict and cause low efficiency, when sampling particles are more, the particle set is divided into more PE.

Supposed the given model transition probability is p_{ij}, model probability is $\{\mu_i(0)\}_{i=1}^{M}$, state value is $\{\widehat{X}_i(k-1/k-1)\}_{i=1}^{M}$ and covariance is

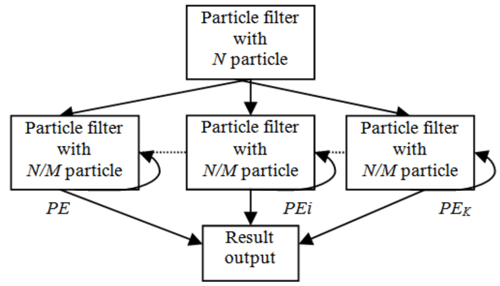

Fig. 1: Parallel structure of the algorithm

$\{\widehat{P}_i(k-1/k-1)\}_{i=1}^{M}$, where $j = 1, 2, ..., M$. Interactive working methods is described by:

$$\bar{X}_j(k-1/k-1) = \sum_{i=1}^{M} \hat{X}_i(k-1/k-1)\mu_{i|j}(k-1) \quad (7)$$

$$\begin{aligned}\bar{P}_j(k-1/k-1) = \sum_{i=1}^{M} \{&[\hat{X}_i(k-1/k-1) - \bar{X}_j(k-1/k-1)] \\ &.[\hat{X}_i(k-1/k-1) - \bar{X}_j(k-1/k-1)]^T \\ &+\hat{P}_i(k-1/k-1)\}.\mu_{i|j}(k-1)\end{aligned} \quad (8)$$

where, $\mu_{i|j}(k-1)$ is model mixed probability, $c_j(k-1)$ is normalization factor, they are defined as:

$$\mu_{i|j}(k-1) = \frac{1}{c_j(k-1)} p_{ij}\mu_i(k-1) \quad (9)$$

$$c_j(k-1) = \sum_{i=1}^{M} p_{ij}\mu_i(k-1) \quad (10)$$

Finally, the system state estimators are computed by:

$$\hat{X}(k/k) = \sum_{i}^{M} \mu_i(k)\hat{X}_i(k/k) \quad i = 1, 2...M \quad (11)$$

SIMULATION EXPERIMENT

We design some simulation scenarios to evaluate the proposed method, in order to simplify the problem, supposed one of the two communication terminals is fixed, the other is equipped on the airborne platform, the communication terminal move in a horizontal plane, the state vector is simplified as X_k= [x, y, v_x, v_y], the sampling period depending on the frame rate of CCD is 0.04s.

In a Cartesian coordinate system, airborne communication platform flies at the altitude of 5km, where initial location at [1000 m, 1200 m] , and initial speed at [-172m/s, 246m/s]. In 400s, the speed of the airborne platform is maintained at 300 m/s, during the time of 56-150s,182-245s, 285-314s and 345-379s, communication platform respectively maintain the maneuver acceleration in 1g, -1.5g, 3g and -2.5g (g = 9.8 m/s2), communication platform maintains constant linear vectioly in other time. Airborne platform tracking models include the *VA* model, *CA* model, left turn

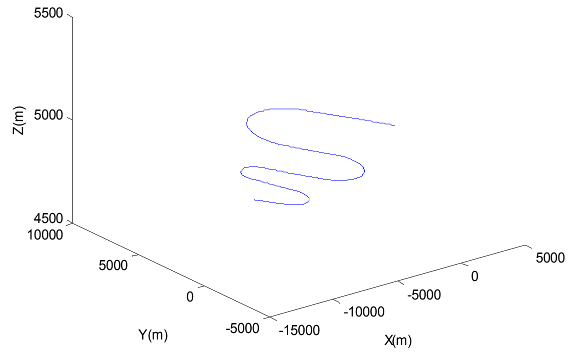

Fig. 2: Airborne platform trajectory

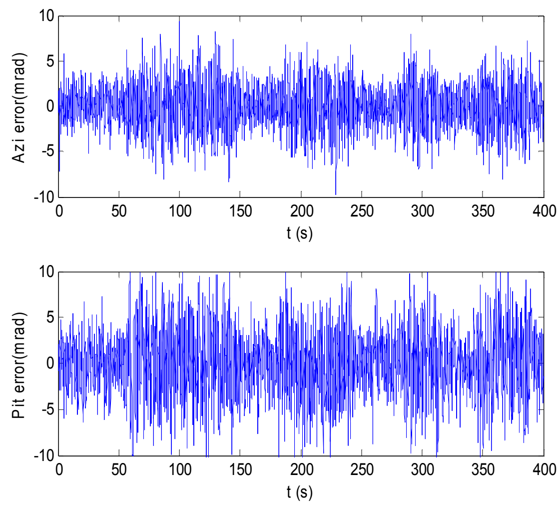

Fig. 3: Tracking error based on the EKF

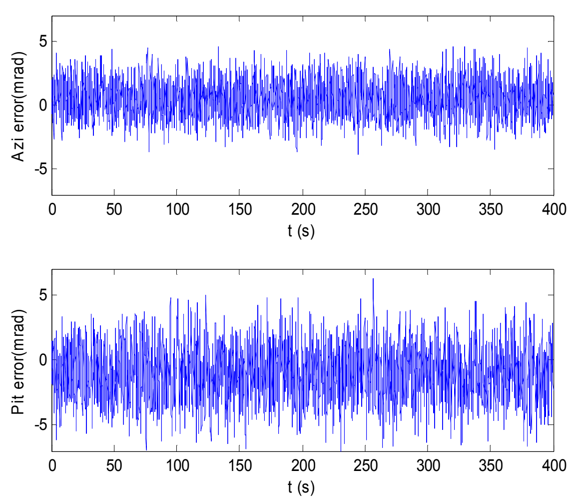

Fig. 4: Tracking error based on the IMMEKF

circumference model and right turn circumference model, above models basically cover the maneuvering state of the platform.

In order to verify IMMPF method, three algorithms including EKF, IMMEKF and IMMPF are simulated

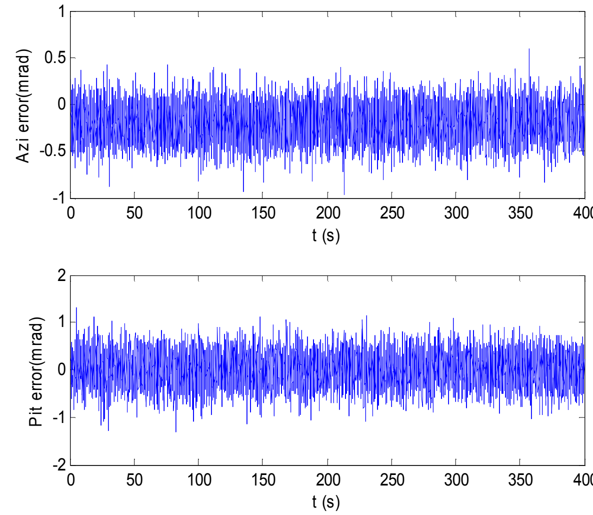

Fig. 5: Tacking error based on the IMMPF

Table 1: Tracking performance of algorithms

Methods	Azimuth error (mrad)	Pitch error (mrad)
EKF	9.94	25.32
IMMEKF	3.12	13.68
IMMPF	1.34	2.420

and compared by virtue of the computer in Core Duo 3.0G and 2G memory, the number of sampling particles in PF algorithm is set to 1000.

From the above Fig. 2 to 5, it is easy to know that tracking accuracy for IMMPF is better than other methods. When airborne platform moves in a variety of maneuvering models, especially in maneuvering model switch, the tracking error for EKF becomes significantly larger. It is obvious that IMM solves the uncertainty of the model; it can apply to maneuvering movement.

Figure 3 illustrates that EKF can't adapt to maneuvering models. In theory, when airborne platform works in weak linear model, because of approximate linearization error, EKF can't keep high tacking accuracy, performance of PF is better, it can be shown from Fig. 4 to 5. Table 1 shows the tracking performance for three algorithms.

Meanwhile, with experimental programming Visual C++, we call API timing function Query Performance Counter ( ) that reaches μs level, supposed 1000 sampling particles is divided into different PE size, such as 10,20 and 30,100,it is shown that speedup lineally grows if we ignore the PE communication cost.

CONCLUSION

Dynamic tracking of airborne laser communication is a typical nonlinear problem, Because of diversity of maneuvering forms, it is possible to apply different models matching the maneuvering forms, in order to solve the nonlinear estimation problem, IMM with improved PF is used in maneuvering platform tracking, which adopt different models to match the different types of filters. In the case of high speed (300 m/s) and high mobility (3g), simulation results verify that tracking accuracy is within the range of 2.5 mrad.

IMMPF method has better tracking performance and robustness. Parallel data processing of PF algorithm significantly decreases the amount of computation, and greatly improves the work efficiency. Dynamic tracking error is smaller, it is more beneficial to improve the tracking bandwidth. Through the ongoing research, we plan to apply the IMMPF method to the FPGA system.

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