IOP Conf. Series: Earth and Environmental Science **81** (2017) 012209 doi:10.1088/1755-1315/81/1/012209

Application of RPF in MEMS gyro random drift filtering

Guowei GAO [1], Yan XIE [2]

[1] Beijing Information Science and Technology University, Beijing 100101, China
[2] Nanjing Gksens Co.,LTD, Nanjing 210036, China

Abstract. With the development of micro-mechanical inertial technology, how to suppress the MEMS gyro's random drift increasingly become a hot topic. In order to filter a certain type of MEMS gyro's random drift, this paper introduces the regularized particle filter algorithm. The derivation of the algorithm and its application in MEMS gyro's filtering process are described in detail in this paper： First, acquiring MEMS gyro's static drift data and conducting data pre-treatment; then establishing the AR model by using time series analysis method, and transforming it into the corresponding state space model; finally, executing the estimation and compensation for MEMS gyro's random drift with regular particle filter algorithm, and comparing it with other common methods in engineering. Tests and simulation results show that the regularized particle filter algorithm could achieve a good effect on the suppression of MEMS gyro's random drift, it has a higher practical application value.

1 Introduction

MEMS gyroscope is a research hotspot in the field of micro-mechanical inertial technology in recent years, especially the digital filtering problem of MEMS gyro random drift. The random drift error of MEMS gyroscope is an important factor to limit its accuracy. The current general method random error model is established, and then used in a variety of filtering technology to compensate. MEMS gyro digital filtering technology has Kalman filter, particle filter, and its improved algorithm. The Kalman filter is a linear minimum variance estimation algorithm, using recursive method to extract the estimated amount from the measurement information. Kalman filter itself is a filtering method for linear system, and does not take into account the environmental noise impact on the system of nonlinear, in strongly nonlinear and non-Gaussian environment using Kalman filter can bring bigger error, severe cases, can appear even filtering divergence [1]. The UKF method is improved and is a form of deformation for the nonlinear system of linear Kalman filtering method, so it is subject to conditions of linear Kalman filtering method, with the state model of non-Gaussian distribution, still using the mean and variance of the probability distribution that will lead to filter performance is not ideal [2]. Particle filter random quantity is not limited by Gaussian distribution condition, do not need to make too many constraints on nonlinear system state, with the increasing of the number of samples, the probability density of the state is gradually tending to the state, so the nonlinear drift can be eliminated. However, with the increase of the number of iterations, particle loss of diversity, namely the lack of a particle count, eventually led to the filtering effect is not ideal, and therefore some improved particle filter algorithm, but most are in the stage of algorithm deduction and model simulation. In this paper, the random drift of the MEMS gyroscope is studied by using the regularized particle filter algorithm.

2 Regularized particle filtering algorithm

2.1 Particle filtering

The state space model of nonlinear dynamic time-varying system can be composed of system equation and observation equation.

$$x_k = f(x_{k-1}, u_{k-1}) \tag{1}$$

$$y_k = h(x_k, v_k) \tag{2}$$

Which represents the state of the system at the time of the K, which represents the measurement vector of the K moment; of the system at the time of the K, which represents the measurement vector of the K moment.

$$f_k : R^n \times R^n \to R^n$$

Said system state transfer function,

$$h_k : R^n \times R^n \to R^n$$

Said System measurement function; u_k is system noise, v_k is the observation noise of the system, u_k and v_k are Independent and independent of system state.

The state space model can be described in a statistical way, that is, the probability density of the state transition probability and the observed probability density of the system state [3,4]

$$p(x_k \mid x_{k-1}) \tag{3}$$

$$p(y_k \mid x_k) \tag{4}$$

In the above state space, the following recursive update method is used to obtain the posterior probability density:

(1) Prediction:

Based on the posterior probability density $p(x_{k-1} \mid y_{1:k-1})$ obtained from the k-1 time, the probability density of the k moment x_k is predicted by using the system model, and the prior probability density of k time x_k is obtained.

$$p(x_k \mid y_{1:k-1}) = \int p(x_k \mid x_{k-1}) p(x_{k-1} \mid y_{1:k-1}) dx_{k-1} \tag{5}$$

(2) To update:

When the y_k value of the k moment comes, it is used to correct the prior filtering probability density, so as to obtain the posterior probability density of k moments.

$$p(x_k \mid y_{1:k}) = \frac{p(y_k \mid x_k)\, p(x_k \mid y_{1:k-1})}{p(y_k \mid y_{1:k-1})} \tag{6}$$

$p(y_k \mid y_{1:k-1}) = \int p(y_k \mid x_k) p(x_k \mid y_{1:k-1}) dx_k$ is The iterative relation (5) (6) is the optimal Bayesian solution, However, it is difficult to obtain the optimal Bayesian analytical solution. Therefore, the particle filter is based on the sequential importance sampling algorithm (SIS algorithm). However, the basic problem of sequential importance sampling algorithm is the problem of sample degradation. Gordon (Resampling) will be re sampling steps using SIS algorithm to overcome the SIS algorithm in the sample degradation, and the resulting classical particle filter algorithm: sequential importance resampling algorithm (Sequential Importance Resampling, SIR [5,6]).

2.2 Regularized Particle filtering

The re sampling step while solving the particle degradation problem but also brought new problems, namely the lack of particles, after several iterations, the original particle set is too small because many particle weight offspring, and a few higher weight particles have many of the same "offspring", after resampling particle collection composed of a large number of repeated particles, all particles tend to the same particle, the particle collection of lost diversity. In order to solve the new problem introduced by resampling, a regularized particle filter (regularized particle filter) algorithm is proposed in this paper. The core idea of the regularized particle filter is to transform the discrete empirical distribution into a continuous distribution, and then generate the needed particles. The difference between the two is that in the process of resampling, SIR resampling from the discrete approximation of the state of the system, and the regularized particle filter resampling [7,8].

$$p(x_k \mid y_{1:k}) \approx \hat{p}(x_k \mid y_{1:k}) = \sum_{i=1}^{N} w_k(i) K_h(x_k - x_k(i)) \tag{7}$$

Among them: $w_k(i)$ is the normalized weight, $K_h(.)$ is a kernel density (Kernel Density) function of the $K(.)$ re calibration of the nuclear density function.

2.3 Modeling and filtering steps based on RPF algorithm

The output signal of the MEMS gyro is a non-stationary random sequence. Firstly, the error model is established by using the time series analysis method. Because the data objects using time series analysis method of model must be stable, normal and zero mean time series, so before model to analyze the pre-treatment and statistics of the original data, this work will not be discussed here, the figure is RPF MEMS Gyro Signal Denoising Based on [9,10] flow chart, see Figure 1.

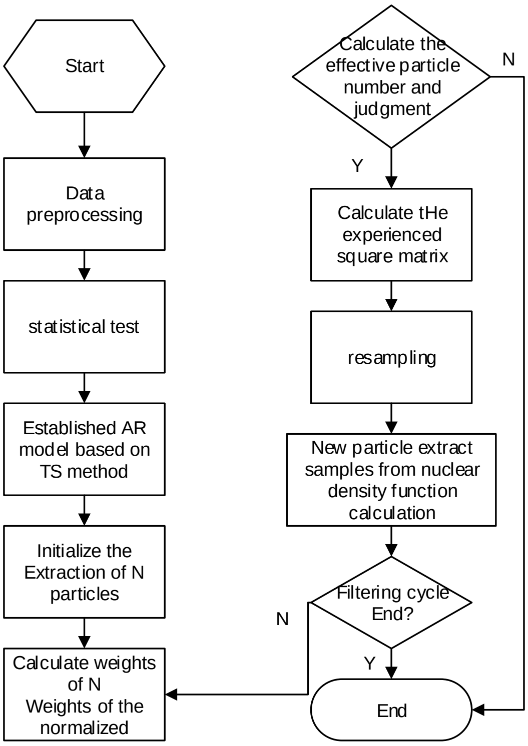

Figure 1: flow chart of MEMS Gyro Signal Denoising Based on RPF

The detailed implementation steps of the RPF algorithm are as follows:

(1) extracting new particles from the state transition probability density

$$x_k^*(i) : x_k^*(i) \sim p(x_k \mid x_{k-1}(i))(i = 1, 2, \cdots, N);$$

(2) using the formula to calculate the weight $w_k^*(i)$ of each $x_k^*(i)$:

$$w_k^*(i) = w_{k-1}^*(i) p(y_k \mid x_k(i))$$

The use of the normalized value of the above is worth $w_k(i)$

$$w_k(i) = \frac{w_k^*(i)}{\sum_{i=1}^{N} w_k^*(i)} \tag{8}$$

(3) state estimation:

$$\hat{x}_k = \sum_{i=1}^{N} w_k(i) x_k^*(i) \tag{9}$$

(4) calculate the empirical variance of the particle, and find the satisfied

$$D_k (D_k)^T = S_k \text{ 的 } D_k \text{;}$$

(5) Resampling

$$\{x_k(i)\}_{i=1}^{N} \text{;}$$

(6) Samples were extracted from the Epanechnikov kernel density

$$x_k(i) = x_k(i) + h_{opt} D_k e_k(i)$$
$$(i = 1, 2, \cdots, N) \tag{10}$$

$x_k(i)$ is a kind of particle obtained by resampling from the (7) continuous approximation distribution.

3 Test and Analysis

3.1 Data acquisition

The MEMS test board is fixed on the gyro three axis turntables, the turntable in X axis and the axis of turntable, start, zero static data acquisition of gyroscope, the sampling frequency is 10Hz, collecting 5000 data points.

3.2 Time series analysis model

Then do smooth processing of the collected data, the random time series, see Figure 2, then model with time series analysis method, TS model with autoregressive (AR) model, moving average (MA) model and autoregressive moving average (ARMA) model 3, we construct a fixed AR (2) at the beginning of the model parameters estimation model, establish the AR model of X axis data [11, 12]:

$$z_k = 0.5235 z_{k-1} - 0.2411 z_{k-2} \tag{11}$$

The state equation of gyro drift is chosen as state $x_k = [z_k, z_{k-1}]^T$:

$$x_k = A x_{k-1} + B w_{k-1} \tag{12}$$

Among them:

$$A = \begin{bmatrix} 0.5235 & 0.2411 \\ 1 & 0 \end{bmatrix}, B = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

The measurement equation is

$$y_k = C x_k \tag{13}$$

Among them: $C = [1 \quad 0]$.

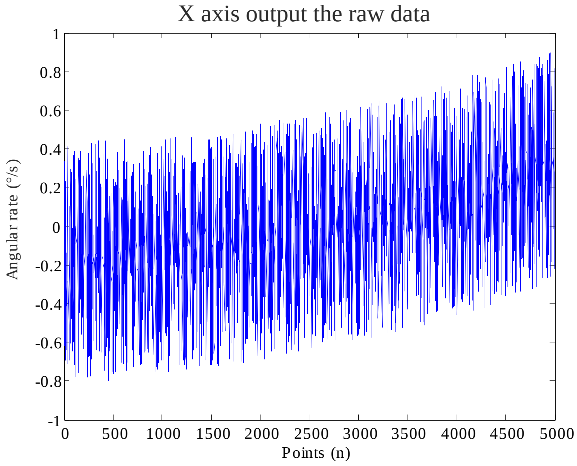

Figure 2: MEME gyro output signal

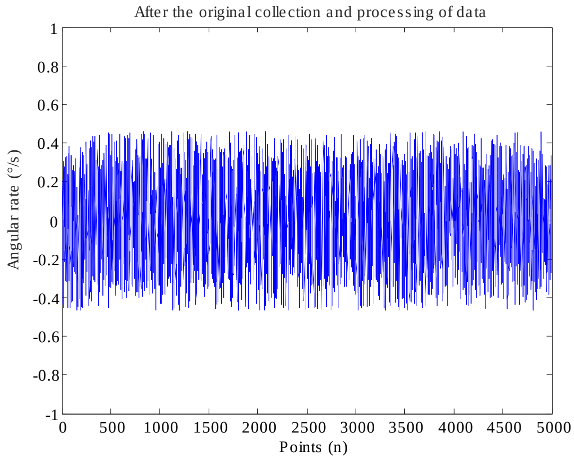

Figure 3: The result of smoothing the original data

3.3 Simulation and analysis of RPF algorithm

According to the state equation and the measurement equation using the regularized particle filter algorithm of time series of gyro drift are filtered, and using the classical particle filter algorithm (PF) and unscented Kalman filter (UKF) were compared with results. The numbers of particles N select 50,100,200, and carry out 100 independent simulation, see Figure 3.

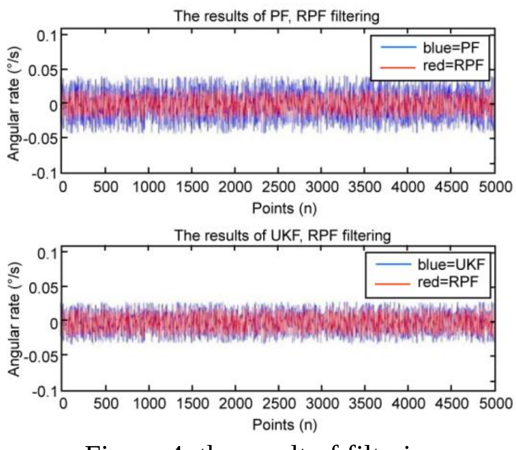

Figure 4: the result of filtering

Finally, we use the root mean square error (RMSE) analysis (see Table 1) and Allan variance analysis (see Table 2) to quantify the performance of the three filters. The root mean square error (RMSE) analysis is a traditional performance estimation method:

$$RMSE = \left(\frac{1}{T} \sum_{k=1}^{T} \frac{1}{N_{MC}} \sum_{j=1}^{N_{MC}} \left[x_k^{true} - \hat{x}_k^j \right]^2 \right)^{1/2} \tag{14}$$

N_{MC} is Monte Carlo simulation

Allan variance analysis is a general method for gyro random error frequency stability analysis. It is based on gyro noise distribution in different frequency bands, to separate the sources of error of gyro drift, and can determine the contribution of each error of total error. This paper uses the Allan analysis of variance of the gyro output signal method, according to the random error of MEMS gyroscope with quantization noise, angle random walk, the bias instability, the table is 100 times the mean noise coefficient [13] independent test results.

Table 1: the root mean square error of each filter algorithm in different experiments

RMS error	Particle number		
	50	100	200
PF	1.05280	0.90772	0.66667
RPF	1.03591	0.72980	0.35690

Table 2: Comparison of the performance of the two filtering methods

Allan Variance	Quantization noise $(Q)/''$	angle random walk $(N)/^\circ \cdot h^{1/2}$	Zero bias instability $(B)/^\circ \cdot h^{-1}$
Gyro drift	0.92541	0.00314	0.02985
PF（50）	0.36520	0.00251	0.02067
PF（100）	0.34295	0.00252	0.01982
PF（200）	0.32967	0.00250	0.02153
RPF（50）	0.32110	0.00247	0.01995
RPF（100）	0.31984	0.00246	0.01999
RPF（200）	0.30145	0.00248	0.02016
UKF	0.32160	0.00361	0.01893

Table 1 Comparison of calculation results were given experimental results of single root mean square error, RPF algorithm is slightly better than the PF algorithm. Moreover, with the increase of the number of particles, the accuracy of PF and RPF is also increasing. However, when the number of particles is large, the calculation is relatively large.

Table 2 gives the results of 100 experiments the average noise coefficient, three kinds of filtering algorithm can effectively suppress the quantization noise, and with the increase of the particle number inhibition effect is better, for the angle random walk and bias instability, two filtering algorithms were inhibited, but the influence of population change on the results is not significant. Generally speaking, the three filtering algorithms can filter the random drift of MEMS gyro, but the effect of the regularized particle filter is better than that of the classical particle filter and UKF.

4 Conclusion

In order to overcome the impact of the characteristics of MEMS gyro random drift of the non-stationarity and non-linearity, this paper used the particle filter algorithm in the treatment, and compared with other algorithms, the experimental results and the comparison of the data analysis shows that this method effectively suppressed MEMS gyro random drift. With the classic Kalman filter and Kalman filter, compared to many improved algorithm, particle filter overcomes the nonlinear characteristic of MEMS Gyroscope Random Drift from the essence, but both the classical particle filter, or the regularized particle filter do not have negligible weaknesses, for example, the sample degradation and loss of particle diversity. So, the particle filter has a long way to go on, but in view of the particle filter in nonlinear filtering of the innovation and effectiveness, its application prospect is very good.

Acknowledgements
The project is partially financial supported by the National Natural Science Foundation of China (No.61571053).

References

[1] W.CUI, W. C. CHEN, *Sensor world*, 2011, 17, 6-8.
[2] H. ZHAO, Z. Y. WANG, *Sensor Technology*, 2011, 24, 642-646.
[3] N.J. GORDON, D.J. SALMOND, *Institute Electric Engineering*, 1993, 140, 107-113.
[4] S. Q. HU, Z. L. JIN, *Science Press*, Beijing, (2010).
[5] S. Q. HU, Z. L. JIN, *Control and Decision*, 2005, 20, 361-365.
[6] M. CUI, *Sensor Technology*, 2011, 24, 1275-1278.
[7] M. LIU, N. Q. CHEN, S. Y. YANG, *Transmission and Reception*, 2012, 36, 108-111.
[8] B. TIAN, L. GUO, *Journal of Beijing Institute of Technology*, 2001, 30, 562-566.
[9] B. RISTIC, S. ARULAM, N.J. Gordon, “Beyond the Kalman filter: particle filters for tracking applications [M], Artech House, London, 2004.
[10] A.DOUCET, N.J. GORDON “Sequential montecarlo methods in practice” [M], New York, Spring-Verlag, 2001.
[11] J.ZHAO “Research on gyro error model and compensation based on particle filter”, *Master thesis [D]. Taiyuan: North Central University*, 2010.
[12] J. LIANG “Particle filter algorithm and its application”, *Master thesis [D]. Harbin: Harbin Institute of Technology*, 2009.
[13] C. Piro, D. Accardo, IEEE Aerospace Conference, 2007, 3, 1-12.