Nonlinear Non Gaussian Kalman Filtering Algorithm Based on Gauss and 7th Order Volume

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Abstract: In the irregular Gaussian filter, the average quadratic root volume Kalman filter (sckf) has no filtering effect. In order to solve the problem of sckf and Gauss filtering, a new algorithm of Gauss root's average square volume Kalman filter is proposed. The algorithm uses Gauss type and formal type approximate non Gauss probability density, sckf as sub filter, updates the time and measurement of each Gaussian component, and effectively solves the problem of non-linear non Gaussian filtering. The simulation results show that the estimation accuracy of Gaussian filter and RMS volume Kalman filter is higher than that of particle filter, Gauss filter and extended Kalman filter. Nonlinear and non Gauss filtering algorithms for balancing tracking accuracy and real-time performance.

1. Introduction

Filtering is based on the set of unknown parameters and measurement data containing noise to calculate the value of unknown parameters. That one is widely used in science and engineering. The general classification of filtering is linear filtering and nonlinear filtering. Linear filtering corresponds to Gaussian linear system model, and nonlinear filtering corresponds to non Gaussian or nonlinear system model. For the linear filtering problem, Kalman filter (KF) is the best solution of Bayes regression estimation problem. It is good for researchers because of its repeatability which is suitable for computer processing. For nonlinear filtering, KF is no longer applicable. The extended Kalman filter (EKF) is a general nonlinear filtering method which assumes Gauss white noise, but this linearization produces a lot of errors[1]. Especially in the case of very nonlinear. The unscented Kalman filter (UKF) uses sigma points to perform nonlinear transformation directly instead of linearizing the system model, but needs to determine the sigma scaling factor manually. Gauss Hermite filter (GHF) and central difference filter (CDF) are proposed. It is pointed out that the head and tail of UKF and GHF are the same under some conditions, and their accuracy is better than EKF. Based on the radial transformation of sphere, a new nonlinear filtering method is proposed. Compared with EKF and UKF, the new algorithm has better nonlinear approximation performance and numerical accuracy. Sckf directly avoids the square of covariance matrix by introducing choleschi decomposition. All of the above filtering methods are Gaussian filters. In other words, it is assumed that the distribution of states before and after is approximately Gaussian.

2. Under the Condition of Non Gauss, Gauss Filter May Cause Serious Errors or Even Divergence

In order to describe the probability distribution, the previous methods used the GSF and PF algorithm with multiple random samples. However, the traditional pf uses the pre transition distribution of non current measurement data as the importance density function, and introduces a larger weight distribution. In order to solve this problem, the particle importance function is designed by using EKF, UKF and CKF. After integrating the measurement data, the filtering accuracy of the three algorithms is higher than the previous PFp[2]. However, because it is obtained

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in the framework of local filtering, the calculation amount of the algorithm is larger than the previous PF, so it is difficult to meet the application requirements in the case of high real-time requirements. GSF method is based on Gauss sum theory. This is to use multiple identical filtering algorithms (such as KF, EKF, UKF or PF) as sub filters, and use parallel computing to obtain global filter estimation[3]. GSF generally uses fewer Gauss terms for non Gauss approximation, which is much smaller than EPF, UPF and CPF in PF framework. In the GSF framework, a compensation memory Gauss and a filter (fmgsf) using KF as a sub filter are proposed. The algorithm uses KF as auxiliary filter, so it can't deal with nonlinear condition. In this paper, we derive the GSF in the case of complete nonlinearity and non Gauss, and use their KF as auxiliary filters. The problem of EKF makes the filtering of gsktf ineffective in the case of non Gauss with high nonlinearity. The difference filter (DDF) is used as an auxiliary filter to improve the filtering accuracy when the likelihood density is located at the tail of conditional migration probability density. Like GHF, UKF and CKF, DDF is used in each filter program. Covariance matrix has square root operation. The wrong definition of matrix leads to the termination of algorithm. Moreover, this will seriously affect the stability of the algorithm. By using pf as a sub filter, the two combinations generate a lot of computation.

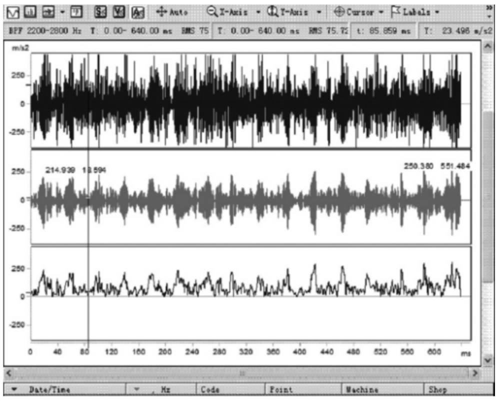

Figure 1 Simulation results of data distribution and filtering identification

3. Root Mean Square Volume Kalman Filter

CKF and sckf propose a nonlinear KF algorithm based on spherical moving diameter standard[3]. In order to solve the problem of Bayesian filter integration, a new method is proposed to encapsulate the nonlinear estimation problem by using the set of equidistant volume points. However, in practical application, the rounding of the finite language length of computer introduces errors. Moreover, the covariance matrix does not satisfy the above hypothesis. Sckf can avoid the direct covariance matrix generated by coeschi decomposition and improve the stability of the algorithm.

4. Gauss Function and Root Mean Square Volume Kalman Filtering

Because sckf is Gauss filter, the noise can be approximately Gaussian distribution and the filtering accuracy can be greatly reduced when solving the filtering problem of non Gaussian noise. According to citation 1 of , any probability density can be approximated by overlapping forms of different mean and variance Gauss distributions[4]. By applying Gauss filter to every Gauss component, we can get GSF algorithm. Aiming at the subject of EKF, UKF, GHF and PF as sub filters, as sub filters updating Gaussian components, sckf with high filtering accuracy and stability is used, and gssckf is obtained [5]. In the GSF framework, P question NP . Then, the amount of computation increases correspondingly, and the real-time performance of the algorithm degrades. In order to consider the real-time performance and the accuracy of the algorithm, the upper limit of the number of Gaussian terms in gsktf and gssckf is 20, while the number of particles in PF and CPF is 200. The actual state value of the system and the calculated value of each algorithm expand the local tracking results. , various algorithms can track the state of the system. The accuracy of PPF and gssckf is relatively high, the former is better than the former [6].

5. Kalman Filter (KF) Algorithm is Widely used in Filter Estimation of Dynamic System

The observation noise of the used navigation signal is reduced, the navigation accuracy is improved, the radar tracking system is suitable for KF, the solution of radar tracking problem Finally, the tracking accuracy is improved[7]. On this basis, a variety of related algorithms are being developed, including EKF, UKF, CKF, cqkf, IKF and other algorithms. EKF algorithm realizes the primary application of KF filtering by linearizing the filtering objects. The UKF algorithm introduces a deterministic sampling strategy to deal with the estimation of highly nonlinear dynamic systems, which can achieve three measurement accuracy. CKF algorithm uses a better sampling strategy than UKF to improve the stability of filtering. In order to realize the approximation of line integral, czkf algorithm uses the method of sampling point approximation to improve the approximation accuracy of line integral based on the sphere radius, and then improve the filtering accuracy. In recent years, the algorithm of high-order filtering accuracy has been proposed. Five times of UKF, five times of CKF, five times of embedding, five times of embedding, five times of embedding, five times of ickf algorithm, five times of ickf algorithm and the same high-order algorithm as cqkf algorithm, the filtering accuracy of all the previous three algorithms is improved. The higher-order algorithm increases the number of sampling points of deterministic sampling, and gets a higher approximation accuracy than the lower order algorithm in Gaussian approximation theory. However, due to the high complexity of the high-order algorithm, it is difficult to determine the set of sampling points of the high-order algorithm[8]. Therefore, there are fewer higher-order algorithms with higher precision than the 5th. In order to further improve the filtering accuracy, a 7-order orthogonal volume Kalman filter (7cqkf) algorithm is proposed. Based on the existing high-order CKF algorithm, the sphere radius sampling benchmark is extended, and the 7cqkf sampling method is determined. In the framework of Gauss filter, a new filter is proposed in detail. The simulation results show that the new method improves the filtering accuracy， Particle filter is such a method. Different from Gauss filter, particle filter approximates the probability distribution of state conditions based on sequential Monte Carlo method. Therefore, particle filter is a global approximate optimal filtering method..

6. 7th Orthogonal Volume Kalman filter (7th cqkf)

Based on CKF algorithm, cqkf algorithm uses the high-order CQF algorithm in Chebyshev [9] to expand the orthogonal volume benchmark in online integration, and improves the approximation accuracy to 5 times. In this paper, seven orthogonal volume standards are derived. According to the orthogonal volume standard, the sampling points and weights of cqkf under 7 times standard are determined for the first time. First, there are two kinds of integral forms of optional order function. First, in the formula of $Y_k = \frac{1}{N}\sum_{i=1}^{N}\delta(x_k - x_k^i)$, the linear integral form of the quadrature $I_N(f) = \sum_{i=1}^{2n} w_i f(\xi_i)$. The second type proves the sphere area fraction form, that is, when the integral equation reaches 7 times accuracy, the two integrations must meet 7 times accuracy at the same time. Similarly, in order to obtain the 7-level accuracy CKF filtering algorithm, the sampling criteria of line integral and spherical region division are derived in this paper, so that the two integration criteria can reach the 7-level approximate accuracy.

7. Conclusion

Under the GSF filtering framework, Gauss and filtering algorithm based on sckf are proposed. The algorithm completes the time update and measurement update of each step through sckf to improve the performance of non-linear non Gaussian filtering. Compared with gscscf and PPF, gssckf improves the tracking performance[10]. Compared with CPF, gssckf reduces the computation while maintaining the tracking accuracy, and improves the real-time performance of the algorithm[11]. Gssckf is a good trade-off choice when considering the accuracy and operation efficiency of the algorithm.

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