Research on the Relationship Between Information Fusion Method and Information Failure Mode in Integrated Navigation System

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Abstract: On the basis of the basic principles of weighted fusion, Kalman filtering and BP neural networks, the basic principles of information fusion methods used in integrated navigation systems are expounded. Through the analysis of the basic principles, the association of information fusion methods commonly used in integrated navigation systems and information failure modes is obtained: the information fault mode of weighted fusion method The model is closely related to the specific weight allocation method, which depends on the fault mode of the sensor or sub-system in which the weight is dominant; the information fault mode of the Kalman filtering information fusion method is a continuous mutation fault corresponding to the nonlinear time interval of the system; the information fault mode of the BP neural network method is gradual with time. The information failure mode of the BP neural network method is a slowly varying fault that gradually accumulates over time. Starting from the complexity associated with the information fusion method and the information failure mode, it is pointed out that in order to systematically express the relationship between the information fusion method and the information failure mode, further research can be carried out.

Keywords: Integrated navigation system; Information fusion; Information failure mode

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1. Introduction

The essence of the integrated navigation system is the optimization processing system of navigation information of two or more navigation devices. Information fusion technology is one of the key technologies of integrated navigation. Information fusion, also known as data fusion, can be summarized as: Using computer technology, the observation information of several sensors obtained in time series is automatically analyzed and integrated under certain criteria to complete the required decision-making and estimation tasks.

At present, the common information fusion methods of integrated navigation systems are mainly divided into weighted fusion method, Kalman filtering method and BP neural network method according to their different fusion algorithms. There are differences in the basic principles of different information fusion methods. The operating environment and scope of application have different focuses. Each type of method has its own advantages and disadvantages. Based on the basic principles of these algorithms, this paper analyzes and expounds the relationship between different information fusion methods and information failure modes, and provides useful reference for researchers engaged in information fusion and information fault diagnosis.

2. Common Information Fusion Method for Integrated Navigation System

2.1 Weighted Fusion Method

The weighted fusion method performs a weighting operation on the same measurement value provided by different sensors, and the result is used as a fusion value. The weighting coefficients in the weighted fusion method reflect the sensor signal confidence. The rationality of the weighting coefficient is the key to determine the performance of fusion. The most widely used one is the optimal weighted fusion.

The basic principle of optimal weighted fusion:[1]

Suppose that an unknown sensor Y is observed with N sensors, and the observations of the sensors are respectively $\{Y_j\}(j=1,2,\ldots,N)$, the observation of the j-th sensor can be expressed as $Y_j(t)=Y(t)+n_j(t)$, $n_j(t)$ indicates the white noise superimposed on the real signal $Y(t)$, the variance of $n_j(t)$ is defined as $\sigma_j^2=E\left[n_j^2(t)\right]$, in which $E[\cdot]$ represents mathematical expectations. If the observations are unbiased and independent of each other, the estimate of Y can be expressed as $\hat{Y}=\sum_{j=1}^{N}W_jY_j$, in which W_j is the weighting factor, and $\sum_{j=1}^{N}W_j=1$. The estimated variance is $\sigma^2=\sum_{j=1}^{N}W_j^2\sigma_j^2$, in which σ_j^2 is the noise variance of the j-th sensor. Construct a helper function to find W_j that minimizes the estimated variance σ^2 as follows:

$$f(W_1, W_2, \ldots, W_N, \lambda) = \sum_{j=1}^{N} W_j^2 \sigma_j^2 + \lambda(\sum_{j=1}^{N} W_j - 1) \tag{1}$$

The problem of estimating the minimum value of the variance under the condition $\sum_{j=1}^{N} W_j = 1$ is attributed to the following conditional extreme value problem:

$$\begin{cases} \frac{\partial f}{\partial W_1} = 2W_1\sigma_1^2 + \lambda = 0 \\ \frac{\partial f}{\partial W_2} = 2W_2\sigma_2^2 + \lambda = 0 \\ \cdots \\ \frac{\partial f}{\partial W_N} = 2W_2\sigma_N^2 + \lambda = 0 \\ \sum_{j=1}^{N} W_j - 1 = 0 \end{cases} \tag{2}$$

Namely:

$$\begin{cases} W_j = \frac{\mu}{\sigma_j^2}, \quad j = 1, \ldots, N; \ \mu = -\frac{\lambda}{2} \\ W_1 + W_2 + \cdots + W_N = 1 \end{cases} \tag{3}$$

From the above equation, we can find that:

$$W_1 + W_2 + \cdots + W_N = \mu(\frac{1}{\sigma_1^2} + \frac{1}{\sigma_2^2} + \cdots + \frac{1}{\sigma_N^2}) \tag{4}$$

Namely $1 = \mu \sum_{i=1}^{N} \frac{1}{\sigma_i^2}$, and $\mu = 1 \Big/ \sum_{i=1}^{N} \frac{1}{\sigma_i^2}$, bring this result to $W_j = \frac{\mu}{\sigma_j^2}, \quad j = 1, \ldots, N$, we can find that:

$$W_j = \frac{1}{\sigma_j^2 \sum_{i=1}^{N} \frac{1}{\sigma_i^2}}, \quad j = 1, \ldots, N \tag{5}$$

2.2 Kalman Filter

Federated filters have received extensive attention due to their flexibility in design, small computational complexity, and good fault tolerance.[2,3] The federated filter is now selected as the basic algorithm by the US Air Force's fault-tolerant navigation system "Public Kalman Filter" program. The essence of the Kalman filter information fusion method using the federated filter structure is to assign the global state information and system noise information of the integrated navigation system to each sub-filter using the principle of information distribution, and use the variance upper bound technique to eliminate the estimation results of each sensor sub-filter. Correlation, and by measuring the statistical properties of the model, the statistically optimal fusion data estimates are derived.

2.2.1 Kalman Filter Basic Equation

We use discrete Kalman filter as an example to introduce the basic equations of Kalman filtering.

Commonly used discrete system dynamic models:[4]

$$\begin{cases} X_k = \Phi_{k,k-1} X_{k-1} + \Gamma_{k-1} W_{k-1} \\ \quad Z_k = H_k X_k + V_k \end{cases} \tag{6}$$

Where: Z_k is the measured value of the system; X_k is the system state; $\Phi_{k,k-1}$ is the system state one-step transfer matrix; Γ_{k-1} is the system noise matrix; W_k and V_k are mutually independent Gaussian white noise sequences, and have the following as:

$$\begin{cases} E[W_k W^T{}_j] = Q_k \delta_{kj} \\ E[V_k V^T{}_j] = R_k \delta_{kj} \\ E[W_k] = 0 \\ E[V_k] = 0 \end{cases} \tag{7}$$

Where: Q_k is the variance matrix of the system noise sequence, assumed to be non-negative; R_k is the variance matrix of the measurement noise sequence, assuming a positive definite matrix. If the estimated state X_k satisfies the equation (6), the magnitude measurement Z_k for X_k satisfies equation (6), the system noise W_k and the measurement noise V_k satisfy equation (7), the system noise variance matrix Q_k is non-negative, and the measurement noise variance matrix R_k is positive, the measurement at time k is Z_k, then the estimated $\hat{X}_k$ of X_k is solved by the following equation:

One-step state prediction:

$$\hat{X}_{k|k-1} = \Phi_{k,k-1} X_{k-1} \tag{8}$$

State estimation:

$$\hat{X}_k = X_{k|k-1} + K_k(Z_k - H_k X_{k|k-1}) \tag{9}$$

Gain filtering:

$$K_k = P_{k|k-1} H_k^T [H_k P_{k|k-1} H_k^T + R_k]^{-1} \tag{10}$$

One-step prediction mean square error:

$$P_{k|k-1} = \Phi_{k,k-1} P_{k-1} \Phi_{k,k-1}^T + \Gamma_{k-1} Q_{k-1} \Gamma_{k-1}^T \tag{11}$$

Estimated mean square error:

$$P_k = [I - K_k H_k] P_{k|k-1} \tag{12}$$

Equation (8) to (12) is the basic equation of discrete Kalman filtering.

2.2.2 Federated Kalman Filter Structure

In order to improve the real-time performance and high failure rate of the centralized Kalman filter, Carlson proposed the federal filtering theory in 1988. The federated filtering algorithm is a decentralized filtering algorithm with parallel two-level structure. Each navigation system forms a subsystem with a common reference system (such as an INS) that is processed by a sub-filter. A variety of navigation devices can form a number of subsystems, and then use a main filter to fuse the information of each subsystem. In the filtering process, the process information of the system is reasonably allocated to each sub-filter and main filter according to the information distribution principle, thereby avoiding the reuse of information and eliminating the correlation between the sub-filters, in which the sub-filters can be locally estimated independently, and the global optimal estimation can be obtained by a simple fusion algorithm.

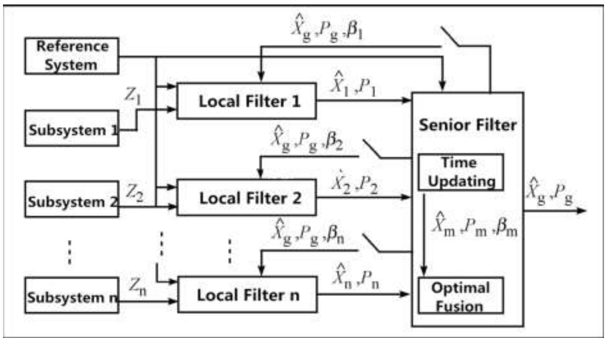

Figure 1. Federal Kalman Filter Structure

2.3 BP Feed-forward Neural Network

BP Feed-forward Neural Network (Back Propagation Feed-forward Neural Network), is a feed-forward neural network for backward propagation learning. The essence of the BP algorithm is to use the gradient method to find the objective function, and use the gradient method to find the steepest descending static optimization method of the minimum value.[5] The basic algorithm of BP neural network is as follows:[6]

Let the network input be X, the number of input neurons is r; the hidden layer has s1 neurons, the excitation function is F1; the output layer has s2 neurons, and the corresponding activation function is F2. The output is Y and the target vector is T.

Forward transmission of information:

The output of the *i*-th neuron in the hidden layer is:

$$y1_i = f1(\sum_{j=1}^{r} w1_j\, x_j + b1_i)\; i = 1,2,\ldots s1 \tag{13}$$

The output of the k-th neuron in the output layer is:

$$y2_k = f2(\sum_{i=1}^{s1} w2_k\, y1_i + b2_k)\; k = 1,2,\ldots,s2 \tag{14}$$

The error function is defined as:

$$E(W,B) = \frac{1}{2}\sum_{k=1}^{s2}(t_k - y2_k)^2 \tag{15}$$

The change of weight and the back propagation of error:

Output layer weight change:

The weight change from the first input to the first output is:

$$\Delta w2_{ki} = -\eta\frac{\partial E}{\partial w2_{ki}} = -\eta\frac{\partial E}{\partial y2_k}\frac{\partial y2_k}{\partial w2_{ki}} = \eta(t_k - y2_k) f2' y1_i = \eta\delta_{ki} y1_i \tag{16}$$

In Equation (16),

$$\delta_k = (t_k - y2_k) f2' = e_k f2'; \qquad e_k = t_k - y2_k$$

In the same way, we can find that:

$$\Delta b2_k = -\eta\frac{\partial E}{\partial b2_{ki}} = -\eta\frac{\partial E}{\partial y2_k}\cdot\frac{\partial y2_k}{\partial b2_{ki}} = \eta(t_k - y2_k)\cdot f2' = \eta\cdot\delta_{ki} \tag{17}$$

Implicit layer weight change:

For the weight from the j-th input to the i-th output, the amount of change is:

$$\Delta w1_{ij} = -\eta\frac{\partial E}{\partial w1_{ij}} = -\eta\frac{\partial E}{\partial y2_k}\cdot\frac{\partial y2_k}{\partial y1_i}\cdot\frac{\partial y1_i}{\partial w1_{ij}} = \eta\sum_{k=1}^{s2}(t_k - y2_k) f2'\cdot w2_{ki} f1'\cdot x_j = \eta\cdot\delta_{ij}\cdot x_j \tag{18}$$

In Equation (18),

$$\delta_{ij} = e_i f1', e_i = \sum_{k=1}^{s2}\delta_{ki} w2_{ki}$$

In the same way, we can find that:

$$\delta_{ij} = e_i f1', e_i = \sum_{k=1}^{s2}\delta_{ki} w2_{ki}$$

3. Association Analysis of Common Information Fusion Method and Information Failure Mode in Integrated Navigation

3.1 Information Failure Mode Analysis Based on Weighted Fusion Method

According to the Equation (5) in Section 2.1, it can be seen that the optimal weighting factor is determined by the variance of each sensor, and the weight coefficient is inversely proportional to the measured variance of each sensor. Literature[7,8] groups multi-sensor measurements in the same state. For the arithmetic mean of each set of measured variables, a multi-sensor grouping weighted fusion algorithm is proposed according to the principle of maximum likelihood. However, how to choose the weighting factor reasonably needs further research; literature[9] through experimental methods to determine the weight of each subsystem in the multi-sensor system, based on the experimental results to give a more reasonable weight distribution, but this method is not general; the literature[10] proposed that, the optimal allocation of weights during measurement should be performed using a method of random weighted estimation. But so far, there is no general optimal weight assignment method.

According to the basic principle of the weighted fusion method, through analysis, its information failure mode is closely related to the specific weight distribution method. Taking a certain type of SINS/GNSS integrated navigation system as an example, the system has multiple navigation modes, and the weighted fusion weight assignment methods in different navigation modes are different. Under normal circumstances, the system adopts the joint navigation mode. The weights of the GNSS and SINS subsystems are 0.76 and 0.24 respectively. At this time, the fault mode of the integrated navigation system is similar to that of the GNSS subsystem, and most of them are step-type sudden faults. When there is bad weather or signal occlusion, the system adopts autonomous navigation mode, and the weights of GNSS and SINS subsystems are 0.13 and 0.87, respectively. At this time, the failure mode of the integrated navigation system is similar to that of the SINS subsystem, and is mostly slowly changing faults that gradually accumulates and diverge. Therefore, the information failure mode of the weighted fusion method depends on the failure mode of the sensor or subsystem that dominates the weight value.

3.2 Information Failure Mode Analysis of Kalman Filtering Method

Extended Kalman Fliter (EKF) is currently the most widely used Kalman filter algorithm. The EKF algorithm is an approximation method that performs a Taylor series expansion near the state estimate and truncates it in the first order, then use the obtained first-order approximation term as the approximate expression of the original state equation and the measurement equation to achieve linearization. It is also assumed that the linearized state still obeys the Gaussian distribution, and then the linearized system uses standard Kalman filtering to obtain the state estimation.

Although the EKF algorithm has been widely used in practical engineering, it has unavoidable defects:

1) Due to the existence of the first-order truncation error, the EKF algorithm must satisfy the assumption of small perturbation, that is, the difference between the theoretical solution and the actual solution of the nonlinear state equation is a small amount;

2) The calculation of the Jacobian matrix increases the complexity and error rate of its algorithm operation;

3) The quality of EKF filtering results is also related to the statistical characteristics of state noise and observed noise. In the recursive filtering process of EKF, the covariance matrix of state noise and observed noise remains unchanged. If the estimation of the two noise covariance matrices is not accurate enough, it is easy to generate error accumulation, which causes the filter to diverge.

Through the above analysis, the information failure mode of the Kalman filter information fusion method is determined by the inherent defects of the algorithm itself. Still taking the SINS/GNSS integrated navigation system as an example; the system error state equation under normal working conditions approximates a linear small error equation. When the GNSS is occluded due to signal occlusion or equipment abnormality, the nonlinearity in the system error state equation Factors cannot be ignored, and continued EKF filtering of the system linear small error model will result in a sharp increase in state estimation error during the nonlinear time period, which will continue until the system returns to normal. By summarizing the above analysis, it can be concluded that the information failure mode of the Kalman filter information fusion method is a persistent mutation fault corresponding to the nonlinear period.

3.3 Information Failure Mode Analysis of BP Neural Network Method

BP neural network has many advantages such as nonlinear mapping, self-learning and self-adaptive ability, generalization ability, etc., which has attracted extensive attention from many researchers at home and abroad.[11] However, BP neural network also has the following shortcomings and deficiencies:

1) Local minimization problem: As a local search optimization method, BP neural network, the weight of the network is gradually adjusted by the direction of local improvement. This will cause the algorithm to fall into local extremum, and the weight will converge to a local minimum;

2) The convergence speed of BP neural network algorithm is slow: Since BP neural network algorithm is essentially gradient descent method, the objective function to be optimized is very complicated. Therefore, there will inevitably be a "saw-tooth phenomenon", which makes the BP algorithm inefficient; Since the optimized objective function is very complicated, it will inevitably have some flat regions in the case where the neuron output is close to 0 or 1, in which the weight error changes little, and the training process is almost stopped;

3) BP neural network structure selection is different: BP neural network structure selection has not yet had a unified and complete theoretical guidance, and generally can

only be selected by experience. The choice of network structure is too large, the efficiency in training is not high, and over-fitting may occur, resulting in low network performance and reduced fault tolerance. If the selection is too small, the network may not converge;

4) BP neural network sample dependency problem: The approximation and promotion ability of the network model is closely related to the typicality of the learning sample. It is a very difficult problem to select a typical sample instance to form a training set from the problem.

In summary, the shortcomings of the BP neural network method itself make it difficult to apply it to the integrated navigation system with high real-time requirements. In the information fusion of the integrated navigation system, the BP neural network is generally used to model the system error. The Kalman filter is corrected by an error model. Taking the SINS/GNSS integrated navigation system as an example, BP neural network is used to establish the error model of the system under faultless conditions. When the GNSS subsystem loses lock, Correct the Kalman filter through the BP neural network can effectively eliminate the outliers and jumps that occur during the loss of lock; When the SINS subsystem has a gradually accumulating slowly changing information fault, the Kalman filter is corrected by the BP neural network, which can reduce the error accumulation in a certain period of time, but will eventually gradually diverge. In summary, the information failure mode of the BP neural network information fusion method is a slowly varying fault that gradually accumulates over time.

4. Conclusion

Based on the basic principle of the common information fusion method of integrated navigation system, this paper analyzes and expounds the relationship between common information fusion methods and information failure modes. The information failure modes of weighted fusion method, Kalman filtering method and BP neural network method all have their own characteristics:

1) The information failure mode of the weighted fusion method is closely related to the specific weight distribution method, depending on the failure mode of the sensor or sub-system whose weight is dominant;

2) The information failure mode of the Kalman filter information fusion method is a persistent mutation fault corresponding to the nonlinear period of the system;

3) The information failure mode of the BP neural network method is a slowly varying fault that gradually accumulates over time.

There are many kinds of information fusion methods in integrated navigation system. The paper only analyzes and expounds the information failure modes of the above three most commonly used information fusion methods. Even if the information fusion method is the same, when the system distribution structure is different or the sensor types of the system are different, the information failure mode will be different. The specific situation depends on the specific method and object, and the relationship between the two is very complicated. Further research can be carried out.

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