基于模糊自适应 UKF 的船舶动力定位多传感器融合

徐树生，李　娟
（青岛农业大学 机电工程学院，山东 青岛 266109）

摘　要：为了改善船舶动力定位系统多传感器融合性能，基于模糊自适应 UKF 建立了一种多传感器分级融合算法。利用协方差匹配原理建立模糊自适应算法，利用新息建立测量质量控制算法和子系统故障诊断算法，将这三种算法与 UKF 相结合构成模糊自适应 UKF 算法。利用滤波状态参数构建第一级相互平行的融合算法，再基于相互独立的第一级融合性能建立第二级融合，从而构建基于模糊自适应 UKF 的多传感器分级融合算法，实现多传感器的动态分级融合。仿真结果验证了所建算法的有效性。

关键词：UKF；分级融合；模糊自适应；故障诊断

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Vessel Dynamic Positioning Multi-sensor Fusion Based on Fuzzy Adaptive Unscented Kalman Filter

XU Shusheng，LI Juan
(College of Electromechanical Engineering，Qingdao Agricultural University，Qingdao，Shandong 266109，China)

Abstract：To improve the performance of multi-sensor fusion of vessel dynamic positioning system (DPS)，a hierarchical fusion algorithm based on fuzzy adaptive unscented Kalman filter (UKF) is proposed. It combines the fuzzy adaptive filter algorithm established by using the covariance matching principle，the measurement quality control algorithm and the sub-system fault diagnosis algorithm established by using innovation. Then，the first-level parallel fusion algorithm is set up by using filter state parameters and the second-level fusion is established based on the mutually independent first-level fusion performance. In this way，a multi-sensor fusion algorithm is thus established based on fuzzy adaptive UKF，and the dynamic hierarchical fusion of multi-sensor is achieved. The numerical simulation results verifies the effectiveness of the proposed algorithm.

Key words：unscented Kalman filter；hierarchical fusion；fuzzy adaptive system；fault detection

Conventional UKF has no capability to adapt itself to changing conditions of the measurement system. The uncertainty of the process and measurement noise usually degrades the performance of the filter. Therefore，a robust algorithm must be introduced so that the filter can make itself insensitive to measurements in case of malfunctions and correct estimation process without affecting the good estimation behavior[1-2]. Based on multiple model and residual adaptive filter，algorithms can be built. In multiple-model-

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作者简介：徐树生(1966—)，男，山东淄博人，副教授，博士，主要从事水下机器人、智能检测与控制、多源信息融合研究，本文通信作者. E-mail：xuss0319@163.com
李　娟(1969—)，女，教授，博士，主要从事智能检测与控制、嵌入式系统应用、故障诊断和容错控制等应用研究.

based adaptive estimation, more than one filter runs parallel under different models in order to satisfy the filter's true statistical information[3]. In residual-based adaptive filter, the covariance matrices of the measurement and/or system noise are adjusted adaptively to overcome their uncertainties[4-6]. The fuzzy technique can be applied to adaptive filter to achieve the adjusting factor for noise covariance matrices[7-9].

To improve the local filter accuracy and robustness, the measurements must be inspected, and the subsystem fault must also be detected dynamically. Based on the filter innovation, different data quality control algorithms[10-11] as well as many fault detection and isolation methods[12-13] have been proposed. All the approaches have improved the filter performance and the robustness of the system.

In order to improve the fusion performance, the accurate credibility parameters of local filters are required to calculate the weighted factors for the global fusion. Many fuzzy methods have been developed by using several filter state parameters to obtain the credibility parameters of filters[3,9]. These approaches can improve the fusion accuracy.

In this paper, a fuzzy adaptive UKF and a multi-level hierarchical fusion algorithm are built. Based on the proposed fuzzy adaptive UKF, not only can the measurement noise covariance be adjusted, but the measurement data can be inspected and the sensor faults can be detected as well. According to the idea of multi-sensor data fusion, this paper proposes a multi-sensor hierarchical fusion algorithm using some state parameters of the filter. This approach can improve the fusion accuracy and the system fault-tolerance. The three redundancy heading measurement systems of vessel dynamic positioning are regarded as the research object to illustrate the algorithm. A semi-physical simulation system is to be carried out to evaluate the performance of the proposed algorithm.

1 Fuzzy adaptive UKF algorithm

1.1 The model of the vessel heading measurement system

The horizontal motion of a surface ship is usually described by the motion components in surge, sway, and yaw. To describe the motion of the vessel, the North-East-Down and the body-fixed reference frames need to be built[14]. The related two-dimensional reference frame is shown in Fig. 1.

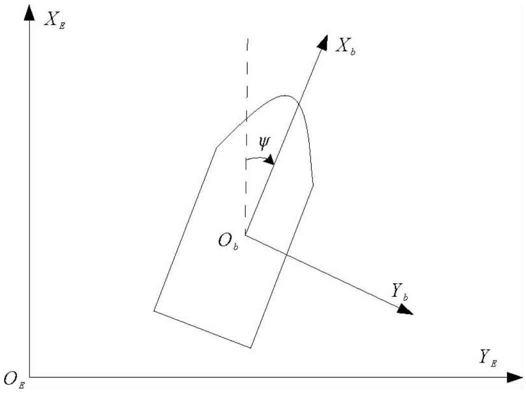

Fig. 1 The two-dimensional reference frame

As discussed above, vectors $\boldsymbol{P}_E$ and $\boldsymbol{V}_b$ are defined as:

$$\boldsymbol{P}_E=[x \quad y \quad \psi]^{\mathrm{T}}, \boldsymbol{V}_b=[u \quad v \quad r]^{\mathrm{T}}. \tag{1}$$

Where variables x, y and ψ represent surge, sway, and yaw respectively, and the u, v and r represent the corresponding speed variables respectively.

Neglecting the elements corresponding to heave, roll and pitch finally, the approximate relationship between the two vectors is shown in Eq. (1):

$$\dot{\boldsymbol{P}}_E=\boldsymbol{J}(\psi)\boldsymbol{V}_b. \tag{2}$$

Where the conversion matrix $\boldsymbol{J}(\psi)$ is:

$$\boldsymbol{J}(\psi)=\begin{bmatrix}\cos\psi & -\sin\psi & 0\\ \sin\psi & \cos\psi & 0\\ 0 & 0 & 1\end{bmatrix},$$

The differential equation of the heading is shown as:

$$\dot{\psi} = r 。\tag{3}$$

We define new state vector $\boldsymbol{X} = [\psi, r]^{\mathrm{T}}$, where ψ represents the yaw angle and r represents the yaw rate. So the vessel heading system is described as:

$$\dot{\boldsymbol{X}}(t) = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \boldsymbol{X}(t) + \begin{bmatrix} 0 \\ 1 \end{bmatrix} \boldsymbol{W}(t) .\tag{4}$$

The observation equation is written as:

$$\boldsymbol{Z}(t) = [1 \quad 0] \boldsymbol{X}(t) + \boldsymbol{V}(t) .\tag{5}$$

Where $\boldsymbol{W}(t)$ is the process noise vector, and $\boldsymbol{V}(t)$ is the measurement noise vector.

Considering the simulation system, the sampling period is set to $T = 0.1$ s , and then the system models (4) and (5) in discrete-time equivalent form leads to

$$\boldsymbol{X}(k+1) = \boldsymbol{\Phi X}(k) + \boldsymbol{\Gamma W}(k) ,\tag{6}$$

$$\boldsymbol{Z}(k) = \boldsymbol{HX}(k) + \boldsymbol{V}(k) .\tag{7}$$

Where $\boldsymbol{\Phi} = [1 \quad 0.1 \quad 0 \quad 1]$, $\boldsymbol{\Gamma} = [0 \quad 0.1]$, $\boldsymbol{H} = [0 \quad 1]$.

In Eq. (6) and Eq. (7), both the vectors $\boldsymbol{W}(k)$ and $\boldsymbol{V}(k)$ are zero-mean Gaussian white sequences having zero cross correlation with each other:

$$E[\boldsymbol{W}_k] = 0, E[\boldsymbol{W}_k \boldsymbol{W}_j^{\mathrm{T}}] = \boldsymbol{Q}_k \delta_{k,j}$$

$$E[\boldsymbol{V}_k] = 0, E[\boldsymbol{V}_k \boldsymbol{V}_j^{\mathrm{T}}] = \boldsymbol{R}_k \delta_{k,j}$$

$$E[\boldsymbol{W}_k \boldsymbol{V}_j^{\mathrm{T}}] = 0$$

Where $\boldsymbol{Q}_k$ is the process noise covariance matrix, and $\boldsymbol{R}_k$ is the measurement noise covariance matrix.

1.2 Fuzzy adaptive unscented Kalman filter

1.2.1 Unscented Kalman filter

The unscented Kalman filter(UKF) is a recursive estimator based on the optimal Gaussian approximate Kalman filter framework. A nonlinear dynamic system is defined by Eq. (6) and Eq. (7), the UKF algorithm is summarized[15].

• Initialization: $\hat{\boldsymbol{X}}_0 = E[\boldsymbol{X}_0]$, $\boldsymbol{P}_0 = E[(\boldsymbol{X}_0 - \hat{\boldsymbol{X}}_0)(\boldsymbol{X}_0 - \hat{\boldsymbol{X}}_0)^{\mathrm{T}}]$

For: $k=1,\cdots,\infty$。

1) Calculate sigma-points:

$$\boldsymbol{\xi}_{i,k-1} = \hat{\boldsymbol{X}}_{k-1}, i = 0 ,\tag{8}$$

$$\boldsymbol{\xi}_{i,k-1} = \hat{\boldsymbol{X}}_{k-1} + (\sqrt{(n+\lambda)\boldsymbol{P}_{k-1}})_i^{\mathrm{T}}, i = 1,\cdots,n ,\tag{9}$$

$$\boldsymbol{\xi}_{i,k-1} = \hat{\boldsymbol{X}}_{k-1} - (\sqrt{(n+\lambda)\boldsymbol{P}_{k-1}})_i^{\mathrm{T}}, i = n+1,\cdots,2n .\tag{10}$$

Where $\lambda = n(\alpha^2 - 1)$, $0 \leqslant \alpha \leqslant 1$ and α should ideally be a small number to avoid sampling non-local effects when the nonlinearities are strong.

2) Time-update equations:

$$\boldsymbol{\xi}_{i,k|k-1} = \boldsymbol{\Phi}(\xi_{i,k-1}) ,\tag{11}$$

$$\hat{\boldsymbol{X}}_{k|k-1} = \sum_{i=0}^{2n} W_i^{(m)} \boldsymbol{\xi}_{i,k|k-1} ,\tag{12}$$

$$\boldsymbol{Z}_{i,k|k-1} = \mathbf{H}(\xi_{i,k|k-1}) ,\tag{13}$$

$$\hat{\boldsymbol{Z}}_{k|k-1} = \sum_{i=0}^{2n} W_i^{(m)} \boldsymbol{Z}_{i,k|k-1}, i = 0,\cdots,2n .\tag{14}$$

Where $W_i^{(m)} = W_i^{(c)} = \dfrac{1}{2(n+\lambda)}$

3) Measurement-update equations:

$$\boldsymbol{\Lambda}_k = \boldsymbol{Z}_k - \hat{\boldsymbol{Z}}_{k|k-1} \ , \tag{15}$$

$$\boldsymbol{P}_{k|k-1} = \sum_{i=0}^{2n} W_i^{(c)} [\boldsymbol{\xi}_{i,k|k-1} - \hat{\boldsymbol{X}}_{k|k-1}][\boldsymbol{\xi}_{i,k|k-1} - \hat{\boldsymbol{X}}_{k|k-1}]^{\mathrm{T}} + \boldsymbol{\Gamma}\boldsymbol{Q}_{k-1}\boldsymbol{\Gamma}^{\mathrm{T}} \ , \tag{16}$$

$$\boldsymbol{P}_{zz} = \sum_{i=0}^{2n} W_i^{(c)} [\boldsymbol{Z}_{i,k|k-1} - \hat{\boldsymbol{Z}}_{k|k-1}][\boldsymbol{Z}_{i,k|k-1} - \hat{\boldsymbol{Z}}_{k|k-1}]^{\mathrm{T}} + \boldsymbol{R}_k \ , \tag{17}$$

$$\boldsymbol{P}_{xz} = \sum_{i=0}^{2n} W_i^{(c)} [\boldsymbol{\xi}_{i,k|k-1} - \hat{\boldsymbol{X}}_{k|k-1}][\boldsymbol{Z}_{i,k|k-1} - \hat{\boldsymbol{Z}}_{k|k-1}]^{\mathrm{T}} \ , \tag{18}$$

$$\boldsymbol{K}_k = \boldsymbol{P}_{xz}\boldsymbol{P}_{zz}^{-1} \ , \tag{19}$$

$$\hat{X}_k = \hat{\boldsymbol{X}}_{k|k-1} + \boldsymbol{K}_k(\boldsymbol{Z}_k - \hat{\boldsymbol{Z}}_{k|k-1}) \ 。 \tag{20}$$

1.2.2 Measurement noise covariance adjusting algorithm

The degree of divergence (DOD) parameters of the UKF for reflecting the change of measurements can be determined. The DOD parameter $\beta(k)$ can be defined as the trace of innovation covariance matrix at present epoch[1]:

$$\beta(k) = \boldsymbol{\Lambda}^{\mathrm{T}}(k)\boldsymbol{\Lambda}(k) = \mathrm{tr}(\boldsymbol{\Lambda}(k)\boldsymbol{\Lambda}^{\mathrm{T}}(k)) \ , \tag{21}$$

$$\rho(k) = \sum_{i=1}^{m} |\ \boldsymbol{\Lambda}(i)\ | \ . \tag{22}$$

Where m is the length of the time window and $\boldsymbol{\Lambda}(k)$ is the filter residual.

If the mathematical model of the system is accurate enough, the innovation sequence will be zero-mean white noise, and then $\beta(k)$ and $\rho(k)$ will be close to zero. If these parameters drift from zero for a long-time, the measurement noise covariance matrix $\boldsymbol{R}(k)$ will be adjusted.

The parameters $\beta(k)$ and $\rho(k)$ are the inputs of a fuzzy inference system (FIS), and the adjusting coefficient $S(k)$ can be obtained by the FIS, and then the $\boldsymbol{R}(k)$ will be adjusted.

$$\boldsymbol{R}(k) = S^b(k)\boldsymbol{R}(k-1) \ . \tag{23}$$

Where $\boldsymbol{R}(k)$ is the measurement noise covariance matrix at time k, and b is a factor for adjusting the response rate.

The proposed fuzzy UKF is shown in Fig. 2, where $\beta(k)$ is denoted by β_k and others are similar.

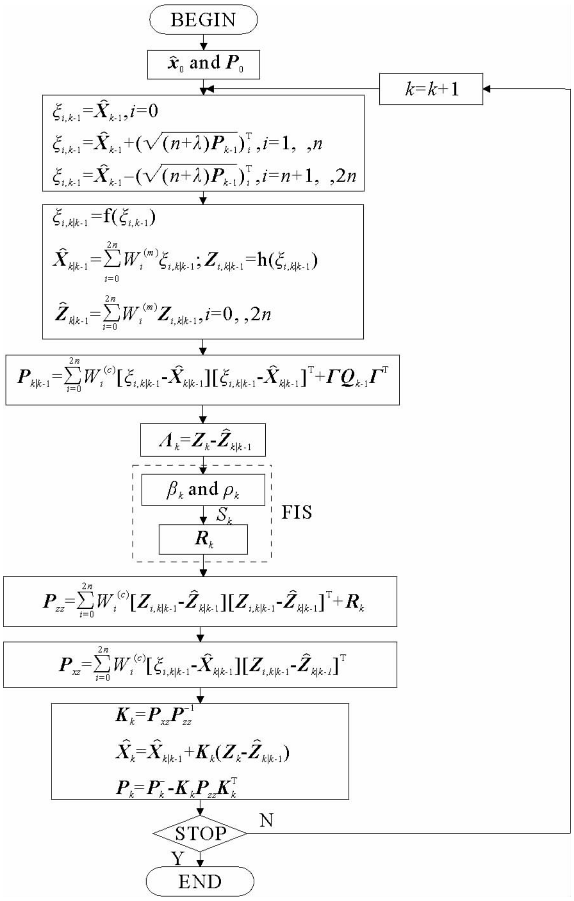

Fig. 2 The flow chart of the proposed fuzzy adaptive UKF

1.2.3 Fuzzy logic system

As discussed above, a FIS can be proposed for adjusting the measurement noise covariance. The fuzzy set of $\beta(k)$ is {Z (zero), S (small), L (large)}, and the domain is [0 0.5]. The fuzzy set of $\rho(k)$ is {Z (zero), S (small), L (large)}, and the domain is [0 1]. The fuzzy set of $S(k)$ is {D (decrease), M (maintain), I (increase)}, and the domain is [0.7 1.3].

According to theoretical and empirical researches, the definition of the fuzzy control rules is shown in Tab. 1.

Tab. 1 Rules of fuzzy control

ρ \ β	s	z	L
S	M	M	I
Z	M	M	I
L	D	D	D

As discussed above, the fuzzy inference system has been established.

1.3 Measurement data quality control algorithm

Based on the residual of the UKF, a data quality control algorithm is proposed. The data quality control function is defined as:

$$q(k) = \sqrt{\boldsymbol{\Lambda}^{\mathrm{T}}(k)\boldsymbol{\Lambda}(k)/\mathrm{tr}(\boldsymbol{P}_{zz}(k))}\,. \tag{24}$$

Measurement data quality control rules are defined as:

$q(k) > T_D$, the measurement is bad.

$q(k) \leqslant T_D$, the measurement is good.

The threshold T_D can be set based on the different accuracy requirements and the actual motion of the system.

1.4 Subsystem fault detection algorithm

For the multi-sensor data fusion systems, filter algorithm must have a real-time fault detection method[12]. In this paper, a fault detection algorithm is proposed based on the residual of the UKF. The fault detection function $\alpha(k)$ is defined as:

$$\alpha_i(k) = \frac{|\,\mathrm{tr}(\boldsymbol{U}_i(k))\,|}{\sqrt{\mathrm{tr}(\boldsymbol{P}_{zz}(k))}}\,. \tag{25}$$

Where $\boldsymbol{U}_i(k)$ is the innovation of the UKF.

Two hypotheses are defined: no-fault (H_0) and fault (H_1) as:

$$H_0 : \alpha_i(k) \approx 1$$

$$H_1 : \alpha_i(k) \neq 1$$

Suppose ε represents the preset deviation, a fault detection interval is defined as:

$$\Omega = [1-\varepsilon \quad 1+\varepsilon]$$

If $\alpha_i(k) \notin \Omega$, the subsystem i has a fault, and the innovation of the UKF is set to zero. If $\alpha_i(k) \in \Omega$, the subsystem i has no fault, and the fusion are normal.

The fault factors $M_i(k)$ are defined as:

$M_i(k) = 1$, no fault occurs,

$M_i(k) = 0$, a fault occurs.

The fault factors will be applied to the fusion algorithm to realize faults isolation.

2 Hierarchical fusion algorithm

In general, the state covariances of the local filters are usually applied to calculate the weighted factors for the global fusion, but only one parameter is difficult to reflect the true local filter performance. In order to improve the fusion accuracy and fault-tolerance, this paper adopts two state parameters of the local filter to realize two independent first-level fusions, and then the global integration for the first-level fusions can be obtained. The algorithm increases small computation complexity, but it improves the fusion performance. The proposed fusion algorithm is shown in Fig. 3.

2.1 The first-level fusion algorithms

Assuming the state estimate $\boldsymbol{X}_i(k)$, the state covariance $\boldsymbol{P}_i(k)$, and the parameter $\beta_i(k)$ of the local UKF i have been obtained. In this paper, the parameters $\boldsymbol{P}_i(k)$ and $\beta_i(k)$ are chosen for the first-level fusions. Assuming the state estimates of the first-level fusions are $\boldsymbol{XI}_1(k)$, $\boldsymbol{XI}_2(k)$ respectively, then the first-level algorithms can be derived as below.

2.1.1 Fusion algorithm using parameter $P_i(k)$

This algorithm is widely used for multi-sensor data fusion. The weighted factor $\xi_i(k)$ can be computed:

$$\xi_i(k) = ((1/\mathrm{tr}(\boldsymbol{P}_i(k))/\sum_{i=1}^{N}(1/\mathrm{tr}(\boldsymbol{P}_i(k)))\ . \quad (26)$$

Where N is the number of sensors of the system.

For the subsystem i, assuming the state estimates is $X_i(k)$, the fault factor is $M_i(k)$ respectively, and then the state estimation $\boldsymbol{XI}_1(k)$ can be calculated:

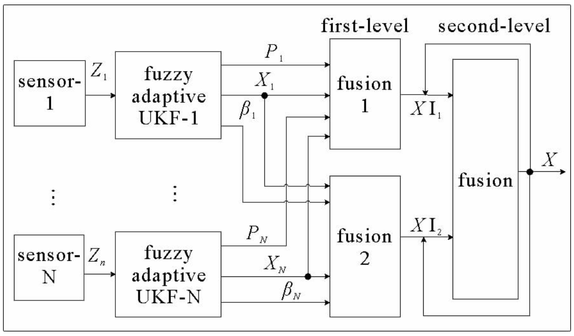

Fig. 3 The proposed hierarchical fusion algorithm

$$\boldsymbol{XI}_1(k) = \sum_{i=1}^{N} M_i(k)\xi_i(k)X_i(k)\ . \quad (27)$$

2.1.2 Fusion algorithm using parameter $\beta_i(k)$

As parameter $\boldsymbol{P}_i(k)$, the parameter $\beta_i(k)$ can also be applied to the fusion approaches. A fusion algorithm based on the parameter $\beta_i(k)$ can be built.

The weighted factor $\zeta_i(k)$ can be calculated using $\beta_i(k)$:

$$\zeta_i(k) = \frac{1}{\beta_i(k)}/\sum_{i=1}^{N}(1/\beta_i(k))\ . \quad (28)$$

Where N is the number of sensors of the system.

Similarly, the other state estimation $\boldsymbol{XI}_2(k)$ can be calculated:

$$\boldsymbol{XI}_2(k) = \sum_{i=1}^{N} M_i(k)\zeta_i(k)X_i(k)\ . \quad (29)$$

Where $\boldsymbol{X}_i(k)$ is the state estimate and $M_i(k)$ is the fault factor of the subsystem i, respectively。

2.2 The global fusion algorithm

The state estimates $\boldsymbol{XI}_1(k)$ and $\boldsymbol{XI}_2(k)$ of the hierarchical fusions have been obtained. The weighted factors can be calculated using the covariance of these estimates for the second-level fusion. Assuming that the state estimation of the global fusion is $\boldsymbol{X}(k)$, the initialization $\boldsymbol{X}(0)$ is defined as:

$$\boldsymbol{X}(0) = (\boldsymbol{XI}_1(1) + \boldsymbol{XI}_2(1))/2\ . \quad (30)$$

According to the definition of covariance, the corresponding covariance $\sigma_i^2(k)$ can be calculated.

$$\sigma_{\mathrm{i}}^2(k) = [\boldsymbol{XI}_i(k) - \boldsymbol{X}(k-1)]^{\mathrm{T}}[\boldsymbol{XI}_i(k) - \boldsymbol{X}(k-1)]\ . \quad (31)$$

Where $i = 1,2,\cdots,N$, $\boldsymbol{X}(k-1)$ is the state estimation of the system at time $k-1$, N is the number of the first-level fusions.

The weighted factors $\tilde{\omega}_i(k)$ will be calculated:

$$\tilde{\omega}_i(k) = ((1/\sigma_i^2(k))/\sum_{i=1}^{N}(1/\sigma_i^2(k))\ , \quad (32)$$

The state estimate $\boldsymbol{X}(k)$ can be obtained:

$$\boldsymbol{X}(k) = \sum_{i=1}^{N} \bar{\omega}_i(k)\boldsymbol{XI}_i(k) . \tag{33}$$

Where N is the number of the first-level fusion.

3 Simulation experiments

Simulation experiments have been carried out to evaluate the performance of the proposed algorithm in comparison with that of the other methods for multi-sensor fusion. Simulation experiment was conducted by a semi-physical experiment system which is shown in Fig. 4.

By the experiment system, we can simulate the station keeping and the tracking control of the DPS. The data coming from the experiments which simulating the station keeping and the tracking control of the DPS are denoted by data_1, data_2, respectively. To clearly show the simulation results, one part of the data and one part of the simulation figures are only selected.

Fig. 4 The semi-physical simulation system

The initial values of the process noise covariance matrix is set $\boldsymbol{Q}_0 = [0.4]$ and the measurement noise covariance matrix is set $\boldsymbol{R}_0 = [0.01]$. The initial values of the state $\boldsymbol{X}_0$ and the estimation error covariance matrix $\boldsymbol{P}_0$ can be obtained by calculating the average of the first five measurements.

3.1 Simulation on the fuzzy adaptive UKF algorithm

3.1.1 Simulation on the adjusting measurement noise covariance

The simulation experiments have been performed to evaluate the performance of the proposed fuzzy adaptive UKF algorithm in comparison with that of the conventional UKF. Two algorithms are denoted by alg-a and alg-b, respectively. The simulations using data_1 and data_2 are shown in Fig. 5 and Fig. 6. The variables e , x and t which are in the simulation figures represent fusion error, state estimate and time, respectively, and this definition is also applicable to the following sections.

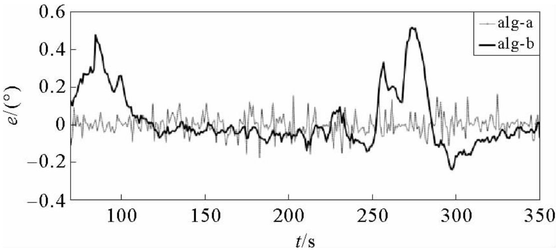

Fig. 5 Comparison of two algorithms with data-1

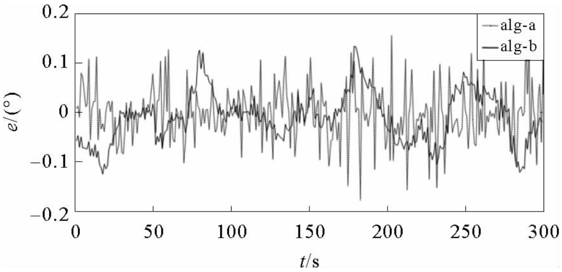

Fig. 6 Comparison of two algorithms with data-2

The simulation of the algorithm alg-a is shown as dashed line, and the algorithm alg-b is shown as solid line. In Fig. 5, when the motion of vessel changes sharply, the state estimation error for the algorithm alg-a is smaller than that for the algorithm alg-b. When the motion of the vessel changes small, the performance of the algorithm alg-a is not better than that of the algorithm alg-b, as shown in Fig. 6. It demonstrates that the algorithm for adaptively adjusting measurement noise covariance can apply to the environment which the vessel motion changes sharply. On this situation, the measurement noise varies heavily and the measurement noise covariance will be adjusted. When the motion of the vessel changes small, the measurement noise will change little, so in this case the measurement noise covariance does not require adjusting frequently.

3.1.2 Simulation on the fault detection algorithm

To validate the performance of the proposed algorithm for data quality control and subsystem fault detection, the data_1 is added 1° arbitrarily and the random faults are set with the fault rate of 8.3%. A single sensor system is selected to evaluate the performance of the proposed detection algorithm.

The proposed detection algorithm is denoted by alg-1 which is shown as solid line, and the algorithm that the wild points will not be detected and the fault sensor will be removed directly is denoted by alg-2 which is shown as dashed line. The simulation is shown in Fig. 7. The simulation result indicates that the proposed data quality control and the subsystem fault detection approaches are effective.

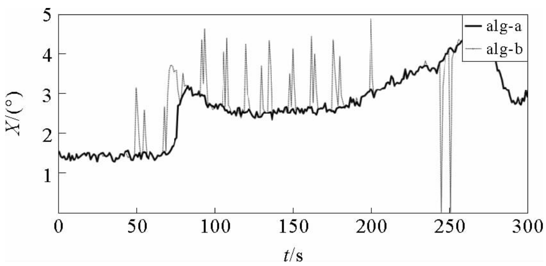

Fig. 7 Simulation of the data quality control and fault detection algorithms

3.2 Simulation on the multi-level fusions algorithm

To assess the performance of the proposed multi-level fusion algorithm, two fusion algorithms that are based on the credibility of the UKF which will be evaluated by a fuzzy reasoning system[9] and the conventional fusion algorithm using the state estimates error covariance are selected. These three algorithms are denoted by alg-4, alg-5, alg-6, respectively. The simulations on them are shown as thick solid line, thin solid line and dashed line. The simulation is shown in Fig. 8 and Fig. 9.

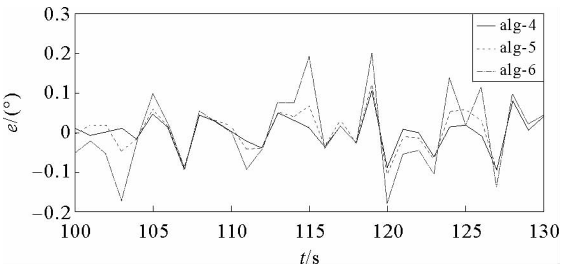

Fig. 8 Comparison of three fusion algorithms with data_1

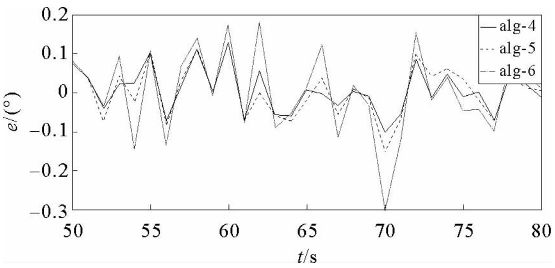

Fig. 9 Comparison of three fusion algorithms with data_2

The simulation results indicate that the fusion error of the proposed algorithm is smaller than those of the algorithm alg-6. The difference of the fusion error between alg-4 and alg-5 is not significant. This is because both the approaches use two state parameters of the filter to perform the fusion. Although the two methods are different, they both make full use of the more accurate performance of the filter for fusion, so they all have higher fusion accuracy. However, the computational complexity of the algorithm alg-4 is smaller than that of the algorithm alg-5, but it is somewhat larger than that of the conventional algorithm with the state covariance matrices.

4 Conclusions

In this paper a multi-sensor hierarchical fusion algorithm based on fuzzy adaptive UKF has been presented. The proposed algorithm improves the fusion accuracy and fault-tolerance.

A fuzzy adaptive UKF for the case of measurement malfunctions is developed. By the use of defined adaptive factor, faulty measurements are taken into consideration with small weight and the estimations are corrected without affecting the characteristic of the accurate ones. The fuzzy adaptive UKF is performed only in the case of malfunctions in the measurement system. According to the feature of the residual, the data quality control and the subsystem fault detection approaches are also built. These algorithms will improve the accuracy of the filter and fault-tolerance.

A hierarchical fusion algorithm has been proposed. This method will increase the virtual redundancy of the system by the hierarchical fusions using several state parameters of the fuzzy adaptive UKF, so the performance of the system will be improved.

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