Multi-sensor data fusion method based on adaptive Kalman filtering

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ABSTRACT

Since the data collected by a single sensor often cannot meet the needs and is far from forming a comprehensive and complete perceptual description of complex systems, multi-sensor data fusion technology is required to comprehensively process the data and obtain more accurate results. The application of Kalman filter to multi-sensor data fusion has become a hot topic in recent years, but when the noise matrix design of Kalman filter is unreasonable, filtering divergence is prone to occur, so an adaptive Kalman filter algorithm is proposed, which uses correction coefficients to correct the filtering process by obtaining the dynamic change of the residual in real time. The anti-collision system of ship unloader is used as the application background to verify the effectiveness of the proposed algorithm. Experimental results show that the proposed algorithm improves the estimation accuracy and reduces noise interference in the actual environment.

KEYWORDS

Multi-sensor data-level fusion, AKF,Correction factor,Ship unloader collision avoidance system

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1 INTRODUCTION

At present, multi-sensor data fusion technology has developed rapidly and has been applied in many fields, including industrial, military, autonomous driving and other fields. Commonly used data fusion algorithms include weighted average method [1][2], DS evidence theory [3][4], fuzzy theory [5][6], artificial neural network method [7][8] and Kalman filter method [9][10].

Classical Kalman filtering requires the initial state of the system, and if the initial state is inaccurate, it will affect the effectiveness of the filtering. For a real system, the surrounding complex environment will lead to problems such as model uncertainty or dynamic changes in sensor noise, which will affect the filtering effect of standard Kalman filter algorithms, which greatly reduces the estimation accuracy. Therefore, an adaptive Kalman filtering algorithm is proposed based on classical Kalman filtering. The algorithm obtains the dynamic change of the residual in real time, and uses the correction coefficient to correct the measured noise, so as to effectively suppress the filter divergence and improve the accuracy of filter estimation.

Aiming at the problems of complex environment, large error of single sensor, and difficulty in fixing measurement noise in the process of multi-sensor fusion of ship unloader anti-collision monitoring system, the data fusion is carried out by the Mahalanobis distance and adaptive Kalman filtering algorithm proposed in this paper. After experiments and analysis, the effectiveness of the proposed method is verified.

1.1 Related Work

In order to improve the accuracy of ranging and reduce the false alarm rate, there are three methods of multi-sensor data fusion according to different fusion levels [11]: decision-level fusion, feature-level fusion, and data-level fusion.

Decision-level fusion is the highest level of data fusion, which makes decision-making judgments while fusing data. Feature-level fusion mainly extracts the feature values of the collected data, and then processes and fuses the feature values.

Data layer fusion belongs to low-level fusion, and the data processed by the fusion at this level are the original data obtained by the sensor field, so the information of the observation object is fully and completely preserved. Di Song et al. [12] improved the reliability and accuracy of crack detection by calculating the Mahalanobis distance to measure the similarity between the original sample and the group, and fused the same type of sample at the data level, but did not involve the practical engineering application data of complex comprehensive noise. Andres J. Barreto-Cubero et al. [13] obtained more accurate object distance readings based on artificial neural network multi-sensor data-level fusion. Chao Xiang et al. [14] proposed a blind spot warning algorithm by fusing the semantic information from the camera and the distance information from lidar in the data layer in order to reduce traffic accidents caused by visual blind spots. FENGJUN HU et al. [15] proposed a multi-sensor data-level fusion ranging method based on adaptive error correction extended Kalman filter algorithm, which optimizes the system noise parameters and measured noise covariance in the extended Kalman filter by using the evolutionary iterative mechanism of the genetic algorithm, and compares and adjusts the information detected by the sensor, so as to reduce the influence of error on the estimated value.

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This paper adopts data-level hybrid data fusion, which retains more information, has good adaptability, strong stability, and can obtain more accurate distance information. Figure 1 shows the hybrid fusion framework.

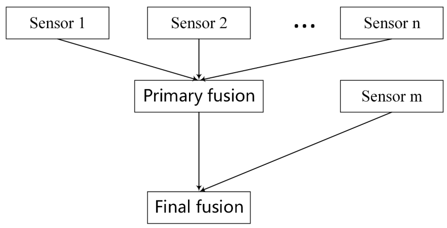

Figure 1: Hybrid fusion framework

1.2 Contributions to this article

Although researchers have made great achievements in data-level data fusion, most of the existing data-level data fusion has problems such as large amount of sensor data, resulting in increased system power consumption. This paper mainly studies the data-level data fusion algorithm with short processing time and relatively accurate data. The main contributions are as follows:

1. An adaptive Kalman filter algorithm is proposed. By fitting the sensor measurements of a certain time series, the residual variance is calculated to obtain the initialization measurement noise. Establish adaptive rules, obtain the dynamic change of the residual in real time, generate the correction coefficient of the measurement noise, and dynamically adjust the measurement noise.
2. A two-level fusion method is proposed to realize the data-level fusion of heterogeneous sensors. By calculating the Mahalanobis distance of the sample data and the average of the sample data, the data-level fusion of similar sensors is carried out to obtain preliminary fusion. The adaptive Kalman filter is used to fuse the data level of different types of sensors after the preliminary fusion to obtain a distance closer to the real data.

2 DATA FUSION ALGORITHM BASED ON MAHALANOBIS DISTANCE AND ADAPTIVE KALMAN FILTERING

2.1 Data Preprocessing

Due to the different start time and data update frequency of each sensor, the least squares method is used to synchronize the sensor information, and the spatial alignment of the sensor is carried out through the coordinate system rotation and translation to complete the spatial synchronization.

Let the sampling period of sensor S1 data be recorded as $T1$, the sampling period of sensor $S2$data be recorded as $T2$, calculate the scale factor of the sampling period and write it as $o = T_1/T_2$, and the moment of the latest state estimation of sensor data $S1$ is $(t-1)T1$, and the current moment is $(t-1)T1 + oT2$, which means that the estimated number of target states of sensor $S2$ data in one cycle of sensor $S1$ is o.

2.2 Mahalostobis distance algorithm flow

The Mahalanobis distance is used to judge the similarity between the data, and determine the weight of each data according to the relationship between the data, the smaller the Mahalanobis distance, the greater the weight.

Given the set of data $x = (x1, x2, \cdots, xm)$, xi, for the same type of sensor, the Mahalanobis distance is

$$md(x_i, \bar{x}_i) = \sqrt{(x_i - \bar{x}_i)^T \sum^{-1} (x_i - \bar{x}_i)} \tag{1}$$

where $\sum$ is the covariance matrix of multidimensional random variables; $\bar{x}i$ is the mean of x.

The variance of data set x is expressed as equation (2).

$$\sigma^2 = \frac{1}{m} \sum_{i=1}^{m} (x_i - \bar{x}_i) \tag{2}$$

Through the Mahalanobis distance and variance, the weight of each data is appropriately assigned to obtain the same type of sensor fusion value.

$$w(x_i) = \frac{\frac{md(x_i,\bar{x})}{\sigma^2}}{\sum\limits_{i=1}^{m} \frac{md(x_i\bar{x})}{\sigma^2}} = \frac{md(x_i, \bar{x})}{\sum\limits_{i=1}^{m} md(x_i\bar{x})} \tag{3}$$

$$\breve{x} = \sum_{i=1}^{m} \mathrm{W}(x_i)x_i \tag{4}$$

where xi is the observed value of the same type of sensor; $m$is the amount of data of similar sensors; $w(xi)$ is a weight of xi; $\breve{x}$ is the result of fusion.

2.3 Flow of adaptive Kalman filter algorithm

Noise suppression can be suppressed by properly setting the system noise and sampling noise matrices of Kalman filtering. Noise matrices usually require a lot of experimentation and prior knowledge to adjust and set to fixed values. However, the fixed value is easy to cause unstable filtering, so the residual and correction coefficients are used to adaptively estimate the noise to optimize and improve the Kalman filter. The algorithm flow of adaptive Kalman filtering is as follows.

1. Build a model. During the operation, the ship unloader observes the state of the objects around the driver's cab.The velocity and acceleration of an object do not change in a short period of time, so the velocity and acceleration are used to express the change in the motion of the object, which is expressed as

$$\dot{x} = \lim_{t \to 0} \frac{x_t - x_t - 1}{t} \tag{5}$$

$$\begin{aligned} \ddot{x} &= \lim_{t \to 0} \frac{\Delta \dot{x}}{\Delta t} \\ &= \frac{\lim\limits_{t \to 0} \frac{x_t - x_t - 1}{t} - \lim\limits_{t \to 0} \frac{x_t - 1 - x_i - 2}{t}}{t} \\ &= \lim_{t \to 0} \frac{x_t - 2x_t - 1 + x_t - 2}{t^2} \end{aligned} \tag{6}$$

where $\dot{x}$ represents the velocity of the object; $\ddot{x}$ indicates the acceleration of the object; t represents the sampling period; xt and $xt - 1$ represent sensor observations at t and $t - 1$ moments, respectively.

The equation of state is shown in Equation (7).

$$\hat{x}_t = x_{t-1} + \int_0^t (\dot{x} + \ddot{x}t)dt \tag{7}$$

where $\hat{x}_t$ is the predicted value of time t;x_{t-1} is the$t-1$moment sensor observation.

2.Time Update. According to Equation (7), the target state and state covariance are predicted.

$$\hat{x}_t = F\hat{x}_{t-1} + BU(k) \tag{8}$$

$$P_t^- = FP_{t-1}F^T + Q_{t-1} \tag{9}$$

where $\hat{x}_t^-$ is the prior estimate of the time t; $\hat{x}_{t-1}$ is the optimal estimate at the time of $t-1$; $P_t^-$is the prior covariance matrix of the estimation error; $Q$is the covariance matrix of the state estimation error.

3. Calculate measurement estimates and determine the observation matrix. Combine the measurements of all sensors in the form of vectors, as in Equation (10).

$$Z_t = [x_1, x_2, x_3, \cdots x_m]^T \tag{10}$$

where$x1, x2, x3, \cdots xm$ represents the observed values of $m$sensors.Determine the observation matrix $H = [1, 1, 1]^{\mathrm{T}}$ from the measurement vector Zt.

4. Adaptive adjustment of measurement noise. Due to the uncertainty of the target motion state and the measurement error of the sensor, the measurement noise in the system is dynamically changed, so the measurement noise is dynamically adjusted.

The measured values of a certain time series of sensors are fitted to obtain the fitted sequences of various measured values of different sensors as shown in Equation (11).

$$F = fit(t, Z_t) \tag{11}$$

where fit is the fitting function; t represents time; Zt represents the sequence of measurements.

The residual within time t is the difference between the fitted sequence and the actual observation, as in Equation (12).

$$r_t = z_t - F \tag{12}$$

where F represents the fitted sequence of Zt.

It is known from the literature [16].

$$\hat{\mathrm{V}}_t = \frac{1}{l}\sum_{i=t-W+1}^{t} r_i r_i^T \tag{13}$$

$$R_{0it} = \hat{\mathrm{V}}_t + H_t P_t H_t^T \tag{14}$$

where l is the selected sequence data length, $t \geq l$; $\hat{\mathrm{V}}t$ is the estimated variance of the residuals; $R0it$ is the initialization measurement noise.

The initialization measurement noise matrix at time t is as shown in equation (15).

$$R_0 = [R_{01t}, R_{02t}, R_{03t}, \cdots R_{0mt},]^T \tag{15}$$

The stability of the measured values of each sensor is detected to generate a correction factor η such as Equation (16).

$$\eta = \left\{ \begin{matrix} \frac{|r_t|}{c}, & \frac{|r_t|}{c} > 1 \\ 1, & \frac{|r_t|}{c} \leq 1 \end{matrix} \right\} \tag{16}$$

where c is the threshold value of the measured value and is set to a constant to reflect the volatility of the measured value. Therefore, the correction matrix for measuring noise is as shown in Equation (17).

$$\vec{\eta} = [\eta_1, \eta_2, \eta_3, \cdots \eta_m] \tag{17}$$

Use $\vec{\eta}$ to adaptively adjust the initialization measurement noise matrix $R0$ to obtain that the measurement noise matrix is

$$R_t = \vec{\eta} R_0 \tag{18}$$

5,Calculate the Kalman gain.

$$K_t = P_t^- H^T (HP_t^- H^T + R_t)^{-1} \tag{19}$$

where Kt is the Kalman gain matrix at moment t; $H$is the observation matrix; R_t is the covariance matrix of the measured noise.

6.Revised estimates. When a new measurement $Zt$is obtained at time t, it is compared to the predicted measurement $\hat{x}_t^-$ based on prior state estimation. The errors of the two are weighted with the Kalman gain Kt, and the predictions of the state vectors are updated to generate the best estimate.

$$\hat{x}_t = \hat{x}_t^- + K_t(Z_t - H\hat{x}_t^-) \tag{20}$$

7.Update the covariance matrix. Update the uncertainty of the new estimate.

$$P_t = (I - K_t H)P_t^- \tag{21}$$

where P_t^- and P_t are the prior covariance matrix and the posterior covariance matrix of the estimated error at time t; I is the identity matrix.

3 APPLICATION IN SHIP UNLOADER COLLISION AVOIDANCE MONITORING SYSTEM

During the operation of the ship unloader, due to the complex terminal environment and the driver's high-altitude operation, there is a large blind spot. In order to improve work efficiency and reduce accidents, distance information is acquired by sensors. Since a single sensor is susceptible to environmental influences and has a large ranging error, it is necessary to obtain more accurate distance information through the data fusion algorithm proposed in this paper, provide a more comprehensive field of view and warning information, and provide more reliable and efficient technical means for the research and application of anti-collision systems.

To verify the effectiveness of the proposed multi-sensor fusion method, three sensors were deployed around the driver's cab of a ship unloader collision avoidance monitoring system: ultrasonic rangefinder, lidar, and binocular camera. 22 ultrasonic rangefinders, 1 lidar, and a binocular camera are installed around the driver's cab, and each sensor obtains status information through its own detection algorithm: time, azimuth, distance, etc. Lidar generates 640,000 pieces of data per second, including real distance data, as well as noise data caused by the environment, etc. Aiming at the problem of huge amount of lidar data, the nearest point substitution method is used to reduce the data dimensionality. The deployment of each sensor is shown in Figure 2.

Table 1: Sensor measurements by region and RMSE metrics for comparison fusion algorithms.

Method	1	2	3	4	5	6	7	8
Ultrasonic (%)	4.5	5.6	5.4	6.1	5.7	5.5	5.9	4.6
Lidar(%)	3.3	4.1	3.7	3.5	3.4	3.8	4.8	4.4
Binocular(%)	6.2	5.7	5.7	5.1	4.9	4.5	5.8	4.7
WA (%)	3.2	4.0	3.1	2.5	3.2	3.4	3.4	3.2
KF(%)	3.1	3.9	3.3	2.9	3.2	3.6	4.2	3.6
AKF(%)	3.0	3.6	2.8	3.4	3.1	3.7	3.9	2.4
MD+AKF(%)	2.5	2.4	2.7	2.1	2.9	3.3	3.2	1.9

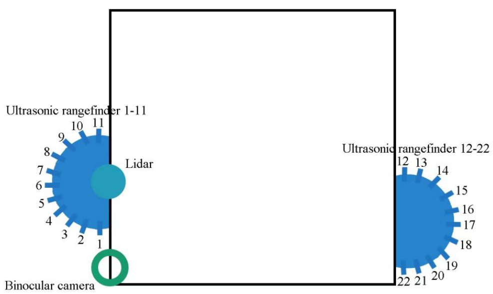

Figure 2: Schematic diagram of sensor deployment around the driver's cab

4 EXPERIMENTS AND ANALYSIS

4.1 Experimental datasets

Build a ship unloader collision avoidance monitoring platform and collect data using ultrasonic rangefinders, lidar and binocular cameras. The dataset contains 199 ultrasonic rangefinder data, 724 lidar data, and 130 binocular camera data. Name the dataset CAM (Collision avoidance monitoring).

The Root Mean Square Error (RMSE) index of the observed value of each sensor and the estimated value of the fusion algorithm relative to the true value is calculated statistically and quantitatively compared.

The root mean square error is the square root of the square of the deviation of the predicted value from the true value to the square root of the ratio of the number of observations. It represents the sample standard deviation of the difference between the predicted value and the observation. The root mean square error indicates how dispersed the sample is, and the smaller the RMSE, the better.

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(\hat{x}_i - x'_i\right)^2} \tag{22}$$

Where $\hat{x}i$ represents the predicted value; $xi^{'}$ stands for true value.

4.2 Experimental results and analysis

Let Φ be the sampling angle to divide the current environment into 8 regions, each region is $(\Phi, \Phi + 45°]$.Mahalanobis range and adaptive Kalman filtering were used to fuse the range information

Mahalanobis of ultrasonic rangefinders, lidars, and binocular cameras.

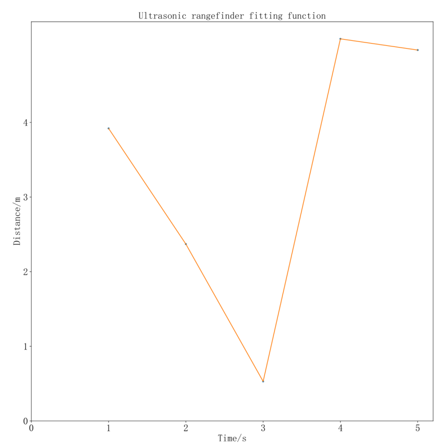

Figure 3: Ultrasonic rangefinder fitting function

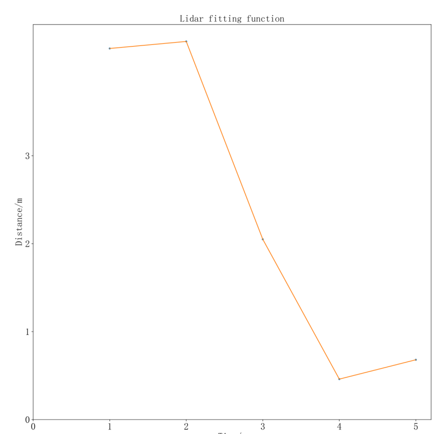

Figure 4: Lidar fitting function

The measurements of a certain time series of sensors are fitted four times polynomically to obtain the fitting functions of various measured values of different sensors.

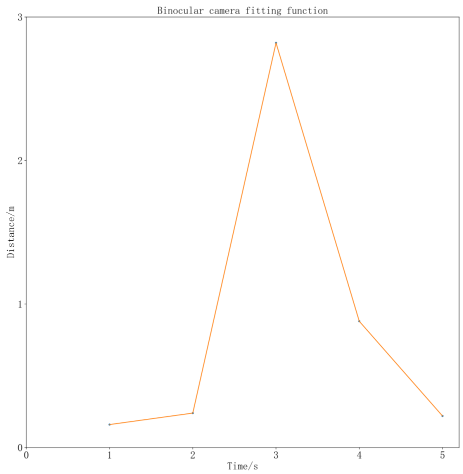

Figure 5: Binocular camera fitting function

The measurements of a certain time series of the ultrasonic rangefinder are fitted, and the fitting function is shown in Figure 3. The measurements of a certain time series of lidar are fitted, and the fitting function is shown in Figure 4.

Fit the measurements of a certain time series of binocular cameras, and the fitting function is shown in Figure 5.

The Mahalanobis Distance (MD) and Adaptive Kalman Filter (AKF) mentioned in this paper were used to fuse the sensor data of eight regions in the CAM dataset collected by a ship unloader collision avoidance monitoring system, The measured values of each sensor (ultrasonic rangefinder, lidar, binocular camera), the classical weighted average algorithm (WA), the Kalman Filter (KF) and the data fusion method proposed in the literature [17] were compared with the Adaptive Kalman Filter (AKF) and the true value (Ture). The results of the fusion of sensor data from each region are shown in Figure 6 below.

In Figure 6 below, in order to verify the effectiveness of the Mahalanobis distance and adaptive Kalman filtering algorithm proposed in this paper, the results of sensor data fusion in various regions are plotted. From this comparative analysis, it can be seen that compared with the measured values of single sensors and various contrast fusion algorithms, the proposed algorithm can improve the accuracy of distance information and reduce noise interference.

The measured values of each sensor and the root mean square error of the estimation value of the fusion algorithm relative to the true value are statistically calculated and compared. The measured values in Table 1.

WA algorithm fusion results, KF algorithm fusion results, AKF algorithm fusion results, and MD+AKF algorithm fusion results and true value rms error RMSE indicators.

Figure 1 according to the figure below, it can be seen that the MD+AKF algorithm in this paper improves the distance accuracy. 13.2% better estimate accuracy compared to single-sensor measurements; Compared with the weighted average algorithm, the

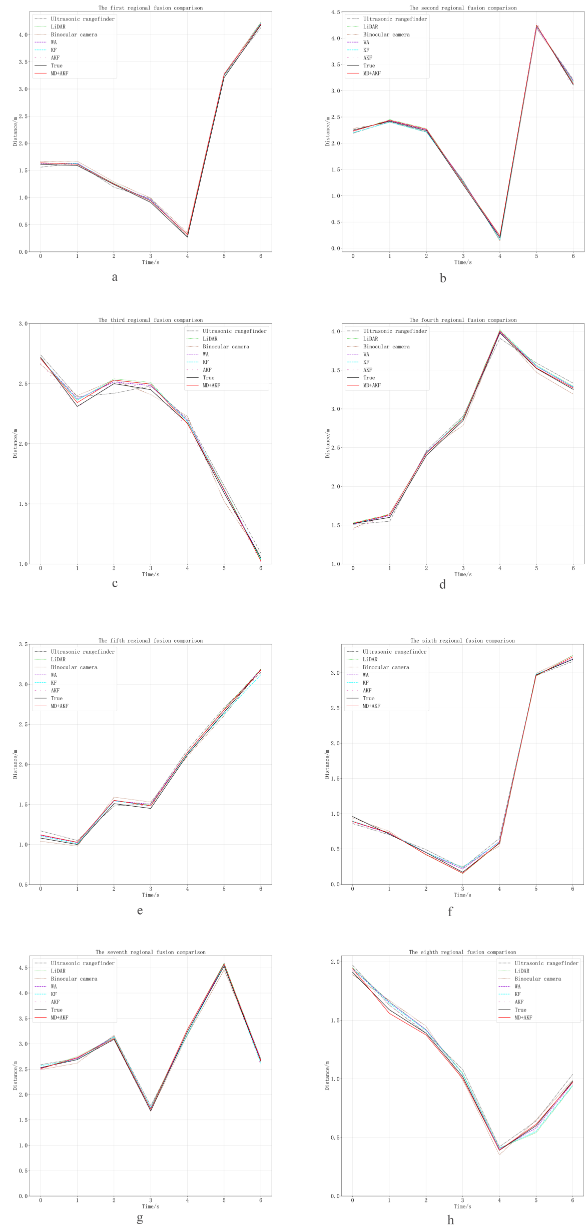

Figure 6: Comparison results of regional integration

estimation accuracy is improved by 8.8%. Compared with the classical Kalman filter algorithm, the estimation accuracy is improved by 9.4%. Compared with the AKF method proposed in the references, the estimated accuracy of this paper is improved by 3.6%. Therefore, the MD+AEF algorithm in this paper can improve the accuracy of estimation and reduce noise interference.

5 CONCLUSION

Aiming at the problem that the sensor measurement noise in the multi-sensor data fusion process of ship unloader collision avoidance system is difficult to fix, a two-stage fusion method based on Mahalanobis range and adaptive Kalman filtering is proposed.First, the data is time-synchronized. Then, by calculating the Mahalanobis distance of the sensor measurement data and the average of the measured data, the data-level fusion of similar sensors is carried out to obtain the preliminary fusion results. Finally, adaptive Kalman filtering is used to fuse the secondary data of different types of sensors after preliminary fusion to obtain a distance closer to the real data. The experimental results show that compared with the measurement value of single sensor and other fusion methods, the MD+AKF algorithm in this paper improves the estimation accuracy and reduces the noise interference.

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