Information fusion of train speed and distance measurements based on fuzzy adaptive Kalman filter algorithm

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Abstract: The measurement accuracy of speed and distance in high-speed train directly affects the control precision and driving efficiency of train control system. To improve the capability of train self-control, a combined speed measurement and positioning method based on speed sensor and radar which is assisted by global positioning system(GPS) is proposed to improve the accuracy of measurement and reduce the dependence on the ground equipment. In consideration of the fact that the filtering precision of Kalman filter will decrease when the statistical characteristics are changing, this paper uses fuzzy comprehensive evaluation method to evaluate the sub-filter, and information distribution coefficients are dynamically adjusted according to filtering reliability, which can improve the fusion accuracy and fault tolerance of the system. The sub-filter is required to carry on the covariance shaping adaptive filtering when it is in the suboptimal state. The adjustment factor of error covariance is obtained according to the minimized cost function, which can improve the matching degree between the measured residual variance and the system recursive residual. The simulation results show that the improved filter algorithm can track the changes of the system effectively, enhance the filtering accuracy significantly, and improve the measurement accuracies of train speed and distance.

Key words: information fusion; federated Kalman filter; fuzzy comprehensive evaluation; train speed and distance measurements

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0 Introduction

With the globalization of high-speed railway and the continuous improvement of traffic speed, a single speed measuring method has already been unable to meet the requirements of railway operation safety and efficiency. And it is a new development trend of train control system to improve the train self-control capability and measure the speed and distance independently under the conditions that reduce the reliance on the wayside equipment[1]. With the rapid development of the multi-sensor information fusion technology, multi-sensor combination positioning has been gradually applied in the railway system, which collects more complementary information to provide more accurate information for train control system, so as to ensure the reliability and accuracy of the train information[2-3].

At present, federated Kalman filter is widely used in information fusion system because of small computation and high reliability. But in practical applications, the sub-filter usually uses a standard filter, which requires accurate statistical characteristics of noise and mathematical model to ensure filtering accuracy. However, during the train operation, the statistical characteristics will change and lead to filtering accuracy decreasing or even diverging. In the current train control system, the measurement accuracies of speed and distance are not high and there is a large difference between the measured results and actual situations[4]. In Ref.[5], a standard filter is used for information fusion and adaptive filtering is not implemented. This paper uses the ground balise to calibrate location information which overly relies on wayside equipment. In Ref.[6], an improved method for Kalman filtering is proposed, which adds sensor

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noise estimation in the filter to estimate and correct statistical features, but fails to dynamically adjust the information distribution coefficients. In Ref. [7], the robust adaptive kalman filtering is introduced. And the self-adaptation of the process noise covariance matrix or measurement noise covariance matrix are processed respectively according to the different types of aircraft faults.

To solve practical problems, it is a pressing task to select the sensors that need to be combined, determine the structure of information fusion, reduce the computation load, and so on. In order to improve the measurement precision and save costs, this paper combines speed sensor, radar[8] and global positioning system (GPS)[9] to measure train speed and distance, and calibrates the running mileage with the precise position provided by GPS, which does not rely on the balise. Federated Kalman filter algorithm is adopted to realize multi-information fusion and fuzzy comprehensive evaluation method is used to evaluate the filtering effect of each sub-filter. The information distribution coefficients are dynamically adjusted according to the filtering confidence of the sub-filters, so as to achieve the global optimum estimation. If the sub-filter is in sub-optimal state, it will carry on covariance shaping adaptive adjustment process, and the filtering accuracy and robustness can be guaranteed by reducing the mismatch between the residual variance and the measured residual variance.

1 Train integrated positioning system

At present, speed sensor is the basic measurement device of speed and distance in the railway field. In China, the speed is measured only by use of speed sensor in the train control system when the speed is under 200 km/s. The 300T uses speed sensor and radar to obtain four-way speed measurements, and the ATP uses the maximum value to calculate the speed monitoring curve[10], whose measuring precision and traffic efficiency are low. Moreover, there are accumulated errors in the calculation of running distance by integral. Although the ground balise is used to realize the running distance calibration and eliminate the accumulated errors, a large number of balises needed will lead to some problems such as high cost, difficult line update, unavailable speed calibration, calibration discontinuity, and so on. In view of the above problems, this paper adopts GPS to assist speed sensor and radar to realize combination speed measurement and positioning, so as to improve the measurement accuracy of train speed and distance, reduce the dependence on the ground equipment and improve the capacity of train self-control.

In Table 1, the advantages and disadvantages of the commonly used speed measuring methods are compared, and the principles of measurement and errors sources are different.

Table 1 Comparison of commonly used speed measuring methods

Speed measuring method	Advantage	Disadvantage
Tachometer motor	Simple	Poor accuracy and reliability
Laser velocimetry	Simple	Poor accuracy and being interfered easily
Speed sensor	High cost-performance, stable work and no environmental impact	Error accumulation, affected by idling, sliding and wheel wear
Doppler radar	Continuous and real-time speed, direction and location information	Affected by car body vibration, installation angle and weather environment, and high failure rate
Inertial positioning system	Strong autonomy, high measurement accuracy, anti-interference	High cost, complex structure, poor maintainability, and errors accumulation over time
Global positioning system	Low cost, ease of maintainance, real-time measurement, high accuracy and no accumulation of errors	Signal blind areas

2 Application of federated Kalman filter

Since the sensor itself can not eliminate the impact of measurement noise and external random interference on measurement accuracy, it is necessary to use filtering algorithm for multi-sensor information fusion. Moreover, the internal computer can not store large amounts of data during the train running and the fusion of speed and distance information must be carried out in real time, so the federated Kalman filter[11] with small computation, good real-time and good fault tolerance performance is the first choice to solve the problem of dynamical integration of train speed and distance information.

In this paper, the federated Kalman filter structure consists of a main filter and three sub-filters. The three sub-filters work in parallel to realize time update and measurements update independently to obtain the local optimal state of train information and then input the local optimal state to the main filter for global fusion.

The structure is shown in Fig. 1. The state equation and measurement equation of each sensor in the system are established as

$$\boldsymbol{X}_i(k) = \boldsymbol{\phi}(k-1)\boldsymbol{X}_i(k-1) + \boldsymbol{G}(k-1)\boldsymbol{W}(k-1), \tag{1}$$

$$\boldsymbol{Z}_i(k) = \boldsymbol{H}_i(k)\boldsymbol{X}_i(k) + \boldsymbol{V}_i(k), \tag{2}$$

where $i=1,2,3$, represent speed sensors, radar and GPS, respectively; $\boldsymbol{X}_i(k)$ represents the train state vector at time step k; $\boldsymbol{\phi}(k-1)$ represents state transition matrix; $\boldsymbol{W}(k-1)$ represents the system process noise vector at time step $k-1$; $\boldsymbol{Z}_i(k)$ represents the sensor observed value; $\boldsymbol{H}_i(k)$ respresents the sensor measurement matrix; and $\boldsymbol{V}_i(k)$ respresents the measurement noise vector.

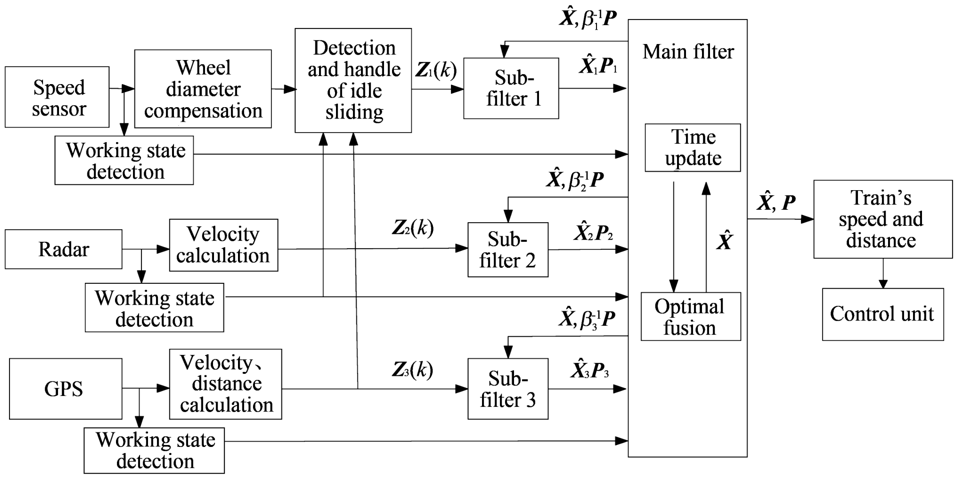

Fig. 1 Information fusion structure of train speed measuring and positioning system

In the main filter, global information fusion is implemented as

$$\hat{\boldsymbol{X}}(k) = \boldsymbol{P}(k)\sum_{i=1}^{3}\boldsymbol{P}_i^{-1}(k)\hat{\boldsymbol{X}}_i(k), \tag{3}$$

$$\boldsymbol{P}(k) = \left[\sum_{i=1}^{3}\boldsymbol{P}_i^{-1}(k)\right]^{-1}, \tag{4}$$

where $\hat{\boldsymbol{X}}(k)$ is the global state estimation at time step k; $\hat{\boldsymbol{X}}_i(k)$ is the state estimation of sub-filter; $\boldsymbol{P}(k)$ is the global state vector covariance at time step k; and $\boldsymbol{P}_i(k)$ is the covariance estimation of sub-filter.

At the same time, the main filter also dynamically returns the noise information, initial condition information and common observation information to each sub-filter, as shown in Fig. 1, where $\sum_{i=1}^{3}\beta_i = 1$. The difference of information distribution coefficients directly affects the filtering accuracy and fault tolerance of the fusion system, so the determination of the information distribution coefficients is the key to use federated Kalman filter.

3 Adaptive adjustment of information distribution coefficients

During the train running process, the information distribution coefficients are dynamically adjusted according to the measurement accuracy and reliability of the sensor, which can further optimize the fusion accuracy of the system. Since the relationship between the filter results of the sub-filter and its associated state parameters is ambiguous, this paper evaluates the sub-filter performance by using the fuzzy comprehensive evaluation method[12-13] and gives the filtering confidence of each sub-filter, then dynamically adjusts the information distribution coefficients.

This paper chooses $tr(\boldsymbol{P}_i)$ and $CH_i(k)$ as evaluation factors, where $tr(\boldsymbol{P}_i)$ is the trace of sub-filter's error covariance, which represents the filtering effect of each sub-filter, and the smaller the value, the better the filtering effect; $CH_i(k)$ is the difference between the actual covariance and the theoretical covariance of the innovation, which represents the prediction accuracy of each sub-filter, and the smaller the value, the higher the prediction accuracy. The output of system is the confidence of sub-filter. The classification results are divided into 4 grades by using grade division method, namely $\boldsymbol{R}_i=$ {excellent, good, general, poor}. Its specific evaluation procedures are as follows.

1) Determining evaluation indexes and evaluation levels, respectively, here are $\boldsymbol{U}_i=\{CH_i, tr(\boldsymbol{P}_i)\}$ and R_i. Determining the membership degree curve of each evaluation index, and the triangular membership function is adopted in this paper.

2) According to the membership function, the comprehensive evaluation matrix of each sub-filter at each sampling point can be obtained, here it is

$$\boldsymbol{D}_i=\begin{bmatrix} R_{c1} & R_{c2} & R_{c3} & R_{c4} \\ R_{t1} & R_{t2} & R_{t3} & R_{t4} \end{bmatrix},$$

where R_{cj} and R_{tj} represent the evaluation grade of CH and $tr(P)$, respectively. The weight vector of evaluation index is $\boldsymbol{W}=[0.5, 0.5]$. Therefore, the evaluation result of each sub-filter is

$$\boldsymbol{A}_i=\boldsymbol{W}\boldsymbol{D}_i=$$

$$\left[\frac{\boldsymbol{R}_{c1}+\boldsymbol{R}_{t1}}{2} \quad \frac{\boldsymbol{R}_{c2}+\boldsymbol{R}_{t2}}{2} \quad \frac{\boldsymbol{R}_{c3}+\boldsymbol{R}_{t3}}{2} \quad \frac{\boldsymbol{R}_{c4}+\boldsymbol{R}_{t4}}{2}\right].$$

3) In order to obtain the filter confidence at each sampling point, the specific parameters of the filtering level should be specified. The confidence intervals of the filter results and the corresponding parameter vectors are determined based on the experience and simulation results, which are shown in Table 2. The grade parameter column vector is $\boldsymbol{Z}=[0.95, 0.8, 0.5, 0.05]^{\mathrm{T}}$. The evaluation result $\boldsymbol{A}_i$ is taken as the weight vector, then the filtering confidence of the sub-filter is $\boldsymbol{d}_i=\boldsymbol{A}_i\boldsymbol{Z}$.

Table 2 Filtering results classification

Filtering level	Filtering effect	Confidence interval	Grade parameter
Level 1	Excellent	[0.9,1]	0.95
Level 2	Good	[0.7,0.9]	0.8
Level 3	General	[0.2,0.7]	0.5
Level 4	Poor	[0,0.2]	0.05

4) The information distribution coefficient of each sub-filter is $\beta_i=\dfrac{d_i}{\sum_{i=1}^{3} d_i}$, where $d_i\in(0,1)$. According to the sub-filter filtering confidence value at each sampling point, we can query Table 2 and determine the filter result level, so as to determine whether adaptive filtering is necessary.

4 Covariance shaping adaptive filtering

During the train running process, since the changes of the system environment, train traction and other factors result in the changes of system model parameters and measurement statistical characteristics of the sensors, the filtering effect is affected. When sub-filter is in the sub-optimal state, adaptive filtering is needed to constantly adjust the gain matrix to ensure the better filtering effect. This paper introduces covariance shaping method and the Frobenius norm minimization considered as the optimization index[14], so as to obtain the adjustment factor for the system's residual variance and realize the adaptive adjustment of the process noise and measurement noise in sub-filter system. Thus the algorithm can improve the matching degree between the measured residual variance and the system recursive residual, and enhance the filtering accuracy.

The residual error of sub-filter is

$$\boldsymbol{e}_i(k)=\boldsymbol{H}_i(k)[\boldsymbol{X}_i(k)-\hat{\boldsymbol{X}}_i(k)]+\boldsymbol{V}_i(k). \quad (5)$$

The measurement residual variance of sub-filter is

$$\boldsymbol{S}_i(k \mid k-1)=\boldsymbol{H}_i(k)\boldsymbol{P}_i(k)\boldsymbol{H}_i^{\mathrm{T}}(k)+\boldsymbol{R}_i(k), \quad (6)$$

where $\boldsymbol{R}_i(k)$ is the measurement noise covariance of the sensor.

The error covariance matrix can also be written as

$$\boldsymbol{P}_i(k \mid k-1)=\boldsymbol{P}_i^0(k \mid k-1)+\alpha\boldsymbol{P}_i^1(k \mid k-1), \quad (7)$$

where α is the adaptive adjustment factor.

The estimated residual covariance matrix of Kalman filter can be obtained by Eqs.(6) and (7), namely

$$\boldsymbol{S}_i(k \mid k-1)=\boldsymbol{H}_i(k)P_i^0(k \mid k-1)\boldsymbol{H}_i^{\mathrm{T}}(k)+$$
$$\boldsymbol{H}_i(k)\boldsymbol{P}_i^1(k \mid k-1)\boldsymbol{H}_i^{\mathrm{T}}(k)+\boldsymbol{R}_i(k), \quad (8)$$

where

$$\boldsymbol{S}_i^0(k \mid k-1)=\boldsymbol{H}_i(k)\boldsymbol{P}_i^0(k \mid k-1)\boldsymbol{H}_i^{\mathrm{T}}(k)+\boldsymbol{R}_i(k),$$
$$\boldsymbol{S}_i^1(k \mid k-1)=\boldsymbol{H}_i(k)\alpha\boldsymbol{P}_i^1(k \mid k-1)\boldsymbol{H}_i^{\mathrm{T}}(k).$$

The measurement covariance matrix of the system is obtained by

$$\bar{\boldsymbol{S}}_i=\frac{1}{N}\times$$
$$\sum_{i=1}^{N}\{\delta\boldsymbol{Z}(k-N+1+i)[\delta\boldsymbol{Z}(k-N+1+i)]^{\mathrm{T}}\}, \quad (9)$$

where N is the number of sampling points and $\boldsymbol{\alpha}$ is the parameter to be optimized. The deviation between the theoretical covariance and actual covariance of sub-filter is taken as the minimum cost function, and it can be expressed in Frobenius norm as

$$\min = \{J(\boldsymbol{\alpha}) = \| \bar{\boldsymbol{S}}_i - [\boldsymbol{S}_i^0(k \mid k-1) + \boldsymbol{S}_i^1(k \mid k-1)] \|^2\}, \tag{10}$$

where $\boldsymbol{\alpha} > 0$ is diagonal matrix. To minimize the cost function, its partial derivative is 0 and $\boldsymbol{\alpha}$ is

$$\boldsymbol{\alpha} = \mathrm{diag}[(\boldsymbol{HP}_i^1(k \mid k-1)\boldsymbol{H}^{\mathrm{T}})^{-1}(\bar{\boldsymbol{S}}_i - \boldsymbol{S}_i^0(k \mid k-1))]. \tag{11}$$

Then, the adaptive factor is obtained according to Eq. (11) to realize the adaptive matching between theoretical residuals and actual residuals during the train running and improve the filtering accuracy and robustness of the system.

5 Simulation and analysis

5.1 Establishment of train motion model

During the train running process, the acceleration is variable. In this paper, considering non-zero acceleration mean, the discretization equation of train motion is obtained based on the current statistical model, and the formula is

$$\begin{bmatrix} s(k) \\ v(k) \\ a(k) \end{bmatrix} = \begin{bmatrix} 1 & \dfrac{T(-1+aT+\mathrm{e}^{-aT})}{a^2} & 0 \\ 0 & 1 & \dfrac{1-\mathrm{e}^{-aT}}{a} \\ 0 & 0 & \mathrm{e}^{-aT} \end{bmatrix} \times \begin{bmatrix} s(k-1) \\ v(k-1) \\ a(k-1) \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} w_s(k-1) \\ w_v(k-1) \\ w_a(k-1) \end{bmatrix}, \tag{12}$$

where a is the correlation time constant of the train acceleration[15]; $s(k)$, $v(k)$ and $a(k)$ are the train running distance, speed and acceleration, respectively; T is the sampling period; $w_s(k)$, $w_v(k)$ and $w_a(k)$ are the system noises that respectively affect the train running distance, speed and acceleration, and they are belong to zero-mean white Gaussian noise, of which the standard deviations are δ_s, δ_v and δ_a, respectively.

Speed sensor sub-system: Its observation vector is $\boldsymbol{Z}_1(k) = [s(k), v(k)]^{\mathrm{T}}$. The measurement noise is $\boldsymbol{V}_1(k) = [W_{1s}, W_{1v}]^{\mathrm{T}}$, where w_{1s} and w_{1v} are the zero-mean white Gussian noise, of which the standard deviations are δ_{1s} and δ_{1v}, respectively. Its observation matrix is $\boldsymbol{H}_1 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}$.

Radar sub-system: Its observation vector is $\boldsymbol{Z}_2(k) = v(k)$. The measurement noise is $\boldsymbol{V}_1(k) = W_{2v}$, where W_{2v} is the zero-mean white Gussian noise and the standard deviation is δ_{2v}. Its observation matrix is $\boldsymbol{H}_2 = [0 \quad 1 \quad 0]$.

GPS sub-system: Its observation vector is $\boldsymbol{Z}_3(k) = [s(k), v(k)]^{\mathrm{T}}$. The measurement noise is $\boldsymbol{V}_3(k) = [W_{3s}, W_{3v}]^{\mathrm{T}}$, where w_{3s} and w_{3v} are the zero-mean white Gussian noise, of which the standard deviations are δ_{3s} and δ_{3v}, respectively. Its observation matrix is $H_3 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}$.

5.2 Simulation and analysis

In this paper, the integrated train positioning system consisting of speed sensor, radar and GPS is used as the experimental platform, and the simulation is carried out in the Matlab 2016 environment. When adding the simulation noise, the standard deviation of speed noise is $\delta_v = 0.1$ m/s, the standard deviation of distance noise is $\delta_s = 0.5$ m and the standard deviation of acceleration noise is $\delta_a = 0.1$ m/s^2. The simulation related parameters are set as follows: $T = 1$ s, $a = 1$, $\delta_{1s} = 5$ m, $\delta_{1v} = 1.5$ m/s, $\delta_{2v} = 1.1$ m/s and $\delta_{3s} = 1$ m/s. Then the measurement noise variance matrix of speed sensor sub-system is $\boldsymbol{R}_1 = [\mathrm{t}^2, 0; 0, 1.5^2]$, the measurement noise variance matrix of radar sub-system is $\boldsymbol{R}_2 = [0, 1.1^2]$, and the measurement noise variance matrix of the GPS sub-system is $\boldsymbol{R}_3 = [4^2, 0; 0, 1^2]$. In order to meet the requirements of high-speed railway running speed, the initial velocity is $v_0 = 50$ m/s. The simulation time is set at 200 s. The carrier moves at a speed of 50 m/s within 0—50 s. In 50—100 s, the carrier does varying accelerated motion, and the acceleration is set at $3\sin(t/5)$ m/s^2, which is used to simulate process changes. The carrier does uniform accelerated movement in 100—150 s, and the acceleration is 1.5 m/s^2. At the same time, the observation noise covariance is increased by four times of the initial value, which is used to simulate the changes of measurement noise statistical characteristics. In 150—200 s, the carrier does variably accelerated motion and the observation noise covariance is increased by four times of the initial value, which is used to simulate the simultaneous variation of observation noise and process at the same time. The simulation experiments are carried out by comparing the adaptive federated Kalman filter proposed in this paper, the standard federated Kalman filter and the improved Kalman filter proposed in Ref. [6]. The simulation results are shown in Figs. 2 and 3.

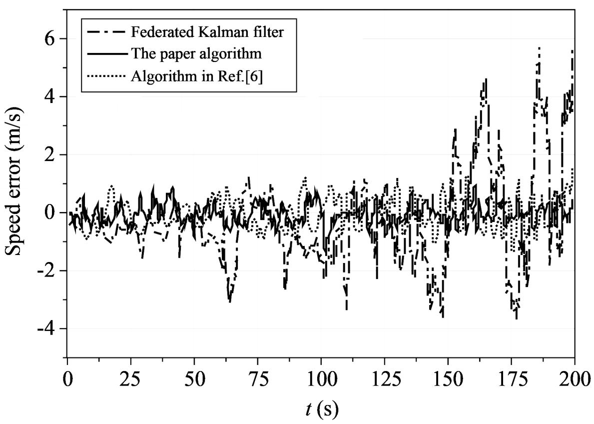

Fig. 2 Comparison of speed errors of three algorithms

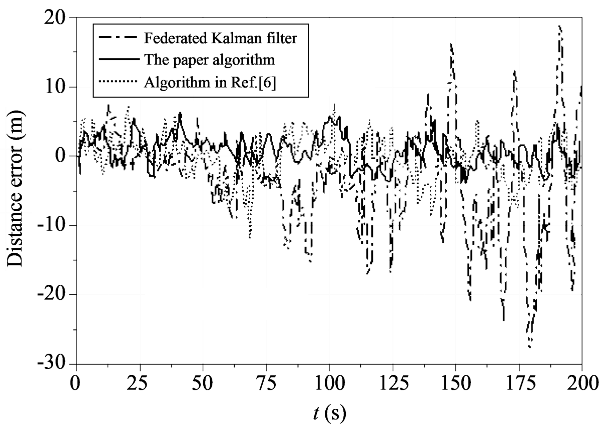

Fig. 3 Comparison of distance errors of three algorithms

In Figs. 2 and 3, as a comparison of the three algorithms, the simulation results of speed error and distance error are presented, respectively. It can be seen that because the carrier is subject to uniform motion in 0—50 s, the motion model and system noise statistics are accurate, and the filtering effects of the three algorithms are almost the same. But in 50—200 s, the carrier does the variably accelerated motion firstly, as a result, the measurement noise increases and the noise statistical characteristics are changed, which results in the increase of distance error and speed error. The filtering effect has declined especially in 150—200 s. When the process and measurement noise change at the same time, the standard Kalman filter is very incapable meeting the requirements of train speed measurement and positioning. But the algorithm in this paper and the algorithm in Ref. [6] still can track this kind of change better and obtain the better filtering effect. This is because the process noise and measurement noise of the system in Ref. [6] are estimated and modified in real time, which is able to improve the filtering accuracy. In this paper, the system automatically carries out adaptive filtering according to the filtering effect. In point of residual comparison, considering the error caused by the changes of process noise and measurement noise, the changes of the system can be better tracked. In addition, the information distribution coefficients can be adjusted adaptively in this paper and the relevant information that returns to the sub-filter can be adjusted dynamically, so as to improve the fusion accuracy, whose filtering effect is better than that of the algorithm in Ref. [6]. Therefore, the algorithm proposed in this paper is suitable for multi-sensor information fusion, which can reduce the measurement error and improve the measurement accuracy of speed and distance. The Information fusion structure is available.

6 Conclusions

After the simulation and comparative analysis, the following conclusions are obtained.

1) This paper adopts GPS to assist speed sensor and radar to realize combination speed measurement and positioning, which can effectively eliminate distance error accumulation, carry out distance calibration in real time, and improve train self-control capability.

2) This paper uses fuzzy comprehensive evaluation method to evaluate the sub-filter, and the information distribution coefficients can be dynamically adjusted according to the filtering confidence, which can make the fusion system obtain better filtering accuracy and improve fault tolerance.

3) This paper adopts covariance shaping adaptive filtering method and minimizes the cost function, which can simultaneously track the changes of process noise and measurement noise. In addition, the algorithm improves the matching degree of the measured residual variance and recursive residual, so as to optimize the filter and improve the information fusion accuracy of the train speed and distance significantly.

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基于模糊自适应联合卡尔曼滤波算法的列车测速测距信息融合

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摘　要： 高速列车的测速定位精度直接影响着列控系统的控制精度和行车效率，为了提高列车自主控车能力，本文以GPS辅助速度传感器、雷达进行组合测速定位，以提高测速定位精度并减少对地面设备的依赖。针对卡尔曼滤波在统计特征变化时滤波精度下降的问题，运用模糊综合评判方法对子滤波器进行评价，根据滤波置信度动态调整信息分配系数，提高该系统的融合精度和容错性；当子滤波器处于次优状态则进行协方差成形自适应滤波，依据最小化代价函数获得误差协方差的调节因子，来提高实测残差方差和系统递推残差的匹配度，增强滤波精度。仿真结果表明，本文提出的改进滤波算法能够有效跟踪系统变化情况、明显增强滤波精度及提高测速定位精度。

关键词： 信息融合；联合卡尔曼滤波；模糊综合评判；列车测速测距

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