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A Hierarchical Adaptive Information Fusion Method Based on Multimodal Kalman Filtering

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In the multi-sensor information fusion tracking system, there are many uncertain or happens often unforeseen changes in environmental factors, if does not consider these factors in the design of the fusion algorithm, in the practical application may leads to the fusion system accuracy decreased or even complete failure. Therefore we must design a system which can adjust the algorithm adaptively. In this paper, the author will for sensors in the system the number or types of changes caused by the model change, puts forward a multiple model Kalman filter based adaptive fusion algorithm, and has carried on the simulation analysis, this method not only improves the flexibility and fault tolerance of the system, and the full integration of the complementary information and redundant information, and the method is simple, strong versatility.

1. Introduction

As a result of the Kalman filter is based on the specific system model, once reflected in the filter matrix model has been defined, all in the definition of the sensor will be in the iterative process of the filter provides information and unable to provide other kinds of sensors. If one of these sensors fails to provide information for the current iteration, the output of the filter will go wrong. However, in some applications, requirements can be added or deleted (a type) sensor without modifying the fusion algorithm. Kalman filter does not support this variability, therefore, only using a Calman filter cannot meet the need (Aslan and Saranlı, 2011).
A simple adaptive sensor fusion method is proposed in this paper. The idea is to use a cluster of Calman filters to represent different sensor combination models. A model selection procedure to select the appropriate filter for the actual system. This method overcomes the problem that the Calman filter cannot support the system to change the sensor types.

2. The establishment and selection of multi Calman filter model

The specific Calman filter model in the filter cluster depends on the following parameters:
1) To detect the parameters. For general state (tracking) level fusion systems, 5 parameters are required: decarr coordinate position, linear velocity, linear acceleration, initial Euler angle, and angular velocity. Various sensors can be used to track the system, but all the sensors in the system are directly or slightly changed to provide a measurement of these parameters. If you do not use the polar coordinates, the parameters are only three: position, speed, acceleration (Aziz, 2011). The polar coordinates can be transformed to Cartesian coordinates, so here only consider the three parameters.
2) The dimension of the representation of each filter. The position of the object is represented as a two-dimensional vector: the X, Y's linear position in the decarr coordinate system. The sensor can measure any one of the three parameters in the two-dimensional. In order to simplify the algorithm, the decision of each dimension in the two-dimensional filtering.
In addition, consider the original measurement data into filter before the data conversion. The data transmitted by a specific sensor need to be processed before it can be sent to the calman filter. For example, a sonar system is polar angles and distances, and should be converted to decarr coordinates, and a inertial rate sensors should remove the influence of the rotation of the earth. As a result, some sensor measurement

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information before pass filters for registration. All the transformation work as part of the pre-treatment and consistency inspection procedures. Outside the filter (Hajiyev, 2012).
From the above analysis, Kalman filter model of the basic equation can be expressed by formula (1) (which p represents position, v is the speed, a is the acceleration, dt is the interval of time), when the use of different sensors, H and X in formula (1) are vary.

$$X(k+1) = HX(k) + Gw(k) = \begin{bmatrix} 1 & dt & dt^2 \\ 0 & 1 & dt \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} p(k) \\ v(k) \\ a(k) \end{bmatrix} + Gw(k) \tag{1}$$

Consider all of these factors, for a tracking system that contains the location information, the model requires only 4 different filters. All sensors are combined into the following models: position, position-velocity, position-acceleration, position-velocity-acceleration.
The model selection of the filter depends on the number and characteristics of the current sensor used. When the system is initialized (Havlicek et al., 2011) the number and types of sensors being used will be provided to the fusion system. After knowing what type of sensor is being processed, the fusion system can easily select the appropriate model from the 4 models.
In the process of the system, if you want to add a new sensor, you can send a command to the fusion system, the system will reselect the model. To remove a sensor from the fusion system is the same. For example, when you encounter a sensor failure, you can achieve the exclusion of the fault by re selecting the model does not contain the sensor and system reconstruction (Sangeetha and Kalpana, 2012).

3. Fusion algorithm for processing redundant information

The multimodal Kalman filtering method solves the problem of the flexible processing of the data of complementary sensors (such as: the position sensor, speed sensor and acceleration sensor); When there are redundant sensors (such as two position sensors) in the system, we can learn from the structure of the federal Kalman filter, and divide the redundant sensors into different subsystems, and establish the hierarchical fusion structure. Each subsystem local estimation is obtained by Kalman filter, and then the parameters of the local estimation into the fusion centre for fusion, the final global estimate.
Fusion algorithm 1: a fusion algorithm based on Federated Kalman filtering theory
That is the use of the 3.2 section of the algorithm for information fusion. For example, there are two sub systems, denoted ‘,x $_1$ as local filter 1 estimates, ‘,x $_2$ estimates for local filter 2, P1 and P2 respectively for their covariance matrix, then the global estimate of ‘,x $_g$ is given by the formula (2). The smaller the estimated covariance, the greater the contribution it will make to the global estimate[8].

$$\hat{X}_g = \left[P_1^{-1} + P_2^{-1}\right]^{-1}\left[P_1^{-1}\hat{X}_1 + P_2^{-1}\hat{X}_2\right] \tag{2}$$

Fusion algorithm 2: a fusion algorithm based on mathematical statistics theory
After local Kalman filtering, it is concluded that the nth local estimation of parameters on the same target, the ith local estimation for xi, where i=1,2,…,n. Since Xi is obtained by the sensor measurement, obviously it has randomness, generally obey the normal distribution, and the Gauss probability density function is described as the formula (3.).

$$P_i = \frac{1}{\sqrt{2\pi\sigma_i}}\exp\left[-\frac{(x_i-\mu)^2}{2\sigma_i^2}\right] \tag{3}$$

Where σ_i is the variance, μ is the mean, and represents the parameter characteristic.
The mutual support degree between different local estimates is expressed by the confidence distance d, and the confidence distance between Xi and Xj is defined as follows.

$$d_{ij} = d_{ji} = P\left(|Z| \le \frac{|x_i - x_j|}{\sqrt{\sigma_i^2+\sigma_j^2}}\right) = 2\int_0^{\frac{|x_i-x_j|}{\sqrt{\sigma_i^2+\sigma_j^2}}} \frac{1}{\sqrt{2\pi}}\cdot e^{-\frac{x^2}{2}}dx \tag{4}$$

where z is random variables of normal distribution N(0,1)
If r_{ij} = 1-d $_{ij}$, i,j=1,2,…,n, the support matrix between the estimated values is

$$R = \begin{bmatrix} r_{11} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots \\ r_{n1} & \cdots & r_{nn} \end{bmatrix} \tag{5}$$

Obviously R is the positive symmetric matrix, the maximum model is λ>0, the corresponding feature vector is $Y=(y_1 \;\; y_2 \; \Lambda \; y_n)^T$, that is, $R^TY = \lambda Y$. Expand to

$\lambda_k = y_1r_{1k}+y_2r_{2k}+\Lambda+y_nr_{nk}$, k=1, 2,…,n

The integrated support degree (i.e., the weighted fusion coefficient) of the kth local estimator is

$$a_k = \lambda_k \Big/ \sum_{i=1}^{n} \lambda_i$$

(6)

The final global convergence value is

$$\widehat{x}_g = \sum_{k=1}^{n} a_k x_k \tag{7}$$

This fusion algorithm based on the mathematical statistics theory is evolved from the consistency checking algorithm. It can also be used to directly fuse sensor measurements, but that must be aware of the distribution characteristics of each sensor measurement; In the hierarchical fusion structure proposed in this paper, the measured values are fused after local filtering, and a certain relationship can be established between the local estimation covariance P_i and the normal distribution variance σ_i, and the distribution characteristics are obtained (Haykin et al., 2011).

4. System workflow

After the above analysis, the basic working process of the system is shown in Figure 1.

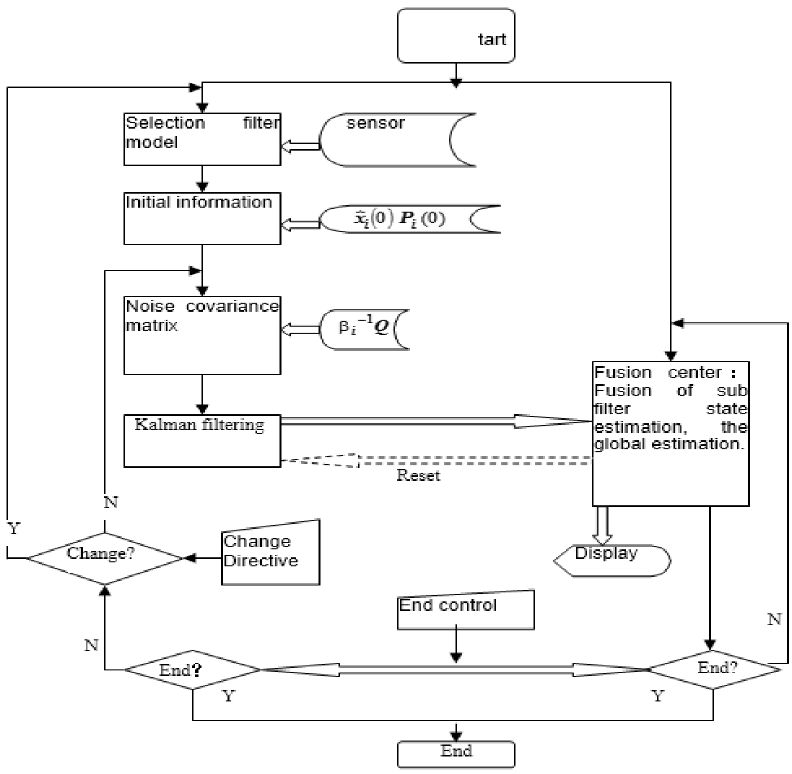


Figure 1: Multi Kalman filter adaptive fusion system workflow

When the system starts to work, each sub filter is selected according to the type and the number of sensors needed to be processed in the 4 filter models, and initialization; After the end of the initialization, the sub filter to start the Kalman filter, come to a local estimate, into the fusion centre; According to the method of 3.3.3 section, the fusion centre can fuse the local estimation, and get the global estimation ,x_g, and output the result; Finally, according to the structure of the fusion system to determine whether the sub filter to reset. When a fusion cycle is over, the control can be manually ended to decide whether to end the program. If it does not end, the next fusion cycle begins. In the process of the system (Lucey and Ashraf, 2013), if there is a request for the change of the sensor (such as: a subsystem to add the sensor, or detect the failure of a subsystem sensor), then this subsystem to reselect the filter model (Han and Wang, 2012) (Wang et al., 2012).
The fusion period of the main filter can be longer than the sub filter cycle, that is to say, the sub filter can be sent to the main filter after several filtering cycles.

5. Conclusion and simulation

Sub filter is the basic form of Kalman filter, which is used to fuse the measurement information of different parameters, and then the output of an optimized state estimation (Tang et al., 2012). For example, it can be used to fuse data from a speed meter and a sonar positioning system, to get a better position estimation. The multi Kalman filtering method provides a more flexible and accurate filtering method for this process. The hierarchical structure of the whole system is used to fuse redundant information to get a more accurate global estimate.
In order to demonstrate the effectiveness of the hierarchical fusion algorithm based on multi model Kalman filter, this section is given two examples. All the results are obtained by MATLAB simulation. The data acquisition and Simulation of the noise sensor is achieved by adding white noise to the parameter values. For simplicity, the orientation information in all examples is only one dimension, and the results obtained are similar to those obtained in other dimensions.
Firstly, a multi-sensor information fusion system, which is composed of a positioning sensor and a speed sensor, is considered in the work of “position-speed” model. After a period of time for each sensor to work (Figure 3.11 t=100), the speed sensor failure, the simulation results shown in Figure 2.

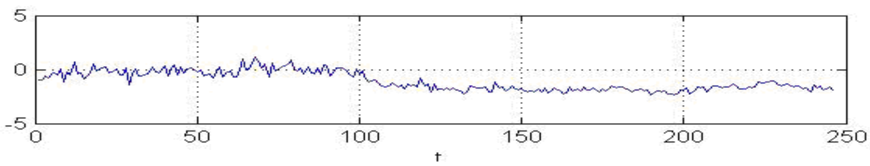


Figure 2: Kalman filter estimation error with speed sensor fault

(Did not use the multi model Kalman filtering method)

See from figure 2, after the speed sensor failure, if still use the original filter, then the position is estimated to be a significant deviation. Here with the same parameters for the use of multi model Kalman filtering method of the system simulation. The error is estimated as shown in Figure 3.

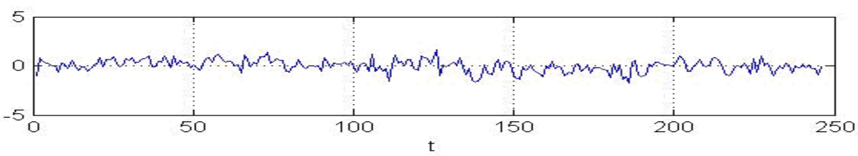
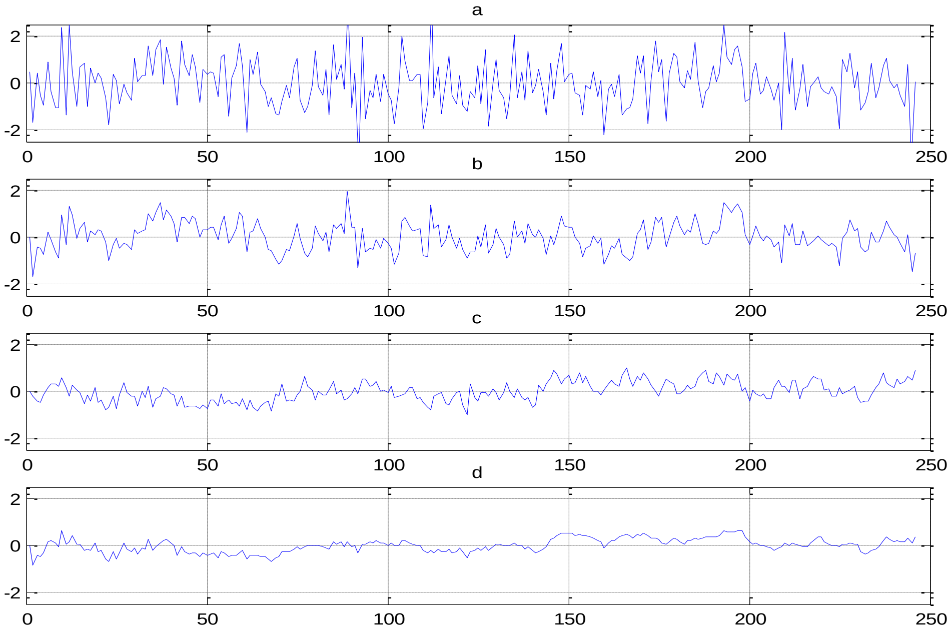


Figure 3: Kalman filter estimation error with speed sensor fault

(Using the multi model Kalman filtering method)



a: Measurement error before filtering; b: Estimation error of sub filter 1 (position model);c: Estimation error of sub filter 2 (position-velocity model);d: Estimated error after fusion

Figure 4: Estimation error comparisons before and after system fusion

In Figure 3, the system uses the “position-velocity” model to filter the Kalman filter in two sensor under normal working conditions. After the speed sensor fails, the filter is changed to use the “position” model. Although the estimation error is larger than the original one due to the lack of the information of a sensor, the estimation error caused by the sensor fault is overcome, which greatly improves the system adaptability and fault tolerance.

Next to the two sonar positioning system and a speed sensor combination of underwater ranging system as an example, based on the federal Kalman filter without feedback structure of the fusion method for simulation. Sonar positioning system 1 is subsystem 1, sonar system 2 and speed sensor combination is subsystem 2. The subsystem 1 chooses “position” model, and the subsystem 2 chooses “position-velocity” model.

The simulation results are shown in figure 4.

Two sub filters have different covariance matrices. Subsystem 1 filter the measured value of a positioning system and the sub filter 2 has been integrated with a positioning system and a speed sensor information, so the estimation error of sub filter 2 is smaller than the sub filter 1. After the fusion of the main filter, the global estimation is smaller than the estimation error of any sub filter.

6. Conclusions

This paper introduces the state level fusion in multi-sensor information fusion technology- Kalman filtering technology, and systematically studies the application in modern complex multi sensor information fusion system of the distributed fusion method -- the Federal Kalman filter. It analyses the influence of the structure, precision, fault tolerance and the information distribution coefficient of the federated Kalman filter on the filtering structure. On the basis of this, an adaptive adjustment information distribution coefficient method is given based on fuzzy decision of the estimation variance trace and the new variance trace . For multi-sensor information fusion system sometimes need to add or remove a sensor problem, this paper proposes a model based on Kalman filter method of hierarchical multisensory information fusion method, and a simulation analysis was carried out.

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References

Aslan M.S., Saranlı A., 2011, A tracker-aware detector threshold optimization formulation for tracking maneuvering targets in clutter, Signal Processing, 91(9):2213-2221, DOI: 10.1016/j.sigpro.2011.04.004.

Aziz M., 2011, A novel all-neighbor fuzzy association approach for multitarget tracking in a cluttered environment, Signal Processing, 91(8):2001-2015, DOI: 10.1016/j.sigpro.2011.03.007

Hajiyev Ch., 2012, Tracy–Widom distribution based fault detection approach: Application to aircraft sensor/actuator fault detection, ISA Transactions, 51(1):189-197, DOI: 10.1016/j.isatra.2011.07.008.

Han S.L., Wang J.L., 2012, Integrated GPS/INS navigation system with dual-rate Kalman Filter, GPS Solutions, 16(3):389-404.

Havlicek M., Friston K.J., Jan J., Brazdil M., D. Calhoun V., 2011, Dynamic modeling of neuronal responses in fMRI using cubature Kalman filtering,Neuroimage, 56(4):2109-28,DOI: 10.1016/j.neuroimage.2011.03.005.

Haykin S., Zia A., Xue Y.B., Arasaratnam L., 2011, Control theoretic approach to tracking radar: First step towards cognition, Digital Signal Processing, 21(5):576-585. DOI: 10.1016/j.dsp.2011.01.004.

Lucey S., Ashraf A.B., 2013, Nearest neighbor classifier generalization through spatially constrained filters, Pattern Recognition, 46(1):325-331, DOI: 10.1016/j.patcog.2012.06.009.

Sangeetha R., Kalpana B., 2012, Distributed data association for multitarget tracking-a mathematical perspective, Procedia Engineering, 30(1):1005-1012, DOI: 10.1016/j.proeng.2012.01.957.

Tang X.J., Liu Z.B., Zhang J.S., 2012, Square-root quaternion cubature Kalman filtering for spacecraft attitude estimation, Acta Astronautica, 76(4):84-94, DOI: 10.1016/j.actaastro.2012.02.009.

Wang S.S., Che W.F., Feng J.F., Wang F.N., Bai Y., 2012, Data association algorithm for bistatic radar network, Procedia Engineering, 29:2405-2409, DOI: 10.1016/j.proeng.2012.01.323.