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A New Method of Multi-sensor Data Fusion Based on Multiscale Analysis and UKF

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Abstract

Unscented Kalman Filtering (UKF) and signal multi-scale analysis are frequently implemented in the application of multi-sensor data fusion technology. This paper proposed a new algorithmic method based on Unscented Kalman filter and wavelet transform for multi-sensor data analysis. Details of five modeling technologies were presented in this research, including distributed multi-sensor dynamic system model, mathematical expression of Kalman filtering model and wavelet transform, the representation method and the fusion estimation algorithm of multi-scales signal. The procedure of multi-sensor data fusion started with filtering applied on the multi-sensor data collected using Unscented Kalman filter, and then, wavelet decomposition was conducted on the model of multi-scale to remove the high-frequency interference signals that contaminated the measuring signal. After that, the filtered signals were reconstructed assisted by wavelet reconstruction, it was necessary to perform confluent procedure for reconstructed data utilizing adaptive weighted algorithm. Simulation experiment has indicated that, compared with other data fusion algorithms, the method proposed could effectively enhance the anti-interference performance of supervision system and improve the reliability and accuracy of the sensor detection system.

***Keywords**: Unscented Kalman Filter, Multiple sensors, Multiscale analysis, Wavelet transform, Data fusion*

1. Introduction

With the development of micro-processor and industrial technology, the Internet of Things and wireless sensor network technology has achieved great progress, which are nowadays widely applied in many domains. However, in some battlefield environment of harshness or severe noise, sensor nodes are required to spread in designated areas to detect moving targets, influence such as external environment, sensor type, measurement noise, monitoring location and other factors will affect the supervision accuracy, causing the data collected by sensor network uncertain, untrue and unreliable, as a result, monitoring deviations and errors occur during the supervision process [1]. In order to guarantee the data collection of sensor more reliable, a number of scholars have proposed some multi-sensor data fusion solutions, nevertheless, many of them often lead to unbalanced information among sensor nodes in the process of data fusion. Due to the relatively lower precision and resolution of single sensor itself as well as environmental noise and other factors, the measurement data are incomplete or with a large uncertainty, which are more likely to get the wrong data. However，multi-sensor data fusion can realize better accuracy than a single sensor node in data detection. When a node invalidates, data fusion can be executed and compensated adaptively by other nodes to ensure that the following data processing and decision-making are complied with the right execution. Due to the advantages as mentioned, multi-sensor data fusion has

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attracted a large amount of attentions and become a focus that many international experts concern [2]. Currently, data fusion method are mainly categorized into classic fusion algorithm, of which the representative are weighted average method, least squares method, likelihood estimation, Kalman filtering, multi-Bayesian estimation, DS evidential reasoning, and modern intelligence fusion algorithm, of which the representative mainly includes Expert Systems, Cluster Analysis, Production Rules, Rough Set Theory and Neural Networks algorithm [3].

Traditional data fusion algorithms generally concerned with improving the accuracy of data fusion, seldom considering precision and efficiency of integration as well as the uncertainty in procedure when sensor nodes are monitoring, from which the results are susceptible to external interference in harsh environments [4]. New design of a novel fusion algorithm with high accuracy and better efficiency has long been a research emphasis in the domain of multi-sensor data fusion. Zhe Wang [5] has proposed to implement the extended Kalman filter (EKF) in inertial measurement unit of sensor data fusion, which could significantly improve the measurement accuracy of the orientation and position of the sensor. Similarly, Xianming. X and Yiming. P [6] presented a method that applying Unscented Kalman filter into practice of radar interferometer, noise filtering was executed for signals collected by radar using UKF to improve the measurement precision of the sensor and accuracy. Rong and Qiao [7] have proposed multi-sensor data fusion algorithm for fuzzy neural system, the adaptive neuron fuzzy inference system (ANFIS) and Kalman filter were used in the multi-sensor data fusion algorithm. Liu and Chen [8] have solved the problem of error registration of multi sensor data fusion, they utilized an Unscented Kalman filtering method to train the neural network and thus proposed an adaptive algorithm for multi-sensor data fusion.

Although these methods have improved the measurement accuracy of the sensor node, multi-scale properties of sensor data was seldom considered, this will produce lower efficiency of data fusion and longer integration time. In this paper, a novel adaptive multi-sensor fusion algorithms based on multi-scale UKF is proposed. The algorithm proposed here makes advantage of real-time performance and optimal estimation of Unscented Kalman filter, meanwhile, multi-resolution and other characteristics of multi-sensor are also taken into account. Theoretical proofs and experimental results indicated that our proposed algorithm could efficiently improve the anti-jamming capability of detection system and ensure the reliability and accuracy of the sensor system.

2. System Description

Consider a distributed dynamic system with single model of multi-sensor.

$$x(N,k+1) = A(N,k)x(N,k) + w(N,k) \tag{1}$$

$$z(i,k) = C(i,k)x(i,k) + v(i,k) \tag{2}$$

where coefficient $i(i=L,L+1,\ldots,N)$ in (i,k) represents the number of dimension, N represents the thinnest dimension, L is the widest scale, $x(N,k)$ is the status vector on the thinnest dimension, $x(N,k)\in R^{n\times 1}$ is the system state vector, $A(N)\in R^{n\times n}$ is the system matrix, and larger dimension N indicates higher sampling rate N , $w(N,k)$ is the noise during the operation satisfying the following relationships :

$$E\left\{w(N,k)w^T(N,k)\right\} = Q(N,k)\delta_{kj} \tag{3}$$

$$E\left\{w(N,k)\right\} = 0 \tag{4}$$

$z(i,k)$ and $C(i,k)$ are system measurement vector and measurement matrix collected by sensors of different sampling rate on different dimensions, scale of sampling rate of the sensors between two dimensions is 2:1, namely, $x(i,k)=x(N,2N\text{-}ik)$, system noise $w(N,k)$ and observation noise $v(i,k)$ are white noise sequences with no relationship between each other and of zero-average values, and $v(i,k)$ is the measurement noise at different scales to meet

$$E\left\{v(i,k)v^T(i,k)\right\}=R(i,k)\delta_{kj} \tag{5}$$

$$E\left\{v(i,k)\right\}=0 \tag{6}$$

Here we have assumed that $x(N,k)$, $w(N,k)$ and $v(i,k)$ are uncorrelated[9].

3. Unscented Kalman Filter and Wavelet Transform

3.1 Unscented Kalman Filter

Kalman filter is designed to calculate the required measurement signals using the system observation equation and state equation, and the estimated signal is the most optimized state estimation in the significance of minimum mean square deviation of linear system [10] .With the continuous development of technology, there has been extended Kalman filter and Unscented Kalman filter. Unscented Kalman filter replaces the linear approximation of transmission mode with statistical properties in extended Kalman filter algorithm with the unscented transformation method, and after that, Unscented Kalman filter is produced [11].

Implementation steps of the Unscented Kalman filter is as follows:

1. Calculation of weights w_i corresponding to sample points using $\hat{x}_{k-1|k-1}$ and $P_{k-1|k-1}$ given previously, $w_i^m=w_i^c=0.5/\left(L+\lambda\right)$, here $i=1,2,\cdots,2L$, λ is the dispersion degree of sample points, w_i^m is the weight coefficient of the first-order statistical properties, and w_i^c is a function of second-order statistical properties of the required weight coefficients.

2. Propagation function of the state evolution equation related to the sample points should be calculated as follows: $x_i\left(k+1|k\right)=f\left(x_i\left(k|k\right)\right)$.

3. The statistical characteristic functions $\tilde{x}\left(k+1|k\right)$ and $P\left(k+1|k\right)$ should be calculated assisted with forecast sampling points $x_i\left(k+1|k\right)$ and weights w_i ,

$$\tilde{x}\left(k+1|k\right)=\sum_{i=0}^{2L}w_i^m x_i\left(k+1|k\right) \tag{7}$$

$$P\left(k+1|k\right)=Q\left(K+1\right)+\sum_{i=0}^{2L}w_i^c\left[x_i\left(k+1|k\right)-\tilde{x}\left(k+1|k\right)\right]\times\left[x_i\left(k+1|k\right)-\tilde{x}\left(k+1|k\right)\right]^T \tag{8}$$

4. Calculation of dispersion function derived from measurement equation of sample points that are obtained by utilizing UT transformation, $y_i\left(k+1|k\right)=hx_i\left(k+1|k\right)$.

5. The predicted value and the measured value of the statistical characteristics should be calculated by $\tilde{z}\left(k+1|k\right)=\sum_{i=0}^{2L}w_i^m y_i\left(k+1|k\right)$,

$$P_{ZZ}=R\left(K+1\right)+\sum_{i=0}^{2L}w_i^c\left[y_i\left(k+1|k\right)-\tilde{z}\left(k+1|k\right)\right]\times\left[y_i\left(k+1|k\right)-\tilde{z}\left(k+1|k\right)\right]^T \tag{9}$$

$$P_{XZ}=\sum_{i=0}^{2L} w_i^c\left[x_i\left(k+1|k\right)-X\left(k+1|k\right)\right]\times\left[y_i\left(k+1|k\right)-\hat{z}\left(k+1|k\right)\right]^T \qquad (10)$$

Here P_{ZZ} for the measurement error covariance matrix, P_{XZ} for the covariance matrix of the state vector and the measured values.

6. Amplification of Unscented Kalman filter should be calculated, simultaneously, it is required to updates system characteristic function $K\left(k+1\right)=P_{XZ}\cdot P^{-1}{}_{ZZ}$,

$$\hat{x}\left(k+1|k+1\right)=\hat{x}\left(k+1|k\right)+K\left(k+1\right)\left(z\left(k+1\right)-\hat{z}\left(k+1|k\right)\right) \qquad (11)$$

$$P\left(k+1|k+1\right)=P\left(k+1|k\right)-K\left(k+1\right)P_{ZZ}K^T\left(k+1\right) \qquad (12)$$

It indicates that the Unscented Kalman filter is relatively less complicated to implement but has higher estimation accuracy than the general Kalman filter and Extended Kalman filter, meanwhile, it can be applied to any kind of non-linear models [12]. Although Unscented Kalman filter has been widely used in the estimation of dynamic systems, it is established on the condition that the object is in the dynamic model and observation model of time domain dynamic, without considering the multi-scale characteristics of the object and is deficient in multi-scale analysis for target data [13]. However, the wavelet transform, as a powerful tool for multi-scale analysis, has exactly remedied the disadvantage of Unscented Kalman filter in multi-scale analysis of multi sensor.

3.2 Wavelet Transform

Wavelet transform of an energy-limited signal $f\in L^2(R)$ is defined as $Wf\left(a,b\right)=\int_{-\infty}^{+\infty} f\left(t\right)\psi_{a,b}\left(t\right)dt$, where the kernel function of this transform is $\psi_{a,b}\left(t\right)=\frac{1}{\sqrt{a}}\psi\frac{\left(t-b\right)}{a}$, $a>0, b\in R$. In the formula, $\psi(t)$ is known as the mother wavelet function and $\int_{-\infty}^{+\infty}\psi\left(t\right)dt=0$. $\psi_{a,b}\left(t\right)$ is sub-wavelets generated by the mother wavelet function, here a is scale factor , b is translation factor [14].

Considering signal sequence $x(i+1,k)\in(l^2)^n,(k\in Z)$ with scale i+1, the analysis and integrated form of discrete orthogonal wavelet transform are $x(i,k)=\sum_l h(2k-l)x(i+1,l)$ $d(i,k)=\sum_l g(2k-l)x(i+1,l)$, $x(i+1,k)=\sum_l h(2k-l)x(i,l)+\sum_l g(2l-k)d(i,l)$, where $x(i,k)$ and $d(i,k)$ is respectively smooth signal and detail signal of $x(i+1,k)$, $h(k)$ and $g(k)$ respectively correspond to the low-pass filter and high-pass filter [15]. Procedure of data processing utilizing wavelet transform method is as follows. First, the sensor signal is decomposed into approximations part of low frequency and detail part of high frequency, after that, approximate signals of low frequency is further decomposed, detail signals of high frequency is omitted because it is considered to be noise interference [16]. In this paper, the sensor data is processed to be decomposed with method of three-layer wavelet decomposition by choosing "db3" wavelet as a mother wavelet. Daubechies 3 wavelet function is shown in Figure 1.

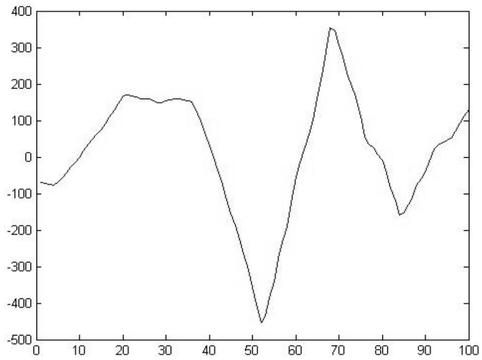

Figure 1. Daubechies 3 Wavelet Function

4. Multi-Scale Representation Method Of Signal

Assuming that the signal sequence $\{x(i,k)\}_{k\in Z}$ is divided into data blocks with length $M_i=2^{i-1}(i=N,\ldots,L,M,M_N)$

$$X_m(i)=\left|x^T(i,mM_i+1),x^T(i,mM_i+2),\cdots,x^T(i,mM_i+M_i)\right|^T \tag{12}$$

The dynamic relationship between status variable data block $X_{m+1}(N)$ and $X_m(N)$ can be described as:

$$X_{m+1}(N)=A_m(N)X_m(N)+W_m(N) \tag{13}$$

$$A_m(N)=diag\left\{\prod_{K=M}^{1}A(N,mM+k),\prod_{K=M+1}^{1}A(N,mM+k),\cdots,\prod_{K=2M-1}^{1}A(N,mM+k)\right\} \tag{14}$$

$$W_m(N)=B_m(N)\begin{bmatrix}w(N,mM+1)\\ \vdots\\ w(N,mM+M)\\ \vdots\\ w(N,mM+2M-1)\end{bmatrix} \tag{15}$$

$$B_m(N)=\begin{bmatrix}\prod_{K=M}^{2}A(N,mM+k) & \prod_{K=M}^{3}A(N,mM+k) & \cdots & 1 & \cdots & 0\\ 0 & \prod_{K=M+1}^{3}A(N,mM+k) & \cdots & A(N,mM+M+1) & \cdots & 0\\ \vdots & \vdots & \ddots & \vdots & \cdots & \vdots\\ 0 & 0 & 0 & \prod_{K=2M-1}^{M+1}A(N,mM+k) & \cdots & 1\end{bmatrix}$$

(16)

$Wm(N)$ has statistical properties $E\{W_m(N)\}=0$,

$$E\{W_m(N)W_m{}^T(N)\}=B_m(N)Q_m(N)B_m{}^T(N) \tag{17}$$

$$Q_m(N)=\{Q(N,mM+1,Q(N,mM+2),\cdots,Q(N,mM+2M-1)\} \tag{18}$$

Meanwhile, with regard to scale value i ,observation value and error, symbolled as $Z_m(i)$ and $Vm(i)$ respectively, can be written in the form of data blocks as equation (12) shows, then there has the following equalities

$$Z_m(i)=C_m(i)X_m(N)+V_m(i) \tag{19}$$

$$C_m(i)=diag\{C(i,mM_i+1)\delta(i),\cdots,C(i,mM_i+M_i)\delta(i)\} \tag{20}$$

$\delta(i)$ is a matrix of $n \times n^{2N-I}$ dimension, where the ultimate n columns compose a single matrix and other elements are zero. $V_m(i)$ has statistical properties $E\{Vm(i)\}=0$,

$$R_m(i) = diag\left\{R(i, mM_i+1), R(i, mM_i+2), \cdots, R(i, mM_i+M_i)\right\} \tag{21}$$

$$E\left\{V_m(i)V_m^T(i)\right\} = R_m(i) \tag{22}$$

5. Multi-Scale Information Fusion Estimation Algorithm

The initial value of data block $X_m(N)$ are $X_{0|0}(N)$ and $P_{0|0}(N)$, they can be calculated by the following equation

$$X_{0|0}(N) = \begin{bmatrix} X(N,1) \\ X(N,2) \\ \vdots \\ X(N,M) \end{bmatrix} = \overline{A}_0(N)x_0, \quad P_{0|0}(N) = \overline{A}_0(N)P_0\overline{A}_0^T(N) + \overline{B}_0(N)Q_0\overline{B}_0^T(N),$$

$$\overline{A}_0(N) = \begin{bmatrix} A(N,0) \\ A(N,1)A(N,0) \\ \vdots \\ \prod_{k=M-1}^{0} A(N,k) \end{bmatrix}, \quad \overline{B}_0(N) = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ A(N,0) & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \prod_{k=M-2}^{0} A(N,k) & \prod_{k=M-2}^{1} A(N,k) & \cdots & 1 \end{bmatrix},$$

$$\overline{Q}_0(N) = diag\left\{Q(N,0), Q(N,1), \cdots, Q(N,M-1)\right\} \tag{23}$$

Assuming that estimation value $X_{m|m}(N)$ of the m-th state vector $X_m(N)$ and estimation covariance error matrix $P_{m|m}(N)$ corresponding to $X_{m|m}(N)$ have been obtained, both of them are based on global information fusion, therefore the follow equations can be concluded.

$$X_{m+1|m+1}(N) = P_{m+1|m+1}(N)\left[\sum_{i=1}^{N} P_{i,m+1|m+1}^{-1} X_{i,m+1|m+1}(N) - (N-1)P_{m+1|m+1}^{-1}(N)X_{m+1|m+1}(N)\right] \tag{24}$$

$$P_{m+1|m+1}^{-1}(N) = P_{m+1|m}^{-1}(N) + \sum_{i=1}^{N}\left|P_{i,m+1|m+1}^{-1}(N) - P_{i,m+1|m}^{-1}(N)\right| \tag{25}$$

$$X_{i,m+1|m+1}(N) = X_{m+1|m+1}(N) + K_{i,m+1}(N) \times \left[Z_{m+1}(i) - C_{m+1}(i)X_{m+1|m}(N)\right] \tag{26}$$

$$X_{m+1|m}(N) = A_m(N)X_{m|m}(N), \; P_{m+1|m}(N) = A_m(N)P_{m|m}(N)A_m^T(N) + B_m(N)Q_m(N)B_m^T(N) \tag{27}$$

$$K_{i,m+1}(N) = P_{m+1|m}(N)C_{m+1}^T(i)\left[C_{m+1}(i)P_{m+1|m}(N)C_{m+1}^T(i) + R_{m+1}(i)\right]^{-1} \tag{28}$$

$$P_{i,m+1|m+1}(N) = \left[1 - K_{i,m+1}(N)C_{m+1}(i)\right]P_{m+1|m}(N) \tag{29}$$

Procedure of multi-scale data fusion algorithm for multi-sensor:

(1) Assuming that filter estimation is conducted on a signal of length L according to the observed data utilizing Unscented Kalman filter on a single scale N. Due to large amount of noise contained in the original signal, filtering effect is not ideal, but estimated sequence $X(N)$ can be obtained. This sequence is regarded as the initial sequence, of which the estimation value need a further correction on the scale axis.

(2) $X(N)$ wavelet is decomposed to the coarsest scale i to get decomposed sequence $\{X_H(N\text{-}1), X_H(N\text{-}2), \ldots, X_H(i),\ X_L(i)\}$, after reconstruction, $X'_1(N)$ get updated. Wavelet decomposition and reconstruction procedure of single-route sensor filtered by Unscented Kalman filter are shown in Figure 2.

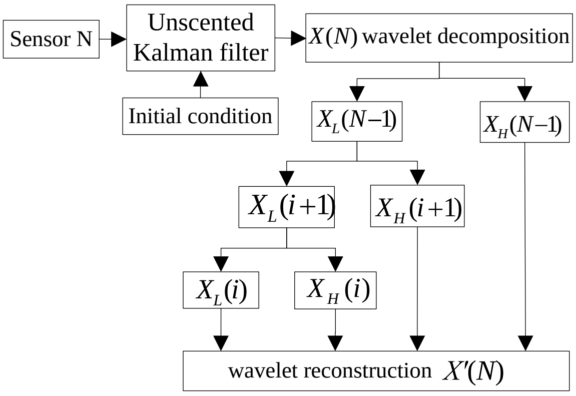

Figure 2. Single Sensor and Multi-Scale Wavelet Decomposition Flow Chart

(3) Other sensors repeat steps 1 and 2 mentioned above, the signal is first processed with Unscented Kalman filter, then multi-scale decomposition using wavelet transform is conducted on the signal to decompose the original signal into approximate part of low frequency and detail part of high frequency, afterwards, approximate signals of low frequency is further decomposed and detail signals of high frequency is omitted, finally reconstructed $X'_2(N)$ and $X'_3(N)$ are obtained.

(4) Adaptive weighted least squares (WLS) algorithm is applied on the three-route sensor signals to realize the weight adaptive fusion of multi-sensor, consequently, this can eliminate the unreliability of single-sensor detection data caused by factors such as uncertainty, diversity, complexity, redundancy that are related to the performance of detection information in sensor network. However, adaptive weight data fusion with multi-sensor and multi-scale used in this paper are capable of avoiding the uncertainty in single-sensor measurement, as a result, measurement accuracy and fusion efficiency get improved. Algorithm procedure of adaptive weight data fusion with multi-sensor and multi-scale are shown in Figure 3.

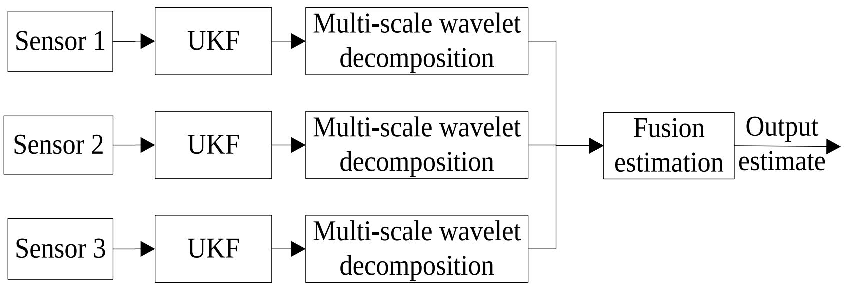

Figure 3. Multi-Sensor, Multi-Scale Data Fusion Model Flow Chart Algorithm

6. Experimental Results and Analysis

To test the effectiveness of the algorithm, experiment was carried out with computer simulation. Utilizing magnetic resistance sensor, the purpose was to measure and recognize magnetic flux when the experimental car travelled through the magnetic field. Aactual sensor data were collected to evaluate the proposed algorithm.

(1) Computer simulation

The simulation experiment is implemented in assistant of Matlab installed in a computer (Intel Core 2 of 2.0GHz, 4GB RAM). Assuming that the ideal sensor signal is a sinusoidal signal $X(n)$, the measurement signal is a random noise interference added to sinusoidal signal, measurement signals of sensor 1, sensor 2 and sensor 3 are $Y_1=X(n)$ +randn (1,1024) ×0. 2, $Y_2= X(n)$ +randn (1,1024) ×0. 25, $Y_3=X(n)$ +randn (1,1024) ×0. 3. These three sets of measurement signals Y_1, Y_2 and Y_3 are processed to be filtered respectively by Unscented Kalman filter, wavelet transform and adaptive data fusion with three-route signal. Take one group of the processed signals of measurement data as example, signal filtered are showed in Figure 4, which indicates a comparison among the original measurements, the UKF algorithm and the wavelet transform algorithm mentioned in [6] and [15], For convenience, Unscented Kalman filter method, Kalman filter and wavelet filter algorithm and the method proposed in this paper are respectively defined as method 1, method 2 and method 3. “db3” wavelet transforms is selected here and simultaneously, three-layer wavelet decomposition is conducted.

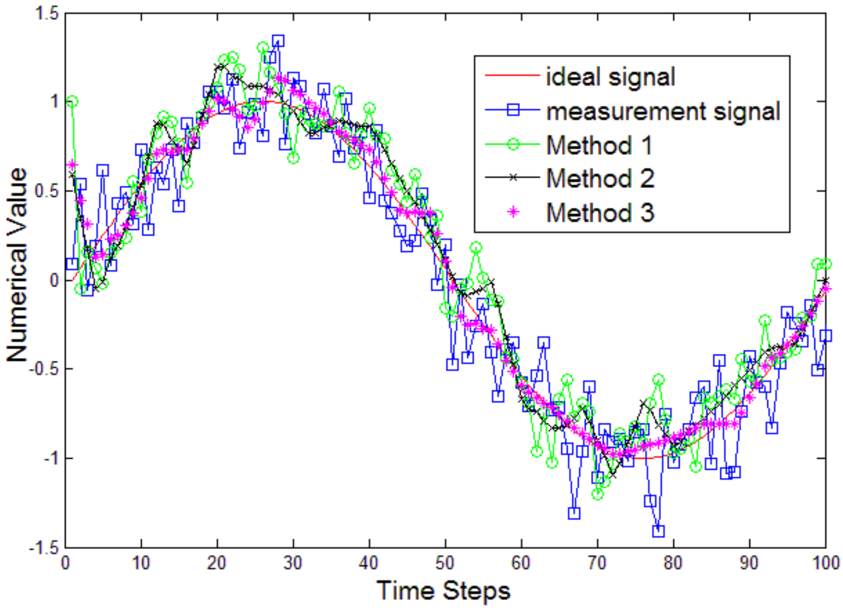

Figure 4. Comparison Of Several Algorithms For Filtering The Analog Signal

As can be seen from Figure 4, Unscented Kalman filter, wavelet analysis and adaptive fusion algorithm are effective in filter process for measurement signals, they have a commendable performance in maintaining original signal to guarantee that the signal is more stable and smoother. In order to further analyze the specific effects of each method in data processing, measurement data Y_1 in Figure 4 is taken as example to presents the error comparison of each algorithm. Figure 4 illustrates that Unscented Kalman filter has the largest error of all the three methods, followed by wavelet analysis algorithms with a little decrease of error. Processed by Unscented Kalman filter and wavelet analysis, adaptive weight data fusion algorithm produces the smallest error, indicating that adaptive-weight data fusion algorithm with multi-sensor, proposed in this paper and based on Unscented Kalman filter and wavelet analysis, is proved to be efficient in data filter process. Compared with other algorithms, our algorithm has higher accuracy and closer measurement to the real value.

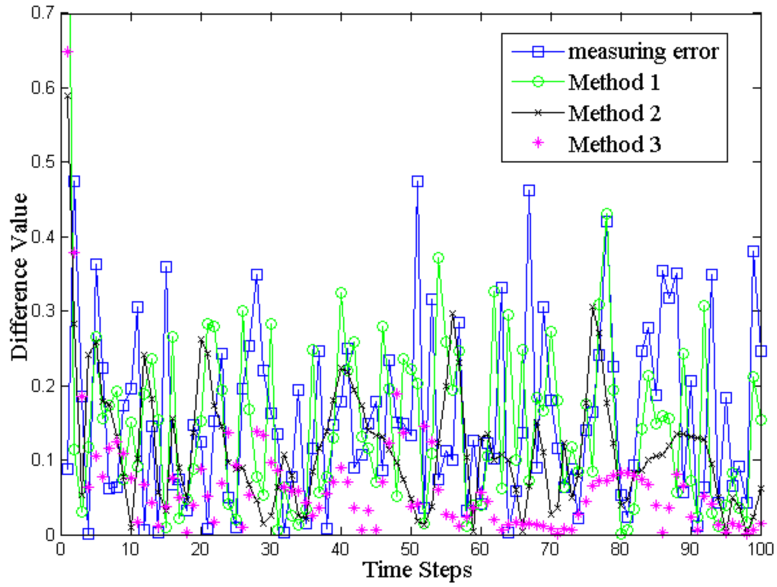

Figure 5. Error Comparison of Several Algorithms Filtered

In order to better illustrate the effect of these filter algorithms, mean absolute error(*MAE*), maximum relative error(*Max RE*) and root mean square error (RMSE) are adopted for evaluation, they are respectively defined as: $MAE = \frac{1}{n}\sum_{k=1}^{n}\left|x_k - x'_k\right|$, $Max\,RE = \max\left|x_k - x'_k\right|$, $RMSE = \sqrt{\sum_{k=1}^{n}(x_k - x'_k)^2 / n}$, where x_k is the actual value measured by the sensor, x'_k is the value filtered and processed by Unscented Kalman filter (Method 1), Unscented Kalman filter and wavelet analysis (Method 2), it is also a result of merged data utilizing adaptive-weight data fusion with three-way sensor data (Method 3) , n is the number of samples. Comparison of algorithm error is showed in the Table 1.

Table 1. Comparison of Several Algorithms of Error Values

Algorithm	MAE	Max RE	RMSE
The measured value	0.154	0.647	0.197
Method 1	0.139	0.569	0.173
Method 2	0.098	0.425	0.122
Method 3	0.063	0.229	0.078

In simulation experiment, by comparing error index of mean absolute error (*MAE*), maximum relative error (*Max RE*) and root mean square error (*RMSE*), a conclusion can be drawn that adaptive-weight data fusion algorithm with multi-sensor, proposed in this paper and based on Unscented Kalman filter and wavelet analysis, is proved to be more accurate and has closer measurement to the real value than original measurements and filter algorithm mentioned in references [6] and [15].

(2) Implementation of magnetic resistance sensor into actual measurement

This experiment was conducted in sunny outdoor environment to detect and recognize the moving target as well as testing the influence that experimental car contributed to magnetic resistance. Honeywell HMC5883L was selected as magnetic reluctance sensor to measure the variation of magnetic field when the car passed through. Due to the directionality problems of magnetic resistance sensor, directions along +Z axis of the three sensors were set perpendicular to the road surface and just in front of the road, +Y axis was parallel to the road and +X axis was vertical to the other two axes. In order to verify the measurement effect of magnetic resistance sensor and distinguish the orientation, the experimental car was operated to travel from north to south and then return in the opposite direction with a steady speed of 10 m/s, magnetic resistance sensors were placed in the path through which the car passed. Experiments were conducted repeatedly within a distance of 3m between the car and the sensors to guarantee the accuracy in magnetic detection of magnetic resistance sensor. One group of data generated by the three sensors was extracted for data processing, data of the three sensors are named Y_1, Y_2 and Y_3 respectively. It was necessary to standardize and normalize the sensor data to avoid the impact on the accuracy of data processing caused by large difference between them. Sensor data was normalized to interval [0, 1], operation were executed as follows: $x'_k = (x_k - x_{\min})/(x_{\max} - x_{\min})$, where x_k represented the measurement value of sensor at time k, x'_k represented normalized measurement value at time k, $x_{\min}$ and $x_{\max}$ were the minimum and maximum of all the measurement values at time k. Similar with simulation, the three groups of normalized signals Y_1, Y_2 and Y_3 would be processed using Unscented Kalman filter, wavelet decomposition and reconstruction and adaptive filter fusion with three-way signal, the filtered signal was shown in Figure 6, “db3” wavelet transform was chosen again when applying wavelet transform, simultaneously, three-layer wavelet decomposition was conducted.

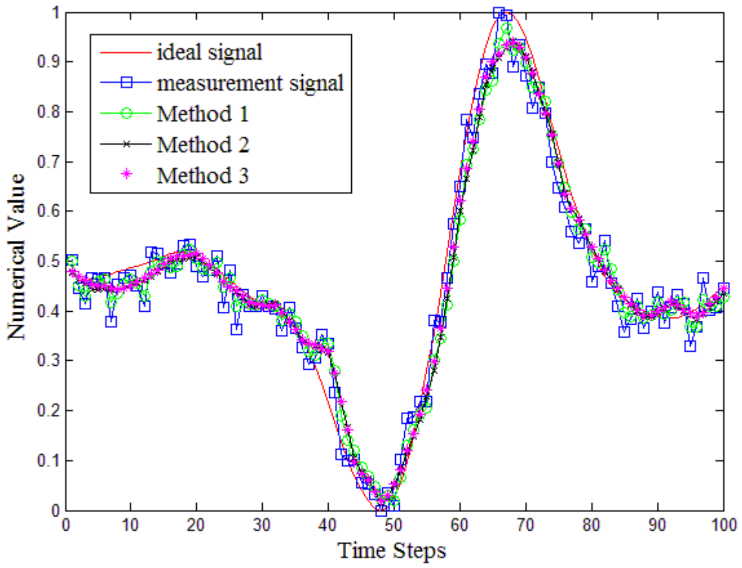

Figure 6. Comparison of Several Algorithms for Measuring Signal Filtering Processing

As can be seen from Figure 6, Unscented Kalman filter, wavelet analysis and adaptive fusion algorithm are effective in filter process for measurement signals, they have a commendable performance in maintaining original signal to guarantee that the signal is more stable and smoother. In order to further analyze the specific effects of each method in data processing, measurement data Y_1 in Figure 7 is taken as example to presents the error comparison of each algorithm. Figure 7 illustrates that Unscented Kalman filter has the largest error of all the three methods, followed by wavelet analysis algorithms with a little decrease of error. Processed by Unscented Kalman filter and wavelet analysis, adaptive weight data fusion algorithm produces the smallest error, indicating that adaptive-weight data fusion algorithm with multi-sensor, proposed in this paper and based on Unscented Kalman filter and wavelet analysis, is proved to be efficient in data filter process. Compared with other algorithms, our algorithm has higher accuracy and closer measurement to the real value, it possesses the best performance in signal processing and can effectively remove the external noise and the measurement error of sensor.

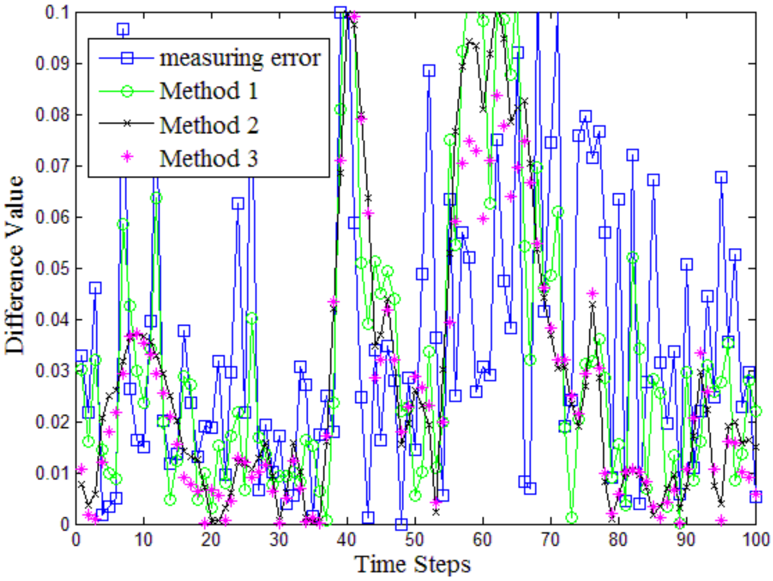

Figure 7. Error Comparison of Several Algorithms Filtered

In order to better illustrate the effect of these filter algorithms, *MAE*, *Max RE* and RMSE are adopted for the evaluation, error comparison of these algorithms are shown in Table 2.

Table 2. Comparison of several algorithms of error values

Algorithm	MAE	Max RE	RMSE
The measured value	0.036	0.118	0.046
Method 1	0.032	0.116	0.042
Method 2	0.028	0.095	0.038
Method 3	0.027	0.073	0.036

By comparing error index of mean absolute error (*MAE*), maximum relative error (*Max RE*) and root mean square error (*RMSE*), a conclusion can be drawn that adaptive-weight data fusion algorithm with multi-sensor is proved to be more accurate and has closer measurement to the real value than original measurements and filter algorithm mentioned in references.

7 .Conclusions

An adaptive fusion algorithm, based on multi-scale Unscented Kalman filter, was developed for multi-sensor signal filtering. This scheme combines multi-sensor data fusion and multi-scale analysis, taking advantages of real time, recursion and the optimized estimation of Unscented Kalman filter, meanwhile, other properties such as multi-resolution of multi-sensor was also utilized. Simulation experimental results indicated that, compared with other data fusion algorithms, the algorithm proposed in this paper could effectively enhance the anti-interference ability of detection system and reliability and accuracy of sensor system got guaranteed. However, for different implementation occasions, the algorithms have different requirements on sampling rate and real-time property of data processing, contributing to result variation when filter algorithm changes. Future research will emphasize on the choice ofg appropriate filter fusion algorithm according to different implementation backgrounds, which can execute proper fusion method on sensor data and satisfy the command of real time.

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