THE OPTIMIZATION ALGORITHM FOR BLIND PROCESSING OF HIGH FREQUENCY SIGNAL OF CAPACITIVE SENSOR

YUANJIA MA *
Guangdong Provincial Key Laboratory of Petrochemical Equipment Fault Diagnosis
Guangdong University of Petrochemical Technology, Maoming, China

Abstract. At present, the high frequency signal processing algorithm of capacitive sensor based on RBF has the problems of poor filtering effect and high level of signal detection and poor quality of signal separation. In this paper, an optimization algorithm for blind processing of high frequency signal of capacitive sensor is proposed. Based on the gradient method, and the calculation way of improved variance gradient estimation, the gradient of square single-error sample is taken as the estimation of mean square error to filter the capacitive sensor signal, and adjust the filtering step by adjusting the threshold, which can enhance the filtering effect of the sensor signal. The detection threshold is calculated by determining the false alarm probability. The decision condition is used to detect the target signal and get the high accuracy sensor signal. The initialization separation matrix is set according to the number of observation signals, and the correlation matrix of the source signal can be calculated, so as to achieve the efficient separation of high frequency signals. The experiment shows that the algorithm can effectively solve the problems existing in the current signal processing algorithm, and it is reliable.

1. Introduction. Capacitive sensor takes all kinds of capacitors as sensing elements, which can transforms the measured physical quantities or mechanical quantities into a conversion device of capacitance changes, in fact, it is a capacitor with variable parameters [8]. Capacitive sensors are widely used in the measurement of displacement, angle, vibration, velocity, pressure, component analysis, medium characteristics and so on. The most commonly used are the parallel plate type capacitor or the cylinder type capacitor [6]. The capacitive sensor has the advantages of good temperature stability. The capacitance value of a capacitive sensor is generally independent of the electrode material, which is beneficial to the selection of materials with low temperature coefficient. And because of its own heating is very small, the effect of it on the stability is very little [1,10]. The resistance sensor has copper loss, it is easy to generate heat and zero drift; while the capacitive sensor has the advantages of simple structure, easy manufacture and high accuracy, it can be very small, in order to achieve some special measurement; it can work under high temperature environment, strong radiation and strong magnetic field and so on, and can withstand large temperature changes, high pressure, high impact overload, etc.; It can measure ultra high temperature and low dropout as well as the magnetic field. Because the electrostatic attraction between the charged plates is very small, the energy of the capacitance sensor is very small. Because of its small dielectric

2010 Mathematics Subject Classification. 65D17.
Key words and phrases. Capacitive sensor, high frequency signal, blind processing.
* Corresponding author: Yuanjia Ma.
loss, the capacitance can be supplied with high frequency, so the system has high working frequency. It can be used to measure the parameters of high-speed change, to measure without contact and has high sensitivity. It can measure the vibration or eccentricity of rotary shaft and the radial clearance of small ball bearings and other without contact [9, 13]. Besides the advantages mentioned above, the electrostatic force between the charged plates is very small, and the input force and the input energy are very small. The measurable low pressure, force and small acceleration, displacement and so on, can be done very sensitive, high resolution, to induce 0.01 µm or even smaller displacement [5, 7].

In view of the advantages of simple structure, high temperature resistance, high radiation resistance, high resolution and good dynamic response, capacitive sensors are widely used in pressure, displacement, acceleration, thickness, vibration, liquid level and other measurements [4, 23]. But in the process of its use, there will be a high frequency signal. The processing of this kind of signal has become a major problem [14, 17]. In current, using the average value for processing the high frequency signal, it cannot detect the high frequency signal accurately, the separation effect of the high-frequency signal is poor, and it is difficult to effectively deal with the high frequency signal. In view of this, an optimization algorithm for blind processing of high frequency signal of capacitive sensor is proposed, which can achieve high efficiency processing of high frequency signal.

2. Optimization algorithm for blind processing of high frequency signal of capacitive sensor.

2.1. Signal filtering of capacitive sensor. In the blind processing of the high frequency signal of the capacitive sensor, the adaptive filtering method is used to filter the signal of the capacitive sensor. Adaptive filtering is a filter that can automatically adjust the parameters or structure of filter according to the change of surrounding environment, so as to satisfy some best criterion [2, 18]. In general, adaptive filtering only changes the parameters of the filter, but does not change its structure. The two main components of adaptive filtering are digital filter and adaptive algorithm with adjustable parameters. Adaptive filtering can be divided into open loop system and closed loop system. The main difference between them is whether the adaptive algorithm is related to the output of filter. If the two are related, the adaptive filter is closed loop system, otherwise it is an open loop system. The principle of adaptive filter is shown in Figure 1.

The control signal of open-loop adaptive filter only depends on the input of the system and has nothing to do with the output. The control signal of the closed-loop adaptive filter is decided by the input and output of the system [16]. Because of the better performance of the closed loop system, the application is more extensive. A closed loop adaptive filter is shown in Figure 1 (b). The output signal $y(n)$ which is adjustable after the digital filter is compared with the desired signal $d(n)$, forming the error signal $e(n)$. Through a certain adaptive algorithm, $e(n)$ is used to adjust the parameters of the filter to make $e(n)$ to meet some optimal criteria. Therefore, in fact, adaptive filter is a special filter that can automatically adjust its parameters. Once the input signal changes, it can track this change, automatically adjust the parameters, so that the performance of the filter is re-optimized.

LMS algorithm is used to filter the sensor signal and filter out the burr in the signal. On the basis of gradient method, according to the calculation way of the improved variance gradient estimation, it can take the gradient of the square of a
single error as the estimation value of the mean square error. Among them, the basic part of the horizontal filtering structure of joint parameter estimation is shown in Figure 2:

According to the input signal \( x(n) \) in Fig. 2, the output signal \( y(n) \) of the filter is calculated for the mean square error of the sample:

\[
V(W) = \frac{e(n)^2 \ast x(n)}{y(n)} \tag{1}
\]

The input vector of the adaptive filter, that is, the column vector \( X_k \), is calculated according to the formula 1.

\[
X_k = [x_k, x_{k-1}, \ldots] \ast V(W) \tag{2}
\]

Where, \( x_k \) and \( x_{k-1} \) represent the elements of the column vector centralization. The weighted vector, that is, the parameter vector of the filter is:

\[
W_k = [wx_k, wx_{k-1}, \ldots] \tag{3}
\]

Where, \( w \) represents the weight value. According to Fig. 2, the output of the filter can be obtained as follows:

\[
y_k = W_k X_k \tag{4}
\]
The cross correlation functions of $x(n)$ and $d(n)$ are:

$$r(n) = [d(n) \cdot x(n)]$$  \hspace{1cm} (5)

In order to reduce the filtering error, there are the following operations: the error signal $e_k$ is defined as the error between the expected output $d_k$ and the actual output $y_k$ of the filter, that is:

$$e_k = d_k - y_k$$  \hspace{1cm} (6)

Supposing that $W(n)$ is a constant vector, then there is:

$$V(W) = [e_k^2] = [d_k - X_k]$$

$$= [d_k - d_kX_kW_k - X_kd_k + W_kX_k]W_k$$

$$= [d_k] - 2[d_kX_kW_k] + W_k[d_kX_k]$$

$$= [d_k]^2 - 2[d_kX_k]W_k + [X_k]W_k$$  \hspace{1cm} (7)

Formula (7) is a mean square error performance function. In order to simplify the function, $R$ is defined as a square matrix.

$$R = [X_kX_k^T] = \begin{bmatrix} x_k & x_kx_{k-1} \\ x_kx_{k-1} & x_k \\ x_k & x_{k-1} \\ x_{k-1} & x_{k-2} \end{bmatrix}$$  \hspace{1cm} (8)

Where, $[X_kX_k^T]$ represents the set of parameter vectors of the filter, and $x_k^2$ represents the parameter vector of the filter. The matrix of formula (8) is called the input correlation matrix, the main diagonal line is the mean square of the input component, and the cross term is the correlation value between the input components. Similarly, it can be assumed that $P$ represents the cross correlation vector of the input vector $x(n)$ and the expected response $d(n)$, that is:
\[ P = \begin{bmatrix} R(0) \\ R(1) \\ \vdots \\ R(m+1) \end{bmatrix} \quad (9) \]

Where, \( m \) represents the cross factor. According to the formula (9), there are:

\[ V(W) = 2PW_k + d_kRW_k \quad (10) \]

In order to minimize the mean square deviation, it is necessary to make \( V(W) / W(n) = 0 \). Because

\[ V(W) / W(n) = -2P + 2RW_k \quad (11) \]

So when \( R \) is a full rank, the formula (11) has unique solution. The weight vector \( W^* = R^{-1}P \) of the best transverse filter is obtained from the inverse operation of the matrix. At this time, the adaptive adjustment process of the weight vector can be expressed as:

\[ W_{k+1} = W_k + \mu \quad (12) \]

Where, \( \mu \) represents the adjustment threshold, which is used to adjust the step length and maximize the filtering effect on the sensor signal. Its dimension is the reciprocal of the power of sensor signal [3,22].

To sum up, \( \varepsilon \) as an estimated value is selected directly. In each iteration of the adaptive process, the gradient estimates have the following form:

\[ \nabla = 2\varepsilon \begin{bmatrix} \varepsilon \\ \mu \end{bmatrix} \quad (13) \]

According to the gradient value of formula (13), an optimal form of adaptive filtering can be derived.

\[ W_{k+1} = W_k + \mu (-\nabla) = W_k + 2\mu X_k \quad (14) \]

The expected value of the guaranteed weight vector converges to the best solution \( W^* \), and the range of \( \mu \) is controlled in the following formula:

\[ 0 < \mu < \frac{1}{tr[R]} \quad (15) \]

Where, \( tr[R] \) represents the sum of diagonal elements of the \( R \) matrix.

2.2. **High frequency signal detection of capacitive sensor.** Based on the filtering of sensor signals in Section 2.1, the burr signal is removed and the high frequency signal is detected.

Supposing that a stationary determination signal of sensor’s high frequency is:

\[ a(N) = Ae^{\omega_0N} \quad (16) \]

Where, \( \omega_0 = 2\pi k_0/N \) represents the discrete frequency of the sensor signal, \( k_0 \) represents a real number that satisfies the condition \( |\omega_0| < \pi \), \( A \) represents the amplitude of the signal, \( N \) represents the number of sampling points, and \( e^{\omega_0N} \) represents the dispersion coefficient of stationary signal.

Assuming that a discrete sampling of an uncertain signal \( s(N) \) is performed at \( N \) points, there will be two possible scenarios for the signal \( s(N) \):

\[ s(N) = a(N) + \eta(N) \quad (17) \]
\[ s(N) = \eta(N) \quad (18) \]
Where, $\eta(N)$ represents the complex Gauss white noise of zero mean value, and the imaginary part and the real part are independent of each other, and the variance of $\eta(N)$ is $\sigma^2$. Formula (17) represents there is a certain signal $a(N)$ at the same time in signal $s(N)$ and the complex Gauss white noise, and formula (18) represents there is no definite signal $a(N)$ in the signal $s(N)$.

To sum up, the discrete Fourier transform of signal $s(N)$ is as follows:

$$s(k) = \xi \eta_F(k)$$  \hspace{1cm} (19)

In the formula (19), $\eta_F(k)$ represents a complex Gauss white noise with zero mean, and $\xi$ represents the discrete Fourier transform coefficient, and its transformation condition varies according to the case of $s(N)$. Supposing that $s(N)$ is the form in formula (17), then $\xi = 1$; assuming the $s(N)$ is the form in formula (18), then $\xi = 0$.

In summary, the spectrum $|s(k)|^2$ of the signal $s(N)$ is:

$$|s(k)|^2 = s(k) s^*(k)$$  \hspace{1cm} (20)

Where, $s^*(k)$ represents the weighted spectrum. The estimation of $\xi$ is to determine whether the signal $a(N)$ exists or not. The estimated value of $\xi$ can be expressed as:

$$\xi = \begin{cases} 
1, & \max |s(k)|^2 > q_{s^2} \\
0, & \max |s(k)|^2 \leq q_{s^2} 
\end{cases}$$  \hspace{1cm} (21)

Where, $q_{s^2}$ represents the detection threshold.

By testing the threshold, the article considers the following detection:

1. There is a definite signal $a(N)$ and $\xi = 1$ in the signals $(N)$. And in the process of detection, $\max |s(k)|^2 > q_{s^2}$, $\xi = 1$.

2. There is a definite signal $a(N)$ and $\xi = 1$ in the signal $s(N)$. But in the process of testing, $\max |s(k)|^2 \leq q_{s^2}$, that is, $\xi = 0$. In this case, the determination of the existing signal $a(N)$ is not detected, which is called a leak detection.

3. There is no definite signal $a(N)$ and $\xi = 0$ in signal $s(N)$. In the process of detection, $\max |s(k)|^2 \leq q_{s^2}$, that is, $\xi = 0$.

4. There is no definite signal $a(N)$ and $\xi = 0$ in signal $s(N)$. But in the process of detection, $\max |s(k)|^2 > q_{s^2}$, or $\xi = 1$, it is called false alarm.

The following is the derivation of detection threshold under the condition of constant false alarm probability. The false alarm probability $p_{fa}$ can be defined as:

$$p_{fa} = p[|\eta_F(k)| > q_{s^2}] = 1 - p[|\eta_F(k)| \leq q_{s^2}]$$  \hspace{1cm} (22)

Among them, $p[|\eta_F(k)| \leq q_{s^2}]$ represents the occurrence probability of event $|\eta_F(k)| \leq q_{s^2}$.

For a random variable of Gauss distribution, the absolute value of the quadratic square is a random variable, so there is:

$$p[|\eta_F(k)| \leq q_{s^2}] = 1 - \frac{q_{s^2}}{\sigma^2}$$  \hspace{1cm} (23)
According to the formula (22) and the formula (23), we know that:

\[ p_{fa} = 1 - \left(1 - \left(\frac{q_{sx}}{\sigma^2}\right)^2\right) \]  
(24)

According to the formula (24), as long as the false alarm probability \( p_{fa} \) is known, the corresponding detection threshold of \( q_{sx} \) can be obtained.

\[ q_{sx} = -\ln \left(1 - \sqrt{1 - p_{fa}}\right) \sigma^2 \]  
(25)

To sum up, the process of Fourier detection for signal \( s(N) \) can be summarized as follows:

1. the probability of false alarm is determined.
2. the threshold of the calculation is calculated.
3. the judgment condition is used to judge whether the target signal exists.

2.3. Blind separation for high frequency signal of capacitive sensor. In order to identify and utilize high frequency signals in capacitive sensors and remove redundant signals, the blind source separation algorithm is used to separate high-frequency signals based on the detection of sensor signal burr and high-frequency signal in Section 2.1 and 2.2. First, the linear instantaneous aliasing model of the source signal is established, as shown in Figure 3.

In Figure 3, the mixed matrix \( B \) is the simulation of the propagation characteristics in the signal receiving process, and the prior information of the mixed matrix \( S(t) \) and the source signal is unknown. Only the mixed signal \( z(t) = B \ast S(t) \) can be received. The aim of blind source separation is to recover the independent source signal \( S(t) \), that is, the high frequency signal of the sensor, according to the observed signal \( z(t) \). To sum up, the blind signal separation model is as follows:

\[ Y(t) = \rho_{i\phi} \ast z(t) \]  
(26)

Among them, \( \rho_{i\phi} \) represents the separation matrix, and on the basis of the formula (26), it can be obtained:

\[ Y(t) = \rho_{i\phi} \ast z(t) = \rho_{i\phi} \ast B_{i\phi} \ast S(t) \]  
(27)

![Figure 3. The linear instantaneous aliasing model of the source signal](image-url)
Assuming that the number of observation signal $\iota$ is equal to the number of source signal $\phi$. By finding the separation matrix $\rho_{\iota\phi} = B^{-1}$ by iterative optimization algorithm, we can achieve the separation of source signals, and $Y(t)$ is the estimated value of the separated source signals. However, in practical problems, the situation of that the number of observed signals is equal to the number of source signals is less, so it is necessary to study how to obtain $\rho_{\iota\phi}$ [12, 21].

In order to separate the source signal from the observation signal and avoid the estimation of the number of the source signals before the blind separation, the $\iota \times \phi$ dimensional separation matrix $\rho_{\iota\phi}$ is used, of which $\iota$ is the number of observation signals, and $\phi$ is the number of the source signals, and the separation model is formula (27). At this time, the $\iota$ dimension signal will be separated by the formula (27). In the blind source separation algorithm of the number of known or estimated, when the global matrix of blind separation algorithm is iterated and updated to become generalized switching matrix, the output signal of separation algorithm is almost equivalent to the real source signal (without considering signal amplitude and sequence change), then it thinks of that the blind separation has been reached, namely the real separation of source signals. For the blind source separation model of unknown number, assuming that all the real source signals are reconstructed at least once, the purpose of blind separation is achieved [15, 19]. Therefore, when the separation signal of algorithm model formula (27) has $\phi$ independent source signal component, and the other $\iota - \phi$ signal components are copies or zero signals of one or more independent source signal components, it can be considered that the algorithm achieves the purpose of signal separation. Through several computer simulations, it is found that $\iota$ needs more than $\phi$.

In order to achieve the accurate separation of the source signals, the next step is to calculate the correlation coefficient matrix for the $\iota$ separated source signals.

$$
C = \begin{bmatrix}
C(S_1, S_1) & C(S_1, S_2) & \cdots & C(S_1, S_\iota) \\
C(S_2, S_1) & C(S_2, S_2) & \cdots & C(S_2, S_\iota) \\
\vdots & \vdots & \ddots & \vdots \\
C(S_\iota, S_1) & C(S_\iota, S_1) & \cdots & C(S_\iota, S_\iota)
\end{bmatrix}_{\phi \times \phi}
$$

(28)

Among them, $[\cdot]$ represents the value of the correlation coefficient matrix elements of $\iota$ source signal. The diagonal element of the matrix in formula (28) is the autocorrelation coefficient of the separation signal. Therefore, the diagonal elements are 1, and the other elements of the matrix represent the cross correlation coefficient between the $\iota$ separate signals. If an element is approximately equal to 1 or $-1$, or equal to 1 or $-1$, it means that two signals are very similar, or for the same signal, or they are mutually opposite to each other. In signal processing, one of them is considered as a redundant of another signal [11, 20]. By calculating the correlation coefficient matrix $C$, the same or similar signals are merged and redundant signals are removed, and the accurate separation of the $\phi$ source signals is realized.

### 3. Experimental results and analysis.

The overall effectiveness of the proposed algorithm is verified, and a capacitive temperature and humidity sensor are used to do the experiment, as shown in Figure 4. The experimental platform is built on Simulink, and the output signal of the sensor is 0–5V voltage signal. The sensitive component of the sensor is MSR-3B type polymer humidity sensitive capacitance. The main parameters of the sensor are as:
(1) capacitance: 130–170pF (0%-100%RH);
(2) working temperature: −40–70°C;
(3) sensitivity: 0.25pF/%RH;
(4) temperature coefficient: less than or equal to 0.15% RH/°.

The experiments are carried out in the following aspects:
(1) the filtering effect of the algorithm;
(2) the detection effect of the algorithm on the high frequency signal of the sensor;
(3) the separation effect of the algorithm on the high frequency signal of the sensor.

The results of the experiment are as follows:
Analysis of Figure 5, experimental results show that the current algorithm is locally superior to the operation and filtering effect of sensors, but the overall is poor, which can not remove the burrs of sensors and fluctuate greatly. The signal to noise ratio curve of this algorithm is relatively slow, and it has been in a high signal to noise ratio state. In this paper, the algorithm to filter the sensor signal by using the LMS algorithm, the glitch in the signal is filtered off. Based on gradient method, and the estimation method of the improved gradient variance value, the gradient of the single-error square is taken as the estimation of mean square error, filtering the capacitive sensor signal. The adjustment threshold is used to adjust the filter step size, which can enhance the filtering effect of sensor signal to a maximum extent, and has absolute superiority compared with the current algorithm.

The circle in Figure 6 represents the high frequency signal of the sensor, and the triangle represents the low frequency signal, in order to observe the detection effect of different algorithms on high frequency signals.

As shown in Figure 6, the high frequency and low frequency signals are distributed in different laws in the operating network of a capacitive sensor. The accuracy of the current algorithm detecting high-frequency signals is low. Compared with the current algorithm, the proposed algorithm detects the threshold by determining the false alarm probability, and detects the high frequency signal of sensors by judging the existence of target signals by judging conditions. Among them, the false alarm probability and the detection threshold are determined, which improves the detection precision of the proposed algorithm.

About the experiment of the separation effect of high-frequency signal, in Figure 7 (a), the five corners represent the high frequency signal of the actual
Figure 5. Comparison of filtering effect of sensor operation by different algorithms

(a) state of operation by the original sensor

(b) the filtering effect of sensor operation by the current algorithm

(c) the filtering effect of sensor operation by the proposed algorithm
The current algorithm for detecting high frequency signal of sensor and the rest are redundant signals, so as to observe the separation effect of different algorithms on the high frequency signal of sensor. The analysis of the experimental results of Figure 7 shows that there are many different frequency signals or the same frequency redundant signals in the experimental model of the separation effect of the sensor’s high frequency signal. When the current algorithm is used to separate the high frequency signal of the sensor, there are still a few redundant signals, and the separation effect is not ideal. Using this algorithm to separate the high frequency signal sensor, linear instantaneous mixing model is established for the source signal, and in the blind source separation algorithm in which the number of source signals is known or estimated, when the global matrix iteration of the blind separation algorithm is updated to a generalized switching matrix, the output signal of the separation algorithm is basically the same as the copy of the real source signal. Then we can think that the purpose of blind separation processing has been achieved, which realizes the separation of real source signals. In order to achieve the accurate separation of the source signals, the correlation coefficient matrix of the separated source signals is calculated and the same or similar signals are merged to remove the redundant signals, which greatly improves the separation effect of the high-frequency signal.
4. **Conclusions.** Capacitive sensor is made up of upper and lower electrodes, insulators and substrates. When using non-contact measurement, capacitive sensor has average effect, which can reduce the influence of rough surface and so on, and has wide application area. However, the high frequency signal processing in capacitive sensor has been optimized. In this paper, we use the operation of signal filtering, high-frequency signal detection and separation to achieve effective processing of high-frequency signal. In the future research, the article will start from the following aspects:
there are many processing aspects of the high frequency signal of the sensor, which can be studied in the related fusion of high frequency signals.

(2) on the determination of the detection threshold of the high frequency signal for the sensor, it can be further optimized to improve the detection effect of the high frequency signal.

Acknowledgments. The research is supported by the Guangdong Young Innovative Talents Foundation of Department of Education (No. 650019).

REFERENCES

[1] G. A., Fabrication of fiber-optic distributed acoustic sensor and its signal processing, in American Journal of Hypertension, 5 (2015), 483–491.

[2] A. Bertrand and M. Moonen, Distributed canonical correlation analysis in wireless sensor networks with application to distributed blind source separation, IEEE Transactions on Signal Processing, 63 (2015), 4800–4813.

[3] X. R. Chen, Nonlinear distortion suppression algorithm of complex optical sensor network communication, Bulletin of Science & Technology, 58–60.

[4] Y. Chen, Stability of polytopic-type uncertain singular stochastic systems, Journal of Interdisciplinary Mathematics, 20 (2017), 47–62.

[5] H. D., Y. K., X. L. and et al, Optimal parameter estimation under controlled communication over sensor networks, IEEE Transactions on Signal Processing, 63 (2015), 6473–6485.

[6] J. Edwards, Signal processing powers a sensor revolution [special reports], IEEE Signal Processing Magazine, 33 (2016), 13–16.

[7] F. Erden, S. Velipasalar, A. Z. Alkar and A. E. Cetin, Sensors in assisted living: A survey of signal and image processing methods, IEEE Signal Processing Magazine, 33 (2016), 36–44.

[8] H. F., Intelligent sensor networks - the integration of sensor networks, signal processing and machine learning, Measurement Techniques, 535–537.

[9] A. Gunes and M. B. Guldogan, Joint underwater target detection and tracking with the bernoulli filter using an acoustic vector sensor, Digital Signal Processing, 48 (2016), 246–258.

[10] A. Hassani, A. Bertrand and M. Moonen, Gevd-based low-rank approximation for distributed adaptive node-specific signal estimation in wireless sensor networks, IEEE Transactions on Signal Processing, 64 (2016), 2557–2572.

[11] S. P. Jia, J. Zeng and L. R. Guo, Designing implementation of signal sorting semi-physical simulation analysis platform, Journal of China Academy of Electronics & Information Technology, 59–65.

[12] S. Kisseleff, I. F. Akyildiz and W. H. Gerstacker, Digital signal transmission in magnetic induction based wireless underground sensor networks, IEEE Transactions on Communications, 63 (2015), 2300–2311.

[13] J. Li, H. Pang, F. Guo, L. Yang and W. Jiang, Localization of multiple disjoint sources with prior knowledge on source locations in the presence of sensor location errors, Digital Signal Processing, 40 (2015), 181–197.

[14] H. L. Liu, Planning wetland ecology-based outdoor education courses in taiwanese junior high schools., Eurasia Journal of Mathematics Science & Technology Education, 13 (2017), 3261–3281.

[15] B. M., C. D., M. A. and et al, Wavelet dt method for water leak-detection using a vibration sensor: an experimental analysis, Jst Signal Processing, 396–405.

[16] J. Ma and S. Sun, Optimal linear estimators for multi-sensor stochastic uncertain systems with packet losses of both sides, Digital Signal Processing, 37 (2015), 24–34.

[17] K. A. Mamun, C. M. Steele and T. Chau, Swallowing accelerometry signal feature variations with sensor displacement, Medical Engineering & Physics, 37 (2015), 665–673.

[18] R. K. Miranda, J. P. C. L. D. Costa and F. Antreich, Low complexity performance assessment of a sensor array via unscented transformation, Digital Signal Processing, 190–198.

[19] S. S. Q., L. J. Y., J. C. D. and et al, Least-square weighted smoothing filter technology applied in magnetic resonance sounding signal processing, Journal of Jilin University (Engineering and Technology Edition), 98 (2016), 985–995.

[20] L. Staiger, On the hausdorff measure of regular omega-languages in cantor space, Discrete Mathematics and Theoretical Computer Science, 17 (1998), 357–368.
[21] H. Y. Xiang, L. I. Ting-Ting, L. I. He and Y. Yang, Roller coaster acceleration signal processing based on matlab, *Computer Simulation*, 245–249.

[22] H. Ying, L. Cheng-Chew and C. Sheng, Triple i fuzzy modus tollens method with inconsistent bipolarity information, *Journal of Intelligent & Fuzzy Systems: Applications in Engineering and Technology*, 32 (2017), 4299–4309.

[23] G. Zheng and B. Wu, Polarisation smoothing for coherent source direction finding with multiple-input and multiple-output electromagnetic vector sensor array, *Iet Signal Processing*, 10 (2016), 873–879.

Received August 2017; revised December 2017.

E-mail address: Mayuanjia@foxmail.com