

Sensors Fault Detection and Diagnosis Based On Morphology-wavelet Algorithm

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Abstract—This paper proposed a novel method to fault detection and diagnosis of sensors using trend analysis of input and output signals related to the sensor itself. Firstly, generalized morphological filter with multi-structure elements is designed to filter the random noise and impulse noise in sensor's input and output signals. And secondly, to effectively extract the incipient fault and abruptly fault characteristic, a wavelet transform was used to decompose and analyze the filtered signals in this paper. Through the Multi Resolution Analysis (MRA), the fault can be located accurately. There typical sensor faults such as fix, gain, bias, drift faults were studied. The simulation results show that this algorithm is capable of locating accurately.

Keywords—fault detection and diagnosis, Morphology-wavelet, sensor, Multi Resolution Analysis (MRA)

I. INTRODUCTION

Process supervision and control rely fundamentally on the process measure information obtained by sensors. Consequently, a sensor's fault may be lead to the measurements corrupted or the whole control system ineffective. For this reason, fault detection and diagnosis of sensors have received particular attention.

The methods of model-based and model-freed about sensor fault detection and diagnosis were studied in these years. In reference [1], the Kalman filter was designed to the diagnosis of incipient sensor faults. However, the unknown inputs such as system disturbances and noises were not considered in this paper. A new descriptor estimator was constructed via the Linear Matrix Inequality (LMI) to decouple both the input and output disturbances completely and simultaneously estimate the descriptor system state. Then the new estimator was applied to the sensor fault diagnosis [2]. However, the diagnosis scheme was relayed on the model. In the large-scale systems, model-based methods are inefficiently when the process model is not available or not easy to obtain.

Recently, the knowledge-based approaches in sensor's detecting and diagnosing also have been published in [3]. In reference [4], the multisensor information fusion technique based on Dempster-Shafer theory is applied to the sensors fault detection and diagnosis. But there are some drawbacks. If the number of sensor is larger, the method can be indeed heavy to computing. In reference [5], to address the problems associated

with detecting and identifying faults that occur in the sensor of dynamical systems with discrete-valued input and output signals.

At present, wavelet analysis, which processes signals with both time and frequency domain localizations, is powerful tool for processing transient signals to handle the problems of model-restricted. Wavelet transform was introduced in to the sensor of abrupt diagnosis [6]. The major drawbacks of wavelet analysis approaches mentioned above is that it is unsuitable for extracting abrupt fault information. But due to the limited number of scales, a single wavelet amplitude map has not enough scales to describe all details of the signal. To make up for the deficiency of wavelet transform in the application of abrupt diagnosis, multi-wavelet packets transform was introduced into abrupt sensor fault diagnosis[7]. This method has been proved to be quite effective in the detection of sensor abrupt fault. However, when the sensor signal was changed slowly (incipient faults), the method is not accurately. Because wavelet transform requires the use of a window of adequate length and a high frequency to ensure that the all details of fault component is extracted by the wavelet transform. But the signal is difficult to be separated from interference noise when the frequency is too much high. To make sure wavelet transform relatively extract full-valued information, some new techniques are adopted to remove random noise (white noise and impulse noise).

Mathematical Morphology (MM) is developed from set theory and integral geometry, and is concerned with the shape of a signal waveform in the complete time domain rather than the frequency domain. MM has been widely applied in the areas of image processing [8], pattern recognition; signal processing [9] for their robustness in preserving the shape while suppressing the noise. MM can be developed as an efficient nonlinear filter. Using morphological filters, the radical shape of the disturbed can be recognized, even if the original is mixed with strong noise (white noise and impulse noise). In addition, MM has the feature of easy calculation and implementation.

Therefore, it is desired to seek for a systematic way to deal with how to exactly detect and diagnose the fault when the full-valued information was drowned by the noise. In this paper, the method of morphology-wavelet to deals with the detection and

diagnosis of sensors was proposed. Firstly, generalized morphological filter with multi-structure elements is designed to filter the white noise and impulse noise in sensor's input and output signals. And secondly, to effectively extract the drifting incipient fault and abruptly fault characteristic, a wavelet transform was used to decompose and analyze the filtered signals in this paper. Through the Multi Resolution Analyzing (MRA), the fault can be located accurately. The efficiency and relativity of the morphology-wavelet algorithm are verified by super-heated steam temperature sensor of power plant.

II. THEORY OF MORPHOLOGICAL FILTER AND WAVELET TRANSFORM

A Morphological Filter

The Mathematical Morphology (MM) is nonlinear signal transformation concerned with the shape of a waveform in time domain rather than frequency. The morphological filtering technique is to process signals by a function, known generally as Structuring Element (SE) or the structuring function in order to capture signals, keep detail and reduce noises.

In MM, dilation and erosion are two basic operations. Using the umbra of a function, the binary MM operators can be extended to 1-dimension (1-D) and n-dimension (n-D) signals. Here we only present the 1-D transformation.

Definition 1 Let $f(n)$ and $g(n)$ denote two real-valued functions defined on the two discrete domain $F = \{1, 2, \dots, N\}$ and $G = \{1, 2, \dots, M\}$, respectively. It is further assumed that $M < N$. $f(n)$ is an input signal and $g(n)$ is a structuring element. Then the four basic morphological operations are defined by:

$$\text{Erosion: } (f \ominus g)(n) = \min_{p=1,2,\dots,M} \{f(n+m) - g(m)\} \quad (1)$$

$$\text{Dilation: } (f \oplus g)(n) = \max_{p=1,2,\dots,M} \{f(n-m) + g(m)\} \quad (2)$$

$$\text{Opening operator: } (f \circ g)(n) = (f \ominus g \oplus g)(n) \quad (3)$$

$$\text{Closing operator: } (f \bullet g)(n) = (f \oplus g \ominus g)(n) \quad (4)$$

Where " \ominus " is the symbol of erosion. " \oplus " is the symbol of dilation. " \circ " is the symbol of opening. " \bullet " is the symbol of closing.

Opening and closing are two operators commonly used in morphological filter and they smooth a signal in different ways. Opening can be thought of as moving the structuring element beneath the graph of the signal and removing positive impulse that do not match the shape of the structuring element. Closing can be thought of as moving the structuring element above the graph the signal and filtering negative impulse that the structuring element does not fit into. In morphological filtering, the results of the operations depend on not only the form of morphological transformation but also the size and shape of the structuring element. Usually, a flat structuring element which

the values are all zero is used if there is no a priori knowledge about the profile of the signal.

In (3) and (4), opening and closing filters defined by Maragos use the same structuring element. In order to effectively remove all positive and negative impulsive noise and suppress additive white noise in signals, the generalized opening and closing filter with different sized structuring elements are proposed as follows.

In order to improve existing methods, this paper constructs a kind of parallel composite filter with different SE. This kind of filter also keeps more useful information. Flat line function can be chosen as the shape of SE in this paper.

$$\text{First level: } g_1(n) = \{0, 0, 0, 0, 0, 0, 0\} \quad (5)$$

$$\text{Second level: } g_2(n) = \{0, 0, 0, 0\} \quad (6)$$

Suppose that there is an input signal $f(n)$ and SE aggregation $\{g_1, g_2\}$. The structures of new morphological filters are:

$$\psi_{oc}[f(n)] = \text{MAX}(OC_{g_1}, OC_{g_2}) \quad (7)$$

$$\psi_{co}[f(n)] = \text{MIN}(CO_{g_1}, CO_{g_2}) \quad (8)$$

$$\text{Where, } OC_{g_i} = (f \circ g_i \bullet g_i)(n) (i=1,2)$$

$$CO_{g_i} = (f \bullet g_i \circ g_i)(n) (i=1,2)$$

$$\text{Thus } y(n) = \frac{1}{2}(\psi_{oc} + \psi_{co}) \quad (9)$$

Then the output signal of morphological filter is the average value of both outputs, this result could be much approach the practical signal.

B Wavelet Transform

Wavelet transform has powerful ability in signal processing. Since wavelet transformation can localize sensor signal characteristics both in time and frequency domain.

The study of sensor fault detection and diagnosis is based on the singularity of continuous wavelet transformation. Firstly, according to the wavelet transformation of input and output signals, extract the useful information to locate the singularity of input and output signals. Secondly, through compare the maximum which is mutated by input and output signals, get the ride of the maximum which is mutated by input signals. Then the other maximum are the faults of sensor.

The wavelet transform of a continuous signal $f(t)$ is defined as

$$WT_f(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t) \psi\left(\frac{t-b}{a}\right) dt \quad (10)$$

Where

$WT_f(a, b)$ is the wavelet transform of coefficient. $\psi(t)$ is the mother wavelet, a is the time scaling factor and b is the time shifting factor.

C Multi-Resolution Analysis

The concept of multi-resolution is described as follows: square integrable function $f(t) \in L^2(R)$ can be regarded as the limit case of certain gradual approach, every approximation is the result of the smoothness of low-pass smooth function $\varphi(t)$ towards $f(t)$, the smooth function $\varphi(t)$ is also expanding and contracting gradually while approaching by degrees, that is, the analyzed function $f(t)$ is approached gradually by using different resolution.

Here is a realization of signal Multi-resolution decomposition.

As the orthogonal WT above is adopted, multi-resolution analysis can be applied to decompose random signal $f(t) \in L^2(R)$ (square integrable function) as follows [12]:

$$f(t) = \sum_{k \in Z} c_{j,k} \varphi_{j,k}(t) + \sum_{m=1}^j \sum_{k \in Z} d_{m,k} \psi_{m,k}(t) \quad (11)$$

$$\text{Where } c_{j,k} = \langle f(t), \varphi_{j,k}(t) \rangle \quad (12)$$

$$d_{j,k} = \langle f(t), \psi_{j,k}(t) \rangle \quad (13)$$

The decomposing coefficient $c_{j,k}$ is called discrete smooth approach signal, and $\varphi_{j,k}(t)$ is called scale function; the decomposing $d_{j,k}$ is called discrete detail signal, which reflects the detail difference between two smooth approaches of any adjacent scale, and $\psi_{j,k}(t)$ is called wavelet function.

In order to further apprehend multi-resolution analysis, here takes a decomposition of a 3 scales for example, the wavelet decomposing tree is shown in Fig. 1.

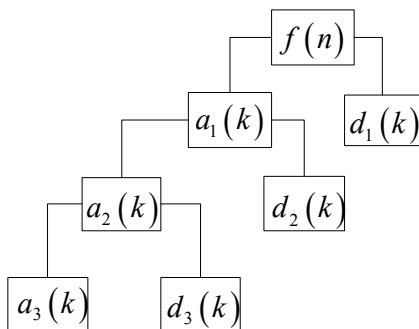


Fig1. The block diagram of 3 scales multi-resolution decomposing tree.

III. MORPHOLOGY-WAVELET ALGORITHM FOR FAULT DETECTION

Wavelet transform has been applied in various areas benefiting from its outstanding ability of detecting singular signal and the great filtering ability, while morphological filter is a new non-linear tool for digital signal processing; both of them have their superiorities. Wavelet algorithm is superior to the morphological filter in aspect of the filtering effectiveness on white noises, but it is less effective on suppressing the impulsive noises. This paper presents a novel type of integrated filter named morphology-wavelet algorithm. Firstly, generalized morphological filter with multi-structure elements is designed to filter the white noise and impulse noise in sensor's input and output signals. Then, the multi-resolution wavelet transform applied to extract the drifting incipient fault and abruptly fault characteristic. And, wavelet transform can also advance to filter ability, especially deal with white noise.

Consider linear systems:

$$y(s) = G(s)u(s) + \Delta G(s)u(s) + E(s) \quad (14)$$

Where $y(s)$ is output signal; $u(s)$ is input signal; $G(s)$ is system transfer function. $\Delta G(s)$ reflect the change of system parameters; $E(s)$ is random noise.

Morphology-wavelet algorithm for fault detection and diagnosis of this system is presented in 4 steps. The framework of the morphology-wavelet algorithm is shown in Fig.2.

Step1: The generalized morphological filter with multi-structure elements is employed to filter the white noise and impulse noise in sensor's input $u(t)$ and output $y(t)$. The filter's outputs are $y_u(t)$ and $y_y(t)$ respectively.

$$y_u(t) = \frac{1}{2}[(u(t) \circ g_i \bullet g_i) + (u(t) \bullet g_i \circ g_i)] \quad (i=1,2) \quad (15)$$

$$y_y(t) = \frac{1}{2}[(y(t) \circ g_i \bullet g_i) + (y(t) \bullet g_i \circ g_i)] \quad (i=1,2) \quad (16)$$

Step2: The wavelet transform is applied to analyze the filter's outputs $y_u(t)$ and $y_y(t)$. Through the multi-resolution analysis, useful information is extracted to locate the singularity of input and output signals. According to the transformation results $W_u(s,t)$ and $W_y(s,t)$, the maximum of input and output signals can be calculated.

$$W_u(s,t) = \langle y_u(t), \psi(t) \rangle \quad (17)$$

$$W_y(s,t) = \langle y_y(t), \psi(t) \rangle \quad (18)$$

Step3: Through comparing the maximums mutated respectively by $W_u(s,t)$ and $W_y(s,t)$, maximum mutated by $W_u(s,t)$ will be eliminated. Then the other maximum is the fault of sensor. The algorithm is shown as follow:

$$r(t) = W_y(s, t) - \hat{k} W_u(s, t) \quad (19)$$

Where:
$$\hat{k} = \frac{\sum W_y(s, t) W_u(s, t)}{\sum [W_u(s, t)]^2} \quad (20)$$

Step4: Set the soft threshold to remove the disturbances of the detection results. The soft threshold is calculated as follows [13]:

Strength factor:
$$\sigma = \frac{\left(\sum_{n=1}^N |r(n)| / N \right)}{0.6475} \quad (21)$$

Soft threshold:
$$Th = \sigma \sqrt{2 \ln(N)} \quad (22)$$

Where the signal $r(t)$ is sampled as discrete signal $r(n)$. N is the sampled number.

Then the detection result was transformed as below:

$$R'(n) = \begin{cases} 0, & |r(n)| \leq Th \\ r(n), & |r(n)| > Th \end{cases} \quad (23)$$

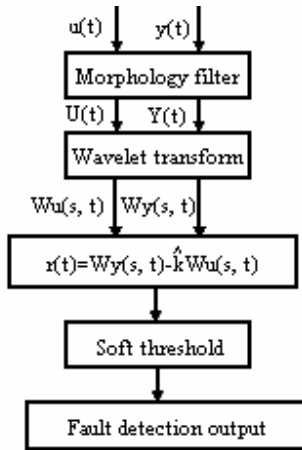


Fig.2. The framework of the morphology-wavelet algorithm

IV. SIMULATION OF SENSOR FAULTS

The possible faults of a sensor may be classified as abrupt faults and incipient faults. This paper focuses on fix, gain, bias faults (abrupt fault) and drift fault (incipient fault) of sensors. The proposed algorithm is simulated in the super-heated stream temperature sensor. The measurement range of the temperature sensor is from 400 °C to 600 °C. And the main steam temperature is varied from 535 °C to 545 °C. Several faults of the temperature sensors are simulated in this paper, such as fix, bias, gain and drift faults. The simulation signals go with heavy noises in this paper.

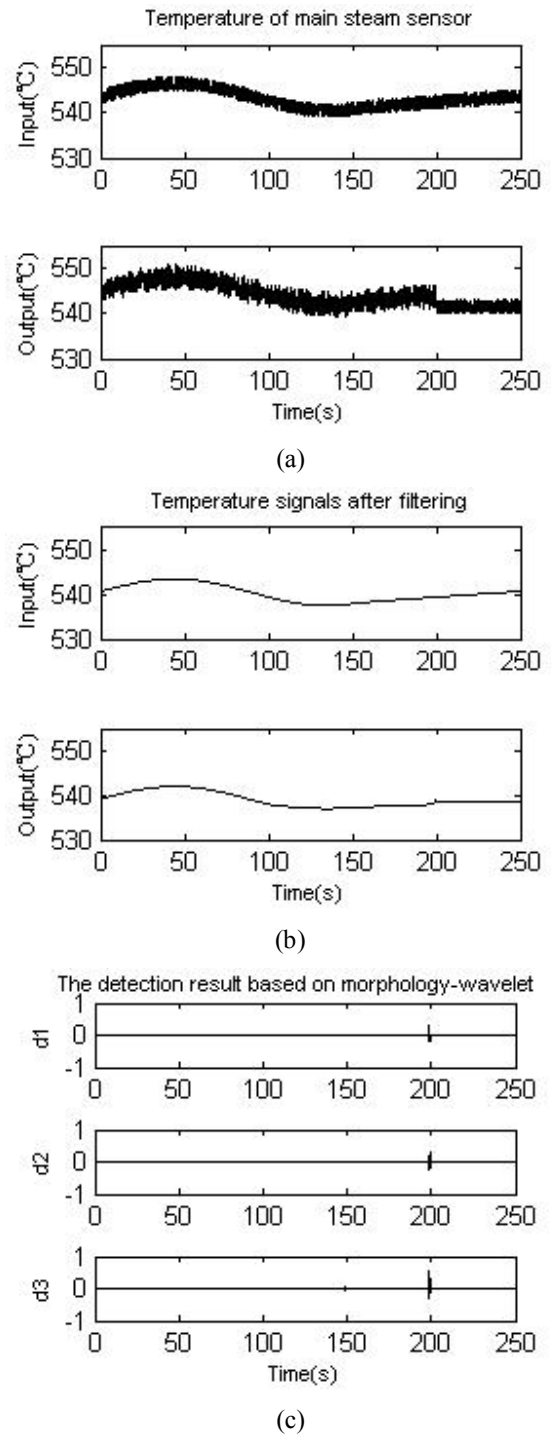


Fig.3. Diagnosis process of morphology-wavelet algorithm.

Assume that fix fault of the super-heated stream temperature sensor signal occurred at the moment of 200s. Under this condition, the original signals and the de-noised signals of the input and fix fault output are shown respectively in Fig.3 (a) and Fig.3 (b), in which the de-noised signals are handled with the morphological filter. Fig.3 (c) shows the components of the signal at different nodes (d1, d2, d3) of the

scale through the wavelet. It shows the diagnosis results of the different scales based on morphology-wavelet algorithm.

In the same sensor condition, the bias fault of sensor output signal occurred at the moment of 50s. Fig.4 (a) illustrated the original input and the bias fault signals of the temperature sensor. Through the morphological filter, the magnitude of the bias fault in the sensor is shown in Fig.4 (b). Fig.4 (c) shows the three resolution analysis (d1, d2, d3) of the wavelet transform.

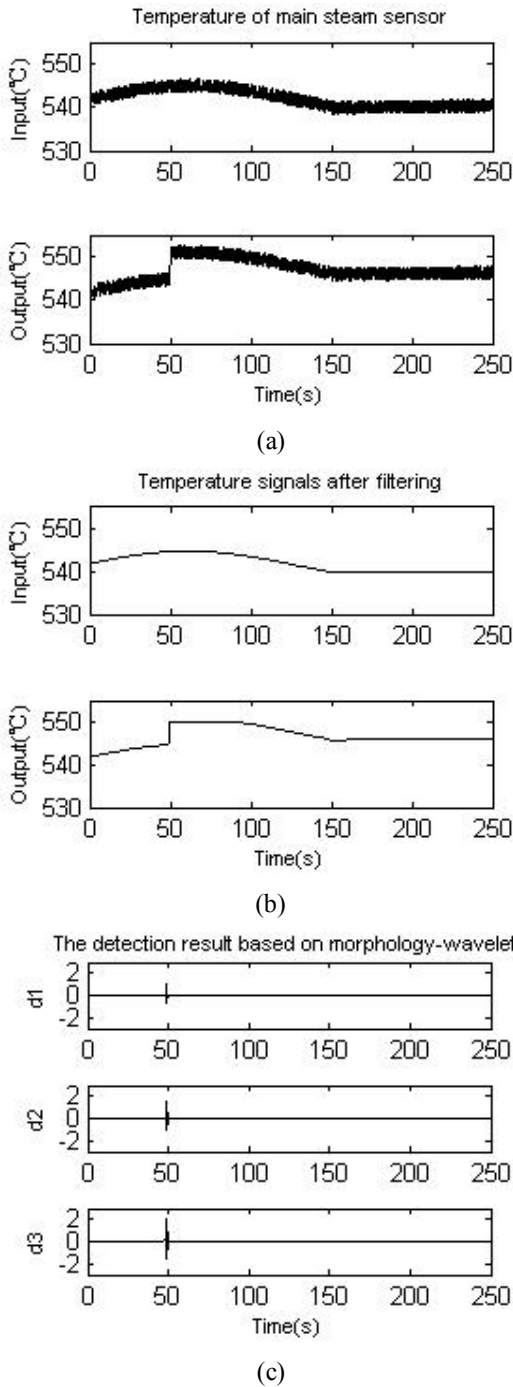


Fig 4. Diagnosis process of morphology-wavelet algorithm.

In the same sensor condition, when the sensor gain fault takes place at 50s. The original input and the gain fault signals of the temperature sensor are shown in Fig.5 (a). Through the morphological filter, the magnitude of the gain fault in the sensor is shown in Fig.5 (b). Fig.5 (c) shows the three resolution analysis (d1, d2, d3) of the wavelet transform. The simulation results as above have shown that the morphology-wavelet algorithm is capable of accurately extracting the abrupt features of sensor fault signals. The transient fault was also presented as below.

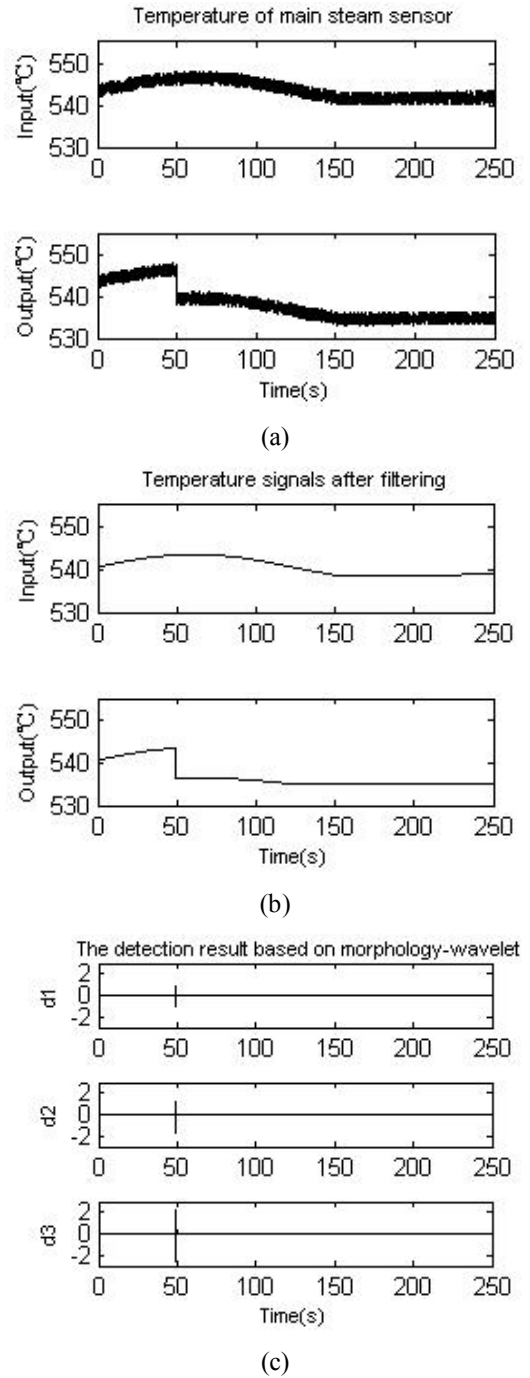
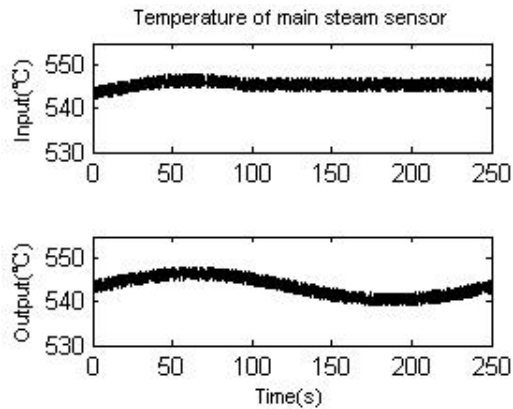


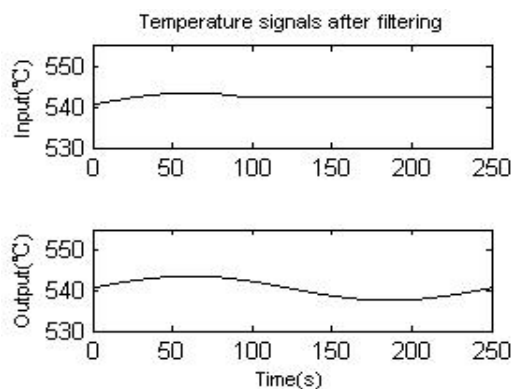
Fig 5. Diagnosis process of morphology-wavelet algorithm.

According to the morphology-wavelet algorithm, the detection and diagnosis of drift fault of the sensors were studied.

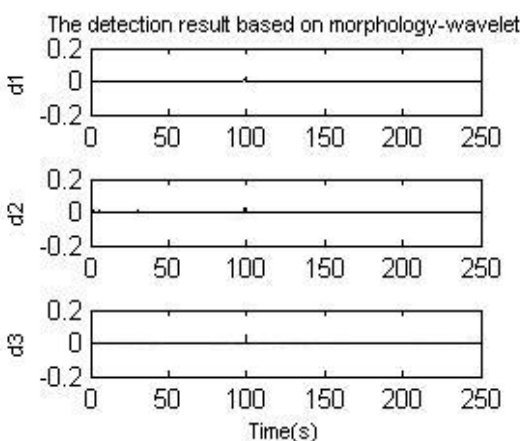
Assume that the drift fault of super-heated stream temperature sensor signal occurred at the moment of 100s. Under this condition, the input and fix fault output original signals and the de-noised signals which handled with the morphological filter are shown in Fig.6 (a)



(a)



(b)



(c)

Fig 6. Diagnosis process of morphology-wavelet algorithm.

and Fig.6 (b), respectively. Fig.6 (c) shows the components of the signal at different nodes (d1, d2, d3) of the scale through

the wavelet. It shows the diagnosis results of the morphology-wavelet algorithm.

V. CONCLUSIONS

A novel model-free method applied to the detection of abrupt and incipient sensor faults has been presented. The morphological filter is good at dealing with the impulse noise while the wavelet transform is good at suppressing white noise. The integrated morphology-wavelet algorithm incorporates the advantages of both morphology and wavelet transform, so it has the excellent capability of restraining white noise and impulse noise. It can also apply to efficiently extracting the incipient fault and abrupt fault characteristic, and the fault can be located accurately.

The simulation results confirmed that the algorithm have effectively used in sensors fault detection. The further study of the morphology-wavelet algorithm will be extended into fault diagnosis of control system.

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