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Paper

Quadratic-Wavelet-Transform-Based Fault Detection Approach for Temperature Sensor

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Addressing the problem of online fault detection of a temperature sensor, a fault detection algorithm based on quadratic wavelet transform is proposed in this paper. First, the discrete wavelet transform is used to extract noise from the process signal; since the process noise signal is related to the internal structure and status of the sensor, a Butterworth low-pass filter is used to filter out the high-frequency electrical interference signal to obtain the process noise signal. Second, the continuous wavelet transform is used to detect abrupt fault from the process noise signal. Experimental results show that the noise-analysis-based fault detection algorithm (quadratic wavelet transform) is better than the process-signal-analysis-based approach and that the quadratic wavelet transform is feasible for thermowell drop fault detection of the temperature sensor. © 2018 Institute of Electrical Engineers of Japan. Published by John Wiley & Sons, Inc.

Keywords: quadratic wavelet transform; temperature sensor; fault detection; noise signal; process signal

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1. Introduction

In the industrial production process, sensors are used to convert the measured electrical signal into digital information, which is fed back to control systems. Sensors are core components in the industrial process, and the measurement accuracy is extremely important. When faults appear in sensors, it will bring huge economic losses to the industrial production process. Thus, an effective fault detection approach is necessary to detect whether sensors are working properly. fault detection and diagnosis (FDD) approaches are classified into model-based approaches and model-free approaches. Both data-driven approaches and signal-based approaches are model-free approaches [1,2]. Analytical redundancies and statistical tests for sensor fault detection are proposed in [3], which belong to the model-based approach. Data-driven approaches use multivariate statistical methods and machine learning tools for FDD, which need a lot of fault-free training data obtained during normal operation. Reference 4 uses deep learning and the generalized likelihood ratio test for the sensor fault detection and classification in nuclear power plants. Unlike the model-based approach and data-driven approach, wavelet transform does not rely on an explicit mathematical model and a large amount of training data and is a signal-based approach.

As a time–frequency analysis approach, wavelet transform has the characteristic of multi-resolution. And it has the ability to represent local features of a signal in the time–frequency domain, which is known as a 'mathematical microscope' [5]. Wavelet transform is the development and extension of the Fourier transform and is especially suitable for nonstationary signals. Wavelet analysis has been gradually emerging as a discipline since the 1990s [6,7]. Wavelet transform can be used in the fields of signal processing, image processing, pattern recognition, speech recognition, seismic survey, machine fault diagnosis, and so on [5]. Zhang [8] used wavelet transform in a general-purpose pressure sensor fault detection and diagnosis. Watson [9] used wavelets to monitor the power output condition of wind turbine generators. A wavelet-based approach was also used to detect stator fault in the inverter-fed induction motor [10] and bearing fault in a three-phase induction motor [11]. Kim [12] proposed an online fault detection algorithm of a photovoltaic system using wavelet transform. However, unlike the earlier papers, this paper uses wavelet transform in the detection of a temperature sensor to judge whether the thermowell of the temperature sensor has dropped. The sensor fault detection approach based on wavelet transform uses the process signal [8], in which the normal step output signal of the sensor can be detected as a fault. A quadratic wavelet transform fault detection approach is proposed in this paper. First, the discrete wavelet transform is used to extract noise from the process signal. Since the process noise signal is related to the internal structure and status of the sensor, a Butterworth low-pass filter is used to filter out the high-frequency electrical interference signal to obtain the process noise signal. Second, continuous wavelet transform is used to detect any abrupt fault from the process noise signal. The quadratic wavelet transform can be used to detect the thermowell dropping fault of the temperature sensor. The normal step output signal cannot be detected as a fault by using the quadratic wavelet transform. At the same time, the edge interference by using wavelet

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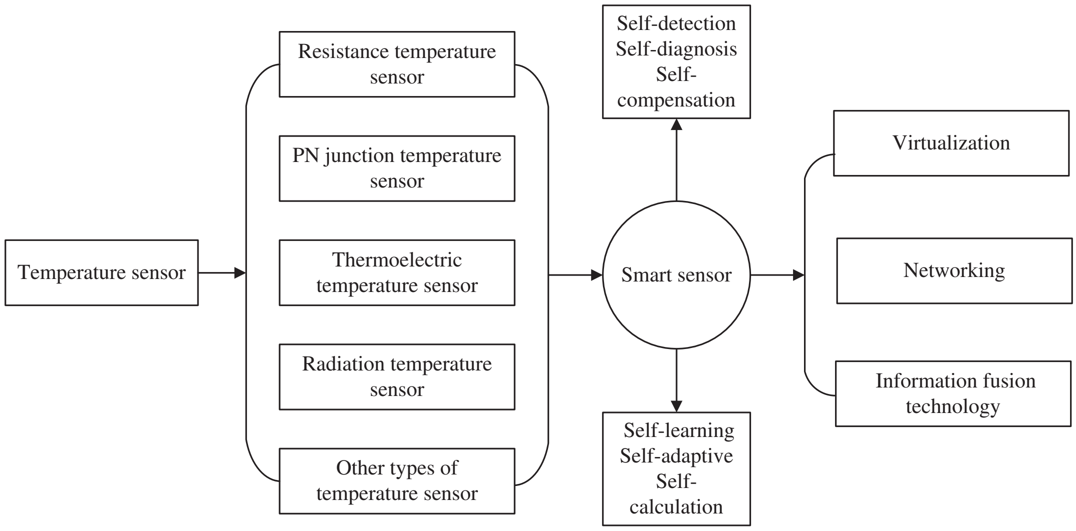

Fig. 1. Temperature sensor classification and development trend

transform based on process signal analysis can be eliminated directly.

The analysis of resistance temperature detector (RTD) failure mode and failure mechanism is introduced in Section 2. Section 3 describes the theory of wavelet transform. Quadratic wavelet transform fault detection approach is given in Section 4, and the simulation and experiment are presented in Section 5. The simulation is used to simulate the normal step output of a normal sensor. The normal data and fault data of the temperature sensor are collected in the experiment, in which Pt100 is selected as the experimental object. The conclusion forms the last part.

2. Analysis of RTD Failure Mode and Failure Mechanism

According to measurement principle, temperature sensors can be of five types: resistance temperature sensor, p–n junction temperature sensor, thermoelectric temperature sensor, radiation temperature sensor, and other types of temperature sensor [13]. The object of this paper is the resistive temperature sensor, Pt100. As a trend, smart sensors are getting more attention in industrial areas [14]. The characteristics of smart sensors are self-detection, self-diagnosis, self-compensation, self-learning, self-adaptive function, and other self-calculation and processing functions [15]. Virtualization, networking, and information fusion technology form the development trend of smart sensors [15], as shown in Fig. 1.

RTD has steady-state and dynamic characteristics. The index of the steady-state characteristic is accuracy, while that of the dynamic characteristic is the response time. Decreased accuracy would result in inaccurate measurement (drift). The response time is the measurement lag time of the sensors. To solve these problems, RTD failure modes and failure mechanisms are analyzed in Section 2. RTD fault detection, diagnosis, and prediction approaches can be studied to deal with these problems, which are shown in Fig. 2. Analysis of RTD failure mode and the failure mechanism is shown in Table I [16].

3. Principle of Wavelet Transform

Fourier transform as well as other signal analysis approaches based on the Fourier transform are applied to deal with stationary signals. Wavelet transform is a signal processing approach that is suitable for nonstationary signals. Fourier transform converts a signal into a superposition of a series of sine waves. However, wavelet transform converts a signal into a superposition of many wavelets, whose energy in the time domain is very concentrated. So the instantaneous time-varying signal is analyzed by wavelet transform [17–19].

3.1. Continuous wavelet transform

Set $\psi[x]$ as a square-integrable function, so $\psi(x) \in L^2(R)$. If $\widehat{\psi}(\omega)$ (the Fourier of $\psi(x)$) meets the following condition (1), $\psi(x)$ can be called the mother wavelet [17]:

$$C_\psi = \int_{-\infty}^{+\infty} \frac{|\widehat{\psi}(\omega)|^2}{|\,\omega\,|} d\omega < \infty \tag{1}$$

Since $\psi(x)$ can satisfy the admissible condition, it can be proved that $\psi(x)$ has better local characteristics in the time–frequency domain. Wavelets also must have positive and negative alternation.

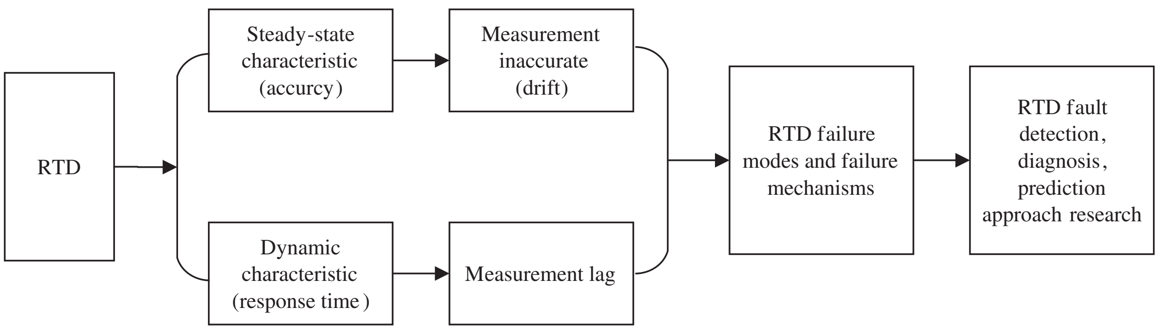

Fig. 2. RTD overall framework analysis

Table I. RTD failure mode and failure mechanism

RTD failure mode	Failure mechanism
Measurement lag	The response time is changed due to impurity in thermowell, improper installation, and thermowell dropping
Extended lead failure	Weld defect
Low insulation resistance	Water entry
Large electromotive force error	The sensing element is doped
Open circuit	The sensor itself is fragile; it is easy to crack or break because of external vibration and pressure. The sensor output is unstable before breaking
Platinum wire refinement	Chemical corrosion (cleaning elements in the manufacturing process), and chemical effects of insulating materials
Measurement inaccurate (drift)	Long-term exposure to the outside world (vibration, temperature cycle, shock effect), the characteristics of material change, expansion coefficient change

A mother wavelet can be scaled and translated. The scale parameter is set as a and the translation parameter is set as b. Thus the mother wavelet can be expressed as

$$\psi_{a,b}(x) = |a|^{-1/2}\psi\left(\frac{x-b}{a}\right) \quad a \neq 0, b \in \mathbb{R} \tag{2}$$

If $\forall f(x) \in L^2(R)$, the continuous wavelet transform of $f(x)$ is as follows:

$$(W_\psi f)(a,b) = \langle f(x), \psi_{a,b}(x)\rangle = |a|^{-1/2}\int f(x)\overline{\psi\left(\frac{x-b}{a}\right)}\,\mathrm{d}x \tag{3}$$

For $f(x)$ in (3), $(W_\psi f)(a,b)$ is the result of its wavelet coefficient. $\overline{\psi\left(\frac{x-b}{a}\right)}$ is the conjugate of $\psi\left(\frac{x-b}{a}\right)$. In order to program (3), it is discretized for execution. That is, a finite set of input data is sampled at equal intervals, and the results are as in (4). In order to compute the coefficients of the continuous wavelet transform, the translation factor b is calculated for each scale parameter a. In this paper, continuous wavelet transform is used to detect an abrupt signal [17].

$$w_a[b] = \sum_{n=0}^{N-1} x[n]\overline{\psi_a(b-n)} \tag{4}$$

3.2. Discrete wavelet transform In the discrete wavelet transform, the scale parameter a and the translation parameter b are discretized. Usually, $b = k/2^j$, $a = 1/2^j\,(j,k \in \mathbb{Z})$, and a two-dimensional array is obtained after a one-dimensional discrete wavelet transform. The discrete wavelet transform [17] formula is

$$(DW_\psi f)(j,k) = \langle f(x), \psi_{j,k}(x)\rangle \tag{5}$$

Let $f(x)$ be the one-dimensional input signal, $\varphi_{jk}(x) = 2^{-j/2}\varphi(2^{-j}x - k)$, $\psi_{jk}(x) = 2^{-j/2}\psi(2^{-j}x-k)$, in which $\varphi(x)$ is the scaling function, and $\psi(x)$ is the wavelet function. $P_0 f = f$, in level j of discrete wavelet transform, $P_{j-1}f$ is decomposed by orthogonal projection $P_j f$ and $Q_j f$, which is shown in (6), where c_k^j, d_k^j are the approximate coefficients and the detail coefficients, respectively.

$$P_{j-1}f = P_j f + Q_j f = \sum_k c_k^j \varphi_{jk} + \sum_k d_k^j \psi_{jk} \tag{6}$$

For a finite length input data sequence $c_n^0 = x_n, n = 1, 2, \ldots, M$, the discrete wavelet transform is

$$c_k^{j+1} = \sum_{n\in\mathbb{Z}} c_k^j h_{n-2k} \tag{7}$$

$$d_k^{j+1} = \sum_{n\in\mathbb{Z}} c_k^j g_{n-2k} \tag{8}$$

When $j = 0$,

$$c_k^1 = \sum_{n=1}^{M} x_n h_{n-2k} \tag{9}$$

$$d_k^1 = \sum_{n=1}^{M} x_n g_{n-2k} \tag{10}$$

In this paper, discrete wavelet transform is used to extract the process noise signal d_k^1, which is translated into the detail signal, which is the noise signal.

4. Fault Detection Algorithm

Sensor faults could cause changes of the system's model parameters, and the output process noise signal would be affected. Therefore, this is the starting point of fault detection based on the process noise signal. However, sensor noise signal contains process noise and non-process noise. Process noise is the inherent fluctuation due to turbulence, vibration, and other effects, whereas non-process noise generally refers to high-frequency electrical and other interferences [20]. Since the process noise signal is related to the internal structure and status of the sensor, a Butterworth low-pass filter is used to filter out the high-frequency electrical interference signal to obtain the process noise signal [21]. Details on the Butterworth low-pass filter can be found in [22].

The temperature sensor detection algorithm is executed as follows. Process data (temperature value) is acquired through the resistance temperature sensor. Then, the first discrete wavelet transform [21] is used to extract the noise from the process data (temperature value). In order to obtain the process noise data, Butterworth low-pass filtering is used to reduce the impact of high-frequency electrical interference. Finally, the second continuous wavelet transform is used to detect abrupt fault from the process noise data. So it is called the quadratic wavelet transform, which is shown in Fig. 3.

Compared to the direct continuous wavelet transform on process signal, the use of process noise signal can effectively avoid false detection. When the sensor is working properly, it will produce a rise or fall in the temperature. False detection occurs when continuous wavelet transform on the process signal is used directly for sensor fault detection. At the same time, edge interferences by using the continuous wavelet transform based on process signal analysis can be eliminated directly. Finally, through experimental verification, the fault diagnosis of the sensor can be carried out by quadratic wavelet transform.

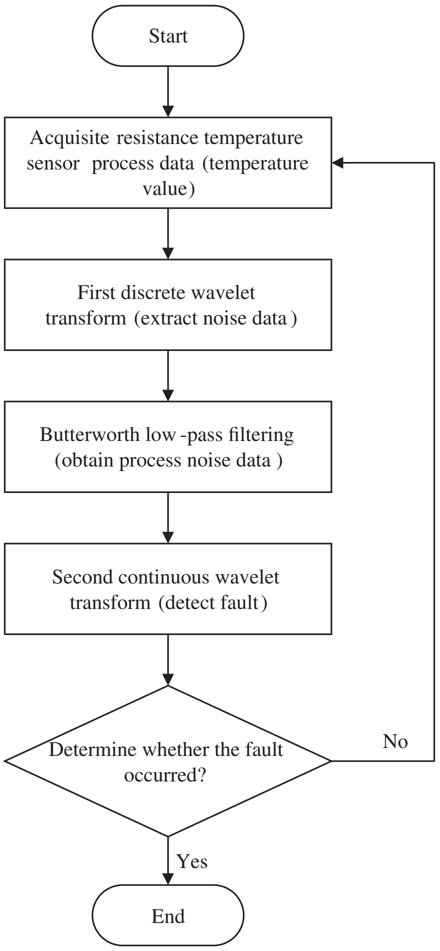

Fig. 3. Fault detection algorithm flow diagram

5. Simulation and Experiment

5.1. Simulation section From the perspective of the control system, the sensor system itself has a transfer function. And each parameter is dependent on the system itself, which is not affected by the input and output. When a fault occurs in the sensor, the sensor transfer function will change (for example, zeroes, poles, and gain), and the accuracy of sensor decreases or the response time changes. The transfer function of a normal sensor is constructed in this section.

It is assumed that the given input signal of a simulated normal sensor is the black line $X(t)$ in Fig. 4. In the actual laboratory experiment, it is very difficult to simulate the step input environment of the sensor in the industrial measurement, so the normal control step input signal in the control system is simulated, whose specific parameters are set as follows: sample time = 0.01 s, and the total time for data acquisition = 50 s. The input of the sensor is set to be a step signal $x(t)$ with noise, whose amplitude changes from 1 to 5 at 15 s. The noise signal $n(t)$ is a random signal with a Gaussian distribution, whose mean value is 0 and variance is 0.1. Finally, the synthesized input signal is expressed as follows:

$$X(t) = x(t) + n(t) \tag{11}$$

Since the thermal resistance sensor in the experimental part of this paper is equivalent to the first-order transfer function, the transfer function $G(s)$ is selected as (12). Therefore, the corresponding sensor simulation output $Y(t)$ is the green line in Fig. 4. As can be seen from Fig. 4, the simulated sensor also produces a step output because of the input of a step signal. The above process is implemented through Simulink in MATLAB

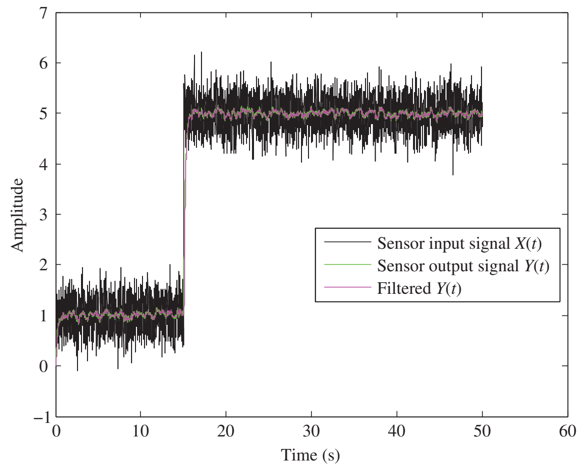

Fig. 4. Simulated sensor input, output and filtered signal

R2012b. The actual step signal is difficult to simulate, which needs special equipment. Therefore, the input normal step signal and corresponding sensor output are simulated.

$$G(s) = 6/(s + 6) \tag{12}$$

The sensor output signal filtered by the Butterworth low-pass filter is the magenta line in Fig. 4. The noise signal is extracted by the discrete wavelet transform in the sensor output signal $Y(t)$. The black line in Fig. 5 is the noise signal, and the magenta line is the process noise that is obtained from the noise signal by the Butterworth low-pass filter. The continuous wavelet transform simulation results based on the filtered process signal are the magenta line in Fig. 6. It can be seen from Fig. 6 that the wavelet coefficients (ordinate) have a mutation at 15 s, and so it can be known that a fault has occurred at 15 s. In fact, the simulated sensor does not fail, and the mutation of the wavelet transform coefficients is caused by the input of a step signal. Therefore, the continuous wavelet transform based on the process signal could produce a false detection, which is the ellipse marked in Fig. 6, and there is edge interference in process signal analysis. The continuous wavelet transform (quadratic wavelet transform) results based on the process noise signal are the blue line in Fig. 6. There is no mutation signal and edge interference in the wavelet coefficients (ordinate), indicating that the sensor has not failed. Thus, the conclusion is that continuous wavelet transform (quadratic wavelet transform) based on the noise signal is more accurate than continuous wavelet transform based on the process signal.

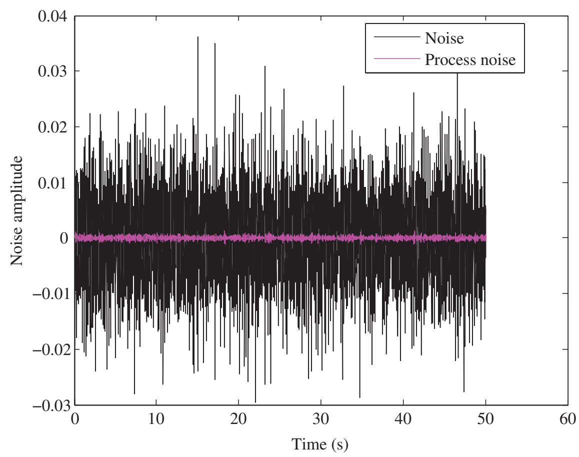

Fig. 5. Noise and process noise

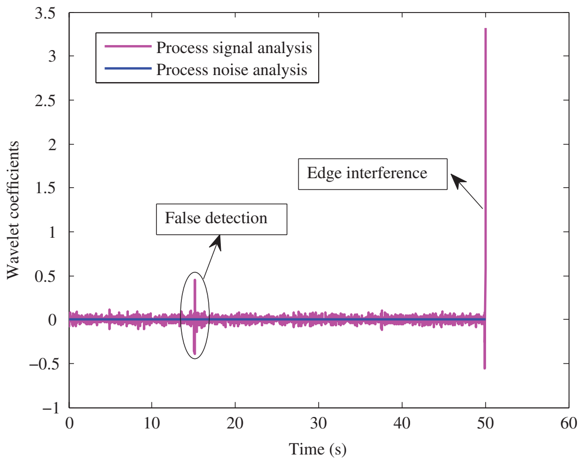

Fig. 6. Simulation results based on process signal analysis and process noise analysis

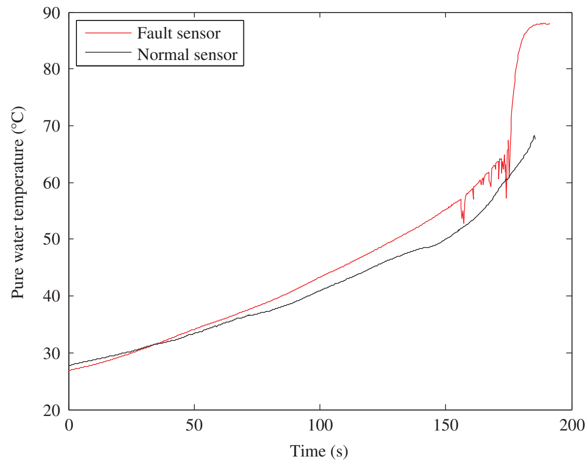

Fig. 7. Pure water temperature measurement value

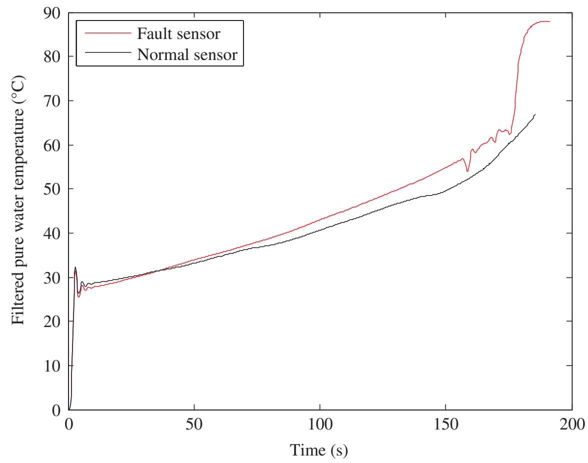

Fig. 8. Filtered pure water temperature measurement value

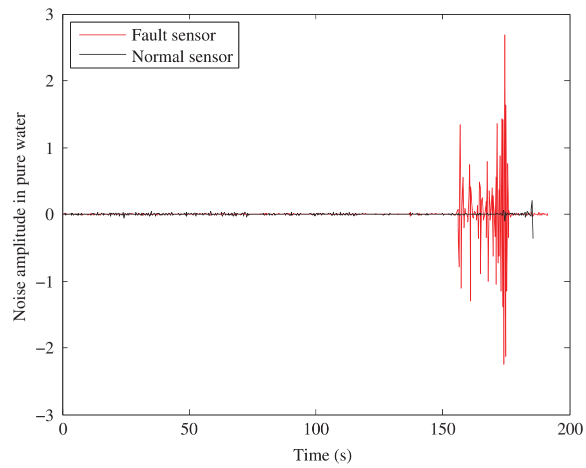

Fig. 9. Noise in pure water temperature measurement

5.2. Experimental section In this paper, a temperature sensor (RTD), Pt100, is selected as the experimental object. The temperature sensor's thermowell is used to validate quadratic wavelet transform for the failure modes of loose connection. The time at which the thermowell of temperature drops can be detected by the quadratic wavelet transform. Pt100 is used in the experiment to measure the temperature change in the different media that are heated (pure water and salt water at the concentration of 0.024 g/ml). In the measurement process, an artificial fault (thermowell drop) is introduced. The room temperature is 24 °C. Through a temperature transmitter, the sensor's actual measured signal is acquired.

The experimental procedure is as follows: The sensor (Pt100) is placed in an electrically heated kettle to measure the temperature change of the medium. In order to realize temperature data acquisition, the measured temperature values are sent to a computer through the serial port of a temperature transmitter. The sampling frequency is 3.4 Hz. In the process of data acquisition, the thermowell of Pt100 is quickly removed to simulate the occurrence of a thermowell drop. So the sensor is transitioned from the normal state to the fault state. After that, the acquired temperature data are used in the fault detection algorithm to determine whether the fault has occurred. As mentioned, the experiments were performed in pure water and salt water at the concentration of 0.024 g/ml, respectively, keeping the experimental condition and environment unchanged.

For temperature measurement in pure water, the acquired data curve under normal temperature sensor is shown by the blacl line in Fig. 7 and that by the faulty sensor by the red line. Figure 7 shows the measurement values of heated pure water temperature. Butterworth low-pass filtering is used to reduce the impact of high-frequency electrical interferences. The filtered pure water temperature measurement value curves are shown in Fig. 8 with the normal and the faulty sensor. The noise data in Fig. 9 are extracted by the discrete wavelet transform from the pure water temperature measurement values. Then, the process noise data in Fig. 10 are obtained through the Butterworth low-pass filter.

The continuous wavelet transform based on process signal analysis in the temperature measurement of pure water medium is shown in Fig. 11. In the wavelet transform based on the process signal, an abrupt signal in the wavelet coefficients (ordinate) can be detected at 157 s, the corresponding ordinate being 1.67. However, there are edge interferences in the wavelet coefficients, which increase false alarms. Also, it cannot be judged whether the abrupt signal is generated from the sensor itself or from the normal system input, because from the simulation (Fig. 6) the normal system step input would also generate mutation in the continuous wavelet transform based on process signal. Therefore, it is difficult to determine the working status of the sensor using the continuous wavelet transform based on the process signal. The results of the continuous wavelet transform based on the noise signal (quadratic wavelet transform) in the temperature measurement of the water medium are shown in Fig. 12. In the continuous wavelet transform based on the process noise signal (quadratic wavelet transform),

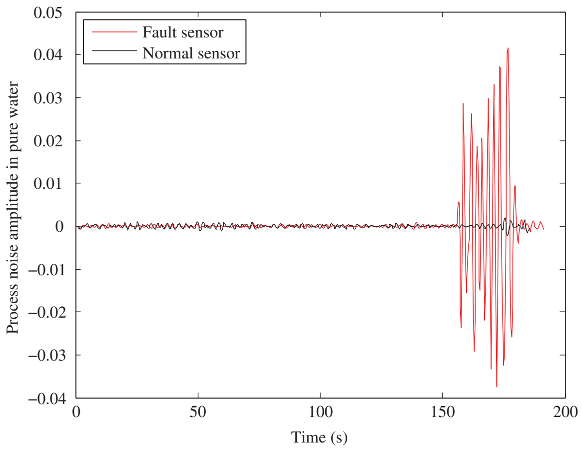

Fig. 10. Process noise in pure water temperature measurement

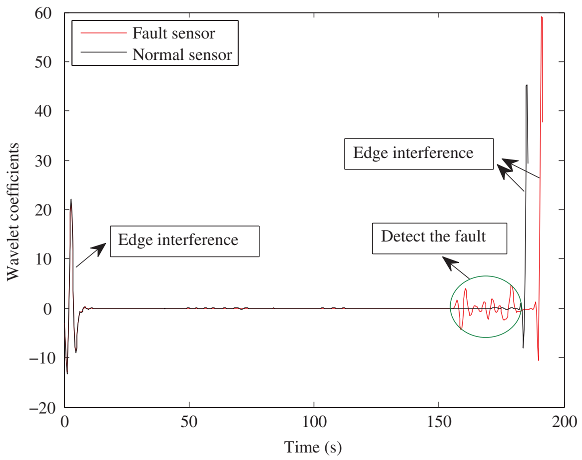

Fig. 11. Pure water measurement experiment results based on process signal analysis

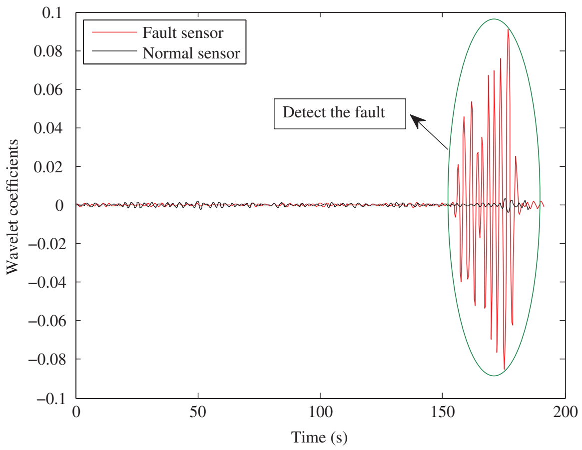

Fig. 12. Pure water measurement experiment results based on process noise analysis

the mutation of the wavelet coefficients (ordinate) can be detected at 156 s, the corresponding ordinate is 0.0208, and there is no interference of the wavelet coefficient edge signal; the amplitude of the abrupt signal is relatively obvious. It is easy to identify the fault of the sensor.

For temperature measurement in salt water, the acquired data curve under normal temperature sensor is the black line in Fig. 13, and that by faulty sensor is the magenta line.

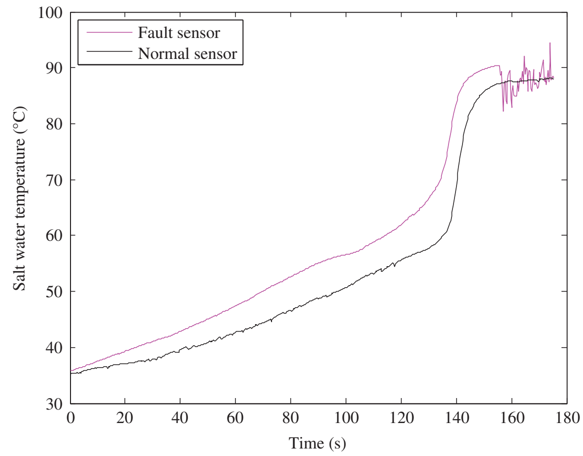

Fig. 13. Salt water temperature measurement value

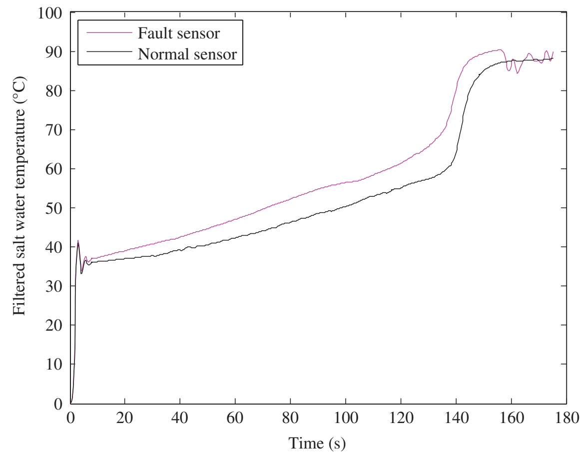

Fig. 14. Filtered salt water temperature measurement value

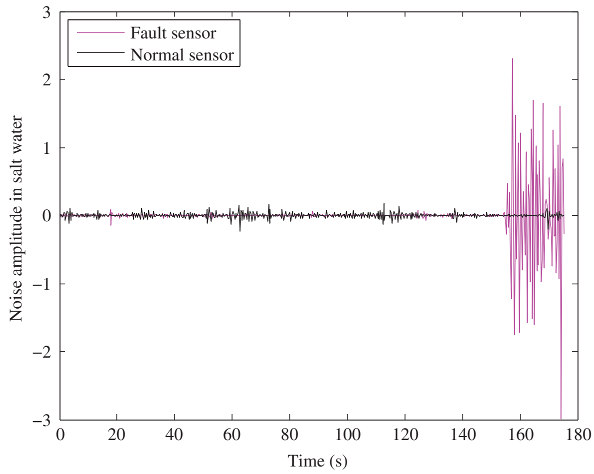

Fig. 15. Noise in salt water temperature measurement

Figure 13 shows the heated salt water temperature measurement values. Butterworth low-pass filtering is used to reduce the impact of high-frequency electrical interferences. The filtered salt water temperature measurement values are given in Fig. 14 under the normal sensor and faulty sensor. The noise data in Fig. 15 are extracted by the discrete wavelet transform from the salt water temperature measurement value. Then, the process noise data in Fig. 16 are obtained through Butterworth low-pass filtering.

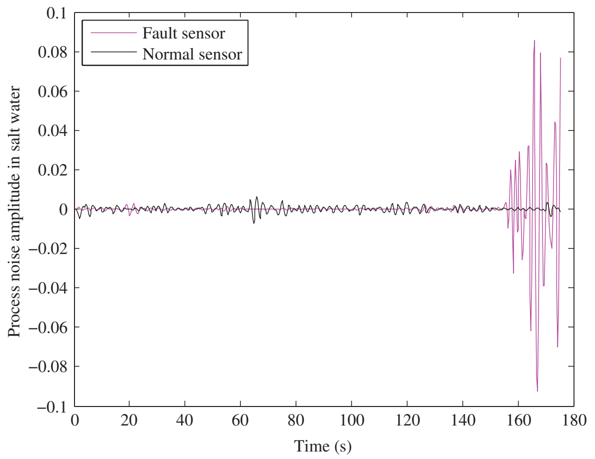

Fig. 16. Process noise in salt water temperature measurement

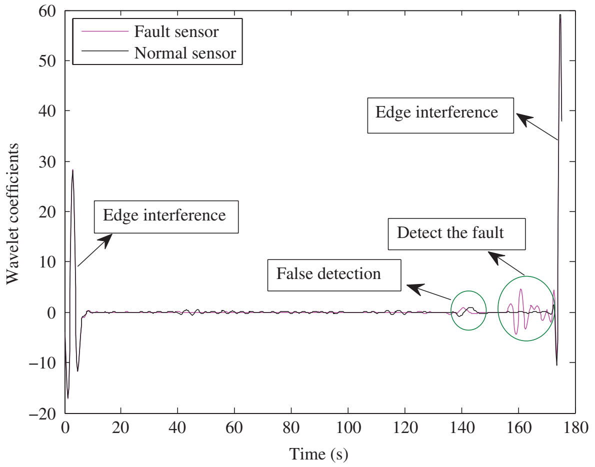

Fig. 17. Salt water measurement experiment results based on process signal analysis

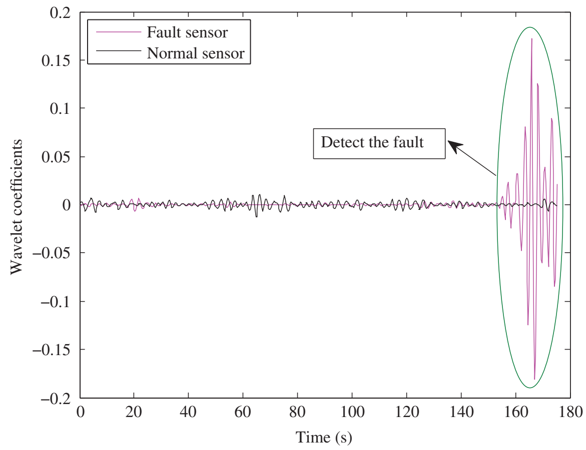

Fig. 18. Salt water measurement experiment results based on process noise analysis

Table II. Results comparison of two fault detection approaches for normal sensors

Fault detection approach	Noise-analysis-based approach (quadratic wavelet transform)	Process-signal-analysis-based approach
Simulation sensor	No fault	False detection, edge interference
Sensor in pure water	No fault	No fault, edge interference
Sensor in salt water	No fault	False detection, edge interference

The continuous wavelet transform based on process signal in the temperature measurement of the salt water medium at the concentration of 0.024 g/ml is shown in Fig. 17. In the wavelet transform based on the process signal, an abrupt signal in the wavelet coefficients (ordinate) can be detected at 157 s, and the corresponding ordinate is 1.79. However, there are edge interferences and false detection in the wavelet transform coefficients (ordinate). It cannot be judged whether the abrupt signal is generated from the sensor itself or the normal system input, because from the simulation (Fig. 6) the normal system step input will also generate mutation in continuous wavelet transforms based on the process signal. Therefore, it is difficult to determine the working status of the sensor using the continuous wavelet transform based on the process signal. The results of the continuous wavelet transform based on process noise signal (quadratic wavelet transform) in the temperature measurement of the salt water medium with a concentration of 0.024 g/ml are shown in Fig. 18. In the continuous wavelet transform based on process noise signal (quadratic wavelet transform), the mutation of the wavelet coefficient (ordinate) can be detected at 157 s, and the corresponding ordinate is 0.0233. There is no interference of the wavelet coefficient edge signal, and the amplitude of the abrupt signal is obvious. It is easy to identify the fault of the sensor.

5.3. Simulation and experiment results analysis

For normal sensors, when the normal step signal is input to the sensor in the simulation, the fault detection based on the continuous wavelet transform of the process signal can detect the abrupt signal, thus making the operator mistakenly believe that the sensor has failed. The fault detection result of continuous wavelet transform based on process noise analysis is shown as the blue line in Fig. 6, which shows no fault occurring and no edge interferences (wavelet transform coefficients have no abrupt signal, which indicates that the sensor has not failed). For normal sensors in the experimental section, the results of process-signal-based analysis in pure water show that no fault happens, but still exist edge interferences from Fig. 11, the results of noise-signal-based analysis in pure water show that no fault happens and no edge interferences from Fig. 12. The results of process-signal-based analysis in salt water show that false fault happens (due to the change of process signal), but still there exist edge interferences (Fig. 17); the results of noise-signal-based analysis in salt water show that no fault happens and no edge interferences (Fig. 18). The comparison of fault detection results based on the two approaches for normal sensors is shown in Table II.

For faulty sensors, when the actual abrupt sensor fault happens in pure water and salt water, the continuous wavelet transform detection approach based on process signal can also detect the abrupt signal and edge interferences (Figs 11 and 17). In the abrupt fault of the actual sensor, the quadratic wavelet transform can accurately detect the fault and with no edge interferences (Figs 12 and 18). Wavelet transform coefficients have abrupt signals, which indicates that the sensor has failed. The comparison of fault detection results based on two approaches for fault sensors is shown in Table III. Quadratic wavelet transform can be used to detect temperature sensor fault based on process noise data. And the edge interferences by using the wavelet transform based on process signal analysis can be eliminated directly in the quadratic

Table III. Results comparison of two fault detection approaches for fault sensors

Fault detection approach	Noise-analysis-based approach (quadratic wavelet transform)	Process-signal-analysis-based approach
Sensor in pure water	Fault	Fault, edge interference
Sensor in salt water	Fault	False detection, fault, edge interference

wavelet transform. Quadratic wavelet transform is independent of the medium being measured, as shown in Tables II and III.

6. Conclusion

The novelty of this paper is that the quadratic wavelet transform is introduced into industrial sensors, and it can detect fault based on noise data. We demonstrated by experiments that the quadratic wavelet transform can indeed judge when the thermowell has dropped. The advantages of the quadratic wavelet transform are that it does not require an accurate mathematical model and is better than the approach of continuous wavelet transform based on process signal because the detection results of the quadratic wavelet transform are not affected by changes in the process signal. The benefit of the quadratic wavelet transform is that it can realize continuous, online fault detection of resistance temperature sensors, avoiding periodic inspections to bring down missed fault detection and huge cost, without industrial loss caused by downtime.

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