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Research Article

An Integrated Denoising Method for Sensor Mixed Noises Based on Wavelet Packet Transform and Energy-Correlation Analysis

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In order to solve the problem of industrial sensor signal denoising, an integrated denoising method for sensor mixed noises based on wavelet packet transform and energy-correlation analysis is proposed. The architecture of proposed method is designed and the key technologies, such as wavelet packet transformation, energy-correlation analysis, and processing method of wavelet packet coefficients based on energy-correlation analysis, are presented. Finally, a simulation example for a specific signal and an application of shearer cutting current signal, which mainly contain white Gaussian noise and impact noise, are carried out, and the simulation and application results show that the proposed method is effective and is outperforming others.

1. Introduction

Generally speaking, sensor signals are often noisy in the transmission process and white Gaussian noise is a common and frequent noise model [1]. Meanwhile, the sensor signals are also contaminated by impact noise resulting from a variety of specific conditions such as high frequency interference, instantaneous disturbance on the startup of large equipment, and working condition change of the sensor [2, 3]. These two kinds of noises have negative influences on a multisensor information fusion system [4]. In order to guarantee the accuracy and reliability of sensing information, the noises should be filtered from the equipment running information and original features of the sensor signals should be preserved in maximum [5].

Traditional signal theories are built on the basis of Fourier analysis, but denoising method based on Fourier analysis is possibly restricted due to its weakness in obtaining partial characteristic of sensor signals [6] and possible Gibbs phenomenon [7]. Wavelet analysis with the key property of characterizing local features in both time domain and frequency domain have rapidly become an important tool in the area of signal processing, image coding, and pattern recognition since a general method of constructing wavelet basis named after multiresolution analysis was established by Mallat in 1992 [8]. With the development of wavelet theory, the concept of wavelet packets extended from orthonormal wavelet transform proposed by Coifman et al. have attracted a significant amount of research attention in recent years and bring new development for signal denoising [9]. Compared with classic wavelet technique, wavelet packet analysis can decompose signal not only in scale space but also in wavelet space which may imply details of undesirable noise [10].

Bearing the above observations in mind, a denoising algorithm based on wavelet packet transform and energy-correlation analysis is proposed to remove the sensor mixed noises and the rest of this paper is organized as follows. In Section 2, some related works are outlined based on literatures. In Section 3, the key technologies such as architecture of the proposed method, wavelet packet transform, energy-correlation analysis, and processing method for wavelet packet coefficients based on energy-correlation analysis are proposed. The simulation example for a specific signal denoising is carried out and the application for shearer cutting current signal denoising is presented in Section 4. The conclusions are summarized in Section 5.

2. Literature Review

Recent publications relevant to this paper are mainly concerned with three research streams: denoising methods, wavelet packet transform, and energy-correlation analysis. In this section, we try to summarize the relevant literature.

2.1. Denoising Method. For sensor signal denoising, traditional method mainly relies on low-pass filtering based on the principle that signal distributes on finite interval in low frequency, while noise in high frequency, such as Fourier transform [11] moving average filter [12] and Wiener filter [13]. Creative algorithms have been put forward in recent years. Time frequency analysis is an important branch of the denoising method. For example, a novel dyadic filter bank for broadband noise is constructed based on empirical mode decomposition (EMD) and a numerical experiment of fractional Gaussian noise is carried out [14]. To remove tremor contribution from postural signals measured by accelerometers, Hilbert-Huang transformation method including EMD and Hilbert spectral analysis is proposed to assess the functional level of balance control in PD patients [15]. For fault classification of rolling bearings, wavelet analysis is applied in denoising the preliminary vibration data [16].

Some methods based on statistical theory are also applied in noise removal. In order to eliminate Gaussian noise, the high order spectrum is utilized for overflow valve fault analysis [17]. The support vector machine (SVM) is adopted as an adaptive noise canceler to eliminate the noise and perturbation in order to achieve good control effect of discrete chaotic systems based on echo state network [18]. Independent component analysis (ICA) and principle components analysis (PCA) are two common statistical theories based on denoising method [19, 20]. Some other methods are also studied by home and broad researchers, such as singular value decomposition (SVD) [21], sparse decomposition [22], and various adaptive filters [23, 24].

2.2. Wavelet Packet Transform. Wavelet packet transform is practical value and is much more advantageous than its predecessor, wavelet transform, and much effort and energy have been devoted to explore the influences of transformation parameters to the denoising effect, such as the influence of mother wavelet [25], wavelet packet bases [26], decomposition level [27], and threshold selection [28]. As a new useful tool in signal analysis, wavelet packet transform has recently appeared in applications of various fields. In [29], a wavelet packet based algorithm is proposed for denoising and harmonic detection, and the effectiveness of highlighting the difference between the noise and the desired signal is verified by experiments. To suppress interference bands in EEG, a new filter is searched by wavelet packet transform and the study of EEG dynamic characteristics in filtering process shows good performance [30]. In [31], an adaptive anisotropic dual-tree complex wavelet packet is applied in image denoising with a bivariate statistical model and achieves more appealing images comparing with 2D dual-tree complex wavelet transform.

2.3. Energy-Correlation Analysis. In order to evaluate the denoising effectiveness and decide the optimal decomposition level in wavelet packet transform, indexes such as root-mean-square error (RMSE), SNR, and smoothness ratio (RS) are utilized [32]. In [33], the wavelet packet node energy is firstly proposed as an innovative feature selection approach which applies the wavelet packet transform to the classification of vibration signals. The energy ratios of wavelet packet nodes between original and reconstructed signals are described in the method of impulse radio signal denoising and detection through wavelet packet transform [34]. Correlation analysis as an approach to judge the relationships among signals is often adopted to indicate the superiority of a denoising method to others [35, 36]. A new algorithm of spike detection contributing to neuroscientific studies utilizes the correlation between wavelet coefficients at different sampling scales to create a robust spike detector [37].

2.4. Discussion. Although the above approaches for signal denoising based on wavelet packet transform or other creative algorithms are highly valuable, most of them either focus on single interference signal or have original intention to eliminate the noise in some special application situations based on the analysis of its statistical property and spectrum distribution. Thus, these approaches cannot satisfy the diversity of signals. Moreover, though the indexes of energy and correlation are often used to evaluate the denoising effectiveness, respectively, energy and correlation are rarely integrated into the denoising procedure.

Therefore, in this paper wavelet packet denoising algorithm is adopted, and from the signal energy point of view, the energy feature combined with correlation analysis is used to modify wavelet packet coefficients so as to remove white Gaussian noise and impact noise more effectively.

3. The Proposed Approach

3.1. Architecture of the Proposed Method. In this subsection, a universal framework of denoising method for impact noise and white Gaussian noise is proposed and the framework is mainly composed of wavelet packet (WP) decomposition, coefficients modification, and WP reconstruction as shown in Figure 1. The key theory supports are elaborated through the following subsections.

3.2. Wavelet Packet Transform (WPT). In WPT, for a given orthonormal scaling function $\phi(t)$ and wavelet function $\psi(t)$, the double scale equation [38, 39] can be described as follows:

$$\begin{aligned}\phi(t) &= \sqrt{2}\sum_{k} h_{0k}\phi(2t-k),\\ \psi(t) &= \sqrt{2}\sum_{k} h_{1k}\phi(2t-k),\end{aligned} \tag{1}$$

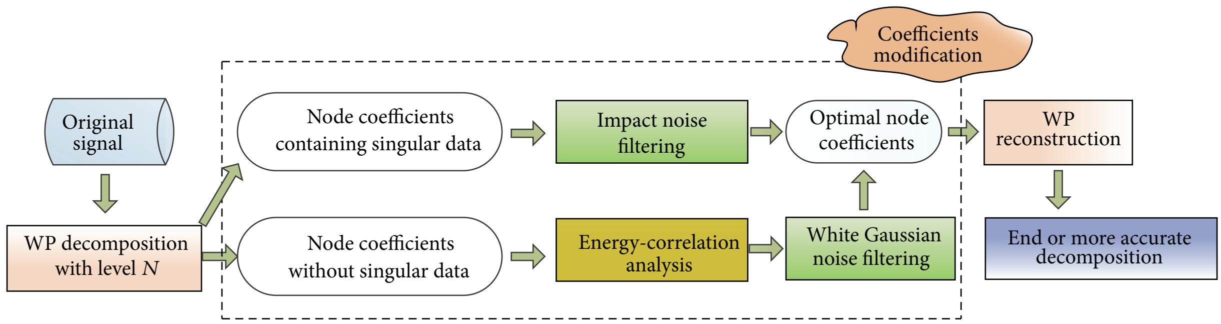


Figure 1: Architecture of the proposed method.

where h_{0k} and h_{1k} are a pair of conjugate orthogonal filter coefficients. Wavelet packet functions for $n = 0, 1, \ldots$ can be defined as follows:

$$w_{2n}(t) = \sqrt{2}\sum_{k\in Z} h_{0k} w_n(2t-k),$$
$$w_{2n+1}(t) = \sqrt{2}\sum_{k\in Z} h_{1k} w_n(2t-k). \quad (2)$$

Then, when $n = 0$, $w_0(t) = \phi(t)$, $w_1(t) = \psi(t)$. $\{w_n(t)\}_{n\in Z}$ is the wavelet packet determined by $w_0(t) = \phi(t)$ and assuming the scaling function can construct standard orthogonal wavelet basis. Hence, scaling functions and wavelet functions included in the wavelet packet have two important properties: orthogonality over both scale and translation, as shown in the following:

$$\langle w_n(t-k)\cdot w_n(t-l)\rangle = \delta_{kl}, \quad k,l \in Z,$$
$$\langle w_{2n}(t-k)\cdot w_{2n+1}(t-l)\rangle = 0, \quad n = 0,1,2,\ldots. \quad (3)$$

In the process of WP decomposition, scale space $\{V_j\}_{j\in Z}$ composed of scaling functions and wavelet space $\{W_j\}_{j\in Z}$ composed of wavelet functions can be expressed in a unified way as follow:

$$U_j^0 = V_j, \quad j \in Z,$$
$$U_j^1 = W_j, \quad j \in Z. \quad (4)$$

From $V_j = V_{j+1} \oplus W_{j+1}$, then

$$U_j^0 = U_{j+1}^0 \oplus U_{j+1}^1, \quad j \in Z,$$
$$U_j^n = U_{j+1}^{2n} \oplus U_{j+1}^{2n+1}, \quad j \in Z,\ n \in Z^+, \quad (5)$$

where, U_j^n denotes the closed subspace of square and integrable space $L^2(R)$, generated by the linear combination of wavelet packet w_n after translation and scaling operation.

During the procedure of multiresolution analysis, objective function is decomposed into the subspace $\{V_j\}_{j\in Z}$, $\{W_j\}_{j\in Z}$ in $L^2(R)$, and carried out further decomposition according to binary mode as follows:

$$\begin{gathered} W_j = U_j^1 = U_{j+1}^2 \oplus U_{j+1}^3 \\ U_{j+1}^2 = U_{j+2}^4 \oplus U_{j+2}^5 \\ U_{j+1}^3 = U_{j+2}^6 \oplus U_{j+2}^7 \\ \longrightarrow \begin{cases} W_j = U_{j+1}^2 \oplus U_{j+1}^3 \\ W_j = U_{j+2}^4 \oplus U_{j+2}^5 \oplus U_{j+2}^6 \oplus U_{j+2}^7 \\ \vdots \\ W_j = U_{j+k}^{2^k+1} \oplus U_{j+k}^{2^k+2} \oplus \cdots \oplus U_{j+k}^{2^{k+1}-1}. \end{cases} \end{gathered} \quad (6)$$

Finally, the wavelet packet coefficients can be computed [40] as follows:

$$d_k^{j+1,2n} = \sum_l h_{0(2l-k)} d_l^{j,n},$$
$$d_k^{j+1,2n+1} = \sum_l h_{1(2l-k)} d_l^{j,n}, \quad (7)$$

where

$$d_k^{j+1,n} = \sum_k \left[h_{0(l-2k)} d_k^{j,2n} + h_{1(l-2k)} d_k^{j,2n+1}\right]. \quad (8)$$

3.3. Energy-Correlation Analysis. The general calculation method of digital signal energy is to extract and square signal amplitude at different positions in time domain and add them together [41, 42]. In order to avoid essential normalization processing to eliminate the influence of relative large energy as described in [43, 44], the sum of absolute values of amplitudes at each sampling points is picked as approximation to evaluate energy, and the calculation method can be shown as follows:

$$e = \sum_{n=1}^{N} |f(n)|, \quad n = 1,2,\ldots,N. \quad (9)$$

Correlation analysis is used to detect nondeterministic relationship between two or more variables. Thus, different

Table 1: The components analysis results of the specified signal.

Effective energy (10^3)	Gaussian energy (10^3)	Impact energy (10^3)	Effective-Gaussian correlation coefficient	Effective-Impact correlation coefficient
8.29	2.55	0.36	−0.0158	0.0102

kinds of signals can be differentiated by exploring the internal relation with correlation analysis. x_i and y_i denote two random variables, respectively; the calculation formula of correlation coefficient can be given as follows:

$$r = \frac{S_{xy}}{\sqrt{S_{xx}S_{yy}}}, \quad -1 \le r \le 1, \tag{10}$$

where

$$S_{xx} = \sum_{i=1}^{n}(x_i - \overline{x})^2, \qquad S_{yy} = \sum_{i=1}^{n}(y_i - \overline{y})^2,$$
$$S_{xy} = \sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y}). \tag{11}$$

This correlation coefficient is named as "Pearson product-moment correlation coefficient," which is usually abbreviated to Pearson's r. When using Pearson's r to estimate relativity, the following principles must be followed.

(1) The nearer Pearson's r absolute value approximates to 1, the higher correlation between variables is. If the Pearson's r absolute value is close to 0, the correlation would be weak.

(2) The sign of correlation coefficient indicates the variety direction of correlation. In the correlation rules, the plus sign and the minus sign signify positive correlation and negative correlation, respectively.

3.4. Processing Method for Wavelet Packet Coefficients Based on Energy-Correlation Analysis. According to the energy-correlation relationship between reconstructed signal confirmed by wavelet packet coefficients and original signal, a real-time online filtering process for white Gaussian noise and impact noise is presented as follows.

Step 1. Carry out WP decomposition of the original signal with appropriate decomposition level and mother wavelet and obtain the corresponding groups of coefficients.

Step 2. During the process of multiresolution analysis, compare all the coefficients in each subspace and eliminate singular data among them based on presupposed threshold a.

Step 3. Reconstruct wavelet packet node signals by the rest coefficients. Then, calculate the ratios of their energy to original signal and get the correlativity between reconstructed node signals and the original signal. The threshold b is used for the processing of subspace unsatisfied coefficients. A series of new coefficients is thus generated.

Step 4. Acquire the reconstruction of the signal based on the modified coefficients on each node, and the removed noise would be obtained. Finally, check whether the result matches the filtering requirement. If so, the process can be finished. Otherwise, increase the decomposition level and repeat the above process. The flow chart of the processing method of wavelet packet coefficients based on energy-correlation analysis is shown in Figure 2.

4. Simulation Example and Application

In order to verify the effectiveness of the proposed algorithm in this paper, simulation experiments are carried out.

4.1. Simulation Example. In order to carry out the simulation, a simulated sinusoidal signal, white Gaussian noise, and impact noise are incorporated into a specified signal. The waveforms are shown in Figure 3 and the components analysis results of the specified signal are shown in Table 1.

Where, the effective energy is the energy of effective signal. In this example, it refers to the energy of simulated sinusoidal signal, Gaussian energy is the energy of white Gaussian noise, and Impact energy is the energy of impact noise. Effective-Gaussian correlation coefficient is the correlation coefficient between effective signal and white Gaussian noise, and Effective-Impact correlation coefficient is the correlation coefficient between effective signal and impact noise.

From the components analyses of the specified signal, we can see that the correlation coefficient absolute values whether between white Gaussian noise and sinusoidal signal or between impulse noise and sinusoidal signal is very small. Thereby, the feasibility of using correlation analysis as index for separating white Gaussian noise and impulse noise from the specified sinusoidal signal is proved.

Based on the analysis of wavelet packet decomposition coefficients and node reconstruction signal, stop the denoising process when the strength of useful signal and interference signal meets the energy-correlation requirement. The coefficients in nodes of the third level wavelet packet decomposition are shown in Figure 4.

The effective signal achieved by the proposed denoising method is presented in Figure 5(a), and the removed signal is shown in Figure 5(b). From Figure 5(b), the white Gaussian noise with impact signals at 112th sampling point and 313th sampling point is eliminated.

For comparison, the same signal using wavelet denoising method is filtered in the following simulation, and the result is shown in Figure 6. The illustration reveals that wavelet

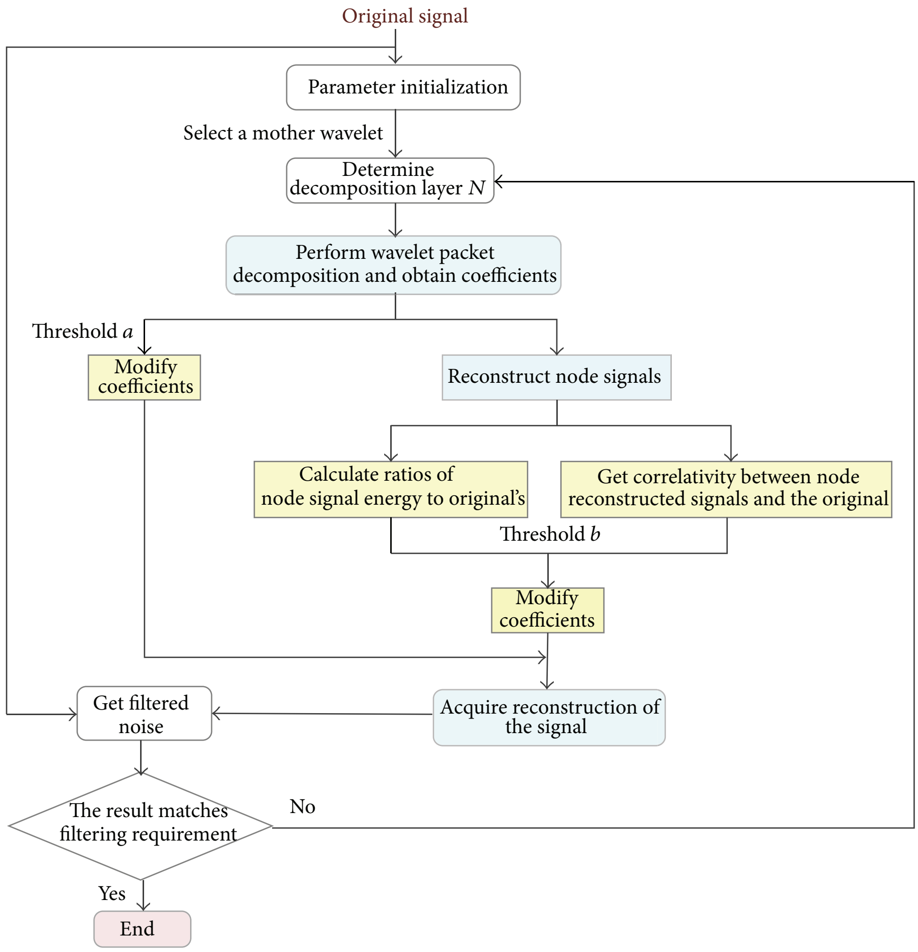


Figure 2: Flowchart of wavelet packet coefficients based on energy-correlation analysis.

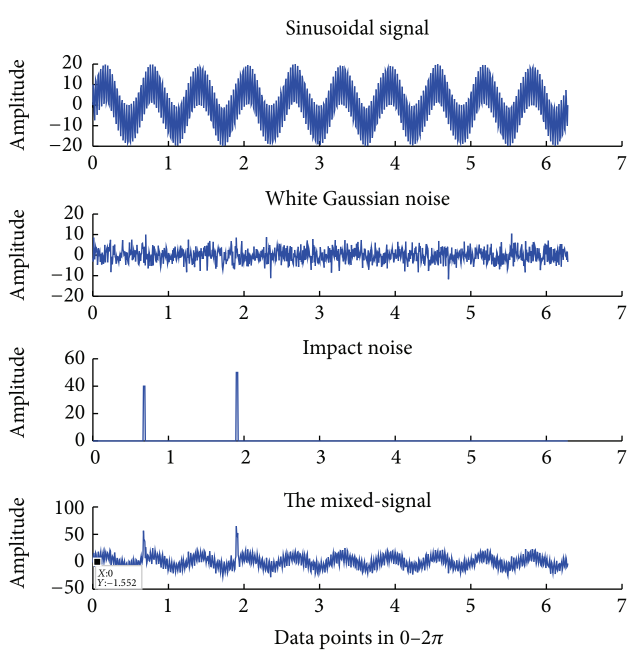


Figure 3: Waveforms of the specified sinusoidal signal, white Gaussian noise, impact noise, and their mixed-signal, 1024 sampling points in 0–2π.

denoising method eliminated the white Gaussian noise but reserved the impact noises at 112th sampling point and 313th sampling point due to the property of wavelet denoising method [45].

The signal achieved by wavelet transform is a step-like signal. This is because not only white Gaussian noise but also some details of original simulated sinusoidal signal are filtered through wavelet transform procedure. The extent of signal details is determined by the threshold selection in wavelet transform.

For the specified signal, the denoising effect of wavelet packet transform based on energy-correlation analysis and wavelet transform were analyzed and compared, and the results were summarized in Table 2.

From Table 2 we can see that the closer sum of the removed noise energy to presupposed mixed noises and the smaller correlation coefficient between noises and original sinusoidal signal both indicate that the denoising methods in this paper has favorable characteristics and better signal denoising effect compared with denoising algorithm based on wavelet transform. Therefore, the denoising methods can be further applied into spot signals denoising.

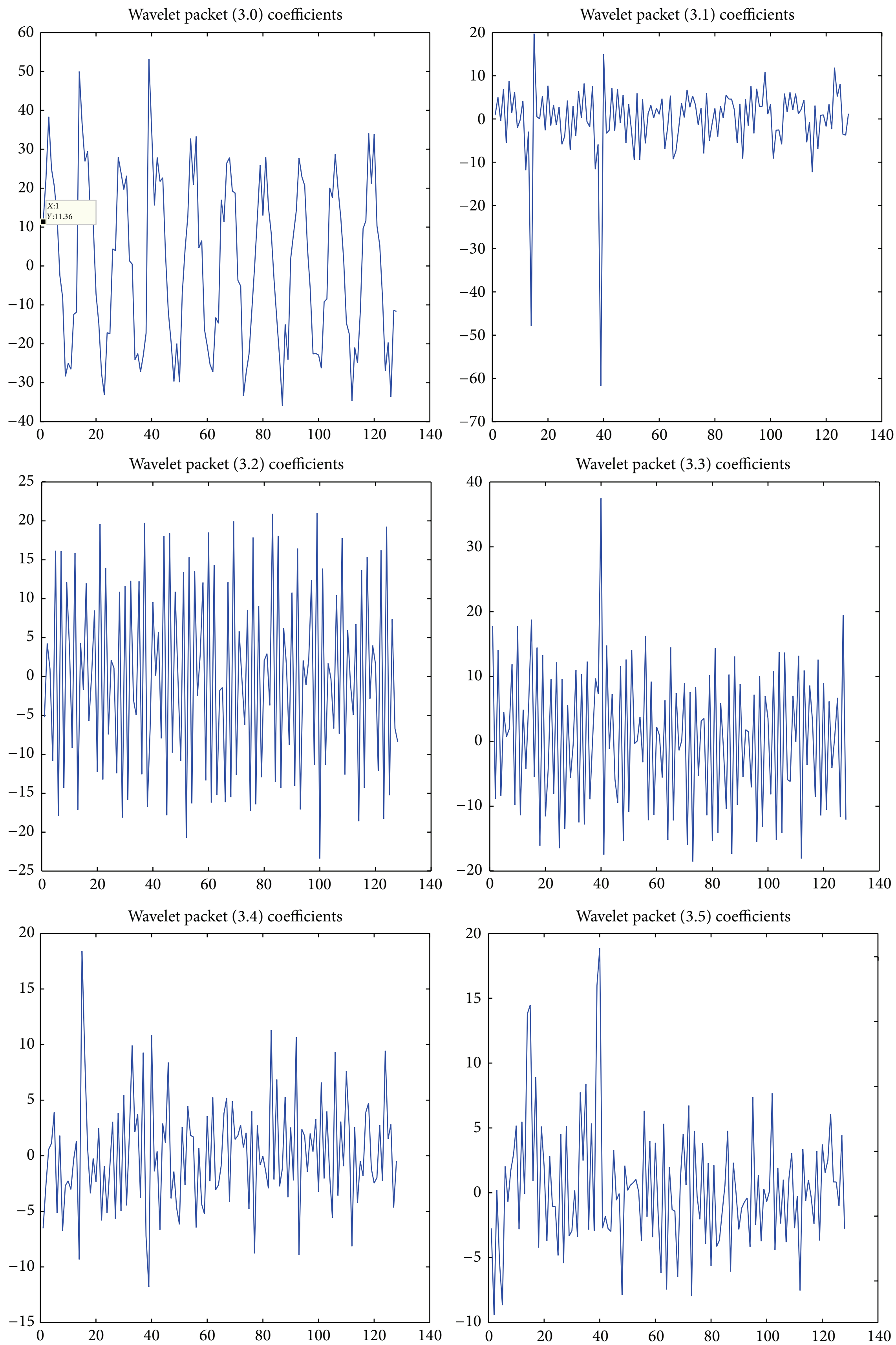


FIGURE 4: Continued.

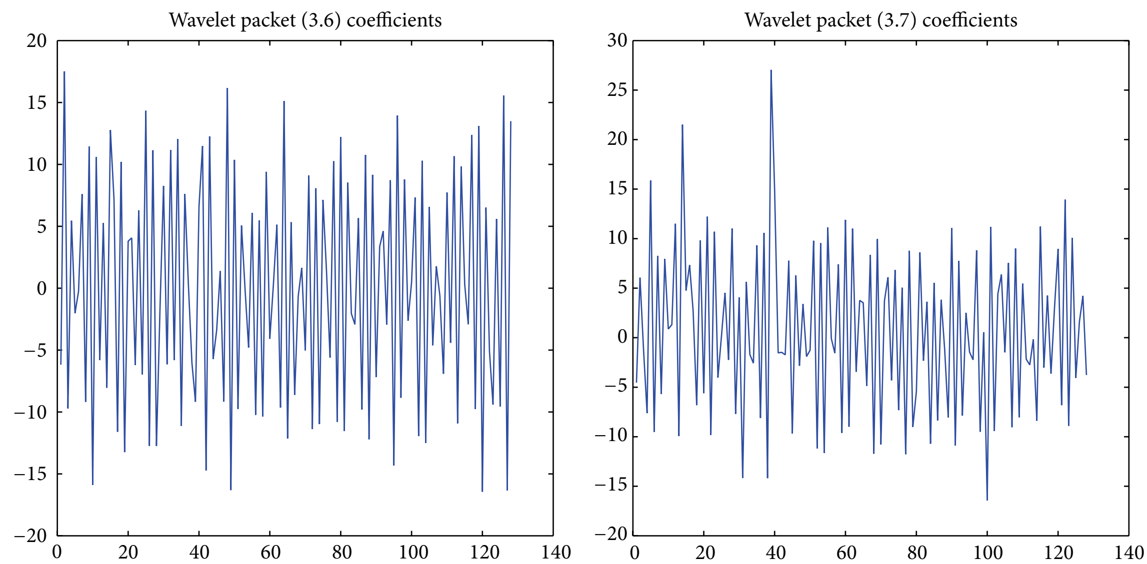
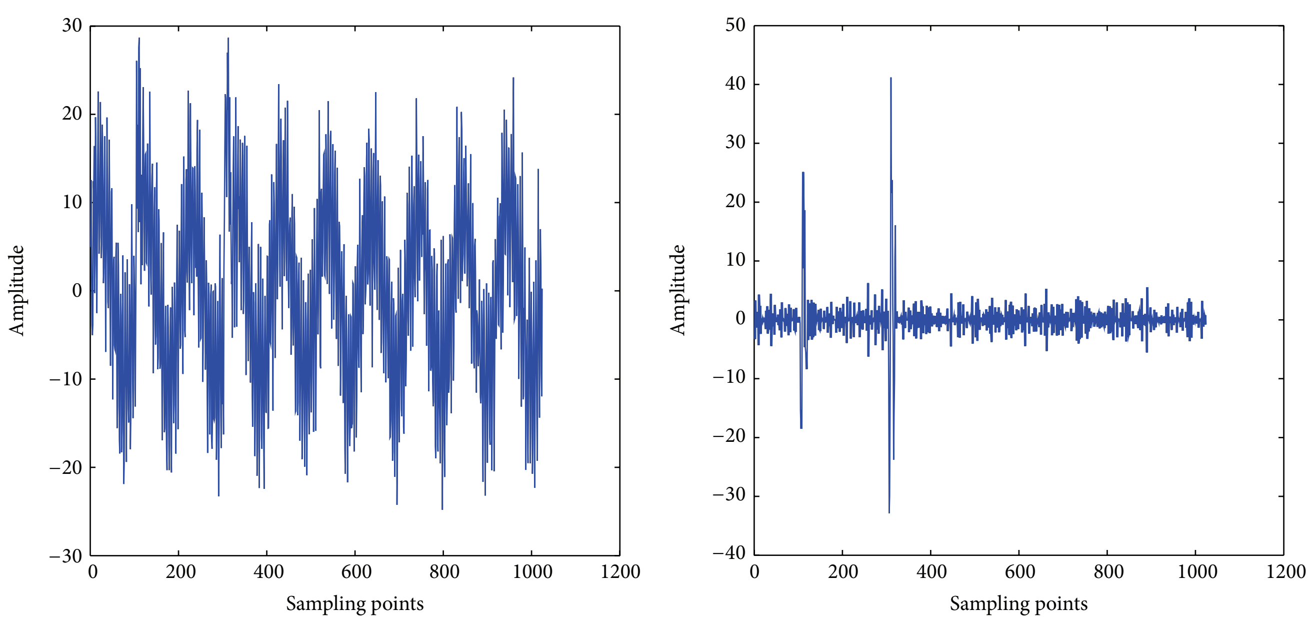


FIGURE 4: The wavelet packet decomposition coefficients.



(a) The signal achieved by wavelet packet denoising

(b) The corresponding removed noise

FIGURE 5: The wavelet packet denoising result of specific signal.

4.2. Application. In this section, the proposed denoising algorithm is applied into automatic monitoring system for mining machine of a coal mine in Henan, China, and the application interface of proposed denoising algorithm is shown in Figure 7.

In order to obtain the original shearer cutting current and the denoised shearer cutting current for the experiment, we changed the primary system and developed an interface for this application, as shown in the Figure 7(a). By simply clicking the button, both the original shearer cutting current and the denoised shearer cutting current would be obtained, as shown in Figure 7(b).

The mining machine is the most important equipment on the underground fully mechanized coal mining face. As the most significant characteristic of mining machine, the shearer cutting current signal reveals the real-time external load of cutting. Thus, it's very essential to obtain the perfect sensing shearer cutting current signal. The original shearer cutting current signal is exported by the system, and waveform of the signal is shown in Figure 8.

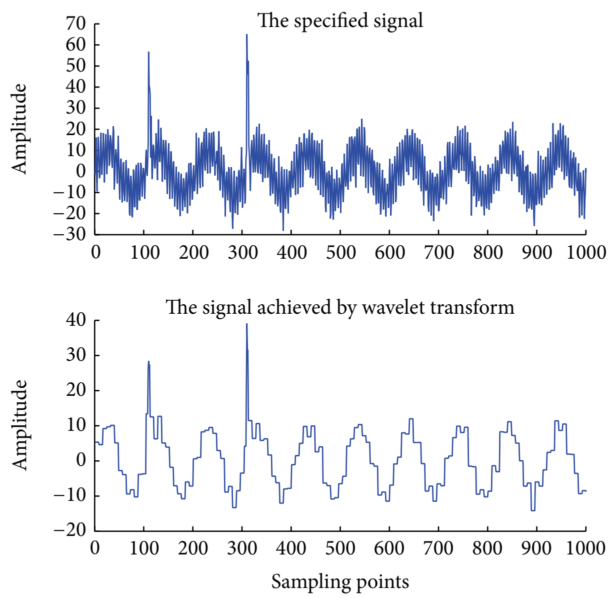
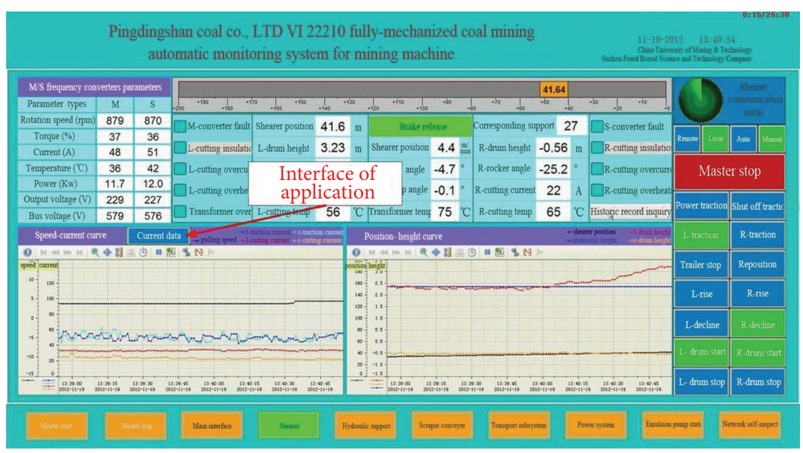
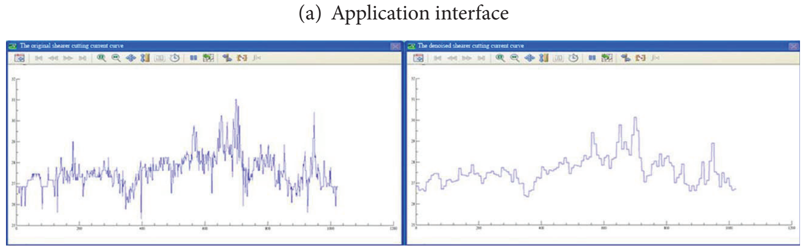


FIGURE 6: The result of wavelet denoising method.



(a) Application interface



(b) Exported shearer cutting current signal

FIGURE 7: Application interface of proposed denoising algorithm.

TABLE 2: The denoising effects comparison.

Objects	Effective energy (10^3)	Gaussian energy (10^3)	Impact energy (10^3)	Effective-Gaussian correlation coefficient	Effective-Impact correlation coefficient
The specified signal	8.29	2.55	0.360	−0.0158	0.0102
Wavelet filtering result	6.79	6.89		0.7304	
Wavelet packet filtering result	8.77	2.16		−0.0001	
Wavelet packet filtering error	5.79%	<10%		<1%	

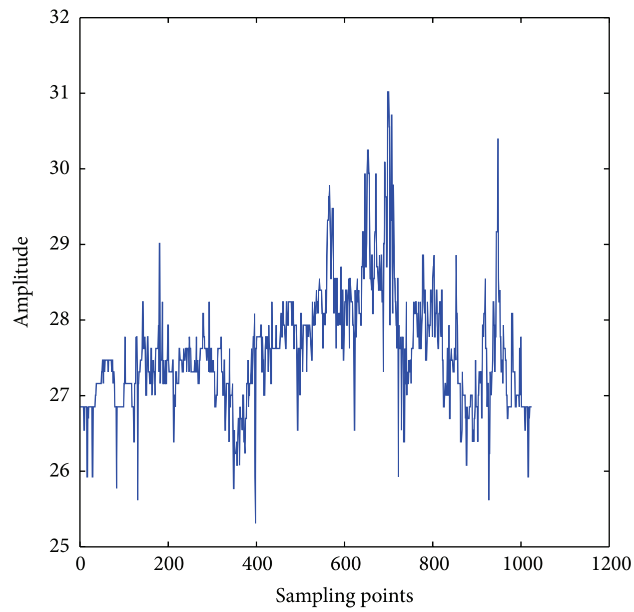
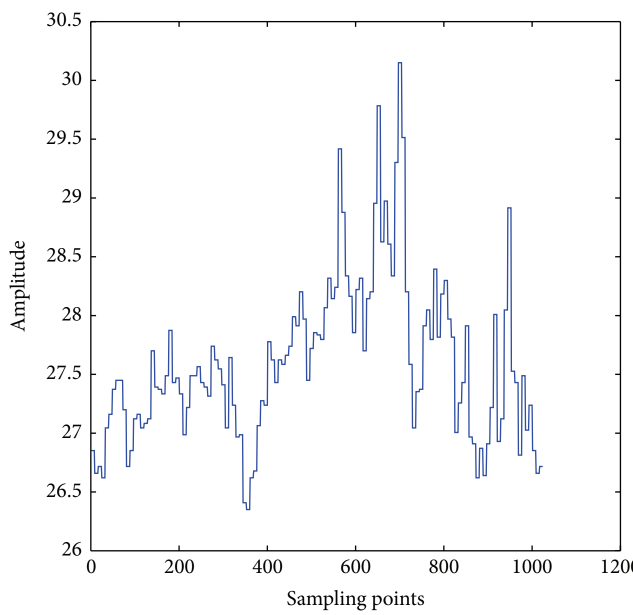
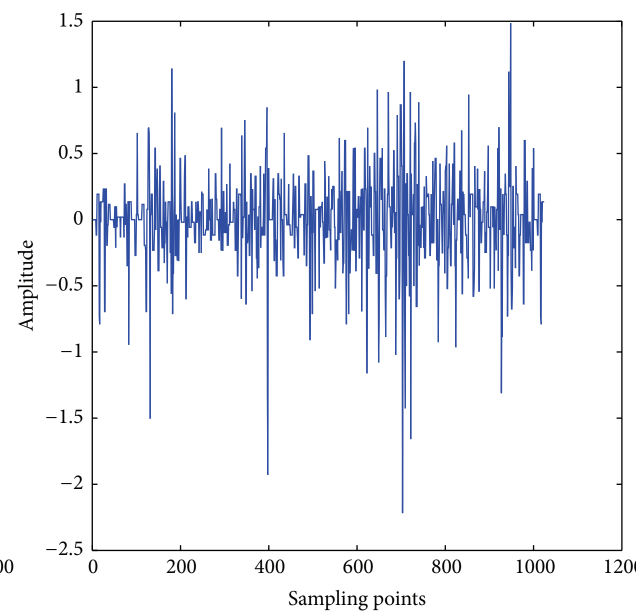


Figure 8: The original shearer cutting current signal.



(a) The waveform of filtered shearer cutting current signal



(b) The corresponding removed noise

Figure 9: The denoising result of shearer cutting current signal.

The signal was denoised with proposed algorithm based on wavelet packet transform and energy-correlation analysis. The denoising result is shown in Figure 9.

Figure 9(a) shows that the denoised shearer cutting current signal is smooth and the detailed information is mainly saved. Therefore, the real-time running status of shearer can be reflected appropriately. It is found from Figure 9(b) that the removed noise signal contains many mutational components whose elimination is of great significance to the stability of sensor signal. The denoising results of the shearer cutting current signal are summarized in Table 3.

From Table 3 we can infer that the impact subjected to shearer cutting current signal is not obvious. Nevertheless, we also achieve good denoising effect since the useful signal and noise obtained by the proposed method is basically uncorrelated.

5. Conclusion

Extracting useful information from original signal collected by sensors is important whether for reflecting equipment running state or data fusion between sensor nodes. An

Table 3: The denoising result analysis of shearer cutting current signal.

Objects	Effective energy (10^4)	Noise energy (10^4)	Effective-noise correlation coefficient
Original signal	2.826	Unknown	Unknown
Wavelet packet denoising result	2.8028	0.0242	0.0001

integrated denoising method for sensor mixed noises based on wavelet packet transform and energy-correlation analysis is proposed in this paper. The key technologies for the proposed approach, such as the architecture of the proposed method, wavelet packet transform, energy-correlation analysis, and the details of processing method, are described. Moreover, a simulation example for a specific signal and an application of the shear cutting current signal from the automatic monitoring system for mining machine are carried out, and the simulation and application results show that the proposed method is effective.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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