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Thermal Measurement Data Preprocessing Based on Wavelet Analysis and Data Fusion

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Abstract: Combined with the advantages of Wavelet threshold denoising method and data fusion technology. A data processing method of thermal measurement based on wavelet transform and data fusion is proposed. After decomposing the thermal measurement signal of each measuring point separately by wavelet decomposition, the high frequency components are first filtered by the threshold noise reduction method, and then the signal of each measuring point after noise reduction is got by wavelet reconstructing to reduce the influence of noise, and then , we normalize the signal of each measuring point, and make the data fusion based on the least mean square of the normalized measuring points, so as to obtain a better reconstructed signal. The experimental results show that this method improves the accuracy and reliability of the measured data and makes the signal features more apparent.
Keywords: Data pretreatment; thermal data; wavelet analysis; data fusion.

INTRODUCTION

At present, the energy supply mode in our country is mainly thermal power generation, while the power plant, as a complex industrial system of the country's major energy production, has such huge social responsibilities as operational safety, energy saving and emission reduction. In order to complete the monitoring of various running equipment performance of the power station, it is necessary to refer to the result of multi-party data analysis. Therefore, accurately measuring various parameters of the running equipment is an important precondition for the equipment monitoring system to perform fault diagnosis and soft measurement.

Wavelet analysis has the advantages of low entropy, multi-resolution, de-correlation, flexibility of choice of base functions. It decomposes the various frequency components in the signal into non-overlapping bands, and provides an effective way for the separation of signal and noise [1, 2]. Thermal measurement data has a lot of uncertainty, however, the fusion of multi-sensor technology can reduce the uncertainty of the information and improve the accuracy of the characterization of the environment. At the same time, the information redundancy can also improve the robustness of the whole system [3]. Combining the advantages of the above two, this paper presents an algorithm based on wavelet analysis and multi-sensor fusion technology for preprocessing thermal measurement data.

Basic Theory

Wavelet denoising theory and technology

Wavelet analysis is a time-frequency analysis method, which has good localization properties in both time domain and frequency domain. According to the different frequency components of the signal, wavelet analysis can automatically adjust the sampling density in time domain or frequency domain. In 1989 Mallat proposed a fast algorithm for tower multi-resolution analysis and reconstruction of signals called the Mallat algorithm.

Mallat decomposition algorithm is:

$$\begin{cases} c_{k+1} = H c_k \\ d_{k+1} = G d_k \end{cases} \qquad (1)$$

The formula: c_k and d_k are the low-frequency and high-frequency signals of the original signal at resolution 2^{-k}; H is a low-pass filter; G is a high-pass filter; $k = 0 \sim K$; K is the maximum decomposition level.

Mallat reconstruction algorithm is:

$$c_k = H^* c_{k+1} + G^* d_{k+1} \tag{2}$$

The formula: H^*, G^* is the dual operator; $k = K-1, K-2, \ldots, 0$. Discrete signal c_0 is decomposed into $d_1, d_2, \ldots, d_k$ and c_K by the Mallat decomposition algorithm, $d_1, d_2, \ldots, d_k$ and c_K are reconstructed for c_K and C_K . Then:

$$X = D_1 + D_2 + \ldots + D_K + C_K \tag{3}$$

The formula: $D_1, D_2, \ldots, D_K$ are high-frequency signals reconstructed from layer 1 to layer K ; and C_K is a low-frequency signal reconstructed of layer K .

A one-dimensional signal model which contains noise can be expressed as follows:

$$s(k) = f(k) + \varepsilon . e(k) \qquad k = 0, 1, \ldots, n-1 \tag{4}$$

The formula: $s(k)$ --Noisy signal; $f(k)$ --Useful signal; $e(k)$ --Noise signal; ε --Noise signal deviation.

In practical engineering, the useful signal usually shows as low-frequency signal or some relatively stable signal, while the noise signal usually shows as high-frequency signal [4-6]. Therefore, the process of noise reduction can be handled as follows:

- Wavelet decomposition of the signal. Choose a wavelet basis and determine the number of layers N for wavelet decomposition, and then calculate the N-level wavelet decomposition of the noisy signal $s(k)$.
- Quantifying the threshold with high frequency coefficients of wavelet decomposition. Threshold quantification is performed by selecting the appropriate threshold or threshold function for the high-frequency coefficients at each decomposition scale.
- Wavelet reconstruction. Wavelet reconstruction is carried out according to the low frequency coefficients of the highest resolution layer of wavelet decomposition coefficients and the high frequency coefficients of each layer after the threshold quantitative processing.

The choice of wavelet basis function and threshold

Considering the time-frequency double localization characteristics closely related to the compactness of the wavelet function, the dbN wavelet system with tight support is chosen. The support length $2 \times N - 1$ is good for the accurate reconstruction of wavelet decomposition coefficients. At the same time, the dbN wavelet system has good orthogonality, which can make the measured data signal closer to the wavelet basis and better express the characteristics of the signal. Combining the orthogonality and the tight support principle of wavelet functions, the db4 wavelet is selected to decompose into the 5 layers.

The basic idea and core content of the wavelet threshold denoising method proposed by Donoho and Johnstone is to apply a certain threshold function and threshold to the decomposed wavelet coefficients, and to adopt different threshold functions or different thresholds will have different denoising effects. The hard threshold [7] is that when the wavelet coefficient is greater than the threshold λ , the retention coefficient is constant and the value less than the threshold λ is set to zero. The hard threshold is better than the soft threshold when noise, so the hard threshold method is adopted. The hard threshold filtering formula is:

$$y_h(x) = \begin{cases} x & |x| \geqslant \lambda \\ 0 & |x| < \lambda \end{cases} \tag{5}$$

The definition of the threshold is:

$$T_2 = \varepsilon \sqrt{2 \ln(N)} \tag{6}$$

The principle of this method is that the probability that the maximum value of the N standard Gaussian variables with independent and identical distribution is less than T_2 is close to 1 as N increases. If the detection signal contains independent and identical noise, the wavelet decomposition coefficients of the noise are also independent and identically distributed. If the noise is independent and identically distributed by wavelet transform, the coefficients of sequence length N , is based on the principle that the wavelet decomposition coefficient maximum probability less than T_2 close to 1, which means that there exists a threshold of T_2 , makes all the wavelet coefficients of the sequence are less than it.

Multi-sensor fusion theory and technology

At present, the theory of data fusion has been widely used in the field of state estimation. The weighted fusion algorithm is a mature one. Many research results have proved the optimal, unbiased and minimum mean square error of the proposed algorithm [8-9].The key of weighted fusion algorithm lies in the determination of weight coefficient, which is inversely proportional to the measurement variance of each sensor. Assuming there are n sensors of different precision with variances of $\sigma_1^2, \sigma_2^2, \ldots, \sigma_n^2$, the measured values of each sensor are $X_1, X_2, \ldots, X_n$ the result of the weighted fusion is:

$$X = \frac{\frac{1}{\sigma_1^2}}{\frac{1}{\sigma_1^2}+\frac{1}{\sigma_2^2}+\ldots+\frac{1}{\sigma_n^2}} X_1 + \frac{\frac{1}{\sigma_2^2}}{\frac{1}{\sigma_1^2}+\frac{1}{\sigma_2^2}+\ldots+\frac{1}{\sigma_n^2}} X_2 + \ldots + \frac{\frac{1}{\sigma_n^2}}{\frac{1}{\sigma_1^2}+\frac{1}{\sigma_2^2}+\ldots+\frac{1}{\sigma_n^2}} X_n \tag{7}$$

From (7), the measurement data with large variance is given a smaller weight and the data with smaller variance is given a larger weight, so this data fusion method can get more reliable than the arithmetic mean measurement results.

Wavelet denoising and data fusion data preprocessing method

In order to improve the accuracy of thermal measurement data and reduce or eliminate the deviation caused by the noise of measurement equipment, this paper uses the combination of wavelet denoising [10] and data fusion [11] to improve the accuracy and reliability of measurement data. The calculation flow is shown in Fig-1. Firstly, the wavelet threshold is used to denoise the measured value of each sensor to reduce the influence of noise. Then, the sensor measurements were normalized, and the normalized values of each sensor are calculated based on Minimum-mean-square data fusion, the better multi-sensor reconstruction signals is obtained. The information provided by the multi-sensor signals provides redundancy, correlation and complementary, so data fusion of homologous data can take full advantage of the measured target information in time and space, obtaining the statistical advantages, and then get accurate description of the measure.

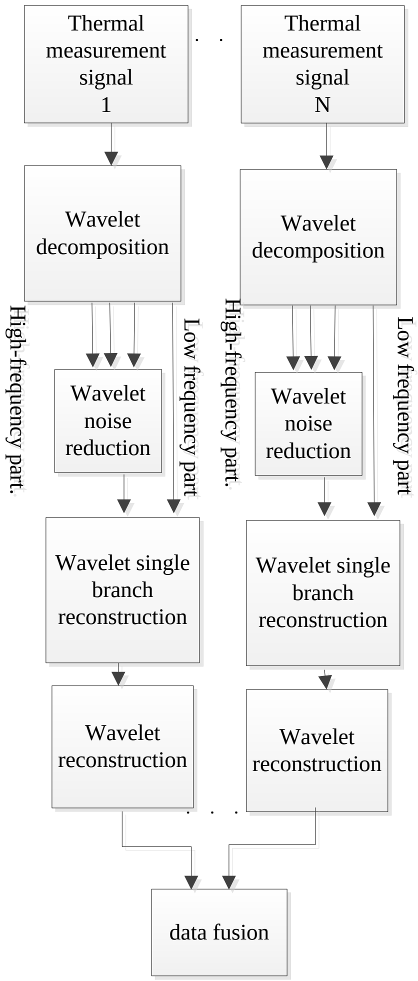

Fig-1: Calculation process

Case Analysis Based on Multiple Sensor Data Fusion Algorithm

Power plants are extremely complex production processes. The whole control system is equipped with a large number of different sensors to complete the corresponding measurement. Drum water level [12] is an important monitoring parameter in boiler operation. It indirectly represents the balance relationship between boiler load and water supply. Maintaining the water level of the drum in the safe range is a necessary condition for ensuring the safe operation of steam turbines and boilers. In actual production, measurement information is often easily drowned by noise. Because the wavelet has the characteristics of low pass filtering, the water level measurement data of the drum is decomposed by wavelet to effectively suppress the noise. The multi-sensor data fusion technology can enhance the reliability of the data, and the fault tolerance performance is superior to the single sensor.

In this paper, 500 sets of measured values of three sensors of the drum level of a power plant are used for multi-sensor data fusion. The db4 wavelet of the drum water level measurement data was selected for the 5 layers decomposition. The decomposition results are shown in Fig-2.

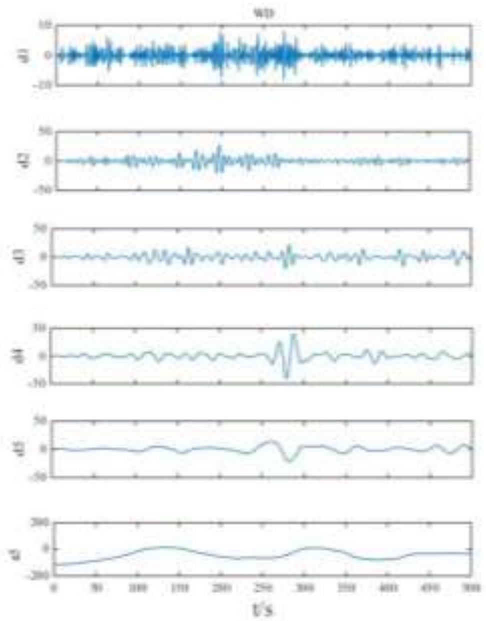

Fig-2: Wavelet decomposition of water level measurement of drum

The decomposition result includes five sets of high frequency detail components d1-d5 and one set of low frequency approximate components a5 from Fig-2. The low-frequency approximate signal and high-frequency detail signal at different levels of resolution are obtained, so that the target signal is observed in detail at each scale, so as to better grasp the characteristics of the water level of the drum and part characteristics. From the 5th layer to the 1st layer of the detail signal, the signal amplitude becomes smaller and smaller; the low frequency approximate component a5 is relatively stable, which reflects the basic characteristics of changes with data of drums water level.

Fig-3 shows the original measured signal of the three sensors and their fusion curves. It can be seen from the figure that the trend of the three drum water level measurements is the same, but the measured values at the same moment are different and fluctuate within a certain range with large noise signal. Fig-4 shows signals and fusion curves of three single sensors after noise reduction preprocessing.

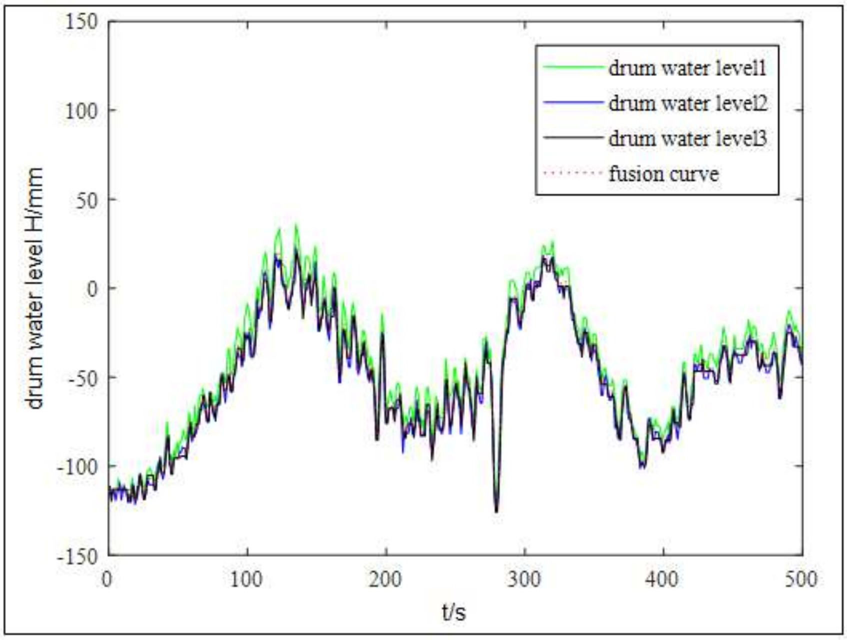

Fig-3: Three sensors original signal and its fusion curve

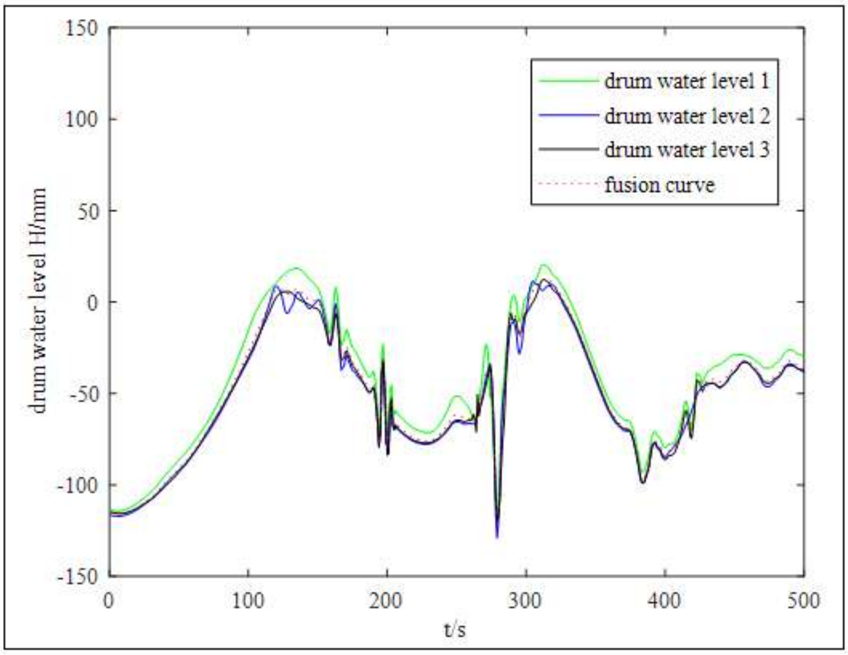

Fig-4: Three sensor signals after preprocessing and their fusion curves

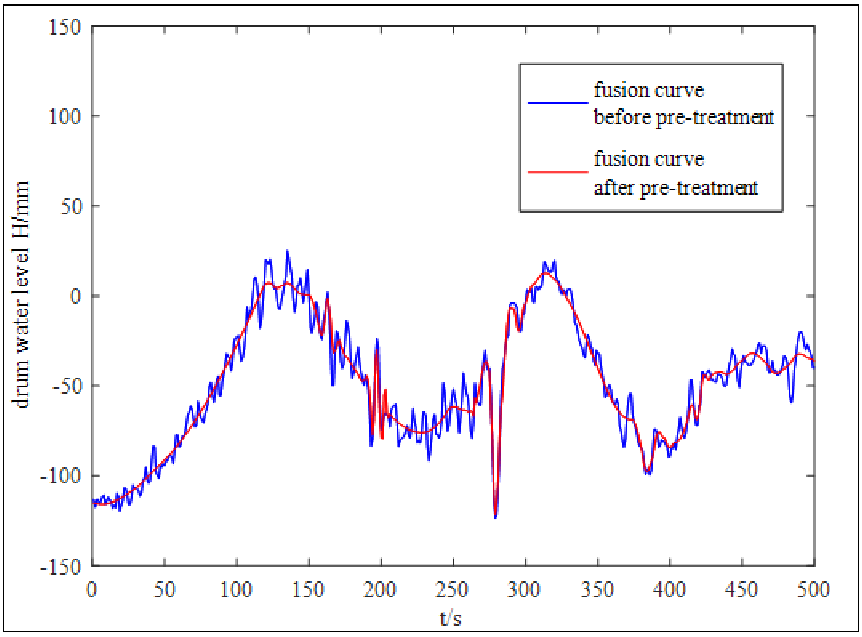

Fig-5: Three sensors before and after preprocessing fusion curve

By comparing Fig-3 and Fig-4, it can be clearly seen that the signal after noise reduction satisfies the principle of smoothness and similarity and effectively reduces the high frequency signal (noise).In Fig-4, the dotted line indicates the estimation results of the fusion of multiple sensors, and the curve has good agreement with each single sensor. For each single sensor measurements and the average value of the three sensor measurements. The results can be obtained that $\sigma_1^2 = 7.4685^2$, $\sigma_2^2 = 5.4472^2$, $\sigma_3^2 = 4.1946^2$ by doing mean square error calculation of each single sensor measurements and the average value of the three sensor. Then calculate the mean square error of the mean value $\sigma^2 = 0.1553^2$ of the fused data and the three sensors. The variance after fusion is smaller than the variance of each sensor, indicating that the fusion algorithm has obvious effect on improving the accuracy and reliability of the data. In Fig-5, by comparing the three sensor measurement signals after fusion with preprocessing and fusion without processing, the former data is smoother, which effectively eliminates the influence of noise and improves the signal measurement accuracy.

CONCLUSION

This paper presents an algorithm based on wavelet analysis and multi-sensor data fusion. Wavelet function has diversity, adaptability of time-frequency window and a variety of excellent performance, which play a very significant role in noise processing. However, data fusion technology effectively processes and synthesizes multi-source information from the same target, generating more accurate and complete estimation and judgment than single source. Taking the drum water level and the boiler feed water flow as an example, the algorithm used in this paper is very effective by comparing the estimation results of multiple sensors and single sensor for data fusion. And in the same data (single sensor, the same number of fusion of the sensor) thermodynamic measurement of signal preprocessing process analysis is better than not doing this process, the most important thing is that the bigger measured noise is, the more obvious the effect is.

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