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REMOVE NOISE FROM FLUORESCENCE SIGNAL OF MINERAL OIL IN WATER USING STATIONARY WAVELET TRANSFORM AND WAVELET ENTROPY

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Abstract*- *In the fluorescence detection system, noise will affect the sensitivity of the system. The method using Stationary Wavelet Transform to de-noise fluorescence signals based on adaptive wavelet entropy is studied. The de-noising effects of dbN families are compared, and then the db7 wavelet is chosen as the optimal wavelet. The noised fluorescence signal is decomposed at 5 levels via Discrete Wavelet Transform or Stationary Wavelet Transform. The thresholded detail coefficients are reconstructed with the approximation coefficients to produce the pure fluorescence signal. It is verified that the de-noising method via Stationary Wavelet Transform has better effect than Discrete Wavelet Transform.

Keywords - Fluorescence Signal; Stationary Wavelet Transform; Wavelet Entropy; De-noising; Threshold

I. INTRODUCTION

The development of industry and agriculture leads the increase of sewage; meanwhile, the pollution of mineral oil in water is getting more and more severe. It is great significant to detect the mineral oil in water accurately. Because the fluorescence analysis method has the advantages of high sensitivity, good selectivity, and ease of design [1-4], it is widely used in the field of water pollution detection, analysis of pesticide residues, and so on[5-10]. In the fluorescence detection system of mineral oil in water, in order to improve the detection accuracy, the Photomultiplier Tube (PMT) is applied to transform the fluorescence signal into the current signal. While in the process of transformation, the noise will be generated. In addition, due to the low concentration of the sample, the internal noise and external interference, the weak fluorescence signal is drowned in the noise. Improving the accuracy of the fluorescence detection and the quality of the fluorescence signal is a key technique in the fluorescence signal processing.

The wavelet analysis has the characteristics of multi-resolution and good localization, so it is widely applied in the field of signal processing, fault diagnosis and so on [11-14]. Mallat algorithm is a swift algorithm of the discrete wavelet transform (DWT). Signals via low-pass and high-pass filtering are down-sampled, and the wavelet coefficients generated by the filters are lack of translation invariance [15]. Some information may be lost after reconstructing the wavelet coefficients. The approximation and detail coefficients generated via stationary wavelet transform (SWT) are not down-sampled; whose length is the same to that of the original signal.

This character ensures the integrity information of the signal. The detail coefficients in each level are divided into n parts. The thresholds are selected adaptively according to maximum wavelet entropy of each part. The method of de-noising fluorescence signal is proposed based on the adaptive threshold of wavelet entropy.

II. PRINCIPLE AND SYSTEM STRUCTURE OF FLUORESCENCE MEASURING MINERAL OIL IN WATER

In mineral oil, the compound molecules which contain conjugated double bonds will absorb luminous energy when irradiated by the excitation light, and then they jump from the ground state to excited states of the energy level. In the excited states, the molecules will transit to the lowest vibration energy level of the first excited state by internal conversion. Then the molecules return to each different vibration energy levels of the ground state while emitting fluorescence [16].

According to the law of Lambert-Beer, the relationship between the fluorescence intensity (IF) and the concentration of the mineral oil(c) is:

$$I_F = Y_F \cdot A \cdot I_0 \left(1 - 10^{-\varepsilon cL}\right) \tag{1}$$

Where, A is a constant, related to the instrument; Y_F is the fluorescent quantum yield of mineral oil; I0 is the intensity of transmission light; ε is the molar absorption coefficient of mineral oil; L is optical path of fluorescence in mineral oil.

According to the Taylor series, when the concentration of mineral oil is low, the higher term can be omitted, thus the formula (1) can be unfolded as:

$$I_F = 2.3 Y_F A I_0 \varepsilon c L \tag{2}$$

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The formula (2) shows that the fluorescence intensity is directly proportional to the concentration of mineral oil, which is the principle of measuring mineral oil in water.

For the mineral oil in water , when the excitation wavelength is shorter than 290nm, the most effective excitation wavelength is 250nm, and the fluorescence peak is located in 352~414nm. When the excitation wavelength is longer than 300nm, the most effective excitation wavelength is 360nm, and the fluorescence peak is located in 420~480nm. The pulse xenon lamp, which has strong instantaneous power and can supply the stable excitation light 200~700nm, is chosen as the excitation light source. The designed instrument is shown in Fig.1. The light resulting from the Xenon light transforms to a certain wavelength monochromatic light through a diffraction grating. The monochromatic light is divided into two parts by an optical coupler, one is reference light, gathered by PMT0, and the other is excitation light, used to excite the mineral oil in water to produce the fluorescence. The fluorescence goes through the diffractive raster and is gathered by PMT1. PMT0 and PMT1 respectively output current signals I0 and I1, the relative fluorescence intensity is I1/I0, which can eliminate the unstable factor like the fluctuation of excitation light source and improve the accuracy of the detection system.

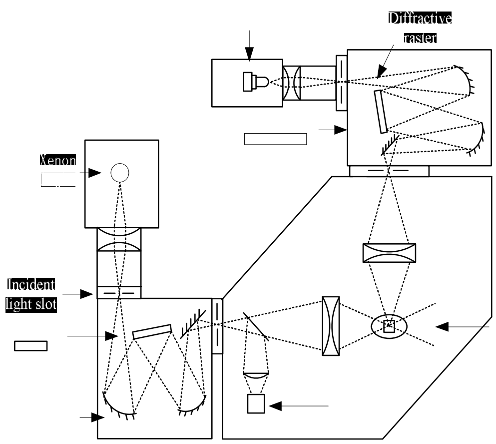

Fig. 1 The fluorescence detection instrument of mineral oil in water

In the process of PMT1 converting fluorescent signals to current signals, the fluorescence signal can be inundated with the noise (shot noise and thermal noise, etc) produced from the detection system.

III. PRINCIPLE OF DE-NOISING VIA STATIONARY WAVELET TRANSFORM

In the fluorescence detection system, the desired signal is relatively stable and low-frequency, while the noise signal usually presents high-frequency. The fluorescence signal is decomposed at j levels to get the low-frequency coefficients and high-frequency coefficients, so the noise signal can be separated from the desired signal.

The one step decomposition and reconstruction process of stationary wavelet is shown in Fig.2. Where, j is the decomposition level, and cj is the approximation coefficient, standing for the low-frequency part of the signal , dj is the detail coefficient, standing for the high-frequency part of the signal, h(t) and g(t) respectively represent the low pass and high pass filter function.

Where, cj+1 and dj+1 are not down-sampled via stationary wavelet transform, and these lengths are the same to the original signal, so the integrity of the information is ensured. The decomposition filters at level j+1 is the up-sampling of the filters at level j. The up-sampling makes redundancy information of the wavelet coefficients and it doesn’t lead the signal excursion.

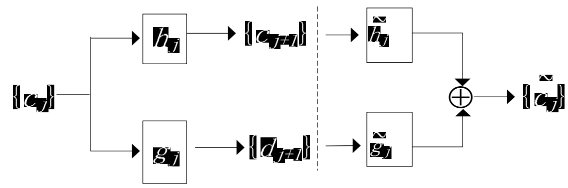

Fig.2 The one step decomposition and reconstruction process of stationary wavelet

IV. WAVELET ENTROPY THEORY AND THE THRESHOLD SELECTION REGULATION

In the wavelet domain, the useful signal’s energy is relatively concentrated, while the noise signal’s energy is relatively dispersive, so wavelet coefficients of the useful signal are larger than that of the noise signal. The smaller wavelet coefficients can be thresholded. Thus, the noise contained in high-frequency signals can be eliminated.

For the framework of the wavelet transform theory, if the wavelet functions are a set of orthogonal basis, the wavelet transform is in accordance with the law of energy conservation:

$$\sum_{j=1}^{N} \left| < f(t), \quad \psi_{j,k}(t) > \right|^2 = \|x\|^2 \tag{3}$$

If the high-frequency wavelet coefficients at level i is $d_i(k)$, and $d_i(k)$ is a stand-alone signal source unit, the wavelet energy at level i is expressed as:

$$E_i = \sum_k |d_i(k)|^2 (i = 1,2,\cdots, \quad j) \tag{4}$$

N is the number of samples, and $d_i(k)$ is separated into n subintervals of equal size, the wavelet energy at subinterval k $(1 \leq k \leq n)$ is [17]:

$$E_{i,k} = \sum^{N/n} |d_i(k)|^2 \tag{5}$$

The probability of wavelet energy existing at subinterval k is:

$$p_{i,k} = \frac{E_{i,k}}{E_i} \tag{6}$$

The wavelet entropy at subinterval k is:

$$S_k = -\sum_i p_{i,k} \ln p_{i,k} \tag{7}$$

The variance of the noise signal is the median of the subinterval, which contains the maximum entropy.

For the soft-threshold formula, the threshold at level i is [18]:

$$thr(i) = \sigma_i \sqrt{2\log(length(d_{i,k}))} \tag{8}$$

The high-frequency coefficients quantized formula is:

$$\hat{d}_{i,k} = \begin{cases} 0 & |d_{i,k}| < thr(i) \\ d_{i,k} - thr(i)\cdot \mathrm{sgn}(d_{i,k}) & else \end{cases} \quad (9)$$

Where $\hat{d}_{j,k}$ is the quantized value of high-frequency wavelet coefficients at level *i*, and sgn(*) is a sign function.

V. EXPERIMENTS AND RESULTS ANALYSIS

The experiment process is shown in Fig.3.

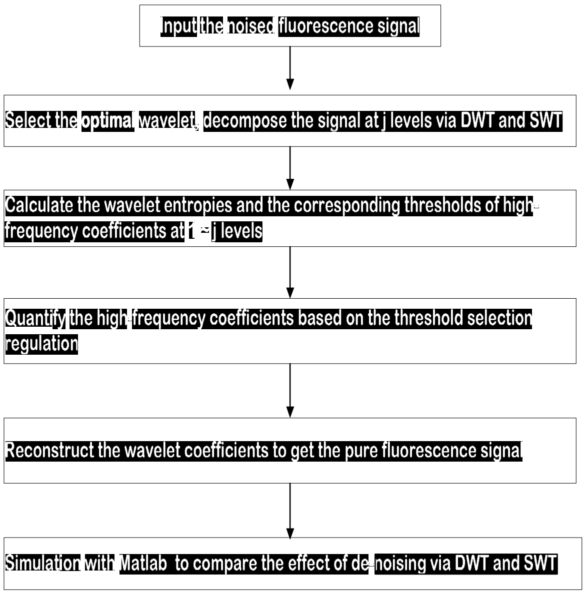

Fig.3 The experiment process

Irradiate the SDS micelles diesel sample with the concentration of 10mg/L by the excitation light of wavelength 360nm to obtain the photoelectric pulse signal, which is generated by the fluorescence detection system and shown in Fig.4.

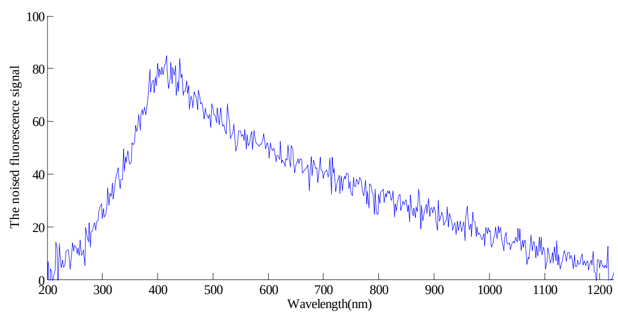

Fig.4 The spectrum of noised fluorescence signal

Different wavelet functions have different orthogonality, compact support, symmetry, regularity and vanishing moment. The selection of wavelet function will affect the de-noising. For the fluorescence signal, due to the length increase of the branch set, it produces some boundary issues. The dbN wavelet family can flexibly balance the border issues, retain the useful signals and smooth out noise. The Signal to Noise Ratio (SNR) and Mean Squared Error (MSE) are applied to evaluate the effect of de-noising.

$$\mathrm{SNR} = 10 * \ln\left(\sum_{i=1}^{N} \frac{y_i^2}{(x_i - y_i)^2}\right) \quad (10)$$

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(x_i - y_i)^2 \quad (11)$$

Where, yi represents the de-noised signal, xi represents the original noised signal, N is the length of the signal. The larger MSE and smaller SNR, the better de-noising effect is. The db1 ~ 15 wavelet bases are selected to decompose the noised signal at 5 levels. The d1~d5 quantified by soft thresholds and the a5 are restructured to obtain de-noised signals. The SNR and MSE are calculated in Table 1.

TABLE I THE DE-NOISED EFFECT OF *db1~db15* WAVELET

Wavelet basis.	SNR	MSE
db1	27.2365	0.0692
db2	31.7413	0.0248
db3	35.3477	0.0114
db4	35.6322	0.0055
db5	32.7503	0.0135
db6	34.5463	0.0093
db7	35.8970	0.0041
db8	35.4270	0.0063
db9	33.6663	0.0105
db10	33.1071	0.0134
db11	31.3371	0.0206
db12	30.2803	0.0255
db13	31.1604	0.0213
db14	33.8867	0.0109
db15	32.4805	0.0145

Table 1 shows that for db4, db7 and db8, the SNRs are larger than 35, and the MSEs are smaller than 0.01, the de-noising effect is better than others. Especially, for db7, the SNR is the largest with 35.897, and the MSE is the smallest with 0.0041. So the db7 is chosen as the optimal wavelet basis.

Set the fluorescence signal sampling points 1024. Choose the db7 wavelet basis to decompose the noised signal at 5 levels via DWT. The approximate coefficients a5 and five levels detail coefficients d1 ~ d5 are obtained and shown in Fig.5. The wavelet coefficients at each level are down-sampled; the signal length at level j +1 is half of the signal length at level j. Most of the noise is concentrated in the detail coefficients d1, d2, and a little in the d3. While the useful information is mainly concentrated in a5, and a small part is concentrated in d4 and d5.

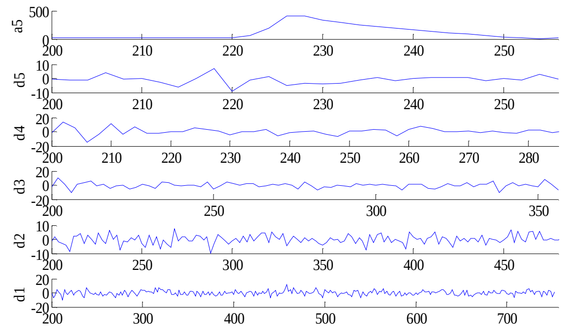

Fig.5 a5 and d1 ~ d5 decomposed via Discrete Wavelet Transform

According to the adaptive threshold selection regulation, the thresholds d1~d5 are calculated: 1.0211, 1.079, 0.7864, 1.0912 and 0.8253. The de-noised high-frequency coefficients are reconstructed with the low-frequency coefficients to obtain the new fluorescence signal, shown on the left in Fig.6. The new signal maintains the characteristics of the original signal, and most of the noises are filtered out. But the curve is so smooth that the important information at key positions is lost. So reconstructing the signal accurately can not be achieved.

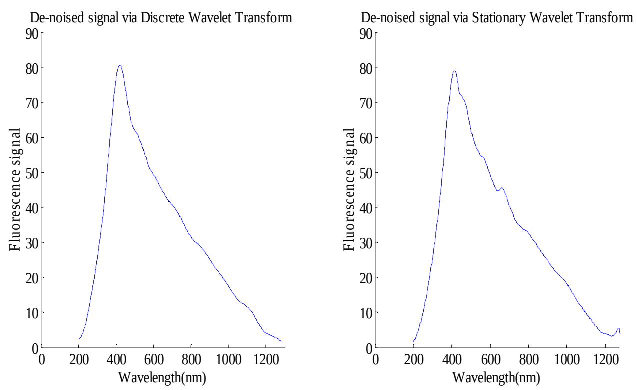

Fig.6 The de-noised signals via Discrete Wavelet Transform or Stationary Wavelet Transform with wavelet entropy threshold

Decompose the noised signal at 5 levels via SWT to obtain 5 levels of approximate coefficients a1~a5 and detail coefficients d1 ~ d5, shown in Fig.7. The a1~a5 and d1 ~ d5 are not down-sampled, whose length is the same to that of the original noised signal. Based on the regulation of adaptive threshold selection, the thresholds d1~d5 are 1.0437，0.8531，0.7991，0.8113 and 0.6149. The de-noised high-frequency coefficients are reconstructed with the low-frequency coefficients to obtain the new fluorescence signal, shown on the right in Fig.6. The de-noised signal carve has good similarity and less distortion, so the useful information can be retained, and the peaks of the noise can be removed.

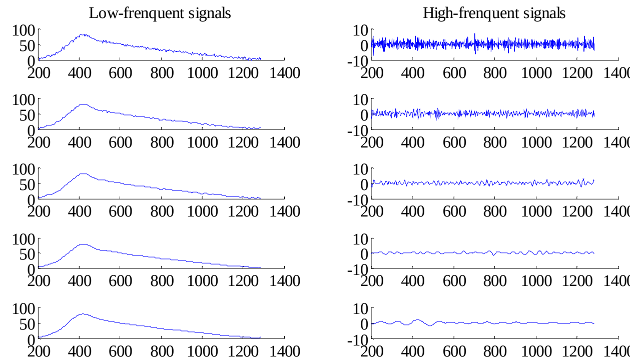

Fig.7 a1~a5 and d1~d5 decomposed via Stationary Wavelet Transform

In order to further prove the superiority of SWT, the original noised signal, the de-noised signal via DWT and the de-noised signal via SWT are placed in the same coordinate system, shown in Fig.8. The de-noised signal via DWT has a certain deviation along the time axis at key positions A, B, C and D, while the de-noised signal via SWT can coincide with centerline of the original fluorescence signal and it has not deviation.

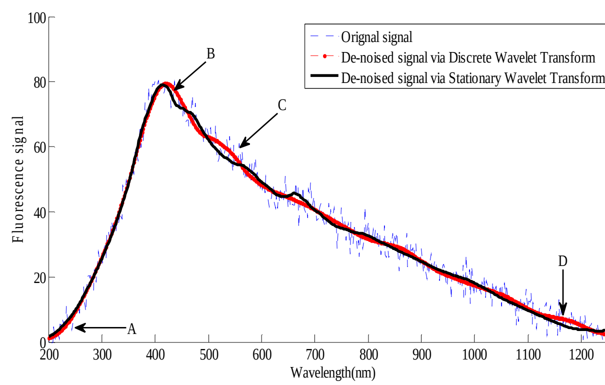

Fig.8 Comparison of de-noised results via Discrete Wavelet Transform or Stationary Wavelet Transform

Amplify the section A (200~260nm) and D (1040~1120nm) to show more clearly in Fig. 9 that the de-noised signal via SWT cannot shift with the time axis.

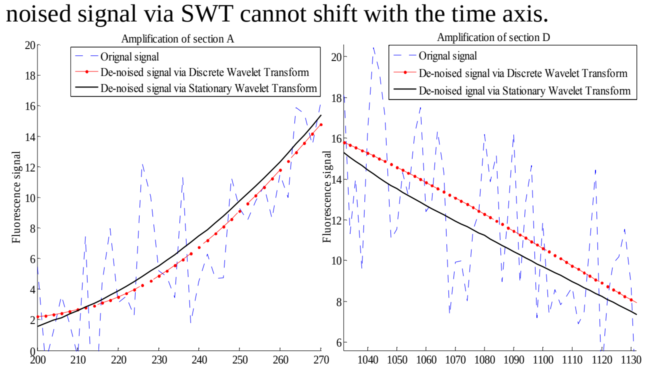

Fig.9 The curve amplification sections of section A and section D

Objectively, In order to compare the de-noising effect of two methods, the SNR and MSE of the de-noised signals are calculated in Table 2.The SNR of signal de-noised via SWT is larger than that of signal de-noised via DWT, and the MSE of the signal de-noised via SWT is less than that of signal de-noised via DWT. It is proved that the SWT with adaptive threshold of wavelet entropy has a good effect on de-noising fluorescence signals.

TABLE Ⅱ THE SNR AND MSE OF NOISED SIGNAL AND DE-NOISED SIGNAL

Signal types	SNR(dB)	MSE
Signal de-noised via DWT	35.8970	0.0041
Signal de-noised via SWT	40.7677	0.0125

VI. CONCLUSIONS

This paper studies the SWT de-noising method, and makes a comparison with the DWT de-noising method. Experimental results show that both methods can smooth out the noise. The signal de-noised via DWT with adaptive threshold of wavelet entropy may lose some important information and exist the deviation along the time axis. In the process of SWT, the wavelet coefficients of the noised fluorescence signal is not down-sampled ,so it can retain the whole useful information and have no deviation . Comparing the SNR and MSE of the signals de-noised via DWT or SWT, the SWT has a better effect on de-noising fluorescence signals.

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