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Research of Particle Size Identification Based on Blind Source Separation

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Abstract

Aiming at effectively identifying the different particle sizes of single particles of the same kind and eliminating the interference of redundant and noise components in the light scattering signals, this paper puts forward a single particle size detection method by processing the light scattering signals of particles with blind source separation. As shown in the test results, the research object, a single-spherical PTFE pellet (4μm in particle size), contains noise and redundant angular intensity scattering signals. The scattering signals are decomposed into by empirical mode 8 components, which respectively serve as the virtual multi-source signals for blind source separation. The redundant noises in different channels are removed by the ICA algorithm to produce the noiseless and non-redundant light scattering signals. Such signals bear the information on the type of particles, and provide a reliable signal source for further, accurate measurement of particle size. It is demonstrated in the simulation experiment and the engineering example that the blind source separation method not only applies to identification of signal source, but also reduces the noise, improves the signal-to-noise ratio (SNR) of the signal, and suppresses the interference in the light scattering signals from redundant and nose components.

Keywords

Light scattering, blind source separation, particle size

1. Introduction

Thanks to the unique advantages of light scattering in particle measurement, light scattering particle measurement has been applied to a variety of scenarios. Based on single property, there are small-angle forward scattering, angular scattering, light extinction, dynamic light scattering and polarized light scattering [1] [2]. According to the particles being measured, the light scattering measurement is divided into: the generalized light scattering that simultaneously measures several particles, and the light scattering that measures a single particle at a time. The multi-particle measurement has a low spatial resolution, and only provides the statistics on the overall particle sizes of all the particles in the measurement area. In contrast, the single particle measurement method is required for the precision measurement of the particle size of small particles, such as the angular scattering, i.e. the classic Mie scattering [3]. Some classic solutions are proposed by Lorenz, Mie and Debye at the beginning of this century. Among them, a feasible method is to calculate the angular scattering distribution based on the relationship between the scattering angle and parameters of a single particle like the diameter D, the refractive index n, the incident wavelength and the scattering intensity I. In other words, the so-called phase function I (θ, λ) has a measurement chart. The particle size, and thus the particle concentration, is obtained by the inverse operation [4]. Currently, many choose to determine the particle size, and then the concentration, by scattering light of 90°. Nevertheless, this approach has several problems: 1. It is assumed that the particles are of the same material, the refractive index is fixed, and the scattering light signals are not affected by the refractive index [5]; 2. The scattering light signals are very weak; the accuracy is reduced when the particle size is small because of the interference from the background noise of the electronic part. In light of the above, this paper employs blind source separation to separate scattering light signals and provides a reliable signal source for further, accurate measurement of particle size. The true light scattering signals of particles, including the particle refractive index signal, are obtained through the removal of the influence of noise and redundant components [6] [7].

2. Light scattering signal processing based on blind source separation

Since the blind source separation can separate the blind signals from mixed signals, it is applied to the signal components decomposed from light scattering signals for the purpose of removing the noise in the signal components of light scattering signals, eliminating the redundant information from each signal component, and separating the mixed elements between different information. The resulting components of light scattering signals are independent from each other and complete on their own. The effect of the blind source separation on the removal of noise and redundant components in light scattering signals is verified by a simulation with light scattering signals mixed with noise. Among all kinds of blind source separation algorithms, this paper selects the ICA algorithm. Below is the flow chart of the light scattering signal processing based on blind source separation (Figure 1) [8] [9].

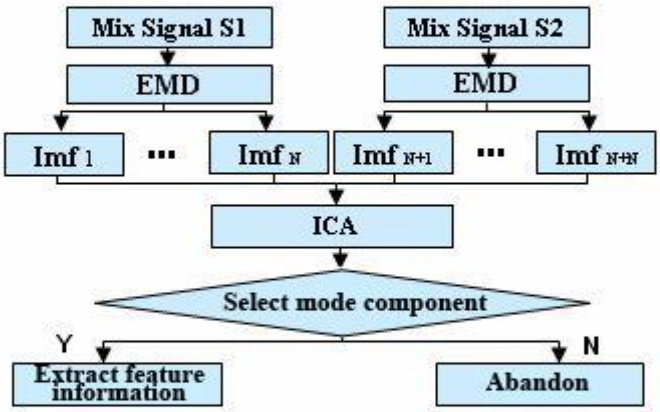

Fig. 1 Flow chart of the light scattering signal processing based on blind source separation

3. Light scattering signal simulation based on blind source separation

Redundant components or noise contamination distort the value of the light scattering signals of particles, making it impossible to identify the accurate size of the particles. When the blind source separation searches for the optimal signal from a group of mixed signals, it actually extracts the information components from a signal source out of the mixed signals. The process eliminates the redundant information components of several mixed signals and ensures the accurate description of the characterization information of the body signal. With the combination of the blind source separation and light scattering, this paper attempts to restore the lost signal characteristics of light scattering of particles, and to resolve the limitations on the particle size identification of particles by light scattering signals. If the signal components have an excessively small frequency ratio or an excessively high energy ratio, the particle size of the particles calculated based on the noisy signals will be seriously distorted. In order to verify the conclusion and resolve the above problems, the author carries out a data simulation experiment. First, a simulation function is constructed to verify the method. The three sinusoidal signals have no phase difference and their frequency is respectively 10Hz, 20Hz and 50Hz. Besides, a white noise sequence (mean value=0; variance=1) is established by the randn function. The white noise sequence follows the normal distribution. Figure 2 displays the time domain frequency spectrum of the four sets of signals [10] [11].

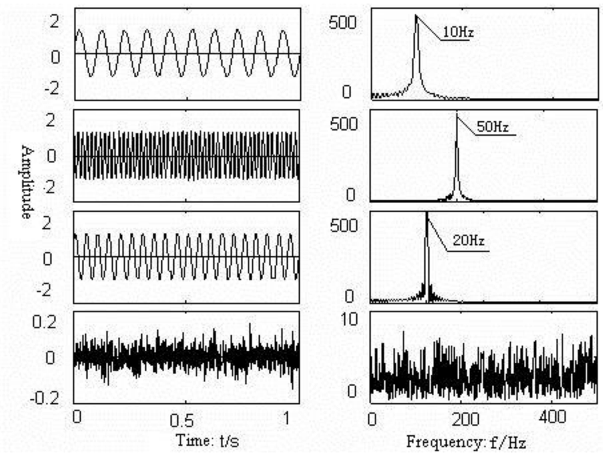

Fig. 2Time domain frequency spectrum of the sinusoidal signals and white noise signal

The white noise signal is mixed into three sinusoidal signals by different proportions. The SNR of the three groups is 27.6db, 28.3db and 30.6db, respectively. Then, the three noisy sinusoidal signals are multiplied by the mixed matrix to get three mixed noisy signals. (Figure 3) Because of the high SNR, the white noise is difficult to discern in the time domain or the frequency domain.

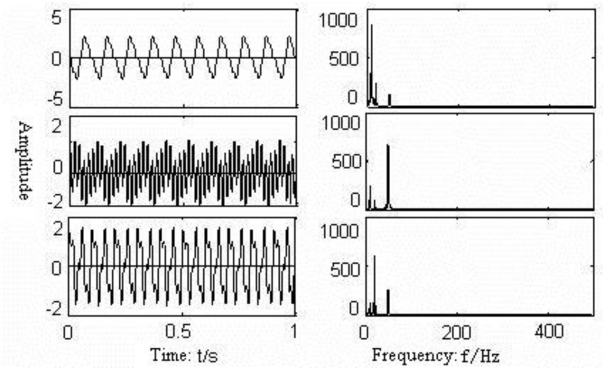

Fig. 3 Time-domain frequency-domain waveforms of noisy mixed signals

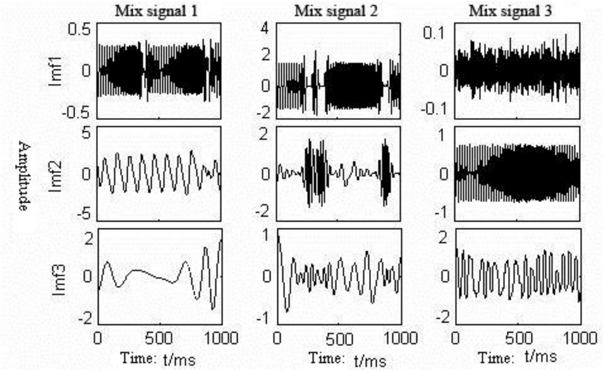

Fig. 4 The first three IMF components of noisy mixed signals

Each of the noisy mixed signal is decomposed by empirical mode. The first three components are displayed in Figure 4. Through the comparison of Figure 3 and Figure 4, it can be seen that the presence of noise has a great impact to the decomposition results although the sinusoidal signals and the mixing matrix remain the same. The first three IMF components in Figure 4 feature significant distortion. Intrinsic Mode Function is called IMF for short. Of course, the phenomenon is not only caused by noise, but also by the low frequency ratio of the signal components.

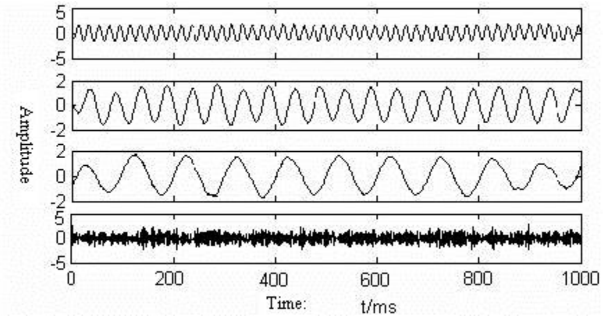

Fig. 5 Estimated IMF components of noisy mixed signals

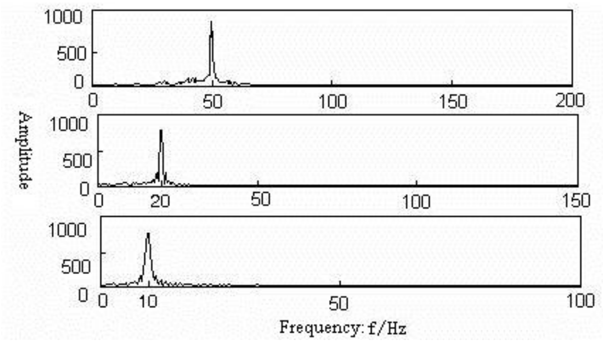

Fig. 6 The specturm of the first three estimated IMF components of the noisy mixed signals

According to the aforementioned philosphy of light scattering signal processing based on blind source separation, the 9 IMF components of the noisy mixed signals in Figure 4 are taken as the inputs of the ICA algorithm. After the ICA operation, the estimated outputs of IMF components are displayed in Figure 5. It can be inferred that the first three estimated IMF components given by the ICA operation have regular sinosudual waveforms. Figure 6 shows the frequency domain waveforms of these components. Their frequency is respectivey 50Hz, 20Hz and 10Hz, which are in line with that of the three sinusoidal signals that form the mixed signals. Moreover, the white noise are basically extracted from each of the mode components, indicating that the noise and redudnant components are removed from the light scattering signals. Through blind source separation, the estimated signal components can accurately characterize the information of the three sinusoidal signals. Of course, the effect of blind source separation will not be so obvious in actual light scattering signal test because the noise contains components other than the white noise [12] [13].

4. Experimental verification

An experimental system is established to verify the feasibility of particle size identification based on the blind source separation light scattering signal processing method. The system structure is shown in Figure 7. A vertical He-Ne laser device (wavelength: 650nm) is used as the incident light source. 6 lenses (f=50mm) are put in front of the laser device, and a photodiode array (N = 512, L = 0.6cm) is placed in the behind [14] [15].

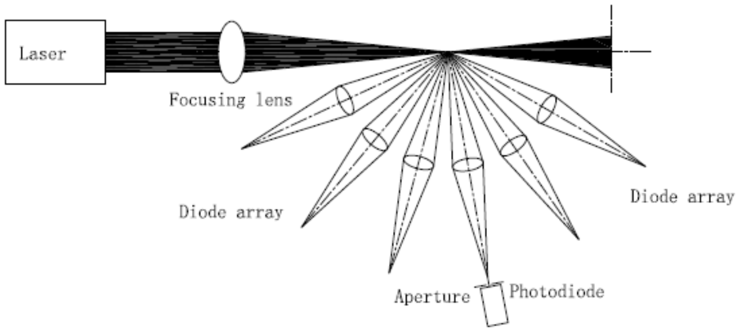

Fig. 7 Sketch map of the structure of the experimental system

To verify the effectiveness of the proposed method, a PTFE pellet (4μm in particle size) is chosen as the reference material. The distribution of measured noiseless angular scattering signals is displayed in Figure 8.

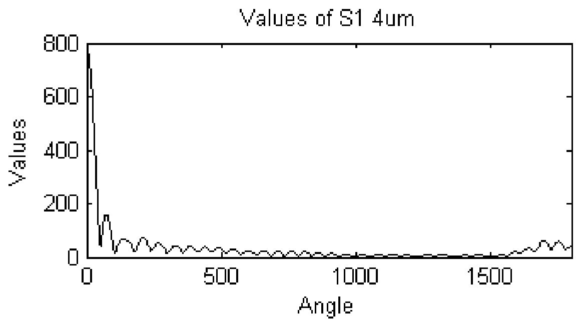

Fig. 8 Light scattering signals of PTFE pellet (4μm in particle size)

Next, noise interference is added to the experimental system. In this case, the measured noisy light scattering signals of the PTFE pellet (4μm in particle size) are shown in Figure 9. It can be seen from Figure 9 that the noisy light scattering signals is more distorted than the original noiseless light scattering signals. Thus, it is impossible to identify the particle size of the PTFE pellet with noisy light scattering signals.

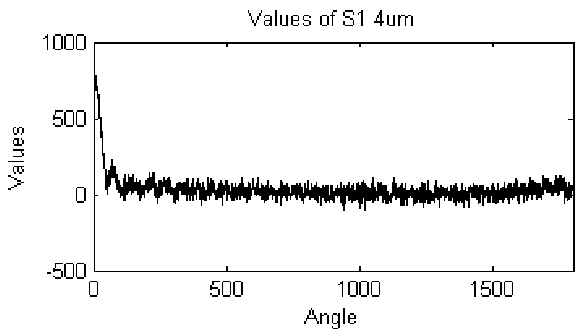

Fig. 9 Noisy light scattering signals of PTFE pellet

Based on the proposed particle size identification method based on blind source separation, the noisy light scattering signals in Figure 9 are decomposed by empirical mode, and the light scattering signal components thus obtained are taken as the input sources of multi-channel signals for the blind source separation algorithm. Through the processing by the blind source separation algorithm, the author eventually acquires the noiseless light scattering signals of the PTFE pellet, and, on this basis, identifies the particle size of the pellet. Figure 10 describes the results of empirical mode decomposition of the noisy signals in Figure 9.

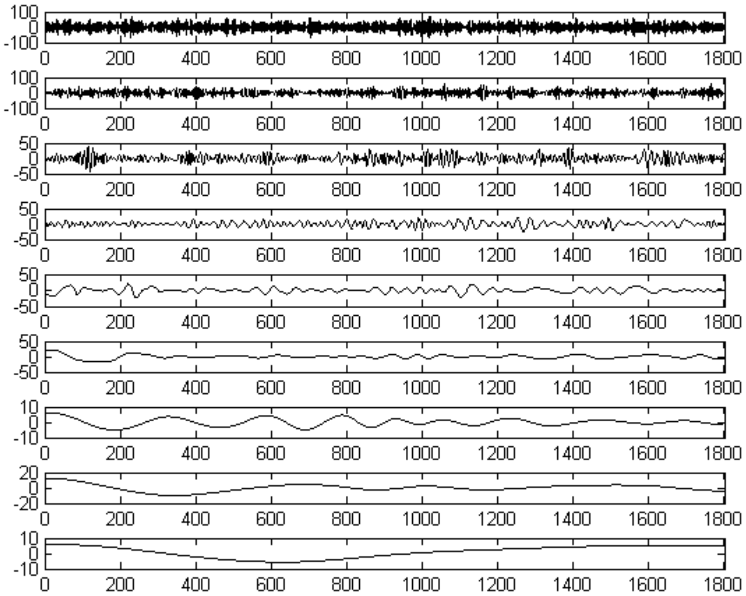

Fig. 10 Decomposition of noisy light scattering signals of the PTFE pellet by empirical mode

The components of the above noisy light scattering signals of the PTFE pellet are taken as the source of observation signals of the blind source separation algorithm, and imported to the ICA algorithm of blind source separation. The calculated results are shown in Figure 11.

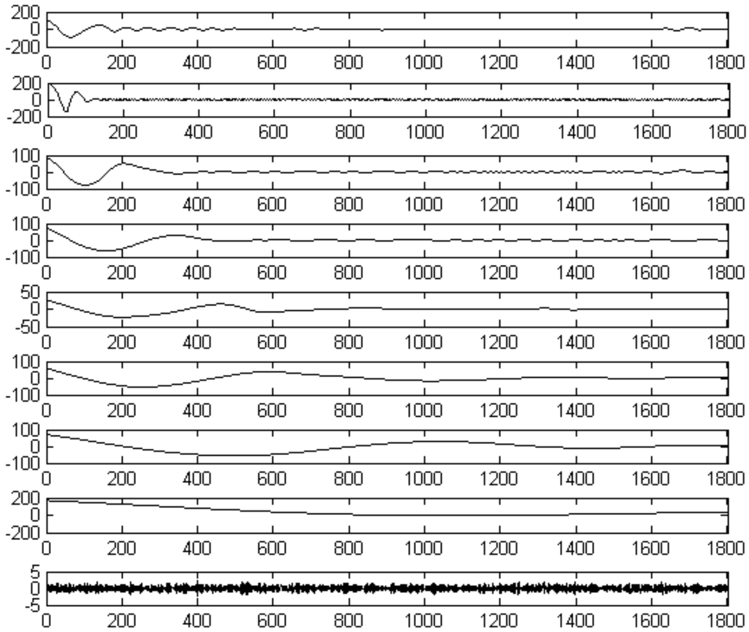

Fig. 11 Results of blind source separation of noisy signal components

According to Figure 11, each of the components decomposed from the noisy light scattering signals of the PTFE pellet by empirical mode has a new sequence and location after the operation of the blind source separation algorithm, and the time domain no longer has one-to-one correspondence. It should be noted that this is one of the characteristics of the blind source separation algorithm and will not affect the synthesis of the subsequent signals. It is also shown in Figure 11 that the last component is apparently a noise component and should be discarded. In comparison with Figure 10, there is much less noise in components other than the noise component. Therefore, suffice it to say that the blind source separation restores the original signal by removing the interference elements from the noise-containing signal components. Then, the author synthetizes the other signal components, except the last noise component, in Figure 11. The resulting light scattering signals of the PTFE pellet after noise reduction by blind source separation are illustrated in Figure 12.

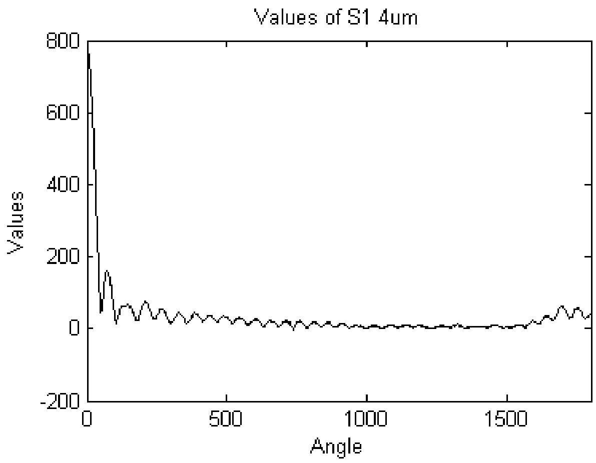

Fig. 12. Light scattering signals after noise reduction by blind source separation

The comparison between Figure 8 and Figure 12 demonstrates that, in spite of a small amount of noise elements, the signal waveform in Figure 12 is very similar to that of noiseless signals, and the treated signals have no negative effect on particle size identification of the PTFE pellet.

5. Conclusion

This paper proposes a noise reduction method based on blind source separation. After discussing the influence of noisy signals on the particle size identification of particles, the author suggests reducing the influence of noise over light scattering signals by treating the light scattering signals with blind source separation. Based on the noisy signal simulation experiment, it is proved that the estimated mode components of light scattering noise reduction based on blind source separation are basically consistent with those obtained from the simulation signal source. Then, a test is conducted on the noisy light scattering signals of a PTFE pellet, which verifies that the proposed method can successfully extract the original light scattering signals of the particles and reduce the noise interference. The above simulation and test indicate that the light scattering signal noise reduction based on blind source separation is capable of eliminating the redundant data and noise between the mode components decomposed from noisy signals so that each signal mode component can express its own mode information more completely and accurately. The proposed method also makes it more effective to remove the noise elements and thereby restore the originally noiseless light scattering signals of the particles.

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