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Material Level Measurement in Ball Mill Based on the Analysis of Sound Signals

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Summary
The measurement of material level in ball mill is a difficult problem for enterprise production. The ball mill should keep appropriate amount of material to achieve high energy efficiency and work efficiency. In order to effectively measure the material level in the mill, we collect the sound signals when the mill is working (mill sound for short). Characteristic frequency band of mill sound is selected by analyzing collected data. Wavelet analysis technique is used to obtain the signal power of characteristic frequency band which reflects material level. The experiment result shows that the proposed scheme can accurately detect the material level of the mill so as to make it work in best load condition.

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1. Introduction

1.1. The system of ball mill

In many thermal power plants, steel ball mill is commonly used in the coal pulverizing system. The diagram of coal pulverizing system is shown in Figure 1. The raw material is put into the rotating ball mill through feeding inlet then ground by rotating ball. The ground material is discharged through discharge hole. The power plants using the coal pulverizing system with storage bunker spend 20% of electricity power consumption on steel ball mill [1]. Therefore, it is vital to improve the energy saving and work efficiency of coal mill in power plants. The mill may work in abnormal condition like over-load and under-load. The abnormal condition may reduce work efficiency and increase energy consumption. Therefore, the material level measurement is the key to realize energy saving.

There are many previous research works about material level measurement methods, e.g., ultrasonic detection [2], radar measurement [3], power method [4] and neural network [5]. The ultrasonic detection uses mechanical wave of air vibration to measure material level. The downside of this method is that the accuracy of measurement is usually influenced by environmental issues e.g. temperature, pressure and airflow. Radar measurement is another important method, it provides accurate measurement result because it is not influenced by environmental factors. This method is also valid to measure powder material. But the cost of radar measurement is high. The power method is to measure material level by detecting mill current. It is not practical in power plant now because the current change is not obvious enough to be accurately detected. Neural network method is studied in many areas. This method can develop by itself and provide accurate detection result. On the other hand, neural network method is adaptable to highly nonlinear system. However, there is a few training data so that the neural network can't be trained well.

Many experiments have proved that the mill sound frequency spectrums are significantly different between two material levels. So, we propose to detect material level by analyzing mill sound. It is a promising method for material level measurement [6]. In addition, mill sound method has low cost and it is simple to implement.

The simple diagram of material level measurement is shown in Figure 2. Mill sound is collected by sound pick-up. The sound signal is transmitted to the material level measurement system and processed in real time. The sound signal will be transformed into frequency domain first because the mill sound in the time domain usually contain many noises. By contrast, the frequency spectrums of mill sound are obviously different between different load conditions [7]. Therefore, the material level could be detected based on analyzing the sound frequency spectrum.

1.2. Mill load

We use load L to represent the material level. The equation for the load is denoted as

$$L\% = \frac{M_m/\rho_m}{V - G/\rho_g}, \tag{1}$$

where L is load, M_m is the quality of material in the mill, ρ_m is the density of material, V is the volume of mill, G

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is the quality of steel balls in the mill, ρ_g is the density of steel ball.

2. The characteristic of mill sound

The mill sound is composed of impact sounds made by all components in the mill ball including grinding medium, liner and material. The collision of steel balls and liner are main parts of mill sound. According to many previous research works [4, 6], the energy spectrum of mill sound is different between different load in the mill. In other words, the mill sound reflects the material level in the mill. The mill sound's energy spectrum in different load conditions is shown in Figure 3. The data is collected in the factory where we use the material level measurement device. The energy spectrum of mill sound is affected by the physical condition, e.g., every steel mill has unique mill sound and ambient noise. However, all steel mills have the same trend of energy spectrum with same mill load. When the material level is low, which means the load in mill is below 10%, the mill sound is mainly composed of impact between grinding medium and liner. The signal power of mill sound in the high-frequency band can be over 46 dB and the sound is crisp. When the mill is filled with material, and the mill sound is mainly composed of impact between material, grinding medium, and liner. The signal power of mill sound mainly stays in the low-frequency band and the sound is dull. When the mill operates in normal condition, the signal power of mill sound mainly stays in the middle-frequency band, and this band's signal power is around 45.5 dB. To avoid the influence of ambient noise, we analyze the energy spectrum of the sound over 300 Hz. Therefore, the material level in mill can be determined by analyzing energy spectrum of mill sound.

Many research works in material level measurement indicate that the mill sound has a characteristic frequency band. The signal power of characteristic frequency reflects the material level in the mill [7]. Therefore, based on wavelet analysis technique, we propose to detect material level of ball mill by analyzing sound frequency.

3. Wavelet analysis technique

3.1. The advantage of wavelet analysis technique

The traditional methods of mill sound analysis usually use short-time Fourier transform. Short-time Fourier transform is to add window functions in the time domain, which divides the signal into short segments with equal length. Then each short segment does the Fourier transform separately. The short-time Fourier transform provides different resolution in either time domain or frequency domain. Compared to short-time Fourier transform with fixed window length and window width, wavelet transform has flexible base function scale. So, wavelet transform can obtain different resolution both in time domain and frequency domain [8]. It can be used to time-frequency localization and partial analysis [9]. Therefore, wavelet transform is a promising method for analyzing mill sound.

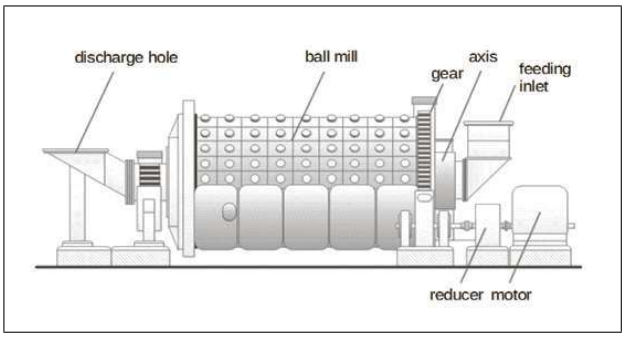


Figure 1. Coal pulverizing system.

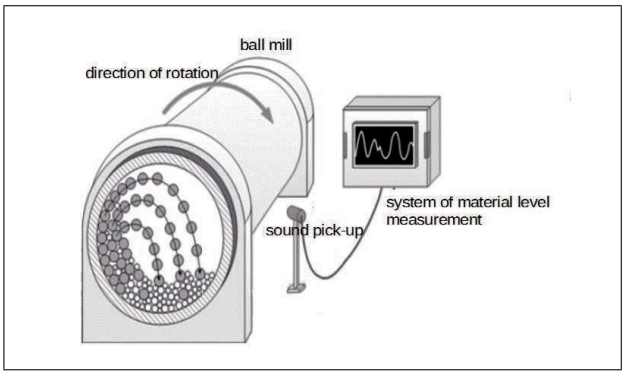


Figure 2. Material level measurement.

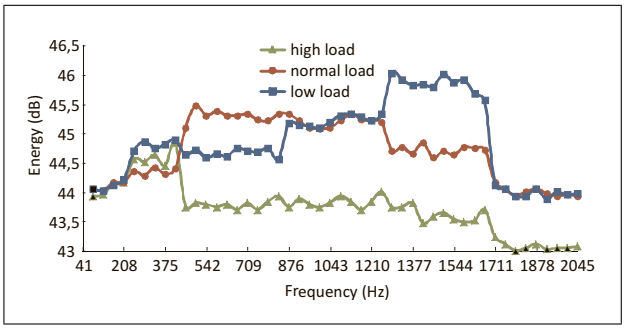


Figure 3. (Colour online) Energy spectrum.

3.2. Introduction to wavelet analysis method

Wavelet analysis method mainly applies the one-dimensional discrete wavelet transform to process the mill sound, which is realized by Mallat algorithm [10]. The principle of this algorithm is like sub-band coding.

$f(n)$ is a spatial sequence that satisfies specific conditions in space $L^2(R)$. We assume that $f(n) \in mV_j$, V_j is the scale space of function $f(n)$. As shown in Figure 4, $h_0(n)$ is a low pass filter, $h_1(n)$ is a high pass filter. The first filter bank divides the original function into approximation component $f_{la}(n)$ and detail component $f_{ha}(n)$. The frequency separation feature is shown in the Figure 5. The scale space V_j is divided into two even wavelet subspace W_{j-1} and V_{j-1}. W_{j-1} and V_{j-1} are orthogonal. The second filter bank is to divide the subspace V_{j-1} into subspace W_{j-2} and V_{j-2}. So, the bandwidth of W_{j-2} and V_{j-2} is quarter of the original function.

This algorithm realizes the level-by-level decomposition of space $L^2(R)$, which is divided into several sets of sub-spaces. Every sub-space contains some sub-spaces of next level. The space V_j of multi-resolution can be obtained approximately by finite sub-spaces. The expression of level-by-level decomposition of space $L^2(R)$ is shown as

$$\begin{aligned} V_j &= V_{j-1} + W_{j-1} = V_{j-2} + W_{j-2} + W_{j-1} \\ &= V_{j-3} + W_{j-3} + W_{j-2} + W_{j-1} = \ldots \end{aligned} \tag{2}$$

3.3. The selection of wavelet function

After using wavelet analysis to process the mill sound, there are many sub-frequency bands. If the signal power in sub-frequency band is more concentrated, the detected material level will be more accurate. Therefore, the appropriate wavelet base should be selected to ensure that the signal power of sub-frequency band is more concentrated after wavelet transform. There are some previous research works compares different wavelet base based on the vanishing moments, symmetry, regularity [11]. According to these works, we tested and compared db1, db4, db8, sym8. Then the wavelet base which can concentrate most signal power in the analytical frequency band is chosen. The sampling rate of mill sound signal is 44100 Hz. According to Mallat algorithm, theoretically, the mill sound can be decomposed into four layers by wavelet, which means mill sound is divided into five sub-bands. Those bands are 0–1378 Hz, 1378–2756 Hz, 2756–5512 Hz, 5512–11025 Hz, and 11025–22050 Hz. The energy spectrum of those frequency bands can be obtained respectively by wavelet transform. According to our analysis, the characteristic frequency band is in the fourth layer. The analysis will be mentioned in the next subsection. The frequency range of the fourth layer's detail coefficients is 1378–2756 Hz. These four wavelet base functions are used to transform the mill sound respectively so that we get the energy spectrum of fourth layer's detail coefficients. Figure 6 shows the wavelet transform results with different wavelet base functions. Theoretically, the signal power of the fourth layer's detail coefficients only stay in the frequency band of 1378–2756 Hz after wavelet transform. The signal power of other frequency bands should be zero. As shown in the Figure 6, the energy spectrums obtained from db1 and db4 not only distribute within 1378–2756 Hz, but also vastly distribute in other frequency bands. On the contrary, the result of db8 and sym8 concentrate the most of signal power in the analytical frequency band. In our work, db8 is selected as wavelet base function.

3.4. The selection of characteristic frequency band

The wavelet transform corresponds to a series of high-pass and low-pass filters. The obtained wavelet sub-band coefficients represent signal energy distribution in different frequency bands. However, the wavelet coefficients cannot directly reflect any frequency features. These coefficients must be reconstructed to original scale before employing

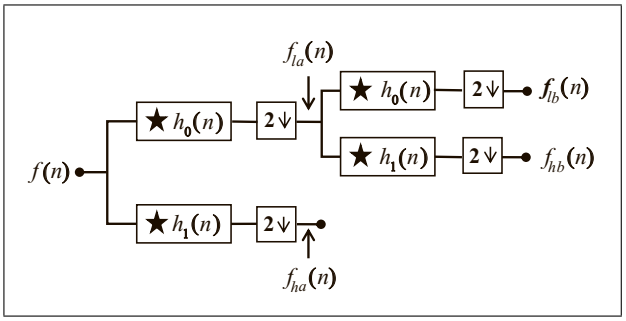


Figure 4. The principle of sub-frequency band coding.

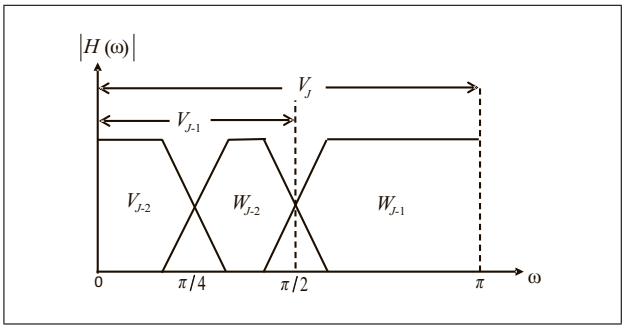


Figure 5. Frequency feature.

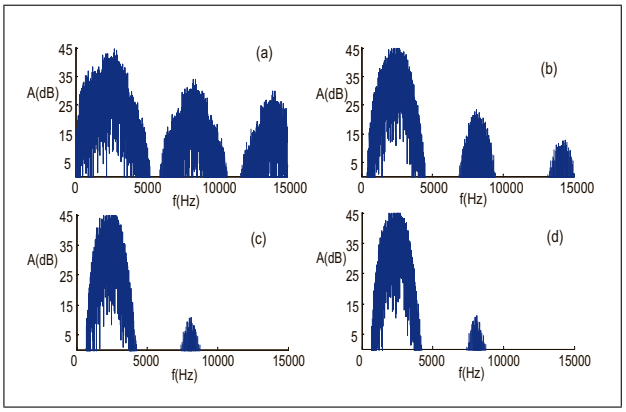


Figure 6. The energy spectrum of fourth layer's detail coefficients by wavelet transform. (a) db1 function, (b) db4 function, (c) db8 function, (d) sym8 function.

fast Fourier [12, 13]. After that, the frequency spectrum of each band can be obtained.

The frequency spectrum of each band is converted into energy spectrum. The process is denoted as

$$E_f(\omega) = \left| F(\mathrm{j}\omega) \right|^2. \tag{3}$$

The signal power of signal $f(n)$ in frequency band f_1–f_2 is as follows, where f_1–f_2 is a sub-band of signal after wavelet decomposition:

$$E_{f1-f_2}(\omega) = \sum_{f=f_1}^{f_2} \left| F(\mathrm{j}\omega) \right|^2. \tag{4}$$

The decibel value of signal power is calculated as

$$I = 10 \log_{10} E/E_{\mathrm{ref}}, \quad E_{\mathrm{ref}} = 1. \tag{5}$$

This study collects five different mill sound signals with different feed rates. Each process lasts 10 minutes. The initial condition is same in the five tests. The sampling rate of signal is 44100 Hz. According to sampling theorem, the frequency range of mill sound signal is 0–22050 Hz. And then, those signals are divided into six layers by wavelet decomposition. According to wavelet analysis method, the signal is divided into 7 sub-bands as 0–345 Hz, 345–689 Hz, 689–1378 Hz, 1378–2756 Hz, 2756–5512 Hz, 5512–11025 Hz, 11025–22050 Hz. We define the low-frequency band is 345–689 Hz, the middle-frequency band is 689–1378 Hz and the high-frequency band is 1378–2756 Hz. These three bands are selected because the mill sound spectrum mainly stays under 3.2 kHz [14]. Finally, the different decibel value at different coal feed rates of those three bands are shown respectively in Figure 7.

The following conclusions can be drawn through the analysis of the results:

1. The low-frequency band contains noise signals which are produced by electrical machine, reducer gears, draught fan and so on. These noises change the energy spectrum of mill sound in the low frequency band. To get rid of these noises, we use wavelet analysis as high pass filter.
2. In the middle-frequency band, there is no obvious correspondence between signal power and the load of ball mill. The signal power is approaching a fixed value.
3. In the high-frequency band, the signal power monotonically decreases when the load of ball mill increases. Consequently, the high-frequency band is chosen as the characteristic frequency band, which is between 1378–2756 Hz.

3.5. The realization of material level measurement

In the characteristic frequency band, the signal power linearly decreases when the load of mill increase. In the factories, upper limit A of signal power of sound is set. When signal power reaches the upper limits, most of materials in the grinding mill are ground, the impact among steel balls increases. In this situation, the impact force among steel balls is wasted and the feed rate of ball mill should be increased. The other case is that the signal power in the characteristic frequency band is low when the load is high. A lower limit B of signal power of sound is set. When signal power reaches to the lower limit, there are lots of raw materials in the grinding mill, the feed rate of grinding mill should be reduced in this situation.

After data analysis, the mapping diagram of signal power and load is as follows.

Under normal operating condition, the relational expression of signal power, load and feed rate can be derived. The expression is denoted as

$$L\% = -2.5e + 105 + fd, \tag{6}$$

where L is the load or material level. e represents the signal power of characteristic frequency band, and fd represents feed rate.

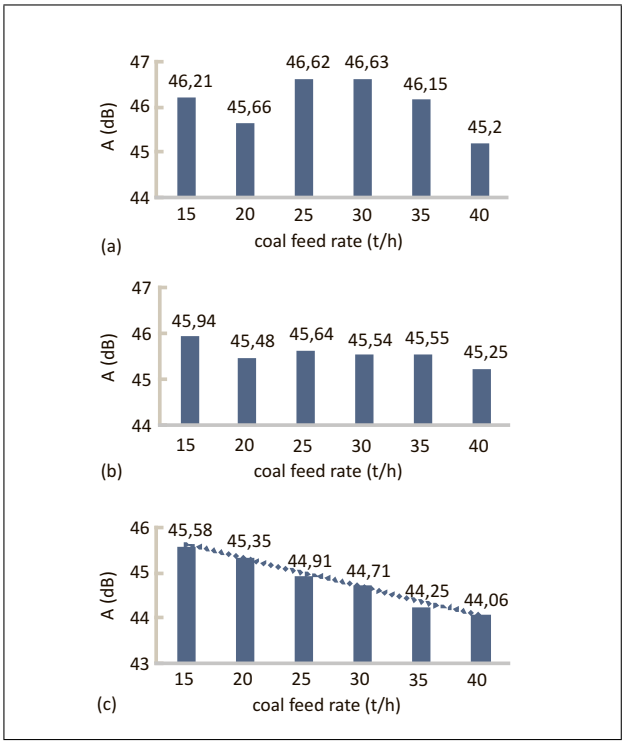


Figure 7. The signal power at different coal rates of three frequency bands. (a) low-frequency band, (b) middle-frequency band, (c) high-frequency band.

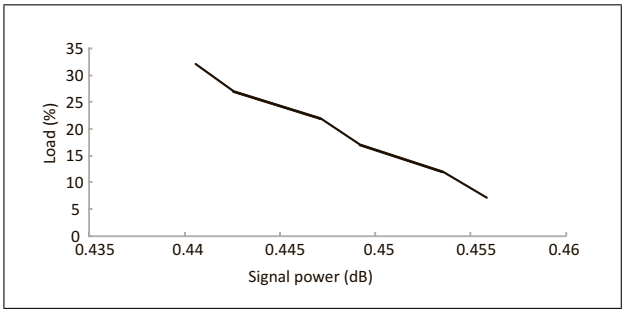


Figure 8. Relation between signal power and load.

4. The application of material level measurement

To evaluate the proposed scheme, this method is experimentally tested in practical factory production. We collected the mill sound then processed the sound signal by our scheme. As a result, the theoretical load is detected. Then we compared the theoretical load and the actual load to determine the accuracy of the proposed scheme. The quantity of balls in the coal mill remains unchanged throughout the experiment. There are experimental settings: The experiment lasted 50 minutes. In this period, the feed rate is changed every 10 minutes from 25 t/h to 28 t/h, 32 t/h, 36 t/h and 38 t/h respectively. T/h stands for tons per hour. The experiment settings are show in Figure 9.

The real-time load detection result is shown in Table I.

In this period, the average load values in five different feed rates are 24.562%, 26.842%, 29.760%, 31.748% and

Table I. Experiment settings.

Time (min)	Feed rate (t/h)
00–10	25
10–20	28
20–30	32
30–40	36
40–50	38

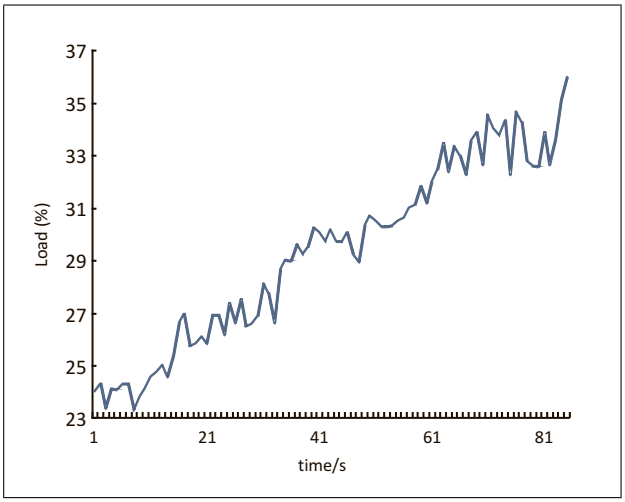


Figure 9. The real-time load detection in different coal feed rates.

33.743% respectively. The calculated load is very close to the real load in ball mill, so our scheme can accurately detect the material level.

5. Conclusions

In this paper, wavelet analysis technique and sub-frequency band coding method are used to obtain the energy spectrum of mill sound in the characteristic frequency band. The optimal material feed rate can be calculated by analyzing the energy spectrum of mill sound. This new method is experimentally verified in practical factory production. The experimental result shows that the real-time material level measurement can be realized.

Mill sound processing based on wavelet analysis can be applied on digital signal processor(DSP) [15], which can accurately reflect the load condition of mill in real time. In addition, sound signal processing based on wavelet analysis theory can be applied to tool wear monitoring, nondestructive testing of aluminum alloy, monitor the state of rolling bearing and fault detection of machine, which proves this research has great value in industrial application.

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