Multi-Channel Vibration Feature Extraction of Ball Mill Using Synchronized Wavelet Based Multi-Scale Principal Component Analysis

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Abstract: - The trait of the ball mill is chaotic in nature due its complex dynamics associated during grinding. Grinding in ball mill generates high-intensity vibration and is too complex on account dependency of multiple variables. In this paper, the vibration signal is acquired using a low power ZigBee based three axes wireless MEMS accelerometer sensor mounted onto the mill shell. Firstly, the exact frequency bands of the mill are identified under variable impact loading using non synchronized and Synchronized Frequency Estimation method (SFE) methods. The synchronization between the mill speed and the sampling rate are put forward by SFE to convert the random non stationary data to quasi stationary data. The actual signal length is calculated using proposed SFE approach and further it is used as window size for wavelet decomposition. Further, to de-correlate the auto-correlated and cross-correlated signal and signal spaces both PCA and Wavelet are used. Finally, the combination of all this techniques, i.e., Synchronized Wavelet Based Multi-Scale Principal Component Analysis (SWMSPCA) is used to extract the vibration feature of the ball mill in the presence of variable density ores i.e., iron ore and limestone.

Key-Words: - Ball Mill, Accelerometer Sensor, ZigBee, Wavelet, PCA, Windowing, SFE, SWMSPCA, Fast Fourier Transform.

1 Introduction

Ball mills are used in mineral processing industries to ground ores to desired sizes (from mm to micron), and comminution in ball milling is a complex phenomenon. The utilization of energy for grinding is generally 1-2% of the supplied energy, so it is indispensable to effectively monitor the process behavior to increase the production efficiency. The dearth of power, as well as the availability of raw materials, motivates a great need for online monitoring of an effective grinding process [1]. The performance of a particular mill is determined by the internal dynamics, i.e., the motion of the balls, hardness of the ore and its composition, impact velocity, excitation frequency of impact, pulp density and the run length of the mill [2, 3]. The trajectory and impact statistics are hard to define analytically; it can only be defined with certain accuracy using a series of experiments on a particular mill with predefined milling conditions. In general, the impulsive force by balls excites the mill to different values of frequencies with variable intensities [4, 5]. The true analysis of frequency and the respective intensity are the key factors to monitor the process behavior of the ball mill [6].

Different analysis techniques have been evoked by many authors on diverse aspects of ball mill, i.e., power drawn of the mill [7, 8], acoustic [9], vibration [10] data analysis etc. The power drawn analysis plays a least significant role as the grinding status of the ore is not closely connected to it. Specifically, the actual process behavior of the mill can be predicted from the acoustic and vibration patterns. As the acoustic and vibration data analyses are concerned, both have a significant impact in analyzing the internal behavior of the mill. But, as the vibration is concerned, each section of (feed,

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midsection and discharge end) the mill along the axes contribute a different level of vibration, and its corresponding acoustic. The acoustic pattern estimation in the noisy industrial environment is quite fuzzy to intercept. To have a better insight into the milling condition, on shell vibration signature can be used to analyze the actual internal process of the mill. In certain cases, perception based analysis is used to evaluate the state of mill load by taking heed to the mill sound. Simply to cope with the variation in the milling conditions, periodic assessment is needed to avert any loss in the production flow, and it can be carried out by utilizing a fusion of sensor based technology and signal processing approach [11].

In the past, a great deal of studies has been carried out by many researchers using sensor technology. The usages of sensor technology, such as vibration, acoustic, force and load sensors, etc. can be used to supervise the internal process associated in the milling. Vibration sensor can measure both static and dynamic vibration, or it can measure dynamic vibrations only. The sensor types, their mounting techniques and their behavior due to environmental effects must be examined carefully prior to the evaluation of the sensors in experimental bed [12]. The vibration test can be performed using a piezoelectric strain transducer installed midway along the axis of the mill shell [13 & 14], or it can be accomplished using sensors at the axial position of the mill. The difficulty with these types of sensors are, it call for external power supply and bulky systems. These can be overcome using ZigBee based MEMS capacitive accelerometers [15]. The transmission loss in wireless medium is high depending on the type of environment, but it is easily accessible for data transmission when the structure to be monitored is rotating in nature [16, 17 & 18]. Once the selection and delineation of the senor are fluxed, suitable signal processing technique can be used to dispense with the chaotic signal produced by the mill [19].

As far as the analysis of vibration signatures are concerned, there are ample of signal processing techniques that can be applied to evoke the desired frequency band from the ball mill during grinding. The signal processing can be executed through different techniques, i.e., Fast Fourier Transform (FFT), Short Time Fourier Transform (STFT), Wavelet Transform (WT) [18], Hilbert Huang Transform (HHT) [20, 21] and Principal Component Analysis (PCA) [22, 23] etc. FFT can be applied to stationary signal and it cannot be applied to transient and non-stationary signals. STFT can be applied to examine the non-stationary signals, but selection of window size as per the frequency requirement is hard to settle for random signals (lack in the multi resolution analysis). The wavelet transform is a better option than STFT, but the selection of basis function affects the analysis of transient signals and it is not adaptive in nature. HHT can be used to extract information of non-linear, non stationary signals, but the sampling rate and the noisy environment may deteriorate its performance. The random behavior of the signal can be predicted using statistical techniques like PCA. In PCA, basically a linear transformation (it can also be non-linear) is applied to the signals that are linearly dependent and it should not have significant outlier. A very broad understanding is required about the algorithm and their significance in the analysis of signals of varying nature and the information contents with or without prominent noise components [24]. The nature of the signal from the ball mill is chaotic in nature. The nature of the signal does not permit the use of PCA directly. Wavelet transformation along with PCA can be better fusion in the analysis of ball mill.

The fusion of different techniques like PCA along with wavelet transforms [25 & 26] can be a valuable asset in dealing with vibration signal associated during grinding. These PCA-based process monitoring methods employ wavelet analysis to transform time-domain signals into the time-frequency domain [27 & 28]. So, significant events can be recombined to obtain a PCA model for all scales together. Multi-scale PCA is useful for modeling data that changes over time and frequency, i.e. the data of chaotic nature. Since PCA cannot be used to de-correlate the auto-correlated signal, where as the wavelet can be used to de-correlate the auto correlated function (wavelet have good de-correlation and localization properties) and PCA can be used later on to un-correlate the correlated variables.

Many researchers have suggested different methods in analyzing the Vibration features of the ball mill [13, 14 & 29]. Generally, the features are extracted based on the intensity at large rather than proper justifiable sample length selection for proper analysis. The behavioral pattern sometimes lies in the noise floor due to damping incurred by the presence of balls, pulp and the associated property of the minerals. In this paper, the exact frequency and the corresponding intensity of vibration are identified using proposed synchronized wavelet based multi-scale principal component analysis

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(SWMSPCA) and Synchronized Frequency Estimation method (SFE) methods for ball mill. Both techniques are studied briefly on their application point of view and their conjecture in the study of the mill.

2 Wavelet Decomposition

Wavelet based analysis can be used to transform a time domain signal into time and frequency domain. For multi-component analysis, original signal space V_0 is transferred to approximation space V_J and detailed spaces W_j Further the signal $x(t) \in L^2(R)$ can be decomposed as follows in (1).

$$x(t) = \sum_{k \epsilon Z} a(J,K)\, \varphi_{j,k}(t) + \sum_{j=1}^{J} \sum_{k \epsilon Z} b(j,k) \psi_{j,k}(t) \quad (1)$$

Where $j = 1, \dots, J; k \epsilon Z$

Where $\varphi_{j,k}(t)$ & $\psi_{j,k}(t)$ are the scale function for V_J and W_j ; j is the scale factor and k is the translation factor; a(J, K) and b(j,k) the approximation coefficient and detail coefficient respectively; J is called the decomposition level

The scale function of original and transferred signal space can be written as follows in (2) and (3).

$$\varphi_{j,k}(t) = 2^{-J} \varphi(2^{-J}t - k)\ , k \epsilon Z \quad (2)$$

$$\psi_{j,k}(t) = 2^{-j} \psi(2^{-j}t - k)\ , k \epsilon Z \quad (3)$$

The approximation signal $A_J(t)$ and detailed signal $D_j(t)$ can be defined as in (4) and (5);

$$A_J(t) = \sum_{k \epsilon Z} a(J,K)\, \varphi_{j,k}(t) \quad (4)$$

$$D_j(t) = \sum_{k \epsilon Z} b(j,k) \psi_{j,k}(t) \quad (5)$$

The original signal can be formulated as in (6);

$$x(t) = A_J(t) + \sum_{j=1}^{J} D_j(t) \quad (6)$$

3 Principal Component Analysis

Principal component analysis was introduced by Pearson and Hotelling to describe the variation in a set of multivariate data in terms of a set of uncorrelated variables.

Suppose, the data matrix is X with dimension of (n*p). The projection matrix can be derived as in (7);

$$Y = \delta^T X = \delta_1 X_1 + \delta_2 X_2 + \dots + \delta_p X_p \quad (7)$$

Where Y is the output projection matrix; $\delta = (\delta_1, \delta_2, \dots, \delta_p)^T$ is the column vector of weight

$\delta_1^2 + \delta_2^2 + \dots + \delta_p^2 = 1$

The variance and covariance matrix can be written as in (8) and (9);

$$\mathrm{var}(\delta^T X) = \delta^T \mathrm{var}(X), \quad (8)$$

$$C = \mathrm{var}\ (X), \quad (9)$$

Where C is the covariance matrix.

$$C = \begin{pmatrix} v(x_1) & c(x_{1,} x_2) \dots\dots & c(x_{1,} x_p) \\ c(x_{1,} x_2) & v(x_2) \quad \dots\dots & c(x_{2,} x_p) \\ c(x_{1,} x_p) & c(x_{2,} x_p) \dots\dots & v(x_p) \end{pmatrix}$$

Finally, the principal component can be defined as in (10),

$$Y_i = a_{i1} x_1 + a_{i2} x_2 + \dots + a_{ip} x_p; \quad (10)$$

Where i= 1...p; $a_{i1} \dots\dots a_{ip}$ are the weighted Eigen vectors.

Finally, arrange the values of Y_i in the decreasing order to get the principal components.

4 Problem Formulation

To translate the phenomena of vibration and its institution, the paper is streamlined as follows,

Step 1: Experimental Setup: Mounting of wireless MEMS accelerometer sensor on mill shell and data transmission using ZigBee wireless protocol.

Step 2: Vibration feature extraction of ball mill using SFE approach: This analysis is basically carried out to select proper sample length for the windowing the actual signal before wavelet is applied. This step also analyses the effect of variable impact loading (impact by one, four and ten balls; in the absence of ore) in the extraction of mills frequency band under variable window length.

Step 3: Feature Enhancement using SWMSPCA.

Step 4: The synchronized data samples for variable density ores i.e., iron ore and lime stone are analyzed using proposed synchronized wavelet based multi-scale principal component analysis (SWMSPCA) method. This method uses both SFE and WMSPCA for feature extraction of the mill during grinding.

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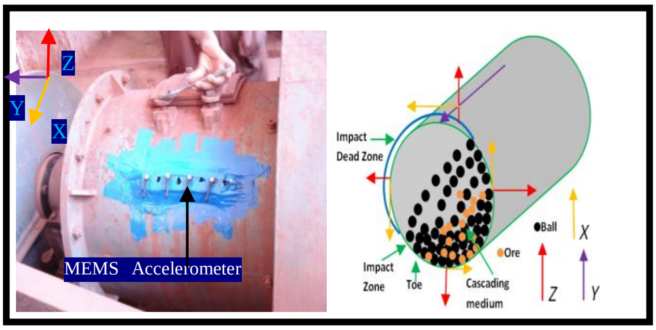
5 Experimental Setup

These experiments are performed on a batch ball mill using a low cost, low power Zigbee based wireless accelerometer sensor. ZigBee based three axes wireless accelerometer sensor of ±10g with sensitivity 100 mV/g is used to acquire the vibration signature of the mill. To acquire signal the sensor is mounted on the mill shell as shown in Fig. 1 (a). Specifically, the three axes are chosen to detect the propagation of wave vectors in different directions of the mill and their significant involvement in the grinding. The phenomena of grinding depends on some prime factors such as impact, attrition and retention time or run length of the mill. Each of these factors contributes significant modulated vibration signal in the three dimensional vector spaces. The MEMS capacitive wireless accelerometer is mounted (adhesive mounting) on the mill shell to acquire the vibration signature along radial (Z, channel (CH)) and tangential (X, CH) vector directions for a sampling rate of 2000 samples/Sec/channel as shown in Fig. 1(a).

At first, the natural frequency response of the mill is tested using variable impact loading in the absence of materials. Firstly, the data analysis under variable impact loading are carried out using non-synchronized actual signal processing technique (to study the effect of random sample length on the vibration response) and, further, it is compared with SFE analysis techniques.



(a) **(b)**

Fig. 1 (a). Position of accelerometer sensors on laboratory ball mill (b) Direction of three axes of accelerometer sensor during rotation

6 Frequency Identification Using SFE Approach

These experiments are performed to differentiate the frequencies generated due to the impacting balls and their forcing function in the excitation of the mill's natural frequency. It is very difficult to pick up the range of frequencies build up due to impulsive forces exerted by the balls on the mill shell. To extract the actual frequency band of the empty mill (in the absence of materials, with balls only), a series of experiments are performed using three different impact states (IS), i.e., with a single ball, with four balls and with ten balls rotating at a rated critical speed.

The vibration signatures are acquired along the tangential and radial direction of the mill for a sampling rate of 2000 samples/sec/channel. Further, the vibration signatures are analyzed using non synchronized and SFE methods. The synchronized and non-synchronized (without SFE) sample length selection methods are related to the angular rotation of the mill and sampling rate of the sensor. The vibration feature obtained for data sample length of 6000 is as shown in the Fig. 2 (a). The intensity and frequency variation for non synchronized sample length of 6000 samples is tabulated in Table 1. As the excitation force increases from one ball to ten balls, the energy level at lower bandwidth (LBW) shifted to Higher Bandwidth (HBW) and is observed for channel Z. The phenomenon of energy shifting at HBW is more along the radial vector component of the mill rather than for the tangential component. The HBW results for channel Z shows that, there is a change in the intensity value from 0.01-0.015 g to 0.015-0.03 g as the excitation increases. But, the validation fails for channel X, as the intensity imparted by for four balls is more than that of ten balls i.e., the vibration intensity drops down from 0.01g to 0.006g. But, in general, the reciprocal is true. It is observed that the random sample length selection affect the signal analysis and results in a wrong extraction of the vibration features.

During data acquisition the analog data are sampled at every second by the ADC, whereas the mill takes 1.47 Sec/revolutions to complete one entire revolution. It is very difficult to locate the position of the sensor at any point of time. In brief, the sensor position changes at every second and the data acquired by the sensor may be under high or low impact state. To segregate the actual milling condition; the angular velocity of the mill and the acquisition rate of the sensor must be synchronized to differentiate between the actual and faux frequency. SFE technique is formulated to avoid impact dead zone present in the ball mill. The SFE length for the exact extraction of the faithful frequency component along the three directions of the sensor can be calculated using eq. (11);

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$$L_{acc} = \frac{60I}{\omega} f_s \qquad (11)$$

Where I, is an integer and I≠0, w is the angular velocity of ball mill in RPM and f_s is the sampling rate of the sensors for each individual channels, L_{acc} is actual window length and $\frac{60I}{\omega}$, must be an integer to properly validate the L_{acc}.
The modified actual Windowed signal constructed using the SFE approach is stated in (12),

$$x_1(n) = x(n)|_{mL_{acc}+1<n\le L_{acc}+mL_{acc}} \qquad (12)$$

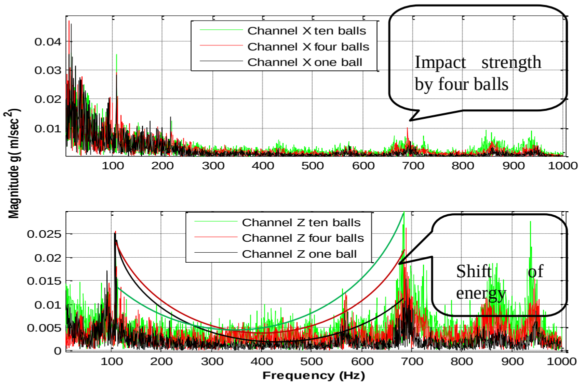
Where $x_1(n)$ is SFE signal constructed from the total set of x(n) data and m is an integer, and is used to change the position of the window or the sliding window.

The FFT for the discrete sampled vibration signal x1(n) is defined in (13);

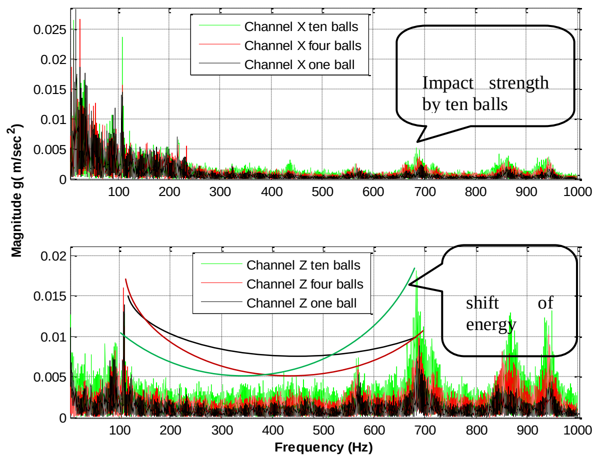
$$X(k) = (2/N) * |\{\sum_{n=0}^{N-1} x_1(n) e^{-j2\pi kn/N}\}| \qquad (13)$$

Where sample length N is 49980 for 17 revolutions.

The validation of the SFE method in analyzing actual vibration signal is as shown in Fig. 2(b), and the observations are in table 1. It is observed that the intensity of vibration for tangential vector for HBW increases with increase in impact forces as contrast to the case without SFE. LBW intensities for tangential vector component are almost constant with little deviation. As far as impact analysis is concerned, the Z channel of the sensor is best suited for analysis as the impact force is more along the radius of the mill (Refer Fig. 1 (b)). It is also observed from the radial vector component that, the intensities at LBW decreases as the impact forces increases i.e., as the impact forces increases, the energy of the LBW shift toward the HBW, and the intensity at LBW decreases from 0.007-0.013g to 0.009g. From the HBW, it is observed that the intensity increased from 0.0075-0.01g to 0.018g. So, a lot more can be presumed from the tangential vector component i.e., it is the impulsive force strength that decides the frequency spreading and elevation in the intensities.
It can be clearly observed from both SFE and without SFE method that in the absence of material only balls can be used to identify the exact frequency of vibration of the mill using the SFE approach rather than selecting random data length for the calculation of mill frequency. This method has tremendous impact in the identification of mill phenomena from the vibration intensities i.e., during grinding the signal may damp at the desired frequency of 660-680Hz and the practitioner may miss interpret the highest intensity at 100 Hz to be the actual frequency of oscillation of the mill.



(a)



(b)

Fig. 2. Frequency response of channels, X tangential (top) & Z radial (bottom) for different impacting balls (a) without SFE approach (b) using SFE approach

Table 1 Vibration signal intensity variation with number of balls

VSL	IS	CH	LBW		HBW	
Without SFE (6000 samples)			f, Hz	g, m/sec2	f, Hz	g, m/sec2
	1	X	25-120	0.030-.045	660-680	0.005
		Z	80-120	0.015-.025		0.01-.015
	4	X	20-120	0.028-.046		0.01
		Z	80-120	0.013-.018		0.01-.025
	10	X	25-120	0.025-.035		0.006
		Z	25-120	0.015-.02		0.015-.03
With SFE (49980 samples)	1	X	25-120	0.015-.03	660-680	0.0025
		Z	80-120	0.007-.013		0.0075-.01
	4	X	27-120	0.015-.025		0.003
		Z	90-120	0.008-.017		0.01
	10	X	23-120	0.023-.027		0.005
		Z	70-90	0.009		0.018

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7 Proposed Method

The analysis of vibration signature of ball mill becomes more complex in the presence of materials. SFE approach is good in extracting the information content of the empty ball mill. But in presence of ore, the feature of the ball mill is analyzed using SWMSPCA, because it uses the auto- correlation and cross-correlation property of both Wavelet and PCA. This feature can delimit the presence of noise, as it has high correlation property as they get modulated with the actual signal along the three axes of the sensor. The process flow of the proposed algorithm for ball mill vibration signature analysis is as shown in Fig. 3. The main objective is to validate the proposed algorithm to extract feature of ball mill during grinding. The experiments are performed on a batch process mill for a total time span of 25 and 20 minutes for iron ore and limestone respectively. The process is carried out till to get a finer product size of 150 microns The vibration signatures are acquired using the three axes wireless sensor to validate the process behavior. The discrete sample data from the sensor for the three axes are initially synchronized using equation (12), and further processed using WMSPCA algorithm to extract the useful content of the signal from the noise.
The objective of using SFE and WMSPCA are detailed as follows;

1. The presence of impact dead zone in ball mill randomizes the signal behavior and it can be rectified using SFE as in (14).

2. After synchronization, the signals in all three dimensions are decomposed using Symlets four wavelet decomposition technique for five levels.

3. Wavelet decomposition is applied to the signals to segregate the low and high frequency signals.

4. PCA is applied to the signal at each levels of the wavelet to decompose the correlated signal present along the radial, tangential and axial direction of the mill and threshold is applied using Kaiser's rule.
5. The un-correlated data matrix is further decomposed using same wavelet coefficient to re-construct the signals.

6. Finally, the appropriate thresholding technique using Kaiser's rule is applied to the reconstructed signal.

$$\mathrm{X(n), Y(n), Z(n)} = \mathrm{x(n), y(n), z(n)}|_{\mathrm{mL_{acc}}+1<n\leq \mathrm{L_{acc}}+\mathrm{mL_{acc}}} \quad (14)$$

Where X(n), Y(n), Z(n) are the synchronized data samples acquired along the three directions of the ball mill.

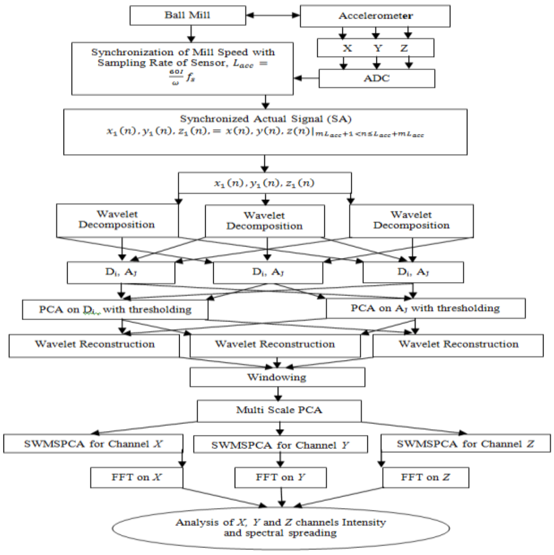


Fig. 3. Flowchart for Synchronized Wavelet Based Multi-scale Principal Component Analysis

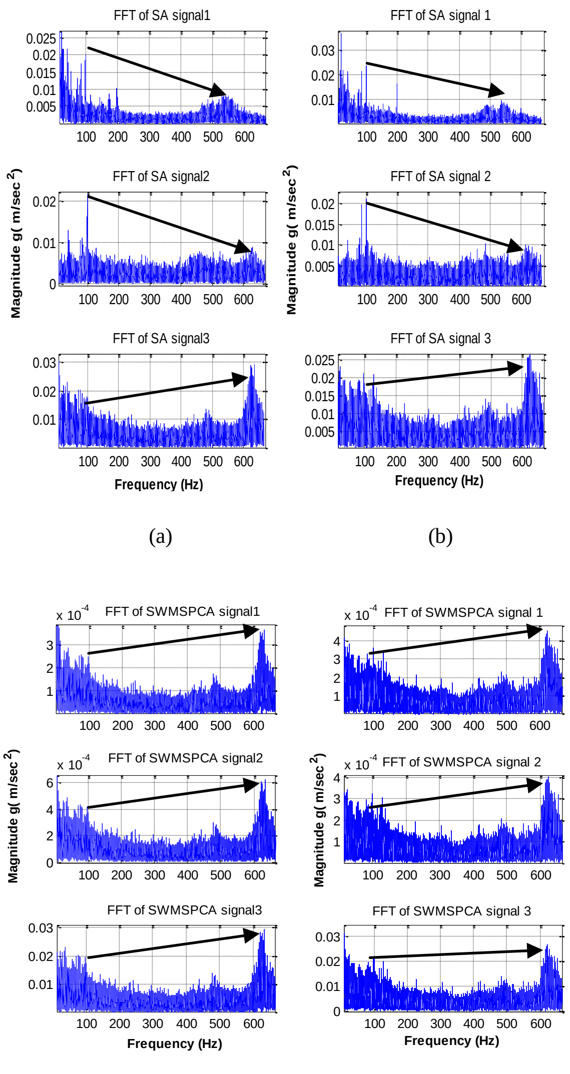
7.1 Experimental results and analysis for iron ore

7.1.1 Signature extraction using SFE and SWMSPCA approach

The experiments are carried out with iron ore and limestone weighting each of 10kg and particle sizes below 50 mm [30]. To grind the ores, 28 kg of iron balls are used as a media in the process. The experiments are performed till to get a finer product size of 150 microns. The vibration signature obtained from the three axes wireless accelerometer sensors are processed using SFE and WMSPCA approach. The SFE approach synchronizes the mill speed with the data acquisition rate of the sensor, further; the synchronized data are processed using WMSPCA. This modified approach is renamed as synchronized wavelet based multistage principal component analysis (SWMSPCA). The feature can be extracted directly using FFT, with SFE as shown in Fig. 2(b). Generally natural frequency response of the industrial ball mill is difficult to identify. If the mill gets loaded then the frequency will get shifted to different values. The presence of material will damp the signature and mislead the information content. The same observation can be put in the cases of intensity variation due to impacting force as shown in Fig. 2(b). When the material is loaded in the ball mill with huge quantity of balls, the balls taking part in the impact processes would be lesser that present at the bottom of the mill at any point of time. Even though the impact is high by the number of balls falling on the materials but due to damping the contribution will be accounted for the lesser number of balls rather than the actual number of balls imparting force.

SWMSPCA is used to reduce the effect of noise and de-correlate the presence of frequency components present along the three different axes that are closely related at each levels of decomposition. SFE technique is used to extract the actual signal feature of the mill under no load condition. But, as the mill gets loaded with materials, the noise will increase drastically and also the desired signal will get damped.

At the initial grinding state when the particles are about 50 mm size (coarse) the frequency of the three channels are observed to be 90-110 Hz with intensity of 0.02g as shown in Fig. 4 (a). But, the frequency and intensity at higher frequency band fall in the range of 550-640Hz with intensity below 0.01-0.03g for Z channel. The observational frequency of Y and X channels gets damped, even though the feature exists along all three direction of the mill. SFE can predict the exact frequency at initial run only from the radial component of the mill as the impact is high along the Z direction. As the intensity is high at 90-110 Hz band and it is effective for all the three channels, the possible analysis may go around this band. The perplexity in the band identification to observe the materials grinding can be analyzed using SWMSPCA; that combine the feature of SFE, wavelet and PCA simultaneously. To extract the actual signal from the noisy signal, a proposed SWMSPCA technique is used to extract the vibration feature as shown in Fig. 4 (c). It is observed that the intensity of vibration for all the channels are higher significant at 610-630Hz as compared to only SFE method. This result can also be compared with the mill test performed without material as in Fig. 2 (b). The analysis process is repeated till the ore obtained the desired finer size of 150 microns. The vibration signature obtained are processed using SFE and SWMSPCA approach as shown in the Figs. 4 (b) & 4 (d). It is observed from the Fig. 4 (d) that SWMSPCA method can extract the actual feature of vibration of the mill even when the ore qualify the desired finer size of 150 microns as contrast to Fig. 4 (b). The quantitative analysis shows that the signal behavior is amplified by the proposed method for channel Y and Z, where as the feature got degraded for X channel. So there is significant possibility to modify the algorithm for ball mill. The mill achieves the observation frequency band at 600-640 Hz with the intensity decreased from 0.03 g to 0.02 g. It can be observed as the ore get finer the signal get damped and it may be buried under the noise if not extracted properly using well advance signal feature extraction algorithm. SFE has its own significance in extracting the feature during grinding by close observation of the radial vector component. SFE can be used for online monitoring as it require less computational time as compared to SWMSPCA approach. But for practical selection of frequency offline for an observational model WSMPCA is a better choice. The iron ore before and after grinding is as shown in the Fig. 5 and it can be compared with [31] for the relative change in the damping during grinding.



(c) (d)

Fig. 4. Frequency detection for iron ore using (a) SA for particle size of 50 mm (b) SA for particle size of 150 microns (c) SWMSPCA for particle size of 50 mm (d) SWMSPCA for particle size of 150 microns

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7.1.2 Grinding status prediction using intensity variation and spectral spreading

The grinding status of the iron ore is predicted from two phenomena, i.e., spectral spreading and damping. It is observed from Fig. 4(c), that the intensity of vibration for Y and Z channels are 0.0006 and 0.03g respectively. As the ore reaches to a final product size of 150 microns, the frequency started spreading to a higher range from 600-640 Hz, with an intensity decreased to a level below 0.03 g. it can be concluded that, as the material gets finer, the energy will be distributed among all the particles and the signal strength will reduce. The ratio between peaks at HBW to LBW decreases as compared ratio between HBW to LBW in case of coarse particle and can be observed from Figs. 4 (c) and (d). Further, the axial component damping can be used for the prediction of mill grinding status, but the same can be observed from the radial component also. The same analysis can be inferred from [32] by Bryce L et. al. The effect of damping on material size is clearly matched to the analysis performed by Bryce through cantilever experiment. Further, to visualize more insight of the mill phenomena experiments are performed using limestone.

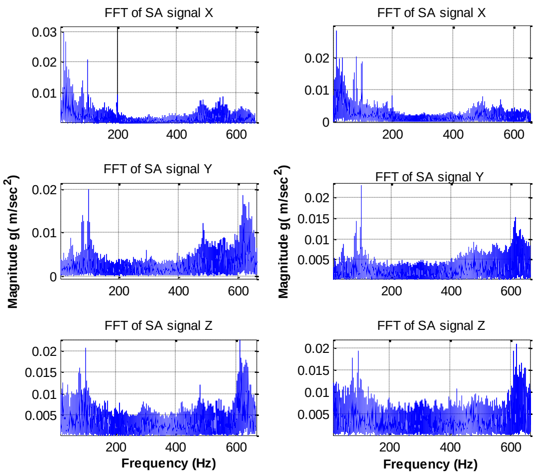
(a) (b)

Fig. 5. Iron ore particle size (a) before grinding (50mm), (b) after grinding (150 micron)

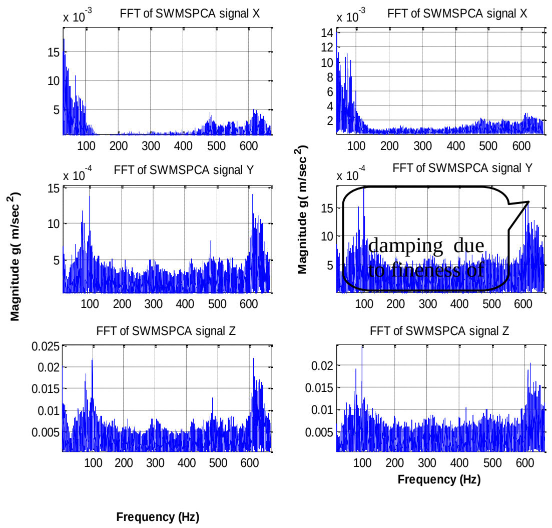
7.2 Experimental results and analysis for limestone

7.2.1 Signature extraction using SFE and SWMSPCA approach

The process is repeated to analyze the variation in the vibration signature in the presence of limestone. At initial run, when the limestone is of 50 mm size (coarse), the frequency of the three channels are at 90-110 Hz with intensity level close to 0.02g using the SFE approach as shown in Fig. 6 (a). But, the frequency and intensity of vibration at higher frequency band fall in the range of 550-640Hz with intensity below 0.01-0.02g. It can be observed from Fig. 6 (c) that the intensity of vibration for all the channels are at 610-640 Hz band, with significant damping for channel X and the frequency get shifted from 550-640Hz to 610-640 Hz band. Finally, when the ore size reaches to 150 microns; vibration signatures are obtained and processed using SFE and SWMSPCA approach as shown in the Figs. 6 (b) & 6 (d). But as fineness increases, the intensities at the frequency band 90-100Hz dominate over that of 600-650 Hz band as contrast to the case for the iron ore as shown in Fig. 4(d). The algorithm even though tries to extract the information content; the increase in damping in limestone does not allow the signal to be extracted significantly. But, the relative intensity extraction using SWMSPCA in Fig. 6 (d) is better than that of the SFE in Fig. 6 (b). So, more modified approach can be proposed to analyze the vibration signature of the mill for variable materials types.



(a) (b)



(c) (d)

Fig. 6. Frequency detection for limestone using (a) SFE for particle size of 50 mm (b) SFE for particle size of 150 microns (c) SWMSPCA for particle size of 50 mm (d) SWMSPCA for particle size of 150 microns

7.2 Comparative study of vibration for iron ore and limestone

The proposed SWMSPCA can be used to extract the information content of the mill during grinding from the noisy signal as it has combinational feature of SFE, wavelet and PCA. The extraction of frequency and intensity is better at initial level of grinding (when ore is coarse) for iron ore and limestone. But, the feature extraction at the finer particle size for iron ore is found to be better than that of limestone. As the enhancement is better in case of iron ore than that of limestone; it means the damping associated with limestone is higher than that of iron ore. Further, the algorithms will be verified in future for different types of materials and mills under variable milling conditions.

8 Conclusion

The vibration signature of the empty ball mill depends on the impacting force and contact time of the balls with the mill at each successive impact. The random selection of data length for vibration signal analysis is not faithful in the extraction of the true analogy of the mill. The SFE approach is having great potential in extracting the frequency of the empty ball mill, and can be used to calculate the actual length of the window for proper signal feature extraction. It is also observed from the variable impact loading and SFE technique that as the excitation increases the energy will shifts from lower to higher frequency band. This study put forward the analysis and extraction of signature that generally gets damped during different state of grinding. This analysis technique for signal feature extraction from the embed noise is carried out using SWMSPCA approach for two variable density ores i.e., iron ore and limestone. The algorithm is used to extract the actual information content as the noise gets de-correlated by simultaneous application of auto and cross-correlation operation performed by wavelet and PCA. The frequency of vibration of the mill during grinding of variable density ores are validated using SFE and SWMSPCA approach. The proposed SWMSPCA method enhances the vibration signature as compared to SFE approach. SWMSPCA can be used to extract the actual grinding information content of the mill as the energy can be distributed from the LBW to HBW. The fineness and coarse nature of the particles are also obtained from the change in the intensity level between 100Hz to 630Hz band. As the particles become finer, relative energy is distributed among each individual particle and the signal gets damped as the frequency band started spreading at HBW (600-630 Hz). Finally, SFE and SWMSPCA algorithms can be studied extensively in the study of vibration signature of dynamic system under variable impact loading and to check the grinding status of the ore and their relative vibration signature.

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