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Acoustic signal characterization of a ball milling machine model

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Abstract. Los Angeles machine is used both for mining process and for standard testing covering strength of materials. As the present work is focused on the latter application, an improvement in the estimation procedure for the resistance percentage of small-size coarse aggregate is presented. More precisely, is proposed a pattern identification strategy of the vibratory signal for estimating the resistance percentage using a simplified chaotic model and the continuous wavelet transform.

1. Introduction
A ball milling machine, is a cylindrical device used in grinding process. A ball mill rotates around a horizontal axis, partially filled with the material to be degraded and the grinding medium. Spherical balls are mostly used as the grinding media, these media cascade within a mill and impinge on the ore thus providing a crushing action. As the balls tumble within tubular mills, they provide a grinding action and forces of attrition, all of which result in further reduction of the size of the rock particles. Impact breakage occurs as balls drop into the toe of the charge and abrasion or attrition occurs as the layer of balls or rods slides over each other or against the mill liner. In designing a plant for size reduction material the two main features of interest are the power required for size reduction and the choice of crushers and grinders [1].

The power or energy required is the sum of the work required to crush or grind the rock as well as rotate the mill. The power required depends on the hardness of the rock, the initial size and the final product size required. In mining industry, the main objective consists in to achieve reasonable liberation of the mineral of interest from the host rock.

Several efforts have attempted to determine the energy required for crushing rocks. It had been observed that in the process of size reduction, as the size of the particles diminishes the surface area of the particles increases. So a measure of size or surface area before and after size reduction would indicate the extent of energy expended in the comminution process. It is worth to mention that this kind of process consumes the 4% of the world energy, being responsible for the 50% of total costs in mining industry [2].

In this work a smaller scale ball mill machine, frequently used in construction industry standard tests, is analyzed. This particular machine covers procedures like testing material resistance of different types and sizes. This paper addresses the particular problem of acoustic signal processing, emitted by this type of ball mill, in order to estimate the material percentage
of resistance to degradation. The traditional test procedure ASTM C-131 [3] takes at least 26 hours, with 24 hours of intense energy consumption (by means of grinding, and drying procedures). Hence, an on-line resistance estimating algorithm is highly desired. An algorithm, based on the methodology proposed in this work, could result in savings of time, energy, and also, may determine a more precise estimative.

In Section 2 the tools and the procedure of the test standard method ASTM C-131 are briefly introduced. The ball milling model methodology is described in Section 3. In Section 4 are reviewed the digital signal processing tools used in this work. In Section 5 the main results obtained are shown. Finally, the main conclusions are presented in Section 6.

2. Test procedure for the resistance to degradation
The traditional test procedure, used for small-size coarse aggregate resistance estimation, considers the following tools [3]:

- Los Angeles machine (small ball mill scale).
- Charge shall, made of steel spheres.
- Sieves(grid with a specified aperture).
- Oven at constant temperature of $110 \pm 10 \, ^\circ \text{C}$
- Precision balance with precision of 0.1 g.

Also, the main parts of the procedure test can be divided in the following stages:

(i) Test sample preparation (1st part)
The sample is sieved, washed and oven-dried, up to 24 hours until achieve a constant weight. This initial weight $W_i$ is recorded.

(ii) Grinding (2nd part)
The sample jointly the charge shall are placed into the Los Angeles machine for 15 minutes.

(iii) Sample preparation (3rd part)
The extracted material is sieved, washed, and oven-dried until achieve a constant weight. Then it is sieved again and the final weight $W_f$ is recorded.

Finally, by means of the formula presented in equation (1), the resistance percentage is calculated using the prior ($W_i$) and the final ($W_f$) weight recorded.

$$P_a = \left( \frac{W_i - W_f}{W_i} \right) \cdot 100\% \quad (1)$$

It must be noticed that the first and third part of the procedure are very similar, depending on the aggregate and the process supervision each one takes from ten to twenty-four hours. Thus, although the grinding stage takes only fifteen minutes, the whole test takes up to 72 hours in regular conditions.

In order to suppress the last part of the procedure and reduce the overall time process, this work proposes an estimations algorithm based on digital signal processing. More precisely, by means of frequency analysis of acoustic and vibration signals, it could be possible to estimate the resistance percentage in a real time solution.

3. Ball Milling modeling methodology
The performance of a particular mill is determined by the system dynamics (also called macro-dynamics) involved in the milling process, such as the motion of the balls, impact velocity, collision frequency, and milling dynamics (also called microdynamics) involved in individual
collision events, such as powder deformation and microstructural evolution [4]. Therefore, system and milling dynamics are inter-related.

Inside the ball mill, the particles are hit by mechanical charge of great power which leads to large plastic deformations and fractures. The particle motion is governed by impulsive forces acting on each collision and no analytical expression for the complete ball trajectory can be obtained. In addition, mechanical systems that exhibit impacts are highly nonlinear due to sudden changes of speed at the moment of impact. Many different types of periodic and chaotic impact motions exist indeed even for simple systems with external periodic excitation forces [5].

A simplified vibratory ball mill model, called Bouncing Ball, is presented in [6] to analyze the chaotic phenomena. This simple chaotic system could represent the ball mill chaotic behavior on a single axis of motion with a single particle [7]. Simulating this model will allow to capture the test data necessary to identify the coarse aggregate degradation pattern, avoiding time and material investments.

The Bouncing Ball system, Fig 1, consists of a ball bouncing on a vibrating table.

![Figure 1: Bouncing Ball system](image)

The Bouncing Ball mathematical model is presented in equations (2) and (3), [8].

\[
0 = A \sin(\theta_k + 1) + v_k \left( \frac{1}{\omega} (\theta_{k+1} - \theta_k) \right) - \frac{1}{2} g \left( \frac{1}{\omega} (\theta_{k+1} - \theta_k) \right)^2 - A \sin(\theta_{k+1} + 1) \tag{2}
\]

\[
v_{k+1} = (1 + \alpha) \omega A \cos(\theta_{k+1}) - \alpha \left[ v_k - g \left( \frac{1}{\omega} (\theta_{k+1} - \theta_k) \right) \right] \tag{3}
\]

In Table 1 are presented the variables and parameters of the Bouncing ball model.

| Variable / Parameter | Description                                      |
|----------------------|--------------------------------------------------|
| \( \theta_k \)      | Table’s phase angle at the \( k_{th} \) impact.   |
| \( v_k \)           | Ball’s velocity at the \( k_{th} \) impact.       |
| \( A \)             | Table’s oscillation amplitude.                    |
| \( \omega \)        | Table’s angular frequency.                        |
| \( g \)             | Gravity acceleration.                             |
| \( \alpha \)        | Restitution coefficient.                          |
In order to show the chaotic behavior of the Bouncing Ball system, the Fig. 2 presents the so-called bifurcation diagram. Where x axis is the table’s amplitude, parameter $A$, and y axis the Ball’s velocity, variable $v_k$.

![Bifurcation Diagram](image)

The restitution coefficient, $\alpha$, varies in the interval $[0, 1]$, where 1 means a completely elastic collision (no loss of speed), and 0 means a completely inelastic collision (kinetic energy lost). In this work, the mathematical model, equations (2) and (3), has been modified so that the restitution coefficient begins in 1 and after each collision it decreases by 0.01, simulating the coarse degradation.

The proposed method utilizes the chaotic model behavior in order to generate several time signals by changing the initial conditions (ball’s velocity and table’s phase), with a decreasing rate of the restitution coefficient. Thus, it is possible to emulate different signals considering different materials and operation conditions of the ball milling machine.

4. Frequency Analysis of the ball displacement variable

In order to obtain a quantified material degradation pattern, the ball displacement variable will be analyzed using digital signal processing methods. The frequency spectrum analysis of vibration or acoustic signals is considered an interesting and auspicious option in order to identify patterns [9], in this case, the degradation pattern. The proposed estimation strategy, consists of three functional units:

(i) Time-Frequency Analyzer.
   Applied in order to recognize a pattern.

(ii) Dimension reduction.
   Which extracts a set of features that retain the essential frequency content.

(iii) Patterns classifier.
   System trained to characterize the set of variables entry.

The present work is focused on the development of modules (i) and (ii).
4.1. Time-Frequency Analyzer

Actually, one of the main solutions for pattern recognition and non destructive techniques are implemented by means of acoustic signal sampling and the continuous wavelet transform (CWT) analysis.

In this sense, this work considers a ball displacement \( x(t) \), consisting in a vector data, \( x_n \), with a sampling time of \( \delta t \).

To define a wavelet function \( \psi_0(n) \), which depends on a "time" non-dimensional parameter \( n \), admissible as wavelet function, it must have a mean equal to zero and must be located in both space-time and frequency. The Morlet wavelet, equation (4), is chosen, for feature extraction purposes, due to it provides an excellent balance in time-frequency localization.

\[
\psi_0(n) = \pi^{-\frac{1}{4}} e^{\frac{jw_0n}{2}}
\]

The CWT of a discrete series, \( x_n \), is defined in equation (5)

\[
W_n(s) = \sum_{n'=0}^{N-1} x_n \cdot \psi^* \left( \frac{(n' - n)\delta t}{s} \right)
\]

Furthermore the CWT, equation (5), can be defined as the convolution of \( x_n \) and the scaled and displaced version of \( \psi_0(\eta) \) [10], rewriting equation (5) in (6).

\[
W_n(s) = x_n \ast \psi^* \left( \frac{n\delta t}{s} \right)
\]

Applying the discrete Fourier transform and then the inverse transform yields equation (7).

\[
W_n(s) = \frac{1}{N} \sum_{k=0}^{N-1} \overline{x_k} \cdot \overline{\psi} (sw_k) e^{j2\pi kn/N}
\]

In equation (7), \( \overline{x_k} \) and \( \overline{\psi} \) are the Fourier transform of \( x_k \) and \( \psi \) respectively. Hence, using a standard routine of the discrete Fourier transform, it is computed the CWT for the whole signal simultaneously [10].

4.2. Dimension reduction

An important task, in order to design a pattern recognition procedure, consists in identify the most suitable attributes of the system that could clarify the differences of separate class behaviors. After the feature extraction performed through the CWT, a dimension reduction algorithm is applied to provide a vector that summarizes the most important features of the signal, called global wavelet spectrum (GWS) [10].

In this work, the GWS, defined in equation (8), is assumed objectifying capture the power spectrum of the signal in a given time interval.

\[
|W|^2(s) = \frac{1}{N} \sum_{n=0}^{N-1} |W_n(s)|^2
\]

As equation (8) shows, the GWS is calculated by summing the Wavelet square values resulting from the continuous wavelet transform at each scale. Moreover, the GWS defines a vector with the same size as scales used for CWT, where each value corresponds to the power spectrum of each scale.
5. Main Analysis Results
In this section the digital signal processing tools, presented in section 4, are applied to the ball’s displacement signal.

The Fig. 3 presents at the top the temporal signal analyzed, and, at the bottom, the wavelet power spectrum (WPS) in dB.

![Wavelet Power Spectrum](image)

**Figure 3: Wavelet Power Spectrum**

The Fig. 4 also presents the wavelet power spectrum (WPS) in 3D, where x axis is time, y axis the frequency and z axis the WPS in dB.

![Wavelet Power Spectrum 3D](image)

**Figure 4: Wavelet Power Spectrum 3D**

Thus, using this time-frequency diagram it is possible to identify the main characteristics components. More precisely, it is possible to observe that:

(i) The power spectrum coefficients are concentrated among lower values (negatives, blue and green) and higher values (positives, orange and red).

(ii) The lower value coefficients (negative dB), grow over time, however due to its low value does not have an important role.

(iii) The higher value coefficients (positive dB) reduce over time, hence in general the WPS decreases over time, showing basically a coarse degradation pattern.
After the feature extraction performed, through the continuous wavelet transform, a dimension reduction algorithm, by means of the global wavelet spectrum (GWS), is applied in order to summarize the most important feature (iii).

As equation (8) shows, the GWS captures the power spectrum of the signal in a given time interval. The Fig. 5 presents the global wavelet spectrum for a specified time interval.

Hence, splitting the signal in several intervals, it is possible to measure the wavelet power spectrum concentration in each interval. In order to obtain a variable, instead of a function, that summarizes the identified pattern, we propose to use the area under the GWS curve.

Finally, the Fig. 6 shows the calculated area under the GWS functions, obtained for seven time intervals.

In order to validate the algorithm proposed, the signal characterization described was applied on two acoustic signals taken from the ball milling machine (using blast furnace tin). The GWS is calculated at seven different time intervals during the fifteen minutes of milling. The Fig. 7 shows the calculated area under the GWS functions, obtained for seven time intervals, on a real acoustic signal.

As Fig. 7 shows, since the area under the curve decreases over time, the GWS function tends to be an appropriate tool for pattern recognition considering a simplified model of the ball milling process. It must be noticed, that the area does not present a monotonically behavior
due to the hard nonlinearities of the system. As future work, an estimator for the resistance percentage instant value should be proposed considering a neural network system in order to take into account the process nonlinear behavior.

6. Conclusion
The signal characterization procedure, presented in this work, has been structured by the following elements: analogous chaotic simplified model, calculation of continuous wavelet transform, pattern identification and dimension reduction through the global wavelet spectrum. Through the extension of the acoustic signal properties generated by the ball mill, this strategy will ensure a reduction of the ASTM C-131 standard test by the third part of the original procedure. Moreover, the time reduction obtained by means of the estimating method could provide mainly savings in energy use.

The main contributions of this work can be summarized as follows: i) It was verified that the pattern found describes a direct relationship between the wavelet power spectrum of the acoustic signal and the instantaneous restitution coefficient of the analyzed material. ii) It was proposed a method that considers the area under the global wavelet spectrum to quantify successfully the pattern in several time intervals. iii) The method was validated applying the GWS on two acoustic signals obtained from a real implementation of the Los Angeles machine. iv) The results verify the pattern found in the proposed simplified model, since the area under the GWS decreases over time.

As future work, a neural network based estimator is objectified to obtain a resistance percentage instant value. Additionally, a real time implementation should be pursued by means of a Digital Signal Processor.

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References
[1] Gupta A and Yan D 2006 Mineral Processing Design and Operations (ELSEVIER B.V.)
[2] Fuerstenau D and Abouzeid A 2002 International Journal of Mineral Processing 67 161-185
[3] Standard test method for resistance to degradation of small-size coarse aggregate by abrasion and impact in the Los Angeles machine ASTM Standards and Test Methods

[4] Huang H, Pan J and McCormick P 1997 *Journal of Materials Science and Engineering A* **232** 53–62

[5] Manai G, Delogu F and Rustici M 2002 *Chaos* **12** 601 – 609

[6] Huang H, Pan J and McCormick P 1994 *COMPLEX ’94* 1 373–379

[7] Andrade J A, Amésteegui M and Romero J F 2008 Estrategia de identificación de características de la señal analógica de vibración, a la denominada máquina de los Ángeles XVII Congresso Brasileiro de Automática, CBA

[8] Tufillaro N, Abbott T and Reilly J P 1992 *An Experimental Approach to Nonlinear Dynamics and Chaos* (Addison-Wesley Publishing Company)

[9] Cohen L 1995 *Time–frequency Analysis* (Englewood Cliffs)

[10] Torrence C and Compo G 1998 *Program in Atmospheric and Oceanic Sciences* **79** 61–78