Towards Automatic Classification of Fragmented Rock Piles via Proprioceptive Sensing and Wavelet Analysis

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Abstract—In this paper, we describe a method for classifying rock piles characterized by different size distributions by using accelerometer data and wavelet analysis. Size distribution (fragmentation) estimates are used in the mining and aggregates industries to ensure the rock that enters the crushing and grinding circuits meet input design specifications. Current technologies use exteroceptive sensing to estimate size distributions from, for example, camera images. Our approach instead proposes the use of signals acquired from the process of loading equipment that are used to transport fragmented rock. The experimental setup used a laboratory-sized mock up of a haul truck with two inertial measurement units (IMUs) for data collection. Results utilizing wavelet analysis are provided that show how accelerometers could be used to distinguish between piles with different size distributions.

I. INTRODUCTION

The mining and aggregate industries have increased their adoption of data analytics and automation to improve their operations [1], [2]. This is typically done by adding sensors to stationary, mobile, and even increasingly robotic equipment to acquire information about system performance, utilization and maintenance needs.

Comminution is the process of liberating the precious metal(s) from a host rock by reduction (e.g., crushing and grinding) in size. This size reduction is an energy intensive process that consumes a significant portion of a mine's operating cost [3], [4] and 3% of global electric power generated [5]. Research focusing on the dynamic optimization of the comminution circuit highlights that large variations in the feed size of rocks can lead to suboptimal operations and increased maintenance costs [6]. Accurate and frequent information is needed to ensure design specifications are met and equipment is operating at optimal levels. Current rock size (fragmentation) estimation technologies use exteroceptive sensors (e.g., cameras, LiDAR) [6], [7]. Drawbacks to these sensors are that they are only able to see the surface of a rock pile, cameras require specific lighting conditions and positioning, and significant time to safely acquire the data.

Our approach is to process data from proprioceptive sensors mounted directly on a haul truck. Haul trucks are used to transport fragmented rock. In this paper, we report on laboratory-scale experiments that used different rock piles, with known fragmentation, that was manually dumped into a mock up haul truck. Two IMUs were mounted to different

(a) Komatsu 930E-5 (Komatsu, www.komatsuamerica.com).

(b) Epiroc Minetruck MT-54 (Epiroc, www.epiroc.com).

Fig. 1: Example surface and underground haulage equipment.

components of the small-scale haul truck to capture the dumping process, with the data logged for offline processing. Preliminary classification results using wavelet analysis on the raw accelerometer data is presented.

II. BACKGROUND

A. Haulage Equipment

Haulage equipment is deployed extensively in the mining, construction, and aggregates industries. Examples of haulage equipment for surface and underground mines are shown in Fig. 1a and Fig. 1b, respectively. With an increasing trend towards automation of haulage equipment, especially in mining, these vehicles are being outfitted with suites of sensors to allow for reliable and safe autonomous operations. Among such sensors are IMUs, which could provide information about the interactions between the vehicle and materials being hauled, which is the subject of this paper.

B. Fragmentation

As discussed in Section I, of particular interest to mining and aggregates operations is the size distribution of the materials being hauled for subsequent processing, otherwise known as *fragmentation*.

1) *Modelling*: One commonly used model for fragmentation is the two parameter Weibull function [8], and the form of the cumulative distribution function (CDF) is given by

$$F(x) = 1 - e^{-\left(\frac{x}{x_c}\right)^n}, \quad (1)$$

where $F(x)$ represents the cumulative mass passing on size x , x_c is the characteristic size parameter, and n is the uniformity

parameter. Taking the log of both sides of (1) makes it possible to solve for x_c and n given a data set containing $F(x)$ and x . However, it is normally impractical to make direct measurements of x and $F(x)$.

2) *Manual Estimation*: Manually estimating fragmentation involves using different sized sieve trays and pouring samples over the trays. The trays are usually agitated either by hand or by mechanical means to ensure all of the rock can be assessed. Once the rock has been agitated the amount remaining on the tray is considered larger than the sieve opening dimension. A set of multiple sieve sizes are used to compute an estimate of the fragmentation distribution. This manual method can be time consuming and disruptive to operations because samples need to be obtained from the rock pile in a safe manner. Moreover, usually only small samples of the pile can be measured.

3) *Exteroceptive Systems*: Technologies that capture images of the surface of the rock pile (e.g., RGB cameras, depth cameras, scanning LiDAR) could also be used to produce fragmentation estimates. Products such as WipWare (www.wipware.com), FRAGTrack (www.orica.com) and MotionTruck (www.motionmetrics.com) also offer the ability to estimate fragmentation parameters. These camera based systems use edge detection software to identify different rock sizes with the end user having the ability to override the edge estimates to obtain better fragmentation estimates. These technologies suffer from the problem of seeing only the surface of the rock pile. Cameras also suffer from lighting conditions and limited product offerings are available for underground mining where all light is artificial. Capturing images or scans also requires close proximity to rock pile, which leads to disruption to the mining process and results in infrequent data capture. Research into using drones outfitted with scanners has attempted to remove the intrusiveness of data capture [6].

III. EXPERIMENTS AND WAVELET ANALYSIS

The novel premise of the research presented by this paper is an investigation into the feasibility of using measurements from the interaction between excavation media (i.e., fragmented rock) and a haulage vehicle that receives this material during a loading process.

A. Experimental Set-Up

A laboratory-scale haul truck was used for the experiments and is shown in Fig. 2.

Two Microstrain 3DM-GX5-25 AHRS IMUs were attached to the haul truck. One was mounted on the haul bed and one was mounted on the chassis as shown in Figs. 3a and 3b. The 3DM-GX5-25 AHRS IMU has a sampling rate up to 1000 Hz, triaxial accelerometer, gyroscope, and magnetometer with a measurement range of ± 8 g, $\pm 300^\circ/\text{s}$ and ± 8 Gauss respectively. A dumping data set nominally consisted of 30 seconds of IMU data and was sampled at 1000 Hz. The precise moment when the sample dump was initiated was not known beforehand, which would pose one potential challenge to a system suitable for deployment in a commercially realistic scenario.

Fig. 2: Laboratory setup of dumping experiment with small-scale yellow truck bucket and orange pail to dump sample.

Fig. 3: Experimental locations (in red boxes) of the two Microstrain 3DM-GX5-25 AHRS inertial measurement units.

B. Rock Piles

Four different rock sample piles of fragmented limestone were used for the experiments. Herein, these are identified as Piles 1, 2, 3 and 4—see Fig. 4. A qualitative assessment of the four rock piles shows that Piles 1 and 2 have similar fragmentation, Piles 3 and 4 contain smaller rocks than 1 and 2, and pile 4 contains significantly more fine sized rocks than the other three piles. Each rock pile weighed approximately 30 kilograms.

Ten dumping trials of Pile 1, ten trials of Pile 2, five trials of Pile 3 and four trials of Pile 4 were performed. After each dump the rock was shovelled back into the pail for further dumping tests. The shovelling process allowed for a different layering of rocks within the pail for each trial.

C. Ground Truth

In order to obtain a ground truth reference for the output of our wavelet analysis, each of the rock piles was processed using a Gilson Testing Screen Model TS-1, shown in Fig. 5.

Samples were placed on the top screen and the machine was set into operation for 5 minutes. The machine allows for

Fig. 4: Top view of haul bed after dumping each rock pile.

TABLE I: Weibull distribution parameters, x_c and n , for the four rock piles.

Pile Number	x_c [mm]	n
1	78	2.1259
2	70	2.3172
3	23	2.3518
4	7	1.2712

six different sized sieve trays to be used. Sieve sizes were selected based on some *a priori* estimate of the fragmentation parameters to ensure individual trays did not become overloaded with material.

The largest sized sieve tray available was 50 mm and Piles 1 and 2 contained a significant portion of rocks much larger than 50 mm. Oversized rocks are those that were visually larger than 5 cm and were removed and weighed individually. Estimating the size of the oversized rocks was done by using the Ontario Provincial Standard Specification (OPSS) numbered 1004 [9]. OPSS provides standards for the construction industry in the province of Ontario, Canada. The results from the Gilson TS-1 were combined with the manually measured oversized rocks to create a data set for estimating the fragmentation parameters x_c and n .

Fig. 6 provides the measured sample values $F(x)$ and x with the corresponding models and the model parameters are given in Table I.

Fig. 5: Gilson Testing Screen Model TS-1.

Fig. 6: Fragmentation measurements and models for the different piles of rock.

D. Wavelet Analysis

Wavelet [10]–[12] analysis is not new and the method has been applied to areas of signal decomposition [13], image analysis [14], and anomaly detection [15], to name a few. Wavelet analysis starts with the mother wavelet Ψ , which has the condition of zero mean and an L^2 norm of one. The mother wavelet can be scaled s and translated τ by

$$\Psi_{s,\tau}(t) = \frac{1}{\sqrt{s}} \Psi\left(\frac{t-\tau}{s}\right). \quad (2)$$

Our approach uses three wavelets to assess the dependency of the results on the wavelet selected [16]. MATLAB version R2019b and wavelet toolbox Version 5.3 was used for data analysis.

The continuous wavelet transform (CWT) can be written as

$$CWT(s, \tau) = \int f(t) \Psi_{s,\tau}^*(t) dt, \quad (3)$$

where Ψ^* denotes the complex conjugate of Ψ . Fig. 7 illustrates the produced scaleograms. The dumping time is a small fraction of the collected data, as seen in Fig. 7. A

process to remove or mask the result outside of the dumping window was required. The developed process uses the first three seconds of each data set to find a threshold,

$$\lambda = \max \left\{ \int CWT(s, \tau) d\tau \right\}, \quad (4)$$

where λ is the sum over scale s at each time step from zero to three seconds. If the dumping process started at time t_d then $\lambda < t_d$. Once λ was computed, the $CWT(s, \tau)$ values were then used to find

$$\Sigma CWT = \int \phi CWT(s, \tau) d\tau, \quad (5)$$

where ϕ is 1 for time index that have $\int CWT(s, \tau) d\tau > \lambda$ and 0 otherwise. The z -axis accelerometer data was used as the input, $f(t)$ in (3).

IV. QUANTITATIVE RESULTS

This section presents the experimental results from the dumping experiments and wavelet analysis.

A. Scaleogram

A scaleogram was generated for each dumping trial to evaluate whether it could be used without further data processing. Fig. 7 presents the scaleogram for one trial of each rock pile. The scale in the scaleograms of Fig. 7 are different for each pile, as expected, with Pile 1 having the largest scale value and to Pile 4 having the lowest. One hypothesis is that there exists a relationship between the fragmentation model parameters and the magnitude of the scaleogram. For example, the maximum magnitude and the corresponding frequency could potentially be used as metric for machine learning algorithms.

B. Haul Bed IMU

The results in Fig. 8, 9 and 10 demonstrate the potential for using wavelets to distinguish rock piles with different fragmentation parameters x_c and n for an IMU mounted on the haul bed. The results Piles 1 and 2 show they are not as distinguishable as compared with Piles 3 and 4. However, this is not unexpected given the similarities between these two rock pile distributions. The parameters x_c and n for Piles 1 and 2 given in Table 6 highlights how similar they are, based on a regression analysis.

The mean and standard deviation of ΣCWT for each pile was computed for the trials shown in Fig. 10.

C. Chassis IMU

The results presented in Fig. 12, 13 and 14 demonstrate the potential for using wavelets to distinguish rock piles with different fragmentation parameters x_c and n for an IMU mounted on the chassis. Visual inspection of the chassis IMU results shown in Fig. 12, 13 and 14 highlights sensor placement may impact the sensitivity of distinguishing different rock piles. This may be due to the mechanical hinge that connects the haul bed to the chassis at the rear as well as the haul bed only resting on the chassis at the front, which could contribute to the low frequency results for Pile 3 that

Fig. 7: Scaleogram results using the Morse wavelet, z -axis accelerometer of the haul bed IMU.

Fig. 8: ΣCWT using z -axis acceleration from haul bed IMU processed using the Amor wavelet.

Fig. 11: Pile mean from the results in Fig. 10.

Fig. 9: ΣCWT using z -axis acceleration from haul bed IMU processed using the Bump wavelet.

Fig. 12: ΣCWT using z -axis acceleration from the chassis IMU processed using the Amor wavelet.

Fig. 10: ΣCWT using z -axis acceleration from haul bed IMU processed using the Morse wavelet.

Fig. 13: ΣCWT using z -axis acceleration from the chassis IMU processed using the Bump wavelet.

Fig. 14: ΣCWT using z-axis acceleration from the chassis IMU processed using the Morse wavelet.

Fig. 15: Pile mean from the results in Fig. 14.

are less distinguishable to Piles 1 and 2 compared to the haul bed IMU. To aid in visualization, Fig. 15 provides the mean and standard deviation (2σ) of ΣCWT for the results shown in Fig. 14.

The next step in this research is to use the features developed in this work with machine learning algorithms for automatic classification of excavation materials. An example of this methodology has already been demonstrated in our earlier work [17] for a simple binary classification of rock and gravel materials.

V. CONCLUSIONS

This paper demonstrates via small-scale experiments the potential for using accelerometer data combined with wavelet analysis to distinguish rock piles of different size distributions (i.e., assess fragmentation) during the dumping process. The advantage of this novel approach is that it uses proprioceptive sensing compared to existing methods that use exteroceptive sensor information (e.g., the use of cameras), that cannot see below the surface of rock piles.

Given the results of these proof-of-concept experiments, the current work could be extended and improved upon by using other suitable machine learning techniques, or

further improvements to the wavelet-based approach, with the aim of directly estimating the parameters of a particle size distribution model. Towards this ultimate goal, the authors plan to scale up the number of tests to allow for the use of other types of classification methods. We also hope to deploy this system at a larger scale, on full-scale haulage equipment and with rock piles of size distributions representative of actual mining/construction/quarrying operations.

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REFERENCES

- [1] Rio Tinto, "Rio Tinto launches big data Analytics Excellence Centre to drive productivity improvements," <https://www.riotinto.com/en/news/releases/Data-analytics-excellence-centre-launched>, 2015.
- [2] World Economic Forum, "Digital transformation initiative: Mining and metals industry," 2017. [Online]. Available: <http://reports.weforum.org/digital-transformation/wp-content/blogs.dir/94/mp/files/pages/files/wef-dti-mining-and-metals-white-paper.pdf>
- [3] J. Jeswiet and A. Szekeres, "Energy consumption in mining comminution," *Procedia CIRP*, vol. 48, pp. 140–145, 12 2016.
- [4] S. Esen, D. La Rosa, A. Dance, W. Valery, and A. Jankovic, "Integration and optimisation of blasting and comminution processes," *Australasian Institute of Mining and Metallurgy Publication Series*, pp. 95–103, 01 2007.
- [5] "Tackling comminution, the largest energy consumer," May 2016. [Online]. Available: <https://www.nrcan.gc.ca/mining-materials/mining/green-mining-innovation/energy-efficiency-mining/tackling-comminution-largest-energy-consumer/18296>
- [6] T. Bamford, K. Esmaili, and A. Schoellig, "A real-time analysis of post-blast rock fragmentation using UAV technology," *International Journal of Mining Reclamation and Environment*, vol. 31, pp. 439–456, 06 2017.
- [7] C. McKinnon and J. A. Marshall, "Automatic identification of large fragments in a pile of broken rock using a time-of-flight camera," *IEEE Transactions on Automation Science and Engineering*, vol. 11, no. 3, pp. 935–942, 2014.
- [8] M. King, *Statistics for Process Control Engineers*. John Wiley & Sons, Ltd, 2017, ch. Weibull Distribution, pp. 447–450.
- [9] "OPS Complete Manual Vol 6," <https://www.library.mto.gov.on.ca>, pp. 53–68, Apr 2020.
- [10] A. K. Louis, *Wavelets: theory and applications*, ser. Pure and applied mathematics. Chichester: Wiley.
- [11] C. K. Chui, Ed., *Wavelets: a tutorial in theory and applications*. San Diego, CA: Academic.
- [12] C. Valens, "A really friendly guide to wavelets," 1999. [Online]. Available: <https://www.cs.unm.edu/williams/cs530/arfgtw.pdf>
- [13] S. G. Mallat, "A theory for multiresolution signal decomposition: the wavelet representation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 11, no. 7, pp. 674–693, 1989.
- [14] Z. Xizhi, "The application of wavelet transform in digital image processing," in *2008 International Conference on MultiMedia and Information Technology*, 2008, pp. 326–329.
- [15] K. Teotrakool, M. J. Devaney, and L. Eren, "Adjustable-speed drive bearing-fault detection via wavelet packet decomposition," *IEEE Transactions on Instrumentation and Measurement*, vol. 58, no. 8, pp. 2747–2754, 2009.
- [16] MATLAB, "Choose a wavelet," 2020. [Online]. Available: <https://www.mathworks.com/help/wavelet/gs/choose-a-wavelet.html>
- [17] H. A. Fernando, J. A. Marshall, and J. Larsson, "What lies beneath: Material classification for autonomous excavators using proprioceptive force sensing and machine learning." To appear in *Automation in Construction*, Accepted August 9, 2020.