Original Article

Performance analysis of optical and X-Ray transmitter sensors for limestone classification in the South of Brazil

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\section*{ABSTRACT}

The present study aims to evaluate the use of sensor-based in the classification of marble ore. These dolomite marbles are quite particular due to a series of felsic and mafic intrusions and syngenetic metapelitic intercalation. In the present study, all the variants of ore and sterile that exist in the deposit were quantified using 3D mapping of mine's surface. Three particles sizes were tested with the sorting equipment in the laboratory: $-25 + 9.5$ mm, $-50 + 25$ mm, and $-70 + 50$ mm. We use indices of recovery, in terms of Calcium Carbonate Equivalent and mass balance, but also performance indices as accuracy, sensitivity, and specificity for interpretation. Recovery values were between 35 and 85\% in the lowest sieve range and between 91 and 98\% in the larger range in the sorting tests within optical sensor. Accuracy is between 43 and 85\% in the lowest range and 97 and 98\% in the largest. Same results occurred with the sensitivity and specificity, which had better separations while increasing the particle size. It was concluded that the X-ray sensor did not perform well and was considered not applicable to the case under analysis. The optical sensor was shown to be applicable in all tested situations, with recoveries between 35\% and 98\%, depending on the condition and particle size of the feed. The grain size was the primary factor influencing the separation performance, implying variations of up to 30\% in the accuracy indexes.

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\section*{1. Introduction}

The present study aims to evaluate the use of sensor-based sorting technology in the classification of limestone, as an alternative to the current sorting and classification process. Many authors have been reporting the use of sorting systems to improve quality and costs reduction in the mining industry [1–3]. Kettelhodt and Bergman [4] and Kurten [5] used sensor-based sorting to coal separation in Southern Africa and Mozambique, respectively. Feierabend et al. [6] used laser-induced breakdown spectroscopy for the analysis of raw materials and waste. Riedel and Dehler [7] report the sorting of diamonds using X-ray transmission. Veras [8] studied
the selective sorting of rare earth-bearing ore, as xenotime, in the laboratory using X-Ray Transmission (XRT) and Coupled Charge Device (CCD Camera) sensor.

The mine studied in this manuscript is located in Caçapava do Sul city, the Rio Grande do Sul State in Brazil, 270 km west of the state capital Porto Alegre. Marbles occur in the region, as dolomite is the main mineral component [9]. Several intrusions also occur, complicating the traditional separation process. In some places, marble developed products of contact metamorphism, such as calcium and magnesium silicates (diopsidium, hornblende, plagioclase, and feldspars), quartz, phlogopite, olivine, serpentine, and talc. Isolated metallic mineralization also occurs in the area which gives a pink pigmentation attributed to the hematite to the marble [10].

2. Methods and materials

This study was subdivided into five stages, from material sampling in situ to characterization tests, preparation of samples, separation tests by sorting, characterization tests and final analysis. Only separation tests the results using the sorting equipment will be detailed in this manuscript.

2.1. Sampling and samples preparation

In addition to marble, there are two classes of waste rock, where human vision color sensitive is the primary sorting criterion. In summary, sorting products are white limestone (WL), gray limestone (GL), pink limestone (PL), waste rock-1 (W1), and waste rock-2 (W2). There are some middlings in this samples but they are considered products by the industry. A 3D georeferenced point cloud of the mine’s surface was classified according to these classes, providing the proportion of the Run-of-Mine (ROM) ores. The 3D point cloud was constructed using the Sim-MVS workflow, with photographs shot by unmanned aerial vehicles. Procedures are according to Viana et al. [20]. The point cloud was classified using color (RGB) and tolerance values using Agisoft Metashape software. Fig. 1 shows an example of the ROM limestone and tailings.

Samples were collected by hand soon after rock blasting, guided by zones delimited in the slope fronts of the pit through the 3D model. Samples were collected in the most coherent portions, in order to guarantee the representativeness of each of the ore and sterile classes existent. The objective is to simulate the separation process in different grain sizes, cleanliness, and moisture. Granulometric ranges and their respective masses were measured. Due to the number of clasts per mass unit is inversely proportional to the particle size, smaller sample masses were considered for the finer granulometry. The granulometric ranges and samples mass are presented in Table 1.

The material collected was taken to the laboratory where it was crushed using Solab Jaw Crusher, model SL-800. After crushing, the samples were classified in steel mesh screens, through the decreasing apertures of 70 mm, 50 mm, 25 mm, and 9.5 mm. The same process was carried out for each of ore, and sterile classes used making up sufficient mass of each one of these classes in each granulometric band established for the tests in the automatic sorter.

2.2. Automatic sorter

The automatic separation equipment is located at the Federal University of Rio Grande do Sul, and it is produced by Comex (Comex Polska Sp (Fig. 2). Three types of sensors are installed in the automatic sorter: laser, CCD camera, and X-

Table 1 - Granulometric bands and samples mass studied.

<table>
<thead>
<tr>
<th>Granulometric bands (mm)</th>
<th>Sample mass (Kg)</th>
</tr>
</thead>
<tbody>
<tr>
<td>−70 + 50</td>
<td>20</td>
</tr>
<tr>
<td>−50 + 25</td>
<td>15</td>
</tr>
<tr>
<td>−25 + 9.5</td>
<td>5</td>
</tr>
<tr>
<td>Total</td>
<td>40</td>
</tr>
</tbody>
</table>

Fig. 1 – types of ore colors (limestones and tailings): white (A), gray (B), pink (C), and tailings – waste rock-1 (D) and waste rock-2 (E).
ray (DE-XRT). In this study, only the X-ray and optical sensors were used.

2.3. **Sensors calibration**

In order to use any of these sensors, a specific calibration step is fundamental, because in this step the parameters for the ore versus tailings selection are defined. Samples of each of the ore and sterile variants were selected, which are part of ROM ore, in the three granulometric ranges studied. All of samples were one by one placed inside the sorter, conducted to the detection zone, and analyzed through the equipment’s software. In this way, the main parameters that allow obtaining product and tailings were defined.

Three calibration conditions were considered to simulate real conditions found in mines (Fig. 3). This was necessary to confirm any changes that could occur with the image sensor responses taking into account its is only sensitive to the sample surface. The analysis was done first by dirty-dry material (SS), by testing the X-ray sensor and CCD camera. In sequence, the material was washed, and a second test was carried out with the optical sensor for the clean-moist material (LU), and then for the clean-dry material (LS).

2.3.1. **X-Ray calibration (DE-XRT)**

Particles detection through the X-Ray captor was obtained by the particle’s density, based on the principle established by Jong and Dalmijn [11]. X-Ray sensor calibration follow these steps: (i) samples are placed inside the equipment, and a grayscale image is generated by the software, where lighter areas are denser [12]; (ii) by the analysis of product versus reject characteristics, histograms of each product are obtained; (iii) density range adjustment of discarded and/or recovered material (threshold) is performed [13].

2.3.2. **CCD camera calibration**

The optical sensor works within the visible range (wave lengths between 390 and 780 nm). This sensor converts the intensities of light captured into electronically measurable signals [14]. In the case of the equipment used in the present study, the calibration of the sensor was performed basically through the analysis and adjustment of the signature obtained in Red-Green-Blue (RGB) colors (Fig. 4). Concerning calibrating of CCD camera, initially, the product and tailings samples are positioned inside the equipment. The sensor captures images, and a background adjustment is performed. Afterward, reflectance histograms of red, green and blue spectra are generated.

2.4. **Quality tests**

Quality standards used to differentiate liming materials include Total Neutralizing Value (TNV), Calcium Carbonate Equivalence (CCE), Fineness, and Effective Neutralizing Value (ENV). Total Neutralizing Value (TNV) or PN is the percentage of the material that can neutralize acid expressed as the CCE of the product, in Brazil’s industry [15,16]. The quality of liming materials typically depends mainly on CCE. CCE generally relates to purity or the neutralizing power per material’s weight relative to pure calcium carbonate. For instance, liming materials like calcitic limestone, which is generally neutral-
ized by calcium carbonate, has a CCE of 100, while hydrated lime has 135 [17].

2.5. Separation performance

Following the proposed by Fawcett [18] and Ooms et al. [19], the confusion matrix presented in Table 2 shows the notions of true-positive (TP) and false-positive (FP) and true-negative (TN) and false-negative (FN). The sum of the TP and FP plots represents the total classified as a product, while TN added to the FN represents the reject fraction.

With the variables extracted from the confusion matrix, we can construct graphs and simulations considering the accuracy, specificity, and sensitivity, according to the equations:

\[
\text{accuracy} = \frac{TP + TN}{P + N}
\]

\[
\text{specificity} = \frac{TN}{FP + TN} = \frac{TN}{N} = 1 - FPr
\]

\[
\text{sensitivity} = \frac{TP}{FN + TP} = \frac{TP}{P} = TPr
\]

Table 2 – Confusion matrix adapted from [18,19].

<table>
<thead>
<tr>
<th>Feed</th>
<th>Product</th>
<th>Tailing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive fraction</td>
<td>True-positive (TP)</td>
<td>False negative (FN)</td>
</tr>
<tr>
<td>Negative fraction</td>
<td>False-positive (FP)</td>
<td>True negative (TN)</td>
</tr>
<tr>
<td>Σ</td>
<td>Product fraction (P)</td>
<td>Tailing fraction (N)</td>
</tr>
</tbody>
</table>

Sensitivity and specificity values were used in the construction of the ROC graph, where separation performance can be classified into three zones (Fig. 5): The superior zone to the diagonal line, called high performance (point 1.0); the zone near the diagonal line, called random, and the zone below this line, called the inverse classification zone (FLACH & WU, 2003)apud [18]).

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3. Results

3.1. Sorting by CCD camera

The first results of the tests with the optical sensor is presented in Fig. 6. The images were obtained during calibration process. Unlike the calibration of the X-Ray sensor, the histograms show a clear difference in the positioning of the curves. Considering that the values correspond to the reflectance of the samples for the RGB parameters, the peaks of the tailings are in the zone up to 60 bytes, while the reflectance peaks of the ore are in the zone near the 100 bytes, allowing a differentiation.

The results of the separation tests, for each that three granulometric bands, were divided into three stages: dirty-dry
3.1.1. CCD camera with dirty-dry material (SS)

The results are presented by ideal vs separated masses, i.e., as all samples were weighed one by one. Then we know the total expected mass as product and tailing.

In the usual conditions, the worst result was obtained using $-25 + 9.5 \text{ mm}$ granulometric range, where it is possible to identify that the curves present a significant discrepancy between the product fraction (left) and the reject fraction (right) (Fig. 7). Another important consideration is that the errors reach mainly the WL and GL limestone types, which are the most abundant ore variants in the mine.

About coarse granulometry ($-70 + 50 \text{ mm}$), the difference between the two lines is minimal, both product and tailing.

In the tailing fraction (right), the classes GL and W1 have a divergence between the lines, but the amplitude and difference are lower than those observed in the smaller particle sizes (Fig. 8).

3.1.2. CCD camera with clean-moist material (LU)

In this situation, there is a loss of WL or GL ores as tailings, whereas there is a recovery of W1 and W2 in both cases (Figs. 9 and 10). Because PL ore is a small fraction of the total sample composition, no significant visible imperfections on the results. The grain size range $-70 + 50 \text{ mm}$ was the one that presented the best results for LU material.

3.1.3. CCD camera with clean-dry material (LS)

Concerning the adjustment between the ideal and the obtained lines, it is clear the existence of a mismatch between the lines, denoting a low recovery of ore, especially about white limestone (Figs. 11 and 12). As for the thicker granulometry ($-70 + 50 \text{ mm}$), there is a practically perfect fit between the lines, except for a small erroneous consignment of GL to the tailings.
3.2. Sorting by X-Ray (DE-XRT)

Regarding the ore response to the DE-XRT sensor, the sorter equipment software allows the simultaneous generation of data (histograms), both for the product and for the tailings, in order to define the density measure that characterizes each one. Considering that the horizontal axis of the histograms represents the relative density of the material in percentage and the vertical axis the number of pixels counted, the density of the two materials analyzed is very similar, with the highest concentration of the pixels of product and tailings in the density range in around 80%. Despite other adjustments to obtain some increase in the contrast, however, in all the cases tested, the distribution of the frequencies occurred identically, and there is a lack of contrast that not allows the separation of the limestone and the tailings with X-Ray. The ore density is approximately 2.8 g/cm³, and that of the tailings is 2.7 g/cm³.
3.3. Performance results

3.3.1. Accuracy
Evaluating the change in the accuracy values when changing the condition and grain size of the feed, the change in grain size has more influence on the accuracy than the condition for the three ore classes tested (Fig. 13). The gray limestone class stands out, because the change in the condition implied a 14% variation in the accuracy index, while the change in the particle size caused a 30% variation.

The lowest accuracy values are the granulometric range of 9.5–25 mm, especially LS material, where accuracy was just above 40%. On the other hand, the LU material was who was less affected by the variation between the first and second particle size range, having accuracy values of 85% and 86%, respectively (Fig. 14).
3.3.2. ROC graph

In the graph shown in Fig. 15, all separation scenarios tested were in the zone above the diagonal line, and the performance obtained with the coarser grain size (−70 + 50 mm) was the best. Regarding the smallest grain size, there is a greater approximation of this to the diagonal line of low efficiency and randomness for both cleaning conditions tested (SS, LU and LS).

According to FAWCETT [18], there are two distinct classes of separation: orthodox and liberal. In the first, where all the tests with higher particle size material and the LS and SS conditions of intermediate particle size are found, we classified as product only specimens with strong evidences of truth, resulting in a concentrate with low FP index. In the second, where the SS and LS conditions of the −25 + 9.5 mm particle size fall, there is a high recovery of the product fraction, we have high FP indices.

4. Conclusions

This study aims to evaluate the possibility of implementation of the sensor-based sorting machine with limestone ore. The main conclusion is that it is possible to separate limestone ore (marbles) positively despite complex mineralogy. The X-Ray sensor did not demonstrate affinity to apply to the classification process of the materials under test in any of the scenarios that were simulated, because ore and waste rock had a similar ratio with a density of 2.8 g/cm³ and 2.7 g/cm³, respectively. The optical sensor was considered very good to be applicable in all simulated situations, presenting recoveries ranging from 34% to 98%, according to the industrial conditions and grain sizes tested. The particle size used in the assays was closely linked to the recovery. An average limestone recovery of 60% was obtained in the smaller granulometry (−25 + 9.5 mm). In the larger particle size range (−70 + 50 mm), mean recovery was 95%.

Concerning the accuracy of the separation, the highest grain size range (−70 + 50 mm) was the one with the best results, with values between 97% and 98% for both conditions tested. Considering three tested feed conditions (dirty-dry, clean-wet and dry-clean), the changes in grain size were the ones that affected the accuracy values, implying variations of up to 30% in the results.

Among the colors of limestone analyzed (white, pink and gray limestone), white limestone was the one with the best average accuracy in the two largest grain sizes, with 88.6% in the −50 + 25 mm range and 98.3% in the strip −70 + 25 mm. However, the accuracy of the pink limestone was 85.6% and 95.6%, and the gray limestone was 71% and 99.3% for the same granulometry.

Conflict of interest

We declare that there is no actual or potential conflict of interest.

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