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Minimizing profile error when estimating the sieve-size distribution of iron ore pellets using ordinal logistic regression

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ABSTRACT

Size measurement of pellets in industry is usually performed by manual sampling and sieving techniques. Automatic on-line analysis of pellet size based on image analysis techniques would allow non-invasive, frequent and consistent measurement. We evaluate the statistical significance of the ability of commonly used size and shape measurement methods to discriminate among different sieve-size classes using multivariate techniques. Literature review indicates that earlier works did not perform this analysis and selected a sizing method without evaluating its statistical significance. Backward elimination and forward selection of features are used to select two feature sets that are statistically significant for discriminating among different sieve-size classes of pellets. The diameter of a circle of equivalent area is shown to be the most effective feature based on the forward selection strategy, but an unexpected five-feature classifier is the result using the backward elimination strategy. The discrepancy between the two selected feature sets can be explained by how the selection procedures calculate a feature's significance and that the property of the 3D data provides an orientational bias that favours combination of Feret-box measurements. Size estimates of the surface of a pellet pile using the two feature sets show that the estimated sieve-size distribution follows the known sieve-size distribution.

1. Introduction

Iron ore pellet sizes are a factor in the efficiency of the blast furnace process in the production of steel. Overly coarse pellets affect the blast furnace process negatively, but this effect can be minimised by operating the furnace with different parameters [1]. An on-line system for the measurement of pellet sizes could improve productivity through fast feedback and efficient control of the blast furnace.

In pellet manufacturing, green pellets are produced primarily from crushed iron ore in a rotating pelletising disk or tumbling drum, after which they are baked in a furnace to produce hardened black pellets. For quality control, manual sampling of the green and black pellets is conducted. Green pellets are fragile and cannot withstand rough treatment. Hence, limited sample sizes can be obtained, as green pellets have to be measured manually. Larger samples can be taken of black pellets, as they are hard and withstand sieving with square meshes. Manual sampling and sieving techniques are the industry standard, and the size distribution of particles is presented as a cumulative percentage by weight for different size classes. However, as the manual sampling is performed infrequently and is time-consuming, there are long response times before an estimate of the sieve-size distribution is available for operators in a pellet plant. The response times can be as long as 12–48 h from a taken sample to sieve-size analysis in the laboratory environment. This makes manual sampling unsuitable for the efficient control of the pelletising process.

Thurley et al. [2] present an industrial prototype that measures the pellet sieve-size distribution among nine sieve-size classes between 5 mm and 16+ mm. A 3D surface data capturing system based on active triangulation is used to collect the data. Segmentation of the data is achieved using algorithms based on mathematical morphology of 3D surface data. It is also shown that sizing of identified pellets gives promising results using the best-fit rectangle [3] measure.

Image analysis techniques promise a quick, inexpensive and non-contact solution to determining the size distribution of a pellet pile. Such techniques capture information about the surface of the pellet pile that is then used to infer the pile size distribution. If image analysis techniques are to be adopted by industry, these techniques need to be able to report the sieve-size distribution as it is reported by industry standards. That is, the size distribution of particles must be presented by image analysis techniques as a cumulative percentage by weight for different size classes.

However, the implementation of an imaging system that is accurate and robust is not a trivial and quick process. Assuming a robust and accurate surface data capturing system with insignificant error is used, there are a number of sources of error relevant to surface analysis techniques that need consideration and investigation. It may be tempting to use multivariate calibration techniques to transfer surface data to known sieve-size distributions. However, it is

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important to consider the following sources of error and minimise them separately to get a general solution that is known to be robust to all errors:

- Segregation and grouping error, more generally known as the Brazil nut effect [4], describes the tendency of the pile to separate into groups of similarly sized particles. It is caused by vibration or motion (for example, as rocks are transported by truck or conveyor), with large particles being moved to the surface.
- Capturing error [5], ([6], Chap. 4) describes the varying probability based on size that a particle will appear on the surface of the pile.
- Profile error describes the fact that only one side of an entirely visible particle can be seen, which may bias the estimate of particle size.
- Overlapped particle error describes the fact that many particles are only partially visible, and a large bias to the smaller size classes results if they are treated as small, entirely visible particles and sized using only their visible profile.
- Weight transformation error describes the fact that the weight of particles in a specific sieve-size class may vary significantly. As a sieve-size class is defined by its upper and lower bounds where particles fall though, elongated particles may have significantly larger volumes than other particles.

The main aim of this research is to minimise profile error by evaluating what size and shape measurements are most efficient at discriminating between different sieve-size classes. To allow this evaluation, we eliminate both segregation and capturing error from the presented study by comparing the results against the actual pellets on the surface of the pile rather than the overall pile size distribution. The weight transformation error is eliminated by comparing only the number of particles of specific sieve-size classes on the surface of the pile and not estimating their weights. We have previously shown that visibility classification can overcome overlapped particle error [7,8]. In short, it is critical to identify and exclude any partially visible particles before any size estimates of particles in piles are made. This is possible with classification algorithms that use a 3D visibility measure and combine it with measures of particle shape. In the presented study, we eliminate overlapped particle error by exclusion of the partially visible pellets from our data.

Work has been published on the size estimation of iron ore pellets assuming that the pellets are spherical [9,10]. However, we have previously shown that spherical fitting is a poor measure of pellet size [11]. More work has been presented on size and shape analysis of rock fragments, and we extend our literature review to include work presented in that field. A comparison of manual sampling and estimates of rock fragment size using 2D imaging analysis has been published [12–15]. It has been reported by Wang and Stephansson [15] that "a systematic error compared to sieving analysis" is found. Furthermore, a comparison of six commonly used particle size and shape measurements was published by Wang [3], showing how the best-fit rectangle is more useful than traditional measurements. Outal et al. present a method to connect 2D raw data to 3D sieving measurements. The 3D surface measurement of rocks has been applied to segmentation where rocks had little or no overlap [16], to shape measurements of individual rock fragments [17], or to rock fragments that lay in piles [6,18]. Kim [16] used a volumetric measurement method to grade fragments into different size classes, and Thurley [6,18] used the best-fit rectangle as a measurement method to categorise fragments into different size classes. With the exception of Al-Thybat et al. [13], previously published works have only used one single measurement when categorising fragments into different size classes. Al-Thybat et al. measured two parameters from 2D images and constructed a joint conditional probability function to accurately determine fragment size.

In the presented research, samples synthesised in a controlled laboratory environment were used to evaluate the significance of commonly used size and shape measurement methods for discrimination among pellet sieve-size classes. For clarification, we note that in industry, manual sampling techniques result in a discretised sieve-size distribution where each sieve-size class is reported as a percentage by weight of the whole sample. We stress that in this study, we only observed the number of entirely visible pellets on the surface of a pile and evaluated how to accurately estimate their size. Therefore, we estimated the discrete sieve-size distribution of the surface, where the sieve-size class percentage by number of particles of the whole sample is reported. We also note that this research does not relate to the choice of classification method, and we used ordinal logistic regression for discrimination among different classes. Other classification methods may be used in practice, but in this research, we used logistic regression because it is based on a theory that does not assume specific distributions for the feature values. Backward elimination and forward selection of features using likelihood ratio to test feature's significance were used to obtain two different feature sets. These feature sets were used to training classifiers and evaluation of the classifiers' performance were made using the hold out method. Finally, size estimates of the surface of a pellet pile were compared with the known surface sieve-size distribution of the pellet pile.

2. Samples of pellet piles

The primary location where an imaging system would be used in a pelletisation plant is directly after the pellets have been formed. That is, right after the rotating pelletising disk or tumbling drum. At this location, the pellets are called green pellets and are, as mentioned in the Introduction, fragile. Green pellets are unsuitable for any extensive use in laboratory work. After the pellets are baked, they are hardened black pellets that withstand rough treatment. Baked iron ore pellets are the product iron ore that pellet producers ship to customers. They are hard and withstand long transportation and falls between conveyor belts. These baked pellets are suitable for laboratory experiments where the pellets may be mixed, dumped and remixed several times. To enable quantifiable analysis, a sample of baked iron ore pellets of around 30 kg was provided by LKAB's pellet plant in Malmberget, Sweden.

Mechanical sieving was used to separate the pellets into individual sieve-size fractions. Mechanical sieving is the accepted industry technique for sizing pellets, where pellets fall through a stack of sieves of different sizes. Sieving is either performed manually using sieve frames that are shaken individually or by automatic sieving machines where a stack of sieve frames can be shaken together. The sample was sieved by a manual process where the pellets are sieved through one frame at a time. For each sieve-size frame, the pellets were spread across the sieve mesh with a hand brush, and the frame was shaken to resolve individual pellets that stuck in the sieve mesh. The sample of baked iron ore pellets was sieved into six sieve-size gradings. Sieve-size frames of 6.3, 9, 10, 11.2, 12.5 and 14 mm were used.

Each sieve-size class was painted and colour coded to allow manual identification of pellet sizes in mixed pellet piles. The pellets were painted with aerosol paint to create a thin and evenly coated surface. Care was taken to prevent the pellet surface from being affected by excessive use of paint. In addition, colours that are easily separable by manual observation were used.

In addition, to overcome overlapped particle error, we define two visibility classes: entirely visible and partially visible. A pellet's visibility depends on how much of a pellet in a pile is visible when viewed from above. We define the class "entirely visible" as particles whose xy-profile is entirely visible or predominantly visible. That is, particles whose xy-profile is not occluded by other particles beyond a minor part of an edge. In more detail, the ratio of data points that are missing because of occlusion to data points that are visible may be around 1 to 10. A note is needed to clarify that this ratio is an approximation by us as we cannot see the occluded part of the particle