XXVII SANTIAGO • CHILE IMPC•2014 | 20 - 24 October 2014, Hotel Sheraton, Santiago, Chile
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PAPER N 30

Measuring the Visible Particles for Automated Online Particle Size Distribution Estimation

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ABSTRACT

Optimisation and control of comminution, pelletization, and agglomeration processes is a complex task with large potential for gains in productivity, energy efficiency, and particle size distribution quality. One factor in realising these gains is the requirement for fully-automated online particle size distribution measurement. Moreover, online particle size distribution measurement that is based on the particles on the visible surface and can avoid or mitigate substantial errors that result from under-sizing overlapped particles and over-sizing areas of fines particles. Literature review indicates a body of substantially 2D photographic based particle size measurement systems that suffer from a large number of significant errors except in the simplest case of a monolayer of particles under good illumination with limited color variation in the material. In order to measure the visible particles on a pile there are a number of requirements including; avoiding particle delineation errors due to variation in material color and shadows, detect overlapping versus non-overlapping particles, and identify areas of fine particles as fines and not large rocks. Results are presented using a fully-automated online measurement system of crushed rock on conveyor belt using a 3D surface laser profile. The system provides continuous online measurement and results are shown on over four hours of production after the primary crusher. Size distribution results are calculated using volumetric estimation of the particles on the surface of the pile. The results show a strong capability to discriminate size variation especially in the 10% and 20% passing values. Furthermore results show that if areas of fines are misclassified as large rocks, and overlapped particles misclassified as small rocks, then a near complete loss of discrimination occurs for the P10 and P20 values which become largely constant values.

INTRODUCTION

Overview

In the mining and aggregate industries a great many processes affect, and are affected by particle size, including blasting, comminution, and agglomeration. As a result significant effort goes into measuring or estimating the size distribution of particulate material in order to evaluate and optimise production in terms of production rate and production costs (energy, material and equipment costs). Mine and quarry operators want to measure the particle sizing results of all of these activities but sieving/screening is an imperfect assessment tool due to slow feedback, and inconsistent measurement due to operator fatigue, or variations in technique. As a result there is an opportunity for on-line, non-contact, fully automated machine vision systems for measurement of particle size to facilitate evaluation and optimisation of mining and particle processes.

Sources of Error

There are however, a number of sources of error relevant to techniques that measure only what is visible on the surface of a pile and it is necessary to consider these errors in order to ensure a measurement system can be stable, reliable, and trend in the right direction. Key errors are summarised here with a more detailed description provided by Thurley (2012).

Particle delineation error refers to the inaccuracies of determining the correct delineation of all the individual particles in the measured surface. This error has been evaluated for the key particle delineation methods used here with 3D surface profile data by Thurley and Ng (2005).

Sub-resolution particle error, relates to the inability of an imaging system to see fine particles below the resolution of the sensor. These sub-resolution particles tend to be grouped into larger areas and may be mis-sized as large rocks.

Segregation and grouping error, more generally known as the Brazil nut effect (Rosato et. al. 1987), describes the tendency of the pile to separate into groups of similarly sized particles when subject to vibration. It is advisable to measure at a point early on the conveyor before the material has been subjected to excessive vibration and segregation.

Overlapped particle error describes the bias towards the smaller size classes results if overlapped particles are treated as small non-overlapped particles. This error can be overcome in piles of particulate material using 3D range data (Thurley and Ng, 2008) successfully providing 82% classification accuracy on hold-out data (Andersson and Thurley, 2008).

Profile error describes the fact that only one side (a profile) of a non-overlapped particle can be seen making it difficult to estimate the particles size.

Sample delimitation and extraction is an error relevant to all methods sampling from conveyor. Overcoming this error requires the correct delimitation of a belt section using two parallel transverse cuts across the belt, and correct extraction of particles where only particles whose centre-of-gravity is inside the delimited region are part of the sample. Refer to Pitard (1993) for a more thorough description.

Weight estimation error results from the difference between non-contact measurement and physical measurement. Size measurement using imaging identifies how many particles are observed, but manual sieving measures the weight of particles in each size class. The presented research uses volumetric estimation of each non-overlapped particle and assumes constant density within a sample to estimate a weight of each particle. Weight of fines is estimated based on the bulk volume of the observed areas-of-fines.

Literature Review

Particle size measurement using vision has been the subject of research and development since the 1980's (Carlsson & Nyberg 1983, Ord 1988) with a legacy of predominantly photographic based systems. Photographic based 2D imaging systems are subject to significant particle delineation error due to uneven lighting conditions, excessive shadowing, and colour and texture variation in the material. Furthermore, photographic systems have no direct measure of scale, suffer from perspective distortion, lack the capability to distinguish between overlapped and non-overlapped particles, and do not demonstrate the ability to automatically detect visible fines in a realistic way. As a result photographic 2D systems typically require manual editing of the particle delineation to provide a reasonable estimation.

In their review of the Split commercial photographic based 2D system Potts & Ouchterlony (2005) report that for their application the system erroneously assumes the resultant size distribution is uni-modal and they conclude by expressing strong reservations saying 2D ``imaging has a certain but limited usefulness when measuring the fragment size distribution in a muckpile or from a belt in an accurate way. It could probably detect rough tendencies in fragmentation variations, if the lighting conditions do not vary too much, and if cover glasses for camera lenses are kept clean''.

Comparisons have been published between photographic methods and sieving, specifically Wang & Stephansson (1996) and Fernlund [1998]. Wang & Stephansson (1996) performed image analysis on overlapping fragments and reported ''a systematic error compared to sieving analysis''.

There are a number of publications relating to 3D size measurement including Noy (crushed rock, 2006), Frydendal & Jones (sugar beets, 1998), Dislaire et. al. (2013) and Thurley (2002,2009,2011,2012). However, Frydendal and Jones (1998) and the presenting author (Thurley & Ng, 2008) are the only published algorithms to remove the bias resulting from overlapped particles.

The focus of this research is on systems for on-line measurement of piled particles (or bulk material) that are non-contact, that is they do not require any additional material handling. If non-contact measurement is required then one must account for overlapped, non-overlapped particles, and areas of fines.

Measurement System Overview

This research uses an industrial measurement system on conveyor belt based on laser triangulation (a projected laser line and camera at an offset angle) collecting highly accurate 3D profiles of the laser line at a spatial distance of 1mm along the conveyor belt. One measurement system is installed at a quarry allowing measurement of a variety of screened and stockpiled products with a narrow range of sizes and it is against these products the measurement system performance is evaluated. Using the same laser triangulation technology it is also possible to collect measurement points at 0.1mm spatial resolution

(Landstrom & Thurley 2012) making it possible to measure particles with a lower size limit of 1mm and be able to detect overlapped and non-overlapped particles on conveyor belt.

The presented analysis algorithms are not particularly dependent on the laser triangulation measurement technology. Any other technique for capturing 3D surface data of a particle pile, such as stereo photogrammetry, laser scanners, or time-of-flight 3D cameras could also be used.

Research Background

The presented research builds upon a series of achievements and research developed on both laboratory rock piles and industrial application. An industrial measurement system on conveyor belt for iron ore pellets (Thurley & Andersson 2007) has been developed using the same laser triangulation measurement technology. The high speed camera system ensures we have a high density of 3D point data at a 0.5mm spacing between consecutive points. This high data density has at least two advantages. Firstly it allows us to detect small sliver regions or crescent-like regions of overlapped particles and ensure that they are not merged into other regions. Secondly, it ensures high resolution when it comes to measuring the size of each iron ore pellet allowing a size distribution with very fine spacing of 5, 8, 9, 10, 11, 12.5, 13, 14, and 16+ mm size classes.

One of the key criteria for particle size measurement is therefore high data density as it defines the capacity to detect small overlapped particles, the lower limit on individual particles that can be reliably detected, and the resolution of size classes detectable.

Furthermore, size measurement of rocks in underground LHD excavator buckets (Thurley 2009) and analysis of blasted rock piles in an open-pit based on lidar based laser scanning (Thurley 2013) has been performed.

One of the key developments of this research is to demonstrate the importance of being able to mitigate overlapped particle error, and sub-resolution particle error, such that it is possible to observe significant variation in material size down in the smaller particle sizes.

METHOD & RESULTS

Data Collection

A number of different products (size ranges of material) were measured in order to evaluate the system at various material sizes including with material below the measurement limit of the system. Measurements have been performed collecting 3D points with a spatial resolution of 1mm. It is reasonable to expect that the system cannot detect individual particles below a size that is several multiplies of this 1mm resolution. In practise, few particles are detected below 5mm. Therefore a data set comprising particles in the range 0-2mm was obtained so that no individual particle would be large enough for the system to identify. Measurements were performed on stockpiled products in the size range 0-2, 10-25, 20-40, 40-70, 60-90mm, and then on three data sets from a primary crusher with material in the range 0-250mm.

Particle Delineation

Particle delineation (image segmentation) techniques have been applied to laboratory rock piles (Thurley & Ng 2005), in an industrial pellet measurement system (Thurley & Andersson 2007) and rocks on conveyor (Thurley 2011), the latter of which forms the basis of the presented results. The technique is predominantly based on morphological image processing (refer to any textbook on image processing), based largely on various edge detection techniques to facilitate seed formation for the watershed segmentation algorithm (Beucher & Meyer 1992).

Figure 1 shows images of the 3D surface profile of rocks on the conveyor for the 20-40mm data set, and 3 sets from the 0-250mm crusher feed. Figure 2 shows the automated particle delineation results. Particles have been removed from the delineation on each end of the conveyor in accordance with the sampling and delineation strategy suggested by Pitard (1993), removing all particles whose centre-of-mass is not placed within a defined transverse delineation zone. The particle delineation is processed further to identify areas-of-fines (Thurley 2009), and non-overlapped particles (Thurley & Ng 2008).

Figure 3 illustrates this capacity to overcome *sub-resolution particle error* and automatically detect areas-of-fines, with the 0-2mm data set shown on the left, with the regions from the delineation that were classified as areas-of-fines shown on the right in coloured blobs. This ensures that areas-of-fines are not mis-sized as large particles. There are regions on the left and right edges of the Figure 3 right data set that were not classified as fines. The data in these areas appears to have some vertically oriented ridges in the data that look significantly like rock structures and so are not detected as fines. However, most of the visible surface is correctly identified as fines. Figure 4 shows all particles automatically identified as non-overlapped and illustrates the capacity to overcome *overlapped particle error* preventing mis-sizing of overlapped particles as small size classes.

Being able to largely eliminate these two sources of error removes error that biases the results towards smaller sizes (*overlapped particle error*) and error that biases towards large sizes (*sub-resolution particle error*). A system with opposing sources of error will tend to be unstable and lack the capacity to trend in the right direction. As we can eliminate these sources of error, the presented research has been consistently demonstrated to trend in the right direction.

Particle Classification & Sizing

Particle sizing is performed using volumetric based sizing using the 3D profile data of each particle, and as a result no ``calibration'' or statistical matching to expected sieve results was performed in this research. The visible partial profile of the non-overlapped particles is used to estimate an ellipsoidal volume for each particle to calculate both the smallest sieve size the ellipsoid would fit through, and a relative weight for the particle. Areas of visible fines are converted into a volume by assuming the depth of the material is equal to the depth of that area of particles on the conveyor belt. This is estimated using a priori information of the 3D profile of the conveyor belt when weighed down. The sieve-size-distribution is calculated by ordering all of the particles by their sieve-size (starting with the fines volume) and calculating the cumulative sum of all of their volumes. Additional details are explained by Thurley (2012).

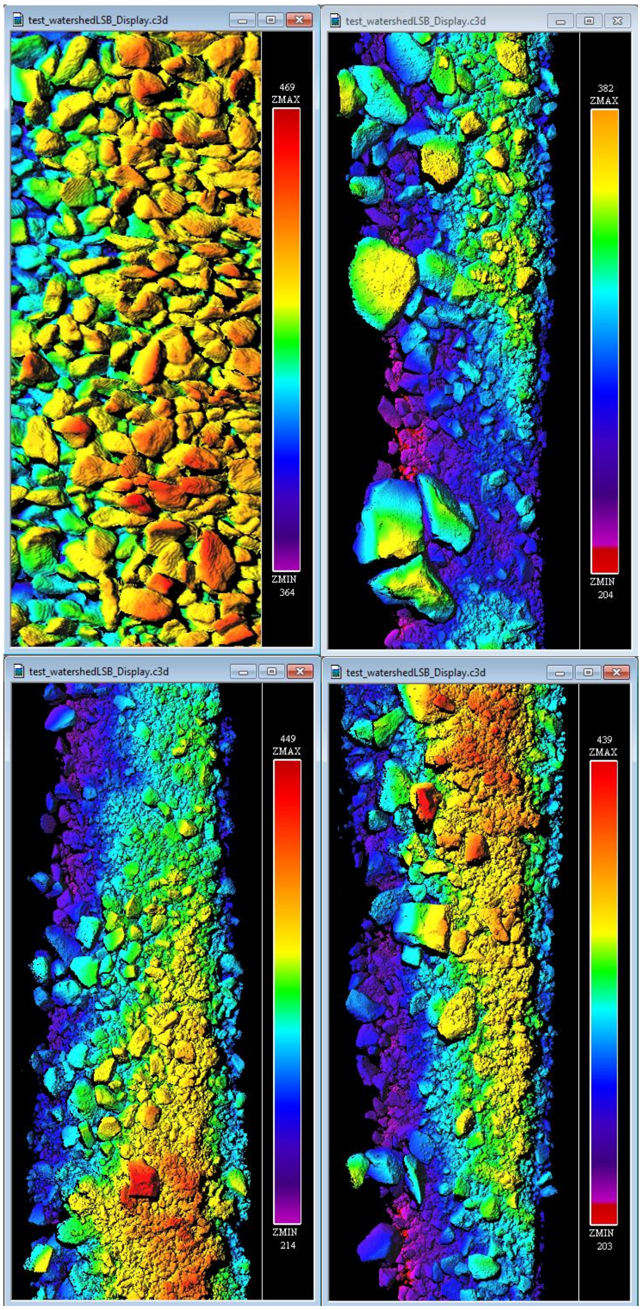

Figure 1. 3D surface profile of rocks on conveyor. 20-40mm product (top left), and three data sets from the output of a primary crusher in the range 0-250mm.

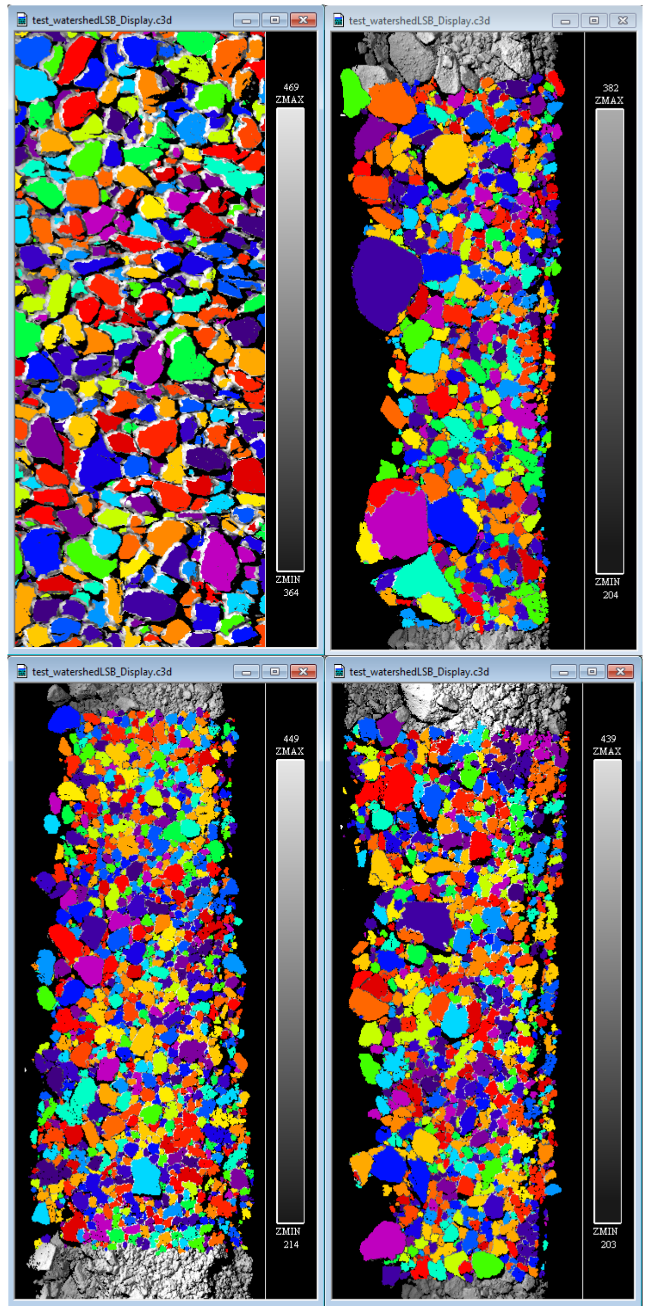

Figure 2. Fully automated particle delineation. 20-40mm product (top left), and three data sets from the output of a primary crusher in the range 0-250mm.

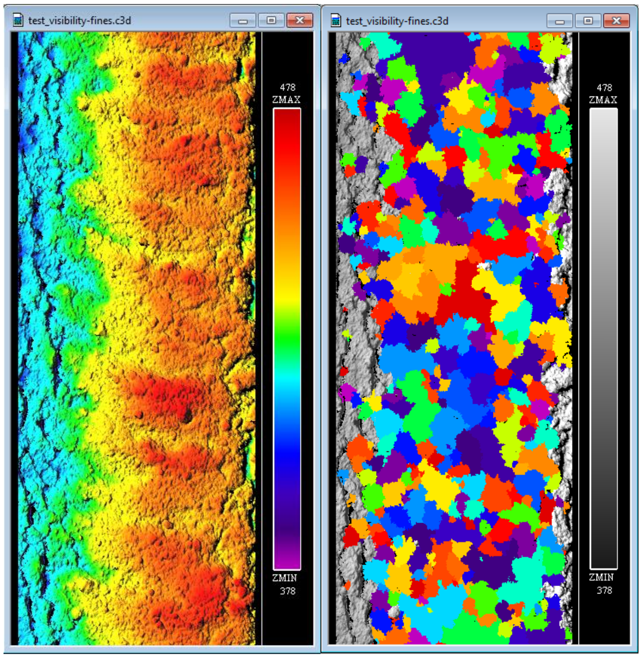

Figure 3. 3D surface profile data and automated delineation for 0-2mm particles, showing large regions detected as areas-of-fines

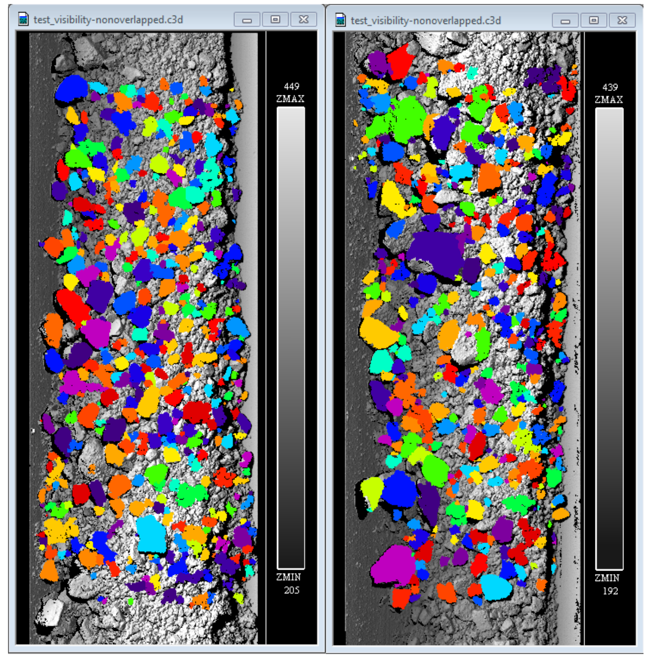

Figure 4. Automatically identified non-overlapped particles. Left image corresponds to Figure 2 bottom left. Right image corresponds to Figure 2 bottom right

Table 1. Calculated 20, 50 and 80 % passing values (mm) for each product.

Sieve-size (mm)	**0-2**	**10-25**	**20-40**	**40-70**	**60-90**		**0-250**	
80% passing	5	26.2	40.7	67.8	96.1	165	67.8	81.5
50% passing	5	20.5	31.4	55.0	76.0	84.1	47.9	58.1
20% passing	5	16.2	22.5	37.4	62.5	47.9	27.0	35.1

The sieve-size distributions for the stockpile products are shown in Figure 5, and the sieve-size-distributions for the primary crusher in Figure 6. Table 1 shows the 20%, 50% and 80% passing values for the curves for both Figure 5 and Figure 6. In addition, Figure 7 and Figure 8 shown the sieve-size distributions when the algorithms to detect areas-of-fines and overlapped particles are turned off. The 0-2mm product becomes mis-represented as a product equivalent to 15-30mm, and the 60-90mm product now contains significant mis-sized rocks in the below 60mm size range

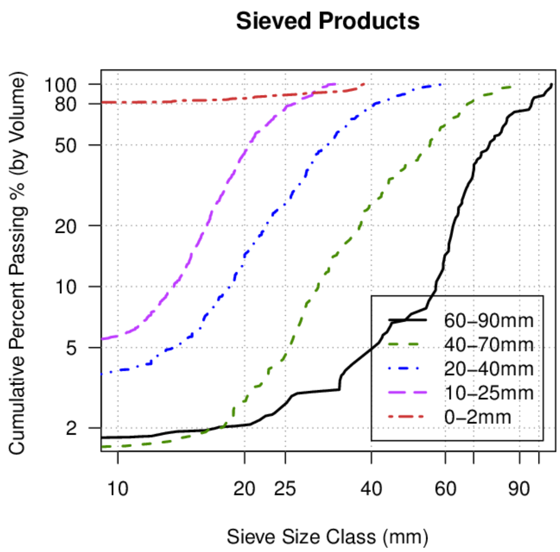

Figure 5. Calculated cumulative sieve-size distributions. From the left most distribution curve the product size is 0-2, 10-25, 20-40, 40-70, and 60-90mm on the far right.

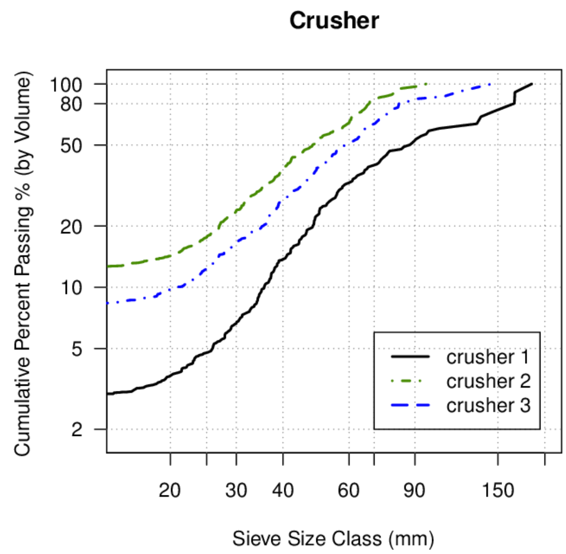

Figure 6. Calculated cumulative sieve-size distributions for three crusher data sets in Figure 1. Set 1 is top right in Figure 1, set 2 is bottom right, and set 3 is bottom left.

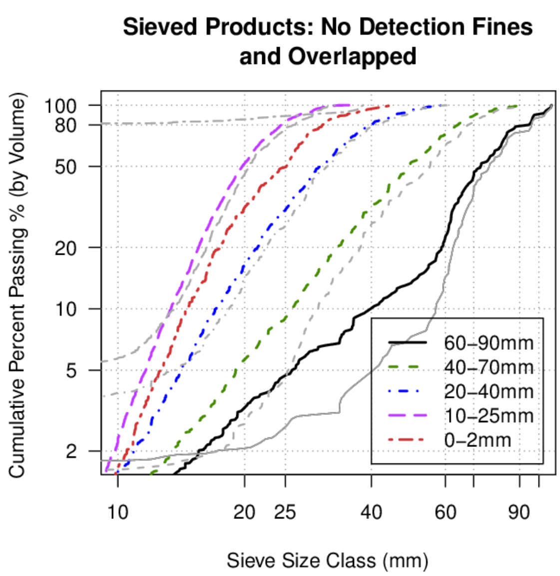

Figure 7. Cumulative sieve-size distributions from Figure 5 but with fines & overlapped detection turned OFF.

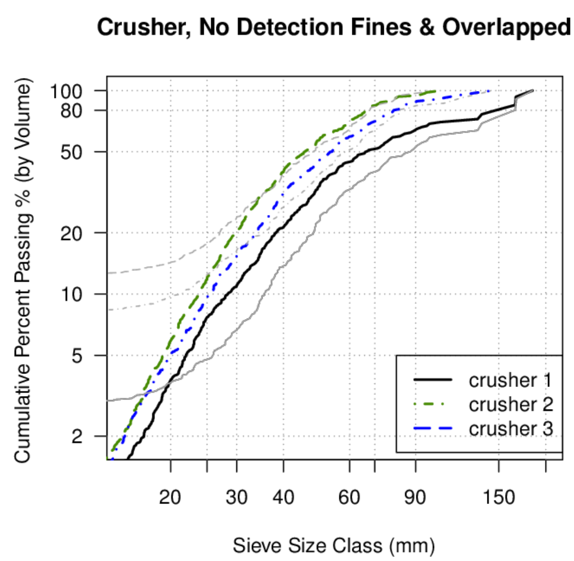

Figure 8. Cumulative sieve-size distributions from Figure 6 but with fines & overlapped detction turned OFF.

Performing the analysis on over 4 hours of measurement data (500 measurements) from the primary crusher produces the graph shown in Figure 9 where the raw measurements are shown in light grey, and a polynomial smoothing is shown in solid color. The 10, 20, 50, and 80% passing values are plotted and one can clearly see significant variation, particularly in the P10 value. However, if the algorithms to detect fines and overlapped particles are turned off, then the results are shown in Figure 10, and the P10 and P20 become close to featureless horizontal lines, losing their capacity to discriminate significant variation in the output from the crusher.

DISCUSSION

The results show a strong relationship to the listed product size range for the pre-sieved products and it is clear from observation of the 3D data in Figure 3 and the cumulative size distributions in Figure 5 and Figure 6, that the results trend in the right direction. That is, when large material is on the belt, the size distribution result is larger. Based on observation of these figures and the results in Table 1 it is clearly identifiable which sieve curve corresponds to which product, and we can observe that the 20% and 80% passing values come reasonably close to the listed product intervals.

As a result, the presented system could readily be used for measurement, feedback, and even control of crushing, grinding, and agglomeration processes. If located before or after a primary crusher the presented system could also provide feedback to blasting.

The capacity to automatically distinguish between overlapped, non-overlapped and areas-of-fines, and to treat each of these three cases differently is a unique contribution of this body or work and it allows a number of sources of error to be addressed.

CONCLUSION

This research demonstrates algorithms and a measurement system for automated, non-contact, on-line, particle size measurement that can be used without the need to calibrate or statistically correct the measurement results against a priori sieving results. Moreover the research demonstrates how relevant sources of error are addressed and mitigated in order to ensure a system that can be reliable and trend in the right direction. Mitigating these errors, particularly *overlapped particle error,* and *sub-resolution particle error*, allows the system to overcome significant sources of error and produce a measurement that shows significant material size variation in the smaller sizes that would otherwise not be observed if the system could not detect fines and overlapped particles

Key results include; sieve-size-distribution results that are close to expected product sizes, results that trend in the right direction, and results that are clearly appropriate for feedback and control of industrial processes. In addition, the underlying algorithms are readily applicable to other mining processes.

ACKNOWLEDGEMENTS

Thanks to Luleå University, ProcessIT, Nordkalk, MBV-Systems, MinBaS, LKAB, VINNOVA and the INTERREG IVA Nord programme of the European Union for their support during this research.

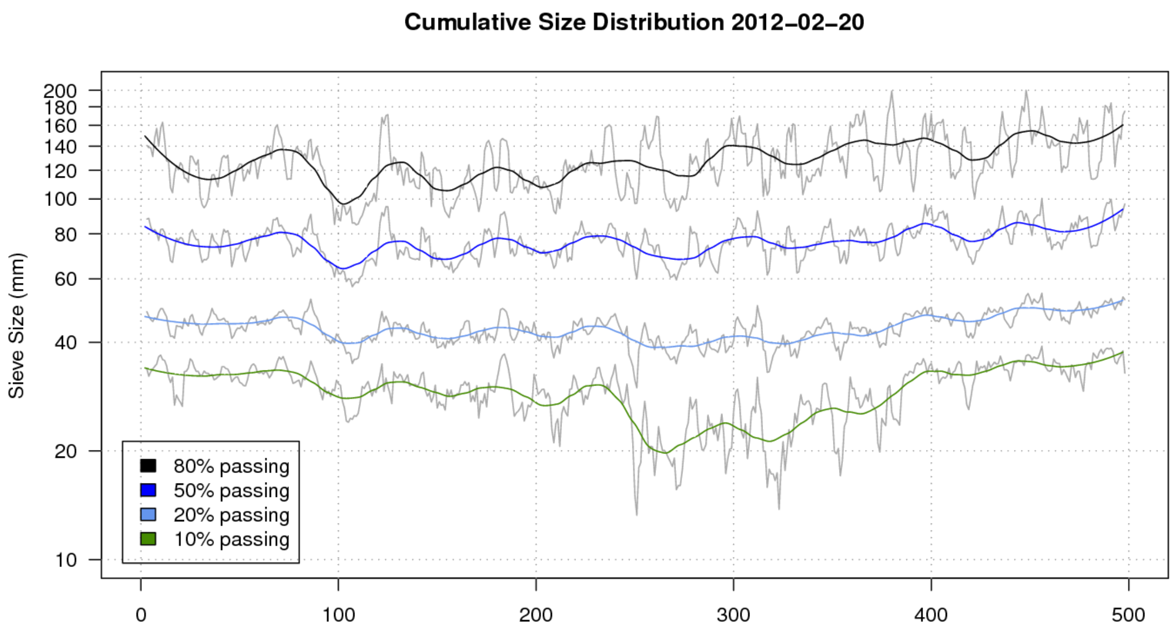

Figure 9. Results for 500 measurements over 4+ hours from a primary crusher

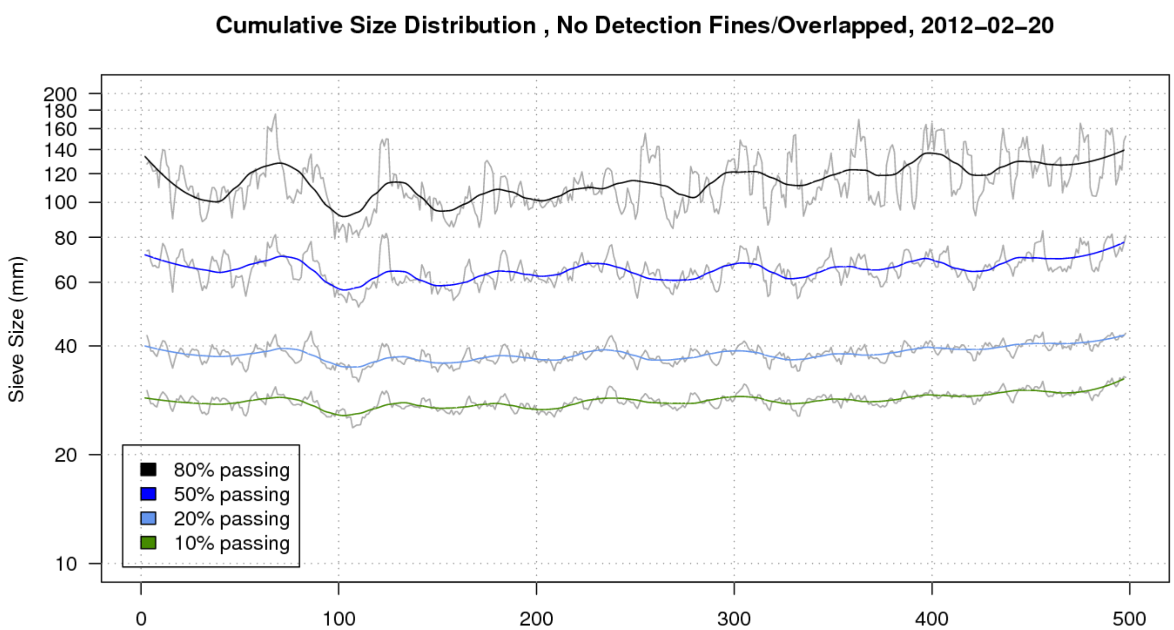

Figure 10. Results for 500 measurements over 4+ hours from a primary crusher but with detection of fines and overlapped particles turned OFF

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