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Utilizing 3D Height Measurement in Particle Size Analysis

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Abstract: This paper introduces a novel approach for performing non-invasive particle size analysis for a material stream running on a standard conveyor belt. The measurements, carried out with a 3D laser scanner and a measuring belt weigher, are accurate, robust and real world physical measures. The 3D data obtained with the laser scanner enables more accurate analysis than the spatial monochrome or colour images that are commonly used in this field. In this paper the proposed analysis method is used in mineral processing application to get information about particle size distribution of the ore flow from the mine to a screening station at the surface. This information can be used to optimize operation of a semi autogenous grinding station used in Pyhäsalmi. However, with certain limitations, the analysis method can be utilized in different kinds of applications.

Keywords: 3D measurements, particle size, image analysis, segmentation, PLS, laser scanner

1. INTRODUCTION

In mineral processing the particle size distribution that is flowing to the grinding circuit is an important factor, especially in autogenous or semi-autogenous grinding processes because the ore is utilized as a grinding media in the mills (Hahne *et al.*, 2003). However, it is often the case that the ore transportation line from the production site to the grinding circuit is quite long and contains large silos. This introduces significant delay that is often measured in days.

Thus, if the ore size distribution is to be controlled before grinding, there should be a size distribution measurement available as soon as possible. Desired properties for the measurement method are robustness and low price as well as good accuracy and sampling rate. Also, the method should be non-invasive in nature so that it would not disturb the ore transportation process.

There exist examples of such measurements in the literature (see e.g. Guyot *et al.,* 2004, La Rosa *et al.,* 2001, Palangio *et al.,* 1995) and they are typically based on a spatial image taken from the target and further processed with image analysis techniques. Another variation to these techniques is presented in Larinkari *et al.,* 2005, where the spatial image describes the shadow lengths that different sized rocks cast when illuminated correctly.

Although the spatial image contains a lot of information of the target, the height of the particles is not easily deduced from that data. Much more suitable measurement for this type of application would be a spatial image where the intensity information (i.e. the z-direction) would be replaced with height information. This way the measurement would represent physical dimensions. Fortunately, in recent years this type of measurement devices have emerged and their prices are in a viable range. There exist examples where 3D surface measurements are utilized for size classification on a moving conveyor belt (see e.g. Thurley and Andersson, 2007).

This paper introduces a new approach for crushed ore analysis that is based on a combination of a belt weigher and a 3D laser scanner installed on a same cross-directional axis. Installation and practical tests were conducted in Pyhäsalmi Mine, which is located in Finland some 500 km's north from Helsinki.

In Pyhäsalmi the blasted ore is fed through a jaw crusher (Nordberg C200B) located in the mine at depth of 1400m. The proposed analysis equipment is located also in the mine on top of a conveyor belt as indicated in Fig. 1.

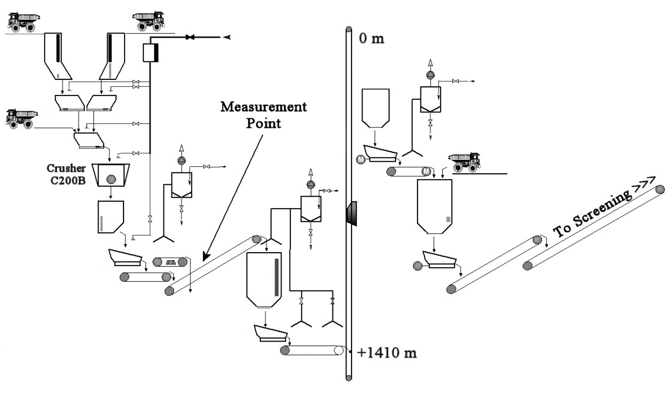

Fig. 1. The measurement point in the mine and the ore transportation chain to the surface (Figure courtesy of Pyhäsalmi Mine)

After the measurement point there are three silos before screening station and their total capacity is around 10 000 tons. Since the production rate at the concentrator plant is around 160 ton/h, this constitutes a delay in the range of 1-3 days.

2. MOTIVATION

Since the large particles of ore are used as a grinding media instead of metal balls, it is clear that the size distribution of the ore feed to the mill must be appropriate in order to achieve acceptable results. If this is not the case additional iron balls must be added and thus additional costs introduced. In Pyhäsalmi the grinding circuit is divided into three stages and one of them can be operated in completely autogenous mode, provided that the ore size distribution is correct. The mine personnel have estimated that if there would be correct size classes in the silos at all times, some 20% savings could be achieved out of 1 000 000 EUR used annually for the iron balls.

As explained in section 1, the transportation delay is a major factor that has to be taken into account when trying to estimate the trends in the silo levels after the screening station. Thus, if the first analysis results are available already in the mine, corrective actions can be made 1-3 days in advance.

The goal is to keep the amount of different size classes in allowed range at all times. This is to make sure that the size distribution will not be a limiting factor for optimal operation of the grinding circuit. When the size distribution is measured right after the first crushing stage it enables modifications to be done already in the mine. These can include changes in production planning, drilling, blasting, and crushing. Furthermore, when integrated to the mine's information system, the analysis results will be available for plant personnel working both in the mine and on the surface. This will increase the level of co-operation and planning between the two groups.

3. MEASUREMENT PRINCIPLE

The general idea of the analysis setup is presented in Figure 2, where the laser scanner (Sick LMS-400) is located on a same cross-directional axis as the belt weigher (Milltronics Accumass BW100). The belt weigher is equipped with a speed sensor and is thus capable of measuring the mass flow under the scanner. This information along with the speed reading is transferred as a standard 4-20mA message to an A/D-board of the analysing computer. Since the laser scanner is located on a same cross-directional axis as the belt weigher, the data coming from these two devices can be easily combined. The scanner is connected to an additional network interface card (NIC) of the analysing computer via a standard Ethernet connection.

The laser scanner scans a cross-section perpendicular to the direction of the conveyor belt 360 times per second. In each of these scans the distance of the ore is measured in 240 points by varying the angle of the measuring laser in small steps. Using these measurements it is straightforward to calculate the height of the ore bed in desired points along the cross-section by applying simple geometry and nearest neighbour interpolation. The height of the ore is calculated in 240 equally spaced points for each cross-section. The points are 3 mm apart; this corresponds to the average spacing of the original measurements. The purpose of interpolation is to simply remove any distortions caused by the varying spacing of the original measurement points.

The cross-section scans are done at a frequency of 360 Hz and the belt is moving at a constant speed of 1 m/s. This means that successive cross-sections are approximately 3 mm apart from each other. By combining measurements from multiple scans, a 3D height profile with grid spacing of 3x3 mm is achieved. The reliability of a single distance measurement was estimated by scanning a stopped belt for 3 seconds. The standard deviation of a distance measurement is approximately 6 mm, which is adequate for this application. Of course the accuracy could be much better with different type of scanners (e.g. structured light based) but, at least in this case, it was found that the achieved performance gain comes with a too high price tag.

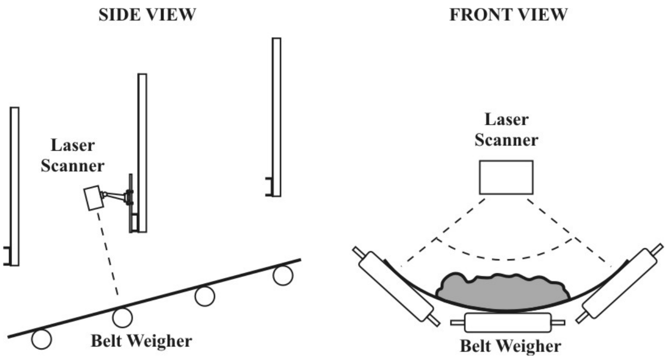

Fig. 2. Measurement setup: Laser scanner and belt weigher installed on top of a conveyor belt

Calculated results are stored in a local database that can be accessed by using a client-software written for this purpose. In addition, the results are automatically uploaded to the automation system, enabling the plant operators a direct access to them.

4. DATA ANALYSIS

When the mine is operating normally the ore is fed to a mechanical screening station located at the concentrator plant. There it is divided into three size classes before grinding; fine ore (0 – 35 mm), pebbles (35 – 80 mm) and lumps (> 80 mm). It is this mechanically screened distribution that is estimated in the mine by using the 3D image and the weight information.

Estimation of the particle size distribution is done in three stages. First, individual rock fragments are recognized (via segmentation methods) from the 3D image. Then the size distribution of these fragments is calculated and in the third step the resulting distribution is fed to a calibrating model for estimation of the size distribution of the whole ore mass.

4.1 Segmentation

The process of dividing an image to its parts in some meaningful way, usually so that these parts correspond to objects in real world is called image segmentation. This is also an effective way to obtain useful information from the 3D image used in this case. The segmentation approach used in this application is based on watershed segmentation algorithm which is run twice for differently pre-processed data. One of the watershed segmentation routines separates background from particle clusters and the other separates individual particles from each other.

Watershed algorithm is a well-known segmentation routine (see e.g. Vincent and Soille, 1991) that starts from local minima at a 3D landscape and "fills up" the areas until common borders are reached. Alternatively, the starting points can be freely defined. This modification is commonly called marker controlled watershed algorithm, where the arbitrary starting points are called markers.

The segmentation process outlined in Figure 3 is described in the following.

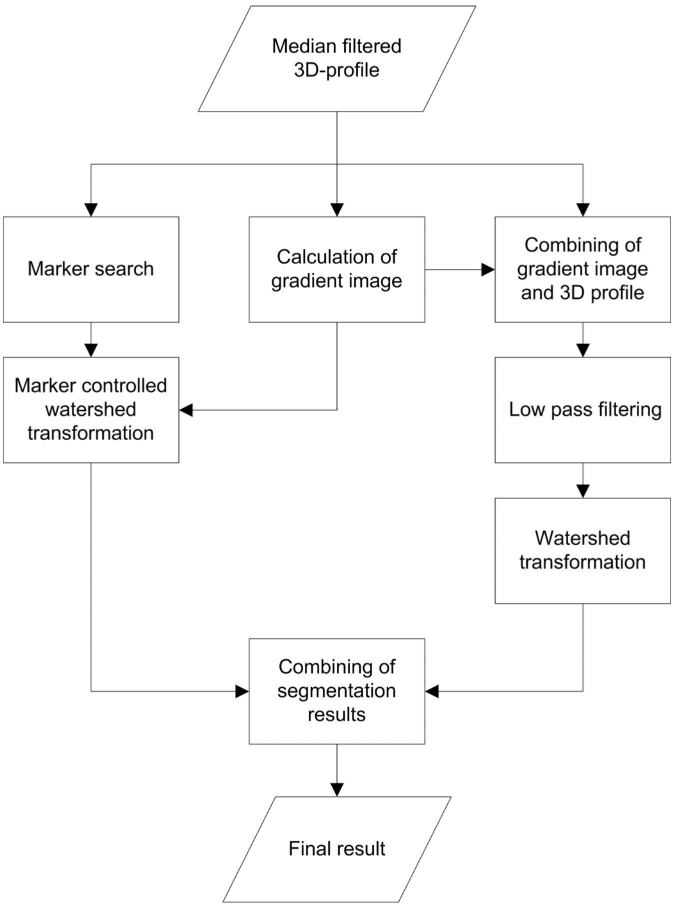

Fig. 3. Outline of the segmentation algorithm

Segmentation is started by using a standard median filtering algorithm (see e.g. Gonzales and Woods, 2002) with a 3x3 mask for the 3D data. This is done to decrease measurement noise. Missing measurements are replaced with the mean of the neighbouring measurements.

The segmentation process that separates particle clusters from the background employs marker controlled watershed segmentation on gradient image formed from the 3D profile. The gradient image is the magnitude of the gradient calculated by using standard Prewitt operator with a 3x3 mask, which is one of the common discrete approximations of gradient (Sonka *et al.*, 1998). Starting points (i.e. markers) for the particles are found by calculating the Laplace of Gaussian (i.e. estimate of the sum of the second derivatives in x and y directions) for the original 3D profile and searching for large continuous areas with negative values. These correspond to convex shapes in the rock mass. Markers for the background are flat areas in the 3D profile. These are found by performing a top hat transformation (Sonka *et al.*, 1998) for the 3D profile and choosing values under a specified threshold.

The second segmentation process that separates individual particles from each other is a standard watershed segmentation performed on a modified and low pass filtered version of the 3D profile. First, the 3D profile and the gradient image are scaled to the interval [0, 1] and summed together. After this filtering is done with a 12x12 mean filter and shallow local minima are removed by using H-minima transformation (Soille, 1999).

The two segmentation results are combined by simply discarding erroneous particle borders that are formed outside the particle clusters. An example of the segmentation process for real data obtained from Pyhäsalmi mine is shown in Figure 4.

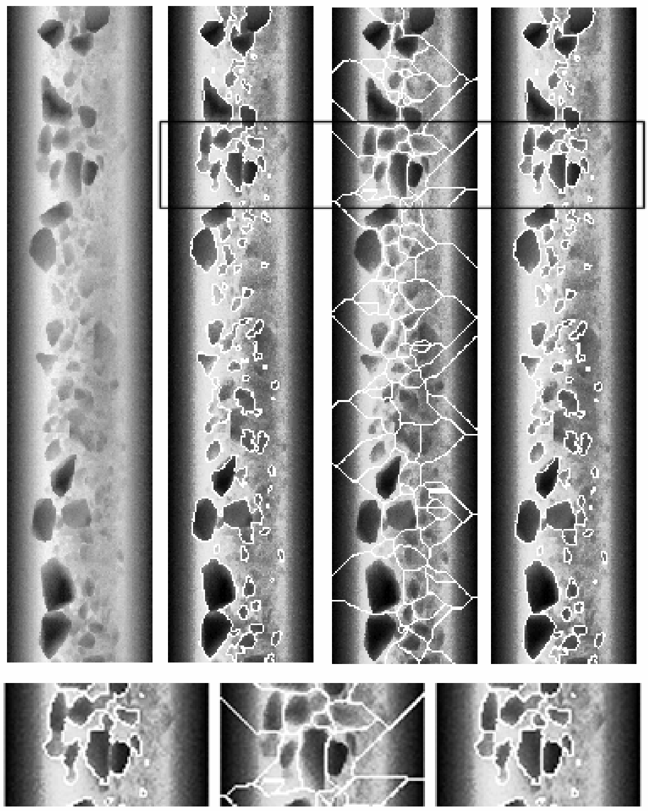

Fig. 4. Segmentation results. Images from the left: original median filtered 3D profile, segmentation into particle clusters, segmentation of individual particles and final segmentation

result. The emphasized rectangular area is shown at the bottom to provide more detailed view.

As can be seen from the final results, the segmentation routine recognises only the largest particles. This is a desired property since the amount of fines can be calculated by subtracting the volume of recognised particles from the total volume. Besides, there would be no sense to even try to perform segmentation for the smallest particles because of limitations in measurement accuracy.

4.2 Virtual sieving and volume estimation

The particles that have been recognized in the segmentation process are classified according to the shortest edge of their bounding box. The bounding box is only calculated in two dimensions, height of the particle is assumed to be smaller than the other two dimensions since this is the most probable alignment for particles when they are dropped to the conveyor belt.

Since the scanner can only see the surface from a single point, there will inevitably be areas that are not visible to the laser eye (see Fig. 5). The volume of the larger particles is calculated by integrating over the particle area that is identified by the segmentation algorithm. At each point the particle height is calculated to be the total height minus the estimated height of the ore bed (i.e. the dark area in Fig. 5). This approach will "cut off" the sunken part of the particle and will in most cases introduce a small error to the volume estimation. However, it would be difficult to estimate the volume of the sunken part with adequate accuracy due to irregular particle shapes and thus this error will be compensated by the calibration model.

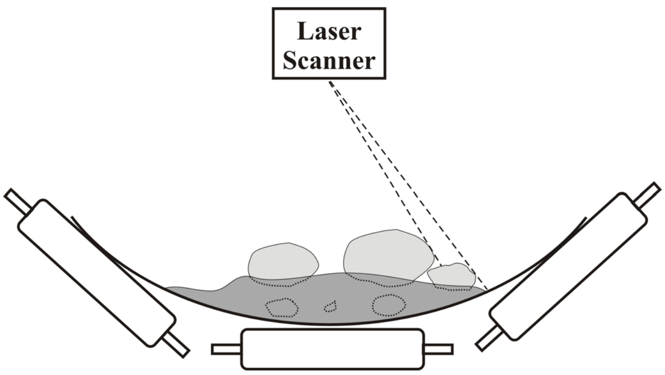

Fig. 5. Illustration of the areas not visible to the scanner

4.3 Calibration model for the particle size distribution

The particle size distribution measured from the surface of the ore is not the same as the size distribution in the whole ore mass. There are two main reasons for this. First, it is possible that segregation has happened in the ore mass due to for example vibration. Secondly, even if the ore mass would be totally homogenous, larger particles have a higher probability to be visible on the surface as illustrated in Figure 5. This phenomenon is explained in more detail and a model for the stack structure is given by Thurley, 2002.

In this particular case the ore contains a lot of fine particles in which the larger pieces of ore are buried. This is a problem when looking for the relation between the size distribution on the surface and the size distribution of the whole ore mass. Therefore calibration is done with regression models that estimate the particle size distribution by using variables calculated from the particles recognised on the surface. Large and small particles are treated differently in these models: Large particles are expected to be mostly visible in the ore mass. Therefore the amount of large particles that are visible is expected to be a good indicator of the amount of the large particles in the whole cross section of the ore mass. Small particles on the other hand are mostly buried in sand, so their amount depends on both the amount of visible small particles and on the amount of sand in the ore mass.

To overcome these problems the non-linear nature of the actual and measured proportion of differently sized particles is taken into account by generating additional non-linear variables for the inputs of the calibration models. The following variables are calculated by using the segmentation results:

$\boldsymbol{X_1}$ = *volume of ore not recognized as an particle*

$\boldsymbol{X_2}$ = *volume of ore classified to size class 50 – 75 mm*

$\boldsymbol{X_3}$ = *volume of ore classified to size class 75 – 100 mm*

$\boldsymbol{X_4}$ = *volume of ore classified to size class 100 – 135 mm*

$\boldsymbol{X_5}$ = *volume of ore classified to size class > 135 mm*

$\boldsymbol{X_6}$ = *(volume of ore classified to size class 0 – 50 mm)**$\boldsymbol{X_1}$

$\boldsymbol{X_7 = X_2\, X_1}$

$\boldsymbol{X_8 = X_3\, X_1}$

$\boldsymbol{X_9 = X_4\, X_1}$

The amount of fine ore is estimated with a standard least squares fit by only using variable $\boldsymbol{X_1}$ as input data. The amount of pebbles is estimated from variables $\boldsymbol{X_{6\text{-}9}}$ with a Partial Least Squares (PLS) model (Sharma, 1996), and finally the amount of lumps is estimated with another PLS model by using variables $\boldsymbol{X_{2\text{-}5}}$ and $\boldsymbol{X_{7\text{-}9}}$.

5. SOFTWARE ARCHITECTURE

In terms of software, the analysis system is designed to be as modular as possible. This makes it possible to separate different tasks into separate code modules which were implemented by using the Component Object Model (COM) scheme (Box, 1998). The different modules (see Fig 6) are described in the following.

User Interface (UI): Provides run time access to the analysis. Enables the user to modify laser scanner and belt weigher settings and provides feedback from the analysis kernel. Provides a connection to an external database. The component is implemented as an executable COM object.

Reader: Connects to the laser scanner through an Ethernet connection. Triggers the scanner for data collection and sets necessary parameters (scan frequency, scan duration, etc.). Returns the collected data to the data buffer of the user interface component. Implemented as an executable COM object. Not visible to the user.

Wrapper / Kernel: All the calculation routines described in section 4 are implemented into the Kernel component, which is automatically generated from MATLAB® code. This enables extremely flexible and powerful development for the analysis routines since all new ideas can be coded and tested with MATLAB®. After this, the final version can be easily converted into COM object and uploaded to the analysing computer. Since the MATLAB® compiler only generates in-process components (i.e. DLL-files) the Kernel is encapsulated into another COM-EXE component (Wrapper) which provides necessary interface for the UI component. Both components are invisible to the user.

TCP-Server: Keeps a local database containing the numeric results as well as images showing 3D data (in the form of a greyscale image), material reflectance image and a labelled image where classified particles are drawn with different colours (see Fig. 7). The server is designed to be connected to with one or more TCP-Clients. The clients can connect through a local area network (e.g. personnel working at the plant) or via Internet (e.g. remote monitoring). Implemented as an executable COM object. Visible to the user.

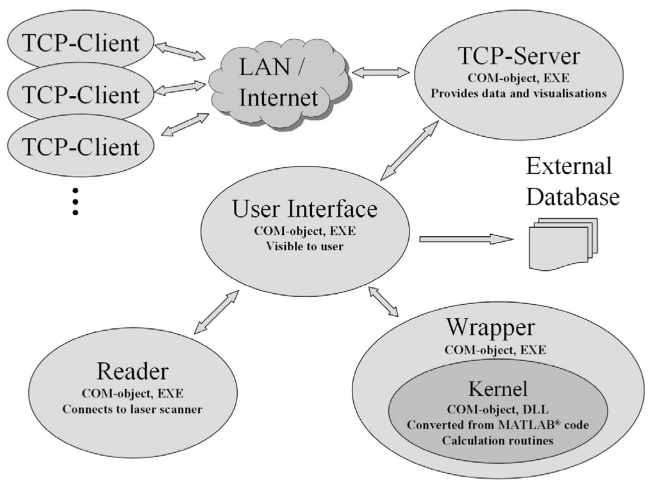

Fig. 6. Overview of the software architecture

The TCP-Client software shown in Fig. 7 communicates with the TCP-Server by using a dedicated protocol built on top of the TCP/IP layer. It displays the calculation results for the particle size analysis as well as silo levels after the screening station. The user can view history trends of desired length and see visual appearance of the conveyor belt. Currently the database contains one minute data for the last 30 days. There is also a password protected mechanism for the power users to set the target levels for different particle size classes.

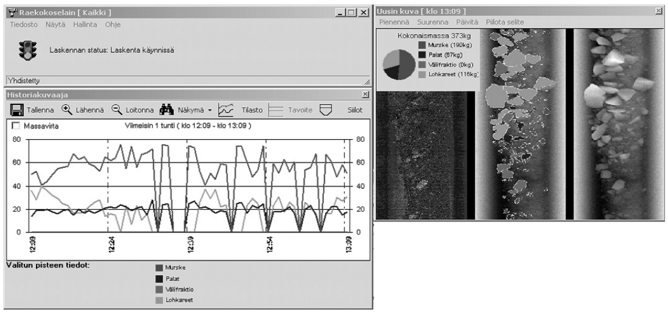

Fig. 7. TCP-Client software

6. RESULTS

The first results look very promising but a long term data collection campaign must be performed before anything definite can be said about the reliability of the analysis system.

Right now, the particle size measurement system has been calibrated and tested by using 32 samples, each 1.5 meters long, collected from the conveyor belt.

The number of samples is barely adequate for the determination of the calibration model parameters, therefore the analysis system have been tested by using leave-one-out cross-validation method. The correlation between estimated and real values is demonstrated in Figure 8.

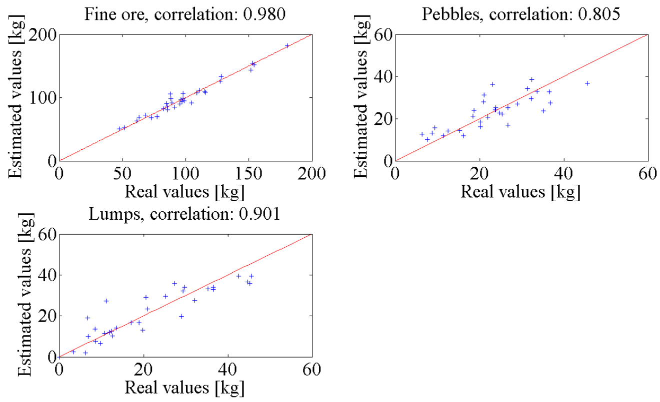

Figure 8. Analysis results for the 32 hand screened samples

The average absolute values for the errors are 4.55 kg for fine ore, 4.33 kg for pebbles and 4.34 kg for lumps. Average total mass of the samples is 143 kg. This means that the average error is around 3% and similar results are expected in the further tests. There would be some work to be done to improve the measurement quality but for this particular application this level of accuracy is good enough and most probably future efforts will be concentrated on development of the ore transportation line model.

7. CONCLUSIONS

Current laser scanners are capable of measuring the crushed ore with resolution high enough to separate individual particles from each other. They are also fast enough to scan the ore from a moving conveyor belt. Measurements done with laser scanner also have fundamental advantage over methods based on photography, since they provide accurate information of the particle height.

Measurement system presented in this paper is a new and accurate way to estimate the particle size distribution of crushed ore with far lower costs when compared to mechanical screening. The system works very well in its current environment but more emphasis should be given to the calibration model before it can be easily implemented in other plants and particle types. For example, if there would be more teaching data available, neural networks might give good results since they are able to model the non-linearities described in section 4 and thus there would be no need for the additional variable creation. However, this would require a large number of samples for teaching and validation data sets and since the samples from Pyhäsalmi must be shovelled, screened and weighed by hand, this would be a demanding task. Having said that, the authors are still fairly convinced with the accuracy of the PLS-based results since the validation was done with a hand screened and weighed samples. But in order to utilize the measurement fully in Pyhäsalmi mine, the ore transportation chain and its effects on particle size distribution must be modelled first. Work is being done on this issue.

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REFERENCES

Box, D. (1998). *Essential COM*, Addison-Wesley, 1998, ISBN 0-201-63446-5

Gonzalez, R. C., Woods, R. E. (2002). *Digital image processing*, Prentice-Hall, 2002, ISBN 0-201-18075-8.

Guyot, O., Monredon, T., LaRosa, D., Broussaud, A. (2004). Visiorock, an integrated vision technology for advanced control of comminution circuits, *Comminution 04,* Perth, Australia.

Hahne, R., Pålsson, B.I, Samskog, P.O. (2003). Ore characterization for-and simulation of-primary autogenous grinding, *Minerals Engineering,* 2003, 16, pp. 13-19

Larinkari, M., Kaartinen, J, Hyötyniemi, H. (2005). Management of particle size distribution of crushed ore, *Mineral Engineering International – Process Systems 05,* November 10-11 2005, Cape Town, South Africa.

La Rosa, D., Girdner, K., Valery Jnr., W. and Abramson, S. (2001). Recent applications of the split-online image analysis system. *Proceedings of the Southern Hemisphere Meeting on Mineral Technology – Volume 1, Rio de Janeiro, Brazil,* 27th May – 1st June 2001, pp 15-19

Palangio, T.C., Franklin, J.A. and Maerz, N.H. (1995). Wipfrag- a breakthrough in fragmentation measurement, *BAI 6th Seminar on Blasting Technology, Instrumentation and Explosives Applications,* Boston, Mass. USA., July 8-13, 199

Sharma S. (1996). *Applied multivariate techniques*, John Wiley & Sons, Inc., 1996.

Soille, P. (1999). *Morphological image analysis: Principles and applications*, Springer-Verlag, 1999, pp. 170-171.

Sonka, M., Hlavac, V., Boyle, R. (1998). *Image processing, analysis and machine vision*, Brooks/Cole Publishing Company, 2nd. ed., 1998, ISBN 0-534-95393-X.

Thurley, M.J. (2002). Three dimensional data analysis for the separation and sizing of rock piles in mining, *Doctoral thesis, Monash University, Electrical & Computer Systems Engineering,* 2002.

Thurley, M.J., Andersson, T. (2007). An industrial 3D vision system for size measurement of iron ore green pellets using morphological image segmentation, *Minerals Engineering,* 2007. (in press)

Vincent, L., Soille, P. (1991). Watersheds in digital spaces: An efficient algorithm based on immersion simulations, *IEEE Transactions on Pattern Analysis and Machine Intelligence,* Vol. 13 No. 6, June 1991, pp 583-598