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DETERMINATION OF ORE SIZE DISTRIBUTION WITH IMAGE ANALYSIS

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Abstract

In the mining industry determination of size distribution is traditionally done with big and very expensive ridars. In this paper a new method for analyzing crushed ore size distribution by means of image analysis from a conveyor belt is introduced. The method introduces a cheap and effective way to do size distribution analysis. Also a special analysis system based on the idea and built at Pyhäsalmi, Finland, is described. With this system the analysis can be performed on-line right after crushing.

Key Words

machine vision, mining, ore, PLS, shadow detection, particle size

1 Introduction

As the computational power of modern computers increases it has enabled researchers to use more and more intensive calculations in on-line analysis or control applications. One important area is image analysis, which usually involves demanding calculations. In this paper a novel image analysis-based measurement system designed to calculate particle size distribution of crushed ore is presented. The system was built on the initiative of Inmet Mining, Pyhäsalmi Mine Oy, Finland, to measure the size distribution after the first crushing stage that is done in the mine right after blasting.

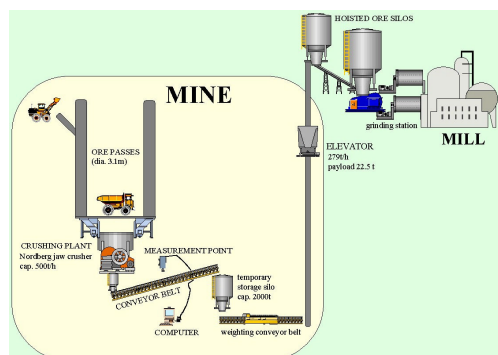


Figure 1. Schematic diagram of the mine.

The analysis system was built in a co-operation project with Helsinki University of Technology – Control Engineering Laboratory, Inmet Mining – Pyhäsalmi Mine Oy and University of Oulu – Systems Engineering Laboratory, all project parties being from Finland.

The system is located 1410 meters below ground level on top of a conveyor belt. The schematic diagram of the mine and flotation plant can be seen in Fig. 1 where the place of the analysis system is also indicated. The reason why this kind of analysis system was needed in Pyhäsalmi was that once the ore is hoisted to ground level it is fed to the flotation plant and the valuable minerals are separated from the invaluable gangue. In order to perform the separation by means of flotation the ore must be ground to small particles approximately 50-100 μ m in diameter (see [1] and [2]). The grinding method in Pyhäsalmi is so called autogenous method where the largest particles of the ore are used as grindstones. If the amount of the largest particles is not optimal, iron balls must be added to the grinding mills to get acceptable results. The annual cost for the iron pellets is around 1 000 000 € and it has been estimated that if the particle size distribution could be improved to be closer to the optimum when leaving the mine some 200 000 € savings per year could be achieved.

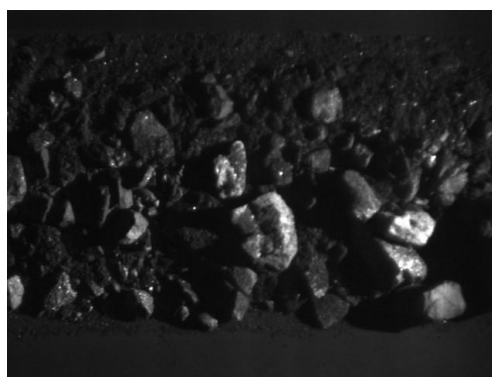


Figure 2. Crushed ore on a conveyor belt

The crushed ore is separated into four different size-classes (0-35mm, 35-85mm, 85-100mm and over 100mm in diameter) in the surface and stored in four different silos. From these silos the ore is fed to the grinding mills

in correct proportions in order to achieve the best possible result. Thus, it is obvious that the ore coming from the mine has to have correct amount of different sized particles, otherwise one or more silos in the surface will run out of ore.

From the level measurements in the silos it is possible to determine the size distribution on the surface and thus see what size classes are running out. However, since the silos are on the surface and there are two additional buffer-silos in the mine the time delay from the crusher to measured change in the size distribution can be even days. This leads to situation where it is very difficult if not impossible to make corrective actions in time. To overcome the problem it was decided to implement size distribution analysis system in the mine, right after the crusher. This way there would be an estimate of the size distribution coming from the crusher that would have only few minute time delay. The basic idea of the analysis is to have a monochrome camera on top of the conveyor belt and a single light source coming from the side. This leads to situation where the rocks form shadows to the image. An example of this kind of image is shown in Fig 2. The length of the shadow is proportional to the size of the rock throwing it. This information is utilized in the calculations.

There are some commercial applications that measure the ore size distribution (e.g. Split Engineering Ltd and Adept Electronic Solutions Pty Ltd) and many published papers around the subject (e.g. [3], [4]), but the idea to use shadow-length information in a statistical way – meaning that there is no segmentation or other difficult and error prone methods (3-D models etc.) – is unique. Also, especially segmentation-based methods would be difficult to implement in this particular case since the amount of fines is fairly large. The system is based on very robust image analysis methods and thus the camera is used just as a robust measurement device that will produce stable image quality to the following image analysis algorithms despite the possible changes in the external conditions.

The structure of the paper is the following: in the next section the physical setup of the system in terms of hardware and software components is described. The following two sections describe the calculations in detail and the last section draws conclusions and describes future research that will be performed regarding the analysis system.

2 The system setup

The analysis system consists of a standard desktop computer running Matlab® and a special analysis and communications software, Sony XC-55 Progressive Scan monochrome camera and a standard 1000W incandescent halogen lamp that is used in theatres. The software and hardware components of the system are described in detail in the following.

2.1 Physical setup

As mentioned earlier the system is built on top of a conveyor belt that transports the crushed ore to a temporary storage silo with capacity of 2 000 tons. The system is attached to one of the rest beams of the conveyor belt (see Fig. 3).

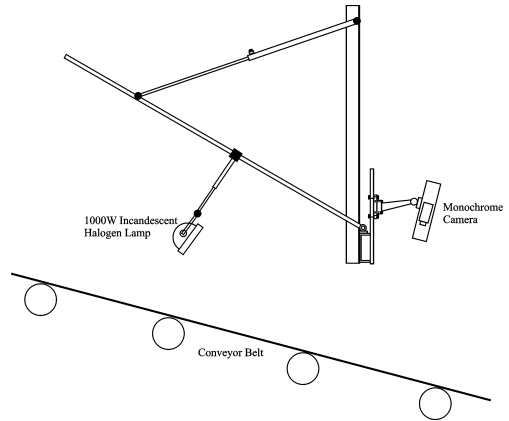


Figure 3. Physical system setup

Interfering illumination in the mine is blocked and the lamp that can be seen in the Fig. 3 is the only source of light to the camera. In order to achieve stable illumination conditions alternating input current is converted to direct current with adjustable rectifier. The dimensions of the system are fixed so that the image area is 110cm x 80cm and the distance along the conveyor belt from the top-edge of the image area to the lamp is 122cm (i.e. $L_1 = 122\text{cm}$ and $L_2 = 110\text{cm}$, see Fig. 4). These measures are important since there will be distortions in the shadow length depending on the place of the rock in the image.

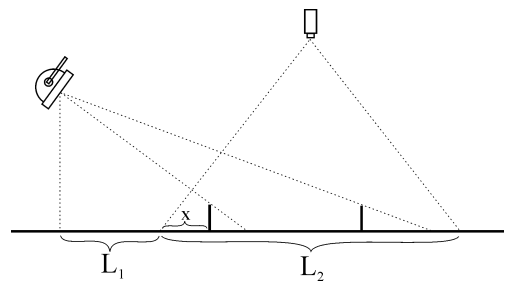


Figure 4. An illustration of the shadow length distortion effect

The influence of the shadow length distortion effect is shown in the Fig. 4, where two sticks of equal length are placed at different locations in the image. It can be clearly seen that the shadow length is significantly larger in the case where the stick is further from the light. All this is trivial of course and the distortions can be compensated simply with the following formula,

$$length_{compensated} = \frac{length}{1 + \frac{L_2}{L_1} x} \quad (1)$$

where x is the place of the rock in the image.

The camera used is a progressive scan type of camera meaning that the CCD-matrix of the camera is read at once when taking a picture. This gives very sharp image quality when imaging moving objects, as is the case in our system. The integration time is set to 1/2000 second. The image is transferred some 50-100m using strongly shielded 50Ω coaxial cable to a standard desktop computer running Windows NT 4.0™ with 1.533GHz Athlon-XP™ processor and 512MB of Random Access Memory (RAM). The image grabber card used is of type Matrox Meteor II – Multichannel.

2.2 Software components

The analysis sequence is conducted by a special software developed with Microsoft Visual Basic™. The software does the image grabbing and invokes analysis sequence that is done with Matlab® by using ActiveX® connection mechanism. The analysis results are returned by the Matlab®, filtered and fed to the automation system giving plant operators full access to the analysis results and history information.

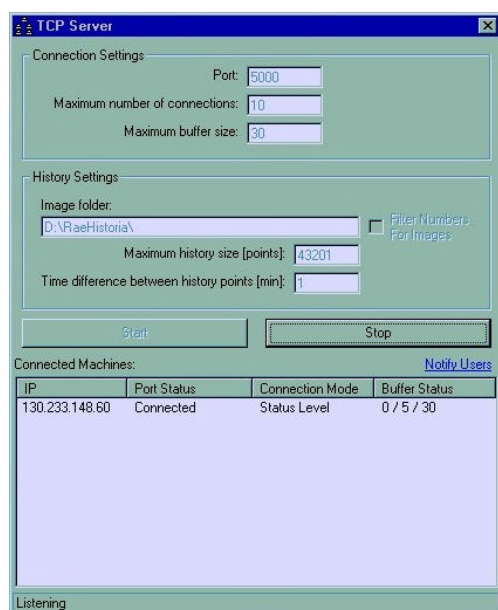


Figure 5. TCP Server program.

In addition to the automation system a separate program was developed that stores the numerical data of the analysis as well as the images (see Fig. 5). It also enables the data to be viewed over the local area network (LAN)

anywhere in the factory, or in the world for that matter as long as the remote viewing is allowed by the company firewall. The viewing is done with client software that can be seen in Fig. 6. Both the server and client applications are developed in the project using Visual Basic™ and they have their own protocol layer on top of TCP/IP layer. The client program allows the user to see the current situation as well as history information. The length of the history and the time difference between samples is determined by the server (currently 30 days and 1 minute respectively). From the history trends different views can be selected and statistical information calculated (mean, standard deviation, min, max).

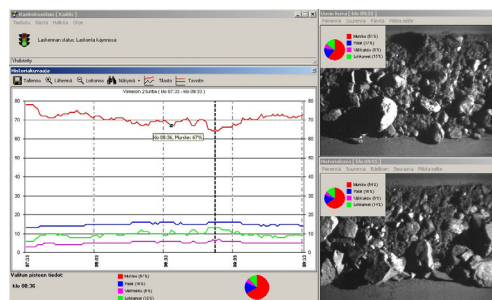


Figure 6. TCP Client program.

The client program is designed to be the main tool for the plant personnel in utilizing the size distribution information coming from the mine. The goal is to have it working as an interactive tool that is used by everyone involved with decision making related to ore production for the grinding mills. One step in this direction was the introduction of the target level curves to the program. The curves can be set with password by authorized person and other users – that is people that can influence the particle size distribution coming from the crusher – can act on that information. Another step would be to have the system calculate the desired target levels automatically. This feature will most probably be implemented to the system in the future.

3 Image analysis

As stated earlier the image analysis is performed with Matlab®, which has the Image Analysis Toolbox and PLS Toolbox installed. However, the calculations are simple enough to be hand written in C-language, for example, and incorporated into Dynamic Link Library (DLL). This would also increase the performance significantly. The analysis can be separated into three main parts: first the raw image is manipulated in order to get uniform image quality for the next stages of the analysis. This is very important in our case since it provides robustness against external changes (e.g. changes in illumination intensity). In the next part the shadow length distribution is calculated and finally a Partial Least Squares (PLS) model is used to map the classified shadow length histograms to

true size distribution values. The analysis is described in detail in the following sub-sections.

3.1 Preliminary manipulation

Since the shutter time of the camera is short in order to get sharp images, the mean value of the image intensity tends to become low. This can be seen in the Fig. 2. However, even if the image looks dark for human eye it is well suited for image analysis in our case. The only problem is with the visualization that is done in the client software. For that reason the intensity distribution must be stretched for the images that are stored into history database.

3.1.1 Thresholding

In this stage the image is thresholded into binary (or labeled) image. The thresholding method itself is a quite good guarantee for robustness but in addition the threshold value is updated continuously and it adapts to changes in the imaging conditions. It could be emphasized that the conditions in the mine are quite demanding and there are many external factors that influence the analysis procedure (e.g. dust). This is why the system is designed to be robust against them and the DC-lighting and adaptive thresholding are very suitable selection to achieve this.



Figure 7. Thresholded image.

The adaptation is done by looking at two narrow bands in the upper and lower parts of the image. In these bands there are never any rocks present. This is because of the shape of the cross section of the conveyor belt. Since it can be trusted that the area under the bands is always “clean” the threshold value can be adjusted so that the resulting image will be nearly white under the bands. The maximum area of black pixels in the bands is currently two percent.

3.1.2 Median filtering and edge detection

Once the image has been thresholded it is median filtered, which is done by running a 3x3 mask through the image and calculating the number of black pixels under the mask. If the number is greater than 4 the center pixel of

the resulting image will be marked as black. Otherwise the pixel will be marked as white. The filtering is done three times and the resulting image can be seen in Fig. 8. The algorithm is such that it converges to some final image no matter how many times the filter is applied. However, since the calculation is numerically quite heavy the number should be selected as small as possible. In this case three times was sufficient resulting in very good filtering results.

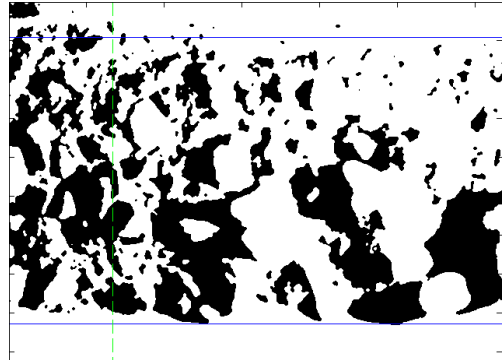


Figure 8. Filtered image.

As can be seen in Fig. 8 median filtering removes much of the noise from the image resulting in an image that is well suited for the following image analysis algorithms.

The horizontal lines mark the edges of the ore bed on the conveyor belt. The edges are detected automatically for every image and the rest of the analysis procedure is performed only to the image area located between the lines. The detection algorithm is heuristic and was developed by the author; Let’s consider the detection for upper line (lower part is similar): the algorithm starts to slide the line from the top of the picture and calculates the area of black pixels between the upper line and the upper edge of the image. The area is further restricted with the vertical line. This is because the light is coming from the right and thus the left part of the image tends to get dark and also the threshold adaptation algorithm described earlier is based on the fact that there should always be some black pixels in the bands (and because the light is coming from the right the black pixels are always on the left). Once the area of black pixels is over the allowed threshold (currently 4%) it means that there starts to be shadows and thus rocks appearing. This means that the edge of the ore bed has been found.

3.2 Shadow-histogram calculations

The next step is to calculate the shadow length distribution of the manipulated image. This is done simply by going through the image pixel-by-pixel and calculating the lengths of continuous zeros (zeros represent shadows in our case) in the image. The traversing is done in the direction of the shadows (i.e. horizontally). Once a

continuous shadow of length l is found it is scaled according to equation 1 and the compensated shadow length is stored in a shadow length histogram. The histogram is simply a vector of length v , where v is the number of pixels in the horizontal direction of the manipulated image. The compensated shadow length is the index of the vector where the value should be increased by one for each shadow found. This results into vector where the index tells the length of the shadow and the value tells the number of the shadows of that length in the image.

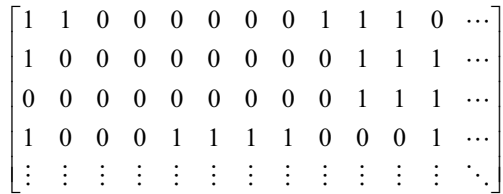


Figure 9. An example of the binary image data

An example of a possible upper left corner of manipulated image can be seen in Fig. 9 where in the first row is a shadow of length of 6 pixels. Notice that the 9 pixels long shadow on the third row would not be included since the algorithm considers only the shadows that are not limited by the edge of the image area.

Once the shadow length histogram is calculated it is classified into four classes of different shadow lengths. One could think that these classes represent the actual four classes of the ore size distribution, but this is not the case. There could be five or six classes just as well. The reason why four classes were selected and the border values of those classes were set to 0-17 pixels, 17-31 pixels, 31-56 pixels and 56+ pixels was just a case of optimizing the Partial Least Squares (PLS) model that will be described in the next section.

4 The PLS model

The model used for interpreting the classified shadow length histograms to real world ore size distributions is a standard Partial Least Squares (PLS) calibration model using SIMPLS algorithm [6]. Basically this means that once the system model is identified, the on-line calculations can be done simply by scaling the mean centered data with standard deviation, multiplying the scaled data with the PLS model regression coefficients and then re-scaling the results. This leads to the desired ore size distributions. To learn more about PLS see [5] and [7], for example.

So the question is: “where to get the model?” In this case the model was obtained by hard work: some 15 000 kilograms of ore was shoveled to get the teaching data. As a curiosity, it could be mentioned here that the author of this paper was also doing this “data mining” for two long

days. The teaching data set consists of 100 samples that were obtained by running the crusher jaws in five different settings and collecting 20 samples from each setting. This was done to ensure that there would be enough variance in the data, meaning that all the possible operating points of the system would be known to the model. The individual data points were collected by stopping the conveyor belt while the ore bed was continuous. Once the belt was stopped an image was taken and the ore situated under the imaging area of the camera was shoveled to container and weighted. Then the ore was further separated to the desired size classes, which were exactly the same as used in the surface (see Section 1) and the masses of these classes were measured. In another words, the size distribution was manually measured for each sample. Also the settings of the crusher were saved for future control purposes.

Once the teaching data was available the number of latent variables for the PLS model was chosen. The selection was done with `crossval` -function of the Matlab’s PLS Toolbox using the leave-one-out method [6]. This means that for every data point a separate PLS model is constructed leaving the data point in question out of the model. Then every model is validated with the data point that was left out and prediction error is calculated for every output.

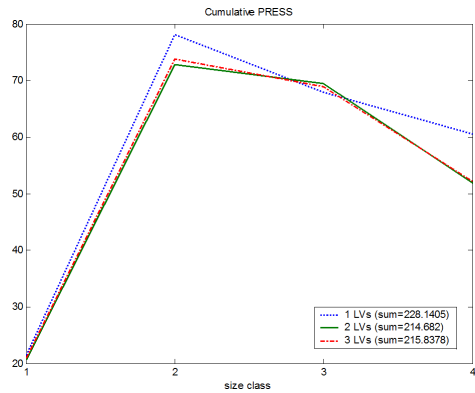


Figure 10. Cumulative predictive residual error sum of squares

If the prediction errors are summed for each output channel (size class in our case) the cumulative predictive residual error sum of squares is obtained for each channel. The calculations were performed for three cases where the number of latent variables was varied from one to three. The results of the calculations can be seen in Fig. 10 where it can be also noted that the total error is minimized when the number of latent variables is set to two.

Once the number of latent variables was selected the image analysis algorithms were optimized to get the best possible PLS model. The optimization was started by

constructing a cost function for the total prediction error so that there is a weighting factor for every class. The weights were chosen to be 3, 1, 1 and 2 from the smallest class to the largest respectively. The values were obtained from the mine personnel by asking the importance of the measurement for the different classes.

There are many different parameters that can be varied when performing the image analysis but most of them have so big effect on the accuracy that they could be chosen by simple manual tests. One example is the case of whether or not to include the shadows that are limited to the edge of the image area. Both options were tested and the case where they were excluded gave much better results. The remaining variables that could not be determined this way were the number of shadow length classes and the border values of those classes. These were optimized automatically by selecting an appropriate starting point manually and iterating all the combinations around that point. The result of the iteration was that four classes with border values given in Section 3.2 give the best results.

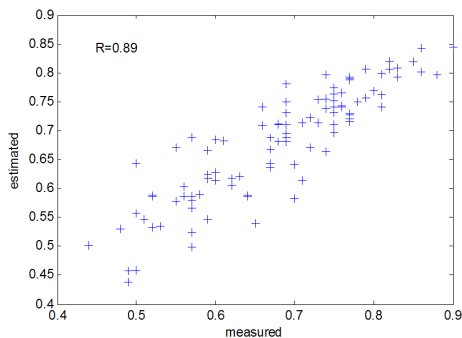


Figure 11. Validation of the smallest class

After the parameter values were fixed the final PLS model could be constructed. An example of the accuracy of the model can be seen in Fig. 11 where the smallest size class is validated with leave-one-out method described above. The correlation coefficient R for the fitting is 0.89.

5 Conclusions and future research goals

The basic structure and the main parts of the analysis algorithms of the automatic crushed ore size distribution analyzer implemented at Pyhäsalmi mine are presented in this paper. The results obtained with the system are promising and there is growing interest towards the system among the personnel at the mine. In fact, there is quite much work being done to integrate the analysis and the end user software (referred earlier as TCP client program) as an integral part of the daily work of the plant personnel involved in ore production and grinding. However, there is still much work to be done. One important aspect of research is to automate the system as much as possible and include more information to the end

user software. At least graphical indicators of the level measurements of the silos on the surface will be added in the near future. Another important improvement would be the automatic setting of the target level curves as described in the Section 2.2. This is also under study and will be implemented if possible.

There is also an idea how to improve the analysis: as described in this paper the result of the analysis are the size distributions of the crushed ore under the camera. However the analysis is indifferent to the mass, meaning that the analysis can give exactly the same results even if the “ore flow” under the camera is doubled. This results to some problems since the plant personnel is used to speaking by mass. One possible solution is to weight the size distributions by the mass flow which could be calculated by utilizing the level measurement of the silo following the analysis and the measured quantity of the ore leaving the silo (which can be measured very accurately by the weighting conveyor belt seen in Fig. 1). Another option to measure the mass flow is to purchase a belt conveyor scale. In Pyhäsalmi this would give far more reliable results since the level measurements of the silos are not very reliable. The purchase is under serious consideration and will most probably take place in the near future.

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