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Machine-vision-based control of zinc flotation—A case study

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Abstract

It is widely accepted that mineral flotation is a very challenging control problem due to chaotic nature of process. This paper introduces a novel approach of combining multi-camera system and expert controllers to improve flotation performance. The system has been installed into the zinc circuit of Pyhäsalmi Mine (Finland). Long-term data analysis in fact shows that the new approach has improved considerably the recovery of the zinc circuit, resulting in a substantial increase in the mill's annual profit.

Keywords: Image analysis; Expert control; Intelligent control; Mineral flotation; Performance analysis

1. Introduction

The possibility of using image analysis in the control of mineral flotation, which is the most common method to separate valuable minerals from ore, has created a lot of interest in the mineral engineering community (see Cipriano et al., 1998; Guarini, Cipriano, Soto, & Cueslaga, 1995; Moolman, Aldrich, Deventer, & Stange, 1994; Moolman, Aldrich, Deventer, & Bradshaw, 1995a, 1995b; Symonds & Jaeger, 1992 to name a few). This is due to the fact that plant operators use the froth appearance as one of the main indicators when they monitor and optimize the running of the flotation process. Hence if the operator's work could be supported or partially automated using a machine vision system and feedback control, considerable improvements in flotation performance could be expected. Fig. 1 shows two froth images from the zinc rougher cell at the Pyhäsalmi mine (Finland). This figure clearly shows how drastically the froth appearance can change due to changes in the operating point of the flotation process.

In the past, research in this area has been merely concentrated on either deriving new image processing algorithms to calculate certain features from the froth images or on analyzing the correlations between image variables and process variables, see references above. However, the ultimate goal should be to use the additional information from the image variables to improve flotation performance through feedback control. Recent results on this topic can be found from Brown, Dioses, and Olst (2001) and Olst, Brown, Bourke, and Ronkainen (2000). These papers, in particular, are interesting, because the authors had the opportunity to run parallel experiments on two identical flotation banks for two months, and it turned out that by stabilising the froth speed (which is measured using image analysis) it was possible to improve the flotation performance through improved recovery.

This paper presents a novel multi-camera set-up combined with expert controllers that at least partially achieves this ultimate goal. When designing this kind of system, the following questions seem to be pertinent:

(1) How to build a reliable measurement set-up that is able to produce high-quality froth images in a rather hostile environment, i.e. a flotation hall?
(2) What are the important features in froth images and how can they be calculated?

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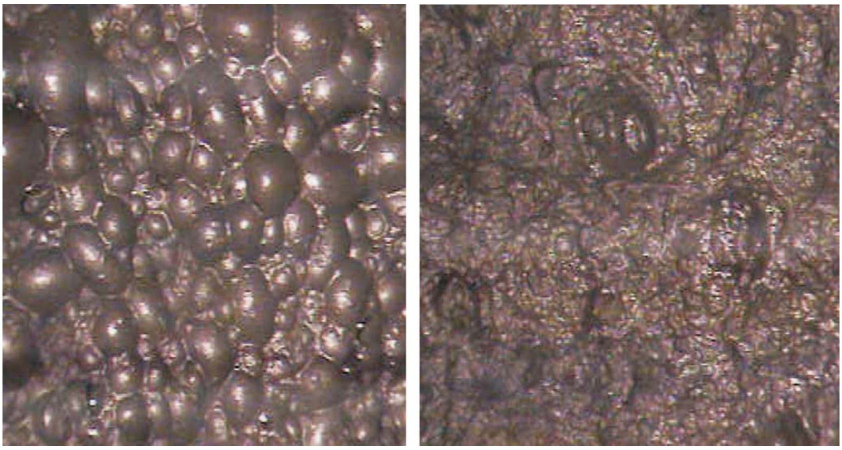

Fig. 1. Visual appearance of zinc froth.

(3) What kind of data analysis methods should be used to analyse image and process data?
(4) How the relevant image variables should be used in feedback control of the flotation process?

This paper shows one particular approach to answer each of these questions. It also reports for the first time (to the authors' best knowledge) that long-term data analysis (5 years) indicates that by utilising the additional information from the image variables in the optimisation of the flotation process, it has been possible to achieve considerable financial benefits through improved recovery.

The rest of the paper is organised as follows: the next section will give a short description of the process and motivates the research undertaken in this paper. Section 3 describes the original single-camera set-up, and its evolution into a multi-camera system. This is followed by a Section 4, which describes the image variables that are calculated by the measurement set-up. Section 5 analyses results that have been obtained by correlating image variables against process variables. After that, in Section 6 an expert controller is introduced that utilises both image variables and conventional process measurements to optimise performance of a particular flotation bank. This section also analyses whether or not the expert controller improves flotation performance. Section 7 concludes the paper and gives directions for future research.

2. Process description and motivation

At Pyhäsalmi both copper and zinc are being flotated. This paper concentrates exclusively on the zinc flotation circuit. The starting point in mineral flotation is grinding, where the particle size of the ore is reduced down to micrometer level. This is done in order to 'free' valuable minerals from gangue. Resulting slurry is fed into conditioning tanks, where the valuable mineral particles are selectively coated with hydrophobic chemicals. After this, slurry is fed into flotation cells where it is mixed with air. Air together with mixing and frothing reagents produce a large number of stable bubbles, and because the valuable mineral particles are hydrophobic, they attach themselves with the bubbles and travel to the surface of the froth due to buoyancy. The valuable mineral particles are then skimmed from the top of the flotation cell using natural overflow. This flow is typically called the concentrate flow. The remaining slurry in the flotation cell is removed from bottom of the flotation cell, resulting in the tailing flow.

The most important indicators of flotation performance are the amount of valuable mineral in the final concentrate (or grade) and recovery. The grade determines the selling price, and therefore it is in the mill's interest to maximise the grade in the final product. Recovery, on the other hand, indicates in percentages how much of the zinc available in the feed is captured into the final product. If recovery is low, the mill is loosing large amount of valuable minerals into the final tailing (i.e. waste), and therefore it is in the mill's interest to maximise recovery as well. These indicators are obviously contradictory, the optimum balance between grade and recovery depends heavily on market prices.

The flow diagram of the zinc circuit is shown in Fig. 2.The zinc circuit is divided into several flotation banks, namely roughing bank, scavenging bank, mid-roughing bank, mid-scavenging bank and cleaning bank. This is done to ensure both high grade in the final product and high overall recovery. Each of these banks have an individual 'role': for example, the rougher bank carries out initial separation of zinc from gangue, and therefore recovery is more important in this circuit than the grade of the concentrate. Cleaning bank, on the other hand, produces the final product, and therefore the grade of the

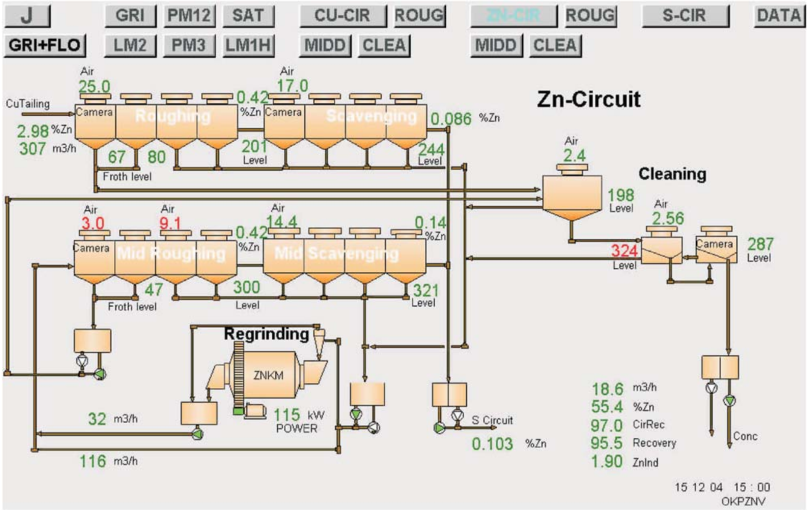

Fig. 2. Flow-diagram of the zinc circuit.

concentrate is more important than recovery. Currently, the zinc grade in the feed is around 3% and zinc recovery is 94%, whereas the final concentrate has 54% zinc concentration, which clearly demonstrates the effectiveness of the flotation process.

As the diagram in Fig. 2 points out, there are several feedback flows in the process. These flows make the process dynamically very complex and therefore difficult to control. The flotation process in itself is also highly stochastic, which further complicates the control of mineral flotation. It is for example almost impossible to build sufficiently accurate mathematical models of flotation processes that could be used in control design. Hence, mineral flotation is a good example of a process where conventional control design techniques that require a linear dynamical model of the process cannot be used. In mineral flotation there is in fact a real need for new 'intelligent' control design methods that can cope with rather vague and sometimes verbal descriptions of the process.

Nowadays the typical approach to control the process is to use on-line X-ray analysis to measure mineral compositions in the most important flows. This feedback information is then used to adjust the different control variables such as chemical flows, air flows and flotation cell slurry levels, so that the target values for grade and recovery would be achieved. In modern mills these optimising control actions are partly done by automated expert controllers and partly by plant operators. In their decision making the operators use mostly the froth appearance together with standard process measurements. The operators are needed in the decision making, because the standard process measurements do not always give enough information why a particular concentrate or tailing grade is either too low or high. However, the operators' experience and motivational levels vary substantially, and therefore one motivation for using image analysis is to further automate the optimisation of the flotation process. This will decrease the need for operator intervention, resulting in a more consistent control policy and possibly in increased flotation performance.

3. Measurement set-up

The measurement set-up has evolved considerably during the course of the research work. Firstly, during an EU-funded research project called 'Characterisation of flotation froth by machine vision' (ChaCo), years 1997–2000, a prototype system was developed only for the rougher bank of the zinc circuit as a single-camera system. After the ChaCo-project, the research work continued in a nationally funded project called 'Intelligent control of flotation', years 2000–2002, where, encouraged by the good results from the single-camera approach, a new multi-camera version system was developed. This section presents both the original system and the current multi-camera approach. The objective of this section is to explain the different features in the measurement set-up and also to describe problems encountered during the prototype phase.

The original measurement set-up is shown in Fig. 3. It consists of a measuring hood attached on top of the zinc flotation cell and a computer located next to the hood. Inside the hood are located a RGB-colour camera and a spectrophotometer. Both instruments have their own measurement compartments, and they are separated by a wall inside the hood. Both instruments have also their own

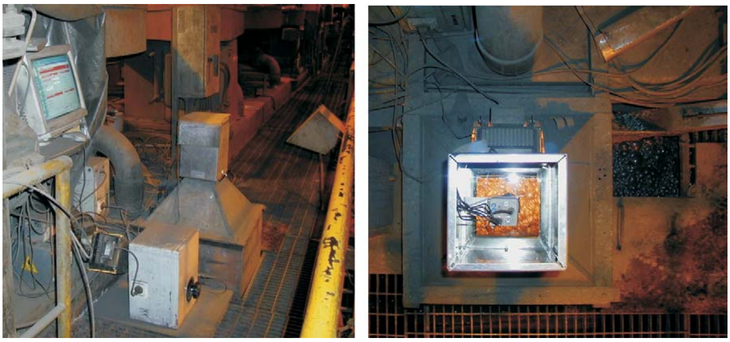

Fig. 3. Measurement set-up.

continuously adjustable light sources, see Kaartinen (2001) for details.

The purpose of the hood is to act as a supporting structure for the system as well as a protective element against the ambient light coming from the flotation hall. This is important since a large number of the different image analysis algorithms used in the system are using the total reflectance point on top of each bubble as a basis for further calculations.

The camera inside the hood is installed so that imaging geometry is perpendicular and the illuminating 500 W incandescent halogen lamp is as close to the camera as possible. This guarantees that single bubbles have only one total reflectance point (i.e. 'bright spot'), which is a very useful property for segmentation algorithms since they can use this bright spot as a starting point for bubble segmentation. In hindsight it can be said that finding the correct imaging geometry and ensuring the image quality remained stable were the key factors that allowed a rather detailed analysis of the froth appearance, see Section 3 for details.

In the original set-up image processing was run on a PC which was located next to the camera installation, see Section 4 for a description of the algorithms used in the set-up. The PC was connected to the concentrator's automation system and could also be accessed remotely by using public telephone lines. Images produced by the RGB-color camera were used to characterise the froth appearance and the spectrophotometer was only used to give additional insight to color measurements. For the spectral measurements the illumination and imaging heads were positioned at an angle of 106°, as shown in Fig. 4. This was done in order to remove the total reflectance points on top of the bubbles since they interfere with the spectral measurements. The 106° angle is called a Brewster's angle and it means that the reflected light coming from the top of the bubble (i.e. from the total reflectance point) will be polarized horizontally. Vertical polarization was carried out by a polarizing filter located in the measurement head, thus removing the total reflectance points completely from the spectral measurements, see Kaartinen (2001).

The original measurement set-up was used to provide 'a proof of concept'. Since initial data analysis demonstrated that the image variables could be used to control the process more effectively, it was decided that the system should be expanded into a multi-camera approach that would allow the measuring of froth appearance simultaneously from different banks in the zinc circuit. Because there were considerable problems to keep the spectral measurement equipment and the PC clean, and the optical cables coming from the measurement heads had to be considerably short, the spectral measurements were dropped from the multi-camera approach. This enabled the transfer of the PC into a less hostile environment, i.e. the mill control room (Fig. 4).

The current set-up covers the whole zinc circuit as is shown in Fig. 5. The system consists of four cameras that are connected to a single computer via coaxial cables. The computer has two frame grabber cards for the image acquisition and specially designed software that analyses the different image sources sequentially. The full analysis cycle takes roughly from 3 to 5 s, which is acceptable for a flotation process of this type where dominant time constants are typically several minutes.

All the acquired froth images are saved into an image database, which contains approximately 10 days of froth image history. The operators and plant engineers can access the database from the automation system. Hence they can monitor changes in froth appearance after they have made a corrective action in the levels of flotation reagents. The database also assists the operators to learn how the quantitative information produced by different image processing algorithms is related to the current visual appearance of the froth.

4. Image variables

Due to the complexity of the froth appearance, it is possible to define a large number of different features that

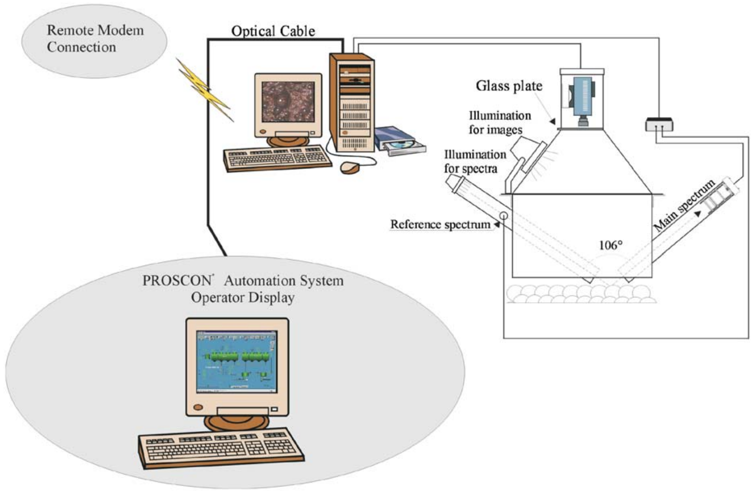

Fig. 4. System architecture.

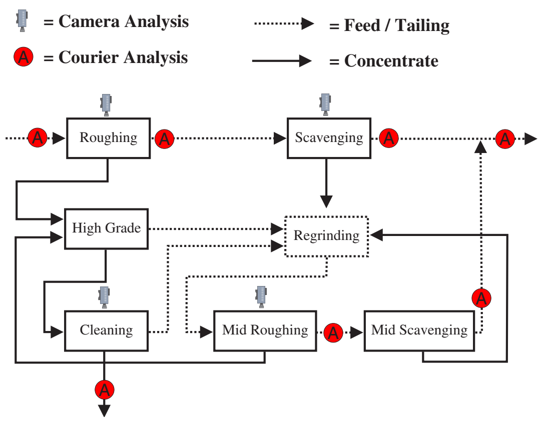

Fig. 5. Camera positions in the zinc circuit.

characterise the froth appearance. This flexibility has encouraged researchers to experiment with a variety of different algorithms, where the algorithms vary from simple thresholding algorithms, see Hätönen (1999), to fractal analysis see Bonifazi, Massaci, and Meloni (2000). However, even if these algorithms are interesting from the image processing point of view, there is no guarantee that they will give any additional information from the state of the flotation process.

In order to find the image variables that reflect flotation performance, an operator inquiry was carried out at the plant, see Hätönen (1999) for details. The main objective of this inquiry was to utilise the operators' experience to find the froth characteristics that reflect the flotation performance. Based on this inquiry it was decided that the image variables shown in the list below should be calculated. The list contains a short description on why these variables were chosen and how they are computed.

(1) *Froth colour*: During the operator inquiry it was found out that colour of the froth should be correlated with the mineral concentration in the froth. In the current set-up the mean and standard deviation for the R, G, and B values are calculated over the image plane. In order to avoid the effect of total reflectance points and shadows, both extremely dark and bright intensity values are excluded from the calculation. For a more detailed description, see Hätönen (1999).

(2) *Bubble size distribution*: In the operator inquiry the operators point out that bubble size can be used to find the optimal amount of frothing reagent. In some cases the bubble size is also correlated with the mineral 'load' of the froth. The bubble size is calculated using a watershed segmentation algorithm, see Bonifazi, Serranti, Volpe, and Zuco (1998), where the boundary of each bubble is determined, see Fig. 6. The total reflectance points are used as starting points in the watershed method. After that each connected area in the 'skeleton image' produced by the watershed segmentation algorithm is labelled. The next step is to calculate the number of pixels in each connected area, which gives the area of each bubble. The final outcome of the algorithm is the mean bubble size of the froth image. For a more detailed description, see Bonifazi et al. (1998).

(3) *Froth speed*: The froth speed reflects the production rate and therefore should be an important variable. The froth speed is calculated from an image pair, where the sampling time between two images is 20 ms. The algorithm calculates the 2-D correlation matrix of the image pair, and the highest peak of the correlation

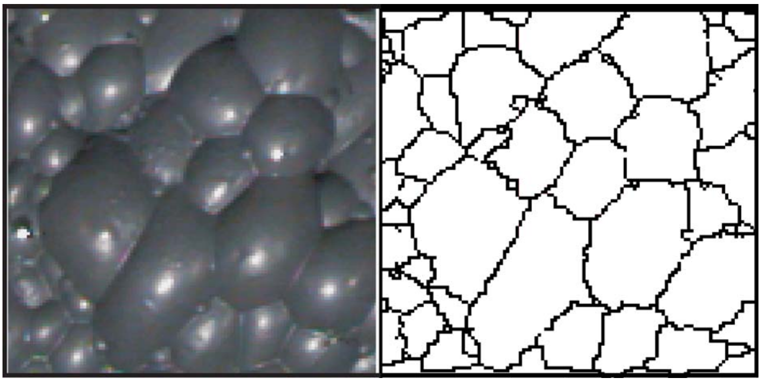

Fig. 6. Illustration of the segmentation algorithm.

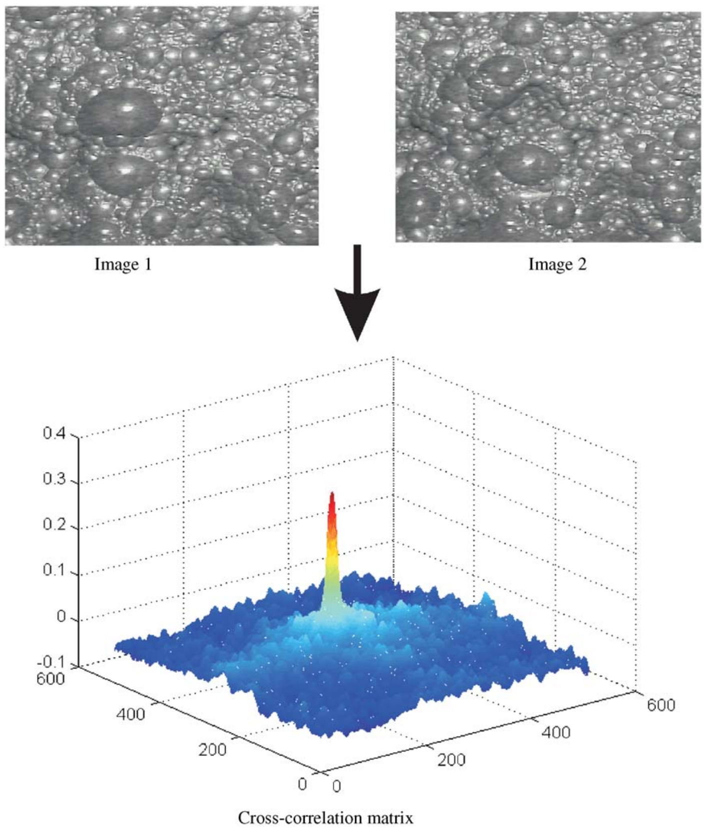

Fig. 7. Illustration of the froth speed algorithm.

matrix determines the amount of pixels the froth has moved during the sampling time, see Fig. 7. The actual implementation of the algorithm is done in the DFT domain in order to minimise computational burden. For a more detailed description, see Hätönen (1999).

(4) *Bubble collapse rate*: According to the operators, bubble collapse rate behaves in a similar manner as the bubbe size. The bubble collapse rate is calculated in

the following way: using the speed information, the latter image in the image pair is translated back to the same position as the first image in the image pair. After that, the difference image between the first image and the translated image is calculated. Finally, the number of pixels is counted in the difference image that exceed in value a given threshold. For a more detailed description, see Hätönen (1999).

(5) *Bubble load*: A visual inspection of the froth images has revealed that bubbles with high mineral load do not have a total reflectance point (i.e. (255,255,255) for a 8-bit RGB image). Consequently, this algorithm calculates the combined area of bubbles that do not have a total reflectance points in percentages of the whole image area. For a more detailed description, see Kaartinen, Hätönen, Miettunen, and Ojala (2002) and Miettunen, Kaartinen, and Hätönen (2001).

Note that these image variables can be divided into two categories: froth colour, bubble size distribution and froth load are static variables that can be calculated from a single image. Froth speed and bubble collapse rate are dynamic variables that describe the motion of the froth. In order to calculate them, an image pair is required. In summary, for an accurate description of the froth appearance, both static and dynamic features of the froth should be computed.

5. Data collection and analysis

After implementing the algorithms into the measurement set-up, a one-year data collection campaign was launched. In this campaign both process and image data were collected during the normal operation of the plant using a 6 min sampling time. Also special experiments were devised, where the effect of the controlled variables on the image variables was analysed using statistical methods. Some of these experiments are reported and analysed in Hasu (1999).

The data collected from the normal operation of the process were analysed using standard cross-correlation analysis. From this analysis it was clear that the rougher bank was not as stable as was expected. The image variables discovered many disturbances that were not registered by standard process measurements or by Courier X-ray analyses. In addition, the image-analyser gave a 15 min earlier warning of those disturbances that were also detected by the Courier X-ray analyses. Another interesting finding was that bubble load, size and collapse rate had a very strong correlation—high mineral load of the bubbles usually indicated small bubble size and low bubble collapse rate and vice versa.

The following two subsections analyse these correlations in detail. The graphs in the subsection are based on 35 days of data, collected at 1-min intervals during February and March 2001. Due to the considerable noise in the image variables and large amount of data points the data were classified first and thus the graph points represent the mean values of the different classes.

5.1. Recovery vs. image variables

The bubble load variable has proven to be the best indicator of the zinc flotation performance. Therefore, the data were classified on the basis of the bubble load into 13 classes. Fig. 8 shows the zinc recovery as a function of the bubble load. The figure also shows the corresponding class averages of the zinc grade of the circuit feed and the froth speed. It can be seen that the recovery is improving when the bubble load is increasing. The feed grade is low with the lowest recovery but below the transparency (opposite of load) values 20 the feed grade averages are about the same.

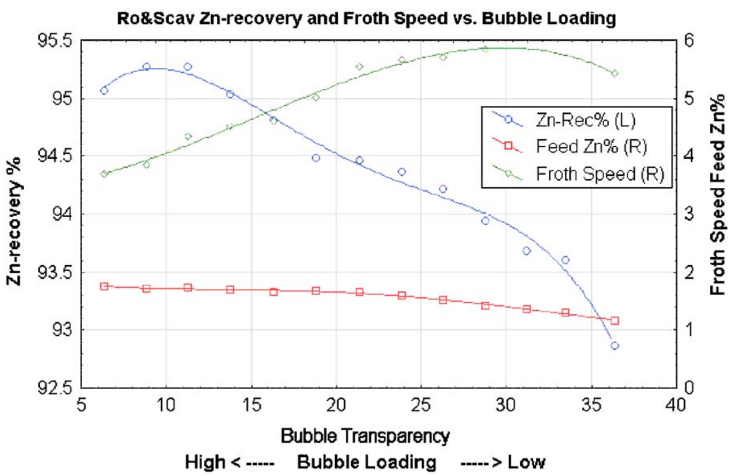

Fig. 8. Zn recovery, Zn-grade of feed and froth speed vs. froth load.

The figure suggests that the optimum value for bubble loading is approximately 10.

Fig. 8 also shows the corresponding class averages of the froth speed. It can be seen that the speed is low when bubble load is close to its optimum value. Thus, the intuitive corrective action to improve low recovery by increasing either air flow or flotation cell levels, which increases the froth speed, and consequently mass-flow out of the cell into concentrate, would be in fact wrong.

Figs. 9 and 10 again show the same recovery vs. bubble load (transparency) curve together with the corresponding bubble size and bubble collapse rate averages. These figures indicate that 'optimal' froth appearance is associated with small bubbles and stable froth, i.e. low bubble collapse rate.

5.2. Concentrate grade vs. image variables

Initial data analysis showed that froth colour is dependent on the zinc grade of the flotation feed. Therefore, it was assumed that the colour could reflect the concentrate grade. Unfortunately, there is no sampling point for the Courier analyser to analyse the rougher concentrate and thus the comparison had to be made between the froth colour of the first rougher cell and the final concentrate (which is known to depend mainly on the zinc grade of the rougher concentrate). Fig. 11 shows a clear correlation between the mean intensity of the red colour channel and the final concentrate grade. In the same figure the corresponding values of zinc grade of the feed and froth speed are shown. The curves indicate that concentrate grade (and the colour) are mainly determined by the feed grade. The froth speed has a negative correlation with the grades, which implies that froth rich in zinc moves slower than froth with a low grade of zinc. Figs. 12 and 13 indicate that small bubble size and low bubble collapse rate are related to high concentrate grade.

A similar data analysis was also carried out for other measurement set-ups in the zinc circuit, and the results were surprisingly similar to the results obtained from the rougher bank. Due to space limitations these results are not reported here. Note that this section has also shown that standard correlation analysis is adequate to explore correlations between image variables and process measurements, and there is no real need to resort to more advanced techniques such as self-organising maps or neural networks.

6. Controller design, implementation and analysis

As the previous section indicates, there are several strong relationships between process data and image variables. Hence the next natural step was to use the image variables in feedback control of the process. In order to achieve this, existing expert controllers were updated that mimic the decision making of an experienced operator. These expert controllers have been used in the plant for 20 years or so. The controllers follow simple '*if then*'-rules, and if two rules are activated simultaneously, each rule has a different priority, and the rule with the highest priority is activated. Due to space limitations, this section concentrates on the copper sulfate ($CuSO_4$) controller in the rougher bank. The rules for this particular controller are shown in Table 1 together with their priorities. The manipulated variable is the amount of copper sulphate fed into zinc rougher cell. $CuSO_4$ is the activator chemical, i.e. when zinc grains are coated with $CuSO_4$-molecules, the zinc grains form selectively a bond with the collector chemical xanthate, see Hasu (1999) and Kuopanportti, Roikola, and Suorsa (2000) for details.

The fundamental idea of the controller is to use the '*if then*'-rules to define a feasible area for the operating point of the process in terms of standard process measurements and X-ray measurements. In the updated

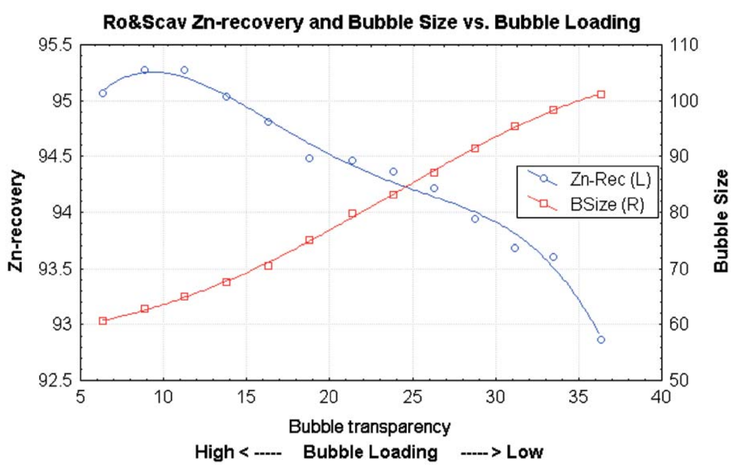

Fig. 9. Zn recovery and bubble size vs. bubble load.

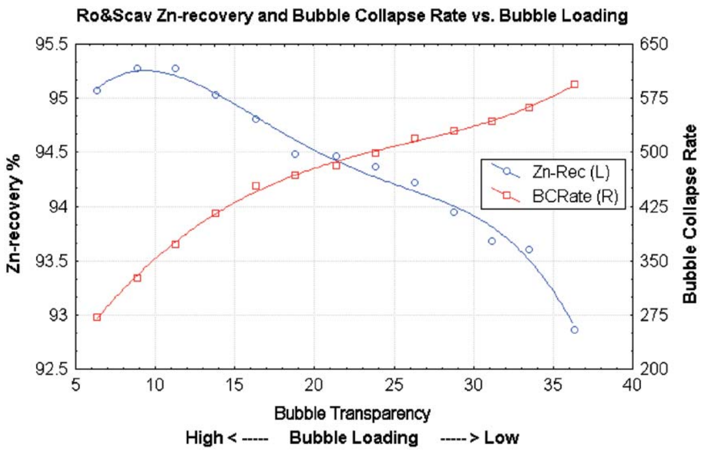

Fig. 10. Zn recovery and bubble collapse rate vs. bubble load.

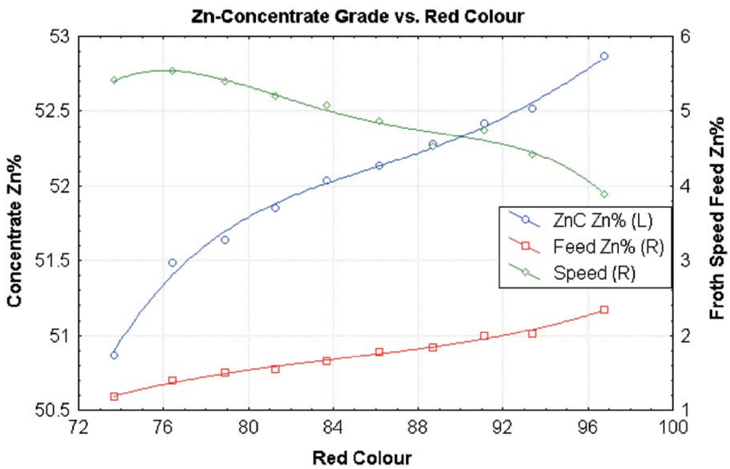

Fig. 11. Zn-concentrate grade, Zn-grade of feed and froth speed vs. red colour.

controller also the new image variables are used. The feasible area for the image variables was derived from correlation analysis presented in the previous section. If the operating point is inside the feasible area, the amount of $CuSO_4$ that is fed into the circuit is kept constant. If, however, the operating point drifts outside the feasible area, a corrective action is taken to force it back. The direction of the corrective action (i.e. whether to increase or decrease the volumetric flow of $CuSO_4$) is determined from the image measurements, the process measurements and the X-ray measurements using the '*if then*'-rules. The main features of the controller are:

(1) If two rules are activated simultaneously, the control action for the rule with a higher priority is executed.
(2) The controller has two possible control actions: either to increase or decrease $CuSO_4$-feed by a fixed step.
(3) The controller is executed every 60th second. This delay allows process transients to die away that are caused by the corrective step-changes before any new corrective actions are made. Consequently, the controller is only compensating for steady-state disturbances in the process.
(4) The variables *setpoints*, *low alarms* and *high alarms* can be changed by the operators. This allows them to re-tune the controller if there are considerable changes in the ore quality.

In summary, the expert controller uses 'crisp rules' instead of fuzzy ones with a fixed magnitude for the corrective

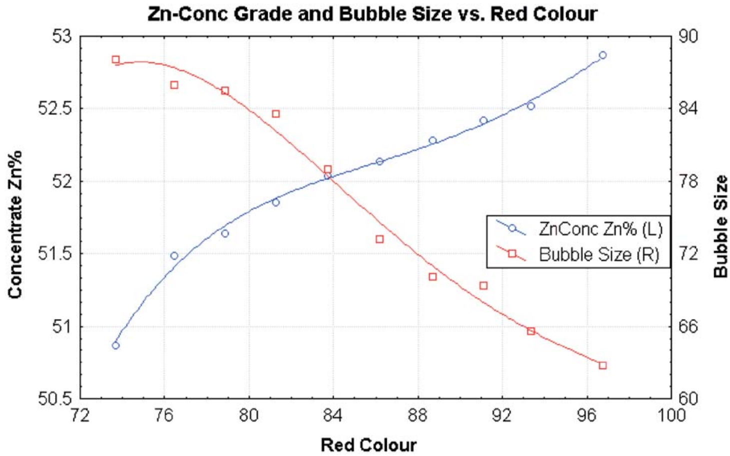

Fig. 12. Zn-concentrate grade and bubble size vs. red colour.

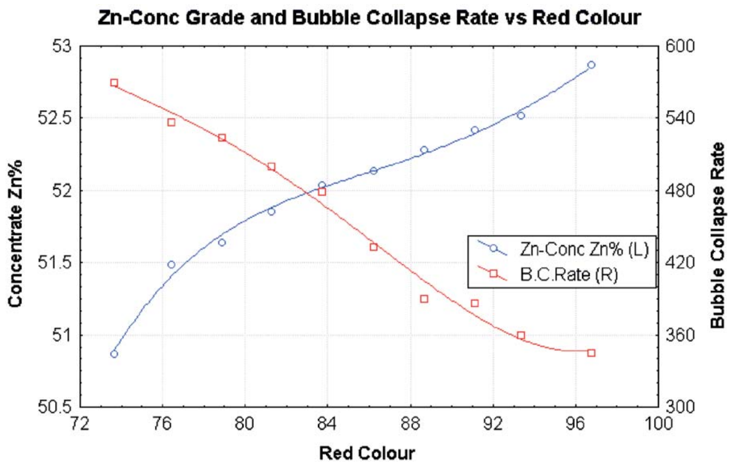

Fig. 13. Zn-concentrate grade and bubble collapse rate vs. red colour.

Table 1
Rule base of the expert controller

Priority	Condition	Action
1.	If froth thickness < setpoint	Decrease
2.	If bubble collapse rate < low alarm or bubble load > high alarm	Decrease
3.	If rougher tailing > setpoint	Increase
4.	If scavenger tailing > setpoint	Increase
5.	If bubble collapse rate > high alarm or bubbled load < low alarm	Increase
6.	If bubble size > high alarm	Increase
7.	If scavenger tailing > 0.7 ∗ setpoint	Increase
8.	If other rules are not active and red colour > low alarm	Decrease

action. Thus, it could be expected that controller performance could be further enhanced by using more advanced controllers such as fuzzy expert controllers. However, because the operators have been using the ‘crisp’ controllers for 20 years, they are strongly opposed to any new, more sophisticated controller structures, and therefore it was only possible to add new rules to the existing controller.

Table 2
Flotation performance 1995–2004

Year	Feed Zn %	Concentrate %	Recovery %	Target recovery %	Difference %
1995	1.7	51.7	88.2	88.8	0.5
1996	1.8	51.1	86.7	88.9	2.2
1997	1.8	51.4	87.3	89.1	1.8
1998	1.7	52.5	89.9	88.7	−1.2
1999	1.6	52.2	87.6	88.0	0.5
2000	1.3	51.5	85.3	86.57	1.3
2001	2.0	54.0	90.0	89.4	−0.5
2002	3.0	54.4	92.6	92.2	−0.5
2003	3.1	54.8	93.8	92.2	−1.7
2004	3.0	54.3	93.0	91.8	−1.25

The updated $CuSO_4$-controller was put into service in January 2000. Other controllers in the zinc circuit were updated in a similar manner between 2000 and 2002, and they have been in operation for 2–3 years. In order to investigate the long-term benefits from using the updated controllers, Table 2 displays grade, recovery, target recovery and the difference between target recovery and obtained recovery for 1995–2004. The blank line in the table indicates that year 2000 was the first year when the new image variable-based controllers were used. The target recovery is calculated based on the feed grade, and therefore the difference between grade and target grade is directly comparable across different feed grades. The actual equation for the target value has been set up by the mill management based on several decades of flotation data, and it reflects the management's opinion what is the desired recovery for a given feed grade. The values in the table are based on yearly averages of monthly measurements of feed and concentrate grades, recovery and target recovery.

Applying the F-test on the original monthly data, which has three weekly samples (i.e. roughly 150 samples per year), shows that the probability that years 1995–1999 and 2000–2004 have different differences between measured and target recovery is 99.95%, and therefore the new controllers have definitely had an impact on the Zn recovery. Furthermore, years 2000–2004 have a mean difference −0.53%, whereas years 1995–1999 have a mean difference 0.76%, indicating an improvement of roughly 1.3 percentage units in recovery. The mill management estimates that this improvement accounts for 200 000–300 000 euros annual increase in profit.

7. Conclusions and future work

As a first step this paper has described a singe-camera image-analysis set-up and its evolution into a multi-camera system at the Pyhäsalmi zinc circuit. The algorithms that are used in the set-up to characterise the froth appearance have been reviewed. Also reasons for choosing these particular algorithms have been given.

Subsequent long-term data analysis has shown that there exists strong correlations between image variables and concentrate/tailing grades. Furthermore, some of the image variables react 15 min earlier to disturbances than on-line X-ray analysis, and therefore the image variables can be used as an add-on in the current control strategy to achieve quicker disturbance attenuation.

To utilise the image information in the feedback control of the zinc circuit, existing rule-based controllers have been updated so that they use also the image variables in the decision making process. These controllers attempt to mimic the decision making of an experienced operator. Long-term data analysis has demonstrated that by using this updated control strategy, recovery of the process has been increased by 1.3%, resulting in 200 000–300 000 euros annual increase in profit. In summary, this paper has demonstrated indisputably that by using the correct image variables in the control of zinc flotation, it is possible to achieve considerable financial benefits in terms of improved recovery.

As a future work a similar multi-camera system will be installed into the copper circuit, and another data collection and analysis campaign will be launched. Based on subsequent data analysis, appropriate updates will also be done to expert controllers in the copper circuit, and performance of the updated controllers will be analysed. Another important area for future work is the accurate measurement of froth colour. Data analysis done so far has shown that colour can be strongly correlated with the grade in froth. RGB-cameras, however, are not designed for absolute colour measurement, and therefore new ways for measuring colour will be sought.

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