AI IN PRACTICE: CASE STUDY ON A FLOTATION PLANT

Heikki Hyötyniemi[1], Raimo Ylinen[2], Jorma Miettunen[3]

[1] Helsinki University of Technology, Control Engineering Laboratory,
Konemiehentie 2, FIN-02150 Espoo, Finland

[2] Systems Engineering Laboratory, P.O. Box 4300,
FIN-90014 University of Oulu, Oulu, Finland

[3] Outokumpu Mining Oy, Pyhäsalmi Mine, P.O. Box 51,
FIN-86801 Pyhäjärvi, Finland

The practice of AI is far from theory. Industrial plants need to operate reliably and fast, and there is no room for unoptimized heuristics. This paper introduces the flotation process, a complex process where new approaches are needed to make the production go on smoothly; AI type methodologies are needed in measurement (analysis of camera images), in monitoring of the process state (categorization of the froth classes), and in control (rule-based operation of the controller). All these tasks are carried out in a "pragmatic AI way", emphasizing speed, reliability, and simplicity.

1. INTRODUCTION

Flotation is used in mineral processing industries for separation of grains of valuable minerals from those of side minerals [9]. In the continuous flow flotation cell (Fig. 1), air is pumped into a suspension of ore and water, and the desired mineral tends to adhere to air bubbles and rises to the froth layer where the concentrate floats over the edge of the cell; the main part of other minerals remains in the slurry. The separation of minerals requires that the desired mineral is water-repellent: in zinc flotation, this can be reached by conditioning chemicals like copper sulphate $CuSO_4$; xanthate is needed to reach lower surface tension, etc.

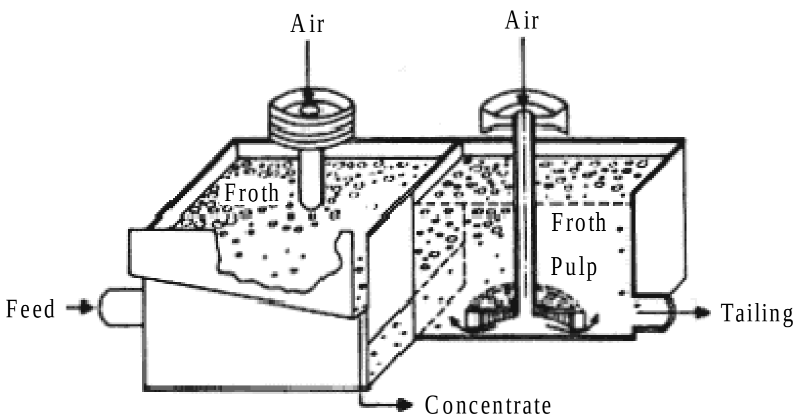


Figure 1. An array of two flotation cells in series

Flotation is one of the most difficult and challenging processes in mineral processing industry. This characteristic of the process mainly arises from the inherently chaotic nature of the underlying microscopic phenomena; there are no good models available that would capture the behaviour of the particles. Additional problems are caused by the fact that today's measurement technology is not able to provide with a description of the current state of the process that would be accurate and reliable enough. It is the froth surface that dictates the quality of the outflowing concentrate; the properties of the froth are reflected in its texture, movement, and colour. No standard measurement devices, however, can capture the outlook of the froth.

Thus, most of the chemical reagents that are used to increase the efficiency of flotation are controlled by the human operators. The operators usually determine the suitable levels of the reagents by analysing the visual appearance of the froth; the control strategies they apply are expert knowledge.

The fast development of information technologies, however, has made it possible to acquire images of the froth in real-time and automatically extract features from the froth image that resemble the features used by the operators. Thus, the limited capacity of the operator to monitor cells continuously (the operator is usually responsible for various circuits consisting of several cells) can be increased by installing a video camera over critical cells and connecting the camera to a computer that is able to process grabbed images in real-time. The importance of this topic is illustrated by the fact that it has been studied extensively in the mineral engineering community, and a large number of different research papers has been published on the subject (for example, see [3], [10], [11], and [12]).

This paper reports the results achieved during the ESPRIT LTR project ChaCo (Characterization of Flotation Froth Structure and Colour by Machine Vision); see [13]. Figure 2 illustrates the overall structure of the system developed during the project.

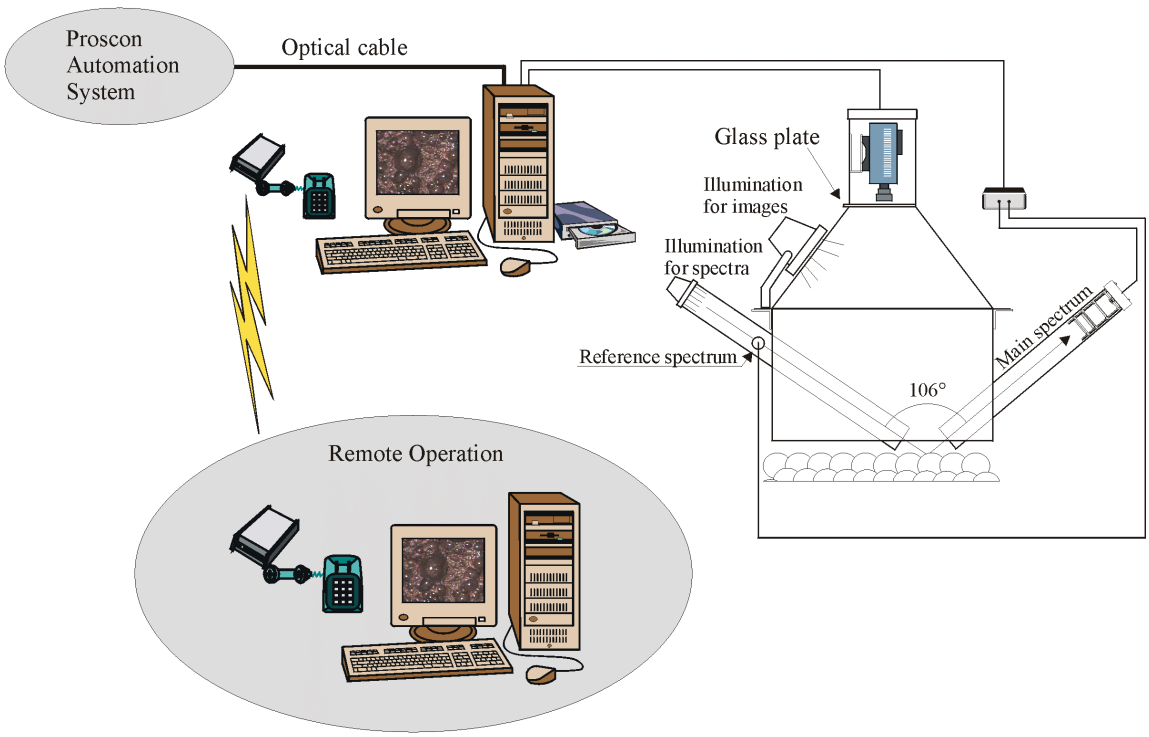


Figure 2. The froth analysis system (courtesy of Mr. Jani Kaartinen)

2. “INTELLIGENT” TECHNIQUES FOR FLOTATION

To realize reliable and efficient operation of an on-line flotation plant, there are various tasks that need to be automated: First, the relevant process variables have to be estimated using machine vision; second, the state of the process has to be detected; and, third, appropriate control actions need to be chosen. All these tasks require “applied AI techniques”, and each of these tasks is discussed separately in what follows.

2.1 “Soft sensors” based on image analysis

The status of the flotation froth cannot be uniquely defined; there are just a few measurements that can be explicitly defined and determined (like the froth level and thickness), whereas most of the factors that characterize the froth properties are more or less conceptual having no explicit definition. However, as compared to many other image analysis tasks, now the pattern recognition task is rather simple; the structure of the images is known beforehand, and only statistical features need to be extracted.

To construct “soft sensors” for the unmeasurable quantities, operator interviews were first carried out to find out what are the most relevant phenomena, and mathematical interpretations for them were derived [6]. It turned out that the static image alone is not enough; it is the dynamics of the froth layer that tells very much about the process state.

Typical “dynamical” variables extracted from the collected froth images are (average) *speed*, *speed variation*, and *bubble collapse rate*. The speed of the froth is obtained by computing the cross-correlation matrix (by using the 2-dimensional Fourier transformation) between two images (captured using 0.2 sec time interval) and determining its maximum value; the speed of the froth is given by the location of the maximum peak. The value of the maximum peak, on the other hand, gives a simple measure for speed variation (homogenous movement of the froth results higher peak in the cross-correlation matrix). The number of pixels in which the difference between two consecutive aligned images is larger than some given threshold, is used as a measure for the bubble collapse rate (BCR).

The *colour* of the froth is also of interest; colour variables are computed in two spaces: RGB (red, green, blue) and HSV (hue, saturation, value). The distributions of colour values are characterized by their mean, standard deviation, skewness and curtosis. Skewness represents the symmetricity of the distribution, and curtosis stands for its “peakedness”.

Examples of extracted structural features are *area*, *aspect ratio*, *perimeter*, *roundness* and *transparency* of bubbles. Aspect ratio is the ratio between the major axis and the minor axis of the ellipse equivalent to the bubble; perimeter stands for the length of the outline of a bubble, and roundness of a bubble determined by the formula $\mathit{roundness} = (\mathit{perimeter})^2 / (4\pi\cdot \mathit{area})$. Transparency is measured by calculating the points with specially high reflection – light reflected from bubbles that are covered with concentrate is rather scattered. To calculate these features the bubble images have to be segmented; for segmentation, the *watershed technique* was applied (see [2]). After segmentation the bubbles can be considered as separate objects and the features that are of interest and also their statistical distributions can be calculated.

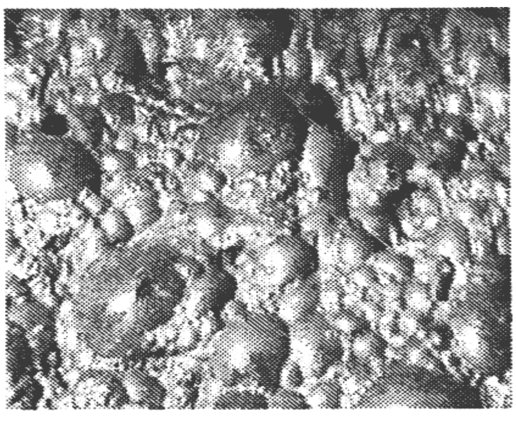
Further, the extracted features were applied for extraction of more advanced information like mineral concentrations. The parameters of the models were tuned by statistical multivariate methods [1]. For instance, principal component analysis (PCA) and partial least squares estimation (PLS) have been applied ([7] and [8]). It was recognized that red color intensity correlates strongly with the zinc concentration in the froth; the spatial variance of the froth speed also correlates positively with zinc content, whereas BCR correlates negatively.

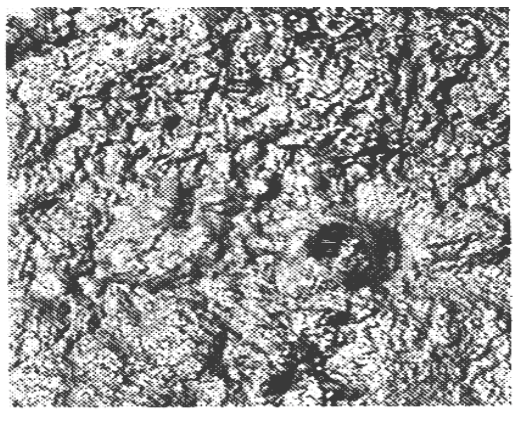
2.2 Categorization of froth layers

When machine vision has been applied to analysis of froth surfaces, normally the froth classes are labelled using rather low-level features – for example, there may be froths with big or small bubbles, etc. [11]. Now, on the other hand, operator interviews revealed that the most interesting (fuzzy) froth categories in zinc flotation are *wet*, *dry*, and *stiff*. Loosely speaking these froth types can be characterized so that wet froth typically has "empty bubbles" (the concentrate load being low); dry froth has "hexagonal bubbles" (the bubble tessellation being rather evenly distributed); stiff froth is "porridge-like". These categories are conceptual and there are no exact mathematical definitions for them; however, many of the extracted low-level features (see previous section) correlate with these categories. For example, for wet froth the transparency value and bubble collapse rate are high, for dry froth the bubble size distribution is even, and for stiff froth the speed and speed variance are low; using the multivariate data analysis terminology, the froth prototype vectors can be seen as (non-orthogonal) latent variables underlying the measured variables.

For the classification of the froth three different methods were implemented in the analyzer prototype. The first was the so called simple froth classifier, which measures the similarity of a given froth image against the predefined froth prototypes. This has been also realized using fuzzy logic. The second method was a tree-classifier, and the third classification method used the so called GGHA method to analyse the statistical structure of the data [5].

Whereas the froth classification is not used directly for control (see next section), its role is important in process monitoring and supervision. The optimal froth is rather dry; bubbles are loaded with concentrate, but the froth still floats out from the cell. The most critical case is the extremely stiff froth: This pathological situation may result in the *collapse* of the froth surface, so that no concentrate flows out; it takes typically 10 – 20 minutes before normal production can be recovered (see Figs. 3 and 4). It turned out that the implemented classifiers were capable of detecting the risk of collapse some 10 minutes before the surface finally collapsed, so that some corrective actions could still be applied (see [4]).





Figures 3 and 4. On the left, a typical "living" froth surface, and on the right, a collapsed one

2.3 "Expert control" of the flotation process

The image analyser gives a number of variables which can used for control. Based on the literature study, operators' knowledge, and on experimental work, the following five variables seemed to be the most important: bubble collapse rate, transparency of bubbles, bubble size, red color intensity, and froth speed. Fig. 5 shows how one of these these image variables (bubble collapse rate) affects one of the process variables, the zinc recovery rate. BCR may be a key variable because it seems to be possible to define an area where it should be maintained in order to guarantee good zinc recovery (minimum in the graph). The optimum area of BCR, however, moves with the zinc content of the flotation feed, as can be seen in Fig. 6.

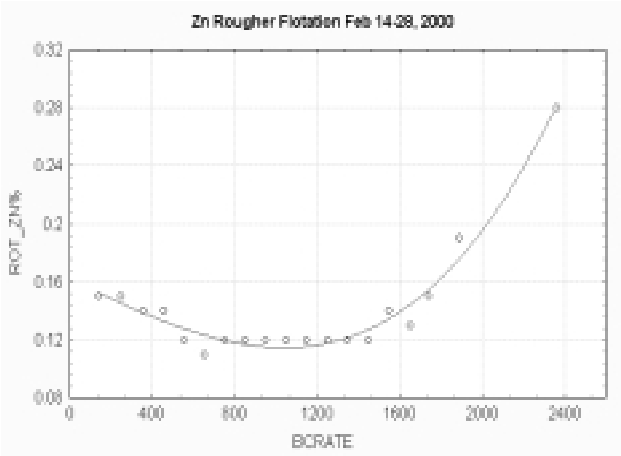
Figure 7 shows the relationship between BCR and the feed of copper sulphate; the figure clearly indicates that BCR can be controlled with copper sulphate. In reality this relationship is more complex because both variables depend more or less on the zinc grade of the feed; however, added copper sulphate should always decrease BCR. It seemed that bubble transparency is also a good indication of the flotation performance. Overdosage of copper sulphate is indicated by a very low value of bubble transparency (Fig. 8). On the other hand a high transparency value means lack of copper sulphate. Like BCR bubble transparency value also depends on the zinc grade of the feed; the optimum area is not quite constant.

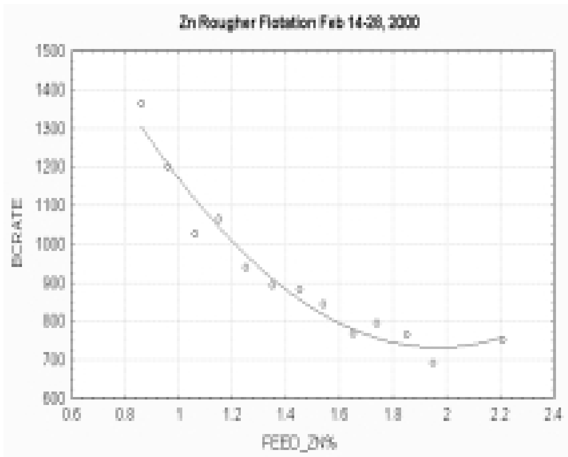
Based on these experiences, a rule-based control algorithm for the dosage of copper sulphate was constructed. The (simplified) rule set can be presented as shown in Table 1. The action part of the rules has very simple form: the flow of $CuSO_4$ is either increased ("+") or decreased ("–") by a fixed amount (about 2% of the operating range at a time). As compared to normal expert systems, now the control flow is fixed: there is a ranking between the rules, so that if a rule with higher priority can be applied, it is always selected instead of the lower priority ones.

The knowledge in the rule base combines the observed relationships within the process with the objectives of production. The controller is non-model-based (there is no dynamic description of the influence mechanisms), only the (assumed) causal dependencies are applied. The basic assumption is that increasing $CuSO_4$ makes more zinc adhere to the bubbles, making them more heavily loaded. The most critical rules with highest ranking try to avoid the froth collapse; that is, if the bubbles are *too* loaded, the dosage of $CuSO_4$ is made smaller. If rule #1 is active (the froth thickness is below some preset value) this is already too late, whereas rule #2 may help in avoiding the collapse. The next rules (#3 and #4) try to minimize the amount of zinc passing through the system and being lost. The next rule #5 prevents the excessive foam. Next, in the rule #6, if any of the image variables indicate too wet bubbles, more $CuSO_4$ is pumped in. Finally, if everything works all right, so that none of the previous rules was active, the consumption of $CuSO_4$ is minimized.

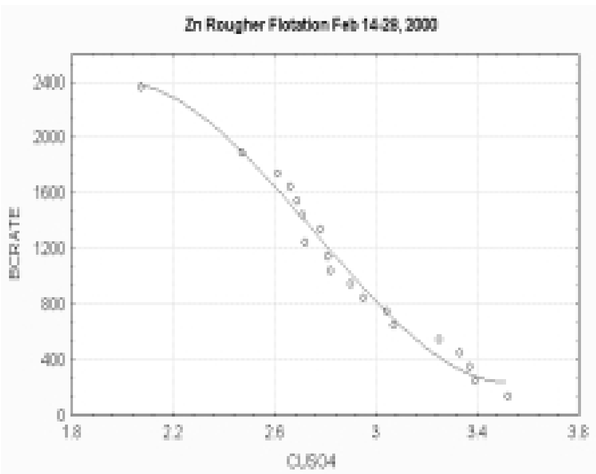
Ranking	Condition	Action
1.	IF *froth thickness* < *lower limit*	–
2.	IF *BCR* < *lower limit* OR *bubble transparency* < *lower limit*	–
3.	IF *zinc content in rougher tailing* > *upper limit*	+
4.	IF *zinc content in scavenger tailing* > *upper limit*	+
5.	IF *froth thickness* > *upper limit*	+
6.	IF *BCR* OR *bubble transparency* OR *bubble size* > *upper limit*	+
7.	ELSE	–

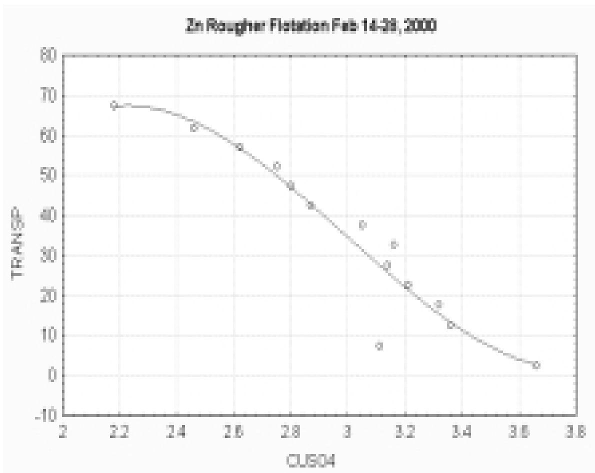
Table 1. The $CuSO_4$ control rule base that mimics the operator actions





Figures 5 and 6. On the left, the Zn content in the rougher tailing (that is, the amount of zinc lost in the first phase of flotation) is shown as a function of bubble collapse rate – apparently, an optimum exists; however, as shown in the figure on the right, controlling the bubble collapse rate is not straightforward, as it depends on various uncontrollable factors, like the incoming Zn grade

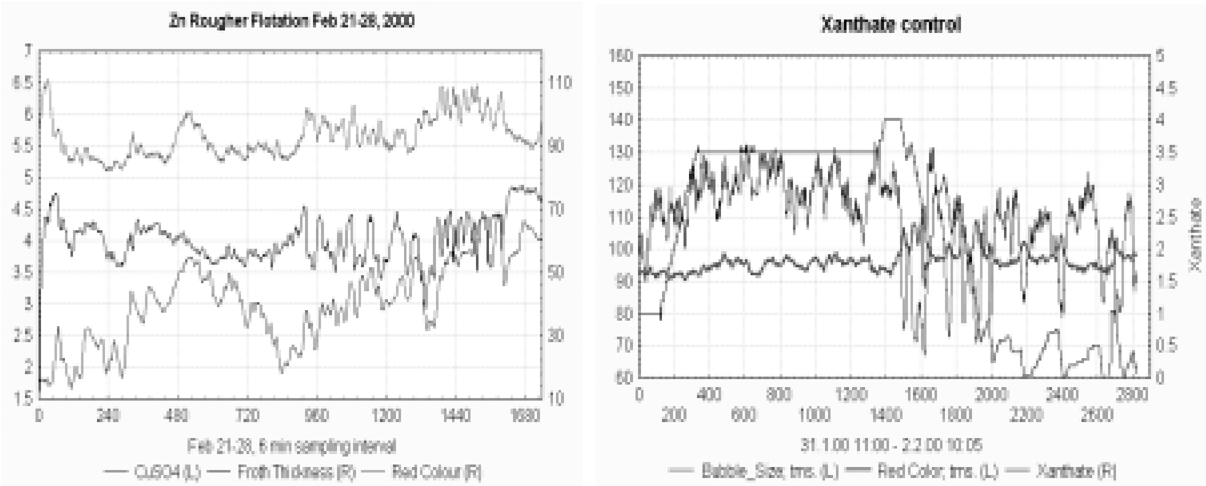




Figures 7 and 8. In these figures, the effect of copper sulphate is shown; as $CuSO_4$ increases the bubble collapse rate decreases (the bubbles become stiffer). This applies also the bubble transparency (the bubbles are more "heavily loaded")

Figure 9 shows one week period of the copper sulphate control. It can be noticed that the control stabilized the system and no collapse situations existed.

Process tests with xanthate showed that red color and bubble size were reacting to the setpoint changes of xanthate. It also seemed that increasing xanthate consumption would replace part of more expensive copper sulphate while the flotation results remained the same or even improved. Therefore a control logic including red color and bubble size was built up. Figure 10 shows results of a test run. In this test the xanthate setpoint has been on the high alarm limit for the first half of the two day period because big bubble size suggested that there is lack of xanthate. During the other half of the period the control was working properly. The reason of the poor control seems to be a low zinc grade in the feed proposing that the bubble size limit should be a function of the feed grade.



Figures 9 and 10. Real-time control using the "expert controllers". On the left, the feed of $CuSO_4$ is shown (lowest curve) against the measured froth thickness and red colour channel intensity (center and top, respectively); on the right, xanthate feed is shown against bubble size and red colour intensity

3. CONCLUSIONS

During the project, the machine vision set-up for permanent recordings at the flotation plant was designed and build. RGB camera, image grabber card, spectroradiometer, and the PC computer equipment were installed at the Pyhäsalmi flotation plant in the first rougher cell of the zinc circuit. The camera was installed inside a metal hood to protect it against dirt. The geometrical shape of the hood was selected so that homogenous illumination of the froth would be obtained for an easy processing of the images. The user interface was implemented in the LabVIEW© environment, and the on-line analysis system was connected to the PROSCON© process automation system.

In July 1999, the froth analyzer was connected in the local network of Pyhäsalmi concentrator plant. The hardware and software have been operating rather reliably since then. In Spring 2000, the analysis system was integrated in the closed loop control system. Because of the natural variations in the incoming ore, unambiquous comparisons against the earlier control performance cannot be made; however, according to visual inspections the results seem promising. Simply being able to avoid the froth collapse situations in advance saves a lot of raw material, time, and money. Perhaps the added value of the new approach is best illustrated by the fact that another identical analysis system is being installed in a separate flotation circuit in Pyhäsalmi; similar system is being experimented also at the Boliden Garpenberg plant in Sweden (Boliden mining company was the other industrial partner in the ChaCo project).

Even though the industrial application seems to be promising, something seems to be missing from the AI point of view: the somewhat obscure feel of "intelligence" vanishes when explicit algorithms can be written for implementing all specific tasks. Expert systems boil down to a set of *if–then* rules, pattern recognition to finding measurements characterizing the process state, and categorization to measuring distances between data clusters. However, after all, the cumulation of complexity in the overall system does the trick: seen from outside, the consistent operation of the controlled plant still looks rather intelligent.

ACKNOWLEDGEMENT

This research was carried out as a part of the EU funded project “Characterization of Flotation Froth Structure and Color by Machine Vision (ChaCo)”.

REFERENCES

[1] Basilevsky, A.: *Statistical factor analysis and related methods*. John Wiley & Sons, New York, 1994.

[2] Beucher, S. and Meyer, F.: The morphological approach to segmentation: The watershed transformation. In *Mathematical Morphology and Image Processing* (Dougherty, E. R., Ed.), 1993, pp. 433–481. Marcel Dekker, New York.

[3] Cipriano, A., Guarini, M., Vidal, R., Soto, A., Sepúldeva, C., Mery, D., and Briseño, H.: A Real Time Visual Sensor for Supervision of Flotation Cells. *Mineral Engineering*, **11** (6), 1998, pp. 489–499.

[4] Hyötyniemi, H. and Ylinen, R.: Modeling of visual froth data. *Preprints of the IFAC Symposium on Automation in Mining, Mineral and Metal Processing 1998* (ed. Heidepriem,J.), International Federation of Automatic Control / Elsevier Science, New York, 1998, pp. 309–314.

[5] Hyötyniemi, H. and Hasu, V.: Independent components of expertise. Submitted to *STeP 2000*.

[6] Hätönen, J.: *Image Analysis in Mineral Flotation*. M.Sc. Thesis, Helsinki University of Technology, Control Engineering Laboratory, Report 116, 1999.

[7] Hätönen, J., Hyötyniemi, H., Bonifaci, G., Volpe, F., Serranti, S., and Carlsson, L.-E.: Using PCA in controller strategy design for a flotation process. *Proceedings of the 14’th IFAC World Congress*, July 5–9, 1999, Beijing, P.R. China.

[8] Hätönen, J., Hyötyniemi, H., Miettunen, J., and Carlsson, L.-E.: Using image information and PLS for predicting mineral concentrations in the flotation froth. *Proceedings of the Second International Conference on Intelligent Processing and Manufacturing of Materials (IPMM'99)*, July 10–15, 1999, Hawaii, USA

[9] Laskowski, J. S. and Woodburn, E. T. (eds.): *Frothing in Flotation II*. Gordon and Breach Science Publishers, 1998.

[10] Moolman, D. W., Aldrich, C., van Deventer, J. S. J., and Bradshaw, D. B.: The interpretation of flotation froth surfaces by using digital image analysis and neural networks. *Chem. Eng. Sci.*, **50** (22), 1995, pp. 3501–3513.

[11] Moolman, D. W., Aldrich, C., van Deventer, J. S. J., and Stange, W. W.: The Classification of Froth Structures in Copper Flotation by Means of a Neural Net. *International Journal of Mineral Processing*, **43** (3–4), 1995, pp. 193-208.

[12] Niemi, A., Ylinen, R., and Hyötyniemi, H.: On the characterization of pulp and froth in cells of flotation plant. *Int. J. Mineral Processing*, **51**, 1997, pp. 51–66.

[13] Ylinen, R., Hasu, V., Hyötyniemi, H., and Sipari P.: Control of Flotation by Machine Vision. *Proceedings of the Automation Days 1999*, Helsinki, Sep. 14.–16.9., 1999, pp. 459–464.