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Al-Janabi Aqeel Bahr Tarkhan, *postgraduate student*
Cherkasy State Technological University
Schevchenko blvd, 460, Cherkasy, 18006, Ukraine,
akyel_eljanaby@mail.ru, akyel_eljanaby@yahoo.com

REVIEW OF USING OF COMPUTER VISION METHODS FOR FLOTATION FROTH QUALITY EVALUATIONS

In the article a detailed review of previous researches concerning executed works with the use of computer vision systems for froth flotation, which is a physical-chemical separation process that is often used in mining and minerals industry to remove unwanted waste (gangue) material from the desirable minerals is presented.

Keywords: *computer vision, flotation control, image processing, flotation.*

Introduction. The process begins with the grinding circuit, where the ore is first crushed, and then milled to obtain a particle size distribution that is typically sub 100 μm. The desired particle size distribution differs from mine to mine, and is typically a function of the ore mineralogy. The reason for the grinding is to liberate the grains of the desired mineral(s). Water is added to the mills to transport the ore through the mill and onwards to the classification section.

The mix of ore and water is known as slurry. Closed loop control of the milling is achieved by using a classification circuit. This is typically achieved using either hydro-cyclones or a set of screens. Hydro-cyclones are density separation devices that have an underflow of coarse particles and an overflow of fine particles. For a screen, the fine particles pass through the screen, while the coarse particles do not. In both cases, the coarse particles are fed back to the mill for regrinding. The fine particles are passed on to the flotation section. It is not uncommon to have multiple mills, screens and hydro-cyclones in the grinding circuit. Fig. 1 shows a typical schematic of a grinding circuit.

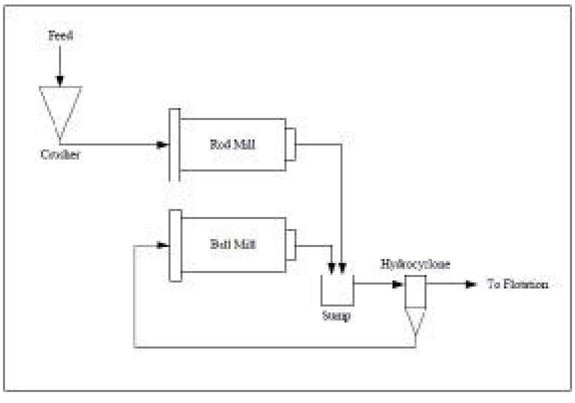

Fig. 1. Typical grinding circuit diagram

Before being pumped into the flotation cells, the slurry typically goes through a set of conditioning tanks. Various reagents are added to the slurry at the conditioning tanks, which allow for the time required for the reagents to react with the slurry before the flotation process begins.

The slurry is pumped from the conditioning tanks into the first flotation cell. A Flotation cell is essentially a large tank that contains an impeller to agitate the slurry/air mix, and by so doing, promote contacting between air bubbles and particles in the slurry. In some flotation cells the rate at which air is added is fixed, while in other models it is possible to set the air flow rate to a desired amount.

The agitation from the impeller creates turbulence within the flotation cell. The turbulence in turn promotes particle-bubble collisions. Hydrophobic particles will attach to the air bubbles, and rise to the surface. The air bubbles form a froth layer on top of the pulp (slurry). The froth layer overflows the top of the cell into a launder, where the concentrated material is collected.

The upward motion of the air bubbles results in the unselective transport of particles to the froth layer in the bubbles' slipstream. Fig. 2 is a cross section through a flotation cell showing valuable particles in red and gangue particles in green.

If the froth depth is shallow, it is likely that these entrained particles (most of which are gangue) will report to the concentrate, lowering the grade. Deeper froth depths have more time for unattached particles to drain back through the pulp due to gravity. The result is fewer gangue particles reporting to the concentrate. A level sensor is used to determine the froth depth, which is controlled in closed loop by varying the flow rate of the pulp through the tailings outlet.

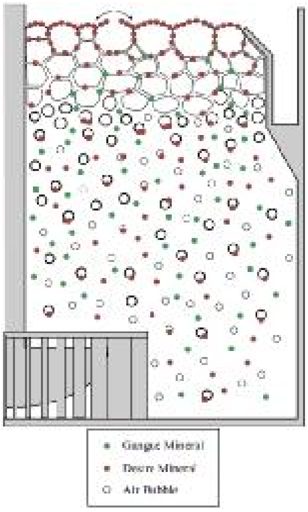

Fig. 2. A cross section through a flotation cell

Flotation banks are generally arranged in banks to allow multistage treatment of the slurry, with recycle loops to ensure that no excess of valuables is lost in the final tailings. Figure 3 shows a typical schematic of a bank of flotation cells. The chemical state of the pulp in the flotation cell is of utmost importance to ensure that optimal performance is achieved.

Computer vision for control of flotation – a review. The appearance of the froth on the surface of a flotation cell has great significance, in that it contains information, which may describe the grade and recovery of valuable minerals in the concentrate [1]. This is hardly surprising, given that visual inspection of the froth is used as the basis for plant control. In the past, little attention has been given to the relationship between flotation performance and froth appearance, mainly because more value is attached to fundamental systematic investigations rather than observations that are difficult to define quantitatively. Indeed, different flotation plants can exhibit different visual characteristics, which may depend on factors such as the type of flotation cells used, ore mineralogy, reagents used, etc. [1].

[1972] In 1972 Glembotskii [2] offered a description of froths and froth "quality" based on visual parameters.

[1975] Sweet [3] applies the algorithms developed by Wright to both batch and industrial cells. He shows that different reagent regimes results in different bubble size profiles for batch flotation tests. Plant test work also showed that the bubble size changes were detectable by the computer vision system when reagent step changes were made.

[1979] Research into predicting tin concentrate grade and mass flow rate was also performed at Nottingham [4]. Tin flotation images were analyzed and a "relative redness" (the difference between the mean gray and red levels of the image, normalized with respect to the gray level) measure was calculated.

[1983] C. Sun and W. G. Wee [5] apply the algorithms developed by Wright to both batch and industrial cells. He shows that different reagent regimes results in different bubble size profiles for batch flotation tests. Plant test work also showed that the bubble size changes were detectable by the computer vision system when reagent step changes were made.

[1986] Kaartinen and Hyötyniemi [6] show that a combination of stability, color, speed and bubble size descriptors can be used to predict the grade of zinc concentrate. They describe a multi-camera system that uses multivariate statistical methods on a number of flotation froth surface descriptors (color, bubble size, velocity, and collapse rate) to predict zinc concentrate grade on an industrial operation.

[1987] Moolman et al. [7] show how both spatial grey level dependence matrices and neighboring grey level dependence matrices can be used in conjunction with a neural network to identify five different froth classes from an industrial copper flotation cell. Hargrave, Brown and Hall [8] show that the process conditions can be used to predict the fractal measurements of the froth structure, and in so doing predict the bubble size distribution of the froth. This is done to be able to understand how changes in the process conditions affect the froth structure. Hatfield and Bradshaw [9] show that the watershed based velocity measure is best suited for specific slow moving froths where its sub-pixel accuracy is desirable. They also show that it is possible to predict the concentrate mass flow rate using froth velocity measurements.

[1988] As early as 1988, Kordek and Lenczowski presented work on analysis of froth images in an attempt to correlate the appearance of the froth with the metal content [10]. The authors obtain Optical Fourier Transforms (using a diffract meter) from images of both laboratory and plant froths.

[1989] In 1989 Woodburn et al. [11] described work relating to the flotation of low-rank coals. It is reported that the froth water content is related to the performance of the flotation process, with high frothier doses producing high recoveries and lower frother doses producing high grades. The water content also correlated with froth stability, in that high water content was characterized by small bubbles with low rates of coalescence, and low water content producing the opposite effect. An optimal froth structure (corresponding to maximum beneficiation) was described as being the point at which the froth changed from close-packed spherical bubbles to a cellular form of polyhedral bubbles. It is asserted that the optimal structure can be identified visually and characterized by image analysis techniques and used to form the basis of a coal flotation control mechanism.

[1990] A further paper [12] again presents research using optical and digital Fourier analysis of still froth images. Once again, useful metal content was the main parameter extracted by the image analysis. The development of a method based on discriminant analysis to classify froth images according to inferred metal content is described, classification results were performed. Moolman et al. [13] show how Sammon maps can be used to reduce the dimensionality of multi-dimensional texture information. They also show the relationship between the Sammon map and concentrate grade so that the metallurgical performance of the cell can be monitored.

[1991] Recently, a "new" product from Crusader Systems, Float-MACS, has been presented. Float- MACS is a visual froth flotation imaging and characterization system [14], which differs radically from previous work by this group in that it makes use of segmentation to analyze the froth images. This paradigm shift by a group that has up to now based much of its research on texture- based analysis serves, in the author's opinion, to indicate the superiority of segmentation-based methods over abstract textural analysis.

[1993] in 1993 A plethora of publications exist on work performed by this group of researchers, who began studying the application of machine vision to froth flotation. An early paper [15] presents results of analyzing froth images from a copper flotation plant. A relationship between the copper content of froth and the ratio of minor to major modal frequencies of the froth image gray scale histogram (the "copper peak") was noted. Bubble shape and size information was extracted using a Fast Fourier Transform and used for froth classification.

[1994] Numerous texture measures have been used to classify froth images into labeled froth classes. Moolman et al. [16] show that the Fourier ring texture measurement can be used to identify different froth classes from an industrial copper operation and that the Fourier coefficients were related to the bubble size and shape of the flotation froth.

[1995] Moolman et al. [17] develop a method of adding froth velocity information to textural measures, by modifying the camera such that froths with high velocity appear blurred. This blurring is in effect a new froth class that can be identified by textural measures. Symonds [18] used a morphological "rolling ball" method to segment froth image, while Liu [19] investigated using a hierarchical watershed segmentation algorithm. Nguyen and Thornton [20] introduce the use of the texture spectrum measurement to classify froths into distinct classes from industrial coal operations. The entire texture spectrum is used, rather than the reduced set of texture features suggested by He and Wang [21] in 1991, because of findings which show no relationship between three texture features and the identified froth classes. Guarini et al. [22] describe their method of making bubble size measurements by searching radially at 30° intervals for minima. The minima are then joined by elliptical arcs to identify the individual bubbles. They suggest that the bubble size together with HSI color measurements are good froth descriptors, but provide no links between the measurements and metallurgical performance.

[1996] Work was done by Hales et al. [23] to monitor copper flotation froth color, bubble size and the "copper peak" histogram peak as defined by workers at the University of Stellenbosch. Factorial tests, were performed where the change in froth appearance as a function of varying the collector dosage rate, the frother dosage rate and the froth depth was measured. Heinrich [24] showed that a relationship exists between the color of copper froths and their concentrate grade. He also proposed a methodology for implementing closed loop control based on his findings. Hatfield and Bradshaw [9], show how computer vision measurements can be used to control the concentrate mass flow rate by adjusting the airflow rate to the cell on the rougher bank of a platinum concentrator. Nguyen [25] describes the pixel tracing algorithm to measure the velocity of flotation froths. The algorithm developed by Nguyen is based on the assumption that there is no distortion between consecutive frames of video. This assumption may well have been valid for the froths on which Nguyen was working, but does not hold for all flotation froths, particularly those with dynamic bubble size distributions. The algorithm was designed to be a fast robust measure. However, due to the rapid improvement of computer technology these limitations are not-longer problematic, with the result that more accurate froth velocity measurements can be made in real time.

[1997] Wang et al. [26, 27] present a set of image processing algorithms to determine bubble size distributions and associated measurements. They initially classify an image based on a calculation on the white spots of the image, and then proceed to delineate individual bubbles using a valley edge detection algorithm. No relationships between the measurements and metallurgical performance indicators are presented.. Aldrich et al. [28] showed that there were strong correlations between bubble size and stability measurements with grade and recovery data from a set of batch flotation tests with varying reagent conditions. The batch tests were performed on a Merensky platinum ore. Wright [29] shows that the comparison of computer vision segmented bubbles to hand segmented bubbles is a difficult task, which the chi-square test is not suited to: it is possible to have confidence that the segmented images are both statistically different and statistically the same depending on the bin width chosen for the bubble size distribution characterization. Later work [30] made extensive use of the fractal dimensions described above as a tool for describing froth structure. Neural network models linking concentrate grade, mass flow rate and water content with froth fractal dimensions were developed for P_2O_5 flotation.

[1998] Francis and de Jager [31, 32] describe three methods for measuring the velocity of flotation froth: block matching, optical flow and a watershed segmentation based method. Moolman et al. [33] compiled a comprehensive review of literature concerning the relationship between flotation froth appearance and fundamental flotation principles. The paper serves mainly as a motivation for machine-based inspection of flotation froths. Cipriano et al. [34, 35] developed a computer vision system, ACEFLOT, which was used to provide an expert system with a number of measurements of the froth surface (velocity, bubble size, color, stability). The expert system identifies in what state the froth is, and then applies a set of (if – then) rules. However, no details are given for the set of rules that the expert system uses and no metallurgical performance data is provided. Francis et al. [10] then compare these algorithms to the pixel tracing algorithm used by Nguyen [36]. Both the optical flow and the block matching algorithms outperform the pixel tracing method. The watershed based velocity estimate is shown to have the poorest performance.

[1999] Oestreich et al. [37] developed a video-based sensor for measuring mineral concentrations in flotation froths and slurries. The sensor made use of a ''color vector" for estimating the mineral composition in dry mixtures, slurries and flotation froths. Good correlations were observed between the color vector values and percentage composition of Chalcopyrite and Molybdenite. Botha [38] identifies the problem of segmenting flotation froth bubbles which have both large and tiny bubbles present. He suggested the use of a marker bubble area ratio threshold to identify areas of fine froth, and acknowledges that there is need for further research into this area. Niemi et al. [39] use the combination of Fourier rings with greyscale values to identify different froth classes. Their sampling of the froth was at a rate of one image every 20 seconds. Woodburn et al. [40] also note the importance of bubble size and shape distributions in giving a sensitive measure of the appearance of an overflowing froth. This point is taken up by many of the authors whose work is described in the literature review. Using image processing techniques to determine these distributions thus seems highly attractive.

[2000] Later work [1] focused on using spatial gray level dependence matrix and neighboring gray level dependence matrix [41] methods for the analysis of froth structures from a textural point of view. Hyötyniemi and Ylinen [42] use the combination of Fourier rings with greyscale values to identify different froth classes. Their sampling of the froth was at a rate of one image every 20 seconds.

[2001] Francis [43], discusses various preprocessing techniques that can be used to improve the results from the bubble segmentation algorithms. These typically take the form of various non-linear filters. Francis and de Jager later introduce the Szeliski metric as a method for comparing motion vector fields in a quantitative manner [44].

[2002] T. Van Schalkwyk [45] show how computer vision measurements can be used to control the concentrate mass flow rate by adjusting the airflow rate to the cell on the rougher bank of a platinum concentrator.

[2004] Ventura-Medina et al. [46] have shown that if air flow rate is increased in a single cell there will be a decrease in solids loading. Moreover, it was found that the attachment of particles decreased movement down the bank in a bank of four cells

[2005] Bartolacci et al. [47] compare grey level co-occurrence matrix based and wavelet transform based texture measurements to determine which is best suited for concentrate grade prediction on an industrial zinc operation. The GLCM based methods provide much better results than the wavelet approach, although both are found to be suited to the task of froth class identification. Bartolacci et al. [47] show how various computer vision algorithms can be used to predict zinc concentrate grade on an industrial flotation plant. They also present results showing that performance is improved when controlling to a bubble size set point by changing reagent dosage. Gorain [48] shows that a linear relationship exists between froth velocity and the concentrate grade for a lead flotation circuit as well as a zinc flotation circuit. Morar et al. [49] show that the molybdenum, iron and copper grade affect the color of the flotation froth. They proceed to show that a linear combination of velocity, stability and color measurements can be used to predict copper concentrate grade.

Botha et al. [1] describe a method of determining froth velocity by tracking markers from the watershed between frames of consecutive interlaced video footage. In this manner, a motion vector field can be created from each bubble in the image, and the average velocity of the flotation froth can be calculated. The author's state that knowledge of the focal length of the transforming lens and the geometric dimensions of the detector allows the size of structures (in this case bubbles). In the analyzed images to be related to light intensity distribution in the diffraction pattern, results obtained concluded that the froth optical density decreases (i.e. the froth becomes darker) with increased metal content, and the bubble size decreases with increasing metal content.

In a later paper [50], Kordek and Kulig report on further optical diffract-gram analysis of froth images. Froth images were also subjected to digital image analysis by means of a digital computer-based Fourier Transforms. Once in the Fourier domain, filters were applied to the image in order to determine the total area occupied by the froth and the average area of a single bubble. Results obtained seem to correlate well with the useful content of metal in the froths. A recent application of the Froth Cam is at Minera Escondida in Chile, where it has been used to measure froth velocity [51]. It is worth noting that no use has been made of the texture spectrum froth characterization part of the system in this application - the system is simply used to control the speed of the froth in the flotation cells.

[2007] Gomez and Finch [52], The volumetric air flow rate is then inferred and volumetric air flow rate per unit cross sectional area of cell (Jg) calculated from the previous calibration. A range of orifice valves needed to suit all gas velocities bring out difficulties with the design as the froth builds up within the system.

[2008] Haavisto et al. [53], A practically continuous online estimate of slurry content reported to reach as these measurements can take with high frequency as opposed to sparse XRF analysis. It also stated that spectral information can be used to accurately predict element contents in the slurry in between consecutive XRF analyses. This measurement would allow rapid identification for any process disruptions.

Bruno et al [54] defined a concept of fractal descriptors as being a set of values extracted from fractal geometry methods and used to characterized artifact in an image, like textures, contours, shapes and so.

[2009] Garrido, [55], a multilayer perceptron is used to relate the bubble illumination intensities to the size distributions of the bubbles. The disadvantage of multilayer perceptrons is that neural networks with multiple hidden layers can be challenging to train and may not yield consistent or robust results.

[2010] Aldrich et al. [56], With dynamic features, the movement or dynamic behavior of the froth is captured by designed descriptors. This includes the froth stability (bubble burst rate, fraction of air overflowing or some notion of the rate of change of the appearance of the froth) as well as mobility (speed and direction of movement).

[2011] Shean and Cilliers [57], the method used in these magnetic flow meters is non-obtrusive. However, as solids and air bubbles decrease the performance, slurry measurement is problematic. Furthermore, de-magnetization is required if magnetic solids are present.

[2012] Morar et al. [58], Froth stability is the key driver of flotation selectivity and recovery. Nonetheless, it is not well understood how the non-linearity of mechanisms occur within the froth or how the mechanistic effects change across different conditions. There is still a need to do research on the effect of the operating variables on the froth stability behavior and its relationship to flotation performance.

[2014] The MathWorks, Inc. [59], Interquartile range (IQR) is a robust estimate of the spread of data. Changes in the upper and lower 25 % of the data do not have an effect on it so possible outliers are left out. Therefore it is more representative than the standard deviation as an estimate of the spread of the body of the data.

Conclusion. The control of the flotation circuit is traditionally maintained by experience plant personnel. These operators visually inspect the state of the froth, and based on their observations, will make adjustments to one or more of the air flow rate to the cell, the froth depth or reagent dosage flow rates. Aspects of the froth which the operator will look at include the froth velocity, color, bubble size distribution, texture and stability. The disadvantages of using such a method for control are numerous. Industrial flotation plants keep increasing in size, while keeping the number of personnel to a minimum. This means that an operator is not able to continually inspect each flotation cell resulting in a lag time between when a flotation cell starts to underperform and when the situation is corrected.

There is no guarantee that two operators will make the same decision when the froth of a flotation cell is in the same state. It is also extremely difficult to determine whether the changes made by the operator do in fact improve the flotation performance as it is the operator's visual inspection which is being used as a performance measure. It is also important to realize that flotation froths from different ore bodies will look very different, so what may be a good froth on one flotation plant is not necessarily good for another plant. This means that operators who are new to a flotation plant will need to learn from others how the froth looks when the circuit is performing well.

References

1. Botha, C. P., Weber, D. M., Olst, M. V. and Moolman, D. W. (1999). A practical system for realtime on-plant flotation froth visual parameter extraction. *Proceedings of IEEE Africon*, Vol. 1. Cape Town, South Africa.
2. Francis J. J. and Jager, G. de (1998). An investigation into the suitability of various motion estimation algorithms for froth imaging. *Proceedings of the 1998 South African Symposium on Communications and Signal Processing – COMSIG '98*, pp. 139–142. Rondebosch, South Africa.
3. Makhoul, J. (1975). Linear predicition: A tutorial review. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, pp. 561–580.
4. Haralick, R. (1979). Statistical and structural approaches to texture. *Proceedings of the IEEE*, (67), pp. 786–804.
5. Sun, C. and Wee, W. G. (1983). Neighbouring gray level dependence matrix for texture classification. *Computer Vision, Graphics and Image Processing*, (23), pp. 341–352.
6. Horn, B. K. P. (1986). Robot Vision. The MIT Press.
7. Maragos, P. and Schafer, R. W. (1987). Morphological Filters – Part I: Their set-theoretic analysis and relations to linear shift-invariant filters. *IEEE Transactions on Acoustics, Speech and Signal Processing (ASSP),* (35), pp.1153–1169.
8. Gonzalez, R. C. and Wintz, P. (1987). Digital image processing. Addison-Wesley Publishing Company, Reading, Massechusetts, 2nd ed.
9. Haralick, R. M., Sternberg, S. R. and Zhuang, X. (1987). Image analysis using mathematical morphology. *IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI),* 9(4), pp. 178–209.
10. Francis, J. J., Jager, G. de and Bradshaw, D. (2000). Motion estimation in froth image sequences. *Minerals Engineering 2000*. Cape Town, South Africa.
11. Francis, J. J. and Jager, G. de (2002). A sum square error based successive elimination algorithm for block motion estimation. *Proceedings of the Thirteenth Annual Symposium of the Pattern Recognition Association of South Africa*, pp. 101–105. Langebaan, South Africa.
12. Gotlieb, C. and Kreysig, H. (1990). Texture descriptors based on co-occurence matrices.

Computer Vision, Graphics and Image Processing, pp. 70–86.
13. Maragos, P. and Schafer, R. W. (1990). Morphological systems for multidimensional image processing. *Proceedings of the IEEE*, (78), pp. 690–710.
14. He, D. and Wang, L. (191). Texture features based on texture spectrum. *Pattern Recognition*, 24 (5), pp. 391–399.
15. Cipriano, A., Guarini, M., Soto, A., Briseo, H., Mery, D. (1997). Expert supervision of flotation cells using digital image processing. *Proceedings of the 20th International Mineral Processing Congress*, pp. 281–292. Aachen, Germany.
16. Moolman, D. W., Aldrich, C., Deventer, J. S. J. van and Stange, W. W. (1994). Digital image processing as a tool for on-line monitoring of froth in flotation plants. *Minerals Engineering*, (7), pp. 1149–1164.
17. Liu, J. (1995). Application of the watershed boundary technique to automatically segment surface froth images. Master's thesis, University of Cape Town.
18. Levine, M. D. (1985). Vision in man and machine. McGraw-Hill Publishing Company.
19. Moolman, D. W., Aldrich, C., Deventer, J. S. J. van and Bradshaw, D. J. (1995). The interpretation of flotation froths surfaces by using digital image analysis and neural networks. *Chemical Engineering Science*, (50), pp. 3501–3513.
20. Nguyen, K. K. and Thornton, A. J. (1995). The application of texture based image analysis techniques in froth flotation. *Proceedings of the DICTA-95, the 3rd Conference on Digital Imaging Computing Techniques and Applications*, pp. 371–376. Brisbane, Australia, Australian Pattern Recognition Society.
21. He, D. and Wang, L. (1991). Texture features based on texture spectrum. *Pattern Recognition*, 24 (5), pp. 391–399.
22. Guarini, M., Cipriano, A., Soto, A. and Guesalaga, A. (1995). Using image processing techniques to evaluate the quality of mineral flotation process. *Proceedings of the 6th International Conference on Signal Processing, Applications and Technology*. Boston.
23. Moolman, D. W., Aldrich, C., Schmitz, G. P. J. and Deventer, J. S. J. van (1996). The inter relationship between the froth characteristics and flotation performance of industrial flotation plants. *Minerals Engineering*, (9), pp. 837–854.
24. Hargrave, J. M., Miles, N. J. and Hall, S. T. (1996). The use of grey level measurement in predicting coal flotation performance. *Minerals Engineering*, 9 (6), pp. 667–674.
25. Moolman, D. W., Eksteen, J. J., Aldrich, C. and Deventer, J. S. J. van (1996). The significance of flotation froth appearance for machine vision control. Int. J. Miner. Process, (48), pp. 135–158.
26. Weeks, R. (1996). Fundamentals of electronic image processing. *SPIE Press*.
27. Wills, A. (1997). Mineral processing technology. Butterworth-Heinemann, 6th ed.
28. Aldrich, C., Moolman, D. W., Bunkell, S.-J., Harris, M. C. and Theron, D. A. (1997). Relationship between surface froth features and process conditions in the batch flotation of a sulphide ore. *Minerals Engineering*, 10 (11), pp. 1207–1218.
29. Wright, B. A. (1997). Investigations into the use of the watershed transform for the real-time segmentation of flotation froth images. Undergraduate Project Report, University of Cape Town.
30. Hargrave, J. M., Brown, G. J. and Hall, S. T. (1997). Use of fractal dimensions in describing froth structure. *Proceedings of the XX IMPC*, pp. 87–93. Aachen, Germany.
31. Francis, J. J., Jager, G. de (1998). Watershed segmentation based motion estimation of froth image sequences. *Proceedings of the Ninth Annual South African Workshop on Pattern Recognition*, pp. 44–49. Stellenbosch, South Africa.
32. Francis, J. J. and Jager, G. de (1998). An investigation into the suitability of various motion estimation algorithms for froth imaging. *Proceedings of the 1998 South African Symposium on Communications and Signal Processing – COMSIG '98*, pp. 139–142. Rondebosch, South Africa.
33. Francis, J. J., Jager, G. de (1998). Watershed segmentation based motion estimation of froth image sequences. *Proceedings of the Ninth Annual South African Workshop on Pattern Recognition*, pp. 44–49. Stellenbosch, South Africa.
34. Cipriano, A., Guarini, M., Soto, A., Brise, H. and Mery, D. (1997). Expert supervision of flotation cells using digital image processing. *Proceedings of the 20th International Mineral Processing Congress*, pp. 281–292. Aachen, Germany.

35. Cipriano, A., Guarini, M., Vidal, R., Soto, A., Seplveda, C., Mery, D. and Brise, H. (1998). A real time visual sensor for supervision of flotation cells. *Minerals Engineering*, (11), pp. 489–499.
36. Nguyen, K. K. (1998) Flotation froth characterization by using vision technology. PhD thesis, University of Queensland.
37. CHACO PROJECT. ESPRIT LTR Project No. 24931 – ChaCo 12-Months Progress Report (1999). [Internet]. Available from: <http://www.hut.fi/Units/Control/projects/ChaCo/ChaCo12m.pdf>
38. Botha, P. (1999). An on-line machine vision flotation froth analysis platform. Master's thesis, University of Stellenbosch.
39. Niemi, J., Hytyniemi, H. and Ylinen, R. (1999). Image analysis and vision systems for processing plants. *The Second International Conference on Intelligent Processing and Manufacturing of Materials*. Honolulu, Hawaii.
40. Jongh, de, Moolman, D. W. and Olst, M. van (1999). Current trends in automation and process control using computational intelligence techniques. *Mineral Processing*: abstracts.
41. Sweet (2000). The application of a machine vision system to relate to froth surface characteristics to the metallurgical performance of a PGM flotation process. Master's thesis, University of Cape Town.
42. Hytyniemi, H. and Ylinen, R. (2000). Modeling of visual flotation froth data. *Control Engineering Practice*, (8), pp. 313–318.
43. Francis, J. J. (2001). Machine vision for froth flotation. PhD thesis, University of Cape Town.
44. Francis, J. J., Jager, G. de (2001). Towards quantitative comparison of motion estimation algorithms. *Proceedings of the Twelth Annual Symposium of the Pattern Recognition Association of South Africa*, pp. 59–64. Franschhoek, South Africa.
45. Schalkwyk, T. van (2002). Multivariable control of a rougher flotation cell. Master's thesis, University of Cape Town.
46. Ventura-Medina, E., Barbian, N. and Cilliers, J. J. (2004). Solids loading and grade on mineral froth bubble lamellae. *International Journal of Mineral Processing* [online], 74 (1-4), pp. 189–200.
47. Bartolacci, G., Pelletier, P., Tessier, J., Duchesne, C., Bossé, P.-A. and Fournier, J. (2005). Application of numerical image analysis to process diagnosis and physical parameter measurement in mineral processes – Part I: Flotation control based on froth textural characteristics. *Centenary of Flotation Symposium*, pp. 73–84. Brisbane, Queensland.
48. Gorain, B. K. (2005). Optimization of flotation circuits with large flotation cells. *Centenary of Flotation Symposium*, pp. 843–851. Brisbane, Australia.
49. Morar, S. H., Forbes, G., Heinrich, G. S., Bradshaw, D. J., King, D., Adair, B. J. I. and Esdaile, L. (2005). The use of a colour parameter in a machine vision system, SmartFroth, to evaluate copper flotation performance at Rio Tinto's Kennecott Utah Copper Concentrator. *Centenary of Flotation Symposium*, pp. 147–151. Brisbane, Queensland.
50. Gorain, B. K. (2005). Optimization of flotation circuits with large flotation cells. *Centenary of Flotation Symposium*, pp. 843–851. Brisbane, Australia.
51. Liu, J. J., MacGregor, J. F., Duchesne, C. and Bartolacci, G. (2005). Flotation froth monitoring using multiresolutional multivariate image analysis. *Minerals Engineering*, (18), pp. 65–76.
52. Gomez, C. O. and Finch, J. A. (2007). Gas dispersion measurements in flotation cells. *International Journal of Mineral Processing* [online], 84 (1-4), pp. 51–58.
53. Haavisto, O., Kaartinen, J. and Hyötyniemi, H. (2006). Optical spectrum based estimation of grades in mineral flotation [online]. *IEEE International Conference on Industrial Technology*, Mumbai, India, pp. 2529–2534.
54. Bruno, O.M., Oliveira Plotze, R. de, Falvo, M. and Castro, M. de (2008). Fractal dimension applied to plant identification. *Information Sciences* [online], 178 (12), pp. 2722–2733.
55. Garrido, C., Toledo, H., San Martin, P. and Villanueva, A. (2008). Calibration methodology and calibration maintenance in courier analyzers for copper – molybdenum flotation process. In: Kuyvenhoven R., Gomez C. Casali A., Procemin V. (Eds.). *International Mineral Processing Seminar*, pp. 339–345.
56. Aldrich, C., Marais, C., Shean, B. J. and Cilliers, J. J. (2010). Online monitoring and control of froth flotation systems with machine vision: a review. *International Journal of Mineral Processing* [online], 96 (1-4), pp. 1–13.
57. Shean, B. J. and Cilliers, J. J. (2011). A review of froth flotation control. *International Journal of Mineral Processing* [online], 100 (3-4), pp. 57–71.

58. Morar, S. H., Bradshaw, D. J. and Harris, M. C. (2012). The use of the froth surface lamellae burst rate as a flotation froth stability measurement. *Minerals engineering* [online], 36-38, pp. 152–159.

59. The MathWorks, Inc., Documentation Center (2014). [online]. United States: The MathWorks, Inc.

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Аль-Джанабі Акіль Бахр Тархан, *аспірант*
Черкаський державний технологічний університет
б-р Шевченка, 460, м. Черкаси, 18006, Україна
akyel_eljanaby@mail.ru, akyel_eljanaby@yahoo.com

ОГЛЯД ВИКОРИСТАННЯ МЕТОДІВ КОМП'ЮТЕРНОГО ЗОРУ ДЛЯ ОЦІНЮВАННЯ ЯКОСТІ ПІННОЇ ФЛОТАЦІЇ

В роботі представлено детальний огляд попередніх досліджень щодо проведених робіт з використанням систем комп'ютерного зору для пінної флотації, яка є фізико-хімічним процесом поділу, що часто використовується в рудній і гірничодобувній промисловості для видалення небажаних відходів (порожньої породи) матеріалу з бажаного мінералу.

Ключові слова: *комп'ютерний зір, контроль флотації, обробка зображень, флотація.*