Imam Khomeini International University
Vol. 4, No. 2, Summer 2019, pp. 31-35

نشریه مهندسی منابع معدنی
Journal of Mineral Resources Engineering
(JMRE)

DOI: 10.30479/jmre.2019.9879.1209

Application Of Froth Images Classification And Clustering Based On Visual Features In Flotation Cell Performance

Jahedsaravani A.[1], Massinaei M.[2*], Khalilpour J.[3]

1- Assistant Professor, Dept. of Electrical Engineering, Khatam al-Anbiya University, Tehran, Iran
alijahedsaravani@gmail.com
2- Associate Professor, Dept. of Mining Engineering, University of Birjand, P.O. Box: 97175-376, Birjand, Iran
mmassinaei@birjand.ac.ir
3- Associate Professor, Dept. of Electrical Engineering, Khatam al-Anbiya University, Tehran, Iran
j_khalilpour@yahoo.com

(Received: 01 Jan. 2019, Accepted: 02 Feb. 2019)

Abstract: Flotation is the most frequently approach for beneficiation of metallic ores in mineral processing plants. Continuous control of flotation circuits is necessary to achieve optimum metallurgical performance. Previous research has established that there is a meaningful correlation between the froth visual features and process conditions and performance. The main objective of the current study is to develop algorithms for extraction of visual (bubble size, froth velocity and froth colour) and textural (energy, entropy and correlation) features from the froth images as well as classification of the images based on the captured properties. For this purpose, flotation tests were conducted in a batch cell under various process conditions and the metallurgical parameters (copper recovery and concentrate grade) along with the image variables were measured. Decision tree and fuzzy C-means algorithms were used for classification and clustering of the froth images. It was found that the developed machine vision system is capable of more accurately classifying the froth images than a manual operatory system. The results indicate that the developed algorithms are capable of accurately classifying the froth images with respect to the visual as well as the metallurgical parameters, which is of central importance for development of a machine vision based control system.

Keywords: Flotation, Froth Images, Image Analysis, Machine Vision, Visual Features.

INTRODUCTION

In the mineral processing industries, froth flotation is a common process for separation of the valuable from gangue minerals [1]. The primary control objectives of flotation circuits are the metallurgical factors (i.e. recovery and concentrate grade) [2]. The on-line measurement and estimation of these variables usually require sophisticated instruments which are expensive to purchase and maintain. Previous studies have shown that the froth visual characteristics reflect changes in the process conditions and can be used to predict the metallurgical factors [3-7].

The main objective of this study is to develop algorithms for extraction of visual (bubble size, froth velocity and froth colour) and textural (energy, entropy and correlation) features from the froth images as well as classification of the images based on the captured properties.

METHODS

The flotation tests were conducted on a sulphide copper sample with d_{80}=75µm in a 2.5 L laboratory flotation cell. The slurry was conditioned with a certain amount of collector (Potassium Amyl Xanthate) and frother (Aerofroth 65) for 2 and 0.5 min, respectively, just prior to flotation. The gas flowrate was measured by a gas flowmeter and manually regulated by a needle valve. The impeller speed was set at 1200 rpm. The froth depth in the cell was kept at a height of 2 cm during the experiment. After turning on the air, the froth layer was formed and the concentrates were collected at time intervals of 0.5, 2 and 5 min. The froth was allowed to freely overflow and the concentrates were analysed for their water, mass recovery and copper content. The tailings were filtered and dried and their copper content was determined. A video camera was mounted on a metal structure with an adjustable arm allowing lateral and vertical adjustment (as shown in Fig. 1). The distance from the top of the cell to the video camera lens was 20 cm. Lighting was provided by a single 50 W *halogen lamp next to the camera*. The flotation experiments were conducted at different operating conditions and concentrate copper grade and copper recovery as well as the froth features were measured and reported for each test. The operating conditions and the range of variables utilized in the flotation experiments are listed in Table 1.

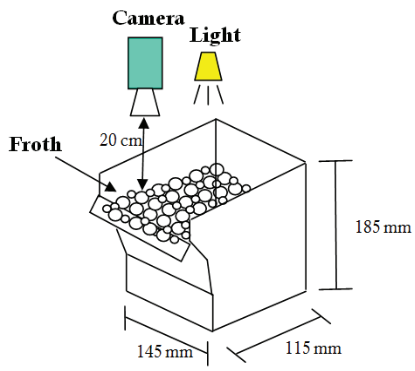

Figure 1. Laboratory-scale batch flotation cell and video camera set-up

Table 1. Input and output variables of flotation experiments

Input variables	Range	Output variables
Gas flow rate (L/min)	5-10-15	Cu recovery (R_{cu}) Concentrate grade (G_{cu})
Slurry solids %	24-28-32	
Frother dosage (ppm)	5-10-15	
Collector dosage (g/t)	20-30-40	
pH	10.8-11.5-12.2	

Image processing algorithms were developed in Matlab environment for measuring the visual (bubble size, froth velocity and froth colour) and textural (energy, entropy and correlation) features from the froth images [8]. A marker-based watershed algorithm was developed to quantify the bubble size distribution. The froth velocity was measured by tracking the bubbles movement in consecutive frames through the block matching algorithm. The froth colour was determined through extraction of the red, green and blue (RGB) values from colour images. The mean value of the R, G and B values were calculated for quantifying the froth colour. The energy textural feature which is a measure of homogeneity of an image was calculated from the following expression:

$$f_1 = Energy = \sum_{i,j} p(i,j)^2 \quad (1)$$

For an inhomogeneous image, the matrix has a large number of small entries with small energy values and vice versa. Energy values are in the range [0, 1].

The complexity or disordering of an image is quantified by entropy feature as:

$$f_2 = Entropy = -\sum_{i,j} p(i,j) \log\, p(i,j) \quad (2)$$

The entropy value is high when the image includes uneven textural units (complex texture). The froth images with a wide range of bubble size, shape and colour have high entropy values.

Correlation is a measure of linear correlation between two neighbouring pixels which is expressed as

$$f_3 = Correlation = \sum_{i,j} \left(\frac{p(i,j)(i-\mu_i)(j-\mu_j)}{\sigma_i \sigma_j} \right) \quad (3)$$

where (μ_i,σ_i) are the mean and standard deviation of the row sums of the matrix and (μ_j,σ_j) are the mean and standard deviation of the column sums of the matrix.

FINDINGS AND ARGUMENT

The correlation matrix between the froth features with the metallurgical parameters is given in Table 2. The results show that there is a meaningful correlation between the froth features and the process performance parameters.

Table 2. Correlation matrix between froth features with metallurgical parameters

Froth Features	R_{cu}	G_{cu}
Bubble size	-0.71	0.70
Froth velocity	0.51	-0.77
Froth colour (R)	0.47	-0.60
Froth colour (G)	0.44	-0.53
Froth colour (B)	0.40	-0.41
Energy	0.44	-0.70
Entropy	-0.38	0.71
Correlation	-0.62	0.45

Clustering technique was employed for classification of the froth images taken at different process conditions. The eight visual and textural features were used for clustering the images. The froth images were classified using the fuzzy c-mean algorithm. In the fuzzy c-mean algorithm, each data point is located in two or several clusters by means of a membership function. The following objective function is minimized:

$$J_m = \sum_{k=1}^{N} \sum_{i=1}^{c} (u_{ik})^m \left\| x_k - v_i \right\|^2 1 \le m \le \infty \quad (4)$$

Where x_k is the k[th] of d-dimensional measured data; u_{ik} is the degree of x_k membership in cluster i; v_i is the d-dimension centre of the cluster; m is any real number greater than 1; and $\|.\|$ is any norm representing the similarity between the centre and measured data.

Figures 2 and 3 show typical samples of the froth classification based on the visual as well as the metallurgical parameters, respectively. The results indicated that the proposed machine vision system is able to accurately classify the froth images based on the extracted features as well as the metallurgical parameters. The importance of such investigations is that a significant contribution towards the development of a machine vision based control system for industrial applications is made.

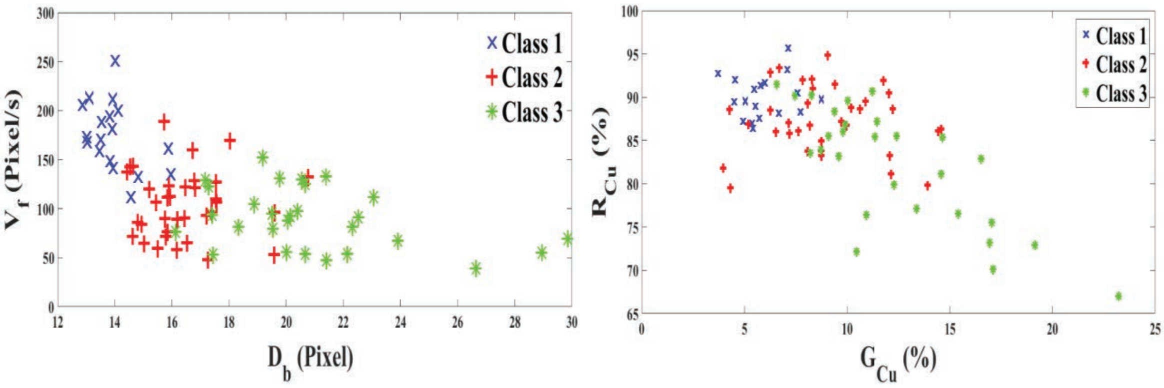

Figure 2. Classification of froth images based on visual features and metallurgical parameters

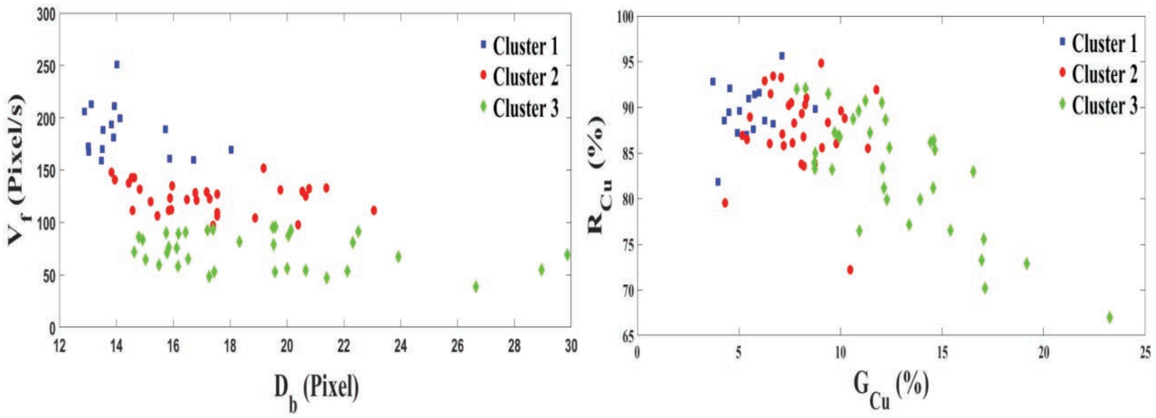

Figure 3. Clustering of froth images based on metallurgical parameters

CONCLUSIONS

1. Accurate and reliable algorithms were developed for measuring the visual (bubble size, froth velocity and froth colour) and textural (energy, entropy and correlation) features from the froth images taken from a batch flotation cell.
2. A meaningful correlation between the froth features and the process performance factors were detected.
3. Decision tree and fuzzy C-means algorithms were successfully developed for classification and clustering of the froth images, respectively.
4. The results indicated that the proposed machine vision system is able to accurately classify the froth images based on the extracted features as well as the metallurgical parameters. This is of great importance for development of a machine vision based control system.

REFERENCES

[1] Wills, B. A., and Napier-Munn, T. J. (2011). *"Mineral Processing Technology: An Introduction to the Practical Aspects of Ore Treatment and Mineral Recovery"*. Butterworth-Heinemann, 267-352.

[2] Bergh, L. G., and Yianatos, J. (2003). *"Flotation column automation: State of the art"*. Control Engineering Practice, 11: 67-72.

[3] Aldrich, C., Marais, C., Shean, B., and Cilliers, J. (2010). *"Online monitoring and control of froth flotation systems with*

machine vision: A review". International Journal of Mineral Processing, 96: 1-13.

[4] Sadr-Kazemi, N., and Cilliers, J. (1997). *"An image processing algorithm for measurement of flotation froth bubble size and shape distributions"*. Minerals Engineering, 10: 1075-1083.

[5] Holtham, P., and Nguyen, K. (2002). *"On-line analysis of froth surface in coal and mineral flotation using JKFrothCam"*. International Journal of Mineral Processing, 64: 163-180.

[6] Kaartinen, J., Hätönen, J., Hyötyniemi, H., and Miettunen, J. (2006). *"Machine-vision-based control of zinc flotation-a case study"*. Control Engineering Practice, 14: 1455-1466.

[7] Mehrabi, A., Mehrshad, N., and Massinaei, M. (2014). *"Machine vision based monitoring of an industrial flotation cell in an iron flotation plant"*. International Journal of Mineral Processing, 133: 60-66.

[8] Jahedsaravani, A., Marhaban, M., and Massinaei, M. (2014). *"Prediction of the metallurgical performances of a batch flotation system by image analysis and neural networks"*. Minerals Engineering, 69: 137-145.

[9] Mehrshad, N., and Massinaei, M. (2011). *"New image-processing algorithm for measurement of bubble size distribution from flotation froth images"*. Minerals and Metallurgical Processing Journal, 28(3): 146-150.

[10] Jahedsaravani, A., Marhaban, M., Massinaei, M., Saripan, M., Mehrshad, N., and Noor, S. (2014). *"Development of a new algorithm for segmentation of flotation froth images"*. Minerals & Metallurgical Processing Journal, 31: 66-72.

[11] Jahedsaravani, A., Massinaei, M., and Marhaban, M. H. (2017). *"An image segmentation algorithm for measurement of flotation froth bubble size distributions"*. Measurement, 111: 29-37.