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Froth-based modeling and control of a batch flotation process

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ABSTRACT

Automatic control of the flotation process is a difficult task due to the large number of variables involved, significant disturbances, and the process's complex nature. Previous research has established that flotation performance is reflected in the structure of the froth's surface. This paper describes the application of machine vision and fuzzy logic in controlling a batch-flotation cell. To perform this process, a laboratory flotation cell was operated under different conditions while process and image data were simultaneously recorded. Then, correlations between the resultant froth features and process variables were modeled, and an interpretable froth model was created. A fuzzy controller was designed and implemented to control process performance through the extracted froth features at the desired level by manipulating the selected process variables. The results indicate that the developed control system is able to handle process disturbances and track reference signals.

1. Introduction

Froth flotation is a physiochemical process for separating valuable and unwanted gangue minerals (Napier-Munn and Wills 2011). Effective flotation-system control is difficult to achieve, owing to the nonlinear, dynamic nature of the process (Bergh and Yianatos 2011; Bonifazi et al. 2002; Shean and Cilliers 2011). The primary objectives for controlling flotation circuits include metallurgical-performance parameters (i.e., recovery and concentrate grade). Online measurement and estimation of these variables usually require sophisticated instruments that are expensive to purchase and maintain. Furthermore, the bulk concentrates of the flotation circuits are often sent to these on-line instruments for analysis and the process behavior at single units cannot be detected. For these reasons, froth-based modeling and control using a combination of machine vision and intelligent control techniques (like fuzzy logic) has been considered as an alternative or supplementary control strategy over the last decade (Holtham and Nguyen 2002; Kaartinen et al. 2006; Liu and MacGregor 2008).

Machine vision is a nonintrusive, cost-effective, reliable technique for monitoring and controlling flotation systems (Aldrich et al. 2010; Bonifazi et al. 2000; Holtham and Nguyen 2002; Kaartinen et al. 2006; Mehrabi et al. 2014; Moolman et al. 1995, 1996a, 1996b; Morar et al. 2012; Vanegas and Holtham 2008). The main objective of a machine–vision system is to automatically capture and measure the froth's visual features (i.e., bubble size distribution, froth color, velocity, and stability) under different process conditions. The extracted froth characteristics can then be used as inputs to a feedback–control system that manipulates the chosen process variables (i.e., air-flow rate, froth depth, reagent dosage) in order to maintain optimum flotation performance (Holtham and Nguyen 2002; Kaartinen et al. 2006).

Expert and fuzzy systems are widely used to control complex grinding and flotation circuits (Bergh and Yianatos 2011; Cipriano et al. 1998; Cipriano et al. 1997; Jovanović and Miljanović 2015; Louw et al. 2003; Shean and Cilliers 2011). Fuzzy controllers are based on simple qualitative-control rules, not precise mathematical models. Control systems based on fuzzy rules can also potentially extend control capability, even under operating conditions in which linear control techniques (like PID) fail (Lewis 1997; Pedrycz 1993).

In the previous study, the authors developed algorithms for measuring the froth visual features and predicted the metallurgical parameters of a batch flotation process (Jahedsaravani et al. 2014b). In the current study, a froth-based model of the above lab-process is developed and then a model-based fuzzy control system is designed and implemented. This promises to make significant contributions to the development of online, computer vision-based control systems.

2. Neural network-based flotation-process modeling

2.1. Data collection

A copper sulfide ore ground to $d_{80} = 75$ µm was conditioned with collector (Potassium Amyl Xanthate) and frother (Aerofroth 65) to be subsequently floated in a 2.5 L laboratory flotation cell. The air flow rate was measured by a gas flowmeter and froth depth was controlled at a height of 2 cm by adding make-up water during the experiments. The concentrate samples were collected at time intervals of 0.5, 2 and 5 min. The froth was allowed to freely overflow and the concentrates

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Table 1
Input and output variables of flotation experiments.

Input variables	Range	Output variables
Gas flow rate, J_g (L/min)	5–10–15	Cu recovery (Rcu); concentrate grade (Gcu); mass recovery (Rm); water recovery (Rw)
Slurry solids %, ρ_{sl}	24–28–32	
Frother dosage, C_f (ppm)	5–10–15	Froth bubble size (D_b); froth velocity (V_f); froth color (C_f); bubble collapse rate (Cr_b)
Collector dosage, C_l (g/t)	20–30–40	
pH	10.8–11.5–12.2	

were analyzed for their water, mass recovery and copper content. The tailings were filtered and dried and their copper content was determined.

A batch-flotation cell equipped with a camera and lighting system was operated under different conditions (i.e., with varying air flow rates, slurry solids %, collector–frother dosages, and pH) and the metallurgical parameters (i.e., concentrate grade and copper, mass, and water recoveries) as well as froth visual features (i.e., bubble-size distribution and froth velocity, color, and stability) were recorded simultaneously (see Table 1). A total of 81 video and process-data sets were captured and analyzed. More details on these experiments can be found in Jahedsaravani et al. (2014b).

2.2. Image processing

The most significant froth features for describing the process's conditions and performance—including bubble-size distribution and froth color, velocity, and stability—were determined. A marker-based watershed algorithm was developed for measuring bubble-size distribution (Jahedsaravani et al. 2014a). Froth color was quantified by extracting red, green and blue (RGB) values from the color images. A block-matching algorithm was used to measure froth velocity. Froth stability, or bubble-collapse rate, was calculated as the difference in the reflectance and shadow created at the froth's surface as a result of bubbles appearing and disappearing in successive frames in the context of froth-velocity data (Jahedsaravani et al. 2014b).

2.3. Froth-based flotation-process modeling

Literature on the use of froth-image variables in flotation control is scarce. What is known is that froth visual features are indicative of process conditions and performance and quickly respond to changes in process variables. Hence, by developing a reliable model that connects visual froth features with process variables, one should be able to control the flotation process.

Of course, a few studies have been oriented toward froth-based modeling and controlling the flotation processes, including the work of Liu and MacGregor (2008). Liu and MacGregor's study is particularly interesting in that it uses bubble-size distribution, the area of black holes (i.e., black regions formed on the froth's surface as a result of overloaded bubbles collapsing), and clear windows (i.e., black regions appearing on under-loaded bubbles) as its output variables. Thus, this previous study asserts that a desired froth structure can be achieved through manipulating process variables, without needing to measure metallurgical parameters. Such a model-based control system can therefore provide better control performance when compared with conventional controllers.

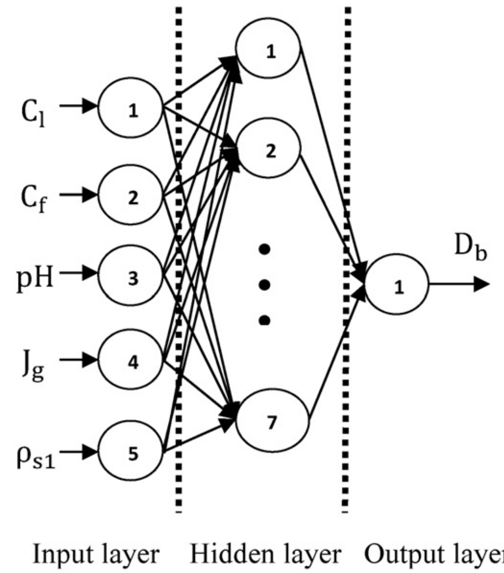

Fig. 1. Structure of developed feed forward neural network for D_b model.

Consequently, the present study models a correlation between froth-image data and process variables using neural networks, as described below. Finally, a fuzzy controller was designed to control flotation performance by manipulating the selected process variables. The results are presented in the next sections.

A matrix of the correlation between process and image variables is shown in Table 2. The results indicate that pH, air-flow rate, and frother dosage are the process variables most significantly related to froth features, and this is of central importance for control purposes.

Neural networks were then applied to model the interdependence of the image and process variables. Different neural networks were developed, and their performance was evaluated using the correlation coefficient (R) and the root-mean-square error (RMSE), as calculated using the following expressions:

$$R = \frac{\mathrm{cov}(y_i, \overline{y}_i)}{\sqrt{\mathrm{var}(y_i) \times \mathrm{var}(\overline{y}_i)}} \quad (1)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \overline{y}_i)^2} \quad (2)$$

where y_i and $\overline{y}_i$ are the observed (actual) and model outputs, respectively.

Finally, three-layer, feed forward-perceptron neural networks were chosen. It should be noted that 70% of the resultant data was randomly

Table 2
Correlation coefficient between process and image variables.

Process variables	Image variables D_b	V_f	C_f	Cr_b
pH	−0.64*	0.35*	0.64*	−0.65*
J_g	0.29*	0.68*	0.22*	0.31*
C_f	−0.28*	0.25*	0.10	−0.15
C_l	0.16	0.15	0.09	0.00
ρ_{sl}	0.07	0.17	0.09	−0.12

* Significant at 95% confidence level.

Table 3
Performance evaluation of developed neural network models.

Image variables	R			RMSE		
	Training data	Testing Data	Total data	Training data	Testing data	Total data
D_b	0.92	0.93	1.14	1.68	0.92	0.93
V_f	0.96	0.95	13.07	17.94	0.96	0.95
C_f	0.93	0.87	2.39	3.75	0.93	0.87
Cr_b	0.96	0.93	0.17	0.23	0.96	0.93