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Recognition of flotation working conditions through froth image statistical modeling for performance monitoring

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ABSTRACT

Accurate identification of the working conditions of froth flotation remains challenging because of the inherent chaotic nature of the underlying microscopic phenomenon. The froth surface is generally used as an effective indicator of the working condition and performance of flotation. In this study, we developed a novel method for determining the complex working conditions of flotation through statistical modeling of froth images. Gabor wavelet transformation was used for modeling because of the optimal localization properties in both spatial and frequency domain of the Gabor functions. The characteristic parameters of the probability density functions of the Gabor filter responses of the froth image, rather than conventional statistics (mean and variance), were then modeled using the empirical probability distribution models, t location-scale and gamma distributions. A simple learning vector quantization-neural network (LVQ-NN) was adopted to obtain an effective classifier for identifying the working conditions of froth phases under different production phenomena. The proposed model was validated through experiments on a bauxite flotation plant located in China and compared with commonly used determination methods.

1. Introduction

Froth flotation, a highly versatile method used to selectively separate hydrophobic from hydrophilic materials, is a complex and poorly understood phenomenon; this process is difficult to robustly and optimally control because of its inherent chaos and upsets (Bergh and Yianatos, 2011). The appearance of the froth surface in the flotation machine can be used as an effective indicator of the working condition and performance of flotation process (Aldrich et al., 2010; Kaartinen et al., 2006; Kistner et al., 2013; Liu et al., 2013; Núñez and Cipriano, 2009).

The working condition of the froth phase cannot be easily identified through naked-eye observation and assessment of several traditional metallurgic parameters because of the following factors. (1) The entire flotation circuit is complex and features a large time-delay process, which consists of several sub-processes; each sub-process possesses a large number of variables coupled with one another. (2) Key metallurgical parameters, such as concentrate grade, recovery or tailing grade, and process variables of flotation, cannot be measured in real time. (3) Naked-eye observation of the froth surface and analysis of measurable process parameters (e.g., pulp level, temperature of slurry, and pulp flow rate) are insufficient to identify the stochastic disturbances of the process operation and the imperceptible changes in the appearance of the surface under different working conditions as a result of fluctuations in feeding grade.

Automatic classification and recognition of the froth behavior are vital aspects in controlling flotation. This study aims to provide a practical solution for automatic identification of the working conditions of froth flotation. This goal was achieved by obtaining distinctive visual features of froth images through image statistical modeling incorporated with the commonly used pattern recognition method, namely, LVQ neural network (LVQ-NN), without performing time-consuming bubble segmentation and other complex image processing techniques.

2. Related works

Various image analysis and feature extraction methods can be used to characterize and evaluate froth images for automatic recognition of the working condition of froth flotation.

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Bartolacci et al. (2006) characterized froth images by using multivariate image analysis (MIA), gray-level co-occurrence matrix (GLCM), and wavelet transform(WT) to monitor flotation performance and process control. The froth structure can be classified using quasi-second-order statistics based froth image analyses, such as spatial gray-level dependence matrix (SGDM) and neighboring gray-level dependence matrix (NGDM) (Moolman et al., 1995). Hargrave et al. (1998) adopted fractal analysis to determine froth characteristics. Some other visual features of froth images are extracted and used to characterize the versatile working conditions of froth flotation; these features include bubble morphological characteristics (bubble size and shape) obtained through image segmentation (Wang et al., 2003). However, current segmentation algorithms for froth images are restricted to images with fully occupied bubbles of various sizes, especially those filled with both large and tiny bubbles.

Feature extraction methods for the morphological characteristics of bubbles are not only time consuming but also yield inaccurate characterization results of the froth surface. By contrast, texture feature extraction methods can be used to accurately depict the froth structure and are thus suitable for effective classification of flotation working conditions.

Previous studies focused on the flotations of heavy metals (e.g., copper and zinc ore) or nonmetallic ores (e.g., coal dressing) on the laboratory scale, where bubbles are relatively regular and can be easily distinguished from the froth image. However, in flotation of light metal–mineral (e.g., bauxite) at the industrial scale, the shapes of froth bubbles in concentrated froth images are irregular and cannot be clearly distinguished. Fig. 1 shows the typical froth images of light metal–mineral (bauxite) flotation under different working conditions. Individual bubbles cannot be easily distinguished from the froth image of bauxite subjected to specific flotation working conditions. Hence, the working conditions of froth flotation cannot be easily determined by human beings or "machines" if traditional froth image processing and feature extraction methods are used. Consequently, controlling the flotation of light metallic ores is difficult to optimally stabilize, which results in unstable production indices and significant waste of mineral resources and reagents.

Image texture is an important element in the computer vision analysis and real machine vision applications (Aujol et al., 2006; Bharati et al., 2004; Geusebroek and Smeulders, 2005; Kassim et al., 2007; Materka and Strzelecki, 1998). Although humans can effectively recognize image texture under most working conditions, naked-eye observation of the froth surface cannot be performed for long durations and individual interpretation of the froth surface is inevitably subjective. As such, the accuracy of the results generally depends on the experience of the observers. Therefore, identification of froth flotation working conditions through human observation is unsuitable for estimating flotation performance and process control.

Depicting the micro heterogeneity, complexity, and uncertainty of the froth surface remains challenging when using traditional image processing and analysis methods for computer vision technologies. Extensively studied processing and analysis methods include gray value-based methods (e.g., GLCM, SGDM, and NGDM) and MR-MIA with PCA-based texture feature extraction(Liu et al., 2005). However, these methods cannot effectively describe the froth texture because they cannot extract the multi-resolution and multi-orientation geometric features of the froth images.

More recently, multiresolution or multi-channel analysis for image texture analysis received considerable attention in the field of computer vision. The Gabor wavelet transform has been recognized as a very useful tool in texture analysis due to its optimal localization properties in both spatial and frequency domain and found widespread use used for image texture feature extraction (Arrospide and Salgado, 2013; Grigorescu et al., 2002; Jing-Ming et al., 2014).

In this study, Gabor wavelets are used for image analysis to determine the distinctive visual features of froth for classifying and recognizing flotation working conditions. Mean and variance are traditional statistics of Gabor filter responses, which are equivalent to the assumption that the Gabor filter responses obey the Gaussian distribution (GD) model. However, several studies demonstrated that the Gabor filter responses of natural images do not present GD. Therefore, obtaining the essential features from the Gabor filter responses in accordance with their inherent distribution profiles is also challenging.

Modeling the statistical structure of natural images or image patches is widely performed in image processing and analysis processes, e.g., image denoising (Cho and Bui, 2005), image sparse representation(Peleg et al., 2012), and texture image classification (Varma and Zisserman, 2005). Through extensive experimentation, numerous researchers explored various local probability density models for image statistical modeling, especially for multi-scaled and multi-oriented image representation (Guerrero-Colon et al., 2008). In particular, researchers found that the marginal distributions of wavelet coefficients typically follow a non-GD and feature high kurtosis in the middle and heavy tails on both sides of the distribution.

To determine the precise statistical features of the froth surface, we investigated the statistical distribution characteristics of the real part of the Gabor filter response (RGFR), the imaginary part of the Gabor filter response (IGFR), and the Gabor amplitude response representation (GARR) of the froth image sorted by a set of Gabor filters. The corresponding parameters of the probability density function (PDF) can be used as the froth feature vector to describe the froth structure without losing essential information on froth surface appearance. The working conditions of forth flotation were then identified using supervised pattern recognition methods (e.g., neural network). Based on the recognition results and operational experiences in different working conditions,

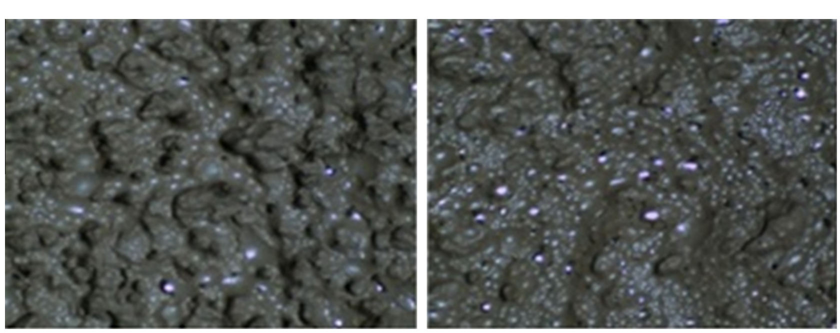

Fig. 1. Concentrated froth image from a bauxite flotation plant. Individual bubbles cannot be distinguished from the froth image. The statistics of the froth image texture can be applied to discriminate the froth production behavior.