Minerals Engineering 83 (2015) 105–116

Contents lists available at ScienceDirect

Minerals Engineering

journal homepage: www.elsevier.com/locate/mineng

Complex networks-based texture extraction and classification method for mineral flotation froth images

Degang Xu, Xiao Chen, Yongfang Xie *, Chunhua Yang, Weihua Gui

College of Information Science and Engineering, Central South University, Changsha 410083, PR China

ARTICLE INFO

Article history:
Received 3 September 2014
Revised 20 August 2015
Accepted 21 August 2015
Available online 1 September 2015

Keywords:
Froth image
Texture feature
Complex network
Minkowski distance
Bubble size

ABSTRACT

With recent improvements in instrumentation and computer infrastructure, machine vision technologies have produced innovative approaches for controlling and monitoring mineral flotation process. In order to efficiently analyze froth image, froth texture is used to accurately and rapidly extract froth characteristics based on the statistics of image pixels. The characterization and identification of texture require a method that can express the context surrounding each pixel by combining local and global texture characteristics. To extract the distinctive froth texture features in different production states, a novel complex networks-based texture extraction and classification method for froth imaging is proposed in this paper. A network model is constructed by expressing pixels as network nodes and similarities between pixels as network links. This method automatically sets the optimal algorithm parameters for the complex network modeling of the froth images according to bubble sizes by using the Minkowski distance. Energy and entropy measurements are used to quantify the properties of the connectivity and topology of the froth-image network model. Copper froth images at different production states extracted from the flotation monitoring system in a flotation plant are used to test the froth-image network model. The experimental results show that the proposed method accurately describes the froth image texture and also robustly classifies the different production states.

1. Introduction

Froth flotation is one of the most commonly used mineral separation methods in the mineral processing industry. It is used to separate valuable minerals from unwanted materials or other materials based on the differences in wettability of the various mineral particles (Aldrich et al., 2010). The flotation process produces froths with different characteristics to carry ore particles. The visual features of the surface of the flotation froth, e.g. texture, color, size and shape, are used to indicate the production states during the process. As a consequence, during the flotation process, operators can accurately evaluate the current production state based on the visual features of the surface of the froth, and modify production strategies accordingly. This task has been implemented manually by using the operators' naked-eye observations and their experiences (Xu et al., 2012). However, this mode of production is affected by subjective factors which are dependent on the individual operator. Thus the flotation process does not always operate at optimal production conditions. To keep process consistency, machine vision technology has been employed to characterize the froth surface and facilitate the control strategy for the mineral flotation process. In the worldwide, this technology has been implemented on many industrial sites (Backes and Bruno, 2010).

The visual mechanisms have inspired many recognition methods used in computer vision. Many mathematical methods by using pattern recognition and computer vision concepts have also been proposed. Image texture is one of the key visual features of the froth image. An image texture is a set of metrics which are calculated in image processing and designed to quantify the perceived texture of an image. Thus the information about the spatial arrangement of color or intensities in an image can be obtained. Texture is the correlation of gray among adjacent pixels in an image and is widely used to identify objects or regions of interest in an image for pattern recognition. The froth texture describes the roughness of the froth surface, and the smooth or wrinkled surface of the froth reflects the state of production (He et al., 2013). Therefore, the investigation on froth image texture extraction can provide guidance for the optimal operation of the flotation process.

There has been a lot of research about texture characterization that basically can be divided into four major categories: statistical, signal processing, model-based and dynamic. What have been intensively studied are statistical-based methods. A commonly used statistical-based method for texture analysis is gray-level

* Corresponding author.
E-mail address: yfxie@csu.edu.cn (Y. Xie).

http://dx.doi.org/10.1016/j.mineng.2015.08.017
0892-6875/© 2015 Published by Elsevier Ltd.

co-occurrence matrix (GLCM). However, the GLCM is not able to automatically discover all the statistical properties of the froth image (Gui et al., 2013). Some improved methods have been proposed for froth image texture extraction, such as spatial gray-level dependence matrix (SGLDM) and neighboring gray-level dependence matrix (NGLDM) (Moolman and Aldrich, 1996). Recently, Gui et al. proposed a color co-occurrence matrix method for froth image texture extraction and established the relationship between texture features and the corresponding concentrate grade (Gui et al., 2013). Other statistical-based methods include fuzzy texture spectrum (Cheng et al., 2009) and local binary pattern variance (LBPV) (Tang et al., 2011). Signal processing-based methods for froth image texture extraction have also regarded as the efficient methods. The wavelet method was firstly introduced into the extraction of flotation froth texture by Bartolacci et al. (2006). However, one defect of such approach is that appropriate wavelets must be chosen for the wavelet decomposition in order to meet some specifications because different wavelets (and corresponding analyzing functions) exist. Liu et al. (2010) proposed an improved method based on Gabor wavelet, which solved the problem for wavelets selection, but the time complexity of this method is high. Dynamic texture analysis also has attracted more interest. Liu and Lu (2002) extracted froth texture according to flotation process time. However, the proposed algorithms cannot be used to monitor the flotation process in real time. Chen et al. (2013) proposed an improved dynamic texture analysis method to extract froth texture in real time. Model-based methods are effective ways to analyze complex image, i.e., flotation froth image, for the existing models and their analytical methods can provide important guidance for image analysis. However, the model-based methods are rarely used in froth image texture extraction. Therefore, this paper investigates the complex network model-based methods for froth image texture extraction.

Image texture is usually defined as a model formed by the repeated arrangements of elements or primitives according to certain direction, density and cycle. It is a common inherent characteristic of object surface. The basic texture primitives are reflected by the spatial variation in pixel intensities (gray values). Therefore, texture characterization and identification require a method that can express the context surrounding each pixel by combining local and global texture characteristics. Recently, a novel image texture extraction method based on complex networks was proposed by Backes et al. (2013). The method provides a novel idea for froth image texture extraction. Many problems of the real-world systems with given structures including those undergoing dynamic changes of the topology can be represented and solved by the complex networks theory (Costa et al., 2007). Complex networks theory is widely used to analyze topological characteristics and features extraction for digital images by building complex network models (Albert and Barabási, 2002; Newman, 2003). For flotation froth image, texture describes the variation of pixel gray values on froth surface, which is closely related to froth physical properties, e.g., shape, size and its distribution. Although the bubbles in the froth image distribute randomly and irregularly, the statistical characteristics of its physical properties in different images may presents obvious similarities or differences, which is reflected by texture. The research of complex network lies at the intersection between graph theory and statistical mechanics. The problem is represented as a complex network followed by the analysis of its topological features obtained by a set of measurements (Gonçalves et al., 2014). The degree descriptors of complex network are rotation invariant and scale invariant. Moreover, these descriptors are robust to the variation of each froth structures since they are statistical characteristics of the whole image. Given the above analysis, froth image texture can be modeled by using complex network and represented by network connectivity. Thus, different froths can be characterized and distinguished accurately by texture feature descriptors based on degree descriptors.

However, the method proposed by Backes et al. (2013) aims at the texture extraction for common digital images. Compared with these images, forth image texture are usually more complex and difficult to extract in terms of different bubble sizes, color and lighting conditions. In addition, two parameters of this method need to be determined by subjective experience, which increases the uncertainty and inaccuracy. Therefore, this paper presents a novel complex networks-based texture method for froth image extraction and classification, which automatically sets the optimal algorithm parameters for texture extraction according to the bubble size. The extracted features are used to identify different classes of froth images. Experimental results are compared with traditional texture identification methods.

The remainder of this paper is organized as follows. In Section 2, the complex networks-based froth image texture extraction and classification method for the flotation process is presented. A method to efficiently classify the production state of flotation cells is proposed based on the texture feature extracted from froth images in Section 3. In Section 4, the experimental results and a discussion of the comparison of the different methods is presented. Finally, the conclusions are presented in Section 5.

2. Froth image texture extraction and classification

In the development of machine vision systems for froth images, froth textures can be used to accurately and rapidly determine froth characteristics based on the statistics of image pixels. The froth characteristics are important inputs to control systems in froth flotation process. Each image pixel can be represented as a node and similarities between pixels can be mapped as links between nodes. It can be observed that various types of textures are closely related with the node degree distribution, which is very distinct from those observed in random networks. Some measurements of the network connectivity are then utilized in order to obtain image feature vectors, which can be used for the texture characterization and classification. Then, the texture feature of an image can be represented, characterized and analyzed in terms of a complex network. This study utilizes complex networks to represent and characterize texture features in froth images. A new method to classify flotation production states based on froth images has also been developed.

2.1. Complex networks and its feature descriptors

A complex network is represented by a graph consisting of a set of vertices and edges. The complex network can be described by its adjacency matrix for undirected and unweighted networks in this study. The adjacency matrix is a symmetric matrix with the elements consisted by zero and one, where one represents that two nodes are linked by an edge and zero means there is no edges

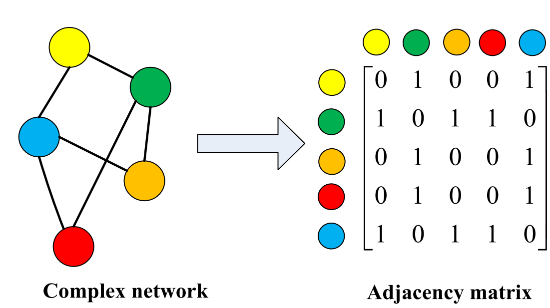

Fig. 1. The adjacency matrix for a network.