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Process working condition recognition based on the fusion of morphological and pixel set features of froth for froth flotation

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ABSTRACT

Process condition recognition is an effective way to improve the froth process performance. In previous condition recognition algorithms based on machine vision in flotation process, the used features including gray value, bubble size distribution, load, etc., are essentially statistical results of gray level images and there is local bubble structure information loss in their extraction procedure. Meanwhile, the large number of image data are not adequately utilized. Thus, in this paper, deep neural network are used to extract the pix set features, and a two-step condition recognition method based on bubble image morphology and pixel set features is proposed, which utilizes the large number of image data. First, froth images are segmented into single bubble images. Next, the morphological feature vector of a single bubble image is extracted and classification labels are assigned to the single bubble images via K-means clustering. A large quantity of historical images is analyzed and labeled to train a convolutional neural network (CNN) by which the pixel set features of each bubble image are extracted. The morphological feature vector and pixel set features of the bubble images are then fused for bubble image clustering using the weighted mean-shift algorithm. The frequencies of various types of bubbles in a froth image are calculated to form a bubble frequency set for the froth image. A two-step working condition recognition strategy based on image sequence over a time period is then proposed. In this strategy, the bubble frequency sets of all froth images and those of the bubble images segmented from the froth images over the corresponding time period are matched with those of the images of typical flotation conditions in two main steps to determine the current working condition. Test results using industrial data demonstrate the high accuracy and calculation speed of the proposed method.

1. Introduction

Froth flotation is the most widely used separation method in mineral processing. Froth flotation takes the advantage of the different hydrophilic properties of different mineral particles to collect useful minerals. In flotation cells or columns, a slurry is stirred and sparged with air to form bubbles. Particles with useful minerals adhere to these bubbles and flow to the top of the slurry to form froth, while gangue particles remain in the slurry and are drained from the tailings. The surface features of the froth are important state parameters that reflect process working conditions and are directly related to the technical indexes of the process (Moolman et al., 1994, 1996; Gui et al., 2013b; Bonifazi et al., 2001). However, the surface features themselves are complex and are related to many other variables through complicated relationships. Therefore, accurate extraction and deep analysis of froth features are critical to froth condition recognition (Gui et al., 2013b; Bonifazi et al., 2001).

Many researchers have studied froth feature extraction methods. For example, an improved marker-based watershed image segmentation method to prevent over segmentation of large bubbles (Jahedsaravani et al., 2014), improved homogeneous gradient method to obtain the size characteristics of bubbles (Botha et al., 1999), froth texture extraction based on a gray level co-occurrence matrix (Gui et al., 2013a), dynamic feature extraction based on a froth image scale-invariant feature transform (SIFT) and Kalman filter (Liu et al., 2013), froth velocity extraction based on macro-block matching (Núñez and Cipriano, 2009), and various other methods have been proposed. Based on these methods and further statistical calculations, additional features, including froth color, bubble size or distribution, and froth velocity, can be extracted (Reddick et al., 2009; Jahedsaravani et al., 2017; Neethling, 2008).

Using machine vision and the aforementioned froth feature

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extraction methods, various froth features have been extracted to perform working condition recognition, modeling, optimization, and control of flotation processes. Moolman et al. (1996) analyzed the relationship between froth surface features and other process data, then constructed a neural network to classify working conditions using froth features. Aldrich et al. (2010) extracted the red component of froth images, froth collapse rate, bubble size, and other features to derive a correlation between the selected features and concentrate grade to predict process working conditions. Tang et al. (2015) utilized a sensitive index and principle component analysis to select key froth features, and then used a correlative function to calculate the relevance between key features and predetermined working conditions. Peng et al. (2016) proposed an improved froth texture extraction method and a support vector machine was used to perform working condition recognition based on the texture. According to Peng et al. (2016), Bartolacci et al. (2006) and Ylinen et al. (2000), among bubble characteristics, texture which is a combination of froth size and morphological features, is the most effective feature for working condition recognition.

Because the froth layer is the aggregation of a large quantity of single bubbles with many tiny particles adhered to them, there is no background and the bubble surface features typically fall within a classical random distribution, meaning some implied features are difficult to describe and extract. However, the froth feature extraction procedure used in most current methods is essentially a statistical calculation based on gray level images. In the extraction procedure, it is unavoidable to lose some local information, meaning certain essential features cannot be obtained. Meanwhile, the flotation process usually varies over time and the features extracted from only a few images cannot accurately represent the conditions of the overall process. However, many current methods only utilize the instantaneous features of froth from a very short time period. The huge quantity of images collected from froth flotation plants are not adequately utilized.

In recent years, industrial big data has become a hot topic. However, most applications based on big data are still limited to social networks and financial systems. Although industrial process operations are rich in data, they lack effective analytical tools and efficient computing technology to derive information from the data, and applications of big data technology to process engineering systems have rarely been studied (Qin, 2014). In real-world process manufacturing, many different kinds of process data are compressed and only limited information has been extracted from them. This is also the case in froth flotation. Therefore, it is suggested to embrace the new machine learning methods developed over the past 20 years for process data analysis (Qin, 2014).

Convolutional neural network (CNN) (Lecun et al., 1989; Hinton and Salakhutdinov, 2006) is a kind of deep neural network. CNNs have been improved considerably over time and applied to image classification, speech recognition, object detection and so on [e.g. (Yu et al., 2016; Oquab et al., 2015; Levine et al., 2017)]. However, the application of CNNs to industrial production is still very sparse, especially in process manufacturing. Considering that the rapid development of deep learning offers a good opportunity for its application to process manufacturing, the extraction of froth features and utilization of big froth image data by using CNN is worth of studying in froth flotation. Furthermore, images can be directly used as inputs of a CNN, which avoids factitious feature extraction and data reconstruction.

Based on the aforementioned problems in froth flotation and the characteristics of CNNs, in this study, we propose a froth image classification method based on the fusion of froth morphological features and pixel set features extracted by CNN. A two-step working condition recognition strategy based on image sequences is also proposed. The remainder of this paper is organized as follows. In Section 2, the main concepts utilized in this study are described. In Section 3, the morphological features of single bubbles in froth images are extracted and the bubbles are pre-classified. In Section 4, a CNN model is established to extract the pixel set features of the bubbles. Next, a method for bubble reclassification by combining two types of features and the two-step working condition recognition strategy are presented in Section 5. The video system for data collection in plant and simulation results are presented in Section 6. Finally, this study is concluded in Section 7.

2. Main procedure of the working condition recognition method

In this study, a large quantity of historical froth image data is processed to build a CNN model. Next, the cluster centers of bubble images and frequency distribution centers of bubble classes are determined. Thereby, a working condition recognition model is established. Finally, the recognition model can be utilized to perform online working condition recognition using bubble video data in a real plant.

When establishing the recognition model, historical images are first pre-processed to eliminate abnormal images related to atypical working conditions, such as froth overflow or slurry underflow (the slurry level is too low). Normal froth images are segmented into single bubble images and each bubble is stored as an independent image. The morphological features of each bubble are extracted using an elliptical structuring element to approximate the shape of the bubbles. The bubbles are then pre-classified and labeled using the morphological features. A CNN model is then trained using the bubble images directly as inputs and the labels as targets to extract the pixel set features of the bubbles. The morphological features and pixel set features are then fused to build a novel classification model for the bubbles. Next, the bubble frequency of bubbles in each class is calculated. Here, bubble frequency of a class which is called bubble type frequency is defined as the ratio of the number of bubbles in one class to the number of all bubbles. Meanwhile, the bubble frequency distribution of different typical working conditions are also prepared. When performing online recognition, real-time images are processed online to obtain morphological and the pixel set features. The bubbles are then classified and their bubble type frequency is calculated and compared to that of typical working conditions to complete the recognition process. This procedure is illustrated in Fig. 1.

3. Bubble morphological feature extraction and pre-classification

According to the experience of operators, froth texture, including bubble size (or size distribution), and froth gray level space were chosen as significant features for froth flotation modeling and optimal control (Gui et al., 2013b). However, when using an entire froth image as a basic object and extracting the average value of its features to represent the process condition, it is inevitable to miss detailed features and obscure certain key process features. Additionally, the differences between the average features of froth images captured over a very short time period may be very large because a camera can only capture a small area of the entire flotation cell and the froth may not be uniform. Therefore, in this study, the features of single bubbles are extracted to examine their details and then the features of images captured over a period of time are analyzed and used for working condition recognition.

3.1. Froth image preprocessing and segmentation

The froth images are preprocessed to eliminate images collected under abnormal conditions caused by bubble collapse and coalescence, mechanical agitation, or aeration. Next, images from normal conditions are used to identify working process performance. Because bubbles are stacked and connected to each other and bubble size varies from large to small, it is difficult to identify the edges of tiny bubbles when using the typical watershed algorithm with constant parameters to perform segmentation directly. Segmentation using typical watershed algorithm with constant parameters usually results in over-segmentation or under-segmentation. The images from normal conditions are pre-processed, including image graying, atypical image removal, and gray image enhancing, and then segmented in two steps based on a watershed