Minerals Engineering 46–47 (2013) 60–67

Contents lists available at SciVerse ScienceDirect

Minerals Engineering

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

Color co-occurrence matrix based froth image texture extraction for mineral flotation

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ARTICLE INFO

Article history:
Received 9 September 2012
Accepted 28 March 2013
Available online 2 May 2013

Keywords:
Froth flotation
Froth image
Color co-occurrence matrix
Gray level co-occurrence matrix
Texture complexity

ABSTRACT

It is well accepted that the surface texture appearance of the flotation froth involves crucial information about its separation process, which can be used as an effective criterion for the qualitative assessment of the flotation performance. To obtain the distinctive characteristic of the froth surface appearance under various production conditions, a texture feature extraction method based on color co-occurrence matrix (CCM) is presented compared to the commonly used gray level co-occurrence matrix (GLCM). First, the HIS (Hue, Saturation and Intensity) color space is employed to exhibit and quantify the froth image, which yields a more intuitive description of the color properties in comparison with the RGB (Red, Green and Blue) color space. Then, the CCM is computed and the corresponding feature statistics of the froth surface texture are extracted based on the proposed matrix. Next, a new feature parameter is defined and extracted to describe the froth texture complexity based on the aforementioned texture feature statistics. After adequate offline froth images have been obtained from a bauxite flotation plant located in China under various production statuses with the corresponding concentrate grade in the froth assayed manually, the qualitative relationship between the texture complexity and the corresponding concentrate grade is investigated. Consequently, the optimal texture complexity range to achieve satisfactory production index is obtained for the further research of the optimal control of the flotation process. Experimental results have verified the effectiveness of the method and demonstrated its superiority over the previous texture feature extraction methods based on GLCM.

1. Introduction

Froth flotation is one of the most broadly used mineral separation methods in the mineral processing industries. It aims to separate valuable minerals from useless materials or other materials based on the difference in wettability of different minerals (Aldrich et al., 2010). During the flotation process, hydrophobic particles tend to adhere to the air bubbles in the solution, which rise up to the top surface of the slurry and then can be separated as froth (Hu, 1991). Due to the inherent chaotic property with the frequent and random disturbances to flotation circuits, the flotation process control is far from satisfactory since it remains a poorly understood process and lacks for generally useful mathematical modeling (Kaartinen et al., 2006). Even worse, the key metallurgic parameters reflecting the flotation performance, such as concentrate grade and tailing grade, cannot be detected in real time. Though some on-stream or in-stream analysis sensors such as X-ray fluorescence (XRF) Analyzers can be used to measure the mineral contents in the slurries to a certain extend, there still exists the problem of detection delay with low detection frequencies and high cost of maintenance of these instruments (Haavisto and Kaartinen, 2009). Recently, the froth surface appearance has been known as an effective indicator of the flotation production performance (Bonifazi et al., 2002). Furthermore, it has long been acknowledged that better understanding of the change of the froth surface appearance in the flotation process is key to understanding the overall behavior of froth flotation systems (Shean and Cilliers, 2011). Hence, the practical operation variables such as chemical reagent, air flow and pulp level are mainly adjusted through the observation of froth surface by experienced operators (Yang et al., 2009a; Xu et al., 2012).

However, many problems exist in the naked-eye observation based flotation process operation and control: (1) Human observation is qualitative and lacking in quantitative measurement of the froth surface. The evaluation criteria of the froth surface appearance vary significantly. Even for the same froth flotation production status observed at the same time, different operators might report quite different perceptional results. (2) Operators cannot monitor the whole flotation circuit effectively because the whole flotation circuit is a long and continuous process including dozens of flotation cells. Furthermore, operators are inevitably tired of the long-term observation and cannot accurately identify the froth state with the instantaneous observation

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http://dx.doi.org/10.1016/j.mineng.2013.03.024

information about the froth surface. (3) It demands highly experienced workers that sometimes might not be available. Therefore, due to the temporal, spatial limitations with the subjective metrics caused by naked-eye observation of the froth surface, it is difficult to maintain the flotation process in the optimal production states stably by naked-eye observation based flotation process control and operation, resulting in either low utilization of the mineral resources or excessive consumption of the flotation reagents with fluctuate product quality. To overcome these defects, machine vision has long been acknowledged as a promising technology introduced to flotation process monitoring and control. By extracting the distinctive parameters of the froth image and analyzing the potential relation between the metallurgical parameters with the froth surface appearance, it is able to provide operational guidelines to the plant operators and effectively improve the production performance.

With the variation of the flotation production states, froth surface appearance exhibits special texture characteristic, which directly reflects the flotation operation condition in return. Froth image texture feature, which describes the roughness of the forth surface, is closely related to the mineral content in froth layer and consequently indicates the concentrate grade (Bartolacci et al., 2006). Therefore, it is worth researching the froth surface texture feature extraction method and investigating the relative model of the texture features with the concentrate grade, which would provide important guidance for the optimal operation and control of the flotation process. Moolman et al. (1996) exploited the methods based on spatial gray level dependence matrix (SGLDM) and neighboring gray level dependence matrix (NGLDM) to analyze the flotation froth texture appearance, pointing out that the extracted froth texture features were directly related to concentrate grade and recovery rate. Three commonly used methods for forth image texture feature extraction were reviewed in the literature (Bartolacci et al., 2006). However, there have been no good conclusive results of predicting or evaluating the concentrate grade of the froth using the proper froth image texture features. More recently, Cheng proposed a froth image texture feature extraction method based on the fuzzy texture spectrum (Cheng et al., 2009), which tentatively analyzed the relationship between the froth texture features and mineral grade. A method based on Gabor wavelet was proposed (Liu et al., 2010), which is used in flotation process state classification and identification in industrial scale. To sum up, among the methods of analyzing the flotation froth image texture, gray level co-occurrence matrix (GLCM) method, derived from gray-scale image analysis and application, is the most commonly used method for froth image feature extraction and froth state classification. Though GLCM based method is a powerful technique to measure the surface property of the gray-level images, it ignores the important color information of the image surface. Unfortunately, it is proved that the froth surface color is an essential factor reflecting the mineral grade of the froth in various mineral flotation plants (Bonifazi et al., 2001). Therefore, it is difficult to take the GLCM based method to accurately describe the comprehensive features of the froth surface texture.

In order to extract more representative froth texture features to provide objective flotation performance evaluation criterion for froth process monitoring, a color co-occurrence matrix (CCM) method is proposed to replace the traditional GLCM method for froth image texture analysis in this paper. Subsequently, an effective froth texture measurement parameter (texture complexity) based on CCM was defined and extracted to capture the more distinctive description of froth surface texture feature. This method is applied to a bauxite flotation plant located in China for single flotation cell performance monitoring and process operation guidance. After collecting a great amount of froth images with the corresponding metallurgical parameter (concentrate grade assayed manually, represented by the mineral content in the froth layer of the monitored flotation cell), the quantitative relationship between the froth texture complexity and the corresponding concentrate grade is analyzed. At last, the best froth texture complexity range for flotation froth phase monitoring and production operation instruction to achieve high concentrate grade is obtained from the established mutual relation.

2. Definition of color co-occurrence matrix

It has been demonstrated that the froth surface color involves essential information of the mineral content in the forth layer by the long-term observation of the flotation process on industrial scale (Haavisto et al., 2006). Hence, froth surface color is an indispensable factor to the flotation performance evaluation and operation instruction. Since the GLCM based image texture analysis is restricted to the gray-level image analysis, much important information is ignored when using the GLCM to froth image texture analysis. To incorporate the color variation information in an image, the color space was first introduced into the color image texture analysis by Shearer with the so called color co-occurrence matrix (CCM) based image texture analysis (Shearer and Holmes, 1990). The CCM based texture analysis describes the color image texture feature by measuring some statistics in the special color space. In this section, we briefly introduce the HSI color space firstly and then describe the details of GLCM and CCM.

2.1. HSI color space

HSI uses H(Hue), S(Saturation) and I(Intensity) to describe the color features. It is a very important and attractive color model for image processing applications because it is similar to the way humans perceive the object color. In this color space, H and S contain the chromatic information, I, which has nothing to do with the color information, stands for the luminance information. In the HSI color space, the Hue component describes the color itself in the form of an angle between [0°, 360°]; the Saturation component denotes how much the color is polluted with white color with range of [0, 1]; the range of Intensity is [0, 1] and 0 means black, 1 means white. Given the range of each component of the RGB color space is [0, 1], the conversion formula from RGB color space to HIS color space is as follows:

$$\begin{cases} I = \frac{1}{3}(R+G+B) \\ S = 1 - \frac{3\times[\min(R,G,B)]}{(R+G+B)} \\ H = \begin{cases} \theta & G \geqslant B \\ 2\pi-\theta & G < B \end{cases} \end{cases} \tag{1}$$

where $\theta = \arccos\left\{\frac{[(R-G)+(R-B)]/2}{[(R-G)^2+(R-B)\cdot(G-B)]^{1/2}}\right\}$.

2.2. GLCM

Gray Level Co-occurrence Matrix (GLCM), which is a popular way of describing the second order statistical texture features of gray images, proposed by Haralick et al. (1973). Since then, this approach has been widely used in a number of applications. GLCM is created from the gray-scale image, which can reveal the certain properties about the spatial relationship of the gray levels in the texture image. Actually, GLCM represents the joint probability distribution of the co-occurring pixel values with an offset of $(\Delta x, \Delta y)$, where $\Delta x = d\cos(-\theta)$, $\Delta y = d\sin(-\theta)$, d is the pixel distance metric from the pixel of interest to its neighbor pixels and θ represents the direction. Each element (i,j) in the resultant GLCM is simply the sum of the number of times that the pixel with value i occurred in the specified spatial relationship to a pixel with value j in the input image. Generally, pixels are restricted to the neighborhood of the predetermined ones, and θ is usually set to four directions 0°, 45°, 90°, 135°. When $\theta = 0°$, $\begin{cases}\Delta x = d\\ \Delta y = 0\end{cases}$; $\theta = 45°$, $\begin{cases}\Delta x = d\\ \Delta y = -d\end{cases}$; $\theta = 90°$, $\begin{cases}\Delta x = 0\\ \Delta y = -d\end{cases}$; $\theta = 135°$, $\begin{cases}\Delta x = -d\\ \Delta y = -d\end{cases}$.

The value of the matrix element (i,j) in the GLCM represents the number of occurrences of the pixels (pixels gray values are i and j respectively) with a distance of $(\Delta x, \Delta y)$ apart in the direction of θ. Assuming an image includes L gray-levels, the dimension of its corresponding GLCM is $L \times L$. An example of GLCM of a quantized gray image of eight gray levels with $\theta = 0°$, $d = 1$ is shown in Fig. 1.

2.3. CCM

Palm (2004) derived color co-occurrence matrix (CCM) in 2004 similarly to GLCM, which measures the spatial color distribution features in an image rather than only the co-occurrence information of the gray values of the pixels. Actually, CCM is an extension of GLCM, which is commonly used for texture feature extraction of color images. Let $m(m = C_1, C_2, C_3)$, $n(n = C_1, C_2, C_3)$ be two of the three color components and $\mathrm{CCM}_{m,n}$ be one of the CCMs among two color components, which measures the spatial color occurrence with a special offset between the color components m and n of the pixels in the color image. However, since the pixel color information of the froth image is significant to flotation performance description, we mainly study the color component similarities in the same position of the image between different color components. Hence, in this work, the element $\mathrm{CCM}_{m,n}(i,j)$ is used to calculate the number of times that any pixel p whose color component value m is equal to i, and its corresponding another color component value n at the same position is equal to j, namely,

$$\mathrm{CCM}_{m,n}(i,j) = \sum_x \sum_y \begin{cases} 1 & m(x,y) = i \& n(x,y) = j \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

For each color image, six CCMs can be obtained from the mutual combination of different color components. Taking an image in the HSI color space for example, whose color space is quantified into eight levels, one of its CCM ($\mathrm{CCM}_{H,S}$ is displayed in Fig. 2.

3. Texture feature extraction based on CCM

A series of statistics representing the image texture features can be calculated based on CCM. The long-term observation reveals that the froth image texture complexity is a dominant feature indicating the mineral content in the froth layer, which hence is an important indicator to the flotation performance. However, froth surface texture complexity is a subjective qualitative expression of the image texture, which lacks of effective quantitative expression method. In this work, we define a novel feature parameter to quantify the froth texture complexity by the commonly used features statistics based on CCMs. The detailed texture feature extraction procedure based on CCM is as follows:

(1) The acquired froth image is converted from RGB color space to HSI color space. A suitable color space for image representation and processing would achieve better results. Though the commonly used color space is RGB color space, Palm compared the performances of several image texture features coded in different color spaces and concluded that HSI color space is more adaptive than RGB for color texture discrimination (Palm, 2004). Hence, in this work, the froth image is represented in HSI color space.

In terms of the powerful cognitive ability of the human vision system, it is beneficial to simulate the visual perception process of human beings to achieve good visual processing results. As is known, humans' visual resolution has certain limitations. For instance, only the most salient features of the object are important to the following visual perception. Therefore, it is necessary to quantize the HSI color space to a small number of color levels to facilitate the subsequent texture feature extraction, thereby retaining some distinctive color information and discarding the trivial information. The detailed method of quantizing the HSI color space by some unequal intervals employed in this work can be found in the literature (Zhang et al., 1999). It reveals that this quantization method is most similar to the human visual model and can effectively reduce the color redundancy for the following visual feature extraction.

(2) The CCMs of the froth image in HSI color space is calculated. Calculate the six CCMs of froth image by using Eq. (2). The six CCMs in HSI plane are $\mathrm{CCM}_{H,H}$, $\mathrm{CCM}_{S,S}$, $\mathrm{CCM}_{I,I}$, $\mathrm{CCM}_{H,S}$, $\mathrm{CCM}_{H,I}$, $\mathrm{CCM}_{S,I}$. As CCMs are very sensitive to significant differences of spatial resolution when measuring the co-occurrence of the pixels, hence it is necessary to normalize these matrices to decline this sensitivity (Each CCM is divided by the sum of its elements, so that the sum of the elements of each CCM is equal to 1).
(3) Haralick features are extracted from the froth images. Based on the CCMs, some image texture statistics of second order, Haralick features (Haralick et al., 1973), are extracted.

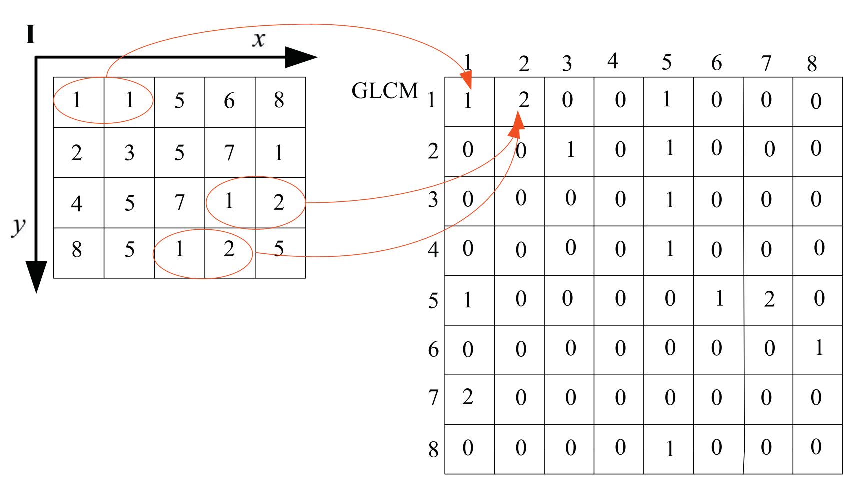
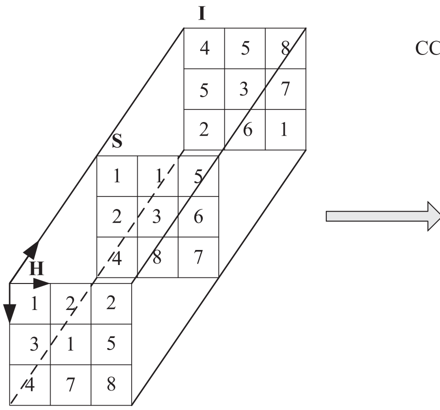


Fig. 1. A paradigm of GLCM.



CCM_{HS}	1	2	3	4	5	6	7	8
1	1	0	1	0	0	0	0	0
2	1	0	0	0	1	0	0	0
3	0	1	0	0	0	0	0	0
4	0	0	0	1	0	0	0	0
5	0	0	0	0	0	1	0	0
6	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	1
8	0	0	0	0	0	0	1	0

Fig. 2. A paradigm of CCM.

Haralick introduced 14 statistics from the normalized CCMs to represent texture features. They are homogeneity, contrast, correlation, variance, inverse difference moment, etc. Since we obtain six CCMs for each froth image, $N = 6 \times 14$ Haralick features can be extracted from these matrices. Among the proposed 14 Haralick features, five of them are generally used by researchers. They are contrast, correlation, inverse difference moment (IDM), entropy and angular second moment (ASM) (Maheswari et al., 2010). Suppose $\hat{p}(i,\ j)$ is the element (i,j) of a normalized CCM, L is the number of the color component levels in the image under quantization, these statistics can be calculated as follows.

(i) Entropy

$$ENT = -\sum_{i=1}^{L}\sum_{j=1}^{L}\hat{p}(i,j)\log\{\hat{p}(i,j)\} \tag{3}$$

Entropy (ENT) is a measure of the amount of information contained in the image. It reflects the degree of image texture complexity or disorder. The more complex texture, the greater entropy, and vice versa.

(ii) Inverse Difference Moment

$$IDM = \sum_{i=1}^{L}\sum_{j=1}^{L}\frac{\hat{p}(i,j)}{1+|i-j|^2} \tag{4}$$

Inverse difference moment (IDM) is a direct measure of the local homogeneity of a digital image. The larger inverse difference moment, the more uniform the corresponding image, and vice versa.

(iii) Angular Second Moment

$$ASM = \sum_{i=1}^{L}\sum_{j=1}^{L}(\hat{p}(i,j))^2 \tag{5}$$

Angular second moment, which reflects image texture roughness, is the quadratic sum of each element in the co-occurrence. Rough texture energy means bigger energy, while fine texture energy means smaller energy.

(iv) Contrast

$$CON = \sum_{k=0}^{L-1}k^2\left\{\sum_{|i-j|=k}\hat{p}(i,j)\right\} \tag{6}$$

Contrast reflects the definition of image and the degree of texture groove depth. The deeper the texture groove, the bigger the contrast of the image and the better the visual effect. On the contrary, the shallower the texture groove, the smaller the contrast and the fuzzier the effect.

(v) Correlation

$$COR = \frac{\sum_{i=1}^{L}\sum_{j=1}^{L}(ij)\hat{p}(i,j)-\mu_x\mu_y}{\sigma_x\sigma_y} \tag{7}$$

where μ_x, μ_y, σ_x, σ_y are the means and standard deviations of $\hat{p}_x$ and $\hat{p}_y$. $\hat{p}_x(i)$ is the i th entry in the marginal-probability matrix obtained by summing the rows of $\hat{p}(i,j)$, namely, $\hat{p}_x(i) = \sum_{j=1}^{L}\hat{p}(i,j)$. Similarly, $\hat{p}_y(j) = \sum_{i=1}^{L}\hat{p}(i,j)$. Correlation is the measure of similarity degree of CCM elements in a row or column direction. Correlation reflects the local texture correlation of an image. When the matrix elements are equal and uniform, the correlation value is big; conversely, when the matrix elements vary greatly, it is small.

(4) Texture complexity of the froth image is defined and calculated. To reduce the computation and preserve the distinctive description of froth image texture complexity at the same time, two features related to the complexity and uniformity of texture directly are extracted from each CCM in the experiment. T is used to indicate texture complexity for froth image and it is defined as the ratio of ENT and IDM according to the froth texture condition reflected by ENT and IDM (Barcelo et al., 2007).

$$T = \frac{-\sum_{i=1}^{L}\sum_{j=1}^{L}\hat{p}(i,j)\log\{\hat{p}(i,j)\}}{\sum_{i=1}^{L}\sum_{j=1}^{L}\frac{\hat{p}(i,j)}{1+|i-j|^2}} \tag{8}$$

It can be seen from Eq. (8) that, the higher the T, the more complex the image texture; the lower the T, the smoother the image texture.

4. Experimental results and discussion

4.1. Experimental procedure

Experiments are carried out on industrial scale in a bauxite flotation plant Located in China. The whole industrial flotation process is a complex, continuous and long-term process, which consists of several flotation banks, e.g. rougher bank, cleaner bank and scavenger bank (or sweeping bank). Each flotation bank is comprised of several flotation cells. Flotation cells are generally arranged in banks to allow multistage treatment of the slurry, with recycled loops to ensure that no excess of valuable particles are lost in the final tailings. A concise flowchart of this flotation circuit is displayed in Fig. 3. Since there are dozens of cells in the flotation circuit, it usually takes more than 1 h from the feeding pulp to the final production concentrate. The froth collecting from the first cell in the cleaner II bank is treated as the final concentrate product under some post-processing. Hence, the froth surface appearance of the first cell in the Cleaner II bank is the direct indicator of the flotation concentrate grade. In order to obtain the distinctive visual features of the froth surface appearance for the objective evaluation of the flotation performance in real-time, we set a pilot image acquisition system mounted on the first flotation cell in the

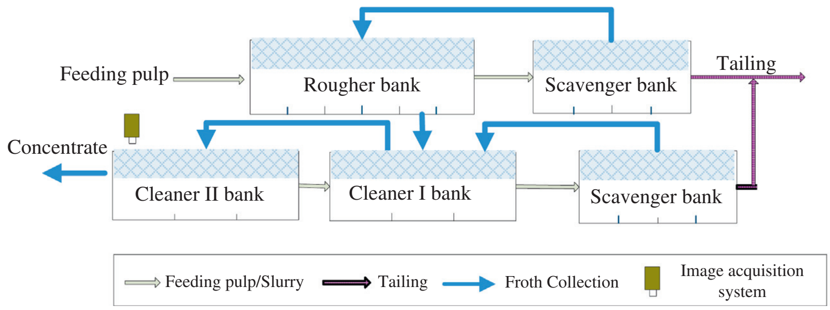


Fig. 3. Schematic of bauxite flotation circuit.

cleaning II bank. The position of the image acquisition set-up is denoted in Fig. 3.

The test set-up consists of RGB cameras with 49 mm lens placed approximately 110 cm above the surface of flotation froth layer. Froth image sequences, derived from videos captured, are collected from individual flotation cell with a volume of 16 m^3. The window size of each image in the cell is 12 $\times$ 9 cm^2. Online videos and froth images with the size of 600 $\times$ 800 pixels are recorded by RGB cameras. As can be seen from the flotation circuit in Fig. 3, froth images collected from rougher cell can reflect the state of feeding ore; images from scavenger provide the information of tailing grade; and images from cleaner can give the situation of product grade.

In this work, we mainly focus on the froth surface appearance of the first cell in the cleaning banks, whose position is explicitly denoted in the Fig. 3 as a camera mark. As the mineral content in the froth layer of first cell in the cleaning banks directly comprised the final concentrate product after some post-processing, we use the concentrate grade of the froth layer to evaluate the flotation performance. The grade of the froth layer measures the metallic content in the froth layer. In this plant, it is measured by A/S, which means the ratio of aluminum content and silicon content in the froth layer. In practice, human operators measured the A/S ratios in the way of chemical titration that takes more than 2 h (Yang et al., 2009b). It's worth noticing that the grade of the source ore is a nontrivial factor to the flotation concentrate product, which, unfortunately, is random, unpredictable and uncontrollable. In order to reduce the influence of the grade fluctuation of the feeding ores and get the comparable experimental data under the same grade of feeding ore, we set a X-ray fluorescence (XRF) analyzer to automatically monitor and record the grade of the feeding pulp (It actually takes 20 min to accomplish the sample analysis), then the metallurgical parameters with the corresponding froth image under generally similar source feeding ore are collected for the following mathematic analysis. In this plant, the grade of the feeding ore is also measured by A/S, which is the ratio of aluminum content and silicon content in the feeding ore, usually varies in a large range from 5 to 9. The experimental samples under steady states with a much narrower range of feeding ore grade are collected for the following analysis, where the A/S of feeding ore is about 6.5–7.5.

4.2. Data analysis and results

A great amount of cleaner froth images of nearly 1 month are captured by the industrial camera in the aforementioned bauxite flotation plant. Their corresponding metallurgical parameters are also recorded manually. The froth image texture features based on CCM are extracted. For each piece of froth images, features are extracted from six CCMs, and the average value of the features are as the final output for froth image.

In order to validate the effectiveness of the texture feature extraction method and to achieve the optimal froth texture range for flotation process monitoring and production performance evaluation, we set three experiments to analyze the relation between the froth image texture features with the metallurgic parameter (the concentrate grade in the froth layer is mainly concerned in this work).

(1) Experiment 1: The stability analysis of the texture feature of the froth images under the comparable production conditions

An effective froth image texture feature extraction method should offer similar texture features for different froth images as long as they are under the similar flotation performance conditions. To validate the effectiveness of the of the proposed image texture feature variables, we compare the image texture features of a bunch of froth images under the similar flotation performance conditions in advance.

In this experiment, 16 frames of froth images are selected manually from the froth image database, whose corresponding concentrate grades in the froth layer are very similar. Five above commonly used Haralick features based on the CCM are extracted from each image. Since we can get six groups of independent feature statistics based on each of the CCMs, the average of these texture feature statistics from the six CCMs are used as the final froth image features in the following data analysis. The computed texture statistics of these images can be seen in Fig. 4. Although the froth images are randomly selected at different time, the texture

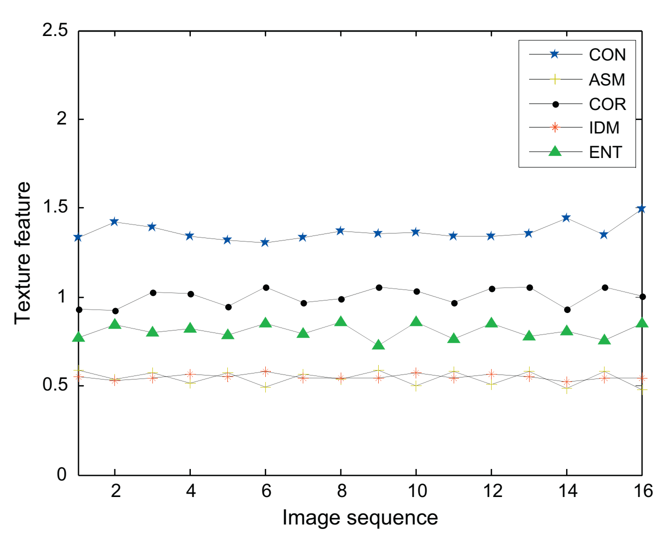


Fig. 4. Haralick features statistics of froth images.

feature parameters of these images calculated based on CCM fluctuate with very low amplitude since the froth images are captured from the comparable production performance conditions. The experimental results indicate the effectiveness of this texture feature extraction method.

(1) Experiment 2: Texture features vs. Concentrate grade

To monitor and evaluate the flotation performance effectively in real time, the relation between the commonly used Haralick features (contrast, correlation, IDM, entropy and ASM) based on CCM and their corresponding froth concentrate grade are analyzed. The data analysis results reveal that there is no very obvious relationship between the commonly used Haralick features and the concentrate grade. However, the proposed texture complexity significantly relates to the concentrate grade, which can be used as an effective indicator to the flotation performance.

In order to qualitatively analyze the relation between the texture complexity and the concentrate grade, three froth videos are used to analyze the texture complexity T_C in advance, captured at different flotation conditions representing different froth concentrate grades. The time interval of the consecutive frames is 2 min. The total acquisition time of each video is about half an hour. The texture complexities of the froth image sequences from each froth video with difference mineral grade are displayed in Fig. 5. For these videos, the variance of the texture complexities of froth images of the video with mineral grade 9.63 is 3.73%, 1.72% is the video with the mineral grade 15.56 and 3.66% is the video with mineral grade 11.88. The experimental results indicate that the froth image texture complexity significantly varies with its corresponding concentrate grade, and hence froth phase with different mineral content manifest different froth texture complexities. The average change of the texture complexity of the froth images within a video is very low, which indicates that froth texture complexity is an effective indicator of the flotation production conditions and can be used as an effective criterion to evaluate the flotation performance.

We also compare the effectiveness of texture complexity to indicate the flotation performance calculated between GLCM and CCM. Fig. 6 displays six froth images each of which represents different mineral grades in the froth layer. Given T_C is the texture complexity based on CCM methods and T_g is the one calculated by GLCM method. The statistical results for the six froth images with corresponding mineral grades are shown in Table 1. It can be seen from Table 1 that, as the texture complexity T_C reduces

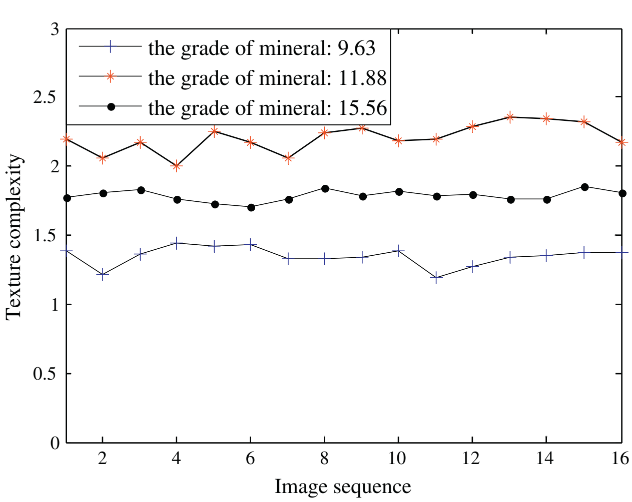


Fig. 5. Texture complexities of froth videos.

successively the textures of the six froth images in Fig. 6 appear smoother and more uniform. It means that the new texture complexity parameter calculated by CCM algorithm can accurately describe the texture changes, reflecting the human visual perception process. But when using the commonly used GLCM algorithm, the texture complexity computed based on GLCM cannot indicate the change of the mineral grade in the froth layer. The main reason is that the froth image texture feature extraction based on GLCM ignores the color information of the froth surface. To sum up, it can be concluded that CCM is better than commonly used GLCM in describing froth image texture features and the proposed texture complexity based on CCM is an effective indicator to the flotation performance.

(3) Experiment 3: Extraction of the best texture complexity range for flotation process monitoring

In order to further analyze the correlation between froth image texture and mineral grade (mineral content of the forth layer, A/S) and to achieve the best texture range for froth phase monitoring, we collect many more froth images under various production conditions for the following data analysis. We calculate texture complexity of each froth image by CCM algorithm, and then statistically analyze the correlation between image parameters and mineral grade. The range of statistical mineral grade is [8.5, 17.29] and texture complexity calculated by CCM algorithm is [1.2037, 2.5301]. In order to visualize the correlation between them, the experimental data points are fitted with a curve line. 85 groups of data are used for fitting analysis, and the fitting result is shown in Fig. 7. As can be seen clearly from Fig. 7, the relationship between the mineral grade and the texture complexity is well fitted by the fitting curve, with the average relative fitting error under 20%. From this we can obtain the best range of the froth texture complexity for flotation performance evaluation and operation guidance.

The fitting result in Fig. 7 indicates that the froth texture complexity is strongly related to mineral grade, and froth texture can reflect the change of mineral grades. Following the increasing of texture complexity, mineral grade first increases and then decreases. The froth layer contains fewer mineral particles when the surface texture complexity T_C is small, which results in low mineral grade. With the increasing of mineral-containing, different wrinkles appear on the bubbles, and texture becomes more complicated. When the texture complexity T_C is bigger than a threshold and a large number of collapse and clay appear on the bubble lamella in the froth layer, the amount of minerals declines and the corresponding mineral grades are thus relatively low. Therefore, there is a reasonable froth texture complexity range in flotation production, which yields relatively high concentrate grade.

Since the froth texture complexity is closely related to the concentrate grade, an effective indicator to evaluate the current flotation performance can be generated based on the froth surface texture monitoring and measurement. According to the curve trend of the fitting result, the best range of texture complexity for flotation production is about [1.6, 2.0], where the corresponding mineral grade is relatively high (the concentrate grade should be greater than 12.9. The assessment criterion is generated in accordance with the real industrial demands in a bauxite beneficiation plant in China, which is believed to have "good" flotation performance). This texture complexity range is convenient for monitoring and evaluating the current froth production states. It is a very useful indicator to remind the operators to adjust the flotation operations timely to maintain the froth production in reasonable texture appearance statuses when the froth surface texture complexity is found by the vision monitoring system to be out of this range.

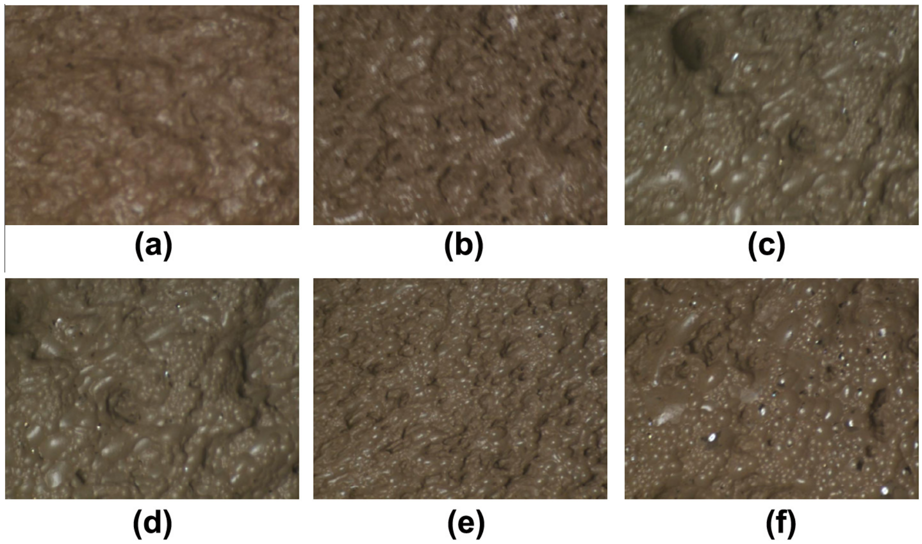


Fig. 6. Froth images of flotation.

Table 1
Features statistics for forth images of flotation.

Image label	T_C	T_g	Mineral grade
Fig. 6a	2.5300	1.5219	10.71
Fig. 6b	1.8680	1.5762	14.63
Fig. 6c	1.8375	1.5354	15.56
Fig. 6d	1.7718	1.3103	14.64
Fig. 6e	1.6362	1.4433	12.39
Fig. 6f	1.5281	1.5257	11.88

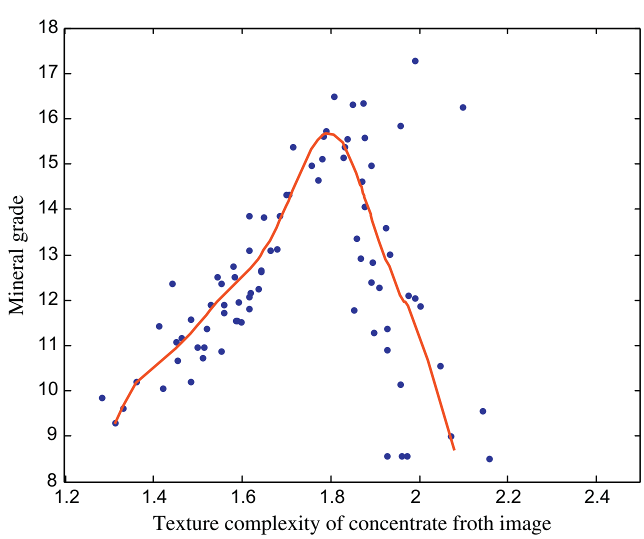


Fig. 7. Correlation between texture complexity and mineral grade.

5. Conclusion

In this work, a froth texture feature extraction method based on CCM is presented to monitor the froth phase. In comparison with the commonly used GLCM based froth texture feature extraction method, the color information of the forth image is taken into account to obtain more distinctive description of flotation froth image texture. Since the HSI color system is similar to the way of human tending to perceive the color information, the froth image is converted from the RGB color space to HSI space, where the CCM is calculated. Haralick features that reflect textures relationship as well as color composition are then extracted for the froth image description. Furthermore, a texture complexity parameter of the froth images is defined and extracted. The optimal froth texture complexity range is obtained based on the relationship analysis between the froth image texture complexity and the concentrate grade. Experimental results demonstrate that, CCM based feature extraction method is superior to the commonly used GLCM based feature extraction method in the description of flotation froth image texture. The extracted best range of the froth texture is convenient for monitoring and evaluating the current froth production state. It can be used to remind the operators to adjust the flotation operation in time to achieve high production performance when the froth texture complexity is found out of the optimum range. This froth phase monitoring method paves the way for the further research of optimal control of the flotation process.

Acknowledgments

The authors would like to thank Dr. H Zhang with Central South University for valuable discussions, and the editors and anonymous reviewers for suggestions and very careful checking that helped to improve the paper. This work is supported by the key Program of the National Nature Science Foundation of China under Grant 61134006, National Science Fund for Distinguished Young Scholars under Grant 61025015 and Nation Nature Science Foundation of China nos. 61074001, 61071176, 61171192 and 61272337.

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