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Texture-based analysis of liberation behaviour using Voronoi tessellations

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ABSTRACT

A liberation simulation is outlined based on image analysis of mineral texture images such as those produced by automated mineralogical analysis. The method relies on a freeware image analysis programme, Fiji, and uses Voronoi tessellations to represent a fragmentation pattern. This pattern is superimposed onto a mineral texture image and the mineralogical composition of each tile is analysed separately to produce a liberation spectrum.

A comparison is presented between actual and simulated data in terms of liberation, shape and size distribution. The correlation (r^2) of simulated to measured liberation data exceeded 0.98 for all minerals assessed but for optimum confidence further validation is required over a larger size range. Comparing real and simulated particle shape gave a correlation exceeding 0.95, and it is shown the particle size distribution of Voronoi patterns can accurately reproduce that of scalped feeds (i.e. a narrow size fraction) of comminution products. Repeatability of the process is shown to be dependent on particle size, but overall is very good. To demonstrate potential applications of this analysis method, quartz liberation spectra for three granites of different grain sizes are included and discussed, and a simulated grade–recovery curves for an Au-bearing pyrite is demonstrated.

1. Introduction

Recovery of valuable minerals necessitates their detachment from gangue minerals of no economic value, i.e. mineral liberation is required. This makes liberation the crucial variable in governing the probability of a particle being recovered into a concentrate or rejected into tailings during downstream beneficiation (Wills, 2011), and therefore it is the most important goal of the comminution process. Consequently Powell and Morrison (2007) clearly identify incorporation of liberation into comminution modelling as the 'holy grail' for this field of research.

The first notable attempt at quantitative prediction and description of liberation was by Gaudin (1939). He superimposed cubes (also known as a tessellation, i.e. an interlocking pattern of 'tiles') as a fracture pattern onto an ore texture, and then analysed the ore mineral content for each of the cubes. Since the seminal work by Gaudin, a considerable number of methods have been formulated to describe liberation, often following the same lines. The approach by King (1979) involves determination of mineral composition of a thin section along a linear intersect, followed by 'fragmentation' of this intersect according to a random breakage tessellation. On the basis of this, King (1979) derived an equation that predicts liberation along this intersect as a function of the particle size distribution.

Since its inception by King (1979), liberation analysis has been much refined, enabled both by vast increases in processing power and more readily available digital textural images (see Bonifazi and Massacci (1995), Matos et al. (1996), Guimarães and Durão (2003, 2007), Evans and Bradshaw (2013), Djordjevic (2013), Evans et al. (2013), Resabal et al. (2014), Wightman et al. (2014) and Wang (2015) for examples). Bonifazi and Massacci (1995) presented a digital version of the Gaudin liberation assessment, and demonstrated the potential to extract grade–recovery curves from images. Evans (2010) used a three-step approach to characterise a micro-texture, simulate breakage using geometric patterns and then simulate flotation behaviour based on surface properties of the progeny particles. Using this method, Evans (2010) demonstrated a link between chalcopyrite surface exposure on modelled particles and flotation recovery, though it was found the model did not account successfully for variation in flotation kinetics of chalcopyrite (i.e. fast-floating vs. slow-floating forms of chalcopyrite). Moreover, in their work liberation predictions were consistently lower than observed values, indicating some degree of selective fragmentation had occurred. Another approach was taken by Djordjevic (2013),

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who used Object-Oriented Finite (OOF) element codes to simulate rock fragmentation. They populated a digitised rock texture image with strength data obtained through micro-indentation and then modelled liberation through slow compression. On the basis of this, Djordjevic (2013) concluded that textural parameters of valuable minerals were more important for fragmentation outcomes than their geomechanical properties. Probably most similar to the presented work is the work by Guimarães and Durão (2007; following initial work presented in 2003 by the same authors), who also used Voronoi patterns to simulate fragmentation through discriminatory size reduction. This work used a programme written specifically for producing Voronoi patterns (termed cellular automata in their paper) to reproduce size reductions and progeny particle composition produced through batch ball milling. The methodology presented by Guimarães and Durão (2007) is similar to that used in this paper, though they focused more on generating particle size distributions and less on liberation. The work presented in this paper can be considered an evolution of the methodology first described by Guimarães and Durão (2007).

Aside from texture-based liberation analysis, first-principle models of liberation have also been formulated, approaching the question from a mathematical perspective. Examples of these models include a combined size reduction–liberation model for a batch mill Andrews and Mika (1975), extension of the population balance equation to incorporate liberation (Herbst et al., 1988), morphological solutions for Poisson polyhedra and Boolean textures with Poisson polyhedra (Barbery, 1992), modelling based on a dispersion equation (Wei and Gay, 1999) and probability–entropy modelling of liberation (Gay, 2004). More recently, Hilden (2014) demonstrated a method to simulate multi-mineral rock textures for liberation analysis. Many of these models possess a mathematical elegance, but often suffer from limitations due to complex mathematics and/or software requirements, extensive experimental requirements to determine input parameters and/or over-simplification of mineral textures for modelling purposes. These practical limitations have so far inhibited wide-spread utilisation of these simulations in industrial scenarios, confining them largely to academic applications.

The goal of this paper is to outline a tessellation-based image analysis method for thin sections, with the aim of prediction of liberation and metallurgical attributes of a given ore. This goal in itself is not unique, as a plethora of liberation assessments have previously attempted to predict liberation behaviour. The novelty in the method followed in this paper is the use of straightforward image analysis applied to mineral texture images from automated scanning electron microscopes. The presented approach requires quantitative mineralogical image data (for instance QEMSCAN®, MLA® or similar images) and uses a freeware image analysis program (Fiji), making it an easily accessible method for liberation analysis. A relatively fast and straightforward method is presented that enables simulation of random liberation based on image analysis of real ore textures using a particular tessellation pattern called a Voronoi tessellation. Aside from outlining the methods, this paper also validates use of Voronoi tessellations for liberation assessments by comparing tile shape and size, as well as liberation predictions to that obtained for real ore particles. Several other attributes of the liberation assessment including minimum resolution and repeatability of the analysis are also reviewed. Lastly, potential practical applications are considered and showcased through several case studies.

2. Methods

2.1. Motivation

The motivation behind the presented methodology was to enable image analysis-based liberation assessment to:

– Provide a repeatable benchmark for completely random liberation of a given mineral texture.
– Predict liberation behaviour of a mineral texture without the need for milling experiments without the need for complicated models or costly dedicated software.

The data presented in this set of papers is based on data from an automated scanning electron microscope (SEM, specifically QEMSCAN® in this paper). However, this does not mean that the presented methodology is limited to such analytical tools. To facilitate straightforward data processing, the key requirements for this liberation method are that image data is available in a digital format with an accurate and well-defined pixel size (in microns or another unit of length), and that mineral phases (or zones) have a unique appearance that allows them to be distinguished from one another. False colour images from any automated mineralogical SEM neatly fit these criteria, but other data sources such as an optical microscope with high resolution digital camera and mechanised stage, or even photographs of halved drill cores or a rock face can also be analysed provided mineralogy (or mineralogical zones) can be easily distinguished.

2.2. Automated mineralogical analysis

Automated mineralogical tools such as QEMSCAN® and Mineral Liberation Analyzer (MLA) produce digitised textural images with mineralogy data represented in user-defined colours, and with resolutions down to the (sub-)micron range. Therefore, liberation analysis through image processing of these automated mineralogy images represents a logical evolution for the approach pioneered by Gaudin (1939), which was based on (analog) optical microscopy.

In this study a QEMSCAN® 4300 was used to generate the mineralogical data and textural images used for the liberation analysis. All analyses were completed in field scan mode with a pixel spacing of 10 μm. Development of the Species Identification Protocol (SIP) database and processing of raw data was done in FEI iDiscover versions 4.2 and 4.3. The procedures for data analysis, outlined in Pirrie et al. (2004) and Rollinson et al. (2011), were followed for data processing and analysis.

Automated mineralogical texture images are normally exported as false colour images to ensure mineral phases are easily distinguishable. For the liberation assessment presented in this paper, use of normal colour values in the red–green–blue (RGB) colour space is possible but this requires recognition of the combination of three colour values that together specify the colour specific to a particular mineral in the false colour image. Having to recognise combinations of colour values convolutes the analysis method presented in this paper, so for ease of subsequent liberation analysis greyscale images were found to be preferable. To this end, standard user-defined RGB colours used in iDiscover for the different mineral species in the Species Identification Protocol (SIP) were redefined to greyscale values (see Fig. 1) before exporting as .tiff images. A brightness value (0–255, where 0 is black and 255 is white) was assigned to every mineral phase in a given image, with the exact value specifically selected and recorded to ensure each mineral has a unique and identifiable brightness. This colour substitution allowed straightforward recognition of each mineral phase during the image and data analysis stage described below.

It should be noted that the redefinition of false colour images to greyscale through simple post-processing of images to greyscale images is unlikely to work, as it is probable that several different RGB colours are assigned the same greyscale value. It is also important to point out this analysis requires greyscale mineral images, which is not the same as backscatter electron (BSE) images, as the latter does not in itself convey which exact mineral species is