USE OF X-RAY MICRO-COMPUTED TOMOGRAPHY (μCT) FOR 3-D ORE CHARACTERIZATION: A TURNING POINT IN PROCESS MINERALOGY

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ABSTRACT

In recent years, automated mineralogy has become an essential enabling technology in the field of process mineralogy, allowing better understanding between mineralogy and the beneficiation process. Recent developments in X-ray micro-computed tomography (μCT) as a non-destructive technique have indicated great potential to become the next automated mineralogy technique. μCT's main advantage lies in its ability to allow 3-D monitoring of internal structure of the ore at resolutions down to a few hundred nanometers, thereby eliminating the stereological error encountered in conventional 2-D analysis. Driven by the technological and computational progress, the technique is continuously developing as an analysis tool in ore characterization and subsequently it foreseen that μCT will become an indispensable technique in the field of process mineralogy. Although several software tools have been developed for processing μCT dataset, but the main challenge in μCT data analysis remains in the mineralogical analysis, where μCT data often lacks contrast between mineral phases, making segmentation difficult. In this paper, an overview of some current applications of μCT in ore characterization is reviewed, alongside with it potential implications to process mineralogy. It also describes the current limitations of its application and concludes with outlook on the future development of 3-D ore characterization.

Keywords: X-ray micro-tomography (μCT), process mineralogy, ore mineral characterization.

INTRODUCTION

Process Mineralogy

Process mineralogy is defined as the study of mineral characteristics and properties with relation to their beneficiation process. The beneficiation process defined here can range from ore beneficiation, metallurgical process, as well as environmental and waste management (Henley, 1983; Lotter et al., 2018a). The key here is that by evaluating the characteristics of the minerals on a representative sample of an ore, one could determine the optimum processing route of such ore based on the characteristics of the minerals (both gangue and valuable minerals) in the ore. As the characteristics of the ore is determined by the sample analyzed, sampling becomes ever increasingly important in terms of process mineralogy (Lotter et al., 2018b).

In contrast to traditional separation between mineral processing and mineralogy, where troubleshooting of processes are often focused more on process parameters; process mineralogy aims to combine both field so both the characteristics of ore and process parameters can be taken into account when designing and troubleshooting mineral processes. Process mineralogy requires combination of knowledge from geology, mineralogy, metallurgy, and mineral processing. This can be illustrated in Figure 1.

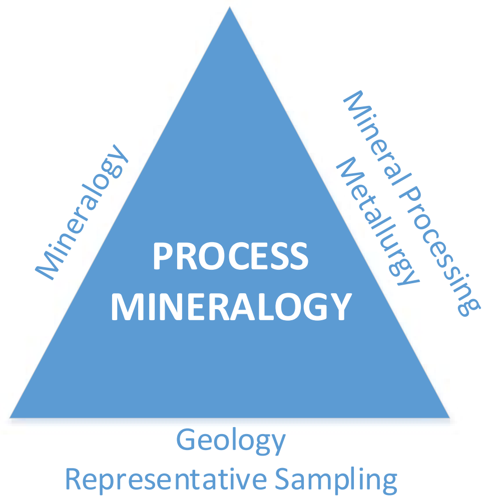

Figure 1. Interdisciplinary of fields in process mineralogy (altered from Lotter et al. (2018, 2002)).

Several instruments and analytical techniques have been developed over the years to evaluate mineralogical characteristics of an ore sample. The development of automated quantitative mineralogical techniques such as Mineral Liberation Analyser (MLA) and Quantitative Evaluation of Minerals by Scanning Electron Microscopy (QEMSCAN) was a significant breakthrough in process mineralogy, as mineral characteristics of ore samples could now be analyzed in an automated, rapid, and statistically reliable way (Fandrich et al., 2007; Gottlieb et al., 2000; Sutherland and Gottlieb, 1991). With such system, information about mineral liberation (Fandrich et al., 2007), size and shape (Leroy et al., 2011; Sutherland, 2007), and stationary textures (Pérez-Barnuevo et al., 2013, 2018; Tøgersen et al., 2018) could be obtained and quantified. This information has been demonstrated to hold significant role in evaluating ore beneficiation processes such as flotation (Alves dos Santos, 2018; Alves dos Santos and Galery, 2018; dos Santos and Galery, 2018; Tungpalan et al., 2015) and comminution (Little et al., 2017, 2016; Tøgersen et al., 2018).

X-ray Tomography for Ore Characterization

While MLA and QEMSCAN offer a rapid data acquisition and processing, it possesses an obvious weakness due to loss of dimensionality. Particles and ore samples are three-dimensional (3D) objects, while automated mineralogical techniques produced a two-dimensional (2D) cross section analysis of the ore samples. This phenomenon is known as stereological bias / error, in which the mineral liberation may be overestimated, as the cross section of the sample might not represent the actual state of the particles (Lätti and Adair, 2001) as shown in Figure 2. Over the years, several correction methods have been developed to address this error in regards to mineral liberation and texture of the particles (Fandrichi et al., 1998; Ueda et al., 2018a, 2018b).

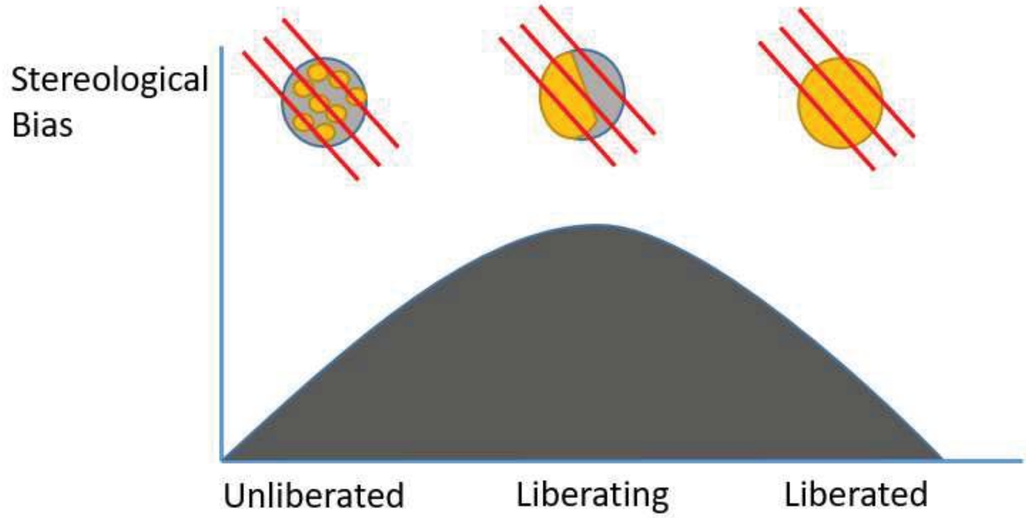

Figure 2. The effect of stereological bias on different type of particles with varying degree of liberation by Spencer and Sutherland (2000). The possible cross-sections analyzed is indicated by the red lines crossing the particles.

This inherent bias gives way to the development of instruments that are capable of acquiring 3D data from an ore sample. Over the last decades, the development of X-ray microcomputed tomography (µCT) in geosciences have received wide attentions. The main advantage of µCT lies on its ability to non-destructively analyze the 3D interior of an object. Several reviews have been done in evaluating µCT application in geosciences (Cnudde and Boone, 2013; Mees et al., 2003), particularly in relation to ore characterization and mineral processing (Kyle and Ketcham, 2015; Miller et al., 1990).

Using µCT, 3D properties of an ore sample such as porosity (Lin and Miller, 2005; Peng et al., 2011; Yang et al., 2017; Zandomeneghi et al., 2010), mineralogy (Ghorbani et al., 2011; Reyes et al., 2017; Tiu, 2017), mineral liberation (Lin and Miller, 1996; Reyes et al., 2018), as well as size and shape (Cepuritis et al., 2017; Lin and Miller, 2005; Masad et al., 2005) could be obtained. Additionally, as 3D data offer additional information about depth, surface properties of an ore can also be evaluated, in which such parameter is important for leaching, flotation, and to some extent grinding (Miller et al., 2003; Tøgersen et al., 2018; Wang et al., 2017; Xia, 2017).

Recent development in µCT instruments also allows in-situ experiments to be carried while scanning is performed, therefore obtaining the so-called four-dimensional (4D) data, which consist of three dimensional of space plus one dimension of time. With such settings, the evolution of ore samples during experiments can be obtained so that the relation of the mineralogical characteristics of the ore to the process can be draw. Such settings have been implemented for example in evaluating ore breakage (L. Wang et al., 2015; Wang et al., 2018) and leaching (Ghorbani et al., 2011). If the key in process mineralogy lies in drawing the relations between mineralogy and mineral processing, then in-situ experiments with µCT scanning could offer a valuable dataset for process mineralogy.

The main limitation of µCT scanning lies on the principle of the X-ray scanning, where minerals are differentiated by their respective attenuation to the X-ray beam. This is reflected in the grayscale intensity of the final image. The attenuation of each materials varies depending on the minerals density, atomic number, as well as the energy of the X-ray beam (Omoumi et al., 2015). This phenomena creates a trade-off situation, where one has to optimize the beam energy so that sufficient contrast between minerals could be obtained. Using lower energy beam often means better contrast, as the attenuation is more dependent on the atomic number of the minerals due to photoelectric effect, but it requires longer exposure time. Using higher energy would mean less exposure time, but the attenuation is now more dependent on density due to Compton effect, therefore making mineral differentiation difficult as many minerals have similar density.

CASE STUDIES

Ore Structural Characterization with µCT

At the early stages, µCT analysis of ore samples was more focused on structural analysis, which includes pore, shape, as well as size analysis. Analysis with µCT could obtain several information of the ore which includes porosity and crack (Deng et al., 2016; Lin and Miller, 2005; Peng et al., 2011; Yang et al., 2017; Zandomeneghi et al., 2010), particle and grain size distribution (Tiu, 2017) as well as particle shape descriptors such as solidity, elongation, flatness, and aspect ratio (Vecchio et al., 2012; Zhao et al., 2015).

Pore and crack analysis is one of the most common application of µCT. While pore and crack analysis is less emphasized in mineralogy, it holds a significant role in petroleum (Markussen et al., 2019) and construction engineering (Yang et al., 2019). Nevertheless, pore and crack analysis is often indispensable when dealing with processes such as leaching, especially in cases with packed particle bed samples, where connectivity of the pores could help in understanding the permeability of the ore (Deng et al., 2016; Wu et al., 2007).

Most of the automated mineralogy technique could produce analysis on particle size and shape, but as said earlier, these parameters often not used in process mineralogy due to the stereological error. Particle and grain size distribution analysis using µCT is quite well established, as several researchers have optimized the image processing algorithm in acquiring such distribution analysis (Lux et al., 2011; Pierret et al., 2002). One of the most commonly used algorithm is granulometry morphological opening, illustrated in Figure 3.

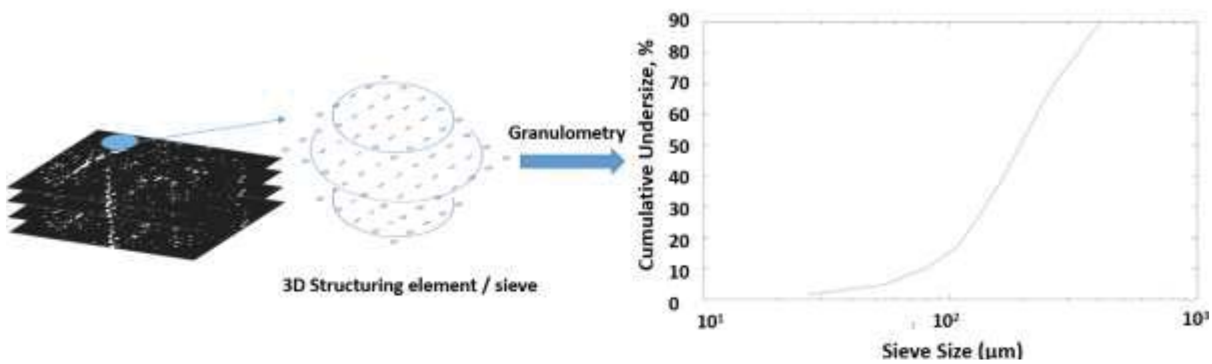

Figure 3. Grain size distribution in 3D as obtained from µCT analysis with granulometry technique. The technique uses a structuring element acting as a sieve, where grain smaller than the sieve is removed. The sieve size is then increased gradually, so the cumulative undersize can be obtained.

Particle and grains are irregular objects; therefore, a descriptor of shape is often needed when describing such parameters. With µCT system, such descriptors could be better acquired, as now the 3D data is available. Most of the available shape descriptors in 3D follow the same logic as the one commonly available in 2D. Particle and grain shapes in 3D can be described with convex hull (Pamukcu et al., 2013; Zhao et al., 2015), bounding box (Vecchio et al., 2012) as well as relation to sphere shapes (Pirard et al., 2009; Van Dalen et al., 2012). Example of bounding box and convex hull of a mineral grain is shown in Figure 4.

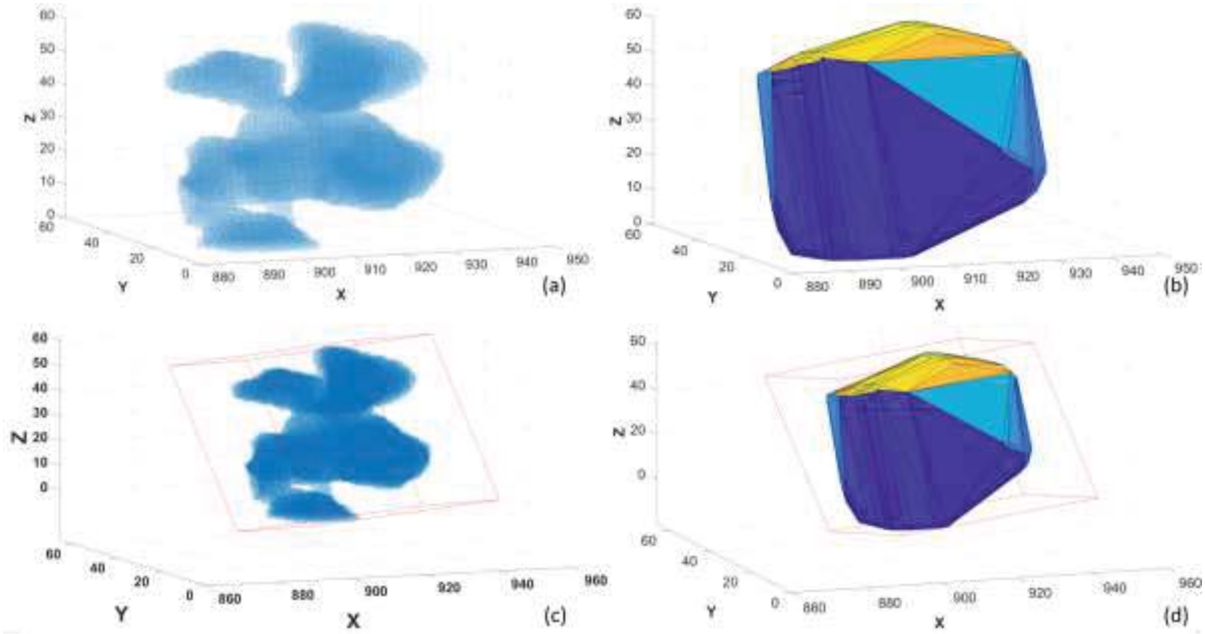

Figure 4. Bounding box and convex hull of an irregular grain. (a) Scatter plots representing the grain; (b) convex hull of the particle; (c) minimum bounding box of the grain; (d) minimum bounding box of the convex hull. Due to the high irregularity (non-convex) particle, convex objects such as polygons often are not the best when describing such particle.

While it is obvious that particle size is of an importance when dealing with most of mineral processes, the effect of shape is not so obvious. It is clear that the choice of comminution equipment affects greatly the progeny particle shape, which then indicates that grain shape could be an important indicator in modelling the breakage mechanism that occurs in the particle (Little et al., 2017, 2016). With flotation, several researchers have analyzed the effect of particle shape (Ma et al., 2018; Pita and Castilho, 2017; Xia et al., 2018), and it is clear that the effect of shape is intertwined with the particle composition and size; in some cases the effect of shape is minimum while in others its effect is more prevalent.

Ore Mineralogical Characterization with µCT

The use of µCT in mineralogical characterization is relatively limited, although it is outlined as one of the future characterization technique in process mineralogy (Baum, 2014). Mineralogical characterization with µCT is often limited to simple mineralogy, such as differentiating the gangue and valuable mineral phases. In these cases, simple thresholding technique such as Otsu could work (Andrä et al., 2013; Yang et al., 2017). Limitations do exist especially if the sample is heterogeneous (Yang et al., 2017), or consist of fine particles with high density / high atomic number, as then the boundary between particles and the background might not be segmented properly due to partial volume effect (Y. Wang et al., 2015).

Several researchers have applied different techniques in dealing with multi-mineral ore samples, especially those that contains minerals with similar attenuations. Such problems can be anticipated earlier by optimizing the scanning conditions through reduction of sample size (Bam et al., 2019; Kyle and Ketcham, 2015), using lower scanning energy (Reyes et al., 2017), or using dual energy scanning (Ghorbani et al., 2011). In other cases, such problem could be addressed later at the data processing stage, such as using machine-learning techniques (Chauhan et al., 2016; Tiu, 2017) as well as combination with SEM-EDS of XRF (Laforce et al., 2017; Reyes et al., 2017; Suuronen and Sayab, 2018; Tiu, 2017). Despite all the steps need to be performing mineralogical analysis with µCT, the mineralogical result does show considerable difference with traditional automated mineralogy techniques (Reyes et al., 2017; Tiu, 2017). Example of the usage of machine-learning in µCT mineralogical analysis is shown in Figure 5.

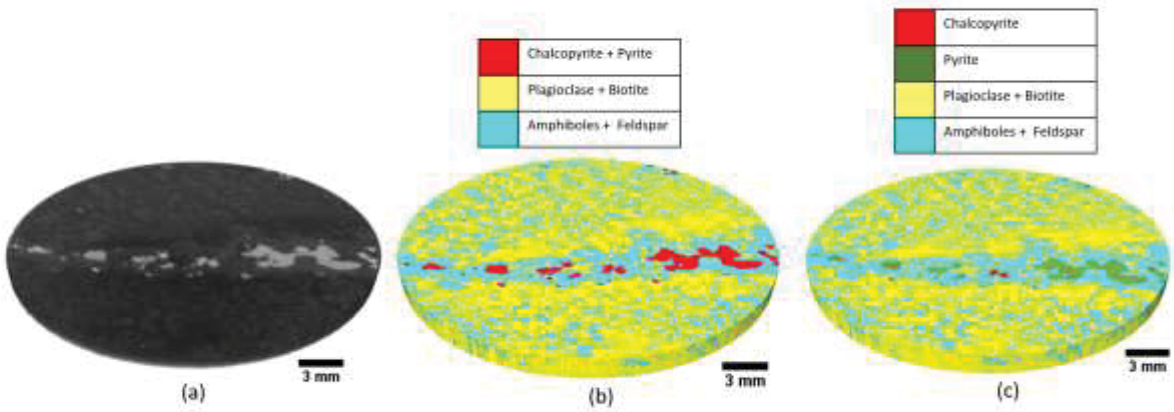

Figure 5. Comparison of different machine learning techniques in mineralogical analysis. (a) Original 3D image of a drill core; (b) Unsupervised machine learning classification; (c) Supervised machine learning classification. By supervised the learning user can better specify the minerals, as in this example pyrite is lacking contrast.

Ore Texture Characterization with µCT

Textural measures such as grain size is well known to have effect to the downstream processes, especially in terms of liberation size (Lotter et al., 2018a). Another equally important texture measure is the spatial distribution (pattern) of different minerals in the ore, often referred as stationary textures (Lobos et al., 2016). While grain size is quantifiable, stationary textures is often descriptive and qualitative. Recent developments are leaning toward the quantification of stationary textures with the help of microscopy based techniques (Donskoi et al., 2016; Koch, 2017; Lund et al., 2015), accounting both grain size and spatial relationship of minerals. Stationary textures have been shown to affect the ore behavior in mineral processes (Butcher, 2010; Dey et al., 2017; Tøgersen et al., 2018) and it has been used as an important measure in geometallurgy (Lund et al., 2015; Pérez-Barnuevo et al., 2018).

µCT analysis opens up a new potential in analyzing textures, especially stationary textures, as now the spatial relationship of minerals can be described in 3D, which in turns leads to better understanding of its effect to the downstream processes (Becker et al., 2016). Additionally, information about surface texture of the ore could be obtained as well, in which parameter such as grain surface exposure affecting leaching processes (Miller et al., 2003; Wang et al., 2017); surface hardness affecting grinding processes (Tøgersen et al., 2018); as well as surface roughness affecting flotation process (Xia, 2017).

In general, µCT ore texture analysis is very limited, as it requires a comprehensive mineralogical analysis, in which µCT has a limitation. Several researchers have tried to use µCT to describe texture better (Barnes et al., 2018, 2017), while others have used µCT data to quantify stationary textures (Jardine et al., 2018). Example of texture quantification in 3D is shown in Figure 6.

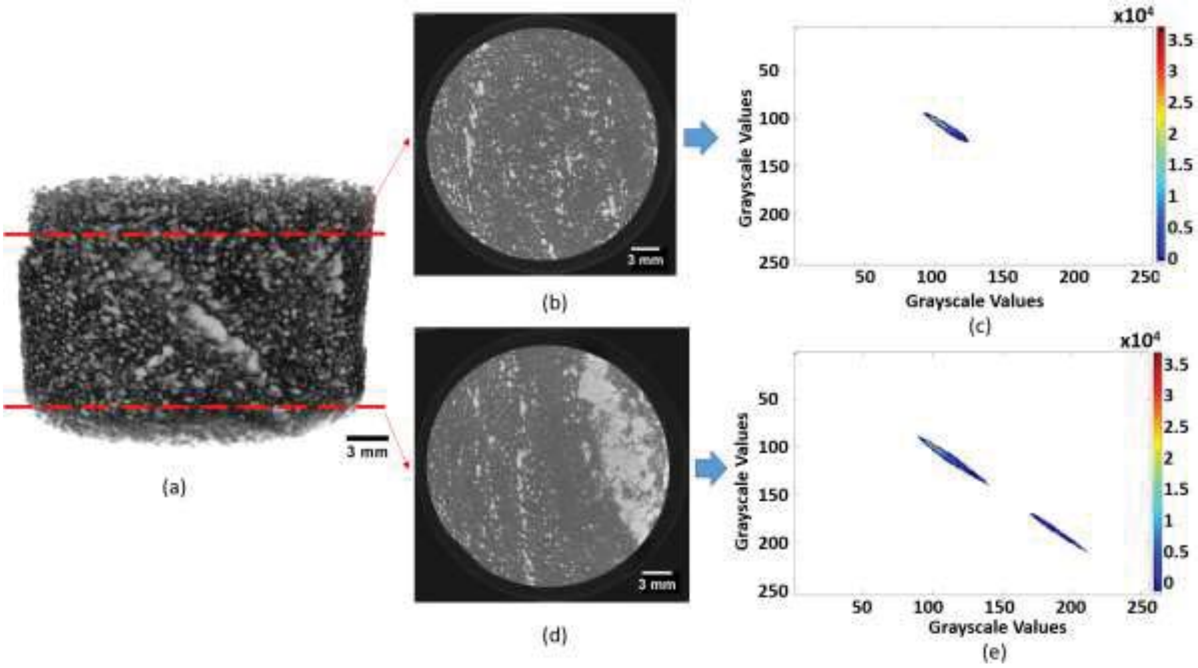

Figure 6. Textural analysis of 3D drill core image acquired from µCT. (a) Original 3D image of a drill core; (b) and (c) Two µCT slices showing different textures; (d) and (e) shows the texture heat map of the slices. The heat map reveals the association of each pixels in the image; more association between high grayscale value pixels means more sulphide mineralization, as shown in (e).

CONCLUSION

The future is wide open for µCT in process mineralogy. Additional dimension in µCT analysis allows better characterization of ore, leading to better understanding of ore behavior in the downstream processes. Future work shall be emphasized to accelerate µCT application in ore characterization through development of both instrumentation and data processing workflow. Development of instrumentation could include sub-micron resolution, in-situ experiments, and combination with µCT other instruments such as XRF, EDS, and XRD. Development of the data processing includes better reconstruction techniques, optimized algorithm to handle large datasets, as well as benchmarking data processing techniques applied in other field of material science.

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