



A methodology for density determination from core imagery and assays

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SUMMARY

Density is an important physical parameter due to its influence on ore resource and reserve estimation. The most efficient form of density measurement is gamma-gamma logging. However, downhole density logging is rarely conducted in non-ferrous metalliferous mines. Accurate prediction of density from core images could provide an alternative means for continuous density estimation.

A Geotek Multi-Sensor Core Logging system has been used to record petrophysical properties and also core imagery on archival drill core from Ernest Henry mine, Queensland, Australia for geometallurgical studies. Mineral grades estimated from the classified core images were not sufficiently reliable for density prediction. However, the fractional volumes can be adjusted to ensure consistency with assay data.

A linear programming algorithm was developed for this purpose. Given corrected volumes and mineral densities, it was then possible to predict density continuously along the drill hole. At Ernest Henry the average relative error between image-based density and Geotek gamma-gamma density was 3.5%.

Key words: Density, Core Imagery, Geotek Logger

INTRODUCTION

Photographs and digital images of hand samples and drill cores are often captured by geologists as a record of rock to which their observations of lithology, mineralogy, texture and alteration refer. Capturing and archiving core imagery is especially beneficial in cases where core is destroyed for mechanical testing or assaying. There are many applications for core image analysis, ranging from mineralogical to geomechanical and geometallurgical studies (Lemy et al, 2001; Bonnici et al, 2009). The technology to acquire high quality digital core images is now available. The capital and operating costs for deployment of core imaging systems at mine sites are very small compared with other costs in a mining operation (e.g. exploration drilling).

Density is an important physical parameter due to its influence on ore resource and reserve estimation. Nevertheless, it is

surprising how little attention is paid to density variations at some mine sites. The most efficient form of density measurement is gamma-gamma logging. However, downhole density logging is rarely conducted in metalliferous mines other than iron ore mines. The main impediment to wider utilisation of gamma-gamma logging is concern about the ramifications in the event that the gamma source becomes stuck downhole. Although this risk is managed at coal and iron mines, it is often considered so grave at base and precious metal mines that density logging is banned. Therefore there is a need for alternative means for accurate and continuous density determinations.

In principle, mineral abundance, inferred from classified core imagery, combined with mineral density has potential to meet this need. In practice, the uncertainties in mineral abundance and density often render the bulk density from core imagery alone unreliable. However, if mineral grades estimated from imagery correlate well with assays, then greater confidence in prediction of density is justified. The uncertainty in image-based mineral grades can be reduced by reconciling the estimated volume fractions against geochemical assays using the chemical formulae of the constituent minerals.

This paper describes a methodology for prediction of density from classified core images and assays. The approach is illustrated on core imagery from the Ernest Henry mine which is located approximately 40 km north of Cloncurry in the Mount Isa district, Queensland, Australia. The orebody is a member of the diverse iron-oxide-copper-gold (IOCG) class of deposit. A comprehensive overview of the geology and mineralogy of Ernest Henry deposit can be found in Mark et al. (2006).

A Geotek Multi Sensor Core Logger system (Vatandoost et al, 2008) was used during the AMIRA geometallurgy project (P843) to measure petrophysical properties on half-cores from six drill holes from the primary ore zone of Ernest Henry mine. Gamma density, magnetic susceptibility, compressional wave velocity and its amplitude were measured along each length of half core. The aim was to characterise the rock type, alteration style and ultimately the ore processing behaviour from the petrophysical data. High resolution core imagery was also captured simultaneously. The Ernest Henry core images were analyzed and then classified via an object oriented approach (Berry, 2008) to map occurrences of the key mineral phases. When adjusted for consistency with assays, the mineral volumes predicted from imagery yielded continuous density estimates with an average relative error of 3.5%.

METHODOLOGY

The bulk density, ρ_{Sample} , of a rock sample comprised of n minerals has the following form:

$$\rho_{\text{Sample}} = \sum_{i=1}^n \rho_i V_i \quad (1)$$

where ρ_i is the density of the i th mineral and where V_i is the corresponding fractional volume of that mineral. Thus the density of a sample can be determined given

- the fractional volumes of all its constituent minerals, and
- the densities of those minerals.

Porosity can be regarded as an additional mineral, with density governed by pore fluid density and degree of saturation.

Determination of mineral grade from core images is subject to error. Firstly, the image quality (including colour values) may vary depending on wetness and condition of the core. Secondly, it must be assumed that the imaged core surface is typical of the entire core volume. Thirdly, the grain size of some minerals can be beyond the resolution of the imaging system. Fourthly, it may not be possible to reliably discriminate between mineral species, e.g. of similar colour.

The densities assigned to the constituent minerals are also uncertain. Mineral density is usually best characterised by a distribution rather than a discrete value. The dispersion arises for three main reasons. Firstly, many minerals exhibit a range of compositions. For example, chlorite composition depends upon relative abundance of Mg, Fe, Al, and F; according to Klein and Hurlbut (1985) its density varies over an enormous range, from 2.6 to 3.3g/cc. Secondly, while physical properties of chemically pure minerals provide a benchmark, naturally occurring mineral samples are impure in almost all cases. Thirdly, direct measurement of density of naturally occurring mineral samples usually involves multiple mineral grains, with defects and porosity.

Given the uncertainties in density of minerals and in estimates of mineral grades, accurate prediction of density from core imagery alone is unreliable. However if estimated mineral grades are consistent with assays, then greater confidence in prediction of density is justified. Therefore it is advantageous to adjust the volume fractions of mineral phases in order to achieve agreement with the geochemical assays. To adjust mineral grades using assays, the weight percent (wt%) of major elements is required. Fe, S and Cu are the major elements at Ernest Henry. The mineral densities in Table 2 were used to predict density of Ernest Henry drill cores from classified core images using Voigt and Reuss models.

Assay data are always available within ore zones. If a sufficient number of elements are assayed, assays alone can provide an estimate of modal mineralogy for simple mixing models (Zhang and Whiten, 2001).

A computer program was developed to maximize or minimize the density for each sample subject to assays for Fe, S and Cu and subject to the volume balance condition (i.e. total volume equal to 100%). The optimisation problem was solved using a linear programming (SIMPLEX) routine (Morris, 1993). Both the volume fraction of individual mineral phases and the

composition of the mixed phases were adjusted. The overall magnitude of the changes to the fractional volumes is restricted according to the estimated accuracy of the initial mineral volume estimates. The sum of absolute errors for the ten mineral classes is bounded. These errors are visualized as realizations of ten independent Normal random variables with mean zero. The error condition imposed on the volumes is

$$\sum_{j=1}^{10} \left| \frac{\delta v_j}{\varepsilon} \right| \leq 10 \sqrt{\frac{2}{\pi}} \quad (2)$$

where δv_j denotes the change in fractional volume for the j^{th} class (the mixtures being classes, as well as the individual minerals), and where ε is an estimate of the uncertainty in the fractional volume estimates. The RHS of (2) is the expected value for the sum of absolute values (Parker and McNutt, 1980).

PREDICTION OF BULK DENSITY AT ERNEST HENRY

Petrophysical properties (density, P-velocity, magnetic susceptibility) were collected on half-core from six selected drill holes from Ernest Henry (EH432, EH446, EH556, EH574, EH633, and EH635). Drill core images were also captured continuously (total length of ~1800mm) at 9cm intervals (optimum sampling interval) and then were stitched together by Geotek MSCL software into ~1m length (i.e. core section length). The imaging camera produces high resolution (40 μm pixel) RGB colour imagery.

Core images were classified using Definiens Developer software in order to produce a classified mineral image (Figure 1). Details of image analysis and classification are described by Berry (2008). For each 1m interval of core, the number of pixels assigned to each mineral species is divided by the total number of pixels to yield a fractional volume for each phase. Estimates from adjacent 1m intervals were then averaged for 2m assay intervals, in order to facilitate combined analysis of mineral grades with 2m assay data.

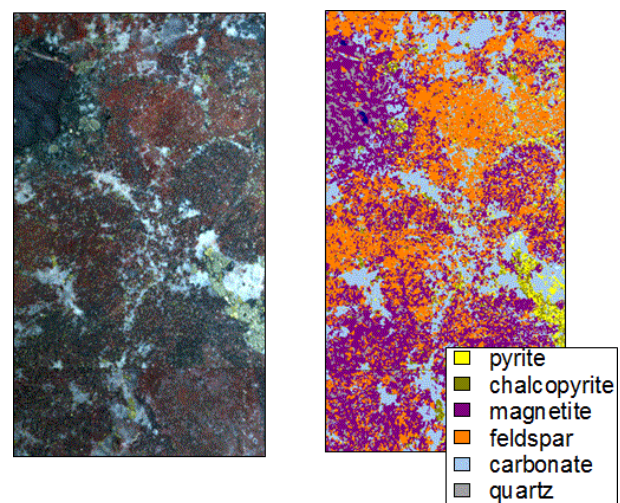


Figure 1. An example of unclassified (left) photographic image of Ernest Henry drill core and its classified (right) mineral map (Berry, 2008).

The predominant individual mineral phases for the Ernest Henry drill cores are quartz, pyrite, chalcopyrite, magnetite, chlorite and K-feldspar (Mark et al., 2006). Table 1 summarizes the identified mineral phases and mixtures from Ernest Henry drill core images.

Table 1. Summary of mineral phases and mixtures identified at Ernest Henry

Individual Mineral Phase	Mixture Phase
Quartz	felsic (Quartz, K-feldspar, carbonate)
K-Feldspar	magnetite/chlorite
Pyrite	magnetite/k-feldspar
Chalcopyrite	quartz-carbonate
Chlorite	
Magnetite	

Aggregates comprised predominantly of feldspar, magnetite and chlorite were too fine-grained to be resolved in the Geotek images. Therefore two mixture classes, “magnetite/chlorite” and “magnetite/feldspar”, were defined during image analysis. In addition, separation of carbonate and quartz was difficult since these minerals are both light in colour. Therefore two other mixture classes were defined: “felsic” (consisting of quartz, feldspar and carbonate) and “quartz/carbonate”.

Assay-based Volume Correction of Mineral Phases

In order to improve the accuracy of density prediction from Ernest Henry core imagery, the volume fraction of each mineral phase was adjusted to ensure that the calculated elemental compositions match the assay data. At Ernest Henry the Cu, S, and Fe assays were used to check the consistency of the fractional volumes estimated from core images.

To adjust mineral grades using geochemical assays, the weight percent (wt %) of major elements is required. The wt% of Fe, S and Cu in the key Ernest Henry minerals, and the corresponding adopted mineral densities, are documented in Table 2.

Table 2. Elemental wt% and densities assumed for key Ernest Henry minerals

Mineral	Composition	ρ (g/cc)	Fe (wt%)	Cu (wt%)	S (wt%)
Quartz	SiO ₂	2.65	0	0	0
Calcite	CaCO ₃	2.71	0	0	0
K-Feldspar	KAlSi ₃ O ₈	2.63	0	0	0
Pyrite	FeS ₂	5.03	46.7	0	53.3
Chalcopyrite	CuFeS	4.20	30.5	34.6	34.9
Chlorite	(Mg,Fe) ₁₀ Al ₂ (Si,Al) ₈ O ₂₀ (OH,F) ₁₆	2.95	19.38	0	0
Magnetite	Fe ₃ O ₄	5.17	72.4	0	0

Determination of the weight percent of Fe and Mg in chlorite is not easy due to the variable substitution of these elements in the chlorite lattice. The chemical composition for chlorite is not universally agreed. The chlorite formula of Whitten and Brooks (1972) was adopted in this study for determination of its wt% Fe (Table 2). The weight percent of Fe in chlorite was calculated based on assumed two chlorite end members (Fe free and Mg free). The Mg free and Fe free members are considered to represent the highest and lowest chlorite density

(i.e. 3.3g/cc and 2.6g/cc) respectively. The weight percent of Fe calculated for Mg-free chlorite (3.3g/cc density) was 38.77%. The weight percent of Fe for chlorite with a density of 2.95g/cc was then estimated as half of the wt% for Mg-free chlorite.

Whitten and Brooks (1972) have quoted an approximate density of 3.0g/cc for chlorite. This corresponds well to 2.95 g/cc, the midpoint of the density range quoted by Klein and Hurlbut (1985). The published density values for quartz and calcite are consistent at 2.65 and 2.71 g/cc respectively. Densities of other minerals in Table 2 were selected on a somewhat subjective basis due to the ranges and inherent uncertainties in published values.

The Cu, S, and Fe assay constraints applied to the Ernest Henry fractional volumes are prescribed below:

$$V_{\text{cpy}} \text{Cu}_{\text{cpy}} \rho_{\text{cpy}} = \rho_{\text{Sample}} \text{Cu}(\%) \quad (3)$$

$$V_{\text{cpy}} S_{\text{cpy}} \rho_{\text{cpy}} + V_{\text{py}} S_{\text{py}} \rho_{\text{py}} = \rho_{\text{Sample}} S(\%) \quad (4)$$

$$V_{\text{cpy}} \text{Fe}_{\text{cpy}} \rho_{\text{cpy}} + V_{\text{py}} \text{Fe}_{\text{py}} \rho_{\text{py}} + V_{\text{mt}} \text{Fe}_{\text{mt}} \rho_{\text{mt}} + V_{\text{chl}} \text{Fe}_{\text{chl}} \rho_{\text{chl}} = \rho_{\text{Sample}} \text{Fe}(\%) \quad (5)$$

where V_{mineral} is the volume fraction of a mineral phase and where ρ_{mineral} is the corresponding mineral density. $\text{Cu}_{\text{mineral}}$, S_{mineral} , and $\text{Fe}_{\text{mineral}}$ are the weight percent of copper, sulphur, and iron in that mineral, as per Table 2. Chalcopyrite, pyrite, magnetite and chlorite are abbreviated as “cpy”, “py”, “mt” and “chl” respectively. For example Cu_{cpy} is the weight percent of copper in chalcopyrite, i.e. 34.6%. $\text{Cu}(\%)$, $S(\%)$ and $\text{Fe}(\%)$ are chemical assays, i.e. weight percent of copper, sulphur and iron respectively in total sample.

Invoking equation (2), if an error with standard deviation 0.01 is attributed to the initial fractional volume estimates, then $\varepsilon=0.01$, and the total change to the original class volumes is restricted by the condition that

$$\sum_{j=1}^{10} |\delta v_j| \leq 0.08 \quad (6)$$

The program has no solution in cases when the assay conditions (Eqns 3 to 5) and the volume balance condition cannot be met for volume changes small enough to satisfy the error condition (Eqn 2). The greater the error (ε), the more likely the program is to find a solution since larger changes in volume fractions are permitted. The level of error in original fractional volumes was considered to be about 3% (i.e. $\varepsilon=0.03$). Adopting this value for ε resulted in failure of the program for only a few samples from each drill hole; 29 failed out of the total 673 samples.

There is uncertainty attached to the mineral properties and, in some case, to the mineral composition, as well as to the estimated mineral grades from core images. However, for simplicity, only errors in volumes are included in the algorithm. The volume adjustment approach produced volumetric estimates of mineral phases which satisfy the assays and which achieve improved correlations between volume fraction of magnetite and Fe grade in all drill holes (Figure 2).

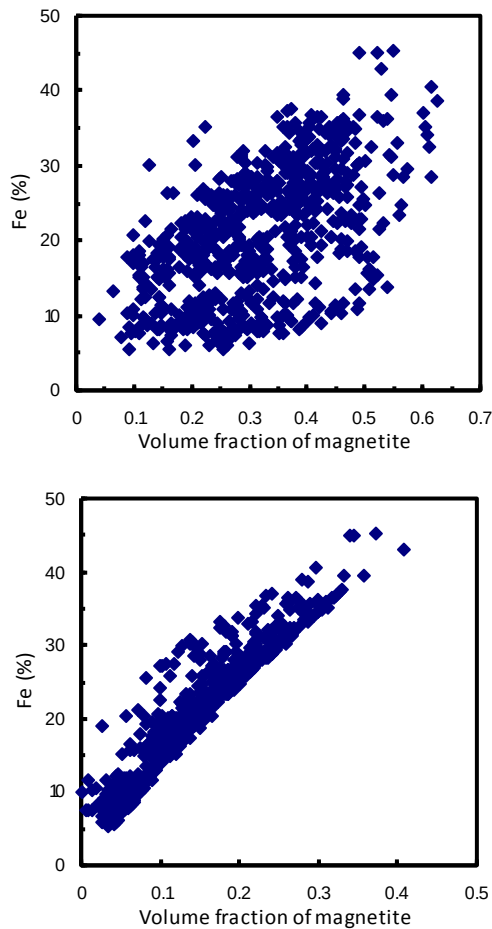


Figure 2. Correlation of volume fraction of magnetite with Fe before (top) and after (bottom) assay-based adjustment. All samples are 2m assay intervals from all six drill holes.

Prediction of Density from Core Imagery and Assays

Minimum and maximum densities were predicted from core images and assays during adjustment of volumes. Predicted minimum and maximum densities for samples from all six drill holes are in strong correlation ($R^2=0.99$). Predicted maximum densities are higher than minimum densities by about 1%. This small difference between maximum and minimum densities is due mainly to an increase in adjusted volume fraction of magnetite when density for each sample is maximized.

In addition to Geotek gamma-gamma density measurements, immersion densities were measured only for some samples derived from six drill holes. Measured densities are compared with maximum densities predicted from imagery (after volume adjustment) in Figure 3. Predicted densities are in good correlation with measured densities. Predicted minimum densities showed the same agreement with measured densities. The average deviation of predicted minimum and maximum densities from Geotek densities were 3.9% and 3.5% respectively. The uncertainty attributed to Geotek gamma density is $\pm 1.1\%$.

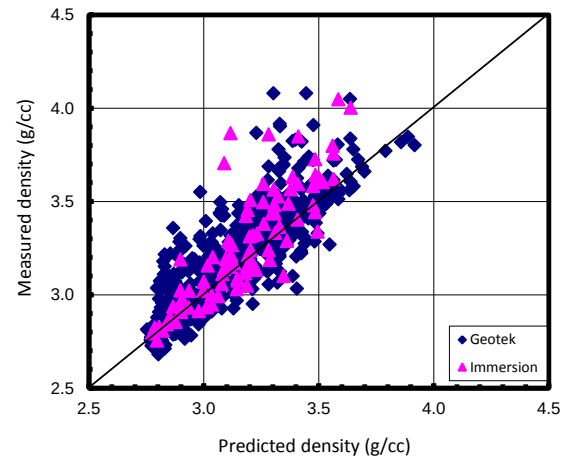


Figure 3. Predicted maximum density from classified core imagery (after volume adjustment) versus measured density (Geotek and immersion) for 2m assay samples from all six drill holes at Ernest Henry.

Comparison of predicted density with the in-house Ernest Henry Mine empirical density formula shows a strong correlation (Figure 4). This engenders confidence in the densities predicted from core imagery. Ernest Henry's empirical model, which is purely based on Fe(%), is much easier for density determination than the approach described here. However, the mineral volume fraction model underlying the new density prediction has value in its own right, e.g. for subsequent prediction of other physical and metallurgical properties (Vatandoost, 2010). Moreover a reliable simple density estimation method based on a single assay parameter is not a situation that exists in all mine sites. Hence the ability to predict density from core imagery and assays may prove advantageous, especially in view of resistance to downhole gamma-gamma logging.

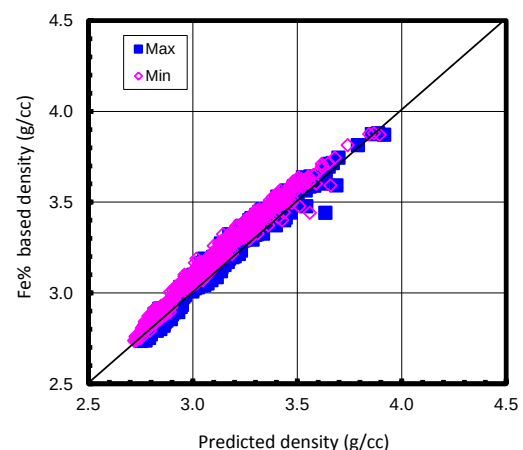


Figure 4. Predicted maximum and minimum densities from classified core images (after adjustment of volume fraction of mineral phases) versus estimated densities for 2m assay samples from all six drill holes using Ernest Henry's density model.

CONCLUSIONS

A new approach for prediction of density based on classified core images and assays was presented. High resolution continuous core images are recorded routinely at many mine and exploration sites.

Reliable prediction of density from classified core imagery could represent an attractive new technique for onsite density determination, especially in view of resistance to gamma-gamma logging at base and precious metal mines.

Prediction of density from core images is affected by factors such as difficulty in identification of mineral phases and uncertainty in intrinsic properties of minerals. Discrepancies in the published intrinsic properties are likely due to variations in mineral composition and microstructure together with the diverse range of protocols used for measurement.

The procedure was demonstrated via application to core imagery recorded by a Geotek MSCL system on half-core from six drill holes at the Ernest Henry mine. The optical estimates of mineral phases at Ernest Henry were not compatible with assay data. Hence predicted density values were not accurate when compared with measured values (average relative error of 8.9%). A linear programming algorithm was developed to improve the volume estimates of mineral phases. This approach improved the density prediction, reducing the average relative error to 3.5% and provides a degree of confidence in prediction of other physical properties.

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