Machine assisted drillhole interpretation of iron ore resource evaluation holes in the Pilbara

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SUMMARY

In minerals exploration, routine drilling is performed and the data logged from these drillholes, including lithological composition, assays, and downhole geophysical measurements such as natural gamma logs, are used to create geological interpretations of the strata within each drillhole. A 3D geological model can be created by identifying corresponding stratigraphic boundaries within multiple drillholes. These models can be used for understanding the formation and the mineral endowment of a deposit.

We introduce a system for producing stratigraphic interpretations of iron ore exploration drillholes in the Pilbara region in Western Australia. The algorithm firstly classifies each data modality independently for each geological interval, for example 2m, with classification results for each stratigraphic unit as output. These classifiers, for geological logging, assays, gamma logs, were trained on historical datasets over a wide range of strata in the Pilbara. The influence of each classifier can be adjusted according to the user's preference, and a novel optimisation algorithm incorporates known geological features such as dykes, faults and thicknesses of various stratigraphic units, to objectively create the best fit interpretation of the geology. A geologist can then adjust this interpretation to include local knowledge.

Manual interpretations of 396 drillholes from a high-grade iron ore deposit are compared to interpretations of the same hole prepared by the algorithm. An interval-by-interval comparison of these interpretations demonstrates that without any human input, similar interpretations are produced while reducing manual effort.

Key words: drillhole interpretation, iron ore, automation, classification, modelling.

INTRODUCTION

The Pilbara in Western Australia is a major iron ore producing region, with the main deposits occurring within the Marra Mamba Formation and Brockman Formation of the Hamersley group (Thorne, 2008). The primary bedded mineralisation is martite-microplaty hematite and martite-goethite. In order to accurately estimate iron ore grades and reserves, the geology and geochemistry of the subsurface must be mapped accurately. In resource evaluation at Rio Tinto Iron Ore, block models are created through drilling and interpreting RC holes (Sommerville et al., 2014). RC chips from these holes are logged and assayed in 2 m intervals. Downhole geophysics comprising gamma, magnetic susceptibility and density readings are recorded every 10 cm. These datasets are used, along with known geology, to interpret the geological cross-section within each RC drillhole.

The Marra Mamba Formation is a banded iron formation (BIF) structure interleaved with shale bands (Trendall and Blockley, 1970). It is overlain by the Wittenoom Formation which consists of dolomite, chert and shale. The Wittenoom Formation itself is overlain by the Mount Sylvia Formation, the Mount McRae Shale, and then the Brockman Iron Formation, which is another BIF structure interleaved with shale bands. The Brockman Iron Formation itself comprises the Dales Gorge Member, overlain by the Whaleback Shale, which itself is overlain by the Joffre Member (Trendall and Blockley, 1970). Hamersley Detrital deposits, located further up the stratigraphic sequence, are derived from weathered bedded ores (Morris, 1994). Dolerite dykes are described by Dalstra (2006) as intruding faults in the formations in some areas.

Each mineralised member is sub-divided into a number of units known as strands, which are the fundamental domains used for mineral resource estimation (Sommerville, 2014). The Joffre Member comprises six strands, labelled from the youngest, J6, to the oldest, J1. These strands alternate between shale-dominated (odd numbered) and BIF-dominated (even numbered) strands. The Dales Gorge Member is similarly subdivided into three units (DG3, youngest, down to DG1, oldest), and the Mount Newman Member is divided into the NE1 and NE2 units, with NE2 further subdivided into upper (N2U) and lower (N2L) strands. These units are illustrated in Figure 1.

Drillholes are interpreted by identifying strand units from the logged data including gamma logs, material type logging, assays, geological mapping and prior geological models, and the resulting interpretations are used to inform block modelling and hence resource estimation for the deposit (Sommerville et al., 2014). Interpretation thus is a critical step in the resource

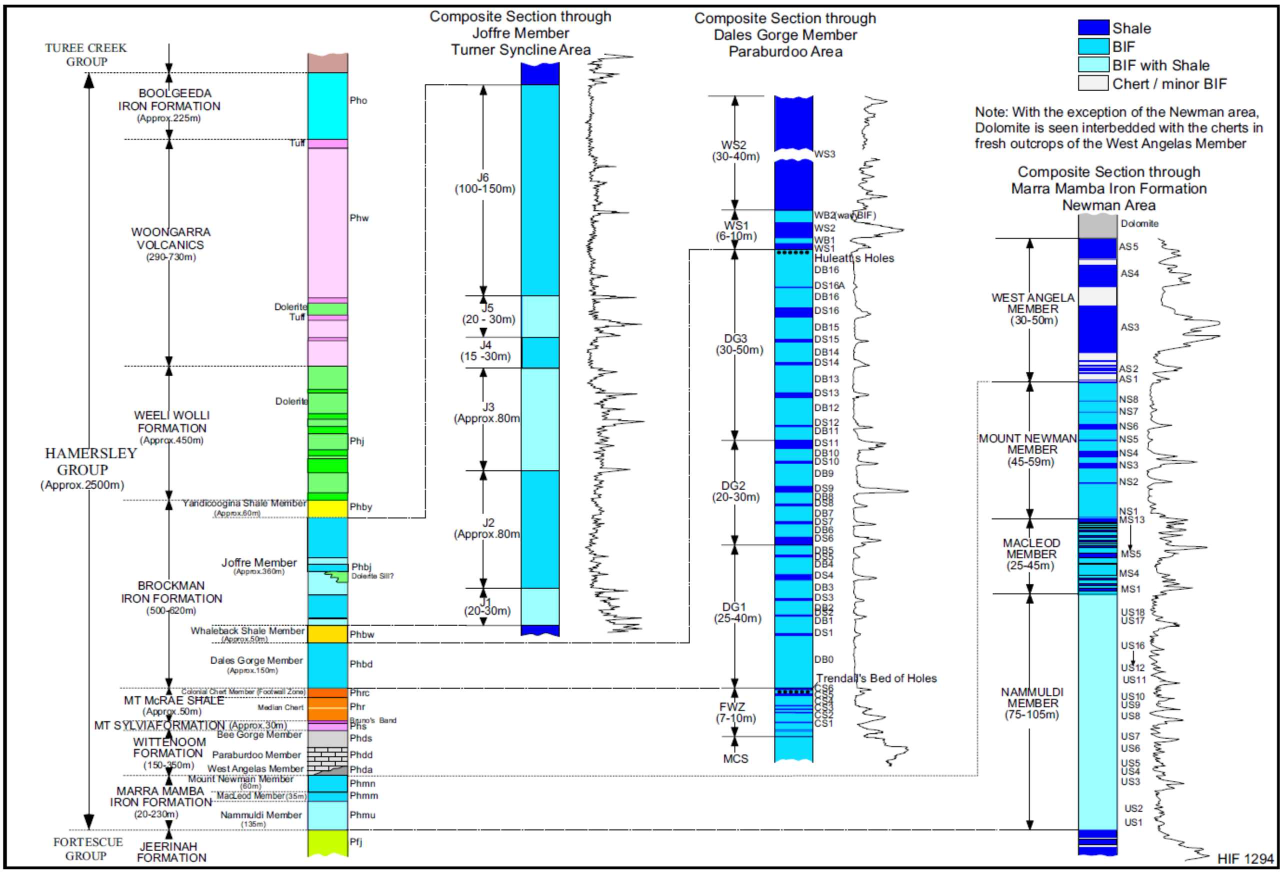

Figure 1. Stratigraphic units, subdivisions, and gamma responses for the Hamersley Group.

evaluation process. As the hundreds of kilometres of holes that are drilled annually need to be interpreted, the interpretation process is a significant processing bottleneck for block modelling. Additionally, during interpretation, users are presented with large quantities of data of various modalities per hole to process and integrate, and any inconsistencies or errors in interpretation directly affect the integrity of block modelling. We present a system combining novel machine learning and optimisation algorithms with user interaction to allow geologists to efficiently create strand interpretations from processing and integrating numerous modalities of drillhole data. The algorithms were trained on vast quantities of historically interpreted drillholes and operate rapidly and objectively. For each drillhole interval, the algorithms independently compute likelihood values for the interval's strand for each data modality, before combining them using an interactive weighting procedure. An optimisation step then determines the best assignments of strands to intervals, while honouring stratigraphic sequence and thickness constraints. The weights of each input dataset can be adjusted and the resulting optimal interpretation recalculated and presented to the user in real-time. The interpretation can be manually adjusted before accepting it for use in downstream modelling.

GAMMA PEAK IDENTIFICATION

Shale bands within the bedded strata emit gamma rays which are routinely logged at 10cm spacing as part of the drilling process. One characteristic of the gamma readings is the consistency of responses from specific shale bands across the Pilbara, even when separated by hundreds of kilometres (Dentith, 1994). Thus, by identifying specific gamma responses, or signatures, within a log, strands within the sequence can be identified. Although these gamma signatures are transformed due to faulting, folding and drilling down-dip, and are destroyed by geological processes such hydration, the gamma signatures are highly useful for modelling purposes (Jones, 1973; Kerr, 1994). In Figure 1, the strand sequence is shown with an aligned reference gamma signal, illustrating the peaks in the gamma response corresponding to narrow shale bands. Some distinctive features include the DS9 shale signature, which has a high magnitude response relative to other shale bands, the triple peaks in the gamma log for the DS6 and DS11 shales, and the twin NS3 and NS4 responses within the Mount Newman Member.

Several automated approaches have been proposed for identifying gamma signatures with specific application to shale bands in the Pilbara. Silversides et al. (2011) used Gaussian Processes to model and identify gamma signatures, and later used dynamic time warping (Silversides et al., 2015) to transform the log against a reference log. Nathan et al. (2017) modelled a gamma signature using a continuous profile model that jointly modelled uncertainty in the amplitude and alignment of a signature. In the proposed algorithm, an approach based on convolutional neural nets (ConvNets) is employed (LeCun, 2015).

GEOLOGICAL LOGGING

A second classifier is used to estimate strand likelihoods independently from the geological logging data. The logging summarises the composition for the interval in terms of material types, as recorded by a geologist on the drill rig from RC chip samples brought to the surface in 2 m intervals. Importantly, some material types provide geological context, whereas some material types may be chemically similar, their presence may be used to determine the stratigraphy, such as detritals versus bedded strata. Additionally, the logged percentage of each type may be useful, for example, the shale type on average has lower percentages logged per interval in mineralised bedded strands, compared to shale strands.

Thus, geological logging can be used as a basis for strand classification, and therefore interpretation. A second classifier has been developed, that classified strand likelihoods from geological logging, also using a neural net framework.

ASSAYS

Assay data is obtained from a second sample retrieved for each drilled 2m interval as previously described. This data is input into a third classifier to estimate strand likelihood values for each interval. In particular, one requirement was to use a soft classifier so that multiple strands can have high classifier outputs. For example, high grade mineralisation is not restricted to a single strand. Although theoretical assay values can be estimated from the material type logging, the same assay values can be represented by different material type combinations.

HISTORICAL MODEL AND SURFACE GEOLOGY

A fourth input utilises the existing geological mapping and model for the area. A surface geology map, recording observations from geological outcrops, can be used to constrain the interpretation to a specific strand for the first interval. The geological map may only record the outcropping unit to the member level rather than the strand level, for example, the area may be identified only as the Joffre Member rather than one of its component strands, in which case the first interval may be constrained to any strand within the Joffre Member, i.e. J1 through to J6.

LOGGED STRATIGRAPHY

A fifth input used is the logged stratigraphy for the interval. As the hole is being drilled, the geologist observes the member drilled for each 2m interval. This is commonly estimated from changes in the colour and texture of the recovered RC chips and other geological observations. For this input, the logged stratigraphy is retrieved for each interval, and all strands of this member are assigned a value of 1.0. The logged stratigraphy may only identify a member rather than its component strand, in which case values are assigned to all component strands.

INTERPRETATION

Strand interpretation combines the outputs from the above classifiers by weighting and summing them to produce a single likelihood output that is used in the interpretation step. This is demonstrated in Figure 2. The weights are specified by the user interactively using the weighting polygon shown in Figure 2f. Each individual classifier is represented by one polygon vertex and weights are selected by positioning a cursor within the polygon. Initially, each component is equally weighted by placing the cursor at the centre of the polygon, and the result of equally weighting the classifiers shown in Figures 2a-e is shown in Figure 2g. Placing the cursor directly over one vertex sets the single classifier output equal to the individual classifier output corresponding to that vertex. Placing the cursor on the edge joining two polygon vertices linearly adjusts the weights of the corresponding component classifiers according to the distance from the vertices. Placing the cursor elsewhere within the polygon weights each individual classifier according to the distance from the cursor to each vertex. Additionally, individual classifiers can be toggled on or off, and the ordering of the vertices can be changed to allow different pairs of classifiers to be weighted preferentially. It is important that the weights are selected such that the historical geological model component does not dominate, as this would create a bias towards the existing model.

The weighted classifier outputs are used as input for the sequence interpretation step, in which a strand is assigned to each interval according to stratigraphic constraints, including the strand sequence and strand thickness.

Although the stratigraphic sequence shown in Figure 1 illustrates the depositional order, geological processes such as faulting and folding cause local changes to the sequence. Further, a dolerite dyke exists that is not shown in the sequence. Therefore, when interpreting the sequence, strands cannot be assumed to appear in a fixed order. Faulting may result in sections of the sequence being repeated or missing, whereas overturning can cause the sequence to be inverted. During interpretation, if the dolerite dyke is observed, the interpretation records the same strand on either side of the dyke.

Further to the sequence constraints, each strand has a thickness range estimated from geological measurements (Trendall and Blockley, 1970). However, drilling down dip can cause the apparent thickness of a strand to increase significantly.

To handle these unique constraints, a novel dynamic programming algorithm was developed to optimise the allocation of intervals to strands that maximises the sum of the weighted classifier outputs for all intervals. The optimisation is subject to numerous constraints, including minimum and maximum strand thicknesses, stratigraphic sequence constraints including variations in the sequence due to faulting and folding; the presence of detritals overlying any bedded member, and further manual adjustments to constrain the interpretation to a specific strand at a specific depth. The resulting algorithm runs in real-time, allowing for interactive editing of extra manual constraints to adjust the interpretation.

RESULTS

We compared the manually-interpreted strand and the algorithm-interpreted strand for each interval and constructed a confusion matrix, shown in Figure 3. The brightness of each entry is proportional to the number of intervals corresponding to that manually-interpreted strand/algorithm-interpreted strand pair. In the ideal case where the algorithm-interpreted strand matches the manually-interpreted strand for every interval, all entries will lie on the diagonal. However, it is important to remember that the manual interpretations are interpretations rather than the ground truth.

In our evaluation dataset of 11429 intervals from 394 drillholes, the algorithm's interpretation was exactly the same as the manual interpretation for 7783 intervals (68.1%). Apart from DET (indicating surface detrital material) and DOR (dolerite dyke), strands are shown in order of increasing depth (and hence age). The main confusion was where the manual interpretation was YS and the algorithm's interpretation suggested the following J6 strand instead (307 intervals), which was roughly double the number of YS intervals correctly classified (177 intervals). The primary reason for this is likely due to the quantity of YS training data for the classifiers (far more training data is available for older/lower strands in the sequence). Another prominent confusion is WS1 mis-interpreted as DG3 in 189 intervals. Considering this confusion of adjacent strands, and the common practice of a geologist adjusting a strand's boundary up or down to provide more consistent interpretations with surrounding drillholes, a more appropriate measure is the percentage of intervals with an interpretation matching the preceding, same or following strand in the stratigraphic sequence. In terms of the confusion matrix, this is the sum of entries lying on or adjacent to the main diagonal (i.e. r = c, or r = c±1 for row r and column c) with the exception of the non-bedded strands DET and DOR. This gives a value of 9821 or 85.93% of intervals.

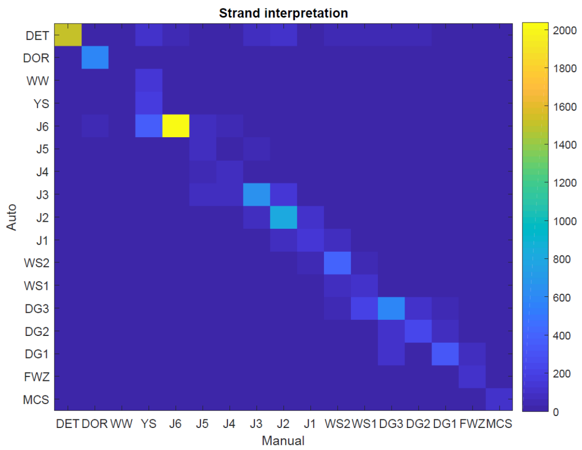

Figure 3. Confusion matrix for manually-interpreted and automatically-interpreted intervals.

CONCLUSIONS

We have introduced a system for processing geoscientific data logged in exploration drillholes, by independently applying classifiers to each dataset, then applying a novel algorithm for producing geological interpretations of the data best satisfying stratigraphic sequence and thickness constraints. Comparisons of the algorithm's interpretations with manual interpretations demonstrated large similarities at an interval-by-interval level, particularly when considering that strand contacts are commonly moved up and down for consistency with surrounding holes as is common practice in geological interpretation. These results demonstrate that the resulting drillhole interpretations are comparable with interpretations of the drillholes produced manually, while being faster and objective.

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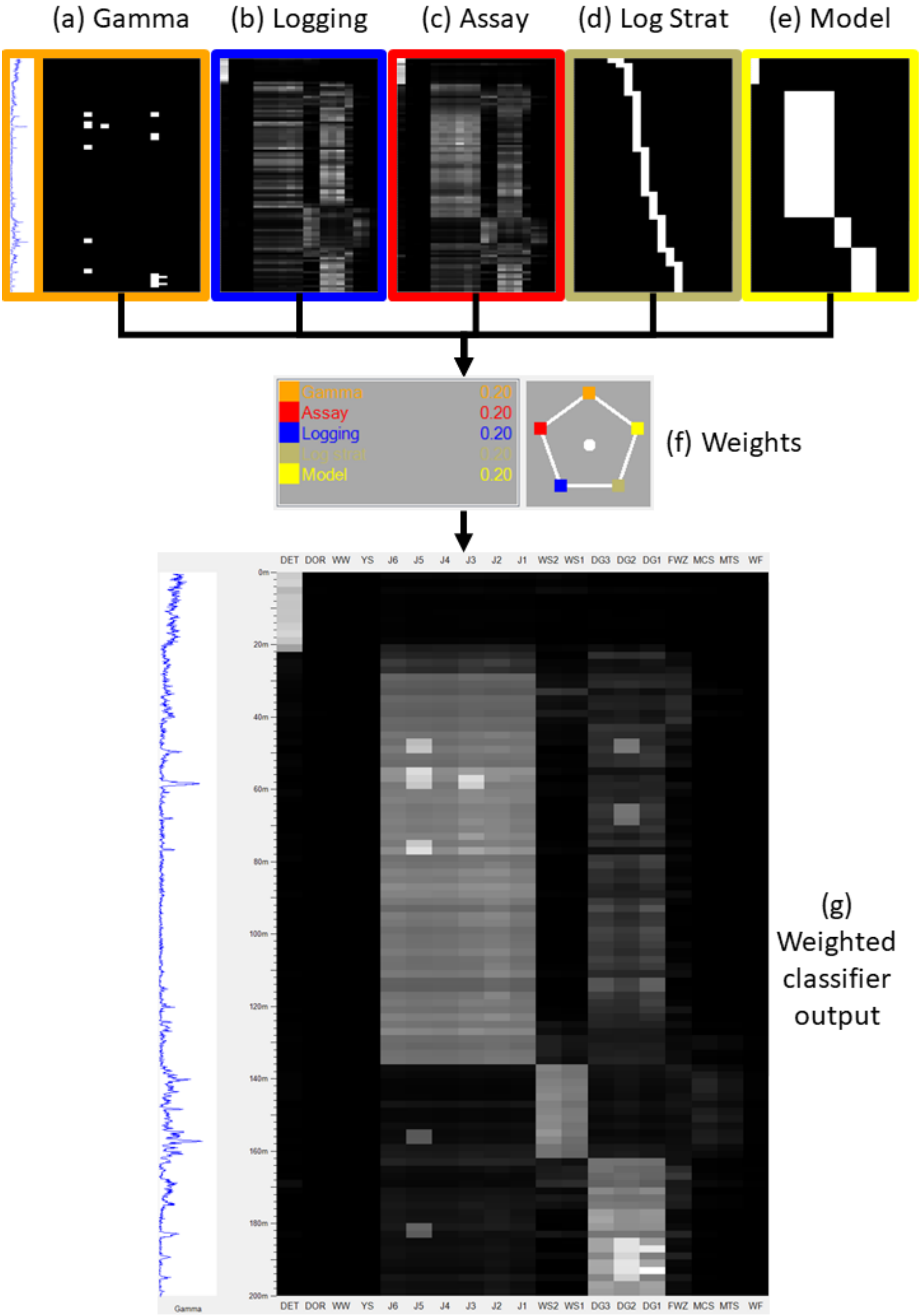

Figure 2. Classifier outputs and weighting to produce a weighted classifier output. Brighter values indicate a higher classifier response for that interval's logging for that strand.