IMPROVEMENT TO GRADE CONTROL IN OPEN CUT MINING

TECHNICAL FIELD

The present disclosure relates to an improved method for grade control and analysis of blasthole cones in open cut mining.

BACKGROUND

Open cut mining involves drilling blastholes and conducting blasting to produce blasted rock that can then be processed to arrive at a mineral ore, such as iron ore.

Obviously, it is expensive and undesirable to drill and blast rock that does not contain a desired grade, i.e., a desired concentration, of mineral ore or may contain hazardous materials, e.g., asbestos-like substances.

Consequently, over the years many different approaches have been used to determine underground regions that are likely to contain desirable ore properties including the quantity and quality of ore, the lumps to fines ratio of iron ore and the relative distribution of the ore underground.

One approach to investigating the properties of underground regions is to conduct exploratory drilling. Core samples obtained through exploratory drilling can be analysed. In more recent years, data from blasthole drilling has also been collected and analysed and may be combined with exploratory drilling data to obtain a clear picture of the morphology of underground ore bearing regions or “geozones” as they may sometimes be called.

Figure 1 depicts a drilling rig 1, drilling a grid of blastholes into a bench 3. Blasthole cones 5 are conical mounds left atop the blastholes post-drilling but pre-blasting. As

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cones 5 are constructed from blasthole material that is displaced by a drill of the drilling rig 1 during the drilling, sampling of one or more of the cones 5 can provide insights into underground ore properties including the quantity and quality of ore, the lumps to fines ratio of iron ore, and the relative distribution of the ore underground.

Blasthole cones hold grade information about the ore quantity and quality held underground within the bench and if well-formed, sampling of blasthole cone material can accurately indicate underground rock and ore layering.

Samples are typically collected from the blasthole cones by shovels, scoops, or hand-held augers. If the samples are taken accurately, and from a well-formed cone, then the samples can represent the underground layers of ore and rock in a manner that is inverted from the real layers. That is, rock layers of the blasthole that are close to the surface are represented at the bottom of the cone whereas deeper rock layers are represented at the top of the cone.

Such sampling of blasthole cones functions similarly to the core samples obtained during the exploration stage but is essentially a free by-product of the blasthole drilling process. Unlike the exploration core samples, the blastholes are drilled for the blasting procedure and thus the resultant cones are not always well formed or accurate indicators of the underground rock layers.

Nevertheless, sampling from well-formed blasthole cones provides grade control information that geologists can make use of to ensure the correct quality and quantity of minerals are extracted and in the most profitable ways possible. Additionally, information gleaned from sampling blasthole cones may enable previously made geological maps from the exploration stage to be updated and corrected.

However, the quality of the information obtained from blasthole cone samples can vary significantly, complicating the sampling process. It has been observed that in some situations samples from some blasthole cones do not provide a good indication of the underlying ore grade. Geologists may inadvertently spend significant time taking

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samples from blasthole cones which do not provide valuable insights as to the underlying geological characteristics for grade controls purposes.

It would be desirable if a solution were provided that assisted in obtaining samples from blasthole cones that would be likely to provide accurate information as to the underlying geological characteristics for grade control purposes.

SUMMARY

According to a first aspect of the present disclosure there is provided a method for improving ore grade control in open cut mining, the method comprising:

acquiring sensing data of a surface of a bench of a mine bearing blasthole cones;

processing the sensing data to produce classifier input data that is compliant with input requirements of a trained classifier;

operating the trained classifier to process the classifier input data to thereby classify the blasthole cones into at least two classes wherein one of said classes comprises a class of blasthole cones suitable for sampling to better indicate underlying geological characteristics of the bench relative to blasthole cones of other of the at least two classes.

In an embodiment the method includes acquiring the sensing data using a sensing assembly.

In an embodiment the sensing assembly includes a sensor on a drill.

In an embodiment the method includes acquiring remote sensing data of the surface of the bench of the mine bearing blasthole cones.

In an embodiment the method includes acquiring the remote sensing data using a vehicle having a remote sensing assembly.

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In an embodiment the remote sensing assembly comprises a LiDAR and/or a RADAR and/or a sonar.

In an embodiment the remote sensing assembly includes a camera.

In an embodiment the remote sensing data includes 3D point cloud data.

In an embodiment the remote sensing data includes images of the bench acquired by the camera.

In an embodiment the vehicle comprises a terrestrial vehicle.

In an embodiment the vehicle comprises an aerial vehicle.

In an embodiment the method includes training an untrained classifier to thereby produce the trained classifier.

In an embodiment the trained classifier comprises a 2D classifier and the method includes training an untrained 2D classifier to thereby produce the trained 2D classifier.

In an embodiment the method includes processing the 3D point cloud data to produce 2D images of blasthole cones.

In an embodiment 2D images of a blasthole cone are indicated to be “perfect” or “imperfect” wherein blasthole cones indicated to be perfect belong to the class of blasthole cones suitable for sampling to better indicate underlying geological characteristics of the bench.

In an embodiment a 2D image of a blasthole cone is indicated to be “perfect” or “imperfect” by manually labelling it as such wherein a “perfect” blasthole cone is generally symmetrical about a central blasthole when viewed from above.

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In an embodiment the manually labelling of a 2D image of a blasthole cone includes specifying coordinates of a bounding box thereabout.

In an embodiment training the untrained 2D classifier includes inputting the 2D images of the blastholes with coordinates of the bounding boxes and perfect/imperfect labels to the untrained 2D classifier to thereby produce the trained 2D classifier.

In an embodiment the 2D images are produced from the 3D point cloud data via a meshing procedure which produces a 3D point cloud mesh corresponding to the 3D point cloud data.

In an embodiment the method includes processing the 3D point cloud mesh to produce a 2D height map of the bench.

In an embodiment the 2D height map is produced by transforming Z-coordinates of the 3D point cloud mesh into a color to thereby ensure that all blasthole cones are visible in the 2D height map.

In an embodiment the 2D height map of the bench is split into a number of images.

In an embodiment each of the number of images contains 10-20 blasthole cones.

In an embodiment the method includes augmenting the number of labelled cones to increase the number of labelled cones available for the training of the untrained 2D classifier.

In an embodiment the trained classifier comprises a 3D classifier and the method includes training an untrained 3D classifier to thereby produce the trained 3D classifier.

In an embodiment the method includes processing the 3D point cloud data of an overall bench to produce 3D point clouds of blasthole cones of the bench.

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In an embodiment the method includes meshing the 3D point cloud data of the overall bench to create a 3D mesh of the overall bench and then separating 3D blasthole cone meshes from the 3D mesh of the overall bench.

In an embodiment the method includes manually classifying the 3D blasthole cone meshes as “perfect” or “tailless asymmetric” or “asymmetric with tail” wherein blasthole cone meshes indicated to be perfect are symmetric about a central blasthole and correspond to blasthole cones of the class of blasthole cones suitable for sampling to better indicate underlying geological characteristics of the bench.

In an embodiment each 3D blasthole cone mesh is initially indicated to be “perfect” or “imperfect” by manually labelling it as such wherein a “perfect” blasthole cone is generally symmetrical about a central blasthole when viewed from above.

In an embodiment subsequent to manually labelling each 3D blasthole cone mesh as “perfect” or “imperfect” the “imperfect” 3D point clouds of blasthole cones are further classified as being “tailless asymmetric” or “asymmetric with tail” to produce a trinary classification of “perfect”, “tailless asymmetric” or “asymmetric with tail”.

In an embodiment the method includes sampling each of the separated 3D blasthole cone meshes to thereby produce corresponding point 3D blasthole point clouds for inputting to the 3D classifier at varying sampling resolutions.

In an embodiment the training of the untrained 3D classifier is varied by changing the sample points from each cone and/or changing batch size of 3D blasthole point cones and/or changing training epochs with the objective producing an optimal trained 3D classifier.

In an embodiment the method includes applying a jitter function to slightly vary the 3D blasthole cone point clouds on each training epoch to thereby vary the point coordinates of the 3D blasthole cone point clouds to cause the 3D classifier to train on varied 3D blasthole cone point clouds every epoch.

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In an embodiment the method includes providing identification of blasthole cones deemed to be in the class of blasthole cones suitable for sampling to better indicate underlying geological characteristics of the bench relative to blasthole cones of other of the at least two classes, wherein the identification of said blasthole cones is provided to a worker for sampling of the identified blasthole cones for ore grade control purposes.

According to a further aspect of the present disclosure there is provided a system for improving ore grade control in open cut mining, the system comprising:

a sensing assembly arranged to sense a surface of a bench of a mine bearing blasthole cones;

a data processing assembly arranged to process sensing data generated by the sensing assembly in respect of the surface of the bench of the mine bearing the blasthole cones to thereby produce classifier input data that is compliant with input requirements of a trained classifier; and

the trained classifier, wherein the trained classifier is configured to classify the classifier input data to thereby classify the blasthole cones into at least two classes wherein one of said classes comprises a class of blasthole cones suitable for sampling to better indicate underlying geological characteristics of the bench relative to blasthole cones of other of the at least two classes.

In an embodiment the sensing assembly comprises a remote sensing assembly arranged to remotely sense a surface of a bench of a mine bearing blasthole cones.

In an embodiment the data processing assembly is arranged to process remote sensing data generated by the remote sensing assembly in respect of the bench of the mine bearing the blasthole cones to thereby produce classifier input data that is compliant with input requirements of a trained classifier.

According to another aspect of the present disclosure there is provided a method for improving ore grade control in open cut mining, the method comprising:

acquiring sensing data of a surface of a bench of a mine bearing blasthole cones;

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processing the sensing data to thereby classify one or more portions of the blasthole cones into at least two categories wherein one of said categories comprises a category of blasthole cones suitable for sampling to better indicate underlying geological characteristics of the bench relative to blasthole cones of other of the at least two categories.

According to another aspect of the present disclosure there is provided a method for analysing blasthole cones in open cut mining, the method comprising:

acquiring sensing data of a surface of a bench of a mine bearing blasthole cones;

processing the sensing data to thereby classify one or more portions of the blasthole cones into at least two categories wherein one of said categories comprises a category of blasthole cones to better indicate underlying geological characteristics of the bench and/or equipment characteristics and/or drilling parameters relative to blasthole cones of the other of the at least two categories.

In an embodiment the categories may comprise classes for a trained classifier or groups based on statistical or direct measurements.

According to another aspect of the present disclosure there is provided a system for improving ore grade control in open cut mining, the system comprising:

a sensing assembly arranged to sense a surface of a bench of a mine bearing blasthole cones;

a data processing assembly arranged to process sensing data generated by the sensing assembly in respect of the surface of the bench of the mine bearing the blasthole cones to thereby classify one or more portions of the blasthole cones into at least two categories wherein one of said categories comprises a category of blasthole cones suitable for sampling to better indicate underlying geological characteristics of the bench relative to blasthole cones of other of the at least two categories.

According to another aspect of the present disclosure there is provided a system for analysing blasthole cones in open cut mining, the system comprising:

a sensing assembly arranged to sense a surface of a bench of a mine bearing blasthole cones;

a data processing assembly arranged to process sensing data generated by the sensing assembly in respect of the surface of the bench of the mine bearing the blasthole cones to thereby classify one or more portions of the blasthole cones into at least two categories wherein one of said categories comprises a category of blasthole cones to better indicate underlying geological characteristics of the bench and/or equipment characteristics and/or drilling parameters relative to blasthole cones of the other of the at least two categories.

According to another aspect of the present disclosure there is provided a method for analysing blasthole cones in open cut mining, the method comprising:

acquiring sensing data of a surface of a bench of a mine bearing blasthole cones;

processing the sensing data to thereby classify one or more portions of the blasthole cones into one or more categories wherein one of said categories comprises a category of blasthole cones to indicate underlying geological characteristics of the bench and/or equipment characteristics and/or drilling parameters.

According to another aspect of the present disclosure there is provided a system for analysing blasthole cones in open cut mining, the system comprising:

a sensing assembly arranged to sense a surface of a bench of a mine bearing blasthole cones;

a data processing assembly arranged to process sensing data generated by the sensing assembly in respect of the surface of the bench of the mine bearing the blasthole cones to thereby classify one or more portions of the blasthole cones into one or more categories wherein one of said categories comprises a category of blasthole cones to indicate underlying geological characteristics of the bench and/or equipment characteristics and/or drilling parameters.

BRIEF DESCRIPTION OF THE DRAWINGS

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Preferred features, embodiments and variations of the disclosure may be discerned from the following Detailed Description which provides sufficient information for those skilled in the art to perform the various aspects and embodiments of the disclosure. The Detailed Description is not to be regarded as limiting the scope of the preceding Summary in any way. The Detailed Description will make reference to a number of drawings as follows:

Figure 1 depicts a drilling rig drilling blastholes into a bench and resultant blasthole cones.

Figure 2 is a block diagram of an autonomous unmanned vehicle (AUV) being an aerial drone equipped with remote sensing assemblies in the form of a LiDAR assembly and a camera.

Figure 3 depicts the AUV flying over a bench containing blasthole cones and acquiring remote sensing data in the form of LiDAR point cloud data and camera images.

Figure 3A depicts a terrestrial AUV travelling over a bench containing blasthole cones and acquiring remote sensing data in the form of LiDAR point cloud data and camera images.

Figure 4 is a top plan view of a blasthole cone which is generally symmetrical about a central blasthole and which may be referred to as a “symmetrical” or “perfect” blasthole cone.

Figure 5 is a top plan view of a blasthole cone which is asymmetrical and which may be referred to as “tailless asymmetrical” or “untailed asymmetrical” or “imperfect”.

Figure 6 is a top plan view of a blasthole cone which is asymmetrical and which has a generally radially extending portion and which may be referred to as “tailed asymmetrical” or “imperfect”.

Figure 7 is a flowchart of a method for acquiring and processing 3D point cloud data and camera images of a bench to create a 3D mesh with color from the images.

Figure 8 is a flowchart of a method for producing a set of augmented 2D images of cones and an accompanying text file of cone classifications and bounding box coordinates for bounding boxes of the cones.

Figure 9 is a 2D image of blasthole cones with bounding boxes around the blasthole cones.

Figure 10 is a flowchart of a method for producing an augmented training set of labelled cone point clouds from a 3D bench point cloud 3D mesh.

Figure 11 depicts a blasthole cone point cloud comprised of 1024 sample points.

Figure 12 depicts a blasthole cone point cloud comprised of 2048 sample points.

Figure 13 depicts a blasthole cone point cloud comprised of 4096 sample points.

Figure 14 is a flowchart of a method for training a 2D classifier.

Figure 15 is a flowchart of a method for classifying images of blasthole cones with a trained 2D classifier.

Figure 16 is a flowchart of a method for training a 3D classifier with labelled 3D blasthole cone point clouds.

Figure 17 is a flowchart of a method for classifying 3D blasthole cone point clouds into one of three classes.

DETAILED DESCRIPTION OF PREFERRED EMBODIMENTS

One known way in which blasthole cone sampling is performed is through the use of a sampling tube or auger. It is also known to use a radial bucket method and a radial channel method as discussed in F. Pitard, *Theory of Sampling and Sampling Practice*. Taylor & Francis Group, 2019, for example.

Accurate sampling from blasthole cones is complicated as the blasthole cones can vary significantly in shape and geometry. This is due mainly to different underlying

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geology, poor drilling practices, equipment faults, curtain failures, groundwater, and weathering effects from wind.

Blasthole cones may vary in shape for a multitude of factors, even despite them all being formed of blastholes that are equal in depth, diameter and drilled from the same drilling rig.

Different material compositions have been observed to produce different cone shapes and weathering effects affect fines more than they do lumps, leading to an overestimation of grade quality which suggests the bench is more profitable than it actually is.

The inventor has conceived of a method to locate blasthole cones, amongst a large number of blasthole cones of a blasthole drilled bench, which are preferable to sample for purposes of ascertaining an understanding of the geological characteristics, such as ore grade, of underlying regions. The method may also be used to locate blasthole cones which are preferable to sample for purposes of ascertaining an understanding of the equipment characteristics, such as age and wear or equipment failures or faults, and/or drilling process, practices and parameters, such as over or under use of water and suitability of the drilling parameters.

In overview, in one embodiment, the method involves sensing blasthole cones of a bench to acquire sensed blasthole cone data, for example by using a sensor located on the drill.

In another embodiment, the method involves remote sensing blasthole cones of a bench to acquire remotely sensed blasthole cone data, for example by using a terrestrial vehicle, an aircraft or potentially a satellite.

For example, remotely sensed blasthole cone data may include data collected with an Autonomous Unmanned Vehicle (AUV) such as an aerial drone or ground-based robot, mounted with a LiDAR sensor and a camera. A block diagram of an exemplary aerial drone 17 is shown in Figure 2.

The aerial drone 17 is comprised of a body 11 about which four motor and propeller assemblies 10 are mounted. Mounted within the body 11 is a suitably programmed microcontroller 12 which interacts with a number of peripheral assemblies including:

1) A data storage assembly 9, such as a solid state drive for storing data such as GPS data, remote sensing data such as LiDAR point cloud data and, photographic images.
2) Flight sensors 13, such as one or more accelerometers, altitude sensor, attitude sensors etc as are conventionally used in commercially available drones.
3) LiDAR assembly 16. LiDAR is an acronym for Light Detection and Ranging. LiDAR works by transmitting laser radiation pulses which are reflected back by external surfaces. By recording the return time of the pulses, a ‘point’ of three-dimensional coordinates can be established for the location on the surface at which the pulse was reflected. Together, many of these points form a ‘point cloud’. The slower the AUV, e.g. drone 17, traverses the field of interest, the greater the density of the resulting point cloud and thus the more accurately the point cloud represents objects that present the surfaces from which the laser radiation pulses are reflected.
4) Camera 7 may be operated by the microcontroller 12 to take terrain images and those images may then be stored in data storage 9.
5) Battery and power management assembly 18 which includes rechargeable batteries for powering the drone and suitable circuitry for managing the discharge and charging of the batteries and monitoring charge level.
6) Motor controller assembly 20, which typically includes power transistors for switching power from the battery and power management assembly 18 to the motor and propeller assemblies 10 under control of microcontroller 12. The motor controller assembly 20 will typically also provide feedback signals from the motor and propeller assemblies 10 back to microcontroller 12. For example, the motor and propeller assemblies 10 may be configured to generate signals such as rotor speed that indicate that the motor and propeller assemblies are operating correctly.

7) GPS assembly 15 generates positional data which the microcontroller 12 may use for logging the drone's position and staying on a predetermined flight path. Accordingly, the positions at which images are made by the camera 7 and points are collected by the LiDAR may be recorded in data storage 11.

A terrestrial drone, such as drone 17a of Figure 3A is very similar except that rather than having flight sensors and propellers it has ground sensors and motorised wheels.

The AUV, in the form of aerial drone 17, traverses slowly over bench 3 as illustrated in Figure 3 operating its LiDAR sensors to produce an overall point cloud of the bench 3 with blasthole cones 5, which it stores in a suitable data storage assembly such as onboard data storage 9. Aerial drone 17 may also take images of the bench with camera 7 which are similarly stored in onboard data storage 9. It will be realised that depending on available wireless connectivity, in some embodiments the captured data may be transmitted directly to a remote data storage assembly.

As an optional precursor to training one or more pattern classifiers, the image of the blasthole cones of the bench is then pre-processed, including demarcating, and labelling each blasthole cone as being "perfect" or "imperfect", where a "perfect" blasthole cone is symmetrical when viewed from above, whereas an "imperfect" blasthole cone is asymmetrical. It will be realised that more than one image of the blasthole cones of the bench may be used.

In some embodiments the imperfect blasthole cone images are further labelled as being either "imperfect tailed" or "imperfect tailless" so that the blasthole cone images are labelled as being one of "perfect", "imperfect tailed" and "imperfect tailless".

The labelled blasthole cone images are used to train one or more pattern classifiers. As will be discussed in more detail, in one embodiment a 2D pattern classifier is trained. In another embodiment a 3D pattern classifier is trained.

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A test image of a bench of blasthole cones may be pre-processed and then applied to one or more of the trained pattern classifiers for automatic classification of the blasthole cones as being “perfect” or “imperfect”. Depending on the type of pattern classifier and how it has been trained it may classify each blasthole cone as being either “perfect”, “imperfect tailless” or “imperfect tailed”. Figure 4 is a top plan view of a perfectly symmetric blasthole cone 19 formed around a blasthole 21. In contrast Figure 5 is a top plan view of an imperfect tailless blasthole cone 23 and Figure 6 is a top plan view of an imperfect tailed blasthole cone 25.

The ‘symmetric cone’ 21 is characterised by a top view circular shape. In general, these symmetric blasthole cones should be relatively well formed with no protrusions or irregular shaping. Symmetric cones are typically found to produce better samples for the geologists and can hence be also described as ‘perfect cones’ for binary classifications.

Tailless asymmetric blasthole condes such as blasthole cone 23 of Figure 5 have a clear non-circular shape which from above may appear elliptical, jagged or amorphous.

Figure 6 depicts a top view of a blasthole cone 25, which includes a tail 27 and which is an example of a ‘tailed asymmetric cone’. Tailed asymmetric blasthole cones clearly have pronounced tail-like features extending generally radially from the central blasthole 19 and so constitute a class of blasthole cone that is different to both the perfectly symmetric blasthole cone and the tailless asymmetric blasthole cone. Both types of asymmetric cones, i.e. tailed and tailless, can be described as ‘imperfect cones’ for binary classification purposes.

A sampler, that may be a geologist or automated/semi-automated sampling machine, may be provided with the classified blasthole cone images, which include the location and classification type of each blasthole, and/or the blasthole cone image labels. Substantial time can then be saved by the sampler only sampling from preferred blasthole cones, such as those labelled “perfect”.

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The “perfect” blasthole cones are those whose layers correspond well, though inversely with respect to height, to the layers of the blasthole and are typically circular in top plan view, such as blasthole cone 21 of Figure 4. Accordingly, the top layer of a perfect blasthole cone is comprised of material from the bottom layer surrounding the bottom of the blasthole and correspondingly the bottom layer of a perfect blasthole cone is comprised of material from the top layer surrounding the top of the blasthole cone.

In an embodiment, blasthole cone data from the blasthole cones may be provided to a model (such as a short-term model) to provide additional insight and analysis from biased data or non-ideal data from those blasthole cones.

In one embodiment, the blasthole cone data from the blasthole cones is provided to a short-term model which may calculate, determine or receive characteristics of the blasthole cone samples. These characteristics may include weight, asymmetry, uncertainty and/or importance of the blasthole cone samples. In a further embodiment, the short-term model may compare the blasthole cone data between blasthole cone samples and take into account any characteristics (if appropriate and/or available) of the blasthole cone samples and data in the modelling process.

In an example of the above, the model incorporating the blasthole cone data is able to use biased (or non-ideal) data from poorly formed/imperfect cones to still be used for modelling geological characteristics with conditions applied based on the characteristics, rather than that data from the imperfect cones being discarded entirely.

Preferred methods for the implementation of two deep learning procedures will be explained. Preferably the YOLOv5 classifier is used for 2D object detection and the PointNet classifier is used for 3D object classification. However, it will be appreciated that other classifiers, or other statistical or machine learning methods, may be used for categorisation such as 2D object detection and 3D object classification.

The input to the YOLOv5 model is a 2D bitmap image. Hence, a level of data preparation is required to convert the point cloud meshes into bitmap format that is

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suitable for inputting to the YOLOv5 classifier. Once passing through the YOLOv5 classifier, the expected output is the same bitmap image but with all blasthole cones localised and identified through means of a bounding box and label.

The input to the PointNet classifier is a 3D point cloud of each individual blasthole cone. Upon passing through a suitably trained PointNet model, a classification of the cone will be provided. As the point clouds contain 3D information as opposed to the images which contain 2D information, the Inventor expected that the PointNet model would identify more distinct features of the blasthole cones and so expected that the PointNet model would be more accurate than the YOLOv5 model in classifying blasthole cones.

When considering 2D object detection, which involves acquiring a 2D birds-eye view image of the cones, it can be seen that the distinction between these three classes may not always be entirely clear. Therefore, 2D object detection will use the perfect/imperfect dichotomy to achieve a binary object detection of the blasthole cones.

On the other hand, with 3D object classification, which takes in the entire 3D mesh, more distinguishing features are available for the algorithm. Hence, for the 3D classifier initially a simpler binary classification model will be established before a trinary classification model following the symmetric, tailless asymmetric and tailed asymmetric.

Figure 7 is a flowchart of a preferred method for processing 3D data, such as data acquired by a LiDAR. At box 100 mine site data is collected, for example by flying drone 17 over bench 3 (Figure 3) to collect point cloud data and terrain images using onboard LiDAR assembly 16 and camera 7. The 3D point cloud data 102 and terrain images 104 are retrieved from data storage assembly 9 once the drone 17 has landed.

At box 106 the 3D point cloud data is processed with a meshing procedure which triangulates the point cloud to produce a mesh 107. At box 108 color from the images 104 is applied to the mesh 107 to produce a 3D mesh with color from the images 104.

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In one example, the 3D point cloud data 102 and images 104 were acquired from a mining bench 3 that was approximately 185m wide and 85m deep and which contained a total of 270 different blasthole cones 5 (Figure 1). The data was of high quality and resolution due to a large number of LiDAR points and resulting relative detail of the mesh. With approximately 3000-6000 points forming each blast cone the LiDAR derived mesh with images of the cones, accurately represented the real-world equivalent and thus formed a solid base for training deep learning classifiers as will be explained.

The YOLOv5 classifier, which is ultimately used classify blasthole cone data, processes 2D bitmap images and requires pairs of image files with corresponding text files describing the coordinates and classification of all contained objects. The 2D data preparation consists of converting the point cloud meshes into 2D bitmap files with further preparation of labelling and augmentation required for the training process.

Figure 8 is a flowchart of a preferred method for converting a mesh into 2D images, which are suitable for processing by a 2D pattern classifier such as the YOLOv5 classifier. At box 112 the 3D point cloud mesh 107 of the bench 3 is processed to produce a 2D height map 114 of bench 3. Box 112 is implemented in the present preferred example by use of point cloud processing software ‘CloudCompare’ (https://www.cloudcompare.org/ retrieved 28 November 2023). The 2D height map 114 is produced at box 112 by simply transforming the Z-coordinates of the 3D mesh 107 into a colour based on a tuneable scale. In the presently described preferred example the desired scale ran from red to blue to white and was manually configured to ensure all blasthole cones were visible in the resulting 2D height map 114.

At box 116 the 2D height map 114 of the bench 3 was processed by splitting it to produce twenty separate 1024x480 bitmap images 118a,…,118n, each containing about 10-20 blasthole cones. At box 120 images 122a,…,122m with no objects (0 cones) were also produced in accordance with the ‘best training principles ’ advised on the YOLOv5 developer page.

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At box 124 bitmap images 118a,…,118n are processed using a labelling software product such as LabelImg (https://github.com/HumanSignal/labelImg retrieved 28 November 2023) which facilitates the manual labelling of each cone into as either “perfect” or “imperfect”. That is, as an imperfect cone such as a tailless asymmetric blasthole cone e.g. blasthole cone 23 of Fig. 5, or a tailed asymmetric blasthole cone 25 of Fig. 6, or as a perfect cone such as perfectly symmetric cone 21 of Figure 4. In this process, special care was taken to ensure the cones were correctly labelled in accordance with the full 3D original data and bounding boxes were accurately extended to contain the entirety of the cone shapes.

Box 124 generates a set 126 of images $2DImg_1,\ldots,2DImg_p$ of cones with bounding boxes about each labelled cone as shown in Figure 9. In Figure 9 an example image $2DImg_i$ is shown with bounding boxes 21a,..,21d around perfect cones, bounding boxes 23a,…,23f around imperfect cones (being tailless asymmetric cones) and bounding boxes 25a to 25d around further imperfect cones (being tailed asymmetric cones).

The manual labelling at box 124 also produces a set 128 of text files $tF_1,\ldots,tF_p$ that correspond to image files $2DImg_1,\ldots,2DImg_p$. Each text file tF_i contains, for each blasthole cone in corresponding image $2DImg_i$ a classification i.e. “perfect” or “imperfect” followed by four parameters setting out the bounding box coordinates for the blasthole cone. Consequently, by referring to text file tF_i and image $2DImg_i$
The location in the image of a blasthole cone, classification of the blasthole cone and 2D shape of the blasthole cone can be retrieved.

At box 130 the set of images 126 is augmented to increase the number of labelled cones available for subsequent training of the YOLOv5 classifier. The augmentations applied at box 130 include vertical flipping, two rotations 45 degrees in the clockwise and anticlockwise directions and after these, a grey-scale was performed to all images. Box 130 produces a set of augmented images 132 and a corresponding set of augmented text files 134. The augmentation process at box 130 multiplied the training sample size by a factor of eight to facilitate a more robust level of training of the YOLOv5 pattern classifier.

As previously mentioned, in contrast to the YOLOv5 classifier, the PointNet model, requires inputs in the form of individual point clouds, i.e. 3D data, for each blasthole cone.

Figure 10 is a flowchart of an exemplary method for processing bench mesh 110 (which was generated as previously discussed in relation to Figure 7).

At box 140 the CloudCompare software product was used to remove blasthole cone point cloud meshes one by one from the overall bench point mesh 110 and saved as individual blasthole cone meshes 142. This process was relatively time intensive and various methods to expedite the process were attempted without success. For example, it would make sense to remove the entire ground level from the bench point cloud mesh and then separate the cones from there, however, this did not work due to the fact that the ground level was not a flat plane but rather a hilly surface with changing inclines.

After the blasthole cone meshes are separated then, at box 144, they are manually classified as a perfect cone mesh (box 146) or an imperfect cone mesh (box 148).

At box 150 the cone meshes classified as imperfect are further classified into asymmetric with no tail (i.e. “tailless asymmetric”) and asymmetric with tail (i.e. “tailed asymmetric) to produce produced a trinary classification 152 of “perfect” 152a “imperfect no tail” 152b and “imperfect with tail” 152c classes.

As the PointNet 3D pattern classifier requires point cloud inputs, cone meshes 152a, 152b, 152c were then sampled at box 154 to create corresponding classified blasthole point clouds 160a, 160b, 160c. Additionally, augmentation was also applied (at box 162) to increase sample size by producing multiple different point cloud samples for each blasthole cone mesh, resulting in an augmented training set 164 of imperfect tailed, imperfect tailless and perfect cone point clouds 164a, 164b and 164c.

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The cone meshes may be sampled at different resolutions to create cone point clouds of differing densities. For example, Figure 11 illustrates a cone point cloud 160c-1 comprised of 1024 sample points. Figure 12 depicts a cone point cloud 160c-2 comprised of 2048 sample points and Figure 13 depicts a cone point cloud 160c-3 comprised of 4096 sample points.

Previously, it was explained with reference to Figure 8 and Figure 9, how LiDAR point cloud data and terrain images are preferably processed to produce a training set of augmented blasthole cone images and corresponding text files containing cone classification “perfect” or “imperfect” and bounding box coordinates that are suitable inputs for training a 2D pattern classifier such as the YOLOv5 classifier.

The YOLOv5 classifier was chosen for classifying blasthole cones as it can operate very quickly whilst still maintaining high levels of accuracy.

As previously mentioned, the YOLOv5 classifier requires images for input, in this case a top view bitmap image of the blasthole cones, for example as illustrated in Figure 9. The bitmap images are fed through a backbone, which is preferably the CSPDarknet53 backbone Convoluted Neural Network (CNN) for feature extraction.

The backbone CNN creates feature maps which when fused together, can accurately detect objects within an image. This detection process consists of first finding objects, creating bounding boxes around these objects, and then classifying them. The output will be the same image but with the objects localised and identified.

The YOLOv5 classifier was acquired via the YOLOv5 github page and Python 3.10.6 as well as Pytorch 2.0.0 were downloaded in accordance with the YOLOv5 requirements.

With reference to Figure 14, to enable the YOLOv5 model to train on the custom blasthole cone data, a configuration file was required, e.g. the text file 134 of augmented cone classifications and bounding box coordinates of Figure 8. This file

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outlined the two classes Perfect, and Imperfect and referenced the file location of the cone image-label pairs 132

The implemented model also utilised a pre-trained YOLOv5s classifier which has been pre-trained on the Common Objects in Context (COCO) dataset to a mean Average Precision (mAP) of 56.8%. The COCO dataset contains 80 separate classes of everyday items ranging from cars to cats to cakes. In particular, some classes such as potted plants, bowls, and vases may be of benefit when training the model to find the blasthole cones. Ultimately, by utilising this pre-trained classifier, the classifier will train faster at box 166 on the new blasthole cone data to produce a trained 2D classifier 168.

To verify the trained model, ‘unseen cones’, data not used in the training procedure, were utilised. These cones were obtained from sectioning off a portion of the overall bench for testing procedures only.

Figure 15 is a flowchart illustrating the processing of unseen cones, i.e. test images of cones 170 being classified at box 172 with the trained 2D classifier 168 to classify the test cones as “perfect” 174 or “imperfect” 176.

The data contained 182 imperfect and 88 perfect for a total of 270 blasthole cones. Through data augmentation, this increased to 656 perfect and 826 imperfect for a total of 1482 blasthole cones across 20 separate images. These images were then split into an approximate 80-10-10 split for training, validation and testing in accordance with the best training principles for the YOLO algorithm.

	Training	**Validation**	**Testing**	**Total**	**% of Total**
Perfect Cones	492	102	62	656	44.26
Imperfect Cones	628	70	128	826	55.74
Total	1120	172	190	1482 Total Cones	
% of Total	75.57	11.61	12.82		

The two main model parameters varied were the epochs and batch size. Batch size refers to the number of training samples per training period, in this example, a batch

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size of 2 would mean that two pictures are put together to train the model. The epochs is the number of training periods. Typically, a higher level of epochs leads to a better trained model with a higher accuracy, though this comes at the cost of training speed.

Each parameter was varied one at a time to best find the optimal values. Batch sizes tested include 2,4,8 and 10. Epochs tested included 20, 40, 60, 80 and 100.

Hyperparameters, such as learning rate, momentum, and warmup epochs, for model fine tuning were left untouched at their default values.

The PointNet classifier utilises CNNs to learn features about different 3D point clouds to best classify them into different and distinct classes. The PointNet classifier utilises the Adam algorithm as disclosed in "*Adam: A Method for Stochastic Optimization*" by Diederik Kingma and Jimmy Ba in ICLR 2015, to optimise training.

Additionally, the activation functions for the output layers was softmax for the trinary case and sigmoid for the binary case.

With reference to Figure 16, as the PointNet 3D classifier requires a point cloud input, the first step of the training procedure is the production of a point cloud sample from each cone, e.g. the augmented training set 164 of Figure 10. The PointNet classifier was trained through the PointNet architecture using the Keras library (described at https://keras.io/examples/vision/pointnet/ , retrieved 28/11/2023). Training (box 148) was varied by changing the sample points from each cone, as previously discussed with reference to Figures 11 to 13, changing the batch size, and changing the training epochs with the objective producing an optimal trained 3D classifier 150.

To verify the trained model, 'unseen cones', data (e.g. box 152 of Figure 17) not used in the training procedure, were utilised. These unseen, i.e. unclassified blasthole cone point clouds, were obtained from sectioning off a portion of the overall bench for testing procedures only.

For the trinary classification, there were 88 symmetric cones, 87 tailless asymmetric cones and 95 tailed asymmetric cones. For each of these classes, 5 cones were taken out for testing purposes. Data augmentation was utilised on the training cones by use of a jitter function to slightly change the cones on each training epoch. This jitter function worked by changing the point coordinates of the cones by small amounts which would lead to the model training on new cones every epoch.

For the PointNet classifier, there was no distinction made between testing (box 154 of Figure 17) and validation data. This is because the validation data in PointNet does not affect the training model like it does in YOLO. Hence, this validation data was essentially unseen data and was used for testing purposes to evaluate the model.

The trained PointNet classifier classified the input unclassified blasthole cone point clouds 152 into three classes being “Symmetric” 156, “Tailless Asymmetric” 158 and “Tailed Symmetric”, as set out in the following table, wherein the “Symmetric” class indicates blasthole cones which are preferable to sample for gleaning ore grade control characteristics.

	Training	Testing	Total	% of Total
Symmetric	78	10	88	32.59
Tailless Asymmetric	77	10	87	32.22
Tailed Symmetric	85	10	95	35.19
Total	240	30	270 Total Cones	
% of Total	88.89	11.11		

Three main parameters for the PointNet model were tested during training, the batch size, training epochs, and sample points.

Sample points are the number of points taken from each mesh to form a new point cloud. As the blasthole cone meshes all had around 2000-6000 triangles, a range of sample points were trialled at 1024, 2048 and 4096. As sample points increased, so would the training time.

The second parameter altered was the batch size of the model. As the training data set was quite small, batch size was started at 2 and gradually increased to 4, 8 and 16.

The third parameter changed was training epochs. The epochs started at 20 and moved to 40, 80 and 100.

Through training and testing, the best YOLOv5 model was found to have achieved a mean Average Precision of 98% and F1 score of 97%. This was achieved on a binary classification of perfect symmetrical cones and imperfect asymmetric cones. Overall, this result was found to be very promising and demonstrated a well-trained model.

The Area Under the Curve of the Receiver Operating Characteristic Curve (AUC-ROC) is a metric for object classification that tests the model at varying confidence thresholds. It does this by graphing the true positive rate against the false positive rate.

The true positive rate is essentially the portion of positives corrected detected:
TPR = TP/(TP+FN).

The false positive rate is essentially the portion of positives incorrectly detected:
FPR = FP/(FP+TN).

The F1 score provides an overall evaluation metric by calculating the harmonic mean of the precision and recall. This metric in effect shows the accuracy of the model whilst taking into account the class distributions.

F1Score = (Precision x Recall) / (Precision + Recall)

The best PointNet model was found to have a 80% AUC-ROC and 75.6% F1 score.

As the PointNet Model is a trinary classification model with each class size being similar, the F1 score random guess would be only 33% while the AUC-ROC random guess is 50%. Even though this does not reach the high levels of accuracy of the

YOLOv5 model, these results are still indicative of a model greatly improved by training.

It will be realised from the preceding description a preferred method for improving ore grade control in open cut mining has been described. In one aspect the method involves acquiring remote sensing data of a surface of a bench 3 bearing blasthole cones 5. The remote sensing data may be acquired by a vehicle such as an aerial drone 17 as illustrated for example in Figure 3 or a terrestrial drone 17a as illustrated in Figure 3A, which is equipped with a remote sensing assembly, for example LiDAR and/or a camera to produce remote sensing data in the form of point cloud data and/or camera images. The remote sensing data, for example 3D point cloud data 102 and images 104 (Figure 7) is processed to produce classifier input data that is compliant with input requirements of a trained classifier. For example, the classifier input data required for a trained 2D classifier, such as the YOLOv5 classifier (or as it may variously be called “model”) includes 2D images of a number of blasthole cones. In contrast the classifier input data for trained 3D classifier is comprised of 3D point clouds of blastholes. The trained classifier, e.g. trained 2D classifier 168 of Figure 14 or trained 3D classifier 184 of Figure 17 may be operated to process the classifier input data to thereby classify blasthole cones into at least two classes. In the case of the trained 2D classifier 168 the two classes are “perfect” blasthole cones and “imperfect” blasthole cones. The “perfect” blasthole cones are generally symmetrical in top view (e.g. generally circular) about a central blasthole whereas the “imperfect” blasthole cones are asymmetric and may have a tail. In the case of the trained 3D classifier the blasthole cones are classified into three classes being a “perfect” or “symmetric” class and two imperfect classes being a “tailed asymmetric” class and an “untailed” or “tailless” asymmetric class. The “perfect” or “symmetric” class comprises a class of blasthole cones suitable for sampling to better indicate underlying geological characteristics of the bench relative to blasthole cones of other of the at least two classes. Consequently, workers such as geologists can be directed to blastholes on the bench which are “perfect” or “symmetric” for them to perform sampling with confidence that samples from those blasthole cones will glean better information as to the underlying ore grade than if they took samples from the “imperfect” blasthole

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cones. Accordingly, time is saved and a more accurate knowledge of the underlying ore grade can be obtained.

In another aspect a system for improving ore grade control in open cut mining has been described. The system includes a remote sensing assembly arranged to remotely sense a surface of a bench of a mine bearing blasthole cones. For example, the remote sensing assembly may comprise a LiDAR and/or RADAR and/or sonar and/or camera that are mounted in a vehicle such as an aerial drone or a terrestrial drone and which is capable of travelling over a bench containing blasthole cones. The system also includes a data processing assembly, for example a processing assembly arranged to implement the processing methods which are described in the flowcharts of the Figures. The data processing assembly is arranged to process remote sensing data generated by the remote sensing assembly in respect of the bench of the mine bearing the blasthole cones to thereby produce classifier input data that is compliant with input requirements of a trained classifier. The system also includes the trained classifier, which is configured to classify the classifier input data to thereby classify the blasthole cones into at least two classes wherein one of said classes comprises a class of blasthole cones suitable for sampling to better indicate underlying geological characteristics of the bench relative to blasthole cones of other of the at least two classes.

In another aspect a system and method for improving ore grade control in open cut mining has been described. The method includes acquiring sensing data (that may be remote or not remote) of a surface of a bench of a mine bearing blasthole cones. The method may include processing the sensing data to produce input data that is compliant with input requirements and processing the input data to thereby classify one or more portions of the blasthole cones into at least two categories. The categories may represent classes for a trained classifier and/or groups based on statistical or direct measurements. One of the categories comprises a category of blasthole cones suitable for sampling to better indicate underlying geological characteristics of the bench relative to blasthole cones of other of the at least two categories.

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The above method may be implemented in a system by way of a sensing assembly and a data processing assembly, as described elsewhere. In particular, the system includes a sensing assembly arranged to sense a surface of a bench of a mine bearing blasthole cones. In addition, the system includes a data processing assembly. The data processing assembly is arranged so as to process sensing data generated by the sensing assembly and make classifications of the one or more portions of the blasthole cones. In this aspect, the data processing assembly is arranged to process sensing data generated by the sensing assembly in respect of the surface of the bench of the mine bearing the blasthole cones to thereby classify one or more portions of the blasthole cones into at least two categories wherein one of said categories comprises a category of blasthole cones suitable for sampling to better indicate underlying geological characteristics of the bench relative to blasthole cones of other of the at least two categories.

In one example, a direct measurement may include a measure of eccentricity of the blasthole cone, The measurement may then be compared to a threshold to determine suitability for sampling and thus classification.

In yet another aspect a system for analysing blasthole cones in open cut mining is provided. The system includes a sensing assembly arranged to sense a surface of a bench of a mine bearing blasthole cones. The system also includes a data processing assembly arranged to process sensing data generated by the sensing assembly in respect of the surface of the bench of the mine bearing the blasthole cones to thereby classify one or more portions of the blasthole cones into at least two categories. One of the at least two categories comprises a category of blasthole cones to better indicate underlying geological characteristics of the bench and/or equipment characteristics and/or drilling parameters relative to blasthole cones of the other of the at least two categories.

A corresponding method includes acquiring sensing data of a surface of a bench of a mine bearing blasthole cones. The sensing data may be remote or not remote. The method also includes processing the sensing data to produce input data that is compliant with input requirements, and processing the input data to thereby classify one or more portions of the blasthole cones into at least two categories. The categories may represent classes for a trained classifier and/or groups based on statistical or direct measurements. One of the categories comprises a category of blasthole cones to better indicate underlying geological characteristics of the bench and/or equipment characteristics and/or drilling parameters relative to blasthole cones of other of the at least two categories.

According to another aspect, there is provided another system for analysing blasthole cones in open cut mining. The system also includes a data processing assembly arranged to process sensing data generated by the sensing assembly in respect of the surface of the bench of the mine bearing the blasthole cones to thereby classify one or more portions of the blasthole cones. The one or more portions of the blasthole cones are classified by the data processing assembly into one or more categories. One of said one or more categories comprises a category of blasthole cones to indicate underlying geological characteristics of the bench and/or equipment characteristics and/or drilling parameters. This aspect may provide for indication and/or identification of certain characteristics associated with the underlying geology, equipment or drilling parameters (or any combination of the three) where all the blasthole cones are classified into a single category. For example, in the event that all blasthole cones (or all portions of the blasthole cones) are poor condition (imperfect), this may immediately indicate a drill curtain failure

In a corresponding method for the immediately preceding system, an aspect of the disclosure includes acquiring sensing data of a surface of a bench of a mine bearing blasthole cones and processing the sensing data. Processing the sensing data allows for the classification of one or more portions of the blasthole cones into one or more categories wherein one of said categories comprises a category of blasthole cones to indicate underlying geological characteristics of the bench and/or equipment characteristics and/or drilling parameters.

In compliance with the statute, the invention has been described in language more or less specific to structural or methodical features. The term “comprises” and its

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variations, such as “comprising” and “comprised of” is used throughout in an inclusive sense and not to the exclusion of any additional features.

It is to be understood that the invention is not limited to specific features shown or described since the means herein described comprises preferred forms of putting the invention into effect. The invention is, therefore, claimed in any of its forms or modifications within the proper scope of the appended claims appropriately interpreted by those skilled in the art.

Throughout the specification and claims (if present), unless the context requires otherwise, the term "substantially" or "about" will be understood to not be limited to the value for the range qualified by the terms.

Any embodiment of the invention is meant to be illustrative only and is not meant to be limiting to the invention. Therefore, it should be appreciated that various other changes and modifications can be made to any embodiment described without departing from the spirit and scope of the invention.