A geological perception system for autonomous mining

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Abstract—There is a strong push within the mining sector to develop and adopt automation technology, including autonomous vehicles such as excavators, trucks and drills. However, for autonomous systems to operate effectively in this domain, new perception capabilities are required to build rich models of a mine. A key element of this is an ability to sense and model the sub-surface geological structure as well as the more traditional robotic models, which typically estimate terrain and obstacles. This paper presents a new automated geological perception system to support autonomous mining. It uses hyperspectral imaging sensors and a supervised learning algorithm to detect and classify geological structures, and ultimately build a rich model of the operating environment. The presented algorithm uses Gaussian Processes (GPs) and an Observation Angle Dependent (OAD) covariance function. Further, the resulting geological model can be improved by fusing data from two hyperspectral scanners which measure different regions of the spectrum. The approach is demonstrated using data from an operational iron-ore mine. Fusion of classification results from the two sensors shows better agreement with ground truth mapping done in the field, compared to results from individual sensors.

I. INTRODUCTION

This work is motivated by a large scale project that aims to develop a fully autonomous open pit mine. Control and automation of vehicles such as haul trucks [8], blast hole drills [16], [17] and excavators [4] is receiving much attention from researchers. However, to be able to use such vehicles autonomously they need to have an understanding of the environment. Therefore, an accurate mine model is imperative to coordinate and track vehicles and equipment, and to control the mining process. A reference frame needs to be provided that will allow robotic machinery to operate efficiently.

A common misconception about mining is that all material removed from an open pit mine is valuable ore. In practice, however, a pit typically contains a mix of ore and waste material. A critical task in the mining process is to classify the material appropriately in a geological model, which is then used to control the mining process. For example, at excavation, haul trucks loaded with waste material would be scheduled to go to a different location than those loaded with ore. The process is further complicated if there are different types of ore that may need to be blended (mixed) or processed differently. As this process becomes more automated, perception systems to detect and classify the geology become critical.

In this paper, we present a geological perception system for autonomous mining that, due to its probabilistic framework, facilitates integration into a more comprehensive mine model. A supervised machine learning method based on Gaussian Processes (GPs) [12] is applied to hyperspectral imagery to determine the distribution of geology on a vertical mine face. Hyperspectral sensors are ideally suited to geological applications because they provide geochemical information of materials [3], however, they have been underused in robotics. Hyperspectral sensors can cover relatively large areas with high spectral and spatial resolution, thus enable thematic maps of the environment to be generated (e.g. [7], [3]). With hyperspectral sensors becoming more compact and less expensive, their use is anticipated to increase, particularly in a robotics context which has, to date, often been constrained to use of RGB colour or broadband infrared images. The increased use of hyperspectral sensors in robotics can be observed, for example, in [19] where the author’s deploy a hyperspectral camera on a rescue robot to detect victims after earthquakes because RGB cameras provide insufficient data. More recently, hyperspectral sensors have been used for automated food control [11] as well as target detection and tracking [6].

In this work, a novel approach of the GP-OAD [14] is presented whereby the GP’s probabilistic framework is exploited to fuse the classifications of the hyperspectral images. This work is the first attempt to include hyperspectral data from multiple sensors for incorporation in an in-ground (geological) model for autonomous mining. Hyperspectral data can provide one part of the geological model and data from other sensors (e.g. lidar) can be incorporated to obtain a more comprehensive mine model. Such a model is needed to drive many of the planning and control decisions made on a mine site.

This paper is organised as follows: Section II puts this work in context to previous and related work, Section III gives a problem formulation, a description of the machine learning algorithm and the covariance function as well as the methodology to classify and fuse the data. Section IV describes the field trial and data acquisition process. Section V presents the results. Section VI discusses the results and the potential of our method to be applied in an autonomous mine. Section VII concludes the paper by summarizing and highlighting the contributions.
II. RELATED WORK

There has been significant work done on the automation of vehicles in mining [8], [21], and perception around the vehicles, however, automated geology perception has received less attention, although it is essential for further tasks in the mining process. Some work on Measurement While Drilling (MWD) has been done [5], [2] to determine rock boundaries in the ground for strategic planning of the mining process. Other geology based work has been reported that supports autonomous mining and robotic systems, for example, by using gamma detection sensors [18].

New techniques are needed to handle such high dimensional data efficiently in a robotics context. [1] demonstrated the effectiveness and superiority of GPs (compared to other kernel methods) to classify hyperspectral data. In previous work [14] the authors demonstrated the effectiveness of the OAD covariance function [9] for hyperspectral data classification. [15] showed that angle based measures (e.g. OAD) outperform distance based measures (e.g. squared exponential covariance function) when the training and test set are acquired under different illumination conditions. The OAD covariance function is designed to handle high dimensional data efficiently and it can be used with GPs and other kernel machines. In this paper we extend the previous work by applying the GP-OAD method to hyperspectral imagery and making use of the probabilistic framework to fuse the outputs of the GP.

III. PROBLEM FORMULATION

This paper introduces a perception system that can be used to acquire geological information and support a rich, real time model of the mine environment. It is desirable to build such a geological model in autonomous mining to drive the many planning and control decisions of autonomous systems. The approach uses hyperspectral scanners to detect and classify minerals on an active mine face. This can both support autonomous mining and provide a useful tool to support existing mining methods.

Hyperspectral sensors are designed to measure light that is reflected from an object (e.g. a mine face). One sensor acquires reflected radiation in the visible near-infrared (VNIR) and the other in the short-wave infrared (SWIR). These scanners can survey large areas with a high spectral and spatial resolution and acquire data in a non-destructive way. Hyperspectral data are acquired in numerous, narrow, discrete and often contiguous bands (Fig.1) as opposed to broad band data (e.g. RGB cameras).

There are, however, some problems inherent with these kind of data which primarily are, (i) the very high dimensionality of the data and (ii) the variability and mixtures of materials. A database is usually used to identify materials, however, it is impossible to include every possible mixture into such a database (also called a spectral library). Rocks in the real world vary in appearance and mineral composition, thus for a successful classification, it is necessary to learn and model these variabilities. GPs are suited to model such variabilities using a training set and predict a class for a test sample. In this work we apply GPs in a least-square classification which enables the implementation in closed form. Closed form implementations are desirable because of their computational efficiency. This is especially important when dealing with high dimensional data as being the case in this work.

The following subsections give a brief background into GPs and the OAD covariance function and describe how the method is applied to the data.

A. Gaussian Processes

A GP is a collection of random variables, any finite number of which have a joint Gaussian distribution. The supervised learning problem uses a given training set $D = \{x_i, y_i\}_{i=1}^N$ consisting of $N$ input points $x_i \in \mathbb{R}^D$ and the corresponding outputs $y_i \in \mathbb{R}$ to compute the predictive distribution $f(x_s)$ at a new test point $x_s$. A GP model uses a multivariate Gaussian distribution over the space of function variables $f(x)$ mapping input to output spaces. A GP is fully specified by its mean function $\mu(x)$ and covariance function $k(x, x')$, so $f(x) \sim \text{GP}(\mu(x), k(x, x'))$. Using $(X, f, y) = (\{x_i\}, \{f_i\}, \{y_i\})_{i=1}^N$ for the training set and $(X_s, f_s, y_s) = (\{x_{s1}\}, \{f_{s1}\}, \{y_{s1}\})_{i=1}^N$ for the test points, the joint Gaussian distribution with $\mu(x) = 0$ becomes

$$
\begin{bmatrix}
y \\
f_s
\end{bmatrix}
\sim 
\mathcal{N}
\left(0,
\begin{bmatrix}
K(X, X) + \sigma^2 I & K(X, X_s) \\
K(X_s, X) & K(X_s, X_s)
\end{bmatrix}
\right)
$$

(1)

In (1) $\mathcal{N}(\mu, \Sigma)$ is a multivariate Gaussian distribution with mean $\mu$ and covariance $\Sigma$ and $K$ is the covariance matrix computed between all points in the data set. By conditioning on the observed training points, the predictive distribution for new points can be obtained as $p(f_s|X_s, X, y) = \mathcal{N}(\mu_s, \Sigma_s)$ where

$$
\mu_s = K(X_s, X)[K(X, X) + \sigma^2 I]^{-1}y,
$$

(2)
\[ \Sigma_x = K(X_*, X_*) - K(X_*, X)[K(X, X) + \sigma^2 I]^{-1} K(X, X_*) + \sigma^2 I. \] (3)

Learning a GP model is equivalent to learning the hyper-parameters of the covariance function from a dataset. In a Bayesian framework this can be performed by maximizing the log of the marginal likelihood with respect to \( \theta \):

\[
\log p(y|X, \theta) = -\frac{1}{2} y^T [K(X, X) + \sigma^2 I]^{-1} y - \frac{1}{2} \log |K(X, X) + \sigma^2 I| - \frac{N}{2} \log 2\pi (4)
\]

The three terms on the right side of (4) represent (from left to right) the data fit term, complexity penalty term and a normalization constant.

**B. Observation Angle Dependent (OAD) covariance function**

The OAD covariance function [9] depends only on the angle (in this case spectral angle) at which points are observed. The spectral angle is a similarity measure between two pixels (i.e. two spectra, a target and reference spectrum) by considering each pixel as a D-dimensional unit vector in \( \mathbb{R}^D \). Because this method uses an angular metric rather than a distance metric, it is invariant to brightness differences between spectra, i.e. the norm of the vector does not affect the resulting spectral angle. Thus, laboratory spectra can directly be compared to spectra acquired in the field at different conditions of illumination. The OAD covariance function is defined as:

\[
K(x, x') = \sigma_0^2 \left( 1 - \frac{1 - \sin \varphi}{\pi} \alpha(x, x') \right), \quad (5)
\]

where \( \sigma_0, \varphi \) are scalar hyper-parameters of the covariance function and \( \alpha(x, x') \) represents the spectral angle (dot product) between a target and a reference spectrum.

**C. Classification process of the sensor data**

Classification is a process by which data are categorised into groups or classes. This process usually simplifies the interpretation of data and also reduces their size and / or dimensions in some way. By classifying hyperspectral imagery using the GP-OAD, we reduce the dimensionality of the data significantly and yield a representation of data which is easier to understand.

For example, a hyperspectral image has the size \( 1882 \times 291 \times 409 \) \( (x, y, z) \), where \( x \) and \( y \) indicate the spatial dimension in pixels of a Cartesian coordinate system and \( z \) represents the spectral domain (i.e. wavelengths). The resulting classification will be an image of the size \( 1882 \times 291 \times 7 \) \( (x, y, z_*) \), where \( x \) and \( y \) are given by the spatial dimensions of the input image. The \( z_* \) dimension, however, is determined by the number of classes in the training set (in this case seven) which in turn is the number of \textit{One vs. All} classifiers applied to the input image.

Hyper-parameters for the GP-OAD are learned in a training stage using a spectral library (training set) which contains a large number of spectra (605), unevenly distributed across seven classes of rock. The algorithm is applied in an \textit{One vs. All} approach.

An image is classified by applying an \textit{One vs. All} classifier for each class of rock present in the training set. For each pixel (spectrum), the GP-OAD yields a probability and standard deviation indicating the likelihood and uncertainty of this pixel belonging to the assumed class.

The classification results have the same lateral size as the input image, however, each pixel has the dimensionality \( M \), where \( M \) is the number of classes that comprise the training set. To assign discrete class labels \( C_i \), where \( i = 1, \ldots, M \), for each pixel, the maximal probability across the \( z_* \) dimension at each pixel in the classification result is determined.

**D. Data fusion of classified hyperspectral images**

Two hyperspectral sensors sample different parts of the spectrum, thus classification of these images can result in very different thematic maps of the geological distribution. To increase the accuracy of the in-ground geological model, fusion of information from both sensors is done (Fig.2). Fusion is done not by combining the data received from the sensors but by simply multiplying the probabilities obtained from the rock type predictions (classification using GP-OAD) from each sensor. The advantage is that the amount of data exchanged between sensors can be significantly reduced and it enables incorporation of further data (e.g. from different sensors). This is discussed in more detail in section VI.

The VNIR and SWIR classifications are multiplied on a layer-by-layer and pixel-by-pixel basis.

\[
P_{\text{Fused}}(x, y, z_*) = P_{\text{VNIR}}(x, y, z_*) \times P_{\text{SWIR}}(x, y, z_*), \quad (6)
\]

where \( P_{\text{Fused}} \) indicates the resulting fused data. In a final post fusion step, class labels are assigned according to the \( z_* \) location as described in section III-C.

**IV. FIELD TRIAL USING TWO HYPERSPECTRAL SENSORS**

A field trial was done in the Hamersley Province, Western Australia in an operational mine using two hyperspectral sensors (manufactured by Specim, Finland, Fig.3, Table I). The aim is to identify geological zones on a vertical mine face using these sensors. The geology of this mine face is comprised of seven rock types, and these were mapped in the field using conventional survey methods.

Sensors were mounted in a side-by-side configuration (Fig.3) to simplify processing steps, such as the co-registration of spatial pixels. The two sensors were mounted on a rotating platform which in turn was mounted on a tripod (Fig.4). The field of view of both sensors was aligned so that a spatial overlap of both images occurred. During image acquisition, a calibration panel (99% reflective Spectralon) was placed in the image scene (Fig.5) so that the acquired raw data could be calibrated to reflectance (in accordance with [10]). Noisy bands, blocked by water vapour in the Earths atmosphere, were removed before further processing.
This illustration starts from the GP-OAD output (i.e., after classification) of the VNIR and SWIR images. Step 1) Probabilities are fused, layer by layer (representing the rock types) on a pixel by pixel basis by multiplying the classification results. This leads to one single image of the same dimensionality as the VNIR and SWIR classifications. Step 2), class labels are assigned based on the highest probability in the \( z \) dimension (layers) for each pixel, this leads to the final result visualised at the bottom. See text for further description.

Image data were spatially co-registered (using standard methods) so that the VNIR and SWIR information of each pixel corresponded to the same object.

The training set (spectral library) was acquired separately to this trial [13]. Our training set is a database of known materials which is used to match unknown data. The spectral library was acquired from materials from the same study area, however, the materials were of two categories. i) Cores of rock - acquired by drilling deep into the ground using a diamond drill core. ii) Bulk rocks collected from mine faces in the Hamersley Province. Cores were selected to be able to acquire the purest spectrum typical for a particular rock type. Bulk rock spectra were included because they better represent the conditions on a mine face. This means that these rocks are contaminated with dust and debris from the surrounding environment and appear in various mixtures. These training data were acquired with a different sensor (FieldSpec3 Pro Analytical Spectral Devices; ASD Inc., Boulder, CO, USA) than the images. Artificial illumination was used to ensure an optimal signal to noise ratio and standard illumination conditions.

V. RESULTS OF NON-FUSED AND FUSED SENSOR DATA

Hyperspectral imagery acquired by the VNIR and SWIR sensors were classified independently from each other. These classification results were used in two different ways to create thematic maps of the mine face geology. (i) Class labels were assigned to the VNIR and SWIR classification results without considering the other classification result. (ii) Classification results (i.e., probabilities) were fused and then class labels were assigned.

The classified VNIR data (Fig. 6a) was able to distinguish only two major geological zones; the mineralised iron-ore zone (left side of the image - yellow) and the non-mineralised materials, i.e., shale (right side of the image - green). This broad separation of geology is correct, however, it is not precise enough to generate a comprehensive geological inground model. This is because rock type ‘3’ (yellow) and ‘5’ (blue) which are both mineralised materials are distinguished at all. Only some of the low-grade material (purple) is detected correctly.

The SWIR image classification is more representative of the distribution mapped in the field (Fig. 6b). Using this classification, it was possible to distinguish between two mineralised types of rock on the left side of the image (yellow and blue). There is however, an over estimation of rock type ‘5’. In addition, in this classification the occurrence of a different shale material (red) in the very right side of the image was determined more accurately. The boundary between the two shales (red and green) and the abundance (i.e., over estimation) of the shale (red) was determined inaccurately.

The true colour composite image of the scanned mine face. The white square in the middle is the calibration panel used for reflectance calibration. Imaging is done by scanning the mine face using the push-broom principle (illustrated by green line and arrow). White lines divide geological zones (roughly). The numbers indicate abstractly the dominant rock type followed by the sub-dominant rock type in each zone. For example, ‘3+2’ indicates a dominant rock type ‘3’ and sub-dominant rock type ‘2’. Rock type ‘4’ only appears very sparsely.
Fusing only classification results, i.e. reduced amounts of data compared to the raw input data, can significantly reduce delays between data acquisition and a final classification result (e.g. a thematic map of geology). For example, the data acquired in this trial were approximately 300MB for the VNIR image and 200MB for the SWIR image. If the raw data ought to be fused and then classified, delays may be caused due to data exchange and the longer time required to classify data with higher dimensionality. Decentralised classification and fusion of probabilities reduces the amount of data that are to be exchanged, for example in the present case, both the VNIR and SWIR classification result had a size of 20MB (double precision values and uncompressed). In addition, it was shown that fusion of classification results is more effective in obtaining an accurate representation of the in-ground geology.

Data presented in this trial were acquired stationary from a tripod with sensors in a side-by-side configuration (Fig.8). For an autonomous mine, however, this is not suitable; thus integration in a multi-sensor vehicle such as an autonomous ground vehicle (AGV) is desirable. This will yield benefits such as data acquisition of a mine face from several positions and at multiple times during the day prior and / or during the excavation process.

Vertical surfaces of complex geometry can cast shadows, this can lead to problems during the classification (e.g.[7]). For example, deployment of hyperspectral sensors on AGVs could also help to reduce classification errors caused by shadow due to repositioning or a scan after changed illumination conditions. This is because hyperspectral sensors could be deployed on AGVs among other sensors (e.g. lidar, radar, stereo-vision and navigational sensors). The geometric information, for example, could be used to infer shadowed areas by detecting overhanging rocks, thus giving these areas a higher uncertainty in the classification. Such information could be feed back into the AGV to reposition itself in order to acquire new data from a different angle or position.

Acquisition of hyperspectral data from several positions within the mine, however, introduces some problems: (i) data need to be spatially associated, so that the VNIR part of a pixel matches the SWIR part of the same spatial position. This can be done using standard methods if global positioning systems and / or inertial navigation systems are used to log and track the positions of each vehicle. (ii) Calibration is necessary for hyperspectral data to convert the units from raw data to reflectance. Such a procedure is essential if image data are to be compared with data in a spectral library. This is even more important when the

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**TABLE I**

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Detector</th>
<th>Spectral FWHM</th>
<th>Spatial</th>
<th>λ range</th>
<th>bands</th>
<th>Digitalisation</th>
</tr>
</thead>
<tbody>
<tr>
<td>VNIR</td>
<td>SiO₂</td>
<td>1.2 nm</td>
<td>2.2 nm</td>
<td>0.4-1 μm</td>
<td>240</td>
<td>12 bits</td>
</tr>
<tr>
<td>SWIR</td>
<td>HgCdTe</td>
<td>5 nm</td>
<td>6.4 nm</td>
<td>1-2.5 μm</td>
<td>169</td>
<td>14 bits</td>
</tr>
</tbody>
</table>

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(a) VNIR classification - labels assigned

(b) SWIR classification - labels assigned

Fig. 6. Classification results for the VNIR and SWIR image. It can be seen that the different sensors pick up different features and therefore come to different conclusions for the classification. A legend of the colours is provided in Fig.7.

Fig. 7. VNIR and SWIR classification fused together resulting in this thematic map after assigning class labels. This image shows good agreement of the geological zones with mappings in the field (Fig.5).

Results of the fused VNIR and SWIR classification showed very good agreement with mappings made in the field (c.f. Fig.5,7). The centre of the image accurately shows more details of several mineralised rock types which were not shown in the individual classifications of the VNIR and SWIR data. The abundance of the different rock types as well as the position and boundaries between them is in close agreement with field mappings and better compared to the individual VNIR and SWIR results.

VI. CONSIDERATIONS FOR INTEGRATION INTO AUTONOMOUS MINING

The GP-OAD was applied to hyperspectral imagery and demonstrated its capability to identify different types of rock based on a training set which was acquired independently from the test data. This demonstrates the usefulness of this method for data classification without specific a priori knowledge of a particular mine face. The GP-OAD provides a probabilistic framework which is ideally suited for data fusion. Significantly better classifications can be obtained by fusing classification results from two different sensors compared to individual sensors. This method is capable of assisting geologists in their work to determine mine face geology with high spatial and spectral resolution while maintaining safety of the operator. For the integration into an autonomous mine further steps have to be considered.
Fig. 8. Conceptual illustration to move from a stationary to a mobile application using a sensors vehicle with a laser scanner.

spectral library was acquired independently from the test data, as being the case in this paper. Presently, this is done using a calibration panel within the field of view of the sensors. Approaches are also been developed which measure down welling incident light directly, thus removing the need for a calibration panel.

Scanning a mine face from different positions within a mine and fusing this information can lead to an improved classification of the geology and thus to a more accurate in-ground model. In this work, the concept and vision of such an autonomous system was introduced. Furtermore, it was demonstrated that fusing spectral information from different hyperspectral sensors can improve classification of mine face geology. Data acquired by conventional methods can be fused using this method, thus supporting geologists in their work. This is the first step using hyperspectral scanners towards a geological in-ground perception model for implementation into an autonomous mine. This geological model is particularly important as it provides the information that will support control of future autonomous mining equipment.

VII. CONCLUSIONS

In this work, the GP-OAD was successfully applied to hyperspectral images acquired in an operational mine in Western Australia by using an independent training set. Fusing classification results of two hyperspectral images was shown to be more accurate in classifying mine face geology than individual classifications. The potential for hyperspectral sensors to be used to support geologist for geological surveys on mine faces was discussed. Futhermore, benefits for using hyperspectral sensors in the automated mining process were discussed. In addition, this work is the first step to generate and incorporate a geological model in a robotics system for autonomous mine controls and surveys.

Further research will focus on integrating more data from different sensors into the in-ground perception model.

VIII. ACKNOWLEDGEMENT

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REFERENCES