

## AUTOMATED STRUCTURE MAPPING OF ROCK FACES

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### ABSTRACT

Mapping of exposed rock walls provides data on geological features such as joints, bedding planes, faults etc critical to the economics and the safety of mine operations. Traditional, manual methods of mapping can be time consuming, error prone and limited in their coverage. New methods have been developed to map exposed faces remotely and safely however the benefits of these methods are only fully realised when exposed structures can be quickly and easily mapped using automated methods.

This paper describes the application of an automated method of analysis of 3D images that provides users with the capacity to map exposed structures automatically. The method is based on the use of vector classification methods used in some neural network systems and provides rapid and reliable identification of exposed planes. CSIRO Exploration and Mining is applying these methods to 3D images for a range of applications from pit mapping to machine automation.

## 1 INTRODUCTION

Knowledge of geological features such as faults, bedding planes and joints reveals information pertaining to the economics and the safety of the mine operation. There are several methods to map the structure of a rock wall. Traditionally, mapping has been accomplished with manual measurement techniques such as those described in Priest & Hudson (1981). These procedures are time consuming, possibly dangerous and the opportunity for errors to occur during measurement and data entry phases is considerable.

More recently, laser range finding (Feng & Rosshoff, 2004) and 3D photogrammetry (Poropat, 2001) have been employed. Both techniques offer superior accuracy and efficiency over manual measurements. Laser ranging methods acquire data as point clouds but require expensive equipment. 3D photogrammetry can be accomplished with a great deal of flexibility using low-cost digital camera technology.

No matter what technique is used to undertake the measurements, the large amounts of data obtained in mapping the surface topography of a rock mass require efficient and reliable processing methods to extract structure information such as the joint set parameters. Ideally, these methods should be automated in order to deal with large or numerous data sets and reduce the influence of measurement bias. This requirement drives the need for a suitably reliable pattern recognition algorithm.

Neural networks of various architectures have been used for a wide variety of pattern recognition, exploratory data analysis and visualization applications (Seiffert & Jain, 2002). The ability of neural networks to quantify and classify vectors of any dimension reduces a multi-dimensional problem into a more manageable low-dimensional (e.g. 2D) one.

This paper describes the use of such techniques to map the structure of rock-walls. The methodologies used and some examples of results are presented below.

## **2 IDENTIFICATION OF PLANES**

### **2.1 Pre-processing The Input Data**

The method we used to acquire stereo images and generate the 3-D data is detailed in Soole & Poropat (2000). In short, using stereo photogrammetry, a number of rock-walls were imaged using the Sirovision system. The system images the subject walls from two defined viewing positions producing 3D spatial coordinates. A triangular mesh representation of the surface is then created to support calculation of surface properties.

The effectiveness of the neural network can be increased by incorporating both surface orientation data and measures of ‘flatness’. These surface properties can be determined computationally using the 3D mesh (Flynn & Jain, 1989). To ensure their accuracy, suitable edge-sensitive smoothing must be applied to the mesh prior to computation. In particular, the flatness data assists in detection of non-planar structures which nonetheless possess regular morphologies (e.g. curved edges, bowls etc).

### **2.2 The Structure Analysis Algorithms**

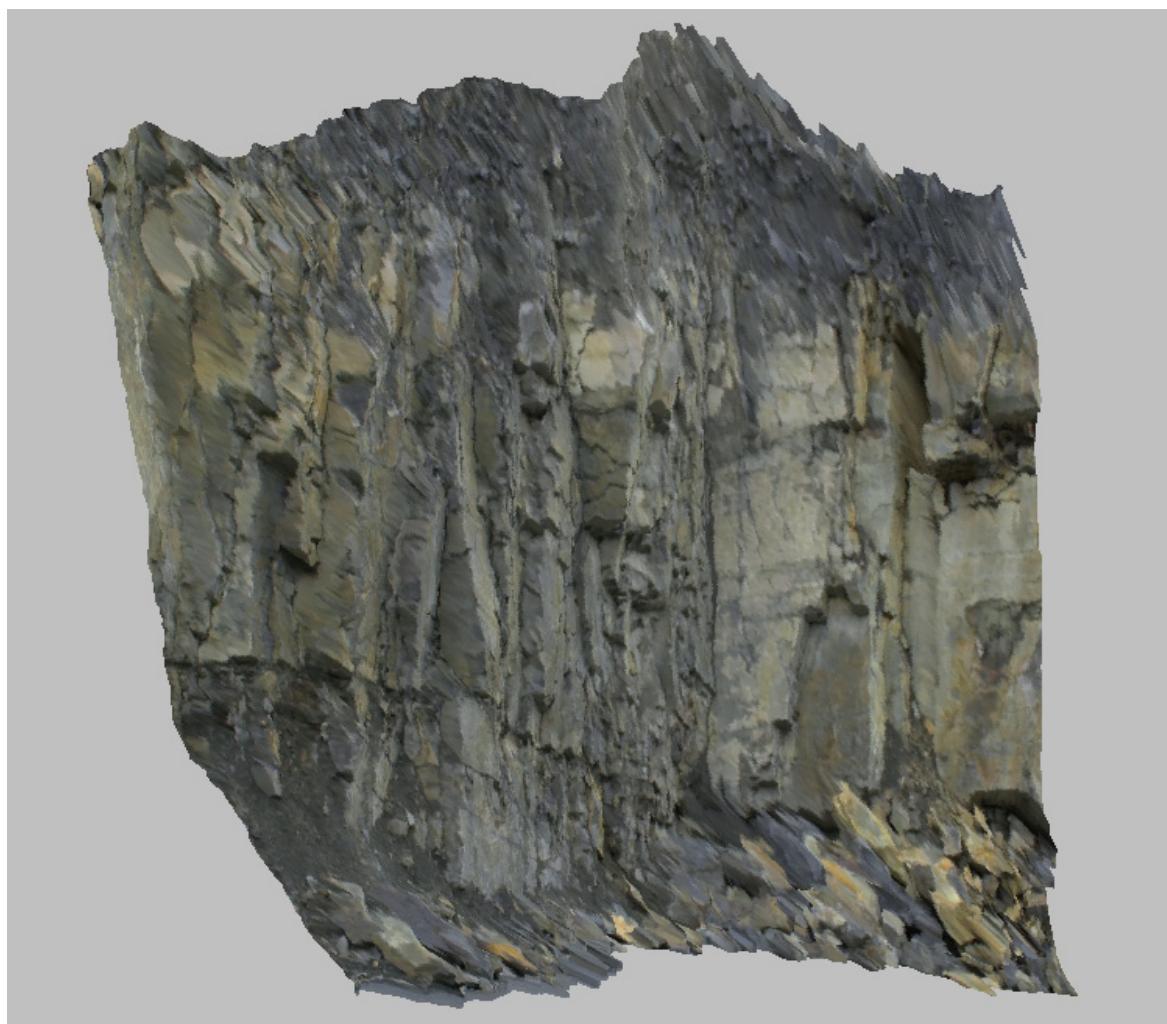
The power of neural networks comes from their ability to accurately scale the topology and distribution of the multi-variate input data space into a conveniently low-dimension space which is more amenable to well established data processing techniques. A clustering algorithm is used to sort the output of the neural network. As the goal of the structural analysis is essentially to detect regular surface types such as planes or edges (hereafter referred to as features) in the data, the number of clusters in the data is directly related to the number of types of such structures exposed on the rock surface.

Automatic determination of the cluster number is possible, although it is often desirable to limit the search to a particular number of prominent joint sets. Visualisation of each of the detected features will reveal spatially separated joints, bedding planes etc. These features have been clustered together based on their similarity as measured using the surface normal and flatness parameters. However, each feature can be labelled individually using image processing algorithms (Haralick & Shapiro, 1992) and thus surface properties (i.e. area, orientation, average flatness, perimeter etc) can be ascribed to each. Thus the structure analysis reveals information about joint sets and individual joints, edge sets and individual edges, loose material and other features.

## **3 RESULTS AND DISCUSSION**

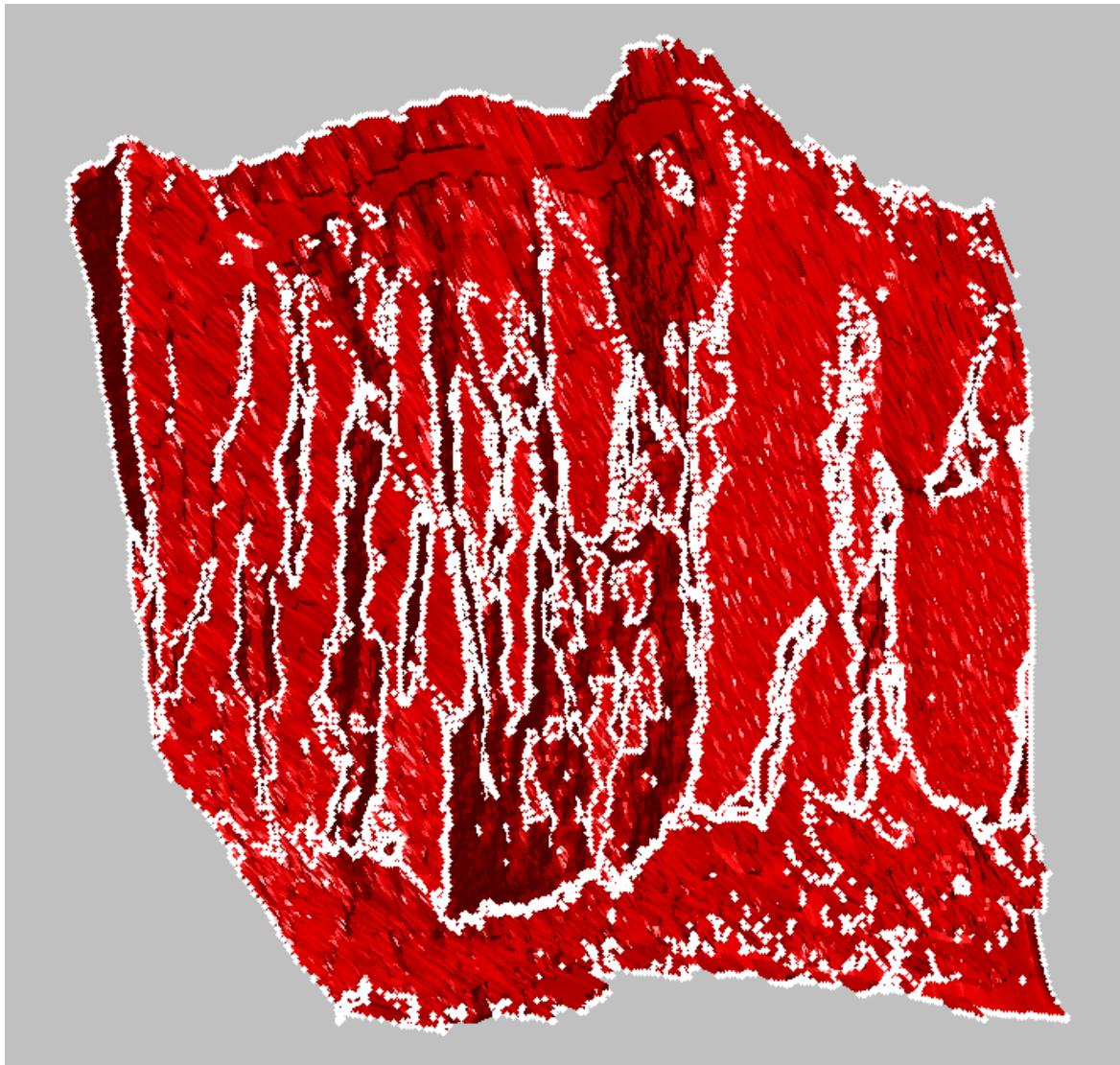
### **3.1 Source Data**

Analysis was performed on Sirovision data acquired at a rock wall. A 6 m x 17 m section of the wall was imaged and is shown in Figure 1. Several distinct features such as joint sets and bedding planes are present as well as some loose material at the base of the wall.



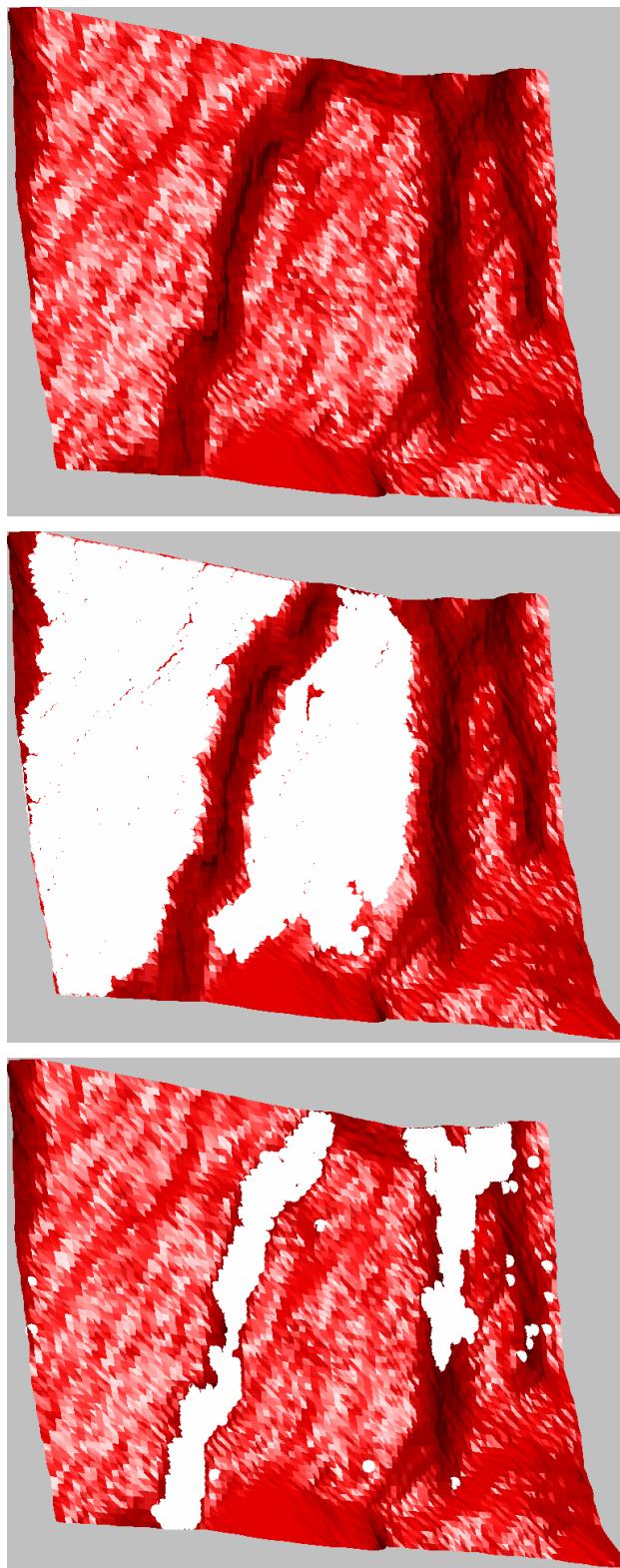
**Figure 1 The rock wall**

The structure detection algorithm successfully identified the major joint faces and several bedding planes present in the rock wall and these are shown in Figure 2. Both large and small planes have been detected, including planes which are nearly parallel to the line of sight. Critically, non-planar regions of similar morphology are also detected by this algorithm, such as the loose material at the base of the wall.



**Figure 2 The major structures detected on the 3D surface**

Figure 3 presents a particular region of interest containing two dominant planes separated by a curved, rounded edge. The results illustrate the ability of the algorithm to distinguish surface regions with complex (non-planar) features from more regular, planar structures. The figure clearly shows successful detection of the boundary between the offset planes.



**Figure 3 The offset plane region of interest (top) and the algorithm results.**

Although full automation is possible, there is some manual control over processing that still can be provided by the user. Filtering based on joint areas can eliminate unwanted detection of small surface irregularities. User control of process tolerance when using

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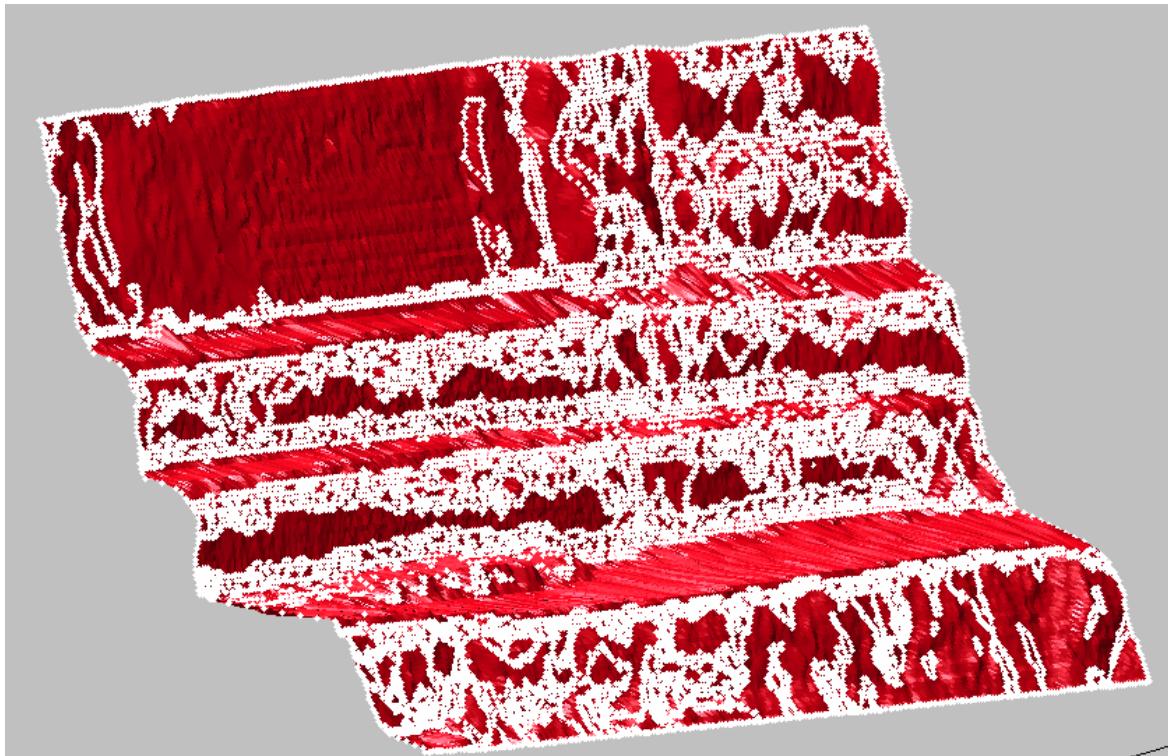
orientation or curvature data can improve both processing efficiency and accuracy. However, meaningful results are possible with no user input (as shown in these figures).

### **3.2 Structural Mapping In Open Pit Operations**

The structure analysis was applied to a 3D model of an open pit as shown in Figure 4. This model represents a much larger surface than the previous example. Further, the resolution of this model is such that small-scale features have been suppressed. Nonetheless, the results in Figure 5 show the algorithm's ability to clearly separate out the bench faces and berms. Further, discrimination of the dominant planes in the face data is also seen.

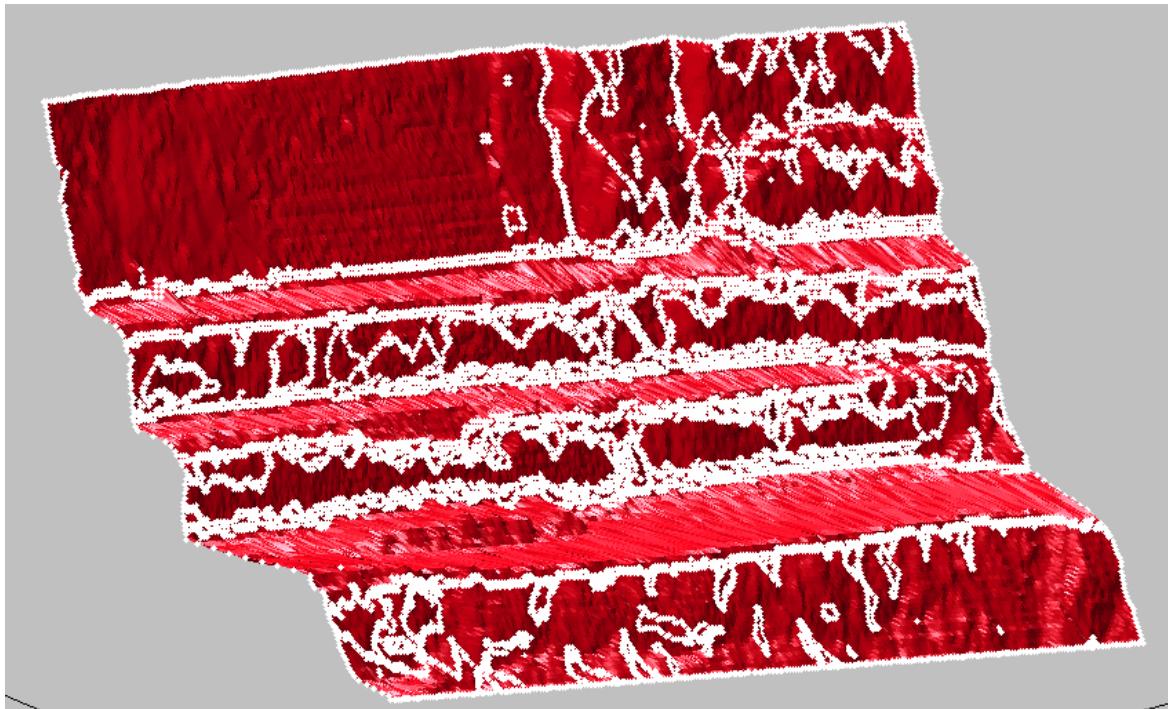


**Figure 4 A 3D image of a section of an open pit**



**Figure 5 Feature detection using the automated algorithm.**

If the number of clusters is (manually) set to 5, only dominant features are detected by the algorithm (Figure 6). Limiting the search to large-scale features produces similar results.



**Figure 6 Manually limiting the algorithm's search to 5 clusters**

## **4 CONCLUDING REMARKS**

Automated structure mapping of 3-D spatial data has been demonstrated. Using a neural network as the pattern recognition tool, with pre- and post-processing of the data involving surface smoothing algorithms and image processing techniques, joint sets and individual joints have been identified and surface properties measured automatically. Future work will involve the implementation of more sophisticated edge detection algorithms to assist the pattern recognition phase of the processing.

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