A Geological Structure Mapping Tool using Photogrammetric Data

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SUMMARY

Accurate and efficient identification and mapping of geological structures has broad application across the minerals industry. Recent advances in data acquisition technologies using Unmanned Aerial Vehicles (UAV), have led to a growing interest in capturing high-resolution rock surface images and analysing those datasets remotely. However due to the large volumes of data that can be captured in a short flight, efficient analyses of these data brings new challenges.

We propose a semi-automated method that allows efficient mapping of geological structures using photogrammetry of rock surface data collected by UAV. Our method harnesses advanced automated image analysis techniques and human data interactions to identify structures and calculate dip and dip angles of structures. Geological features were detected in two dimensional (2D) images and the corresponding three dimensional (3D) features were automatically identified from 3D surface models. The location, dip and dip angle of geological features were then calculated.

A feature map generated by our semi-automated method correlates well with a fault map resulting from visual interpretation by an expert. Some advantages of our semi-automatic method include the following: Firstly; it generates results in few minutes whilst manual interpretation took around an hour, thus contributing significantly in time saving. Secondly; unlike manual interpretation, our software technology provides objective and consistent results that can be reproduced.

Key words: Feature Detection, Photogrammetry, Image analysis

INTRODUCTION

Identification and mapping of geological features is important for a wide range of industries including mineral exploration, CO_2 sequestration, groundwater, and geothermal energy industries. Conventionally, structural mapping is done by visiting the field or mine sites. With recent advances in aerial data acquisition technologies from aircraft and UAVs, there is a growing interest in capturing high-resolution two dimensional (2D) and three dimensional (3D) rock surface images and analysing geological structures within those datasets digitally. This is particularly useful for data collection in locations with limited human access.

Presently, features are identified through manual inspection and digitisation of the photographs. However, this is a subjective and time consuming process, as remote sensing technology captures large volumes of high resolution data. With the recent advances in computer vision research, automated detection of lineaments/planes within 2D and 3D data is possible to speed up the analysis of large volumes of data. In our research we adapt and extend the use of lineament/plane detection methods and photogrammetry techniques to identify dip and dip angles of geological structures. Geological analysis of these images is not a trivial process as it requires the interpretation of complex geometries and subtle colour changes, which results in noisy data. Their analysis requires significant intuition, deductive and inductive reasoning of the interpreter. Thus, it is important that human interaction is allowed to ensure the output is geologically feasible.

Photogrammetry is a technique of capturing 3D information of features from two or more photographs of the same object (Linder, 2009). Photogrammetric techniques allow us to construct accurate 3D surface models in the form of point cloud data by using overlapping photographs. The feasibility of using photogrammetric methods to calculate the location of geological joints has been investigated by Kottenstette (2005) and Roncella et al., (2005). Both of these studies took advantage of user input to identify the feature points from point clouds data.

A few studies have been reported on automatic geological feature detection from remote sensing images. The Likelihood ratio edge detector was used to detect lineaments from satellite images (Wu and Lee, 2007). However, the above author did not provide details on the accuracy of their methods. The Hough transform (Duda and Hart, 1972) is widely used to detect lines from images. Wang and Howarth (1990) used the Hough transform with edge detection techniques, to identify faults. Their study conducted an experiment where an expert manually analysed the data to identify faults and compared this and automated analysis output based on available geological map. It was found that the visual method identified approximately 50% of faults, while the automated method detected just over 54% of the faults. Thus, in some circumstances automated methods can be more effective than visual interpretations for the detection of lineaments.

In terms of characterising the orientation of geological features, dip and dip direction calculations using three methods were compared by Voyat et al., (2006). They compared results from traditional surveys with results from analysis of photogrammetric and laser scanning data. Their results showed the accuracy of measurements, using both photogrammetry and laser scanning data, are acceptable with

an average difference of 3^0. Commercially available close range photogrammetry software is now routinely available to calculate the orientation of discontinuities (Haneberg, 2008; Tonon and Kottenstette, 2006). All the above mentioned methods require user input to identify the features and then measure the feature orientations using automatic methods, but the results of these studies show that digital photogrammetry methods can be used to obtain accurate geological measurements.

In this study, we developed a semi-automated tool to detect geological features in the UAV photographs and interpret the location and orientation of structures from photographs taken by an UAV.

METHOD AND RESULTS

Data

For this study an eight-rotor oktokopter (Figure 1) was used to take approximately 140 photographs at an altitude of 30-40m in Piccaninny Point, east coast, Tasmania. A 250m by 200m area was covered during a 5 minute flight. The images captured a layered meta-sedimentary sequence crosscut by a series of dikes and faults as described in Micklethwaite et al (2012).

Figure 1. Oktokopter, fitted with Canon 550D digital SLR Camera

The point cloud, which is a set of feature points in a 3D coordinate system were created using structure from motion techniques and a Digital elevation model (DEM) was generated using the point cloud, following the methodology of Lucieer et al (2011) (Figure 2). The individual photos were georeferenced and joined together to generate a single mosaic (Turner et al., 2012).

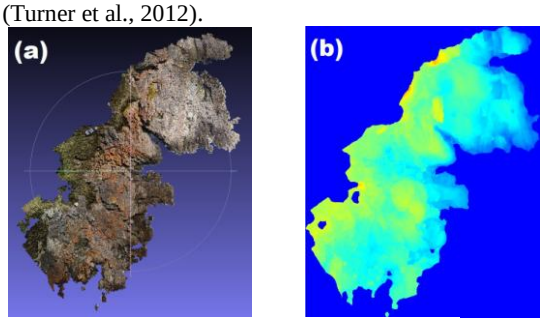

Figure 2. (a) Densified pointcloud (b) DEM

Approach

In our method geological features were detected in 2D photographic images using image processing techniques and the corresponding 3D features were automatically identified from 3D surface models. Then the orientation (dip direction and dip angle) and location of geological features were calculated using automated methods. These parameters are usually attained from field observations and geo-scientific data interpretations.

Feature Detection in 2D images

Edge detection techniques usually detect edges by identifying the points in the image, where the image intensity changes sharply. There are many existing methods to detect edges such as Canny (Canny, 1986), Sobel, Prewitt and Robert. An alternative method known as Phase Congruency also can be used to detect features (Kovesi, 1999). Rather than detecting edges based on image gradient the phase congruency method detects features by identifying points where the Fourier components are maximally in phase. The main advantage of this method over other widely used methods is that phase congruency results are largely invariant to image contrast changes (Kovesi, 2003). Thus, we used the phase congruency algorithm to detect both visually faint and strong edges from images. The phase congruency output is then processed to remove noise and then thresholded to delineate edge pixels from others. Noise is removed by using the non-maximal suppression technique that suppresses pixels which are not part of the local-maxima. Then the noise removed output is thresholded using a technique called hysteresis thresholding that marks all pixels with values above a high threshold as "edges" and reject all the pixels with values below a low threshold. The remaining intermediate pixels are marked as edges only if they are connected to the high threshold pixels (Canny, 1986). The connected edge pixels are joined together and represented as line segments. Figure 3 shows the detected line segment from a sample image.

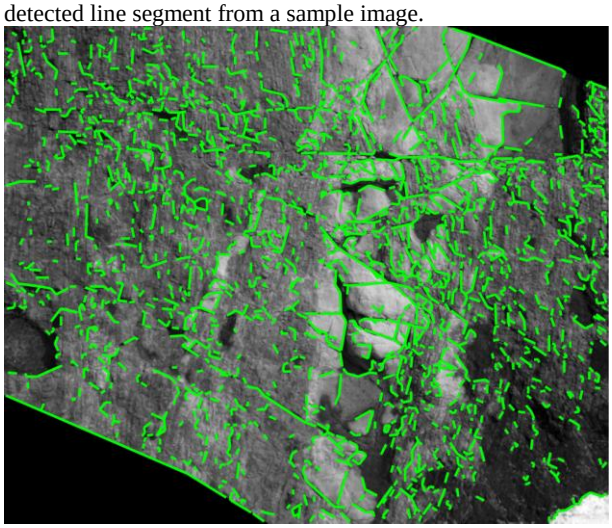

Figure 3. The detected line segments (green colour) on top of the original image.

Aerial images often have a noisy appearance due to camera shake, low resolution image capture, shadows of other structures and the nature of surface contrast. Hence, geological lineaments often appear as discontinuous line segments on original images as shown in Figure 3. This makes automated lineament detection a challenging task. In manual detection, geologists use their knowledge and experience to determine which segments should be connected and which are not. In automated method to detect the features effectively, the line segments from same features need to be connected. In our method to form a final hypothesised geological lineaments map (Figure 4), a segment linking algorithm was developed. Our algorithm automatically links the segments together, if their separation and lateral alignments are within a specified tolerance. Alternatively, the results could be further improved by harnessing the expert

knowledge through user inputs, which will eventually enhance the segment linking process.

Faults were visually interpreted from the image by an expert (prior to automated analysis) and Figure 5 shows the visual interpretation results. Note that our automated method detects faults, joints and jointed bedding surface while the visual interpretation results shows only the faults.

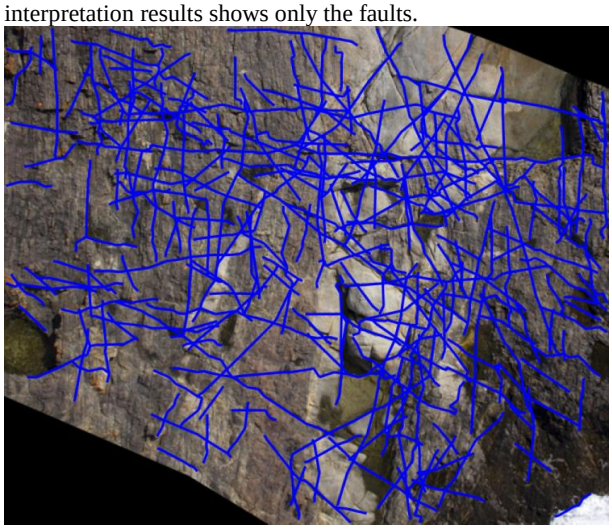

Figure 4. Detected faults, joints and bedding surfaces by our automated method (blue line segments)

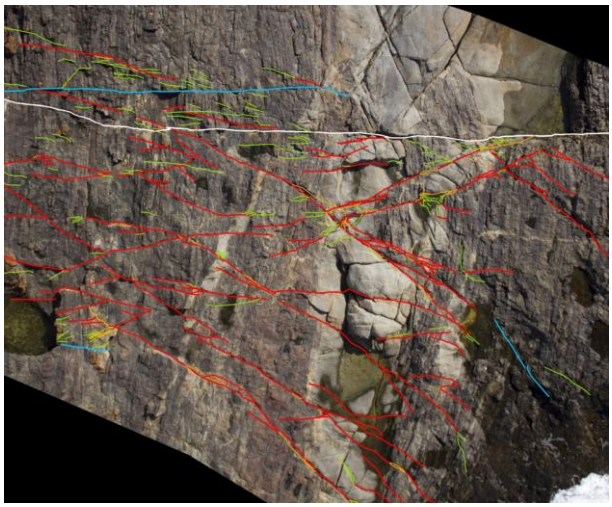

Figure 5. Fault map, resulting from visual interpretation.

Feature Detection in 3D

Once the features were identified in 2D images, the 2D feature points (pixel coordinates) were computed and their corresponding 3D coordinates were automatically calculated using the available DEM. Figure 6 shows an example of a geological feature which was firstly detected within a 2D image, and then their corresponding 3D locations with the use of DEM within the point cloud. The corresponding 3D feature points fit well with the fault in densified point cloud.

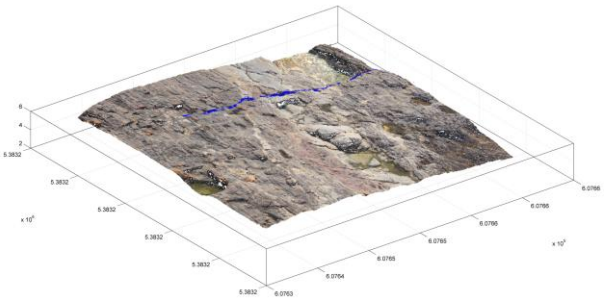

Figure 6. Projection of feature points on point cloud

Once the 3D feature points are identified, we estimate the dip and dip angle of the structure. The RANSAC algorithm (Fischler and Bolles, 1981) was used to find the plane that fits the calculated feature points, using a similar methodology to Ferrero et al (2009). Once discontinuity planes were identified it was relatively straight-forward to extract orientation measurements such as dip and dip angle (Feng et al., 2001) and display results in a stereographic projection (Figure 7).

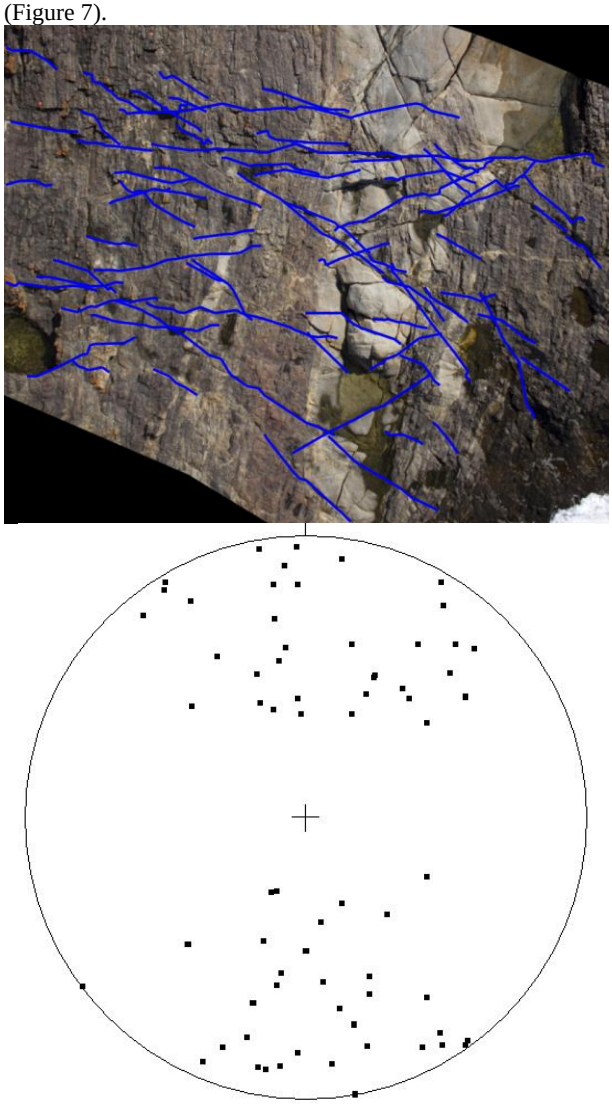

Figure 7. Fault map, resulting from semi-automated method, where faults were selected by user interaction (top) and a corresponding Equal-angle stereographic net (bottom)

CONCLUSIONS

We report a preliminary study to identify geological features from UAV photographs and calculate their orientation using semi-automated methods. The results show a reliable identification of faults and fractures using the automated method. The automatic detection method successfully detects faults, joints and bedding surfaces. User interaction is then able to rapidly select the structural population of interest (in this example (Figure 7) we focus on the faults). There were some false positives due to the presence of noises also some of the features were not detected by our method.

Our on-going research focuses on improving the 2D feature detection results, developing efficient methods to reclassify faults, joints and bedding surfaces by using user inputs and some automated classification methods.

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