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Semi-automatic mapping of geological Structures using UAV-based photogrammetric data: An image analysis approach

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ABSTRACT

Recent advances in data acquisition technologies, such as Unmanned Aerial Vehicles (UAVs), have led to a growing interest in capturing high-resolution rock surface images. However, due to the large volumes of data that can be captured in a short flight, efficient analysis of this data brings new challenges, especially the time it takes to digitise maps and extract orientation data.

We outline a semi-automated method that allows efficient mapping of geological faults using photogrammetric data of rock surfaces, which was generated from aerial photographs collected by a UAV. Our method harnesses advanced automated image analysis techniques and human data interaction to rapidly map structures and then calculate their dip and dip directions. Geological structures (faults, joints and fractures) are first detected from the primary photographic dataset and the equivalent three dimensional (3D) structures are then identified within a 3D surface model generated by structure from motion (SfM). From this information the location, dip and dip direction of the geological structures are calculated.

A structure map generated by our semi-automated method obtained a recall rate of 79.8% when compared against a fault map produced using expert manual digitising and interpretation methods. The semi-automated structure map was produced in 10 min whereas the manual method took approximately 7 h. In addition, the dip and dip direction calculation, using our automated method, shows a mean $\pm$ standard error of $1.9^\circ \pm 2.2^\circ$ and $4.4^\circ \pm 2.6^\circ$ respectively with field measurements. This shows the potential of using our semi-automated method for accurate and efficient mapping of geological structures, particularly from remote, inaccessible or hazardous sites.

1. Introduction

Knowledge of geological structures and their topological relationships (e.g., faults, joints, igneous contacts, and unconformities) is important for a wide range of geosciences research and industry including mineral exploration, CO_2 sequestration, groundwater, and geothermal energy. Possibly the most basic dataset used to capture information on geological structures is the geological map. Structural maps typically show the location, geometry, orientation and trace length of structures of interest. Further information typically captured may also include across-strike spacing, roughness and density (Priest, 1993). The most fundamental of these properties are location, surface geometry and orientation because these properties are critical components of widely used techniques such as two dimensional (2D) cross-section construction, cross-section balancing, three dimensional (3D) visualisation of geology and modelling of geophysical data. In order to obtain the highest resolution data, traditional field techniques include interpretations from photo mosaics or grid mapping. Such approaches can generate abundant and high quality data but can take weeks, even months, to complete.

With recent advances in aerial data acquisition technologies from aircraft and UAVs (Harwin and Lucieer, 2012; Turner et al., 2012), it is now possible to capture high-resolution rock surface images and analyse geological structures within those datasets digitally. Very large digital datasets can be collected rapidly, covering significant surface areas with centimetre-scale resolution in a matter of minutes.

Photogrammetry is a technique that captures 3D information of features from two or more photographs of the same object, obtained from different angles (Donovan and Lebaron, 2009; Haneberg, 2008; Linder, 2009). In particular, structure from motion (SfM), is a photogrammetric technique, where the camera positions and orientation are solved automatically, in contrast to conventional photogrammetry where a priori knowledge of these parameters is required (Snavely et al., 2007). SfM uses overlapping photos to construct 3D point clouds, from which it is relatively, straight-forward to calculate surface models

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such as wireframes or digital elevation models (DEMs) and finally generate orthorectified photomosaics or textured surfaces. With the advent of this technique it is now important to develop methods to analyse the resulting data rapidly and effectively.

Several studies used photogrammetric data to map and measure geological structures (Ferrero et al., 2009, 2011; Kottenstette, 2005). Kottenstette (2005) conducted a study to demonstrate the application of photogrammetric methods to map the locations of geological joints. Ferrero et al. (2009) compared the orientations of geological features (dip and dip direction) derived, from both a field survey and results from a photogrammetric study. Their results show a good agreement with field measurements. There are also commercially available close range photogrammetry software namely Sirovision, ShapeMetrix3D and 3DM Analyst, which are available to calculate the orientation of discontinuities (Haneberg, 2008; Tonon and Kottenstette, 2006). However, the studies mentioned above used manual interpretation to identify each individual structure in the photogrammetric models.

Visual interpretation is a subjective and time consuming process and this is highly dependent on human experience and ability (Hung et al., 2005). Subjectivity is involved in lineament identification and the true extends of it. For example, visual interpretation produces results which are mostly non-reproducible because different interpreters will have different levels of expertise or may use different identification criteria (Sander et al., 1997). Even the same observer does not reproduce all the lineaments in the same locations in multiple trials (Mabee et al., 1994). Such subjectivity can be minimised by integrating results from multiple observers or by employing a single observer across multiple trials (Mabee et al., 1994; Sander et al., 1997). However, both solutions can incur significant man-hours to derive an interpretation.

Automated feature detection in images is an active area of research in image processing, including many applications such as road extraction (Shao et al., 2011; Treash and Amaratunga, 2000) and medical applications (Den Hertog et al., 2010; Mulrane et al., 2008; Onkaew et al., 2011). Image analysis techniques provide an effective and fast method of lineament detection and these techniques can extract lineaments which are difficult to recognise using the human eye alone (Wang and Howarth, 1990). The main advantage of automated or semi-automated lineament detection is speed.

Several studies have reported on automatic geological structure detection from remote sensing images. Wu and Lee (2007) detected edges from satellite images using the Likelihood ratio edge detector, which was originally proposed by Oliver et al. (1996) and mathematical morphology techniques were used to join the edges. The Hough transform (Duda and Hart, 1972) has also been used to successfully detect lineaments (Argialas and Mavrantza, 2004; Vassilas et al., 2002; Wang and Howarth, 1990). Wang and Howarth (1990) conducted an experiment, where an expert manually mapped faults from the images and these results were compared to the output from the automated analysis method and an available geological map. It was found that the visual method identified approximately 50% of faults, while the automated method detected 53.7–69.2% of the faults based on the threshold. Thus, the performance of automated methods can be equivalent to, or slightly more effective than visual interpretations for the detection of lineaments.

However there are some limitations in the previous studies. In automated methods optimum parameter selection according to different contrasts and different terrains is very crucial (Argialas and Mavrantza, 2004). Moreover automated methods often detect lineament like features which are related to non-geological structures such as power lines, roads and man-made features. Thus automated methods detect significantly more features than the actual features present in the study area (Abdullah et al., 2013; Sarp, 2005). These false positives needed to be edited and/or removed to produce a final map which is time consuming (Gustafsson, 1994). The identification of a single structure (fault) as a series of discontinuous line segments is another drawback of the automated lineament detection method (Abdullah et al., 2013; Sarp, 2005). The limitations of automated methods show that some degree of user interaction is required to produce a better structure map.

To overcome these limitations, Lemy and Hadjigeorgiou (2003) used artificial neural networks to separate the actual feature segments from the false positives detected by their automated method. The discontinuous segments were then manually joined together to form the final feature map. In our study we address this challenge by introducing contrast invariant edge detection algorithms to minimise the difficulty of parameter selection. We then incorporate user inputs into the segment linking process to avoid the detection of false positives and to produce more realistic results. The detected structures are automatically located within the corresponding 3D surface models. Then the orientation (dip and dip direction) and location of geological structures are calculated using automated methods. Our preliminary study showed the effectiveness of using advanced image analysis techniques to detect geological structures from photographs (Vasuki et al., 2013).

2. Data acquisition

UAVs are already widely used for a variety of purposes, including the digital reconstruction of architecture (Irschara et al., 2010) and for mapping moss beds to monitor climate changes (Harwin and Lucieer, 2012; Lucieer et al., 2011, 2013). For this study an eight-rotor oktokopter (Fig. 1a) was used to capture approximately 140 photographs at an altitude of 30–40 m at Piccaninny Point on the east coast of Tasmania, Australia. This low altitude flight resulted in high

Fig. 1. (a) Oktokopter Micro-UAV, fitted with Canon 550D digital SLR Camera. (b) Densified point cloud generated from UAV images using photogrammetry.