AUTOMATED AVALANCHE DEPOSIT MAPPPING FROM VHR OPTICAL IMAGERY

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ABSTRACT
Using eCognition we developed an algorithm to automatically detect and map avalanche deposits in Very High Resolution (VHR) optical remote sensing imagery acquired from satellites and airplanes. The algorithm relies on a cluster-based object-oriented image interpretation approach which employs segmentation and classification methodologies to identify avalanche deposits. The algorithm is capable of detecting avalanche deposits of varying size, composition, and texture. A discrete analysis of one data set (airborne imagery collected near Davos, Switzerland) demonstrates the capability of the algorithm. By comparing the automated detection results to the manually mapped results for the same image, 33 of the 35 manually digitized slides were correctly identified by the automated method. The automated mapping approach characterized 201 667 m2, of the image as being representative of a fresh snow avalanche, roughly 8.5% of the image. Through a spatial intersection between the manually mapped avalanches and the automatically mapped avalanches, 184 432 m2, or 89%, of the automatically mapped regions are spatially linked to the manually mapped regions. The rate of false positive was less than 1% of the pixels in the image. The initial results of the algorithm are promising, future development and implementation is currently being evaluated. The ability to automatically identify the location and extent of avalanche deposits using VHR optical imagery can assist in the development of detailed regional maps of zones historically prone to avalanches. This in turn can help to validate issued avalanche warnings.

1. INTRODUCTION

Snow avalanches, in general, are poorly mapped, which is commonly due to the remote location of their occurrence. Often avalanches are only reported if they cause an obstruction to public infrastructure, damage to personal property, or are witnessed and reported by local observers. However, decisions regarding, e.g., the closure of roads and rail lines, and the setting of warning levels rely on information that is derived from knowledge of historic events in combination with metrological data of the recent past and expected future (Bellaire et al., 2011; Armstrong and Armstrong 1987; Frauenfelder et al. 2010).

2. SENSORS AND DATA ACQUISITION

The images used in this study were collected from both airborne and spaceborne platforms. The spaceborne imagery has been collected by the QuickBird satellite, over Western Norway, as illustrated in Figure 1a. The airborne platform has been collected by a fixed wing aircraft with a Leica ADS40-SH52 imaging unit, the images have been collected over Davos, South-eastern Switzerland, as illustrated in Figure 1b.

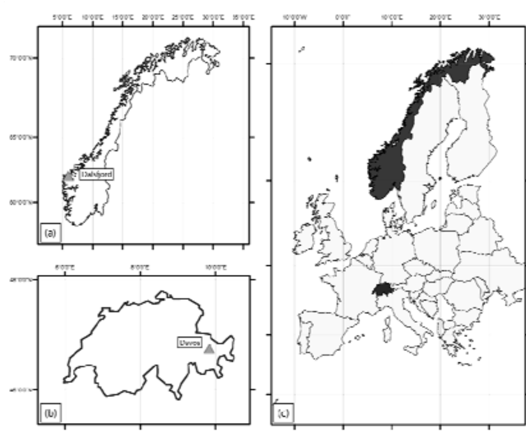

Figure 1: Data collection sites depicted by grey triangles in (a) Norway and (b) Switzerland

The results presented in this paper are limited to the airborne data collected in Davos Switzerland. The authors have submitted a paper in which multiple datasets are included. All images used in this research project have been processed using only the panchromatic band.

3. METHODOLOGY

The prerequisite in the development of the algorithm was that it be stable, repeatable, and logical, i.e. avoiding the use of 'black box' algorithms. The method researched and developed for this paper represents an approach

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to mapping snow avalanche deposits in which the only information required is the orthorectified imagery. The algorithms employ object based image analysis techniques (Definiens 2011). The development of the classification algorithms was done using an iterative approach with successive refinement of the input variables. In effect, hundreds of independent variables were tested, as well as the order and combination of variables. The algorithm development was done so based on a methodical trial and error process. The development was done so using small sections of larger images, this was necessary to accommodate the large number of iterative development in the formulation of the algorithm. The algorithm exploits both standard and texture based image analysis steps (Haralick et al 1973, Haralick 1979)

A visual example of the processing chain is illustrated in Figure 2. At the first step the algorithm assumes that each pixel in the image has the possibility of representing avalanche snow. As the image is processed through various steps, pixels are eliminated as being not representative of avalanche snow. The final step selects only those pixels that pass each gate, and are therefore considered to be representative of a snow avalanche deposit.

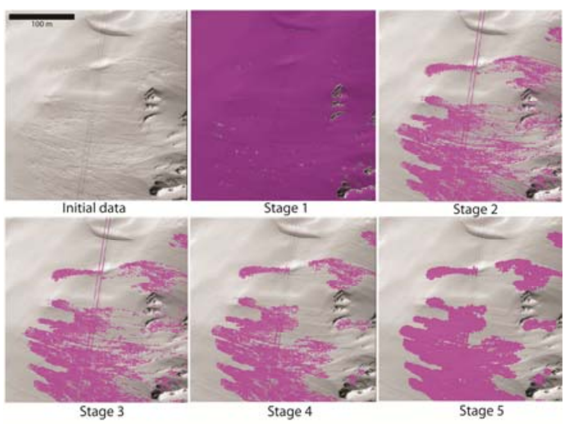

Figure 2: General processing steps and staged results (clockwise from top left) for avalanche deposit identification in eCognition. The steps illustrate the progressive segmentation and classification of the image, resulting in an image with only avalanche deposits identified.

4. RESULTS

The manual mapping and digitizing of snow avalanches through visual analysis resulted in the identification of 35 non-connected and non-overlapping snow avalanche regions, as illustrated in Figure 3. Through a discrete analysis of the regions classified by the automated algorithm versus those that are manually mapped, 33 of the 35 manually mapped snow avalanches are correctly identified by the automated algorithm. Both of the snow avalanche runout deposits not detected by the automated approach are very small deposits and have undergone partial melting. As well, the automated mapping algorithm correctly identified one smaller avalanche runout deposit that was overlooked by the human observer. The results presented herein are more comprehensive than those presented by Bühler et al. (2009) as the object oriented approach is able to identify smaller objects and ‘dirty’ snow as part of the avalanche where as previous methods have failed.

The automated mapping approach characterized 201 667 m2 of the image as being representative of a snow avalanche deposit, roughly 8.5% of the image. Through a spatial intersection between the manually mapped avalanches and the automatically mapped avalanches, 184 432 m2, or 89%, of the automatically mapped regions are spatially overlapping with the manually mapped regions. Allowing for a 5 m buffer to account for digitizing and translation errors the spatial intersection increases to 192 803 m2, or 95%.

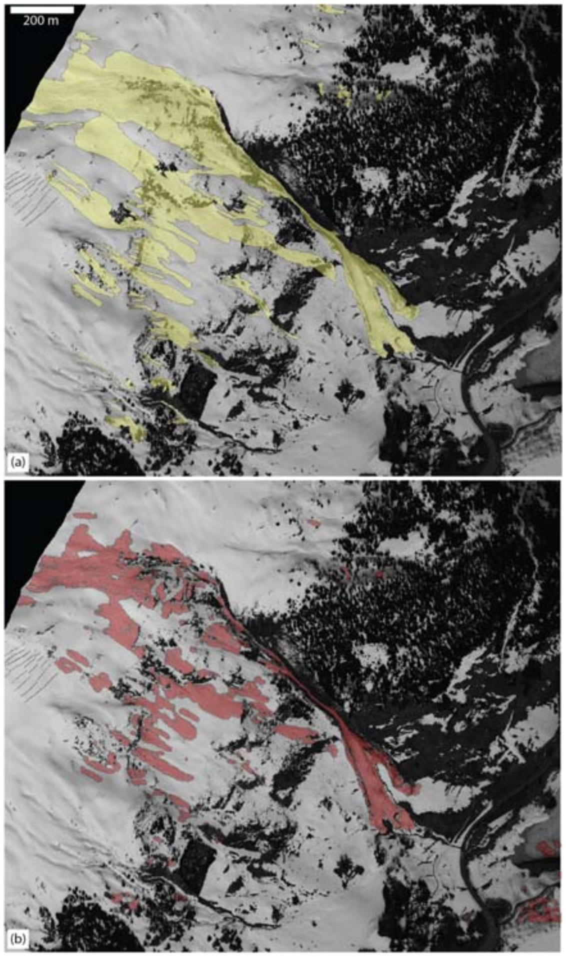

Figure 3: Leica panchromatic imagery collected near the town of Davos. The primary target of this image is the Salezer Avalanche (March 2008). Image a (above) illustrates manual mapping of snow avalanche deposits in ArcGIS, while image b (below) is processed automatically in eCognition and then visualized in ArcGIS.

5. CONCLUSION

The results presented in this paper illustrate the powerful capability of hierarchical object-oriented image processing available through eCognition in the automated detection of snow avalanche deposits from VHR optical imagery. The ability of the software to be programmed in a manner that mimics a human cognitive process is ideal for automated avalanche deposit detection as the characteristics that make a snow avalanche identifiable can be 'taught' to the program and rapidly tested. The automated mapping of snow avalanches has been widely researched and sought after as a valuable tool in the development of forecasting models and for the development of hazard maps based on past events.

Our initial results exhibit the capability and potential use of hierarchical object-oriented image processing for the automated detection of snow avalanches from VHR optical imagery and support findings of previous investigations. The methods presented in this paper provide a number of advantages over traditional digitizing techniques, these include: 1) a greater ability to detect avalanches in the shade, 2) the efficiency of the process, and 3) the ability to analyse multiple images in parallel, as the processing capabilities can be maximized to the extent of the computational resources available. With respect to the quality of the input imagery, pixel resolution and image exposure are the two most important variables to be considered when planning image acquisition.

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