Automated detection and mapping of rough snow surfaces including avalanche deposits using airborne optical remote sensing

Yves Bühler[1]*, Andreas Hüni[1], Marc Christen[2], Roland Meister[2] and Tobias Kellenberger[3]
[1] Remote Sensing Laboratories, Department of Geography, University of Zurich, Zurich, Switzerland
[2] WSL Institute for Snow and Avalanche Research SLF, Davos, Switzerland
[3] Federal Office of Topography swisstopo, Bern, Switzerland

ABSTRACT: The characteristics of snow pack surfaces are spatially and temporally highly variable. Today, in situ field observations provide mostly isolated information on characteristics such as grain size, grain shape, free water content or surface roughness. Remote sensing instruments are promising tools for systematic and wide-area mapping of several snow surface parameters. This study presents a methodology for an automated, systematic and wide-area detection and mapping of rough snow surfaces including avalanche deposits using optical remote sensing data of high spatial and radiometric resolution. A processing chain integrating directional, textural and spectral information was developed using ADS40 airborne scanner data acquired in spring 2008 and 2009 over a test site near Davos, Switzerland. Though certain limitations exist, encouraging detection and mapping accuracies can be reported. The presented approach is a promising addition to existing field observation methods for remote regions, and can be applied in inaccessible areas.

KEYWORDS: Remote sensing, avalanche mapping, airborne digital scanner, rapid mapping, snow surface roughness, wind modelled snowpack

1 INTRODUCTION

Systematic and wide-area information about snow surface characteristics of alpine snow covers such as roughness or optical equivalent diameter (grain size) would be of great interest for diverse application in snow- and avalanche research (Schweizer et al., 2008). Currently, the acquisition of such parameters relies mainly on isolated observations acquired by individual experts in the field. Consequently, the achieved coverage is rather poor as only data from certain regions can be recorded. Large parts of the Alpine region are inaccessible to observers, especially if the avalanche hazard level is high.

Remote sensing instruments are able to acquire data over wide areas without restrictions caused by poor ground accessibility. The use of remote sensing data to retrieve snow cover properties such as optical equivalent diameter of snow grains (Dozier, 1989; Nolin and Dozier, 2000; Painter et al., 2003), free water content (Schanda et al., 1983; Strozzi and Mätzler, 1998), snow depth (Foppa et al., 2007; Schaffhauser et al., 2008) or contamination content (Painter et al., 2001; Warren and Wiscombe, 1980) has been investigated intensively in the past. But the spatial resolutions of the applied instruments were often not able to capture the small-scale variability of alpine snow covers.

The wide-area characterisation of snow surface roughness in particular has been investigated using MISR multiangular satellite data with a spatial resolution of 275 m (Nolin et al., 2002; Nolin and Payne, 2007). But this coarse spatial resolution is insufficient for a meaningful characterisation of snow surface roughness within alpine terrain. This paper presents an automated approach for the detection and mapping of rough snow surfaces such as avalanche deposits over large areas using remote sensing data.

2 ADS40 AIRBORNE SCANNER DATA

In April 2008 and March 2009 Leica Geosystems and swisstopo acquired data with an average ground sample distance of 20 cm over the mountain range west of Davos, Switzerland using the airborne scanner ADS40–SH52. This sensor, built by Leica Geosystems AG, Heerbrugg, Switzerland, is able to acquire high spatial resolution imagery with a dynamic range of 12 bits in five spectral bands simultaneously at three observation angles (Figure 1).

The radiometrically stable instrument belongs to a new generation of airborne sensors, aimed at replacing older analogue airborne cameras used for surveying and topographic mapping (Petrie and Walker, 2007). Due to its high spatial and radiometric resolution, the sen-

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Corresponding author address: Yves Bühler, Remote Sensing Laboratories, Department of Geography, University of Zurich, Switzerland; tel: +41 44 635 65 22; fax: +41 44 635 68 46; email: yves.buehler@geo.uzh.ch

sor is able to detect small variations within snow cover even in shadowed areas, and has therefore great potential for mapping snow surface characteristics. A detailed description of the sensor characteristics is given by Leica (2008).

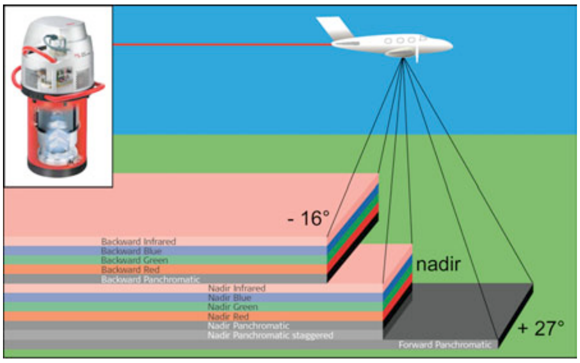

Figure 1. Data acquisition geometry and spectral bands of the ADS40-SH52 sensor used in this study, modified from Leica (2008)

3 METHODOLOGY

By combining different pieces of information derived from airborne scanner imagery and auxiliary datasets, a processing chain to extract rough snow surfaces was developed (Figure 2).

3.1 Multidirectional information

Using one band acquired from the nadir looking angle and one band from the backward looking angle (Figure 1), elevated objects can be distinguished from flat surface features based on radial distortion. The multiangular information is extracted by calculating the Normalized Difference Angle Index NDAI (1) using the nadir and backward looking NIR bands. This index has a demonstrated ability for characterising the surface roughness of snow using multidirectional MISR data (Nolin et al., 2002).

$$NDAI = \frac{NIR_{backw} - NIR_{nadir}}{NIR_{backw} + NIR_{nadir}} \quad (1)$$

3.2 Texture Analysis

The NDAI values are analysed using second order statistical texture measures, accounting for the spatial and spectral dimensions of texture. The number of a specific change in pixel value between neighbouring pixels in one direction is counted within a quadratic filter box. The result is written to a Grey Level Co-occurrence Matrix (GLCM), used to derive further texture measures. A detailed overview of this method is given by Haralick et al. (Haralick et al., 1973; Haralick, 1979; Tuceryan and Jain, 1998). This approach has shown good results for the classification of urban structures (Karathanassi et al., 2000), agricultural structures (Delenne et al., 2008) and sea ice (Soh and Tsatsoulis, 1999). Local texture variations are valuable indicators for rough snow surfaces. To identify the best measure for the separation of the different types of snow surface roughness, different texture measures were tested using varying parameter settings. An entropy measure, specifying the “orderliness” of a texture (Haralick et al., 1973), showed the most stable results and the best separability. High entropy values indicate rough snow surfaces, low values the opposite (Figure 3).

3.3 Object-oriented classification

Contrary to traditional pixel based approaches, object-based methods classify objects formed by adjacent pixels based on a homogeneity criterion. Analysing objects instead of single pixels allows for the inclusion of further parameters such as topological-, shape- and statistical information and for improved classification results (Yan et al., 2006). A detailed overview of the object-based classification approach is given by Benz et al. (2004). The texture analysis results described in section 3.2 are labelled, applying directional filters, statistical object information and neighbourhood relationships.

To distinguish avalanche deposits from other rough snow surfaces, auxiliary datasets are utilised. Even in high mountain terrain, regions exist where the occurrence of an avalanche is implausible. The numerical simulation tool RAMMS (Rapid Mass Movements), developed by the SLF (Christen et al., 2008), models avalanche run-out, velocities and flow-heights by solving a system of partial differential equations using first and second order finite volume techniques. The starting zones are derived automatically from digital elevation data (Maggioni and Gruber, 2003). The model can therefore predict the potential area affected by avalanches. It was calibrated and evaluated using different well-documented avalanche events in Switzerland, mainly from winter 1999 (Christen et al., 2008). In this paper, areas not prone to avalanches are excluded by inverting the RAMMS model result. Very steep slopes are likely to be starting zones of avalanches, but it is very unlikely that an avalanche stops its flow within the same area (McClung and Schaerer, 2006). Therefore, slopes with an inclination of 35° or more are excluded using a digital elevation model with a spatial resolution of 25 meters.

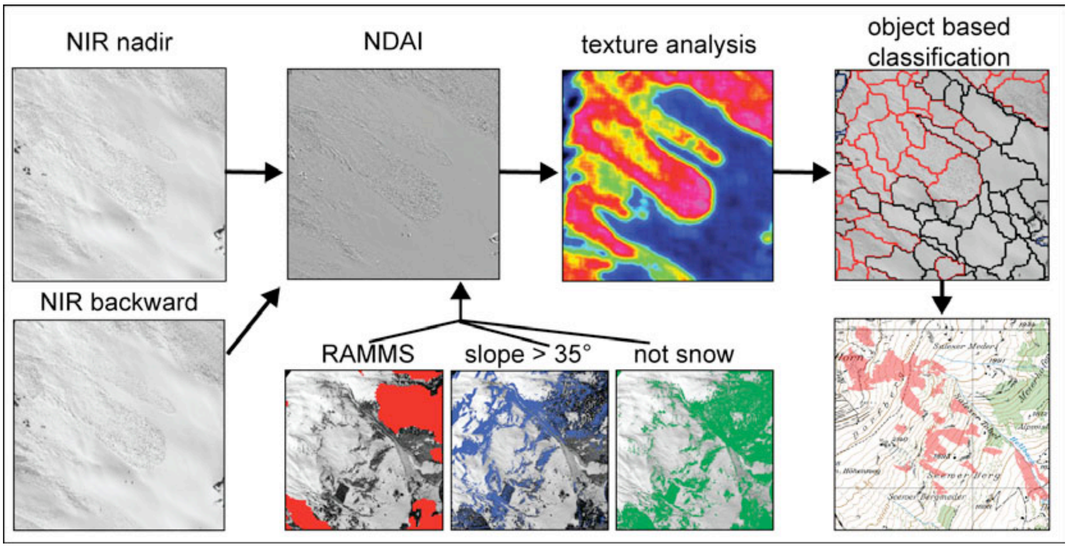

Figure 2. Flowchart of the processing chain for rough snow surface (here: avalanche deposits) detection and mapping showing input, intermediate and output data (Bühler et al., 2009)

4 RESULTS AND DISCUSSION

The local variation of texture proves to be a valuable indicator for snow surface roughness. Wind modelled snow pack, surfaces formed by melt water or disturbed snow covers such as avalanche deposits are indicated by high entropy values and can be well distinguished from smooth snow surfaces (Figure 3).

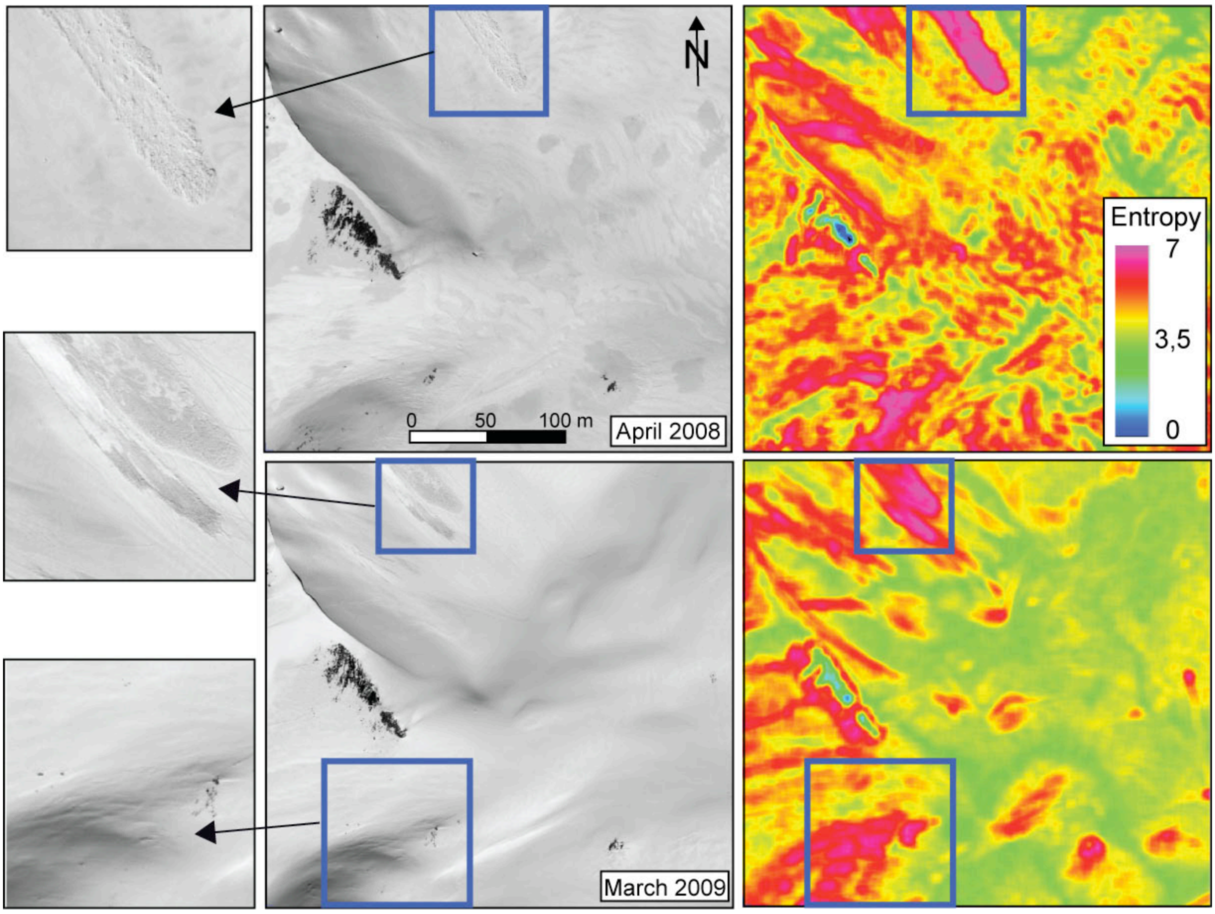

Figure 3. Near infrared bands of the ADS40 data showing a test site near Wannengrat, Davos (left) and derived snow surface roughness indicator entropy for the same area (right). The wind modelled snow pack (bottom inset) and the small avalanche deposits (top and middle inset) are indicated by high entropy values.

In combination with auxiliary information, snow surface roughness can be applied to detect and map avalanche deposits. Qualitative visual comparison of the classification with the full spatial resolution ADS40 data indicates a very good detection rate and mapping accuracy (Figure 4). Even deposits in shadowed areas were correctly detected.

To quantify the reliability of the classification methodology, the digitised avalanche deposits from three different test sites were used as ground reference. Visual interpretation of the ADS40 data with the full spatial resolution of 20 cm was used to determine the location and extent of avalanche deposits. The processing chain detects 94 % of all avalanche deposits within the three test sites correctly (Bühler et al., 2009).

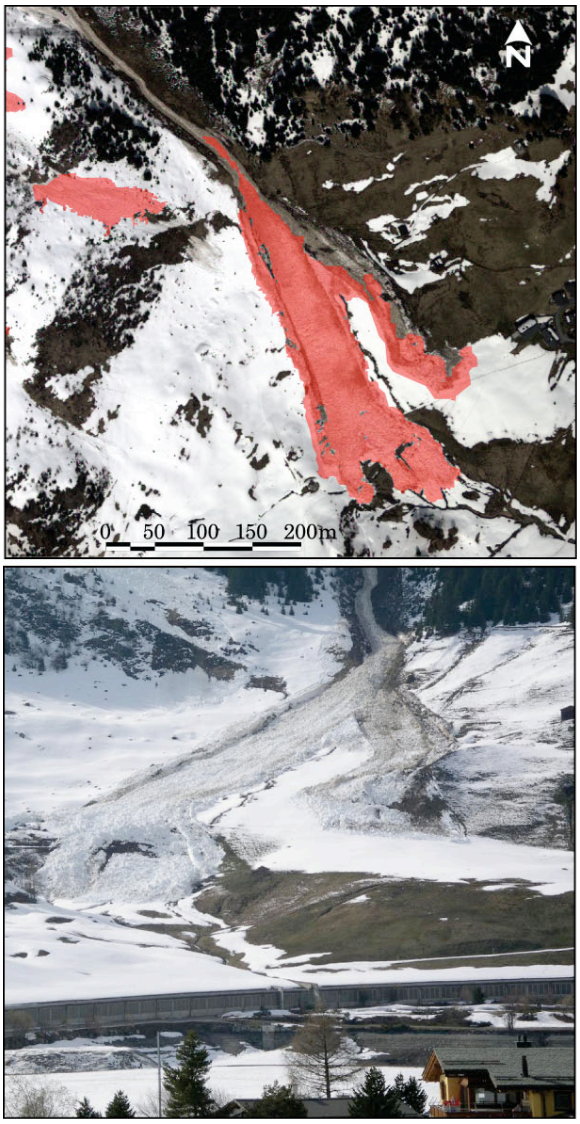

Figure 4. Avalanche deposit mapping result of the Salezer avalanche (red, above) and oblique photograph acquired one day before the data acquisition (Bühler et al., 2009)

4.1 Limitations

Optical remote sensing instruments depend on weather conditions: Fog or clouds can hinder data acquisition. The airborne ADS40 sensor can be operated under cloud cover at high altitudes, but dependency on weather conditions remains strong.

Although the vast majority of avalanche deposits were successfully detected and mapped, certain limitations should be mentioned. Isolated errors of commission occur and cannot be completely eliminated by the object-based classification step. Other rough snow surfaces such as wind modelled snowpack, artificially piled snow, traces and sparsely vegetated snow cover can cause confusion with avalanche deposits. These errors are considerably higher for small avalanche deposits than for large deposits.

5. CONCLUSIONS

Spatially and radiometrically highly resolved, directional optical remote sensing data are suitable for wide-area detection and mapping of rough snow surface features and avalanche deposits (Bühler et al., 2009). The proposed classification processing chain, integrating directional, textural and spectral information provided by the ADS40-SH52 airborne digital scanner enabled the detection and mapping of the majority of avalanche deposits within the test area.

The presented approach can be used to gain information about the status of snow surface roughness and recent avalanche events within remote and inaccessible regions. The algorithm is very sensitive even for low amplitude roughness. The method relieves the recognition of spatially variable snow surface patterns, which may lead to different snow cover evolution and so to different avalanche formation conditions at a small scale. The detection of avalanche deposits (large scale, catastrophic events, as well as medium to small size avalanches) is of fundamental relevance This information may be used to refine decision-making and forecasting, avalanche cadastres, hazard mapping and avalanche model calibration / validation. It substantially complements in-situ observations due to its wide-area coverage, offering additional opportunities for avalanche hazard verification. The applicability is limited by a) the restricted availability of appropriate sensors due to weather conditions and b) misclassifications caused by other rough surfaces such as artificial snow piles, wind modelled snowpack and sparsely vegetated area.

The additional automated detection and mapping of avalanche starting- and translation zones, as well as the extraction of the deposition volume, would be of great value for avalanche research. Further studies have yet to determine whether or not this type of data and methodology can be used to achieve these goals.

Since a spatial resolution of one meter proved to be sufficient for this application, spaceborne optical sensors with stereo capability (e.g. Quickbird, Ikonos, SPOT5) may be suitable. The new generation of spaceborne SAR-Sensors (TerraSAR-X, Cosmo Skymed, Radarsat-2), acquiring data with a spatial resolution of close to one meter, overcome the limitations imposed by weather conditions, but are hampered by layover, radar-shadow and foreshortening in alpine terrain (Lillesand and Kiefer, 2000).

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