REAL-TIME AVALANCHE RISK ESTIMATION ON SKI

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ABSTRACT: Real-time radar avalanche measuring is well established for remote sensing and is often used for automated detection. The ability to generate real-time avalanche detection and risk assessment is a needed innovation for safe skiing in the backcountry. Skiers must rely solely on their own assessments of snow and terrain conditions. Most skier involved avalanches are triggered by the skiers themselves, and 9 of 10 avalanche accidents occur in backcountry conditions. Very often a persistent weak snow layer causes the avalanches and often loss of human life. Knowledge of avalanche risks is essential for safe skiing, especially in remote, high mountain areas. However, data based estimating avalanche risk while skiing is not yet established and is part of our research. We present a portable radar solution for skiers in the backcountry. The device digitally measures a full snow profile including weak layers and snow depth, as well as slope gradient and applied forces. This technology will keep skiers constantly informed about the snow conditions under them, no matter their location. The measurements are used to provide risk assessment “on the fly” during skiing and if an internet connection is established, the data will be sent to the cloud for further analysis, risk predictions and data sharing with the larger ski community.

KEYWORDS: real-time measurements, avalanche risk, radar, simulation.

1. INTRODUCTION

Natural and human-triggered avalanches occur throughout the winter season in mountainous regions around the world. A significant increase in recreational activities and skiing in the backcountry has resulted in an increase in avalanche incidents and fatalities. To mitigate the avalanche risk, several approaches are already employed. Remote devices and sensor arrays are installed in the terrain to monitor and predict avalanches. Measured field-data of avalanche activities are used to estimate morphological and topographical parameters but are often time-consuming or not sensitive enough for real-time predictions.

Our portable radar solution for skiers is a device which digitally measures a full snow profile including weak layers and snow depth, as well as slope gradient and applied forces. This data will be combined with simulation data to close the gap between the measured data and the elastic snow parameters and to estimate the morphological and topographical parameters. These results are used to update models from specific areas to generate reliable avalanche risk maps and to make predictions. The model results are analyzed by machine-learning algorithms to provide avalanche risk predictions for the near future or for the next season. We will show how to combine field-data from skiers, simulation and machine-learning technologies for reliable avalanche risk estimation and future risk assessment.

2. METHODS

Measuring the snow conditions during a ski-trip is essential to predict avalanche risks. A radar based device is installed directly on the ski to measure the snow layer structure below the ski and to predict the parameters as described e.g. Bradford, Harper, & Brown, 2009. In order to predict these snow parameters, the measured field data is compared to synthetic data generated by data inversion. The parameters of the model are changed as long as the synthetic results are not similar to the measured field data in a square root mean sense (e.g. Schuster, 2017).

These results are used to build 2D elastic models to quickly estimate the resulting shear-stress caused by the skier and to assess the machine learning output and avalanche risk. As output for the supervised learning we use the stability index and critical crack length (e.g. Gaume and Reuter, 2017) for the decision-making process. The 3D model is used for a more detailed and more reliable avalanche risk prediction and risk map.

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3. RESULTS

The field data was collected this May at the MyrkDalmen mountain in Norway on a lasting snow-pack of more than 2m thickness. The snow was highly consolidated, but with some identifiable layers. The temperature was just below freezing (-0.2 degrees Celsius) with a hand hardness index from medium (4F) to hard (1F) without any weak layer down to 2m (Fig. 1 and 2).

3.1 Field data

The raw data was processed with static ground clutter removal filter, band-pass filter, source signal deconvolution and stacked 20 times. In order to improve the layer identification, the processed data was Hilbert transformed to get the envelope. This envelope was used to compare the radar field data with the snow profile excavated below the measured line (black line in figure 1).

Figure 1 Field data from a test survey in Myrkdale, Norway in May 2018. The penetration depth is 2m (equivalent to 512 samples) as shown in the b-scan. The red line represents the measured line above a consolidated snow-pack and the black short line the presented radar B-scan profile.

Figure 2 Field data comparison and interpretation between measured signals and the snow profile.

3.2 Simulation data

The 2D radar electromagnetic field simulation was used to build synthetic traces to match with the field data by data inversion. The used finite differences time-domain method solves the Maxwell equations for wave propagation in an elastic medium. The outer boundaries are perfect matched layers to reduce unwanted boundary reflections.

The source signal was a 6GHz Gaussian pulse with approx. 2GHz band-width. For simplification no noise or clutter signatures were added.

Figure 3 shows an example result of a three-layer finite half-space structure of a wet layer between two dry layers (Fig. 3a).

This result show clearly a change of polarity from dry-snow to wet-snow and back to dry-snow as well as changes in the signal signature (Fig. 3b and 3c). These signatures, phases and amplitudes are used to estimate the snow-parameters to build the elastic model.
To our knowledge there exists no direct correlation between the measured electromagnetic radar signal and the shear-stress which is the key to estimate avalanche risk (e.g. Schweizer and Camponovo, 2001, Habermann et al., 2008 for the importance of the knowledge of the shear-stress). However, using the elastic model out of the field data inversion is a suitable approach to connect radar data to the shear-stress and figure 4 shows a 2D example where the ski is parallel to the slope angle.

In order to improve the reliability of the model we use 3D shear-stress simulations and figure 5 shows an example of a pair of skis parallel to the slope angle. The 2D and 3D shear-stress results are used to predict the critical crack length/surface and the stability index.

All the simulation results are used to draw snow condition/parameter maps in combination with other sources, such as weather information or geo-hazard data. Figure 6 shows a synthetic example of a color-coded snow wetness map.

### 3.3 Workflow

Figure 7 provides a simple sketch of the risk assessment workflow for a skier during the ski-tour. As described in chapter 3.1 and 3.2, the 2D and 3D models are used to estimate the snow parameters and the critical crack length together with the stability index. This information is used to train and test our machine learning algorithm and the resulting algorithm is sent to the radar-device on the ski prior to the ski-tour.

During the ski-tour the measured radar data will be used as the input for the machine learning algorithm stored on the radar-device and the output
will inform the skier about possible avalanche risk on the current route using e.g. LED or acoustic sounds.

Figure 7 Risk assessment workflow

4. DISCUSSION & CONCLUSION

We have shown that a radar system connected to a ski is able to measure snow layers while skiing and the reflected radar signals are consistent with an interpreted snow profile. The synthetic radar data was used to estimate the electromagnetic snow properties by data inversion. However, this electromagnetic radar data has no direct link to the necessary elastic snow properties to predict avalanche risk. Simulation results can fill this gap using the layered snow model estimated from data inversion.

When the elastic model is in place finite element simulation can be used to predict the critical crack length/surface and the stability index together with other elastic snow properties.

We are working together with Google on a cloud-based machine learning setup using Tensorflow as machine learning core. Our Tensorflow code will train the machine learning algorithm with synthetic and field data providing estimated elastic snow properties as output for supervised learning.

This winter we will start a field campaign with 250 selected skiers to collect data during cross-country skiing employing our workflow to test the feasibility of avalanche risk estimation for the selected ski areas.

REFERENCES


