

AUTOMATIC CLASSIFICATION OF CONTINUOUS SEISMIC DATA FOR AVALANCHE MONITORING PURPOSES

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ABSTRACT: Seismic monitoring systems are well suited to detect avalanches independent of weather conditions. Nevertheless, seismic monitoring systems are not yet used operationally, as developing algorithms to automatically detect avalanches is far from trivial. Thus far, attempts to automatically identify avalanches in seismic data have focused on using machine learning algorithms with varying degrees of complexity, requiring extensive training data sets and generally resulting in rather high false alarm rates. Recently, a promising new approach was introduced using so-called hidden Markov models (HMMs), a statistical pattern recognition tool commonly used for speech recognition. With this method, the abundance of background noise data is exploited and only one training event is required. We adapted this method to automatically detect avalanches in data recorded by a small aperture seismic array deployed above Davos, Switzerland. While preliminary results were very encouraging, the number of false alarms remained rather high. To eliminate false detections, primarily produced by regional earthquakes or distant airplanes, we introduced a two-step approach to reduce the number of false alarms. First, using HMMs trained at a second array at a distance of 14 km, we compared the automatically detected events at both sites. Any co-detected events were removed. Second, for the remaining events, we used multiple signal classification (MUSIC), an array processing technique, to determine the back-azimuth and the apparent velocity of the incoming wave-fields to obtain information on the direction of the source of the events. In contrast to avalanches, falsely classified events had much larger changes in back-azimuth and could thus be dismissed. We applied this method on data recorded from January to April 2017 and automatically obtained an avalanche activity pattern in line with visual observations performed by the avalanche warning service in the area of Davos. Overall, our new classification approach shows that seismic monitoring systems can be used to automatically provide timely information of large avalanches occurring within a distance of 2-3 km.

KEYWORDS: Snow avalanche, avalanche forecasting, seismic monitoring, automatic detection, event localization

1. INTRODUCTION

To improve avalanche forecasting, accurate information about the current avalanche activity are of great importance. Currently, avalanche activity information is obtained by visual observations which rely on good visibility. Hence it is nearly impossible to obtain reliable avalanche activity data during periods of bad visibility (e.g. snow storms) or at night. Existing avalanche activity data are often inaccurate and contain errors. In this study we use a seismic monitoring array and a machine learning algorithm to provide accurate avalanche activity data for small areas.

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Seismic arrays are well suited to monitor earthquakes, landslides and volcanoes (Suriñach et al. 2001, Suriñach et al. 2005, Esposito et al 2006). In recent years, machine learning algorithms became more important for the analysis of continuous recordings. Hammer et al. (2013) introduced an earthquake and query blast detector based on hidden Markov models. For this approach, one single training sample for each event type was sufficient to construct a reliable classification system. Using this approach, Hammer et al. (2017) identified large avalanches in a 30 km range of a seismological broadband station of the Swiss Seismological Service. They analyzed a 5-day period of high avalanche activity in February 1999 detected 43 confirmed avalanches with only 2 false alarms.

Apart from the detection of seismic events, it is possible to determine the direction of the signal using array processing techniques (Rost et al. 2002) and by using multiple arrays, localization is

also possible (Métaxian et al. 2002). In most studies, a beam-forming approach was used to fulfill these tasks. Lacroix et al (2012) were the only ones who used this method to determine the direction of avalanches. A more advanced technique capable to identify several sources is multiple signal classification (MUSIC) (Schmidt 1986).

In this study we used the approach proposed by Hammer et al. (2012), but applied the automatic detection to data more influenced by noise as we used less sensitive geophones. Due to the limited data, additional post-processing steps were required to obtain reliable avalanche activity data. Furthermore we implemented the MUSIC method to localize avalanche events and tried to reconstruct the avalanche paths.

2. FIELD SITES AND INSTRUMENTATION

We analyzed data recorded continuously at two field sites above Davos, Switzerland, the Dischma and the Wannengrat field site. At both field sites seven vertical geophones are circularly arranged with at least one sensor in the middle. Depending on the ground of the field site, sensors are either attached to rocks using an anchor or are buried approximately 50 cm deep in the ground and covered with soil (Heck 2018). Currently, sensors with an eigenfrequency of 4.5 Hz are used for the monitoring and the continuous seismic data are sampled at a rate of 500 Hz. The distance between the sensors was on average 35 m and cannot be increased due to the used instrumentation. Data are recorded using a low energy data storage system based on a Raspberry Pi and are either transmitted using a long distance wireless link or are retrieved manually.

3. METHODS

3.1 *Automatic detection of avalanches*

Apart from signals produced by avalanches, many additional seismic events such as earthquakes and airplanes can be identified in the seismic data. To differentiate between various types of signals, advanced machine learning methods are required (Heck 2018). One promising approach are hidden Markov models (HMMs), a machine learning algorithm commonly used for speech recognition. For an event detector using a classical HMM approach (e.g. Ohnberger 2001), a high number of training events are required. To circumvent this, Hammer et al. (2012) developed a new approach exploiting the abundance of data containing mainly background signals to learn a multidimensional Gauss-

ian mixture model. This background model represents the overall feature space and serves as seed for deriving HMM parameters for the waveform of rare seismic events (e.g. avalanches) using as little as one single training sample. Based on these promising results, we used the same HMM approach to identify avalanches in continuous seismic data. Since we used less sensitive instruments over longer time periods, we had to adapt the approach presented by Hammer et al. (2012). In particular, we calculated the background model using data within a 24-hour window to cover diurnal variations in the seismic data and it was also necessary to recalculate the background model on an hourly base. To eliminate false detections in the classification results, post-processing steps were implemented in the classification workflow (Heck et al. 2018a).

3.2 *Localization of avalanches*

Since data were recorded using a seismic array, we also used array processing techniques to obtain further information of the detected events. By applying multiple signal classification (MUSIC) we obtained information on the back-azimuth of the seismic source and the apparent velocity of the incident wave-fields (Heck et al. 2018b). Since avalanches have a moving source character, small changes of the back-azimuth with time are visible for avalanche events. Strong changes in the back-azimuth, however, are produced by other seismic events. Hence we also used the array processing techniques as an additional post-processing step to identify false classifications. Additionally, we were able to reconstruct avalanche paths by combining the back-azimuth results obtained using MUSIC with our knowledge of the local topography and avalanches visually observed during a field survey. Doing so, we were able to link seismic events to specific avalanche paths.

4. RESULTS AND DISCUSSION

We analyzed continuous seismic data recorded during the winter season 2016-2017 at both field sites above Davos. The main focus was on reconstructing avalanche activity for the Dischma field site. During this winter season three main periods of high avalanche activity were observed by the avalanche warning service in the region of Davos, in January, in February and in March (red bars in Figure 1). Meteorological conditions at the Dischma field site differed with those closer to Davos, where the vast majority of avalanche observations are made. Indeed at the Dischma field site snow depth in January and February was

lower compared to the rest of Davos and almost no avalanches were observed during field surveys in the Dischma valley during those periods or on images from multiple automatic cameras that were installed there. Only for the period in March many avalanches were visually observed in a field survey performed several days later (blue areas in Figure 2).

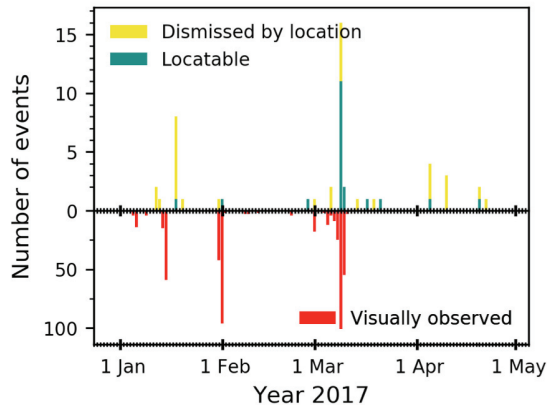


Figure 1: Classification results after applying the combined array classification and localization based classification. Yellow bars are all events dismissed by the location, turquoise bars are considered as avalanches and red bars indicate the number of visual observed avalanches in the surroundings of Davos ($\sim 175 \text{ km}^2$)

We performed the automatic avalanche classification from the beginning of January to the end of April. As already mentioned, we used 24 hours of data to construct the background model and recalculated this background model on an hourly basis. To train the HMMs a one-time event model was used based on a confirmed avalanche recorded on 9 March 2017. For each sensor a background and event model were then calculated. Doing so, data recorded at each of the seven sensors of the array were classified. Once the classification was performed, all detected events with a duration shorter than 12 s and detected by less than five sensors of the array were dismissed, as suggested by Heck et al. (2018a). Doing so, we identified 117 possible avalanche events in the continuous data. A manually inspection of these detections revealed that at least 50% of the classified events were produced by airplanes or earthquake. The time series and seismic features of these events had similarities to avalanches and were therefore falsely classified.

To eliminate these false classifications, we implemented a combined array classification. In this

step we assumed that events that were recorded almost simultaneously at the Wannengrat array 14 km away could not be avalanches. We therefore performed a second classification at the Wannengrat array with the aim to identify airplanes and earthquakes and identified all co-detections by comparing all classifications. Doing so we were able to eliminate 53 false detections and 64 possible avalanche events remained (yellow and turquoise bars in Figure 1). Nevertheless, these 64 events still contained some false classifications. To remove these, in a final step we analyzed the back-azimuths obtained using the MUSIC method. By considering that the back-azimuth of avalanche signals only have small changes, we dismissed all detections with strong variations. Using this post-processing step, we were able to eliminate an additional 37 events and 27 remained (turquoise bars in Figure 1). By applying the automatic classification with additional post-processing steps we were thus able to reconstruct the main avalanche period in March and detected some further single avalanches, which released during the winter season.

As already mentioned above, the two avalanche periods in January and February in the area of Davos were not pronounced at the Dischma field site. This already shows that the detection range of the seismic array is quite limited. To further constrain the detection range, we focused on the avalanche period in March and assigned seismic events to visually observed avalanches. To do so we projected the calculated back-azimuth values on a map and matched them with mapped avalanches. Using this approach we were able to link 11 seismic events to specific avalanche paths within a range of 3-4 km of the seismic array (Figure 2). Since we only had one seismic array at this field site, automatic localization was not possible as we could only estimate the direction of the source.

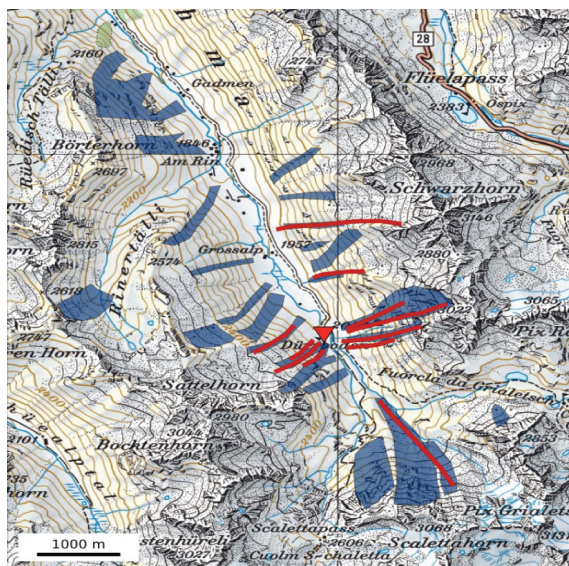


Figure 2: Map of the Dischma field site. Blue areas are visually observed avalanches during a field survey. Red lines are reconstructed avalanche paths based on the MUSIC results.

We also compared the release times of all detected events during the two-day period in March with the measured precipitation (Figure 3). The first avalanche already released with less than 20 cm of new snow measured at a weather station located 7 km to the northwest. Furthermore, avalanche activity stopped once the snow storm was over. This analysis shows that for this particular snow storm, avalanches could be expected at any time during the snow storm, already with small amounts of new snow, and not necessarily near the end of the storm when most of the snow had accumulated.

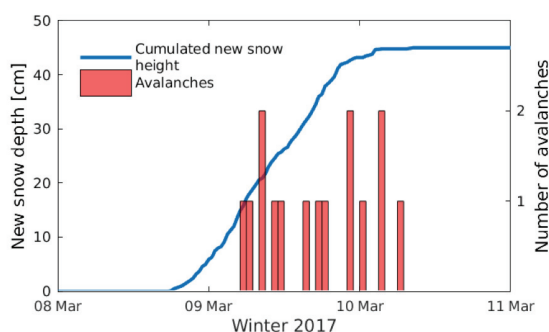


Figure 3: Red bars show the number of avalanches for the avalanche period on 9-10 March 2017. Blue line shows the cumulated height of new snow at this area.

5. CONCLUSION

Seismic monitoring systems are well suited to detect avalanches at remote field sites. By using advanced machine learning algorithms, such as hidden Markov models, automatic classification of seismic data is possible. Our experiment showed that compared to previously published studies, additional post-processing steps are required. This allowed us to detect 27 avalanches within a range of 2-3 km during the entire winter season 2016-2017. By comparing the release time of the avalanches with measured precipitation during a major avalanche cycle in March, we saw no clear peak in avalanche activity, a rather surprising result. In future studies, we plan to deploy several nearby automatic monitoring systems to automatically reconstruct the avalanche paths where avalanche release.

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