Cold Regions Science and Technology 111 (2015) 60–66

Contents lists available at ScienceDirect

Cold Regions Science and Technology

journal homepage: www.elsevier.com/locate/coldregions

Robust snow avalanche detection using supervised machine learning with infrasonic sensor arrays

Thomas Thüring *, Marcel Schoch, Alec van Herwijnen, Jürg Schweizer

WSL Institute for Snow and Avalanche Research SLF, Davos, Switzerland

ARTICLE INFO

Article history:
Received 2 July 2014
Received in revised form 3 November 2014
Accepted 26 December 2014
Available online 4 January 2015

Keywords:
Snow avalanches
Infrasound
Array processing
Automated monitoring
Machine learning

ABSTRACT

Automated detection of snow avalanches is crucial to assess the effectiveness of avalanche control by explosions, and to monitor avalanche activity in a given area in view of avalanche forecasting. Several automated or semi-automated detection technologies have been developed in the past among which infrasound-based detection is the most promising for regional-scale avalanche monitoring. However, due to significant ambient noise content in infrasonic signals, e.g. from atmospheric processes or airplanes, fully automated and reliable avalanche detection has been very challenging. Signal processing is highly critical and strongly affects detection accuracy. Here, a robust detection method by using supervised machine learning is introduced. Machine learning algorithms can take into account multiple signal features and statistically optimize the classification task. We analyzed infrasound data with concurrent visual avalanche observations from the test site Lavin (Eastern Swiss Alps) for the winter of 2011–2012. A support vector machine was trained by using training data from the first half of the winter season and the accuracy was tested on data from the second half of the season. A significant reduction of false detections, from 65% to 10%, was achieved compared to a threshold-based classifier provided by the sensor manufacturer. The proposed method enables reliable assessment of the avalanche activity in the surroundings of the system and paves the way towards robust and fully automated avalanche detection using infrasonic systems.

1. Introduction

Snow avalanches threaten people and infrastructure in seasonally snow-covered mountain regions. Thorough avalanche hazard assessment is crucial for minimizing the risk by avalanche preventive measures such as avalanche control by artificial triggering of avalanches. Hazard assessment relies on weather data and forecasts, snow cover model output and snow instability data (McClung and Schaerer, 2006; Schweizer and Jamieson, 2010). The latter includes field observations of snow instability, in particular results of snowpack stability tests and avalanche occurrence data. Complete assessment of avalanche activity in an area requires continuous monitoring, which cannot be achieved with field observations. In particular during times of poor visibility or at night, when field observations are impossible, automated detection systems are highly desirable. A fully automated system continuously observes an area and generates events which are transmitted to the avalanche safety service in charge. These systems are also needed at avalanche control sites to measure the effectiveness of the artificial triggering by explosions (Schweizer and van Herwijnen, 2013).

A variety of remote sensing techniques and instruments for the automated detection of snow avalanches have been reported in the past. Technologically, they can be classified into techniques based on radio frequency signals (radars) (Gauer et al., 2007; Kogelnig et al., 2012; Salm and Gubler, 1985; Vriend et al., 2013), seismic signals (geophones) (Schaerer and Salway, 1980; Suriñach et al., 2000; van Herwijnen and Schweizer, 2011a, 2011b), optical signals (imagery) (Larsen et al., 2010; Lato et al., 2012) and acoustic signals (microphones, micro barometers) (Adam et al., 1998; Bedard, 1989; Kogelnig et al., 2011; Scott et al., 2007; Ulivieri et al., 2011). Optical imagery enables the assessment of avalanche activity and localization with high spatial resolution; however, its applicability strongly depends on visibility. Avalanche detection using pulsed Doppler radar is very reliable and enables the measurement of avalanche dynamics properties, for instance avalanche velocity. On the other hand, the monitoring area is usually small, typically a well-defined avalanche path. Seismic detection performs well during all weather conditions. However, seismic signals from natural or artificial sources (e.g., earthquakes, airplanes) cause significant background noise (van Herwijnen and Schweizer, 2011b). Several automated detection approaches to separate noise from avalanche events in seismic data have been reported in the past (Bessason et al., 2007; Lacroix et al., 2012; Leprettre et al., 1996).

Similar to seismic waves, flowing and turbulent snow masses by avalanches generate pressure waves (or sound waves) in the air.

* Corresponding author at: Unterhunzikon 1, 6232 Geuensee, Switzerland. Tel.: +41 797770641.
E-mail address: t.thuering@gmx.net (T. Thüring).

http://dx.doi.org/10.1016/j.coldregions.2014.12.014
0165-232X/

These sound waves lie in the frequency range between 0.001 and 20 Hz, known as the infrasonic range (Bedard, 1989). The atmospheric attenuation of infrasound is very low and the waves can travel over large distances. Therefore, infrasonic detection systems can potentially record signals many kilometers away. Infrasound has already been used for monitoring atmospheric processes (Le Pichon et al., 2009), volcanic activity (Ripepe et al., 2007), nuclear explosions (Christie et al., 2001) or snow avalanches (Scott et al., 2006). In mountain regions, infrasonic sensors enable the detection of avalanches releasing several kilometers away from the sensor system (Ulivieri et al., 2011), which is a major benefit compared to other detection techniques mentioned above. Infrasonic systems may consist of multiple sensors (arrays), which enhance the signal to noise ratio (SNR) (Scott et al., 2007) and enable precise source localization (Ulivieri et al., 2011). Several commercial products for automated avalanche detection have been released recently, indicating an increasing demand of infrasound as an alternative or complementary technique to existing technologies. Examples are the ARFANG system by IAV Switzerland or the system by iTEM geophysics in Italy.

Two major issues in infrasonic-based avalanche detection are the presence of ambient noise (e.g., from wind) and of signal sources other than avalanches (e.g. atmospheric processes, airplanes, helicopters, etc.). If such disturbing signals cannot efficiently be separated from avalanche signals, false detections (i.e. false alarms) may frequently occur. Ambient noise can be reduced, either by adding noise filters or by using multiple, spatially distributed sensors (arrays) (Scott et al., 2007). Noise signals of a sensor array are mutually uncorrelated for a sufficiently high sensor spacing, which can be used to increase the overall SNR. Other than uncorrelated noise, correlated signals from real infrasonic sources can become a serious problem, as they may be difficult to separate from avalanche signals. To overcome this, robust signal analysis and classification methods are required. Several classification approaches have been proposed (Chritin et al., 1996; Schimmel and Hübl, 2013; Ulivieri et al., 2011). These methods all use a common classification scheme. First, signal features, such as the infrasonic power, the direction of incidence of an event or the duration of an event, are extracted. Second, features are analyzed and thresholds are defined which separate avalanche events from non-events. Such threshold-based classifiers are easy to control and may perform well under certain conditions. Unfortunately, classification accuracy has not been reported in these studies.

Here, a threshold-based classifier, developed and optimized by the manufacturer of a commercial infrasonic avalanche detection system, is compared to an alternative, machine learning-based approach. A support vector machine (SVM), a well-established machine learning algorithm, was trained and evaluated using infrasonic recordings from a four-sensor-array system installed at an avalanche control site near Lavin in the Eastern Swiss Alps. SVM-based avalanche detection was already demonstrated for the automated detection of avalanches in seismic data, showing encouraging results (Rubin et al., 2012). Using an infrasonic system, an SVM was also applied to the detection of volcanic activities at Mount Etna (Cannata et al., 2011).

In Section 2, after a short overview of the infrasonic sensor hardware, the computational methods are discussed in detail. While SVMs are nowadays a standard tool in data mining problems and can easily be applied to avalanche detection tasks, the extraction of discriminant features which separate positive from negative events remains a crucial and time consuming issue. In Section 3, an SVM is trained based on various signal features and by using avalanche field observation data in the avalanche controlled area from the early winter season 2011–2012 (training phase). Detection performance in the avalanche controlled area is evaluated by using a test data set from the remaining season in 2012 (test phase). Finally, avalanche activity is assessed for the area in the vicinity of the avalanche path during the test phase.

2. Instrumentation and methods

2.1. Infrasonic sensors

A commercial infrasonic sensor array with four sensors from IAV Engineering (Tannay, Switzerland) was installed in 2009 near Lavin (Eastern Swiss Alps) to monitor the Gonda avalanche path where avalanches are triggered artificially by explosives to protect the road passing below. The system is located across the valley from the avalanche path at the bottom of the counter slope; for more details on the site see Meier and Lussi (2010). The four sensors are aligned in a star-shaped geometry with a radius of 30 m to equalize the angular reception sensitivity (Ulivieri et al., 2011; Van Lancker, 2001). The sensors measure pressure variations differentially with respect to the atmosphere (microbarometer) and synchronously acquire infrasonic signals at a sampling rate of 80 Hz. With a cutoff frequency of approximately 0.1 Hz, the available frequency spectrum ranges from 0.1 to 40 Hz. The sensitivity of the sensors is 3.2 V/Pa, the dynamic range is 80 dB and the noise floor is −85 dBFS. Compared to a single sensor, a sensor array has two main advantages. First, uncorrelated noise is suppressed due to the spatial distribution of the sensors. Second, it enables localization of signal sources by measuring time delays of signals between sensor pairs (see Section 2.3). The resolution of source localization depends on the direction of the moving source, the sensor geometry and the sampling frequency. For the system used here, the maximum achievable angular resolution is $\alpha_{\min} \approx 4°$.

2.2. Event classification by supervised learning

Event classification from acoustic signals is a wide research area with a large variety of available algorithms and techniques. The common goal is to classify recorded signals into events based on a set of extracted variables (features) from the raw output signal. A feature represents a signal property which can ideally separate the signal into different classes of interest. A simple and common scheme of a classifier is to define decision thresholds for the extracted features. This usually allows for simple control and optimization of the classification outcome. However, if multiple features must be taken into account, manual definition and optimization of thresholds become difficult to handle and are often prone to mistakes (Kotsiantis et al., 2007). In particular when trying to establish relationships between features, threshold-based classification is not practical.

In contrast to threshold-based classification, machine learning algorithms automate and statistically optimize a classification task (Vapnik, 2000). Supervised machine learning methods "learn" decision margins of features from training data. Therefore, a set of training data with known classification output must be available a-priori. Among the large variety of supervised machine learning algorithms, support vector machines (SVM) are known to perform well when using multiple and continuous features (Kotsiantis, 2007). The algorithm analyzes the multidimensional feature space and calculates optimum decision margins (hyper planes) based on the training data. This allows for taking into account complex mutual dependencies between features, which is a major benefit compared to threshold-based methods. Only a few input parameters are required. A detailed discussion about SVMs and classification theory can be found in the literature (Burges, 1998; Cristianini and Shawe-Taylor, 2000).

We applied an SVM to the classification problem of detecting avalanche events in infrasonic signals. Fig. 1 shows a schematic overview of the different steps in the proposed signal processing workflow. The method is implemented "off-line", meaning that previously recorded infrasonic data are analyzed. The raw data were preprocessed before extraction of signal features. After feature extraction, part of the data was assigned as training data, which were used to train the SVM classifier (learning phase). The classifier was optimized through a 10-fold cross-validation procedure. Finally, the detection of avalanche