Can Avalanche Deposits be Effectively Detected by Deep Learning on Sentinel-1 Satellite SAR Images?

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CAN AVALANCHE DEPOSITS BE EFFECTIVELY DETECTED BY DEEP LEARNING ON SENTINEL-1 SATELLITE SAR IMAGES?

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***Abstract*—Achieving reliable observations of avalanche debris is crucial for many applications including avalanche forecasting. The ability to continuously monitor the avalanche activity, in space and time, would provide indicators on the potential instability of the snowpack and would allow a better characterization of avalanche risk periods and zones. In this work, we use Sentinel-1 SAR (synthetic aperture radar) data and an independent in-situ avalanche inventory (ground truth) to automatically detect avalanche debris in the French Alps during the remarkable winter season 2017-18. Convolutional neural networks are applied on SAR image patches to locate avalanche debris signatures. We are able to successfully locate new avalanche deposits with as much as 77% confidence on the most susceptible mountain zone (compared to 53% with a baseline method). One of the challenges of this study is to make an efficient use of remote sensing measurements on a complex terrain. It explores the following questions: to what extent can deep learning methods improve the detection of avalanche deposits and help us to derive relevant avalanche activity statistics at different scales (in time and space) that could be useful for a large number of users (researchers, forecasters, government operators)?**

I. INTRODUCTION

Remote sensing of avalanche debris in mountain areas offers new opportunities to improve our understanding of avalanche activity and to evaluate the physical models of avalanche hazard forecasts. The location of avalanche debris and the estimation of their sizes are of great interest for studies dealing with the stability of the snowpack and also the variability of natural avalanche activity, which could be related to climate change. In addition, time series of avalanche events, with relevant time and space resolutions, would be highly relevant to better identify avalanche risk zones and periods. Such time series would be a great addition to the existing databases, mostly based on visual observations. Despite their great value, these in-situ data are scarce and are limited by the terrain accessibility, the weather conditions and the danger of avalanches themselves. In this study we use backscatter coefficients at C-band from the SAR onboard Sentinel-1A and -1B satellites launched between 2014 and 2016. The French Alps are observed every 6 days.

The study period covers the winter of 2017-18, which was marked by particularly high avalanche activity recorded in the French Alps. Microwave backscattering over snow surfaces is complex because it combines several phenomena including reflection on the snow surface, scattering within the snowpack (which depends on its layers properties) and reflection at the snow-soil boundary. To detect avalanche debris, change detection methods are typically used to isolate avalanche debris-like features based on the backscatter contrast between avalanche debris and the surrounding undisturbed snowpack [1]. Debris detection is based on major changes in the backscatter coefficients due to changes in snow properties following the avalanche event (height, density, roughness), Figure 1 shows an example of an RGB composition map using 3 Sentinel-1 images at VH polarization. The large avalanche event near "Les Houches" can be seen in green.

Recent work [1], [2] demonstrated the potential of Sentinel-1 SAR data for avalanche mapping on specific examples. Karbou et al. [3] applied a change detection method and combined Sentinel-1 ascending/descending orbits to automatically detect avalanches at the scale of a mountain chain. However, the complexity of the interaction of the radar signal and the snow medium necessitate the development of more advanced algorithms that are also able to better manage the consistent data

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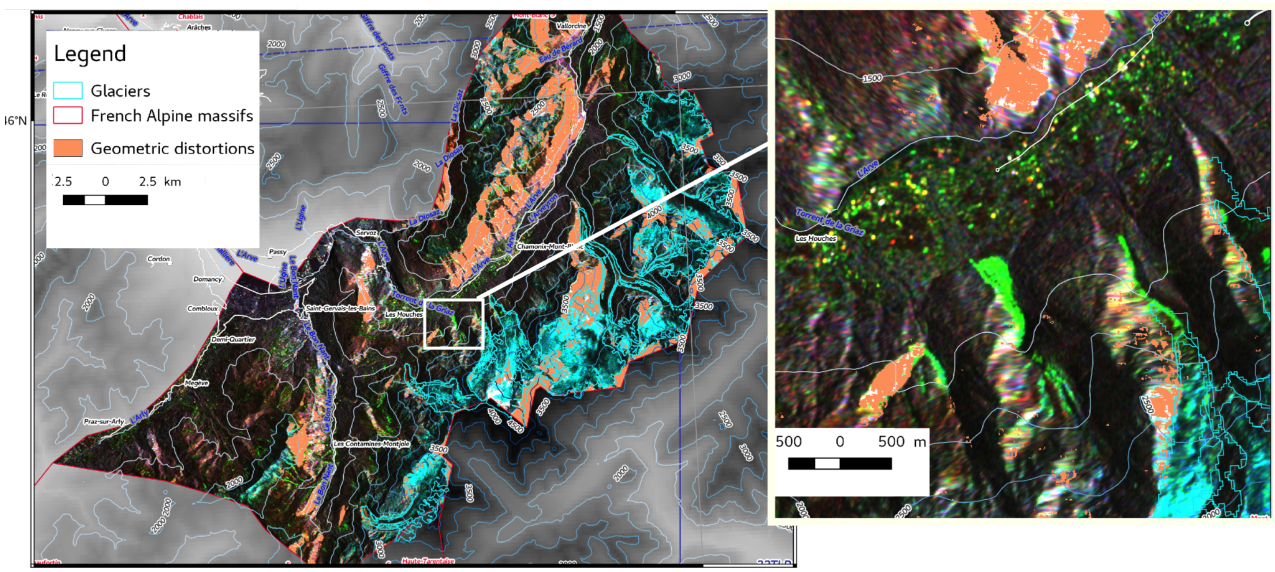


Fig. 1: An RGB composition SAR image over the Mont Blanc chain (one of the 23 French alpine massifs of the database) using 3 sentinel-1 VH images (R: 2017/08/24, G: 2018/01/15, B: 2018/01/09) highlighting avalanche debris signatures in light green for events between the 09th and the 15th of January 2018, such as the avalanche event occurred near les Houches (see zoom).

flow.

With the advances in machine learning, recent works proposed classification methods for this task, using a random forest classifier [4] or convolutional neural networks [2]. The results are very promising; however they both rely on expert labelling from the same SAR imagery. This has two major limitations: i) no study has been made on the accuracy of expert labelling from SAR signals; ii) it is not possible to differentiate between a new avalanche and an old one that is still visible.

We propose in this paper to couple the SAR data with an independent ground truth database which would answer both issues. Specifically, we used an avalanche inventory covering more than 3000 avalanche corridors in the French Alps, which are collected by forest rangers from ONF (Office National des Forêts) and stored by Irstea research institute. From the partial information available in the inventory (the specific delineation of the avalanche is not accessible), we automatically cropped some image patches containing the zone of deposition for every avalanche in the database. We then constructed and trained a convolutional neural network model able to classify the satellite image patches as *avalanche* or *no avalanche*. By using the SAR acquisitions of both current time and previous acquisition (6 days earlier), we trained our network for detecting only the new avalanches. From a database of more than 1300 samples from 16 mountain chains (out of 23 for the whole alps), we were able to detect new avalanches. We compared our results with a baseline method. Moreover, we performed an analysis to generate insights on the types of avalanches that can be identified.

II. Method

A. Data Processing

a) Avalanche inventory: The EPA (Enquête Permanente sur les Avalanches) database includes field observations on more than 3000 paths (mountain corridors where avalanches occur). Avalanche occurrences are recorded, along with quantitative and qualitative data (runout altitudes, release cause, damages, etc.). We used more than 4000 avalanche events annotated from the 2017-18 season and attributed to the different EPA paths. With SAR data, we can observe a relative increase of the backscatter due to snow deposit. Consquently, we automatically extracted the lowest elevation parts of the EPA corridors, where most of the avalanches would have their zone of deposition.

b) Sentinel-1 SAR imagery: We extracted the Sentinel-1 synthetic aperture radar (SAR) polarizations VV and VH on the whole region from the descending relative orbit 139, with a 20m resolution[1]. SAR

[1]We used the Level-1 Ground Range Detected (GRD) products made available through the Copernicus web site https://scihub.copernicus.eu/dhus/.

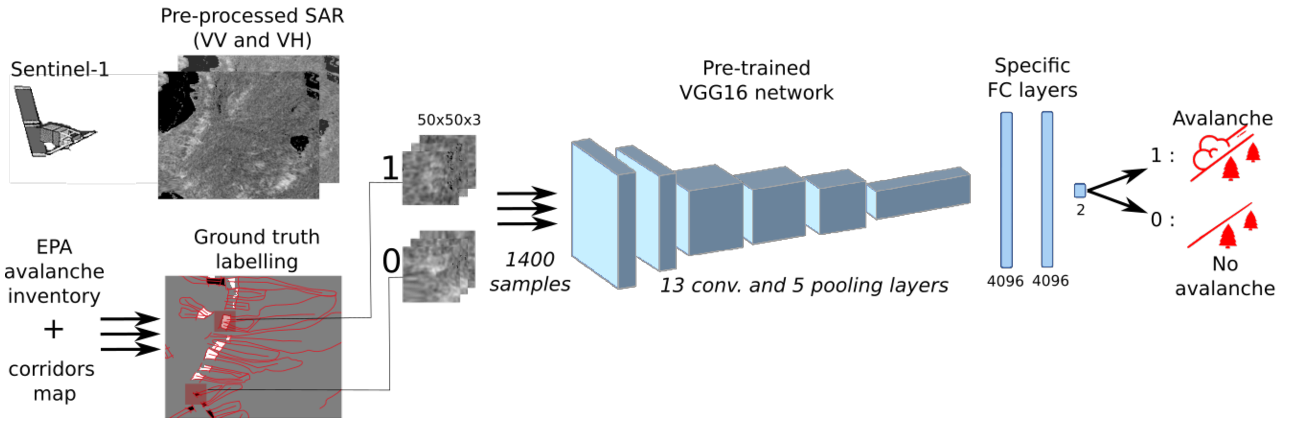


Fig. 2: Avalanche detection pipeline. From an independent ground truth labelling, 50% positive and 50% negative SAR satellite image patches are feeding a convolutional neural network composed of convolutional layers (Conv) and fully connected layers (FC). The 3 input channels are VV^*, VV^*_{old} from the previous satellite acquisition (6 days earlier), and $VH_{diff} = VH^* - VH^*_{old}$.

data have been processed using the ESA Sentinel-1 Toolbox (speckle filtering, radiometric calibration, terrain correction, etc.). With one acquisition every 6 days, we collected a total of 32 dates in the season. Sentinel-1 has a side-looking imaging geometry which causes geometric distortion occurrences in mountains including shadow, layover and foreshortening effects. These areas are screened out. We calculated the images ratio (with respect to snow-free summer images): $VV^* = 10\log 10(VV/VV_{summer})$ and $VH^* = 10\log 10(VH/VH_{summer})$ as well as the difference $VH_{diff} = VH^* - VH^*_{old}$ with the previous satellite acquisition (6 days earlier).

c) Label maps: For every SAR acquisition date, we calculated a label map where a zone is positive if an avalanche was monitored between the last acquisition and this one (6-day window); negative if not. The zones outside of the EPA corridors (thus not monitored) are considered as unknown and not labelled. Moreover, if the uncertainty on the date at which the avalanche occurred was larger than the 6 days between the acquisitions, the zone was also not labelled.

B. Learning Framework

a) Satellite image patches: Because the zone of deposition of every event is roughly localized (from the corridors of the EPA map), a segmentation task is not possible. That is why we used satellite image patches (of 50x50 pixels, so $1km^2$) centered on the lowest elevation part of the corridors, assuming that any snow deposit would be included. We stored 3 feature image channels: VV^*, VV^*_{old} (from the previous acquisition 6 days earlier) and the difference VH_{diff}. 658 positive patches (containing an avalanche) were available, and we randomly extracted the same number of negative patches from non-active corridors. The 1316 samples were randomly separated into 3 sets as follows: train (60%) / valid (20%) / test (20%), where different acquisitions (dates) of a same corridor were kept in a unique set.

b) Convolutional neural networks (CNN) model: Because of the limited number of samples, we developed a transfer learning method that uses a pre-trained CNN network which is then fine-tuned for our specific problem. Following recent studies [2], [5], we used the VGG 16 network [6] (composed of 13 convolutional layers) trained on the ImageNet database, and optimized only the 3 fully connected (FC) layers (see Figure 2). We used a cross-entropy loss as criterion for the classification task. To reduce over-fitting, each sample was subject to random augmentation: flipping of axes and 50x50 cropping from a 64x64 initial patch. Moreover, we also used a 50%-rate dropout on the FC layers. The evaluation was repeated three times and an average score was computed in order to assess the robustness of the random weights initialization. We used an early-stopping model selection on a maximum of 250 epochs.

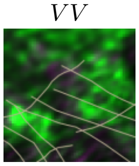
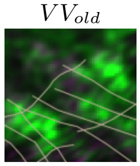
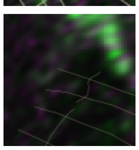
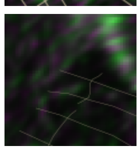
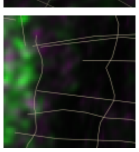
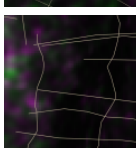
III. EVALUATION

a) Quantitative results: Once the best model using the validation set selected, we present in Table I the results of the test set (kept hidden). We compared our results with the thresholding method [3]. In order

TABLE I:
Comparison between our method and the baseline (thresholding method). Test set: 211 samples from which 1/4 are from the Haute Maurienne chain.

	Haute Maurienne		**All Alps**	
	CNN	**Baseline**	**CNN**	**Baseline**
Accuracy	0.77	0.53	0.69	0.58
Precision	0.81	0.51	0.69	0.57
Recall	0.74	0.72	0.69	0.59
F1-score	0.78	0.6	0.69	0.58

TABLE II:
Examples of classification results. RGB composition of the 2 VV images (as R: VV_{summer}, G: VV, B: VV_{summer}) given as input. The light green should reflect avalanche deposits.

VV	VV_{old}	**Label**	**Prediction**
		**1**	**1**
		**0**	**0**
		**1**	**0**

to automate the threshold for image classification, we calculated the number of positive threshold pixels per image that gave the best result on the validation set (above which the whole patch is considered as *positive*), and used this parameter on the test set. We can see that our method outperforms the baseline on all of the metrics (accuracy, recall, precision and F1-score). We can see that the results in the Haute Maurienne chain (77% accuracy), containing a quarter of the total number of samples, are clearly better than the result on the whole 16 mountain chains (69% accuracy). This seems to indicate that it is easier to detect avalanches in zones where we have a good amount of data, even if the corridors in the test set were unseen. Table II shows three examples of classification in an RGB composition where the green should reflect avalanche deposits.

b) Analysis: The results were then further analyzed, in order to understand what types of avalanches can be detected. We observe no significant difference in terms of season (month) and local slope between true positives (TP, avalanches correctly detected) and false negatives (FN, avalanches missed). Yet, we noticed that the small avalanches (area< $70m^2$ according to the EPA database) were more missed than others (40% of them were not detected). We also noticed a difference in the orientation of the mountain patches. The proportion of FN patches facing East is 69%, while it is only 44% for TP. This might be due to the angle at which the satellite is facing the mountain (seeing better the slopes facing West for the descending orbit). Lastly, as we have seen with Haute Maurienne, the mountain chains with the larger number of samples had the best results, probably because different conditions (orientation, pre-processing of the signal,ect.) are dependent on the mountain zone. This is currently a limitation of the method, however it should be resolved by (i) increasing the size of the database with more seasons (since 2015), (ii) increasing the confidence on the result by combining several satellite orbits (4 relevant ascending/descending orbits in our test zone), for a better coverage of the mountains.

CONCLUSION

This is the first quantitative study combining SAR imaging data with an independent in-situ avalanche inventory. The complexity of the SAR signal and the uncertainty on the labels make this problem particularly challenging. We showed that by selecting some patches centered on the lower part of inventoried avalanche corridors, a convolutional neural network can detect the presence of avalanche debris with an accuracy of up to 77% in the most susceptible mountain zone. Moreover, we identified two causes of misclassification: the size of the avalanche debris, and the orientation of mountains. These new insights can help to make an efficient use of remote sensing measurements on this complex terrain. This is an encouraging first step towards a efficient use of remote sensing for avalanche forecasters and local policies.

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