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Discussions

Interactive comment on "Automatic detection of snow avalanches in continuous seismic data using hidden Markov models" *by* Matthias Heck et al.

Anonymous Referee #1

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This study focuses on the seismic detection and identification of the signals generated by snow avalanches in the Davos area in the Swiss Alps during the winter 2010. The authors tested the capability of a machine learning algorithm (hidden Markov models - HMM) to perform this detection and identification from continuous seismic data. They used a reference catalog to evaluate the performance of the algorithm. The first results showed that the algorithm is capable to achieve relatively high positive identification rates of the avalanches in the catalog (70-95% depending on the station that recorded the signals), but also with a high rate of supposedly false detections. This led the authors to propose a post-processing strategy. Three post-processing steps were investigated: (i) analysis of the duration of the signals; (ii) computation of a correlation

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factor to evaluate the coherence of the signal between each sensor; and (iii) a voting system based on the classification returned by each station for a given event. Using one, or a combination of those proposed post-processing steps, led to a decrease of false alarm rates, but also in most cases to a decrease of the rate of good identification.

The use of seismology to study environmental processes is of growing interest as it allows producing observations with a unique spatio-temporal resolution. This new approach can help to better understand the triggering factors of natural hazards and to mitigate their consequences on our societies. In this context, this study contributes to the continuing effort to develop robust and versatile methods to explore years of continuous data and for the implementation of real-time seismology-based warning systems. Overall, I think the paper is clearly written, and that the Authors have made a good effort to carefully explore the data, explain their approach and discuss their results. Nevertheless I listed below several comments and suggestions that might help to improve this paper.

General comment:

The only major concern I have regarding this work is that the downsides of using the HMM algorithm are not discussed while most of the results presented in this paper suggests that HMM alone, without pre- and post-processing, cannot perform identification of seismic sources with a high success rate. The strengths of the HMM are usually stated to be: i) it does not need any pre-detection or picking (STA/LTA, etc.), which should ensure that no event is missed; ii) it does not require any inputs from experts. Yet this paper demonstrates that i) a pre-detection can be suitable to remove low-amplitude/noise signals (figure 2); ii) post-processing steps with thresholds set by experts (duration, etc.) is needed to achieve a high accuracy.

Moreover, the Authors are building their post-processing strategy based on features that can be incorporated in the identification models constructed with other machine learning algorithms. The post-processing steps the Authors propose seem necessary because the HMM cannot include these features (durations of the signals, coherence between signals recorded at different stations, vote among stations) in the model due to its core design, which is to consider chunk of continuous data and not the entire signal generated by the event. This forces the Authors to manually set thresholds on those features, while with some other algorithms those thresholds are determined through a statistical analysis of the reference data.

I think the authors must include a more thorough and objective discussion on the pros (which definitely exist) and the cons of HMM compared to other algorithms/studies in the light of the results of this work.

Specific comments:

P3 L6-8: Are those false alarm rates related to the choice of the algorithms or to the choice of the features used to parametrized the signals? The latter might be more important and should be mentioned.

Figure 1: I think a colorscale with more colors would allow to better observe the features of the signals generated by the different sources, especially at frequencies below 50 Hz. This is important as the readers might want to understand what guided your choice of features. Also this figure can be larger.

P9 L25-27: How do you compute the duration?

P9 L1-3: How does the voting step in the post-processing would impact the detection of “small” events (especially with a threshold set at 5 stations for a network with 7 sensors)? Are “small” events detected by the whole network? A figure showing the locations of the avalanche corridors and the seismic network would be interesting.

P11 L4-5: Indeed. How would it have impacted your results if you had chosen another master event? Is this has been investigated in Hammer et al. (2017)? If yes it should be mentioned and referenced.

P13 L11-12: So the selection of the threshold on the duration is not done by considering the physics of the sources or the distribution of the durations in the reference catalog, but to optimize the POD-FAR ratio? By applying this threshold to the reference data set you lose 40% of the events (P14, last line). How is this threshold choice impacting the detection of "small" avalanches? Can you show a histogram of the duration of the events in the reference catalog? You state on P3 L24 that "For avalanche forecasting information on smaller avalanches is also required". Hence is the approach you propose suitable to detect the smaller events?

P13 L14-16, P20 L6-7, Table 3: Again, it would be great to have a map of the seismic network to discuss the discrepancies observed at the different sensors. Distance to the sources, travelled paths, attenuation, dispersion, etc., can also be factors impacting the amplitude, the duration and more generally the features of the signals that might in return change the POD at different stations. This could be discussed.

P20 L17-18: So in the best case what is your overall accuracy? Considering which range of avalanche sizes? I think it is this information that the readers will seek.

P20 28-30: Are the results presented in this study supporting this statement or is it based solely on the study by Hammer et al. (2017)?

P21 L4-5: How can you incorporate localization parameters in the HMM? Is this done directly in the model or during the post-processing?

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