Seismic detection of rockslides at regional scale: Examples from the Eastern Alps and feasibility of kurtosis-based event location by Florian Fuchs et al.

Comments referee #2, Naomi Vouillamoz, 02.08.2018

This paper presents a simple approach to automatically detect, discriminate and locate rockslide events using broadband seismic records at regional scale. The feasibility of the approach is evaluated with 21 rockslide events. The automatic detection applies a recursive STA/LTA coincidence trigger where a minimum number of four stations is needed to declare a detection. It was tested on eight-minute continuous data segments around the 21 events, and 19 of the 21 rockslide events (two events being too weak) were successfully detected. For event discrimination between rockslides and earthquakes, 32 earthquakes are selected, which cover the same region and span the same order of magnitudes as the 21 rockslide events. A simple decision criterion based on three seismic features of the earthquakes and rockslide signals enables to successfully discriminate all events. Rockslide events location is performed using a kurtosis-based picker, which permits better picking of the emergent signal onsets and hence an improved and more accurate location of the event. Using this approach, 14 events could be located with deviation ranging from 0.7 to 26 km, 11 events being located with less than 10 km deviation from the true location. A volume-magnitude relation is derived and used to propose a power-law between the seismic amplitude of the signals and the volume of the rockslide event. The authors provide then a detailed discussion about their approach and its potentials for implementation on large continuous seismic datasets. The paper is well written, and well-structured. The approach seems promising. This study should be published with some revisions in the special issue of Earth Surface Dynamics: From process to signal – advancing environmental seismology.

General comments:

Should the title of the paper be refined? You propose a simple (and elegant) automatic detection, discrimination and location scheme for rockslide events at regional scale, using low sample-rate broadband data of national seismic networks. It seems the methods could be easily implemented for real-time applications. I have the feeling there might maybe be something even more appealing than the current title, but it's just a feeling 😉…

I don't see the point including the AlpArray Working Group in the author list! Or is this mandatory because you use AlpArray data? This is a small research paper. An acknowledgment and reference as it is already done at the end of the paper is in my opinion enough in that context...

How was the rockslide dataset established? The authors mention in the last paragraph of the discussion section (P12 L9-12) that much knowledge could be gained by merging or cross-checking national event databases over the borders. However, events published for instance by Dammeier et al. (2016) (see Figure 4 of that paper) or the 'famous' August 2017 event of Piz Cengalo (Bondo) which are located in the study area do not figure in the studied dataset. Why?

The discussion part needs to be reworked. The Event Detection section should be discussed in more details with more specific examples on more sensitive algorithms and how one could optimize computational requirements with false alarm rates. The section Kurtosis picker performance and location accuracy could be better structured. I provide more specific comments about that section below. Event discrimination and volume estimation should be split in two individual sections.

Specific comments:

P3 L1-2. Please specify better how the dataset was established and the events selected, since between 2007-2017 other events are known (see the above general comment).

P3 L2-3. Out of these 21 events, 17 rockslides have been independently …; I see 18 events in the Table (only 3 [b]).

P3 L6. "carried out at the Austrian Central Institute…"

P3 L9-10: Please provide a reference for the distance attenuation function used at ZAMG. Specify in the text that M_L was calculated by ZAMG (instead of only in the Table 1 caption).

P3 Section 2, Dataset: please describe here the 32-earthquake dataset used for event discrimination including a list (and a Table), preferentially providing the same information as for the rockslides.

P4 Table 1. Please provide an event ID reusable in Table 2. Please add a field with the minimal and maximal epicentral distance. Since you use M_L to derive a Volume-Amplitude scaling relation, an information about the number of amplitude reading used in M_L estimation would be interesting, especially if different from the number of stations with positive STA/LTA.

P6 L11. For some events a distinct second arrival is visible: How many events exactly? List the events based on event IDs so the reader can go and have a look on the waveform if interested.

P6 L 16. Time is scanned in steps of 2 s (space is missing).

P7 L6-7. For clarity purposes: (1) the Kurtosis…; (2) the ratio between maximum amplitude…; (3) the ratio of the duration…

P8 L1: For clarity purposes: We extract the same three parameters for the earthquake records in order to …

P8 L22. A local magnitude defined by 4 stations' amplitude reading as it is (?) the case for a couple of rockslide events is not exactly well defined. Moreover, M_L below 2 is always a bit tricky… What makes you think you are less loosely constrained than other references 😉 Please rephrase accordingly.

P9 L22. … we did not check how many false alarms would be introduced. What a pity! A few tests would have provided very interesting information/benchmark in terms of false alarm rates/data process speed, which is key for real-time implementation.

P10 L2. … by gravitational mass movements at regional distances.

P10 L2-3. I would rephrase. Eleven of the 14 locatable events in this study could be located within less than 10 km deviation from the true deviation (see Table 2).

P10 L12-14. These two sentences are not very clear. Do you mention the sampling rate and record bandpass as a potential reason for 'bad' locations? You expect better picking accuracy with higher sampling rate records? Please rephrase.

More generally, I would better structure the first paragraph of that section. Provide the reader with ratings. Which parameters are the most influencing?) How much variation did you observed when playing with the kurtosis-based picker? I expect the outliers to have way much influence on a bad location than the optimization of the kurtosis-based piker (see for example Joswig (2008), p 121, box "*Jackknifing explained*" or Vouillamoz et al. (2016), Figure 6).

P10 L24. For those events presenting a very distinct second arrival…

P10 L27. Most of (?) the other events show no clear second onset…

P11 L4. I find 'we demonstrate' a bit ambitious regarding the low statistical significance of the used dataset. We show that rockslides and earthquakes…

P11 L11-14. To my knowledge, machine learning is usually trained on lots of known events, not a few selected known events. Hammer et al. (2013) developed a classifier based on 1 single known events using Hidden Markov Models, however the random forest algorithm of Provost et al. (2016) is trained on hundreds of events. Please rephrase for clarity.

P12 L6. A general drawback of many studies…. this includes also your study. Even if you present more events than other studies, 21 events is still a limited number of events… Please rephrase…

P12 L 18. Again, I find demonstrate a bit too high… We propose a simple approach to search for seismic signatures of rockslides …

P12 L 20. … can potentially be reduced. I think greatly is too optimistic and actually, 10 km is not bad at all, given the quality of the onsets and the frequently high gap...

P12 L31. you forgot the final point… 😊

P13 L29. Team list. Again, I think referring to the AlpArray work group in acknowledgement and in the reference is enough.

Figures:

Figure 1. Please enhance the contrast between the colors of the permanent and the AlpArray stations. Use M_L scaling in the symbology (0-1, 1-2, >2) so the reader can easily recognize the bigger events. Provide lat-lon information or if you don't want to work in a GIS, maybe you could add IDs as label. Please add a Figure 1b, same area and scale, but displaying the earthquakes (also with M_L scaling) so the reader can visually compare the two datasets.

Figure 4. Caption: Use same date format as in the other figures and tables (YYYY-MM-DD).

Figure 5. Caption: Distribution of the three discrimination parameters…

Figure 6. It would be nice to have a word about the outlier at 10^5 m^3 and M_L 0.

References

Dammeier, Franziska; Moore, Jeffrey R.; Hammer, Conny; Haslinger, Florian; Loew, Simon (2016): Automatic detection of alpine rockslides in continuous seismic data using hidden Markov models. In *J. Geophys. Res. Earth Surf.* 121 (2), pp. 351–371. DOI: 10.1002/2015JF003647.

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Joswig, Manfred (2008): Nanoseismic monitoring fills the gap between microseismic networks and passive seismic. special topic, Leveraging Technology. In *first break* 26, pp. 117–124.

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