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High-accuracy Real-time Microseismic Analysis Platform: Case Study Based on the Super-Sauze Mud-based Landslide

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Summary

Understanding the evolution of landslide and other subsurface processes via microseismic monitoring and analysis is of paramount importance in predicting or even avoiding an imminent slope failure (via an early warning system). Microseismic monitoring recordings are often continuous, noisy and consist of signals emitted by various sources. Automated analysis of landslide processes comprises detection, localization and classification of microseismic events (with magnitude < 2 richter scale). Previous research has mainly focused on manually tuning signal processing methods for detecting and classifying microseismic signals based on the signal waveform and its spectrum, which is time-consuming especially for long-term monitoring and big datasets. This paper proposes an automatic analysis platform that performs event detection and classification, after suitable feature selection, in near real time. The platform is evaluated using seismology data from the Super-Sauze mud-based landslide, which is located in the southwestern French Alps, and features earthquake, slidequake and tremor type events.

Workflow

The SZ10 dataset used in this paper was collected at Super-Sauze mud-based landslide, which was an on-going slow-moving clay-rich debris slide (Vouillamoz et al., 2018). The dataset comprises recordings from 58 days of monitoring during the period 28 May - 24 July 2010. Because of labeled data availability, we restrict analysis to a subset of the whole dataset, comprising in total 174 labeled micro-seismic events: 56 earthquakes, 58 slidequakes, 37 tremors, 11 man-made calibration shots. Other events labeled as undefined were considered as false alarms for this study. Since the number of events per class distribution is imbalanced, after feature construction, we generate synthetic data to balance the training set using the Synthetic Minority Over-Sampling Technique (SMOTE) (Chawla et al., 2002).

The raw input signals are analyzed as follows: (i) Butterworth bandpass filtering to pre-process the recorded signal to the frequency band of interest, which in our case is 1-20 Hz, (ii) event detection, (iii) feature construction and selection, (iv) event classification.

While Short Term Averaging/Long Term Averaging (STA/LTA) (Allen, 1978) is still commonly used for micro-seismic event detection, the main drawbacks of this method are the number of critical parameters that need to be tuned (including window sizes and thresholds) to detect all events of interest and minimized detection of false alarms or undefined events. , This is time-consuming and prone to errors. Wavelet transforms, also increasing in popularity for detection, suffer from setting the detected thresholds with empirical values (To et al., 2009). In this paper, we develop and implement an event detector based on the Neyman-Pearson (NP) algorithm, which relies on hypothesis testing (Neyman & Pearson, 1933). Namely, for a given microseismic signal sequence, we find an optimal detection threshold that maximizes the probability of correct detection while restricting the probability of false alarm to a given limit.

In order to perform classification of events, it is important to identify distinct features describing each class of events. These features are fed to the classifier. Feature construction and selection from the raw seismic signals must be carried out carefully. Too many features could result in the curse of dimensionality and overfitting classification models. Too few could result in not being able to distinguish event types accurately enough. For volcanic event classification, (Malfante et al., 2018) generated 102 features, comprising temporal, spectral and cepstrum features, which are fed to a Support Vector Machine (SVM) classifier. No feature selection is performed to reduce or prioritize the feature set. Random Forest (RF) is used for microseismic signal classification in (Provost et al., 2017) with 71 features and (Curilem et al., 2009) with 63 features. The former used Variable Importance to rank the features while the latter used expert knowledge.

We extract 48 temporal, spectral and cepstrum features. The total number of features is further reduced to 26 features to avoid overfitting the models and reduce complexity via Inf-FS filter feature selection of (Roffo et al., 2017). For classification, we compare two popular classifiers that are recently emerging in the literature: SVM and RF.

Results

The overall results that will be presented include (1) detection results to estimate performance improvement of using the NP detector over STA/LTA and wavelet-based detection; (2) end-to-end classification results comparing the two classification approaches. We observe that the STA/LTA algorithm misses 6 events and detects 354 false alarms, while NP detector detects all labeled 174 events with only 49 false alarms. Intuitively and as Figure 1 shows, fewer false alarms result in improved classification accuracy, which is presented using the commonly used F1 score metric for machine learning, which is a value between 0 and 1, where 1 indicates all labelled events have been correctly classified

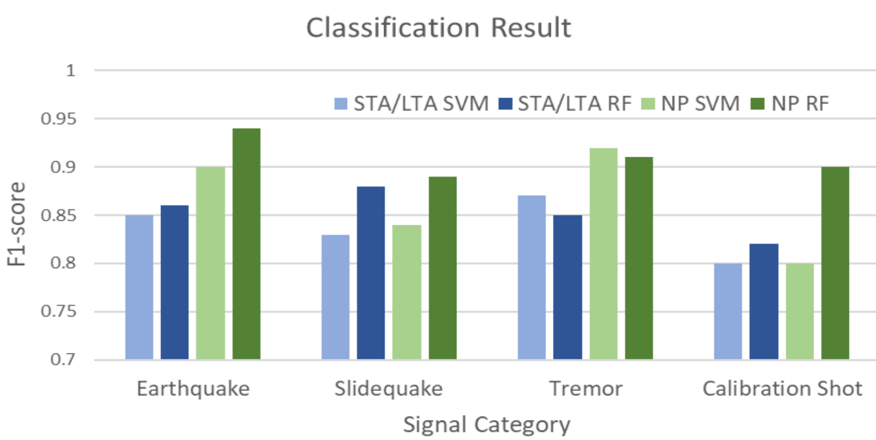

Figure 1. Classification performance, comparing SVM and RF classification with outputs of STA/LTA and proposed NP event detection

Furthermore, NP-based event detection followed by RF has the best classification performance overall. In addition, a discussion of feature selection will be presented, including the optimal features for each class of microseismic event and complexity analysis will be presented showing that the platform can achieve real-time monitoring.

Novel

In this paper, we propose a fully automated microseismic event analysis platform that performs microseismic event detection, feature selection and classification in near real time. Our system can accurately detect and classify four different types of microseismic events: earthquake, slidequake, tremors, and calibration shots, thus providing a better understanding of on-going landslide subsurface processes.

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References

(Allen, 1978) Allen, R. V. (1978). Automatic earthquake recognition and timing from single traces. *Bulletin of the Seismological Society of America*, *68*(5), 1521-1532.

(Chawla et al., 2002) Chawla, N. V., Bowyer, K. W., Hall, L. O., & Kegelmeyer, W. P. (2002). SMOTE: synthetic minority over-sampling technique. Journal of artificial intelligence research, 16, 321-357.

(Curilem et al., 2009) Curilem, G., Vergara, J., Fuentealba, G., Acuña, G., & Chacón, M. (2009). Classification of seismic signals at Villarrica volcano (Chile) using neural networks and genetic algorithms. *J. Volcanology and geothermal research*, *180*(1), 1-8.

(Malfante et al., 2018) Malfante, M., Dalla Mura, M., Métaxian, J. P., Mars, J. I., Macedo, O., & Inza, A. (2018). Machine learning for volcano-seismic signals: Challenges and perspectives. *IEEE Signal Processing Magazine*, *35*(2), 20-30.

(Neyman & Pearson, 1933) Neyman, J., & Pearson, E. S. (1933). IX. On the problem of the most efficient tests of statistical hypotheses. Philosophical Trans. the Royal Society of London. Series A, Containing Papers of a Math. or Physical Character, 231(694-706), 289-337.

(Provost et al., 2017) Provost, F., Hibert, C., & Malet, J. P. (2017). Automatic classification of endogenous landslide seismicity using the Random Forest supervised classifier. *Geophysical Research Letters*, *44*(1), 113-120.

(Roffo et al., 2017) Roffo, G., Melzi, S., Castellani, U., & Vinciarelli, A. (2017). Infinite latent feature selection: A probabilistic latent graph-based ranking approach. In Proceedings of the *IEEE International Conference on Computer Vision* (pp. 1398-1406).

(To et al., 2009) To, A. C., Moore, J. R., & Glaser, S. D. (2009). Wavelet denoising techniques with applications to experimental geophysical data. *Signal Processing*, *89*(2), 144-160.

(Vouillamoz et al., 2018))Vouillamoz, N., Rothmund, S., & Joswig, M. (2018). Characterizing the complexity of microseismic signals at slow-moving clay-rich debris slides: The Super-Sauze (southeastern France) and Pechgraben (Upper Austria) case studies. Earth Surface Dynamics, 6(2), 525-550.