Auto-Reclassification of the Montserrat Volcano Observatory Seismic Event Catalog, 1996-2004

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Things to do before finalizing:

1. Examine peakamp and signal of my dataset, compared to the 5000 p2p (2500 02p) counts used by Langer et al.
2. Try eliminating ‘e’ and also relabelling ‘e’ as ‘r’.
3. Check bandwidth of each class, by channel. Is there a clear separation, e.g. ‘l’ versus ‘h’?
4. How many events are in the total Seisan DB I have, with linked Sfiles->WAVfiles? And how many total traces?

235,804 S-files on hal between 1996/10/21 and 2008/10/16. 12 years of data.

191,592 by 2004/02/16.

cum\_N\_sfiles, cum\_N\_DSN\_wavfiles, cum\_N\_DSN\_traces, cum\_N\_ASN\_wavfiles, cum\_N\_ASN\_traces

235804, 217290, 4072590, 42110, 439569

Original motivation. Eruption. Seismic monitoring best technique. Continuous data problems: need to identify anomalous signals from noise. Andesitic eruptions dominated by transient seismic event signals. 6 classes used by MVO (state them). MVO team seismic overwhelmed by events: often hundreds (sometimes thousands) per day, impossible to classify consistently and objectively. Needed to objectively reclassify catalog. Goal was to detect, classify, locate and quantify every event in real-time. GT part of MVO team seismic from 1996-2004. Approached Langer in 2001, led to papers in 2003 and 2006.

Seismic activity during the eruption of Soufrière Hills volcano comprised various transient signals, which were classified visually by the Montserrat Volcano Observatory (MVO), considering waveforms recorded at several stations. For 217,290 transients detected on the MVO digital seismic network between 1996/10/21 and 2008/10/16, five main classes have been identified: rockfall (ROC: 58%), hybrid (HYB: 19%), long-period (LPE: 11%), lp-rockfall (LP-ROC 5.8%), and volcano-tectonic (VT: 3.1%). Temporal trends in the rate and energy release of these different transients – in addition to swarms and tremor – were key to short-term forecasting of activity throughout the eruption. However, visual classification is highly subjective and non-repeatable, and the inconsistency of the catalog is a barrier to research.

In a pilot study, we automatically removed waveforms with dropouts, and manually verified transient classifications until we had approximately 100 transients of each class (total 522). We found ~21% of these transients were incorrectly classified at MVO. Our re-labelled dataset was then used as a starting point for supervised learning, using code from http://github.com/malfante/AAA that has previously been used to classify transients at Ubinas volcano in Peru. Malfante et al. (2018) transformed each waveform into a set of 102 features: 34 features for each of three domains (time, spectral, cepstral). We added 6 frequency features of our own, including band ratios, peak frequency, median frequency, bandwidth, and frequency change. The resulting 108-point vectors of features were then used for modeling. The dataset is randomly divided 50 times into training and testing datasets, to produce a robust model. One model is produced per channel. We use the Random Forest Classifier algorithm from the scikit-learn library. For each waveform, a probability is computed for each class.

Initial results are promising. Separate models yield accuracies of 76-80%. If the LP-ROC class is omitted (following Langer et al, 2006), accuracy rises to 82-85%. If only VT and LP classes are considered, accuracy is 96-99%. We intend to expand our labelled dataset to 1000 events, build models for each channel, and reclassify the catalog of 217,290 transients by a weighted average of probabilities.

have trained a model with 522 events using 3 vertical component channels.

We aim to objectively reclassify 209,050 transient seismic events originally visually classified at the Montserrat Volcano Observatory (MVO) with machine learning. Events were recorded between 1996/10/21 and 2008/10/16 on a digital seismic network and stored in a Seisan database. The most common MVO classes are rockfall (58%), hybrid (19%), long-period (11%), lp-rockfall (5.8%), volcano-tectonic (3.1%), st\_georges (0.7%) and regional (1.4%). An average of 18.7 traces per event (total 4,072,590 traces).

At first, we trained the model with the dataset given by the OVSG  
consisting of 845 available labeled events (542 VT, 217 nested and 86  
LP) recorded in the period 2013-2018. We obtained an average  
classification rate of 72 %. We determined that the VT class includes a  
variety of signals covering the LP, Nested and VT classes. Reviewing in  
detail the waveforms and the spectral characteristics of the signals  
belonging to the 3 classes we then introduced Hybrid events and also  
defined a monochromatic class (so-called Tornillo) of LP signals, thus  
matching the full description of signals provided in Moretti et al.  
(2020).  
Then, using the new information, a new model was trained with 5 classes  
and tested. We obtained a much better classification average rate of 84  
%. The classification is excellent for Nested events (93 % of accuracy  
and precision) and Tornillo events (93% of accuracy and precision). The  
classification of VT events (90% accuracy, 89% precision) and LP events  
(86% accuracy, 82% precision) were also very good. The most difficult  
class to recognize is the Hybrid class (64 % accuracy, 69 % precision).  
Hybrid events are often mixed with VT and LP events. This may be  
explained by the nature of this class and the physical process that  
includes both a fracturing and a resonating component with different  
modal frequencies.  
Moreover, by using a supervised machine learning model to distinguish  
the events from the background noise, we were able to detect twice as  
many events as the observatory with an STA / LTA method.  
Machine learning is a powerful tool to handle large datasets. We were  
able to improve the classification, correct some misclassification and  
detect more events.

For a preliminary study, we applied our automated data QC to remove traces with dropouts. We then manually reclassified 522 events, and applied

Between 1996/10/23 and 2004/02/16 the Montserrat Volcano Observatory catalogued more than 200,000 transient seismic event signals. Five fundamental classes were identified: VT, hybrid and LP earthquakes, rockfall signals, and

From Oct 1996 - Feb 2004 the Montserrat Volcano Observatory operated a digital seismic network installed by the British Geological Survey. GT was seismic network manager for most of this period.

So far we have done a pilot project. Compare methods and results obtained with Langer et al. 2006.

Now we can design the full project.

* Will instrument corrected data be better than raw waveforms? Probably not since we use a 0.5 Hz high pass, and response is flat above this for all sensors.
* A thrust of my study will be that I combine metrics used by Marielle Malfante and Langer, plus some of my own. I should test autocorrelation traces – perhaps just add them as additional traces. And linearity, planarity and ellipticity traces when other components available. Then perform weighted reclassification. So for example, with 3 Integra stations and 5 Guralps, that is 18 channels in total. I could have: 18 waveforms, 18 auto-correlation functions, 5 linearity, 5 planarity and 5 ellipticity traces. This would be 51 traces in total. 51 separate models. Some models would suck. But this would help me figure out how badly they suck for classification. And it would use ALL THE DATA. And I could figure out ALL THE USEFUL FEATURES. And this would help design an efficient classification model to apply to the full dataset.

Alexis’ abstract – but 418 words is too long. Need 300.

Seismic activity at La Soufrière volcano of Guadeloupe is composed of  
various transient signals, which are classified manually by the  
Observatoire Volcanologique et Sismologique de Guadeloupe (OVSG-IPGP),  
considering waveforms recorded at several stations. Three main classes  
readily distinguishable on seismic traces during the daily analytical  
protocol have been catalogued: Volcano-Tectonic events, Long-Period  
events and Nested events, each related to a distinct physical process.  
Automatic detection and classification of volcano-seismic signals of La  
Soufrière was performed by using an architecture based on supervised  
learning, available at github.com/malfante/AAA. Seismic waveforms are  
transformed into a large set of features (34 features for each  
representation domain) computed from three representation domain of the  
signal (time, frequency, quefrency). The resulting vectors of features  
are then used for the modeling. We are using the Random Forest  
Classifier algorithm from the scikit-learn library.  
At first, we trained the model with the dataset given by the OVSG  
consisting of 845 available labeled events (542 VT, 217 nested and 86  
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