Seismic event detection based on neural networks in the Groningen area, The Netherlands

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Introduction

Over the past decades the seismic monitoring network at the Groningen gas field has been densified in order to acquire more accurate information regarding the onset and origin of seismic events, resulting in increasing amounts of seismic data. This asks for automatic seismic event detection.

Automatic detection of micro-seismic events and the use of neural networks for this has been studied in the past (e.g. Tselentis et al. [2012], Curilem et al., 2009; Doubravová et al., 2016; Tiira, 1999]. Here we explore the operational potential of neural networks for detecting induced earthquakes at the Groningen gas production site. The expected power of the NN is the ability to combine several inputs in an optimized decision.

Case study

In this study we used public data obtained from the KNMI data portal. The data consist of the recordings of all 224 available vertical receivers (from various networks) of the Wagenborgen earthquake of September 21st 2016 (see Fig. 1). The earthquake is interpreted as an induced earthquake (depth around 3 km and had a magnitude of 1.2).

Fig. 1: Location of receivers Wagenborgen earthquake.

The data were processed and then each sample was labelled as “event” or “no-event” based on interpretations by KNMI.

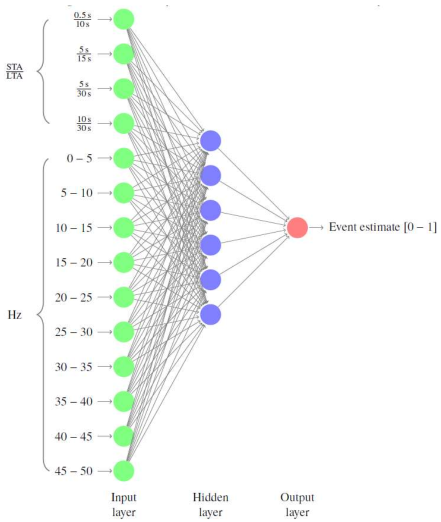

Fig. 2: Three-layer feedforward neural network used.

Neural networks

We used a standard three-layer feedforward neural network in this study (see Fig. 2). The neural networks can have 14 different inputs, all expected to contain complementary information about the onset and duration of the seismic event.

Three networks (named NN1, NN2 and NN12) were implemented and tested using different combinations of these inputs and compared to a standard baseline STA/LTA method used by KNMI:

1. 4 STA/LTA ratios of varying running short and long time windows as input (0.5 s/10 s , 5 s/15 s , 5 s/ 30 s, 10 s/30 s).
2. 10 Mean power spectral densities of sequential frequency intervals between 1 Hz to 50 Hz using short-time Fourier transform.
12. All the above 14 inputs.

Based on the “no event” and “event” annotations of the samples in the data the neural networks were trained using the Newton conjugate-gradient algorithm [Hestenes and Stiefel, 1952]. The trained neural networks were then able to automatically annotate samples in new seismic traces.

Results

To calculate the performance of the neural networks NN1, NN2, and NN12, stratified k-fold cross-validation was applied to the results. This means that for each detection method 20 independent and stratified folds (i.e. containing 19/20 of the data with an equal balance of events vs. no events) a neural network was trained and then the resulting classifier was tested on the remaining 1/20 of the data. For each of the 20 testing results per method the performance was measured by calculation of the sensitivity index:

d' = true positive rate - false positive rate

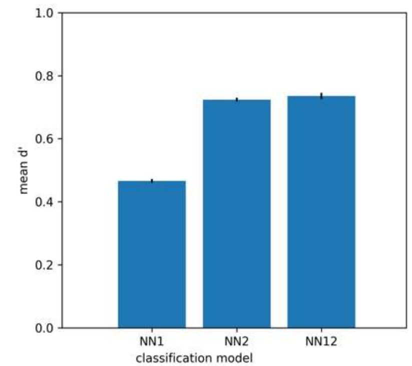

Fig. 3: Performance of the seismic event detection methods.

The figure shows that in this case supplying more information (NN2, NN12) leads to better performance of the classifier. NN2 based on spectral densities performs almost as good as in combination with 4 STA/LTA inputs (NN12).

We also looked at the performance of NN12 versus the distance to the source and compared that to a baseline STA/LTA detection model (see Fig. 4). It can be seen that for larger offsets, where SNR is low, NN12 is much more capable of detecting events than the baseline. Also NN12 shows maximum performances for small distances.

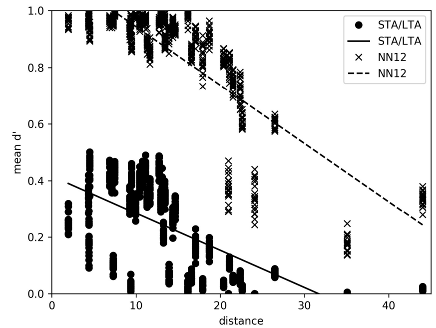

Fig. 4: Performance of the STA/LTA baseline and NN12 detection methods as a function of receiver distance to the seismic source.

Conclusion

This study showed that neural networks based on multiple mean power spectral densities as input can be trained to perform well w.r.t. their capability of estimating the onset and duration of seismic events. This means that these different inputs contain enough information, are complementary and reinforcing enough, and the network structure is flexible enough to train a successful seismic event detector. We furthermore showed that especially for distant seismic traces (with low SNR) the neural networks perform relatively well as compared to the chosen baseline (standard STA/LTA detection method).

References

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