Earthquake Detection in 1-D Time Series Data with Feature Selection and Dictionary Learning

Zheng Zhou¹,², Zhongping Zhang², Yue Wu¹,³, Paul Johnson¹, and Youzuo Lin¹

¹: Earth and Environment Sciences Division, Los Alamos National Laboratory, Los Alamos, NM 87545
²: Department of Electrical and Computer Engineering, University of Rochester, Rochester, NY 14627
³: Department of Computer Science, University of Rochester, Rochester, NY 14627

Abstract

Earthquakes are detected and located primarily by the use of patterns in one dimension seismic waves, or specific phase properties in these waves. Traditional earthquake detection methods built on physics and signal models are still widely used, such as waveform correlation and template matching. On the other side, machine learning techniques for earthquakes detection have also made a giant leap, and they are still in promising development. In this paper, we develop a new method which generates rich features via signal processing and statistic methods and filters out the ones carrying significant information by feature selection techniques. Based on the selected features, dictionary learning skill is applied for the classification task, which determines whether a certain segment of signal belongs to an earthquake event. The models proposed in this paper can combine the properties of both of these two methods. We test our model on Labquake Dataset from Penn State University, and the results outperform most of the existing machine learning methods.

1 Introduction

Earthquake detection, usually is applied to 1-D time series seismic data, is one of the most important tasks in geophysics. Detecting both small and big earthquakes events simultaneously still remain as challenging task for human beings in this field, since the features and characteristics of different level earthquake events could be extremely various. With the prosperous development and successful application of machine learning techniques in time series detection, it is revealed that resolving our earthquake detection task with machine learning skills could be a promising direction. Among all these machine learning methods, dictionary learning has achieved attractive results in signal denoising, signal compression, and classification based on time series data [22]. Traditionally, people manually select most representative signal samples to build the dictionary and let the algorithm run the training and update stage. Different from this pure data-driven approaches, we propose a method which uses the features generated from original signal instead in this paper. Considering that the statics feature generation methods may not always achieve satisfying performance on earthquake detection with various applied situation [23], we novelty take the strategy that generating adequate raw features from fixed length original signal with experienced feature generation methods as well as Python signal feature generation package TsFresh, and then followed by a combination of feature selection methods (including Reilif-F, Gini Index, KL-Divergence and L1 Norm Regular Term) to pick out the features with largest

Copyright © 2018 by the paper’s authors. This volume is published and copyrighted by its editors.

In: Lin Y., Li W., A. Jorge, R.L. Lopes, G. Larrazabal, P. Guillen (eds.): Proceedings of the Workshop on Data Mining for Geophysics and Geology (DMG2), San Diego, California, USA, May 5 2018, published at arXiv.

1
potential contribution. Another advantage brought by feature-based methods is that a bridge can be built between classical data-driven methods and traditional physical model analysis. Since all these features have clear physical meanings, analyzing features which are selected out could provide some hints for future physical research in earthquake detection.

In experiment and evaluation stage, we take the Orthogonal Matching Pursuit (OMP) and Simultaneous Orthogonal Matching Pursuit (SOMP) strategy to solve the dictionary learning problem and show the results obviously outperform the most classical machine learning method SVM. To further improve the detection resolution, we slide one-fifth of the length of cutting window which is used to cut the original signal and produce features, which means most of the signal fragments (other than the fragments near the edge) will be classified for 5 times. Then a voting policy can be applied, only the signal fragments which are classified as positive for greater or equal to 3 times will be considered as a part of detected earthquake events. This kind of voting strategy is also helpful in smoothing the detection results. All these machine learning skills are applied on the Labquake Dataset from Penn State University, and the performance is evaluated by point-wise accuracy and intersection over union (IoU) [5].

Our main contributions in this paper can be summarized as follows:

1. We develop a method of combining multiple feature selection criterion.
2. We introduce dictionary learning skills into earthquake detection task and compare its performance with other classical machine learning methods.
3. Based on dictionary learning classification, we further improve the detection accuracy with overlapping windows and voting technique.

2 Related Works

Our work closely relates to research in traditional earthquake detection, to feature selection techniques, and to dictionary learning.

**Earthquake Detection** During last decades, researchers have developed many seismological methods to detect and analysis earthquake events in one dimension time series data. Some of them build the wave function models to simulate the physical process of earthquake waves spreading in the lithosphere, and further study the patterns and properties [3]. There are also some other detection skills built on signal processing and statistical methods. In seismology, STA/LTA is the most popular used detection method since this method is convenient for practical applications. These methods compute the ratio of short-term average energy and long-term average energy on multiple receivers [1, 2]. Compared with STA/LTA, autocorrelation could achieve a higher detection rate and could be applied to more complicated environment [4]. Autocorrelation is known as a ‘many to many’ detection technique. It searches for similar waveforms when the desired signal waveform is unknown. Based on the idea of previous methods, template matching is developed to achieve a good balance between detection accuracy and computational efficiency, and a user-defined threshold value is used to control the bias of this balance [20, 6]. Template matching takes a ‘one to many’ detection strategy. It computes the correlation coefficient between the sample waveform and the expert-selected candidate waveform data.

**Feature Selection** The basic idea of feature selection is to select a subset of variables from the raw input data, which can efficiently describe the input data while reducing effects from noise or irrelevant variables and still provide good prediction results [15]. At the early stage of machine learning, feature selection highly depended on professionals’ experience [17]. With the development of information theory and machine learning techniques, variable feature selection methods were broadly classified into filter and wrapper methods [18]. Filter methods act as preprocessing to rank the features wherein the highly ranked features are selected and applied to a predictor. In wrapper methods, the feature selection criterion is the performance of the predictor i.e. the predictor is wrapped on a search algorithm which will find a subset which gives the highest predictor performance. Embedded methods [17, 23] include variable selection as part of the training process without splitting the data into training and testing sets.

**Dictionary Learning** Dictionary learning is a representation learning method which focuses on finding a sparse representation of the input data in the form of a linear combination of basic elements as well as those basic elements themselves [24]. These elements are usually called atoms, and the dictionary is composed by them. These dictionary learning algorithms can be classified into two groups. The first group contains greedy algorithms such as the matching pursuit (MP) [25] and the orthogonal MP (OMP) [19], which iteratively select locally optimal basis vectors in every step. In the second group, they are aimed at finding algorithms based on convex relaxation methods such as the basis pursuit denoising [8], least absolute shrinkage (LAS) and selection operator (LASSO) [21].
3 Feature Generation and Selection

3.1 Feature Generation

During the process of generating features, on the one hand, we take the experiential features that have been wildly tested in earthquake detection tasks into consideration; on the other, we also take the usage of a General-purpose feature generation package in Python to produce as rich candidates as possible for the following selection step. In total, we generate 991-dimension raw features for each input signal sample.

**Experiential Features:** According to previous works in earthquakes detection and other tasks in 1-D time series data, we manually pick out 126-dimension features from features which are widely used in earthquakes localization or detection of small abnormal signal structures.

**Tsfresh Features:** Tsfresh is a python package which extracts abundant features can be used to describe or cluster time series. This package has included most of common-used features in signal processing, and the overall generated features dimension is 865.

3.2 Feature Selection

We combine the following feature selection methods together to obtain the key features:

**Relief-F:** Relief-F is an improved version of Relief algorithm. Relief algorithm measures the significance of a feature by its ability to distinguish neighboring instances. If feature distance between data points of same classes is large, it is less useful and gains a low weight. In contrast, if feature distance between data points of different classes is large, it is more useful and will gain a high weight. The final rank depends on the weight of each feature. Relief-F improves Relief by k-nearest neighbors of each class [7].

**Gini Index:** Gini Index (GI) is mainly used to evaluate the inequality within peoples wealth, population, etc. Besides, it can also be applied in feature selection. Here we use GI to measure the ability of a feature to differentiate between target classes. GI coefficient is the ratio of $A/(A+B)$ [9] as Fig.1. shows. When GI is large, it means A is large and samples are distributed unequally between target class. Therefore, features are ranked according to their GI. We are prone to select features with high GI since they contain more useful information.

**Kullback-Leibler Divergence:** The Kullback-Leibler divergence (KL divergence) [11] is also called Relative Entropy. It is used to measure how one probability distribution diverges from a second, expected probability distribution. Suppose $P(x)$ and $Q(x)$ are two discrete probability distributions of $x$, KL divergence from $Q$ to $P$ is:

$$D_{KL}(P||Q) = - \sum_i P(x_i) \log \frac{Q(x_i)}{P(x_i)}$$  \hfill (1)

It represents the reduction in entropy in moving from a prior distribution $P(Y)$ to a posterior distribution $P(Y|x_a)$. Thus, attributes whose KL divergence is large are likely to be discarded to avoid overfitting problem.

**Sparse Regression:** Sparse Logistic Regression (SLR) is an embedding feature selection algorithm utilizing L1-norm regularization. L1-norm Regularization uses a penalty term which encourages the sum of the absolute values of the parameters to be small. According to [12], the number of training examples needed to learn well grows only logarithmically in the number of irrelevant features. In LRS, L1-norm regularization is added to loss function so that the less useful attributes are given little weights. As a result, important features with high weights are picked out during the logistic regression. Since L1-norm can be considered as the optimal approximation of L0-norm, we will apply L1-norm regularization in our detection model.

4 Dictionary Learning

In the field of dictionary learning, a dictionary is usually understood as a collection of atoms and can be used for signal representation. The representation is a linear combination of some of the atoms in the dictionary, it can be exact or be an approximation to the original signal. The dictionary learning methods usually build an over-complete dictionary matrix $D \in \mathbb{R}^{n \times K}$ which contains $K$ column atoms which have $n$ elements respectively, and each column is an input sample. $y \in \mathbb{R}^n$ is the signal which can be represented as a sparse linear combination of different column atoms [19]. The representation of $y$ can be written in the exact form $y = Dx$, or in approximated form $y \approx Dx$, which should satisfy the restriction $\|y - Dx\|_p \leq \epsilon$ ($\| \cdot \|_p$ represents the $L_p$ norm, and in this paper we manually set the value of $p$ as 2). Each element in the vector $x \in \mathbb{R}^K$ can be considered as the coefficients of the input signal $y$. So that the object of dictionary learning can be summarized as
Recent years, a number of methods have been developed to solve the dictionary problem. One of the most popular and simplest method is the orthogonal matching pursuit (OMP) algorithms. One of the crucial point in OMP algorithm is that we have to use $L_2$ norm to normalize each atom in the dictionary, so that $\|D_i\|_2 = 1$ for $i = 1, 2, \ldots, K$. $D(S)$ is a sub-matrix of $D$, which consists of the $i$th columns of $D$ with $i \in S$ and $S \subset \{1, 2, \ldots, K\}$. In each iteration of OMP, the algorithm greedily select the atom which has the most important contribution in reconstruction the input sample. The detailed description of OMP algorithm can be stated as follows:

1. Use the input vector $y$ to initialize the residual $r$, and initialize the selected variables set as $D(c_0) = \emptyset$, where $c_i$ is a set of atom indexes. Set the iteration counter variable $i = 1$.

2. Find the atom $D_t$ to satisfy the maximization function

$$\max_t \{ D_t^T r_{i-1} \},$$

and add the selected atom $D_t$ to the set of selected atoms. Update $c_i = c_{i-1} \cap \{t_i\}$.

3. Let $P_i = D(c_i)(X(c_i)^T X(c_i))^{-1} X(c_i)^T$ and update $r_i = (I - P_i)y$.

4. If the stopping iteration time has been achieved, stop the algorithm and return the residual $r_i$ and selected set $D(c_i)$. Otherwise, let $i = i + 1$ and return to Step 2.

The Simultaneous Orthogonal Matching Pursuit (SOMP) algorithm basically shares the similar idea with OMP algorithm, the only difference is using a set of input samples $y \in R^{m \times K}$ instead of the single input sample $y \in R^K$. In our model\(^\text{[22]}\), we use 6 neighborhood samples (3 samples on the left and 3 samples on the right) and the original sample to build the input matrix $y$. Since the fixed length cutting windows may not cut out the entire earthquake signal, including some neighboring information with SOMP algorithm would be helpful to further improve the detection performance of our model. While applying dictionary learning to binary classification problem such as our earthquake detection task, we need to build a dictionary contains positive sample features and another one consist of negative sample features respectively. After a certain time of iterative training, we will compare the residuals of testing samples on positive and negative dictionary, and classify the test sample to the class with smaller residual.
5 Experiments

5.1 Dataset

Our labquake dataset is provided by the Rock and Sediment Mechanics Laboratory at Penn State University. Labquake data is a time-amplitude representation generated by a machine to mimic real seismic signals. Overall, there are 3,357,566 timestamps in our dataset, and the whole signal lasts for 0.9 seconds. 1,000 seismic events are manually picked. We use 700 events for training, 200 events for validating, 100 events for testing. More detail information about our dataset is shown in Fig.2.

We gather the statistical information of event length. The histogram of event length shows the length distribution in Fig.8. The longest event lasts more than 7,000 timestamps, while the shortest one only spans about 400 timestamps. The mean and median of events lengths are both about 1,500 timestamps.

5.2 Generated and Selected Features

At this stage, we cut the original signal into 2,000-timestamp-long sections. If over 50% time frames are labeled as earthquake events, this section can be considered as a positive sample, otherwise, it will be considered as a negative sample. We generate the 991-dimension features in total with the methods described in Section 3. Then three feature selection method (Relief-f, Gini Index, and KL-divergence) are applied to evaluate the potential contribution of each feature to our detection model. Under each of these selection methods, a score can be produced for each feature to measure their performance. We manually set the rule to discard the features which have the worst 25% performance under each feature selection criterion, and 507-dimension features are left. The detailed information and comparison have been summarized in Table 1.

In Table 1, the experiential features obviously have a higher selection rate while comparing with the features from Python signal package TsFresh, which demonstrates the features based on human experience do have some advantages in 1D time series detection task. Among the features in four different domains (time, frequency, energy and other), frequency properties features seem to make more contribution, since they take a significant proportion in all the features and also have a higher tendency to be selected by our feature selection methods.

To further exploit this point, we apply Logarithm-Based Time-Frequency analysis [10] to both positive and negative samples, and plot the results in Figure 3. In Figure 3, (a1) and (a2) show the time-frequency graph of a small earthquake event and a big earthquake event respectively (Small events usually indicate the earthquake event with smaller amplitude and last for shorter time, while big events have the opposite properties.), (b1) and (b2) demonstrate two examples from negative samples which do not contain earthquake events. From these time-frequency graphs, the frequency components of earthquake samples tend to concentrate in certain frequency bands since the earthquake pattern our Labquake Dataset is relatively simple, and it does not contain too much-complicated noise. While the time-frequency graphs of negative samples do not seem to contain such property. We summarize the distribution of frequency-banded features (which contain some features from frequency and energy domain) in Figure 3(c), and it can be clearly seen that certain frequency bands tend to play more important roles than others in our detection model. This frequency-banded tendency may have some potential values in further physical model analysis [26].
Figure 3: (a1)(a2) Time-Frequency graph of two sections of signal which contain earthquake events; (b1)(b2) Time-Frequency graph of two sections of signal which contain no earthquake events; (c) The distribution of selected features in each frequency band.

| Time Domain | Frequency | Energy | Other | Total Selected | Total Generated | Selection Rate |
|-------------|-----------|--------|-------|----------------|----------------|----------------|
| Experiential| 18        | 32     | 16    | 7              | 73             | 57.9%          |
| TsFresh     | 65        | 156    | 85    | 118            | 434            | 50.1%          |
| Selected    | 83        | 188    | 101   | 125            | 507            | 51.2%          |

Table 1: Table of Feature Selection Results

5.3 Detection Results

We use two different quantitative metrics to evaluate the performance of our detection model: the Point-Wise Accuracy and Intersection Over Union (IoU) [5]. The point-wise accuracy is the detection accuracy of on every time frames, and it can be considered as an overall evaluation. While intersection over union (IoU) is defined as the Formula 5, it especially focuses on the detection performance on positive samples. Since the number of negative samples dramatically exceed the positive samples in our dataset, the overall evaluation is more inclined to be affected by the prediction accuracy on negative samples, IoU can serve as a complimentary on positive samples.

\[
IoU = \frac{Detections \cap GroundTruth}{Detections \cup GroundTruth}
\]  

(5)

In Table 2, we compare the performance of different models. Support Vector Machine (SVM) is not suitable for the classification task with high feature dimension and is tend to overfit during the training process. Generally, our dictionary learning methods could achieve more reliable detection results than SVM methods. Among all the dictionary learning methods, directly fitting the original signal into dictionary perform the worst, since the amplitude of our earthquake signal data could change in a wide range, and the amplitude of some small events close to big events would approach to zero after L2 normalization. The model applies the combination of feature selection methods obviously outperform the models with single feature selection method and raw features, which shows the combination of multiple feature selection could improve the robustness and select the features to make real contribution. The comparison between Orthogonal Matching Pursuit (OMP) and Simultaneous Orthogonal Matching Pursuit (SOMP) shows that the accuracy of these two methods are about the same, while SOMP demonstrates it advantage in IoU. This proves that taking the neighboring information into consideration could play a vital role in achieving a better detection result around earthquake events.

To further improve our detection results and achieve higher detection resolution, we apply a voting strategy. Instead of cutting the original signal into 2,000-time-frame-long windows without overlapping, we slide the cutting window one-fifth
of its length (400-time frames) every time, which means each time window has a four-fifth overlapping with its previous one. We apply our classification model to these overlapping samples, besides the fragments in the beginning and at the end most the 400-time-frame-long signal fragments will be classified for 5 times. We manually set the criterion that only the fragments classified as earthquake greater or equal to 3 times can be considered as positive. In this case, the detection resolution is successfully increased from 2,000-time frames to 400-time frames, and this model achieves the best accuracy. From Figure 4, the comparison between the detection results before and after applying voting strategy also shows that the voting strategy is helpful in improving the smoothness and robustness.

| Method                        | Accuracy | IoU  |
|-------------------------------|----------|------|
| Raw Signal + SVM              | 54.8%    | 0.15 |
| Raw Features + SVM            | 56.5%    | 0.18 |
| Raw Signal + OMP              | 61.5%    | 0.22 |
| Relief-F + OMP                | 68.6%    | 0.27 |
| Gini Index + OMP              | 72.6%    | 0.32 |
| KL divergence + OMP           | 71.3%    | 0.30 |
| Combination Selection + OMP   | 76.9%    | 0.34 |
| Combination Selection + SOMP  | 77.4%    | 0.41 |
| Combination Selection + SOMP + Voting Strategy | 80.4%    | 0.43 |

Table 2: Table of Selection Results

6 Discussion

In this paper, we introduced a novel method for earthquake events detection through uniting feature selection and dictionary learning. We evaluated the quality of our approach through different metrics and compared its performance with several methods currently exist. Although the detection accuracy on the boundary of events could be further improved, the overall performance of our algorithm was better than baselines.

We see our work as opening two possible directions for future research. The first one is applying our method to the dataset of real earthquakes to develop a common-use algorithm. The second direction is to extend our model to other one-dimension time series data with more complicated conditions, such as the waves in lithosphere caused by volcano or fountain.
7 Acknowledgment

We thank for the Rock and Sediment Mechanics Laboratory at Penn State University for providing us the labquake dataset. This work was co-funded by the Center for Space and Earth Science at Los Alamos National Laboratory, and the U.S. DOE Office of Fossil Energy through its Carbon Storage Program.

References

[1] R. Allen. Automatic phase pickers: Their present use and future prospects *Bull. Seismol. Soc. Am.*, . No. 72, Page 225–242, 1982.

[2] M. Withers, R. Aster, C. Young, J. Beiriger, M. Harris, S. Moore, and J. Trujillo. A comparison of select trigger algorithms for automated global seismic phase and event detection *Bull. Seismol. Soc. Am.*, . No. 88, Page 95106, 1998.

[3] Kwiatek, Grzegorz. Theoretical limits on detection and analysis of small earthquakes *Journal of geophysical research. Solid earth*, . Volume: 121, Page: 5898–5916, August, 2016.

[4] J. R. Brown, G. C. Beroza, and D. R. Shelly,. An autocorrelation method to detect low frequency earthquakes within tremor, *Geophysical Research Letters*, . Vol. 35, No. 16, Page. L16305, 2008.

[5] Faruk Ahmed, Dany Tarlow, Dhruv Batra, Optimizing Expected Intersection-Over-Union with Candidate-Constrained CRFs, *IEEE International Conference on Computer Vision (ICCV)*. . Page 18501858, 2015.

[6] D. R. Shelly, G. C. Beroza, and S. Ide, Non-volcanic tremor and low-frequency earthquake swarms, *Nature*, . Vol. 446, Page 305307, 2007.

[7] Robnik-ikonja, M., Kononenko, I. Theoretical and empirical analysis of ReliefF and RReliefF, *Machine Learning*. . Vol. 53, Page: 23–69, 2003.

[8] S. Chen, D. Donoho, and M. Saunders, Atomic decomposition by basis pursuit. *SIAM J. Sci. Comput.*. . Vol 20, No. 1, Page 3361, 1999.

[9] Gastwirth, Joseph L. The estimation of the Lorenz curve and Gini index. *The review of economics and statistics*, . Page: 306–316, 1972.

[10] Brian R Glasberg, Brian C.J Moore, Derivation of auditory filter shapes from notched-noise data. *Hearing research*. . Vol 47, Page 103138, 1990.

[11] Kullback, S.;Leibler, R.A. On information and sufficiency. *Annals of Mathematical Statistics*, . Volume: 22(1), Page: 79—86, 1951.

[12] Ng, Andrew Y. Feature selection, L 1 vs. L 2 regularization, and rotational invariance. *Proceedings of the twenty-first international conference on Machine learning. ACM*, . Page: 78–85, 2004.

[13] Xiaofei He, Deng Cai, Partha Niyogi. Laplacian score for feature selection. *NIPS*, . MIT Press, 2005.

[14] Yi Hong, Sam Kwong, Yuchou Chang, Qingsheng Ren. Unsupervised feature selection using clustering ensembles and population based incremental learning algorithm. *Pattern Recognition*, . Vol. 41, Page 27422756, 2008.

[15] Guyon I, Elisseeff A. An introduction to variable and feature selection. *J Mach Learn Res.*, . vol 3, Page 11571182, 2003.

[16] J. Tropp, Greed is good: Algorithmic results for sparse approximation. *IEEE Transactions on Information Theory*. . Vol 50, No. 10, Page 22312242, 2004.

[17] Guyon I, Weston J, Barhill S, Vapnik V. Gene selection for cancer classification using support vector machines. *Mach Learn.*, . vol 46, Page 389422, 2002.

[18] Kohavi R, John GH. Wrappers for feature subset selection. *Artif Intell.*, . vol 97, Page 273324, 1997.
[19] Michal Aharon, Michael Elad, and Alfred Bruckstein, K-SVD: An Algorithm for Designing Overcomplete Dictionaries for Sparse Representation. *IEEE Transactions On Signal Processin*, Vol. 54, No. 11, Page 4311-4322, 2006.

[20] S. J. Gibbons and F. Ringdal, The detection of low magnitude seismic events using array-based waveform correlation, *Geophysical Journal International*, Vol. 165, No. 1, Page 149-166, 2006.

[21] R. Tibshirani, Regression shrinkage and selection via the lasso. *J. R. Stat. Soc. Ser. B (Method.)*, Vol 58, No. 1, Page 267-288, 1996.

[22] Determe, Jean-Francois and Louveaux, Jerome and Jacques, L and Horlin, Francois, Simultaneous Orthogonal Matching Pursuit With Noise Stabilization: Theoretical Analysis. *in arXiv:1506.05324v1*, 2015.

[23] Langley P. Selection of relevant features in machine learning. *AAAI fall symp relevance.* . 1994.

[24] Karl S, Kjersti E Recursive Least Squares Dictionary Learning Algorithm. *IEEE Transactions on Signal Processing*, Vol 58, No. 4, Page 2121-2130, 2010.

[25] S. G. Mallat and Z. Zhang, Matching pursuits with time-frequency dictionaries. *IEEE Transactions on Signal Processing*. Vol 41, No. 12, Page 3397-3415, 1993.

[26] Bojriquez, Edn, Residual drift demands in moment-resisting steel frames subjected to narrowband earthquake ground motions. *Earthquake engineering & structural dynamics*. Vol 42, Page 1583-1598, 2013.