Machine Learning Based Tremor Detection in Centrarl and Southern California
Report for SCEC Award #19177
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Investigators: Zhigang Peng (Georgia Institute of Technology)

I. Project Overview

A. Abstract

In the box below, describe the project objectives, methodology, and results obtained and their significance. If this work is a continuation of a multi-year SCEC-funded project, please include major research findings for all previous years in the abstract. (Maximum 250 words.)

The increasing volume of seismic data from long-term continuous monitoring motivates the development of algorithms based on convolutional neural network (CNN) for faster and more reliable phase detection and picking (e.g., Ross et al., 2018; Zhu and Beroza, 2019; Zhu et al., 2019). Inspired by the successes of the CNN approach on seismic phase picking, we developed a single station, CNN-based tremor classifier to separate tremor and noises (non-tremor) signals. We first trained the CNN model using a Parkfield dataset that composes 326,904 labelled tremor and noise data. The CNN model reached 93% training accuracy with 0.975 AUC value, suggesting higher ability on separating tremor and noise signals when compare to previously published CNN model. We further applied the classifier to pre-documented tremor and train noise signals in southern California's Anza area in an effort to help clarifying the signal types. The results suggest that these signals are less likely to be events that are similar to Parkfield tremors. We also tested the model on five stations with tremor recordings in the year of 2016 in Taiwan. The test result suggests the CNN model can successfully recognize tremor signals at some stations with high accuracy. This suggests the CNN model has leaned a generic representation of tremors to a certain degree. However, the predictability is low at some stations, which suggests in-situ noises may significantly distort tremor signals and therefore bias the classification results.

B. SCEC Annual Science Highlights

Each year, the Science Planning Committee reviews and summarizes SCEC research accomplishments, and presents the results to the SCEC community and funding agencies. Rank (in order of preference) the sections in which you would like your project results to appear. Choose up to 3 working groups from below and re-order them according to your preference ranking.

Seismology
Computational Science
Mining Seismic Wavefields

C. Exemplary Figure

Select one figure from your project report that best exemplifies the significance of the results. The figure may be used in the SCEC Annual Science Highlights and chosen for the cover of the Annual Meeting Proceedings Volume. In the box below, enter the figure number from the project report, figure caption and figure credits.

Figure 1. (a) The distribution of tremor and stations used in training (top left figure), and the Anza area (bottom right) where the model was applied to classify previous documented tremor and train noise. (b) A schematic view of the CNN model architecture.

D. SCEC Science Priorities

In the box below, please list (in rank order) the SCEC priorities this project has achieved. See *https://www.scec.org/research/priorities* for list of SCEC research priorities. *For example: 6a, 6b, 6c*

3a, 3b, 3c

E. Intellectual Merit

How does the project contribute to the overall intellectual merit of SCEC? *For example: How does the research contribute to advancing knowledge and understanding in the field and, more specifically, SCEC research objectives? To what extent has the activity developed creative and original concepts?*

This project develops a deep-learning based tool for tremor and noise classification. The model trained on Parkfield tremors has learned the generic representation of tremors, and showed the ability of recognizing tremors is other areas such as Taiwan. In an effort to clarify true event types of the pre-documented train and tremor signals, our current model predicts that they are less likely to be tremors. The model we developed in this project also has higher performance as a classifier, compare to other previously published CNN model for tremor/noise classification. By using shorter waveforms as inputs instead of long spectrograms, it also has higher potentials to turn the model into a real-time application.

F. Broader Impacts

How does the project contribute to the broader impacts of SCEC as a whole? *For example: How well has the activity promoted or supported teaching, training, and learning at your institution or across SCEC? If your project included a SCEC intern, what was his/her contribution? How has your project broadened the participation of underrepresented groups? To what extent has the project enhanced the infrastructure for research and education (e.g., facilities, instrumentation, networks, and partnerships)? What are some possible benefits of the activity to society?*

This project supported collaborations of two GT students. Lindsay Chuang and Cenyu Li from School of Earth and Atmospheric Sciences (EAS). Lindsay Chuang is a 3^{nd} year Ph.D. student, and Chenyu Li is a 6^{th} year Ph.D. student graduated in summer 2020. This project will be one component of their Ph.D. theses.

G. Project Publications

All publications and presentations of the work funded must be entered in the SCEC Publications database. Log in at *http://www.scec.org/user/login* and select the Publications button to enter the SCEC Pubications System. Please either (a) update a publication record you previously submitted or (b) add new publication record(s) as needed. If you have any problems, please email *web@scec.org* for assistance.

II. Technical Report

The technical report should describe the project objectives, methodology, and results obtained and their significance. If this work is a continuation of a multi-year SCEC-funded project, please include major research findings for all previous years in the report. (Maximum 5 pages, 1-3 figures with captions, references and publications do not count against limit.)

A. A CNN based binary classifier for tremor and noise (non-tremor)

The increasing volume of seismic data from long-term continuous monitoring motivates the development of algorithms based on convolutional neural network (CNN) for faster and more reliable phase detection and picking (e.g., Ross et al., 2018; Zhu and Beroza, 2019; Zhu et al., 2019). Through training on large amount of labelled seismic data, a CNN model can learn a generic representation of the data, and use them to perform various tasks (e.g. phase picking, event classification). When the learned representation is generic, a CNN model can then be utilized on similar tasks for data at different areas. This project aims to take advantages of the ability of the CNN on generalizing tremor signals, and help clarify the true signal types of pre-documented tremor and train noise in Southern California's Anza area (Hutchison and Ghosh, 2017; Inbal et al., 2018). The model is first trained using 326,904 labelled tremor and noise data in Parkfield, and then applied to tremor and train signals recorded in Southern California Anza area. The result suggests the previously identified tremor and train signals in Anza are less likely to be tremor signals that are similar to Parkfield tremors. Further tests done on tremor dataset in Taiwan suggest the CNN model has learned a generic representation of tremor to a certain degree, and can successfully recognize tremor signals in some stations with high accuracy. However, the predictability differs among stations, which suggests the signals at some stations may be significantly affected by in-situ noises.

1. Data

We constructed the labelled dataset based on the long-term Parkfield tremor catalog (Nadeau and Guilheme, 2009). All the tremor signals recorded by 13 borehole stations of the High-Resolution Seismic Network (HRSN) between 2007 and 2011 are processed and used as the trained tremor data set (Figure 1a). The waveforms recorded between 7 and 13 minutes prior to tremor arrivals are used as noise (non-tremor) dataset. Both the noise and tremor sets are first subjected to mean removal, 2-8 Hz bandpass filtering, and then truncated to several one-minute-long non-overlapping windows. This process results in 160,285 noise labels and 166,619 tremor labels in total. We labelled tremors and noises labelled as 1 and 0, respectively for model training purpose.

2. CNN Model architecture

The CNN model consists of 7 sets of convolutional layer and average pooling layer, followed by a flatten layer, two dense layers, and one final output layer. A schematic view of the model architecture is shown in Figure 1b. We use ReLu function as the activation function for all the convolutional layers and the first two dense layers. A Sigmoid function bounded by 0 and 1 is used at the final output layer. The kernel sizes of convolutional layers are 5x1 for layer 1-3, and 3x1 for layer 4-7.

3. Model training

We randomly shuffle the dataset, and then split the dataset to 70% for training, 10% for validation, and 20% for testing. We train the CNN with mini batch gradient decent using the Adam optimizer of TensorFlow. The loss function we minimize is the binary cross-entropy loss function defined as below:

$$H(p,q) = -\frac{1}{N}\sum(q\log p + (1-q)\log(1-p))$$

where *p* and *q* are the true label and the predicted probability, respectively. We monitor the training progress by evaluating the model accuracy per epoch on the training and validation set. The accuracy is defined as:

$$\frac{TP+TN}{TP+TN+FP+FN}$$

where TP and TN stand for true positive and true negative, and FP and FN stand for false positive and false negative, respectively. The training and validation accuracies increase steadily and reach 93% and 91% at the 35^{th} epoch. After the 35^{th} epoch, they start to possess higher fluctuations and show signs of overfitting (Figure 2). To prevent overfitting, we manually stop the training at the 35^{th} epoch.

B. Performance of the CNN classifier

We investigate the model performance by evaluating the precision, recall, and F1 score on the test dataset. The precision P is defined as:

$$P = \frac{TP}{TP + FP}$$

The recall R is defined as:

$$R = \frac{TP}{TP + FN}$$

The F1 is a summary statistic of recall and precision, and is defined as:

$$F1 = \frac{2TP}{(2TP + FP + FN)}$$

The P, R, and F1 on the test set are 0.90, 0.96, and 0.92, respectively. We set the probability threshold at 0.5 for event class classification (i.e., when the model outputs probabilities > 0.5, the waveform is classified as tremor, and vice versa). We also evaluate the model performance by calculating the receiver operating characteristic (ROC) curves and the area under the ROC curve (AUC) (Figure 3). The ROC curve is a common way used to evaluate the performance of a binary classifier. By plotting the true positive rate against the false positive rate at various thresholds, it can quickly illustrate the diagnostic ability of a binary classifier. For a perfect model, the AUC in a ROC curve is equal to 1. The AUC of our model is 0.975, which suggests the model has high ability to separate tremor and noise in Central California. The shape of the ROC curve also justifies the threshold (0.5) we use while making categorical prediction.

C. Comparison with other CNN model of tremor/noise classifier

The model we developed in this project demonstrates a promising progress on using CNN to discern tremor and non-tremor signals in Central California. Compare to a recent study where a CNN approach was also utilized to classify tremor and noise (Rouet-Leduc et al., 2020), our model demonstrates better performance, which can be seen on the AUC values. The AUC in our study and in Rouet-Leduc et al., (2020) are 0.975 and 0.945, respectively. The higher AUC value of our study suggests that our model is better at correctly classifying the data to the right classes. Another advantage of our approach is that we use filtered waveforms instead of spectrograms as inputs (Nakano et al., 2019). By using waveforms as inputs, we can significantly reduce the computational costs spent on data preprocessing. We also use shorter (one-minute-long as oppose to five-minute-long) input length, which also enables the approach to be more efficiently applied on a real-time setting.

D. Application of the CNN classifier on Southern California and Taiwan

Next we apply the CNN classifier to previously reported train noise (Inbal et al., 2018), and tremors (Hutchison and Ghosh, 2017) in the Anza area in Southern California. The waveforms are one-minute long with mean values removed, and band-pass filtered at 2-8 Hz. Example of waveforms in areas used in this study are shown in Figure 4. Our model predicts most of these events non-tremors when the threshold is set at 0.5. However, one of the previously identified tremor events has probability equals to 0.47, which is close to the probability threshold. The stations, time period, and the predictions of those events are listed in Table 1. We also test the model on tremors documented in 2016 in Taiwan (Chen et al., 2018). The recall rates (the percentage of tremors being classified as tremors) of the predictions vary at different stations, with the highest as 0.95 and lowest as 0.57. These large differences of recall rates are likely due to the different characteristics of noises and the noise levels at different stations. The recall rates per station of the Taiwan tremor data are shown in Table 2.

Table 1

Station	Start time	Type reported in reference	Prediction (Probability)	Reference
SND	2011/06/10 04:31:00	Tremor	Noise (0.47)	Hutchison and Ghosh, 2017
SND	2011/06/06 13:35:00	Tremor	Noise (0.036)	Hutchison and Ghosh, 2017
SND	2011/06/01 04:38:30	Tremor	Noise (0.035)	Hutchison and Ghosh, 2017
SND	2011/05/19 08:56:55	Train Noise	Noise (0.018)	Inbal et al., 2018

Table 2	
Station	Recall
YULB	0.60
BN	0.57
KS	0.93
WTP	0.79
ELD	0.95

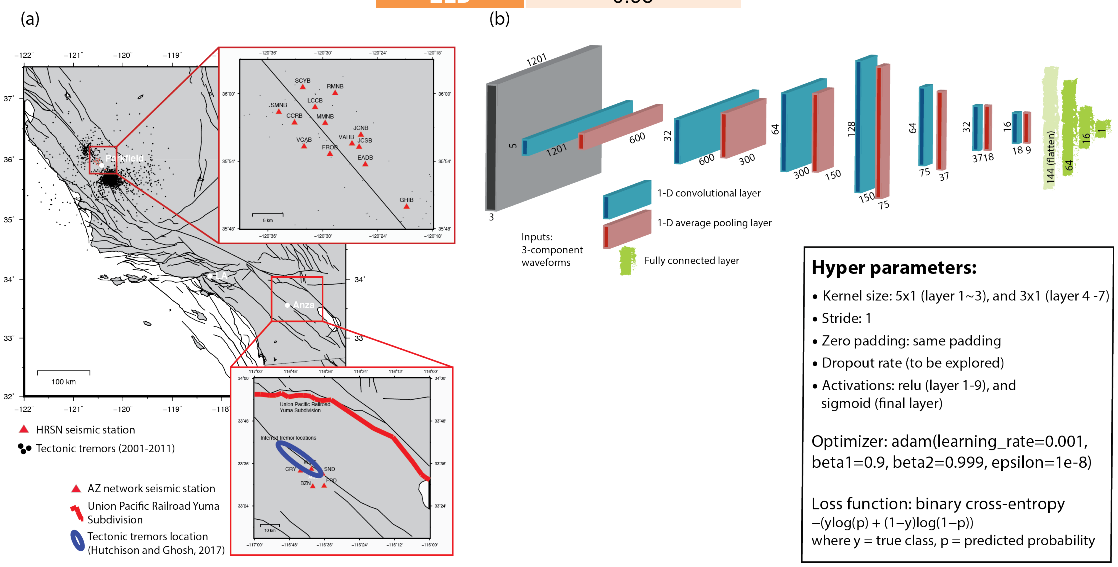

Figure 1. (a) The distribution of tremors and stations used in training (top left figure), and the Anza area (bottom right) where the model was applied to classify previous documented tremor and train noise. (b) A schematic view of the CNN model architecture.

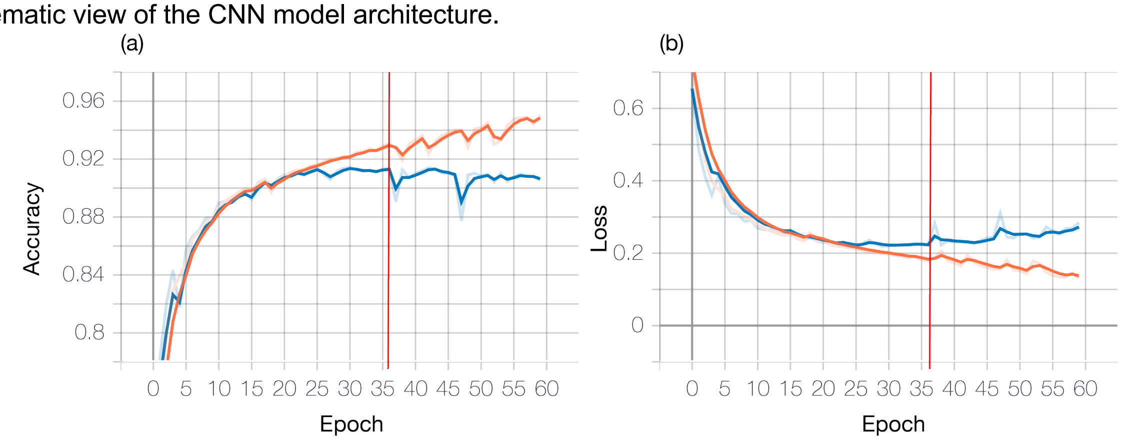

Figure 2. The evolutions of accuracies and loss for the training set and validation set. Blue and orange curves indicate values of training and validation set, respectively. The vertical red lines mark the 35th epoch, which is where we applied early stopping.

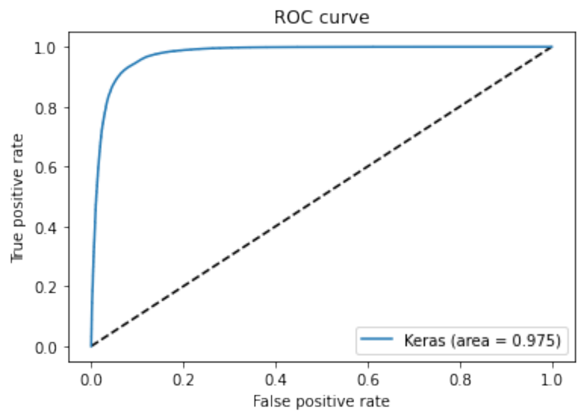

Figure 3. The ROC-AUC curve of the CNN model. The blue curve is the ROC curve, and the dash line marks the theoretical ROC curve when a model is unable to separate two classes. The area underneath the ROC curve (AUC) is 0.975.

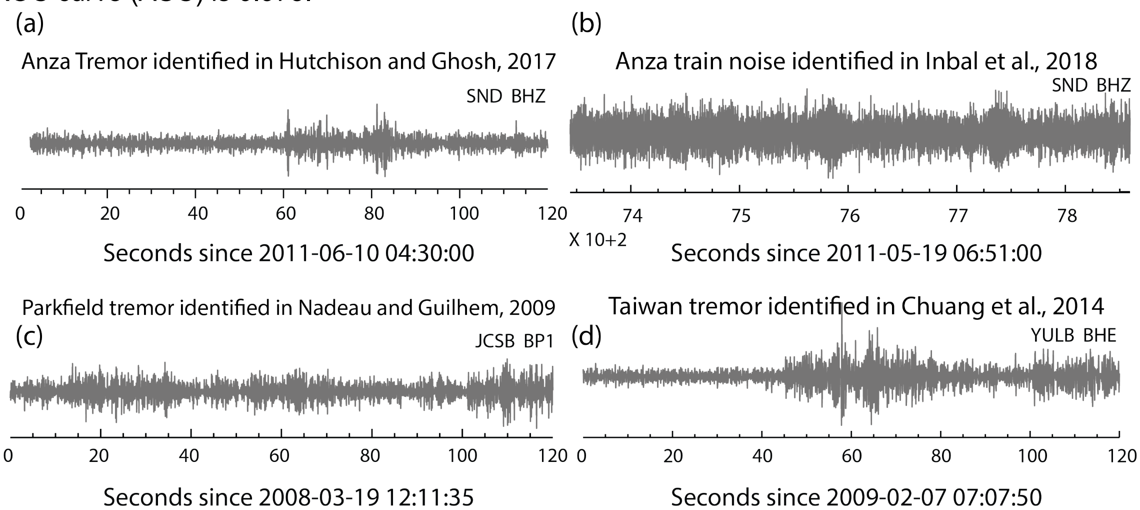

Figure 4. Examples of documented tremor and train signals in (a-b) Anza, (c) Parkfield, and (d) Taiwan.

E. Student Support and Involvement

This project provided 3-month support (1.5-month each) for graduate students Chenyu Li and Lindsay Chuang at Georgia Tech. Li was a 6th year Ph.D. student in School of Earth and Atmospheric Sciences (EAS). She has been using the matched filter detection to study spatial-temporal changes of seismicity in SSGF following nearby and large distant earthquakes as funded by SCEC (Li et al., 2017), as well as detecting aftershocks following a magnitude 7.5 intermediate-depth earthquake in Hindu Kush region (Li et al., 2018a). Recently she was also involved in applying the CPIC to other regions (Li et al., 2018b). Chuang is a 3rd year Ph.D. student in the School of Earth and Atmospheric Sciences (EAS) at Georgia Tech. She has been working on seismic event classification and phase picking using machine learning and CNN since 2019 (Chuang et al., 2019a, 2019b). The proposed work will be part of her Ph.D. thesis.

F. Acknowledgement

We utilized Keras and TensorFlow framework for the CNN model training. The seismic data preprocessing is done by using ObsPy package (Beyreuther et al., 2010). The seismic data used in this study is obtained from the Northern California Earthquake Data Center (NCEDC), the Southern California Earthquake Center (SCEC), and the Broadband Array in Taiwan for Seismology (BATS). This research is supported by the Southern California Earthquake Center (SCEC award 19177). This is SCEC contribution #9383.

G. References (with publications/meeting abstracts supported by this and previous SCEC grants marked in bold)

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