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# Seismic Phase Identification with Deep Learning in Frequency Domain

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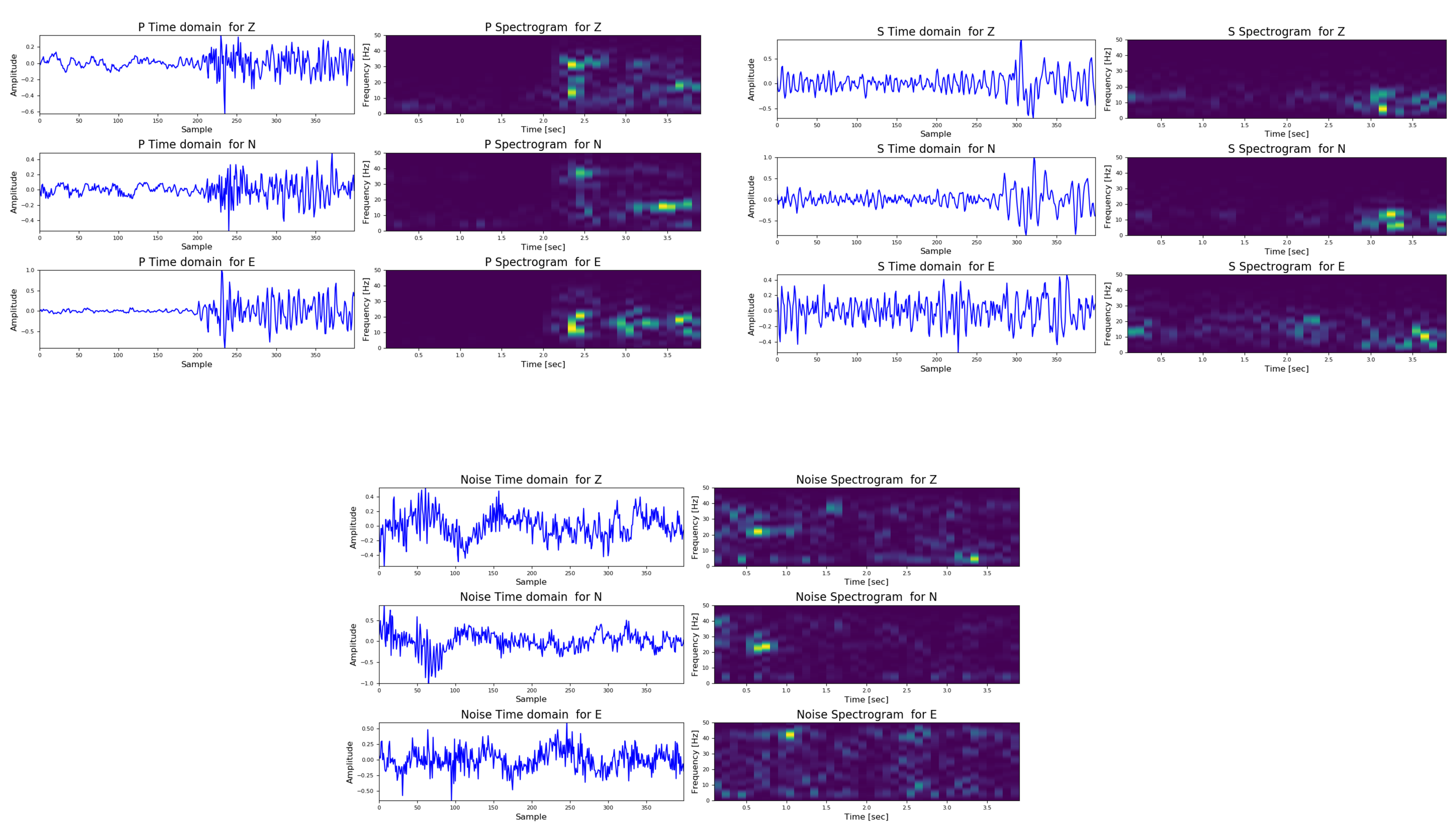
## Abstract

Identifying different seismic phase of a seismograph has been the cornerstone in earthquake processing and location. Most of the efforts of the seismic phase identification is the obligation of the analyst. Deep leaning is offering a powerful tool for analyst experience transfer by learning form the events data already processed. Then, these gained knowledge can be used for upcoming processing and extract missing small events.
Most of the previous seismic waveform processing for phase detection and identification were done in time domain. In this study we suggest using frequency domain in form of spectrogram of the event. Spectrogram is used to represent the varying of the seismic signal power for different frequency bands though time. Using frequency domain allows the deep learning to extract more sensitive, robust and stable features from the signal which can lead to better classification result.
Earthquakes recorded by the SCSN (Southern California Earthquake Data Centre) are used as training and validation data sets which were used in previous similar studied to provide a stable benchmark. The three channels waveform were used to enrich the deep learning algorithm and increases the ability for phase type discrimination.

## Training Data

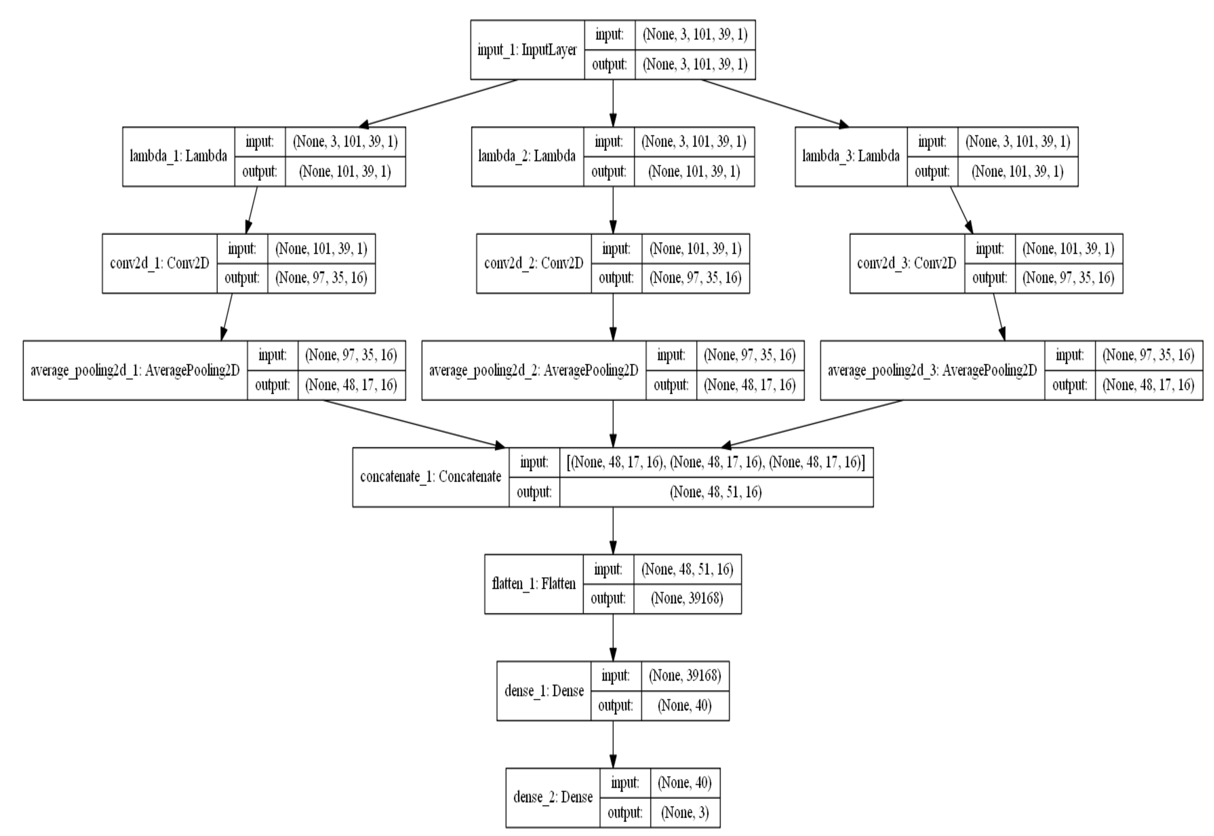
In this study, we used the same data used in [1] which are built based on seismograms for 273,882 earthquakes recorded by the Southern California Seismic Network (SCSN) at 692 broadband and short-period 3-component stations from 2000-2017[2]. A total of 4.5 million 3-component seismic records were used for training and validation. All data are detrended, filtered, normalized and resampled at 100 Hz .These 3-component records consist of 1.5 million P-wave seismograms, 1.5 million S-wave seismograms, and 1.5 million noise windows, with each being exactly 4 s. P- and S-wave windows were centered on the respective analyst pick, while noise windows were defined starting 5 s before each P-wave pick. The even distribution of records between each class ensures that the training process is not biased towards any one class.
All data converted from the time domain into time-frequency domain using spectrogram producing a new data set. The new data set have a two dimension representation of the data reflects the spectrum of frequencies of a signal as it varies with time. Choosing spectrogram parameter(window, Length of each segment and Number of points to overlap between segments) is done through multiple experiments to choose the best data representation with reasonable size.
Each 400 sample window converted into (101,39) matrix represent the spectrogram representation of the window.




## Training

During the recent reintroduced interest in Deep Learning applications among seismologists, some studies have revisited the detection problem (e.g. [3] and [4]). These studies presented successful and promising performances of deep convolutional-neural-networks (CNN) for robust and efficient detection of earthquake signals. It applies a convolution operation to the input and produces an activation map that gives the responses of that filter at every spatial position. Most of these studies used the time domain as the input for their schema to automatically learns the low/mid/high-level features in data. Using the frequency or time- frequency domains instead could results to have more generalize features that can lead to have generalize seismic phase Identifier. This method can be used not only for P,S and noise identification ,but more complex phase type can be classified.
A simple and direct model is used ,consist of :

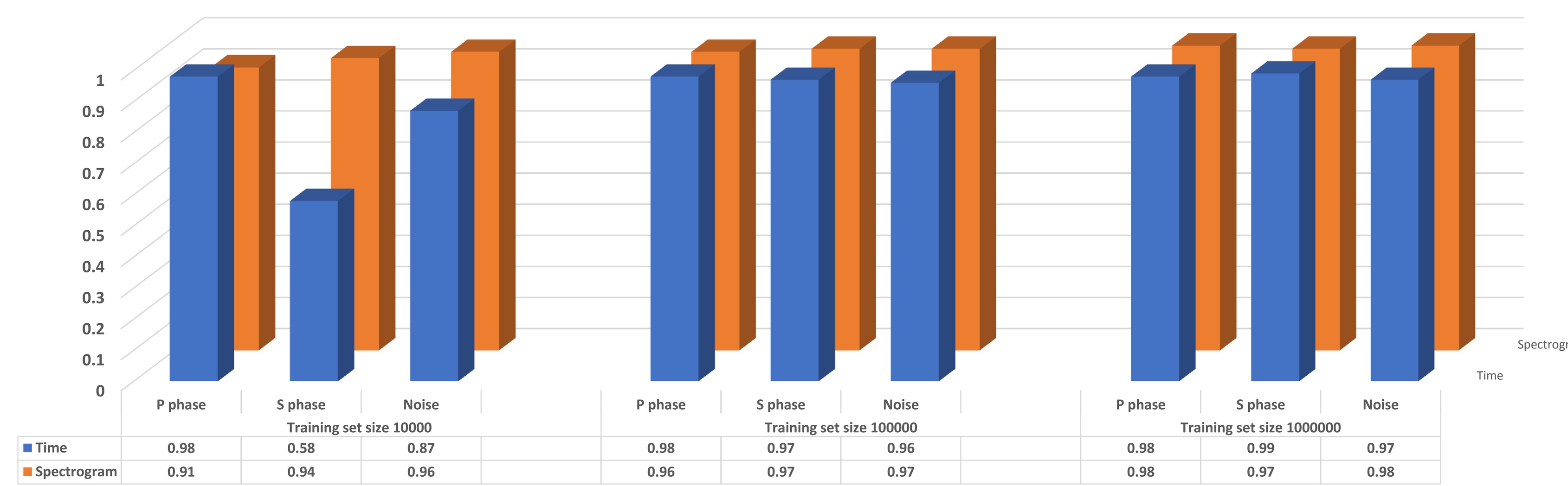
- Lamda layer to separate each channel from the input data, to handle each channel independently
- 2D convolutional layer for feature extraction, with RELU activation function
- Average pooling layer to reduce the features size
- Concatenation layer to merge the features from all channels
- Flatting layer to reshape the features into 1D representation
- Two dense layers(Fully connected ) as the classifier layer



To train the model, we first randomly split the seismograms into a training set (80%) and validation set (20%). Then, the model was trained using a cross-entropy loss function with the ADAM optimization algorithm , in mini-batches of 1024 records with NVIDIA GeForce 150 graphical processing units. For this study, 10 epoch has been used for the training, the accuracy for the training set was 99% while the validation set accuracy was 98%.

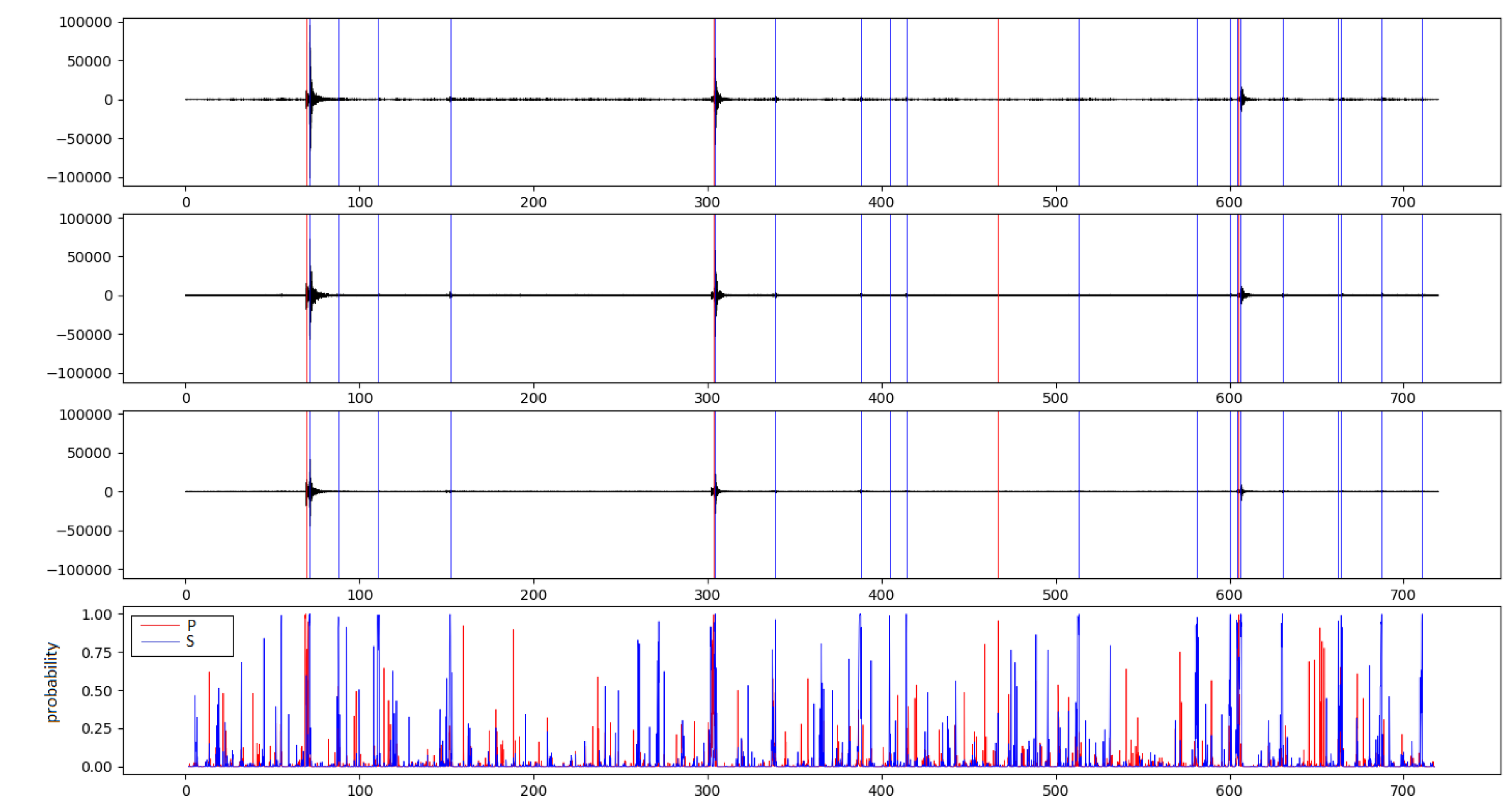
## Results

In order to compare Time domain and frequency domain phase identifying procedures, we tried to train the two models using different data set size (10000,100000 and 1000000 seismograms). The experiment result was that the time-frequency have the ability to learn and achieve acceptable performance even using a small data set size while the time domain only suffer from bad performance with the same data set size . Using the moderate and large data set size works for both with a slight difference in accuracy .

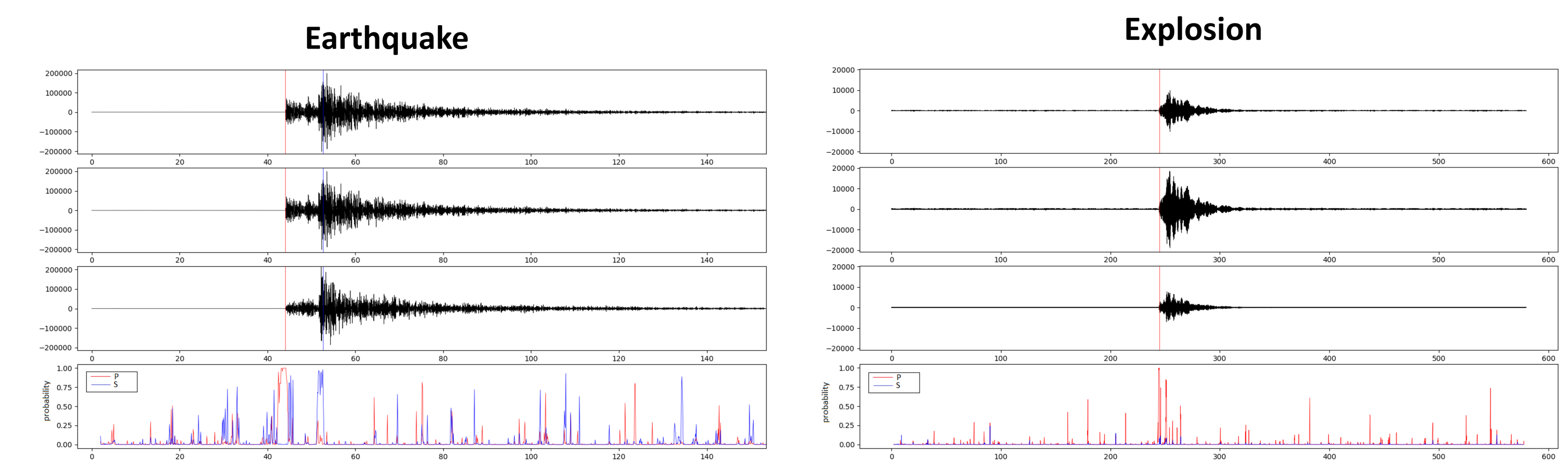



## Real Data Results

Another test has been preformed using real data of the 2016 Bombay Beach swarm. The proposed method able to extract large number of events with acceptable false trigger accuracy.



Testing this model in the Egyptian National seismic Network , demonstrates that the model is broad and could be used even for data different than the data used for the model training. And even could work for identifying P&S phases in both earthquakes and explosions.




## Conclusion

In this study , transforming seismic waveform into time-frequency domain introduces another representation of the data with more clear features domain. This features domain can be a base for complex phase identification schema. In many cases providing large training data sets is not easy. Based on our experiment , extraction acceptable model from small and moderate size data sets is achievable using time-frequency representation. Frequency domain is much more generalized demonstration of the seismic waveforms, so it could generates global model could be used for seismic phase identification.

## References

[1] E. Ross, Zachary & Meier, Men-Andrin & Hauksson, Egill & H. Heaton, Thomas. (2018). Generalized Seismic Phase Detection with Deep Learning.
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[3] Perol, T., Gharbi, M., and Denolle, M. (2018). Convolutional neural network for earthquake detection and location. Science Advances, 4(2):e1700578.
[4]Ross, Z. E., Meier, M.-A., Hauksson, E., and Heaton, T. H. (2018a). Generalized Seismic Phase Detection with Deep Learning. Bulletin of the Seismological Society of America, doi: https://doi.org/10.1785/0120180080