Seismic Data Classification Using Machine Learning

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Abstract

Earthquakes around the world have been a cause of major destruction and loss of life and property. An early detection and prediction system using machine learning classification models can prove to be very useful for disaster management teams. The earthquake stations continuously collect data even when there is no event. From this data, we need to distinguish earthquake and non-earthquake. Machine learning techniques can be used to analyze continuous time series data to detect earthquakes effectively. Furthermore, the earthquake data can be used to predict the P-wave and S-wave arrival times.

Keywords: Earthquake, Seismic waveform, S and P waves, Machine learning, Epicenter, Noise removal, obspy, SVM, Decision Tree, Random forest,

1. Introduction

A strong earthquake may be followed by many aftershocks. When surrounding seismological stations detect those aftershock signals, we could determine the location of aftershocks by analyzing the time that vertical (P) wave and horizontal (S) wave reach the seismograph station. It could provide important reference information for Earthquake Relief. The goal of the paper is to analyze the seismic waveform recorded by the 16 seismological stations and determine the time that P wave and S wave reach each seismological station. The goal is to quickly, accurately and comprehensively detect early aftershocks by using an efficient algorithm.

The data is in Seismic Analysis Code (SAC) file format. The SAC file format contains time series data. Typically, the SAC file consists of a header which has many fields related to the station and station characteristics. SAC file format gives information of all the headers present in the file. In our dataset, each SAC file has an entire day's recording. The approximate number of samples recorded per day is 86400. Analysis at any particular time of the day can be done by focusing or zooming on that part by clipping the data. It is essentially a waveform consisting of sampled points, taken during the required time frame. The waveform can be plotted in relative as well as absolute time. It can be used to study the pattern of p-wave and s-wave.

The data for each station has 3 components on the basis of directions: west-east (BHE), north-south (BHN) and vertical (BHZ).The propagation velocity of P-wave is greater than that of S-wave. Thus, the first recorded shake is P-wave, and the second one is S-wave. The vibrating direction of P-wave is the same as the propagating direction, which means P-wave is more obvious on BHZ(vertical). The vibrating direction of S-wave is perpendicular to propagating direction, and S-wave is more obvious on BHE and BHN (horizontal). Usually, the amplitude of P-wave is less than that of S-wave, and the period of P-wave is also less than that of S-wave.

Usually, the shaking lasts for a very less time, we are only interested in those parts where actual shaking occurs. Hence, it is necessary to clip the data. Multiple earthquakes and aftershocks can occur within 24 hours. This paper will discuss various methods to clip the data in order to detect maximum earthquakes within the 24 hours period. Triggering algorithms help us to detect shakes within a signal. Such a signal can be further analyzed to distinguish between an earthquake and noise. Triggering algorithms can be used for detecting seismic activity by specifying a basic amplitude threshold or tuning it to recognize specific patterns. Recursive STA/LTA is one such efficient triggering algorithm which we can be used to clip the data.

This paper further discusses ways for determining the P-wave and S-wave arrival times. AR Pick algorithm gives us a very good estimate of the p-pick and s-pick times. The arrival time for both is picked using an Auto Regression-Akaike Information Criterion technique. The algorithm can be used for large and diverse data sets as it does not require major location specific settings. We can easily extract p-pick and s-pick time using this algorithm and can use this information as features of the earthquake data.

Another set of features for this paper can be derived by converting the waveform in ASCII format. We get the time-series data in time sample pairs which gives us all the highs and lows of the waveform along with the noise. The classification algorithm can train itself very efficiently based on this data. This paper discusses the importance of all the features and how they are derived. We can easily observe the improvement in the accuracy as more features are used for training the model.

Figure 1, showing the details of the process flow diagram followed while researching this paper.

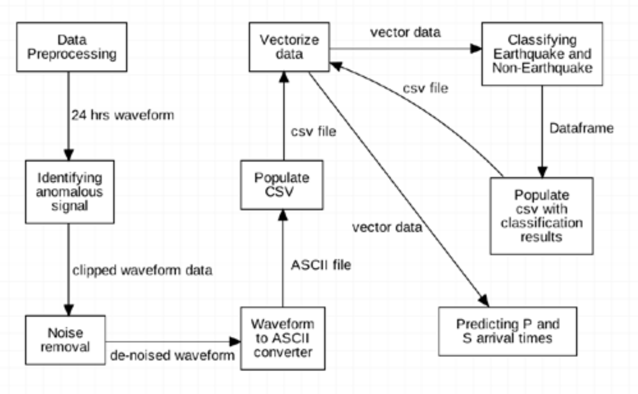

Figure 1 - Process flow diagram of the approach

2. Related Work

A comprehensive study of papers was done to gain insight into the techniques used to process the data, extract the features and how to apply the machine learning algorithms. There has been research on fusing data from multiple channels and using it to develop a framework for classification of the earthquake, seismic noise, and explosion [1]. Sonogram vector features were used along with k-NN for segregating the signals. The accuracy achieved was about 93.4%. The paper by Y. Takase *et al* talk about anomalous electromagnetic waves and LPC cepstrum as its feature for earthquake detection[2]. The daily average of the waves is calculated and HMM is used to observe the energy levels. HMM's are also used with amplitude density distribution of electromagnetic waves for anomalous signal detection [3].

Phase classification is another approach which helps to differentiate between P-waves and L-waves[4]. SVD is used to extract the wave features. An accuracy of 74.61% was achieved in phase classification using kernel ridge regression. Another paper by G. Zhao *et al* compares various techniques like Backpropagation neural networks(BP-NN), SVM and BP-Adaboost for classification of earthquakes and explosion events using seismic signals[5]. A total of 27 features was used which included time-domain features and waveform features. BP-Adaboost and SVM outperformed BP-NN with BP-Adaboost achieving the perfect accuracy of 100%. SVD is again used for feature extraction in a paper by W. Astuti *et al*[6]. SVM is used to predict future earthquakes and the magnitude. The accuracy achieved for earthquake prediction and magnitude by combining SVD and SVM method was 77% and 66.67% respectively. Paper [6] proposes a hybrid technique by combining SVD and SVM for earthquake prediction. Our experiment, on the other hand, uses SVM, Random Forest, and decision trees individually.

2.1. How our approach compares

In our experiment, we have used recursive STA/LTA as described in the paper [1] but as we had uniform time in all three directions BHE, BHN, and BHZ we didn't have to use any data fusion methods. Paper [1] uses KNN for classification purposes whereas we have used SVM, decision trees and random forests for comparing the results. Paper [2] focussed on predicting an earthquake by analyzing the EM wave, the behavior of an EM wave changes approximately 2 weeks before an earthquake.

On the other hand, we analyzed the actual earthquake signals in our paper. Paper [2] used HMM in contrast. Paper [3] also uses

Table 1
Related work summary – showing paper comparison

Method	Paper ID	Preprocessing	Features	Agenda	Results
k-NN	[1]	STA/LTA for window clipping. Data fusion to combine data from the three directions	Sonogram vector	kernel based fusion method for detection of seismic events	Discriminates noise and earthquakes - 93.4%
HMM	[2]	Signal processing of environmental electromagnetic waves	Features of Daily average of EM waves	Predict earthquakes using signal processing of anomalous EM waves.	-
	[3]	Identifying Background noise, Anomalous signal and Abrupt noise.	Amplitude density distribution extracted EM wave	Anomalous signal detection to predict an earthquake	Anomalous signal detected from HMM
Kernel ridge regression	[4]	Feature extraction and data clipping	Waveform data	Local topographical structure surrounding the recording station does not impact the local structure of the feature manifolds	P and L correct classification - 74.61
NN, SVM, BP Adaboost SVD	[5]	Feature extraction	27 features including the time domain features and the wavelet features	BP-Adaboost can obtain better classification results than SVM	Classification - Accuracy BP-Adaboost- 100% PCA-SVM- 99.35% BP-NN - 98.69%
	[6]	Extracting features from Earth's electric field signal.SVD for feature extraction	Feature extracted using SVD	Using SVD to extract features and SVM to predict location and magnitude.	Future earthquake - 77% Magnitude Prediction - 66.67%

features extracted from EM waves to train an HMM, our experiment doesn't deal with EM waves. Paper [4] classifies P and L waves using kernel ridge regressions. The data is in waveform format and it also clips the data. In our experiment, we use linear regression to predict the P and S arrival times. Paper [5] focuses only on being able to discriminate explosive events and earthquakes. Paper [5] also compares a variety of techniques. The number of features used in this paper are far greater than us. Paper [6] also predicts the magnitude of the earthquake along with the location.

3. Data pre-processing for machine learning

Traditionally statistical methods were used to analyze earthquake data such as Fast Fourier transforms. Using machine learning techniques to analyze seismic data is a very new approach. Machine learning algorithms automatically learn seismic patterns. We can make a model learn something and use the same model to classify the data.

3.1 Overview of data pre-processing

We followed same data preprocessing approach for all the machine learning algorithms.

1. Our data is in SAC data format and feature extraction from it was a critical aspect of our machine learning technique. We extracted features from the header files of the SAC data and the X(time) and Y(amplitudes) plots. We extracted six features from the header files viz.
   station- The name of the station

   channel - It could take three values BHE, BHN, and BHZ which indicates the direction in which the data was recorded. Figure 2 [15] shows the direction of propagation of waves.

   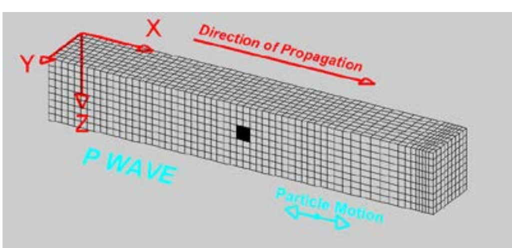

   Figure 2 - P and S waves flow direction

   starttime - The time when the data recording started endtime - The time when we stopped recording the data npts - The number of sample points

   We also derived two other features - maximum amplitude of the wave and standard deviation. The most important feature was the time series data which is basically all the time sample points and its corresponding amplitude. With the help of time series data , the entire wave was represented in ASCII format.
2. We did a lot of data conversions such as transforming the textual data into float values, filling up all the blanks with a default value, merging all the time series data into a single array structure. Word2Vec was used to transform the time series data to the vector format. An assembler was used to assemble all these features together in a label point format. Then the label indexer and feature indexer algorithms were run.
3. A similar approach was followed for non-earthquake data as well.
4. This data was then fed into decision tree model, random forest model and support vector machine model.

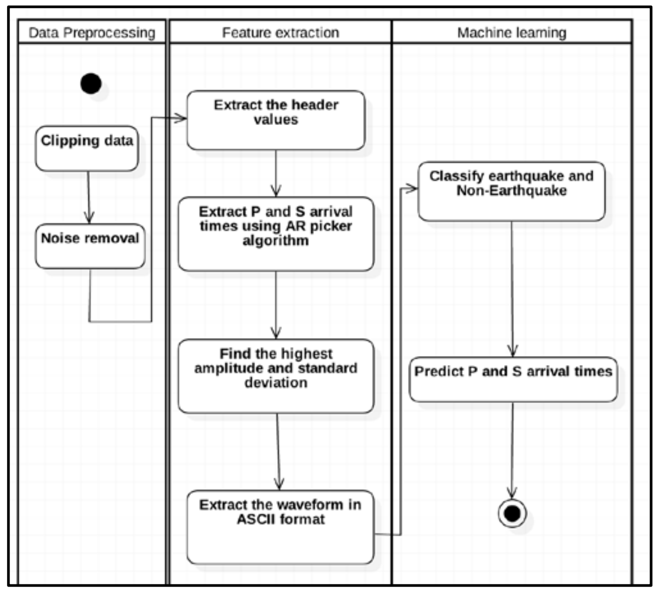

Figure 3 - Work-Flow diagram

3.2 Data Clipping

Each data file is approximately 33 MB. We mostly deal with data from the three directions simultaneously. That is almost 100 MB of data which sometimes causes segmentation faults or slows the program if memory management is not done properly. Also, multiple earthquakes can occur in the 24 hours duration. Aftershocks usually occur immediately after the main earthquake. It is very important to detect these earthquakes as well. In order to accomplish this, we need to clip the data files. We tried the following trigger picker algorithms - z_detect, recursive_sta_lta and classic_sta_lta. Among these algorithms, recursive_sta_lta worked best for our data. The trigger picker algorithms are used for the robust detection of phase arrivals in the presence of noise and clipping data to manageable levels. We chose the recursive_sta_lta as it gave the best results. The successful capturing of the seismic events depends on how well the triggering parameters are set.

4. Machine learning approaches

The approach followed in this paper best fitted the data we had. The other papers had varied data. In this section, we try to compare our approach versus the approach followed in the reviewed other papers

- We have used triggering algorithms to clip our data to distinguish earthquakes, a similar approach is followed by paper [1]. Paper [4] also uses the technique of clipping the data but does not go into its details.
- We have used bandpass filtering, a similar approach as per [3] However, also processed the signal with detrend algorithm to remove all the noise trends and station-related noises to produce a better quality of the signal.
- The reviewed papers covered a variety of machine learning techniques like SVD, Adaboost classifiers, SVM, HMM etc. After studying all the various techniques we chose to compare SVM, Decision trees Random forest and linear regression in this paper. We chose these techniques as it best suited the kind of data we had and the information we wanted to extract from our data.

4.1 Decision Tree

Decision tree comes under supervised algorithms and can be used for regression as well as classification problems. How the data will be split depends on the attributes or data features i.e. the tree follows the rules it learned from the training data to split the data at every step (Figure 4). At every step, the tree takes a decision to add the sample in a labeled class based on the most dominant feature.

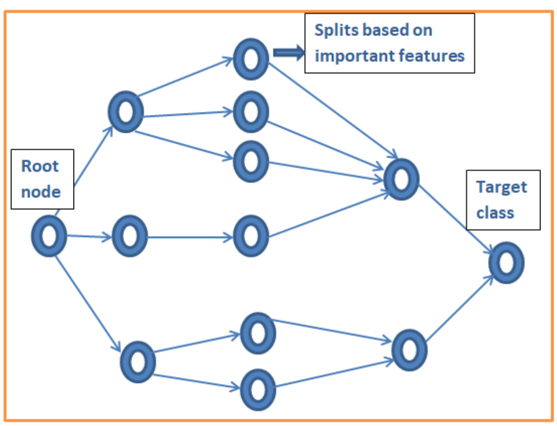

Figure 4 - Decision Tree Model

The identification of dominant features which gives clear separation of the dataset into separate classes is a major task. Gini-index, Chi-square, Information gain are some of the algorithms used in decision trees to find the decisive features or attributes.

4.2 Random Forest

Random forest is one of the popular tree-based algorithms which gives best results for all type of problems. It is part of ensemble learning methods where two or more weak algorithms are combined to form a strong modeling algorithm. The idea is to create too many trees in the forest. Based on the output of the tress voting will be done. As shown in Figure 5 each tree will essentially support a class and the class which has the maximum votes will be the class or label of the sample.

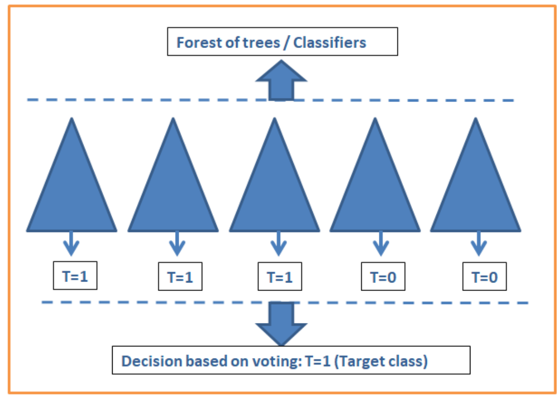

Figure 5 - Random forest Model

4.3 Support Vector Machine

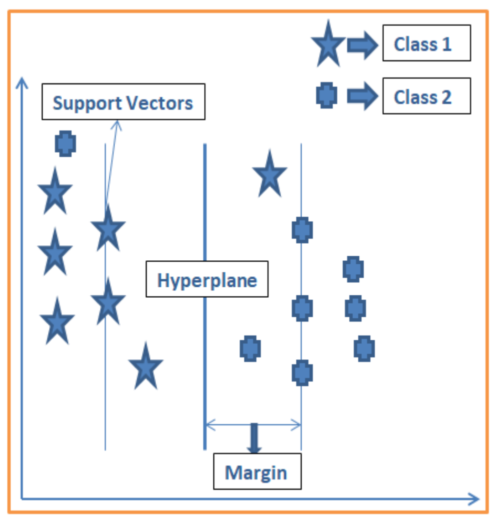

Figure 6 - Support Vector Machine Model

SVM or Support Vector Machine is best used for binary classification problems. Here a feature space is defined in a higher dimension. It is easier to visualize data in the higher dimension. To separate the data clearly into two classes a hyperplane is found. This hyperplane has a very special characteristic of Margin. This margin should be such that it is at a maximum distance from both sets of data points. The reason for that is it helps avoid overlapping of the two classes. Figure 6 shows the hyperplane and the clear separation of margin between two classes.

4.4 Decision Tree Regressor For P And S Wave Arrival Time.

Predicting the P and S wave arrival times was also an important task. The AR_Picker algorithm gives a good estimate of the P and S arrival times.

The same features mentioned in the algorithm above were used except the maximum amplitude and the standard deviation. The decision tree regressor worked really well and gave us an accuracy of approximately 90%

Figure 7 shows the results of SVM, Decision Trees and Random Forest.

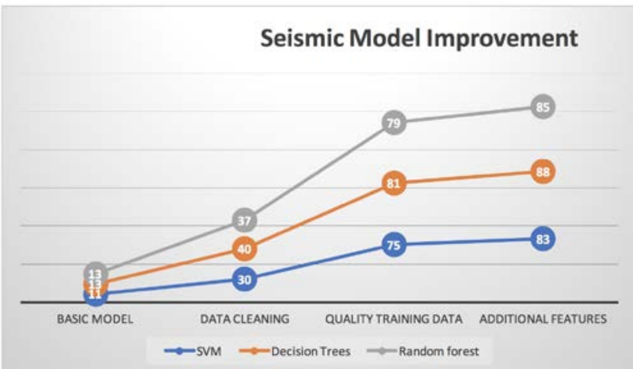

Figure 7 - Seismic Model Improvement

5. Seismic Noise

Seismic noise is a general term devised for any type of unwanted signal in the seismic data which produce no information or bogus information that cannot be used for experiments and calculations. The main reason behind noises is undesirable perturbations of the signal while accumulating data from seismometers. Sources of these noises can include malfunctioning of the recording system, wind motions, any land activities like drilling or constructions, ocean waves, road traffic and volcanic activities. [1]

5.1 Types of seismic noise

Classically noises are divided into three categories:

a) Noise generated by instrumentation errors

This is generally consisted of the errors due to a faulty instrument, or constant vibrations near seismometers which are recorded due to sensitivity. Typically, these types of noises are removed while collecting and processing data from the seismic station. This noise is highly dependent on the surrounding and the instruments from which this is being recorded.

b) Noise generated by human and animal activities.

Noise in the seismic data like vehicle movement, land drilling, building construction and traffic movement are generally cause with unnatural human interaction with the earth.

c) Noise generated by natural calamities.

Mixing up of the seismic waves with the signal waves from ocean flow, river flow, wind current or even volcanic activities generally considered as noisy data and needs to be filtered before can be used for data analysis for any type of prediction and calculation.

5.2 Noise removal algorithms

To be able to predict aftershocks with high accuracy the quality of data is one of the most vital things. Because the data acquired for the calculations and prediction contained a lot of noises, which demanded the removal of noise before data analysis. For each type of noise different algorithm, processes and parameters were needed which required a lot of research and fine-tuning the parameters as per the data and noise level. Generally, removing the unwanted feature or component from any signal is known as a *filter.* [9]

5.2.1 Detrend

Before applying filters to the seismic data, if a constant, linear, polynomial or curved offset is present should be removed from the signal data. It is known as a *trend* and can be recognized as a polynomial or linear variance in the signal data. Detrend is done by using the SciPy[10] and obspy-detrend[8]

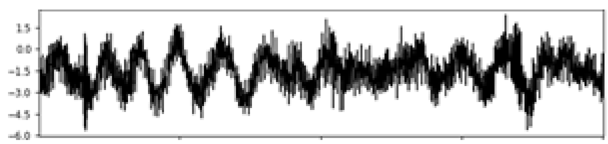

Figure 8 - Signal with noisy trend

Out of all the available filters for signal, we applied four of them for the earthquake data based on the type of the signal data from the stations. [8][10]

a) **Instrument correction:** The parameters for this completely depends upon the earthquake station from where the seismic data is recorded and generally applied right after the collection of the seismic data. [11]

b) **High Pass:** In this all the high frequencies (defined within the parameters) are passed and low frequency signals are removed. This is very useful in the case of the signal which includes the constant noise of very low frequency typically caused by air flow, water current or constant vibrations near seismic sensors. [10]

c) **Low Pass:** In this all the low frequencies are passed and high frequencies are restricted. This is useful in the case of abrupt high frequencies recorded by the seismic sensors typically caused by some controlled explosions, mining, volcanos etc. [10].

d) **Band Pass:** A combination of low pass and high pass filter, which is useful when both high and low frequencies noises are present in the signal. [10]

Since the dataset used for the predictions analysis contained both kinds of noises after comparing and evaluating all filters output, band pass filter was used and produced the best results out of all.

Figure 9 a) and b) are representing the signals before and after that noise removal

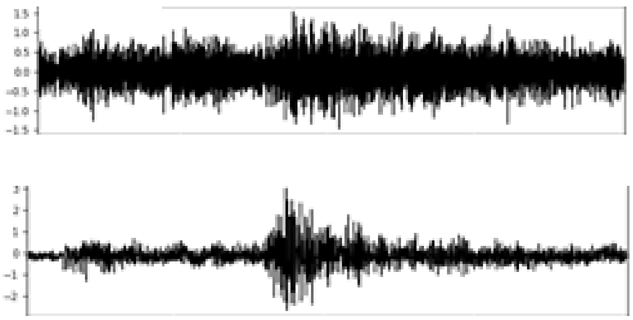

Figure 9 Showing signals, a) With noise. b) After noise removal using band pass

The data for this experiment was the combination of a lot of different type of noise and offsets in data. After comparing the preliminary analysis band pass filtering and linear and simple detrend algorithms were identified as most effective and were applied before slicing and clipping the data and using it for training the prediction machine learning model. Figure 10 showing some samples after detrending the signal and removing the noise from the example in Figure 10. These signals are good to be used for further analysis and prediction.

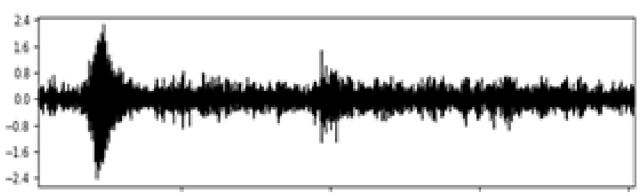

Figure 10 - Signal after removing noise

Below is the table showing the improvement in the results after applying different noise removal algorithms. For the experimental purpose and evaluate the results of the filter we used AR pick algorithm. And based on the result and comparison we took bandpass filter and implemented this within our algorithm.

6. Epicenter Calculation

The Epicenter is the point located on the Earth's surface directly above the earthquake. Seismic stations detect P-and S-wave and record the seismic activities and signals. These signals are recorded in the form of tracings created by the seismographs. Epicenter can be calculated using the tracing made by three separate seismic stations. Along with the seismograph we also need the arrival time of P-And S-wave, and the difference in time of the arrival of the waves at any station. [13]. One of the classical approach using the triangulation techniques is as follows.

1. Measure the time difference between the first P wave and the first S wave. Let suppose they are X sec apart from each other. For the example, it is 4 minutes 50 sec.

2. Find the point for X seconds on the left side of the Time travel graph for S- and P- wave and mark that point. For our case, it was 4 min and 50 sec, and according to the chart, this earthquake's epicenter was 3200 KM away.(Figure 11)

3. Repeat the step 1 and 2 and get the epicenter distance from the other two stations as well.

4. Once we have a minimum of three stations data available and calculated the distance of the epicenter from respective stations we can now plot the same on the graph. We use triangulation technique and draw circles from all the three stations and the point where all the circles intersect it our Epicenter of that earthquake. [14] as shown in the example image [Source : Michigan Tech][14] (Figure 12)

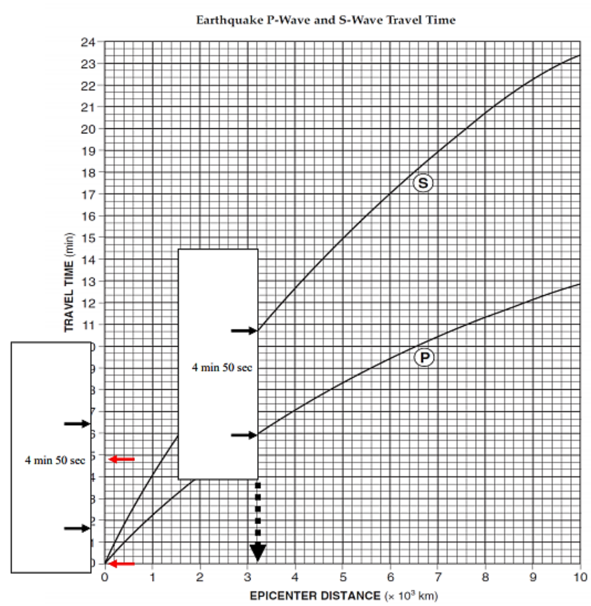

Figure 11 - measuring the distance from the station based on the arrival time difference between P and S wave. [14]

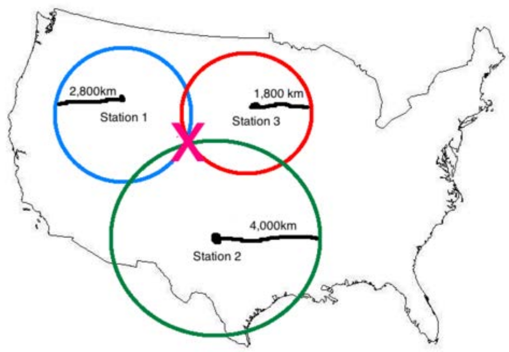

Figure 12 - Using triangulation to predict the epicenter [14]

We applied the above-mentioned triangulation techniques to calculate the epicenter for the earthquake data we are working on and found the following.

a) Randomly picked any earthquake data from the 3 stations and calculated the S and P arrival using algorithm mentioned in the previous sections. (Figure 13)

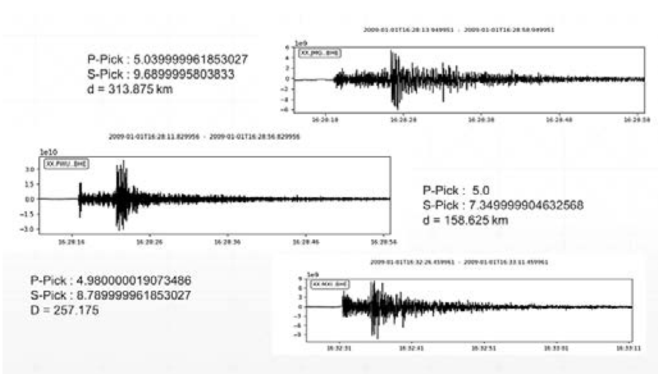

Figure 13 - Showing intermediate calculations and signal plot for epicenter

b) Plotted the same on the maps and used the triangulation algorithm to find the epicenter.

Findings were as follows:

c) As the data do not contain the epicenter information it is yet to validate epicenter calculated by the method.

7. Lessons Learned

Using machine learning techniques for detecting and predicting earthquakes is relatively less explored. Statistical analysis has been used in geophysics for a very long time. It has proved to give good results. But in this age of vast computing power, using machine learning for earthquake prediction seems to be the next logical step. We studied six papers for feature extraction, data preprocessing and earthquake prediction.

We followed a very similar approach that was followed by O. Lindenbaum et al. Our dataset also had multiple earthquakes in a single SAC file of 24 hrs. O. Lindenbaum et al used STA/LTA ratio to find suspected events, we used recursive STA/LTA for the same purpose. Recursive STA/LTA gave us better results than vanilla STA/LTA. We used the AR_picker algorithm to label the P-wave and S-wave times, this algorithm required the data to remain separate in three different directions. On the other hand O. Lindenbaum et al fused the data together from three directions. J. Ramirez et al also clipped their data to make sure each window only has one event. Their paper helped us re-confirm the importance of clipping the data. J. Ramirez et al extracted features from the seismic waveform by using SVD. We, on the other hand, extracted features from the wave and fed the entire seismic wave to the ML algorithms. We extracted features from our seismic data using a similar approach that was followed by J. Zhao et al. But even they didn't use the actual waveform as a feature for their ML algorithm. The results improve drastically when the entire waveform is fed to the ML algorithm. It learns better because the whole waveform pattern is made available to the algorithm. This is a very important observation from our study. Even a weak classifier was able to give good results when the entire waveform was used. We observed that when the quality of our clipping algorithm improved, it also substantially improved our overall accuracy. When the waveform window that is passed to the ML algorithm is clean with minimum noise and the earthquake is clearly visible then the algorithm learns better.

Many papers have analyzed electromagnetic waves for early prediction of earthquakes. Electromagnetic waves in the ELF spectrum can be analyzed for anomalous behavior. This technique can give us a look-ahead of about 2 weeks.

Machine learning algorithms provided a good context in terms of feature selection. Features form an important part in any learning technique. We used many feature extraction techniques which helped us improve the accuracy. We were able to gradually improve our model's accuracy by improving the quality of our data. Without any noise removal and primitive clipping, we got an accuracy of 11%. By gradually improving the clipping algorithm and removing noises we achieved an accuracy of 85%. Our data seismic recordings from 16 stations over a period of three months in three directions. Most papers analyzed very little data. In order for the algorithm for clipping, noise removal and prediction to run over all the waveforms took about two hours. We even optimized the run time of the algorithm from four hours to two hours.

A standard framework which can predict time and location for all the areas is still not available due to the uncertainties surrounding earth's tectonic movements. The papers we saw used a wide variety of algorithms like hidden markov model, support vector machine, ensemble techniques like adaboost and clustering techniques like K- nearest neighbor. We used random forest classifier and decision tree classifier which was not used in any of the papers we studied. Random forest gave better results than SVM. SVM was studied in other papers. Even though our accuracy results were not the best among all the papers, our dataset was much more challenging. It was raw data directly collected from the seismic stations.

The main lessons that we have learned from the experiments listed in this paper are as follows

- The accuracy of data clipping greatly impacts the prediction of P-wave and S-wave arrival time and classification of Earthquake and noise
- Giving the entire seismic waveform to the machine learning algorithm will help it to learn patterns better
- The accuracy results are much better with more features and less noisy data.

8. Conclusion

Machine learning is less explored in the field of seismology. In this paper we surveyed the work done in this field and have implemented machine learning, noise filtering and epicenter calculation algorithms based on our understanding. Machine learning can be used very effectively in the field of seismology and reduce the statistical efforts. The prediction results can be further improved by adding new features that will help in classifying earthquakes. Geographical conditions around the active zones can serve as a good set of features in identifying the earthquake and the damages it can cause. Fine tuning of data labeling algorithm like AR picker will greatly impact the output. A combination of statistical and machine learning methods is another area which can be explored.

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