Prediction of Ground Motion using Data on Seismic Waves

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***Abstract*—This paper presents a methodology for analyzing seismic data from significant earthquakes using the ObsPy Python library. Our dataset encompasses four major seismic events: the 2011 Tohoku earthquake (Japan), the 2010 Chile earthquake, the 2016 Kumamoto earthquake (Japan), and the 2015 Nepal earthquake. The utility of the processed data is demonstrated by applying the Short-Term Average/Long-Term Average (STA/LTA) algorithm to the mean-subtracted waveforms to automatically identify the arrival of P-Waves and S-Waves. A k-Nearest Neighbours (kNN) regression model was used to predict the peak ground acceleration (PGA) and Arias intensity for each event.**

***Index Terms*—Seismic Waves, Instrument Response, Ground Acceleration, Arias Intensity**

I. Introduction

The analysis of seismic data provides crucial insights into earthquake dynamics and Earth's subsurface structure. Various seismic waveform data from several significant earthquakes were processed and analyzed by investigating the relationship between maximum amplitude and distance to the event. This was done by extracting features, using matrix operations and similarity measures. We focus on four major seismic events: the 2011 Tohoku earthquake (Japan), the 2010 Chile earthquake, the 2016 Kumamoto earthquake (Japan), and the 2015 Nepal earthquake. This approach facilitates access to a large volume of data from diverse sources.

II. Literature Survey

Seismic signal processing and analysis have garnered significant attention in recent years, with various machine learning methodologies being employed for classification, event detection, and predictive modeling. This section reviews key contributions in the field, highlighting different approaches and techniques applied to seismic data analysis.

Li et al. [1] investigated seismic data classification using supervised machine learning techniques. Their study focused on extracting features such as spectral content, amplitude variations, and waveform characteristics. They evaluated the performance of multiple machine learning models, including Support Vector Machines (SVM), Decision Trees, and Neural Networks, which were trained on labeled seismic event datasets to assess classification accuracy.

Ramirez and Meyer [2] explored seismic phase classification through manifold learning techniques. Their approach involved mapping high-dimensional seismic data onto a lower-dimensional manifold using Laplacian Eigenmaps, improving classification performance by preserving local waveform structures. Their method demonstrated enhanced differentiation between P-waves and S-waves using nearest-neighbor-based classifiers in the transformed space.

Chakraborty et al. [3] employed statistical feature extraction techniques for micro-seismic event detection. The extracted features included peak amplitude, energy, zero-crossing rate, and entropy. Machine learning models such as Random Forest, SVM, and k-Nearest Neighbors (KNN) were applied to classify seismic events, distinguishing natural seismic activity from noise with improved accuracy.

Shu et al. [4] conducted a comprehensive survey on machine learning applications in microseismic signal recognition and classification. They categorized methodologies into three major groups: feature-based models utilizing statistical descriptors, deep learning models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), and hybrid techniques that integrate statistical feature extraction with deep learning frameworks. Additionally, their survey highlighted key challenges and potential advancements in the domain.

Varshney et al. [5] developed a machine learning-based earthquake monitoring system leveraging real-time seismic data streams. Their approach involved preprocessing seismic data using Fourier and Wavelet Transforms before training classification models, such as Decision Trees and Neural Networks, to detect and monitor earthquake events dynamically.

Chin et al. [6] enhanced earthquake detection accuracy by implementing a hybrid deep learning model integrating CNNs and Long Short-Term Memory (LSTM) networks. Their framework, trained on labeled seismic waveform datasets, incorporated data augmentation techniques to improve model robustness. The proposed system demonstrated superior detection performance compared to traditional signal processing methods.

Shimshoni and Intrator [7] applied ensemble learning techniques for seismic signal classification. Their work utilized bagging and boosting strategies to enhance classification accuracy, demonstrating that ensemble-based neural network approaches could improve differentiation between seismic events.

Agliz and Atmani [8] employed multi-layer perceptron (MLP) neural networks for seismic signal classification. Their methodology involved extracting both frequency-domain and time-domain features from seismic waveforms, which were subsequently used as input to the neural network for classification and training.

Akhouayri et al. [9] introduced a fuzzy expert system for automatic seismic signal classification. Their method defined fuzzy sets based on key signal parameters such as amplitude, frequency content, and duration, allowing for a more flexible and interpretable classification framework compared to traditional rule-based systems.

Curilem et al. [10] investigated the application of genetic algorithms for optimizing neural network classifiers in the context of volcanic seismic signal classification. Their findings demonstrated that evolutionary computation techniques could enhance the performance of neural network models in differentiating between various types of volcanic seismic events.

III. Methodology

A. Data Preprocessing

The ObsPy Python library was used for obtaining seismic wave data within 20° of the epicenter. The epicenter of the earthquake is at 37.52° N and 143.04° E. Using `obspy.mass_downloader()`, waveform data was retrieved in miniSEED format corresponding station metadata in StationXML format from multiple data centers, including IRIS. The downloaded miniSEED files were processed to extract key features for analysis. Time-domain data was converted into CSV files and statistical measures such as mean, standard deviation, maximum amplitude, peak-to-peak amplitude, root mean square, dominant frequency, spectral centroid and energy were added to it. Crucially, station metadata, including station ID, channel, start time, latitude, longitude, elevation, and distance from the event, were also incorporated into the CSV files. This enriched dataset allows for comprehensive analysis, linking waveform characteristics with station location and event information.

The data was categorized into three classes based on the maximum amplitude: the first 33rd percentile was assigned to class 0, the next 33rd percentile to class 1, and the remaining data to class 2. For these classes, the mean (class centroid) and standard deviation (class spread) of the data points were calculated.

B. Training

We trained a weighted k-Nearest Neighbors (k-NN) classifier to predict the class labels based on maximum amplitude and distance. Peak ground acceleration was predicted using several features such as the distance from the station to the earthquake epicenter (in degrees), geographical coordinates of the station, the elevation of the station, the frequencies with the most energy in the signal and the weighted average frequency in the signal. The k-NN model predicts peak ground acceleration at new locations by finding the 5 most similar locations in the feature space and averaging their values of peak ground acceleration, weighted by distance.

80% of the data was used for training and 20% for testing. We further explored the impact of the hyperparameter k by training and testing models with k values ranging from 1 to 11, observing the resulting accuracy trends.

IV. Results

A plot between the maximum amplitude against distance to the event, and a histogram of maximum amplitudes were generated. We evaluated the performance of the k-NN classifier with k = 3, achieving a high accuracy of 0.99. The k=3 model demonstrated a training accuracy of 1.00 and a testing accuracy of 0.99, indicating neither underfitting nor overfitting.

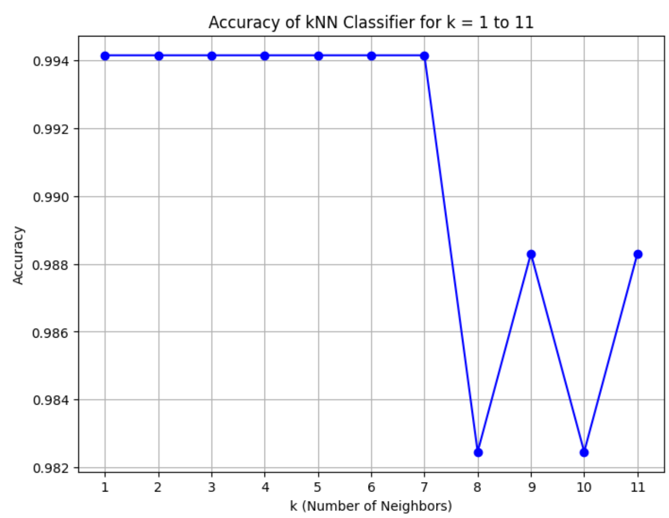

Fig. 1. Accuracy of k-NN Classifiers with Different Values of 'k'

The Euclidean distances between the class centroids showed indication of highly distinguishable classes. The distance are shown below.

The Minkowski distance between class centroids was calculated for orders from 1 to 10.

The below table demonstrates the performance metrics on training.

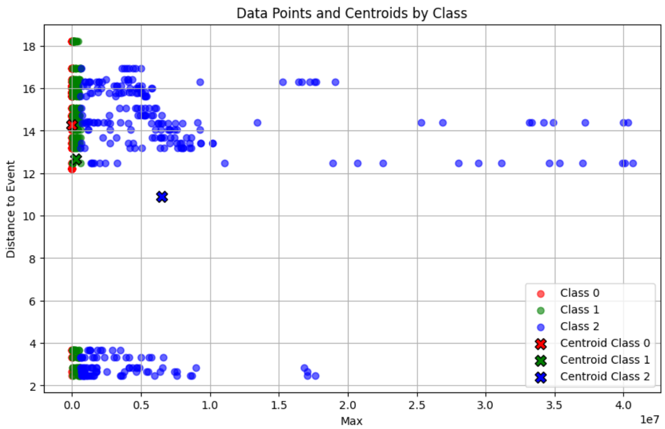

Fig. 2. Data Points and Centroids by Class

TABLE I
EUCLIDEAN DISTANCES

Classes Taken	Distance
0 and 1	262577.78
0 and 2	262577.78
1 and 2	6228234.60

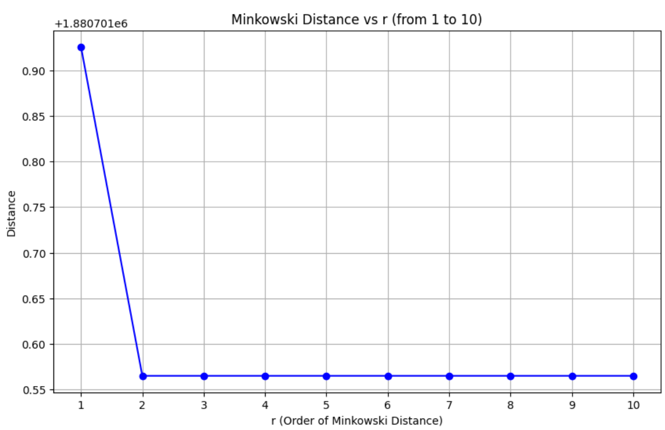

Fig. 3. Minkowski Distances of Different Orders

TABLE II
TRAINING CLASSIFICATION REPORT

	precision	recall	f1-score	support
1	1.00	1.00	1.00	200
2	1.00	1.00	1.00	197
accuracy			1.00	397
macro avg	1.00	1.00	1.00	397
weighted avg	1.00	1.00	1.00	397

On testing the data, the performance metrics were obtained as demonstrated in the below table.

TABLE III
TEST CLASSIFICATION REPORT

	precision	recall	f1-score	support
1	0.97	1.00	0.99	80
2	1.00	0.99	0.99	91
accuracy			0.99	171
macro avg	0.99	0.99	0.99	171
weighted avg	0.99	0.99	0.99	171

The training confusion matrix is shown below.

$$\begin{bmatrix} 200 & 0 \\ 0 & 197 \end{bmatrix} \tag{1}$$

The testing confusion matrix is shown below.

$$\begin{bmatrix} 80 & 0 \\ 1 & 90 \end{bmatrix} \tag{2}$$

The model was also proven to be very accurate as the mean squared error was $6.6643 * 10^{-28}$, the root mean squared error was $2.582 * 10^{-14}$, the mean absolute percentage error was $4.211 * 10^{-15}\%$ and the R^2 score was 1.

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