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. We leverage the `obspy.mass_downloader()` module to efficiently retrieve waveform data in miniSEED format and associated station metadata in StationXML format from multiple data centers, including IRIS. 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. Downloaded miniSEED files are processed to extract relevant features. Specifically, we convert the time-domain data into CSV files containing statistical measures such as mean, standard deviation, maximum amplitude, peak-to-peak amplitude, root mean square, dominant frequency, spectral centroid, energy, and the waveform itself, along with station metadata including station ID, channel, start time, latitude, longitude, elevation, and distance from the event. Finally, we demonstrate the utility of this processed data 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. This approach facilitates efficient data acquisition, feature extraction, and automated phase picking for large seismic datasets, enabling further analysis of earthquake dynamics.**

***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. Methodology

The ObsPy Python library was used for efficient data acquisition and manipulation. Using `obspy.mass_downloader()`, we retrieved waveform data in miniSEED format and 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.

III. 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.

IV. Results and Discussion

The rank of a matrix tells you the number of linearly independent columns present in it. In the case of an observation matrix, each column corresponds to a feature. Hence the rank is a measure of non-degenerateness.

Classification is a type of supervised machine learning which is used to predict labels or catagories. As a dataset, you are given with various features, along with the labels each data point is associated with. The output of a classification model is a class label. You basically use this whenever you want to assign an input some predefined category. Between each of the output classes, there exists a clear decision boundary. There are many examples and types of classification models such as Decision Trees, Random Forest, Support Vector Machines and Neural Networks (for classification). The evaluation metrics used for classification are Accuracy, Precision, Recall, F_1-score and ROC-AUC.

Regression is another type of supervised machine learning which is used to predict continuous values. There are many examples and types for regression models such as Linear Regression, Polynomial Regression, Decision Trees, Neural Networks (for regression). Regression don't have any strict decision boundary. It tries to fit a line or a curve in the dataset, which illustrates the predicted output for each input. The evaluation metrics used for regression are R^2 score, Mean Absolute Error (MAE), Mean Squared Error (MSE).

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