Seismic Phase Picking Automation Using a Deep Learning Model

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Abstract— Seismic phase picking is the crucial first step of a typical earthquake monitory workflow. Traditionally, it is a labor-intensive task as it requires trained analysts to manually identify signals from digital seismic data. The emergence of deep learning-based automatic phase pickers has revolutionized this process, showcasing a remarkable ability to detect and classify seismic phases with high precision, thereby significantly enhancing the efficiency of earthquake monitoring workflows. However, one of the major challenges has been the considerable computational requirements of these deep learning models, which makes it challenging in deploying them on small, low-cost devices. In this paper, we develop an implicit model for automating seismic phase picking on a smaller scale that will be trained and tested on Seisbench's ETHZ (Switzerland Region) seismic dataset. Implicit model is a general class of deep learning model, which encapsulates most deep neural networks as special cases. The proposed approach allows for training a much more compact model, enabling Raspberry Shake devices, which are considerably cheaper and smaller compared to traditional seismometers, to provide a way for inexpensive seismic monitoring for local communities in developing countries. A successful implementation of a compact deep neural network model on RaspberryShake devices will facilitate a wide range of applications, encompassing urban environmental monitoring, earthquake early warning systems, and scientific educational outreach.

Introduction

Seismic phase picking of Primary waves (P-waves) and Secondary waves (S-waves) is the first step to traditional earthquake monitoring. Phase picking is the measurement of arrival times of distinct seismic phases (P-waves and S-waves) within an earthquake signal. These signals are then used to estimate an earthquake's location. Phase picking is a laborious task as it requires trained analysts to manually identify signals from digital seismic data. However, with the rise of deep learning, previous research indicates that using deep learning to automate the picking of P-waves and S-waves has a similar precision to manual picking by human analysts [1].

The implicit model intakes the raw data of the ETHZ dataset, specifically the traces and time stamps of P-waves and S-waves. The implicit model will output We will also be given a probability curve that shows whether a P-wave or S-wave occurred.

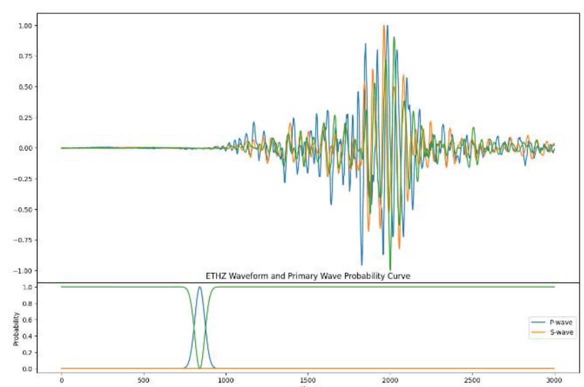

Figure 1. Waveform of seismic phases and probability curve of P-wave occurrence

The ETHZ[2][2] dataset comes from Switzerland's Swiss Seismological Service. Containing 36,743 waveform examples of seismic data points from several seismic networks and stations of which include: CH[3], C4[4], 8D[5], S[6], and XT[7].

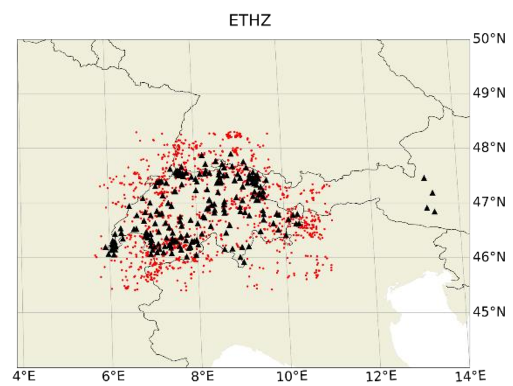

Figure 2. Dataset device location and region mapping

Background

P-waves and S-waves can be used to determine an earthquake's location. This is as P-waves move faster than S-waves, so the time difference between the arrival of a P-wave and its respective S-wave to a seismic device plays a part in indicating where the earthquake originated[4]. This is done via calculating the time difference between the waves at a single station which can be used to infer the distance of the earthquake's source from the station. Using this, graphically, a circle with the diameter value of this difference. Triangulation can be done if there is graphing from 3 different stations.

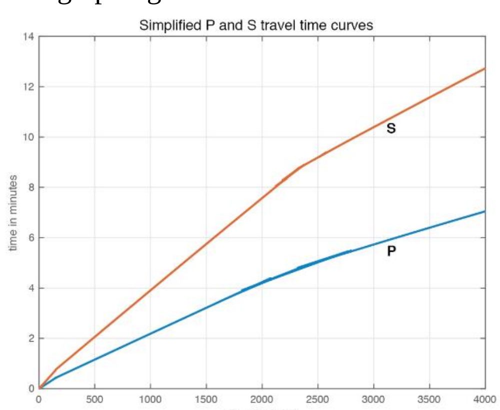

Figure 3[8]. Simplified P and S wave travel curves

Figure 4[8]. Triangulation of an earthquake using P-wave and S-waves

Proposed Algorithm

Although phase picking has evolved with the assistance of deep learning and its ability to detect and classify seismic phases with high precision, one of its major challenges is that it has considerable computational requirements, making it difficult to deploy them on small, low-cost devices.
To reduce the limitations of deep learning's computational requirements, we will use an implicit model, which is more general than a neural network. With the implicit model, we can train it to be able to determine whether a P-wave or S-wave happened.
Implicit model is a general class of deep learning model, which encapsulates most deep neural networks as special cases. It allows for training a much more compact model end-to-end without hand-crafting specific model architecture.
In deep learning, there are various forms of architecture that are available for use but for implicit models, one advantage is that there is no need for handpicking of neural network components.

Implicit Model:

$$\left(\begin{array}{c|c} A & B \\ \hline C & D \end{array}\right) = \left(\begin{array}{cccc|c} 0 & W_{L-1} & \dots & 0 & 0 \\ & 0 & \ddots & \vdots & \vdots \\ & & \ddots & W_1 & 0 \\ & & & 0 & W_0 \\ \hline W_L & 0 & \dots & 0 & 0 \end{array}\right), \quad x = \begin{pmatrix} x_L \\ \vdots \\ x_1 \end{pmatrix}, \quad \phi(z) = \begin{pmatrix} \phi_L(z_L) \\ \vdots \\ \phi_1(z_1) \end{pmatrix}$$

Figure 6. Implicit Model Function

During the training phase, this model intakes a three-component waveform consisting of EHE, EHN, and EHZ components that represent the East-West, North-South, and vertical Up-Down direction respectively. The model will the probability of P-wave and S-wave arrival, which we will use to determine the accuracy of the model for Switzerland's seismic records. This will allow us to continue with automation of phase picking for P-waves and S-waves with a high accuracy.

Results

In comparison to the traditional method of phase picking, automation is possible using deep learning models. Presently, phase picking is automated using deep learning models, but by nature, they require large amounts of computational power to run. In comparison, the implicit model is able to complete the same process with less power due to its generality.

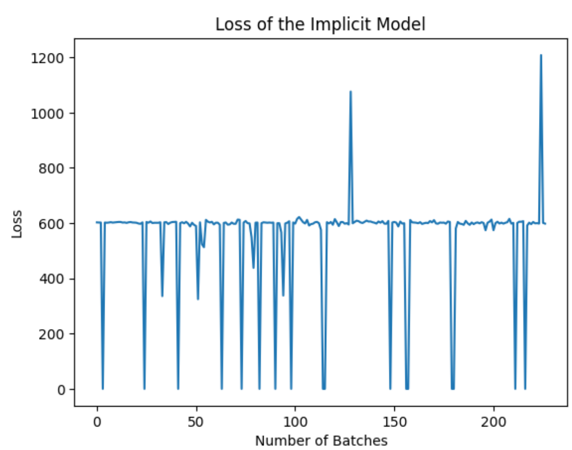

Figure 6. Loss Function Graphical Representation

The loss function is currently fluctuating, indicating that the implicit model requires more in depth investigation in order to reduce the error value overall. However, the implicit model was successful in determining whether a P-wave or S-wave was present in the waveform and ETHZ dataset.

With additional work, the loss value will decrease, and it will become a viable method to automate seismic phase picking, Additionally, it will become applicable to the RaspberryShake devices, which are currently using very simple deep learning models to operate and automate their phase picking systems.

Citations and References

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