24 Using Smartphones to Detect Earthquakes

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24.1 Introduction

We are exploring the use of accelerometers in smartphones to record earthquakes. We have developed an application for Android phones based on previous work with iPhones to record the acceleration in real time. These records can be saved on the local phone or transmitted back to a server in real time. A series of shake table tests were conducted (and more tests will be conducted soon) to evaluate the performance of the accelerometers in these smartphones by comparing them with high quality accelerometers. We also recorded different human activities using these smartphones. Different features were extracted from the recordings and were used to distinguish earthquakes from daily activities. We implemented a classifier algorithm based on an artificial neural network, which shows a 99.7% successful rate for distinguishing earthquakes from certain typical human activities

24.2 Data Sources

Two kinds of smartphones have been used in this research: iPhone and Android phones. The applications on these phones are iShake and droidShake. Data was collected mainly in three ways: (1) Continuous recording of different human activities, e.g. walking, running, sitting, taking the bus, etc. (2) Trigger-based data from various users sent to a server. This method requires that the phone stay steady for certain amount of time. Then, if the acceleration exceeds the pre-determined threshold, it triggers the algorithm to send data before and after the trigger to the server. (3) Data recorded during the shake table tests with earthquake input signals. These three types of data were used to distinguish earthquake signals from non-earthquake signals.

24.3 Detection Method and Classifier

A high pass filter was first applied to the data in real time to eliminate the baseline offset. Then the filtered data was divided into segments using a series of sliding windows. From each of the sliding windows, three parameters were extracted to characterize different types of signals, including maximum number of zero crossings from the three components, peak acceleration, and the ratio of peak velocity over peak acceleration from the vector sum of the three components. These three parameters were then used as input to train the neural network to distinguish earthquakes from non-earthquake signals.

A 10-fold cross validation method was used to determine the optimal size of the time window and the number of neurons in the neural network. Based on the cross validation results, a 150 sample length of time window was found to be optimum, and one hidden layer with 19 neurons was used to configure the neural network.

Table 2.1: Confusion Matrix

		Target Class		%
		Non-EQ	EQ	
Predict Class	Non-EQ	584	3	99.5%
	EQ	1	582	99.8%
%		99.8%	99.5%	99.7%

24.4 Results

The output of the neural network is "earthquake" or "non-earthquake." The results are shown in the confusion matrix in Table 2.1. The overall success rate is 99.7%. Figure 2.45 shows the peak acceleration and maximum number of zero crossings for different activities and earthquake signals. It is obvious that these two parameters alone could distinguish most of the earthquakes from other human activities. The test of the neural network is shown in Figure 2.46

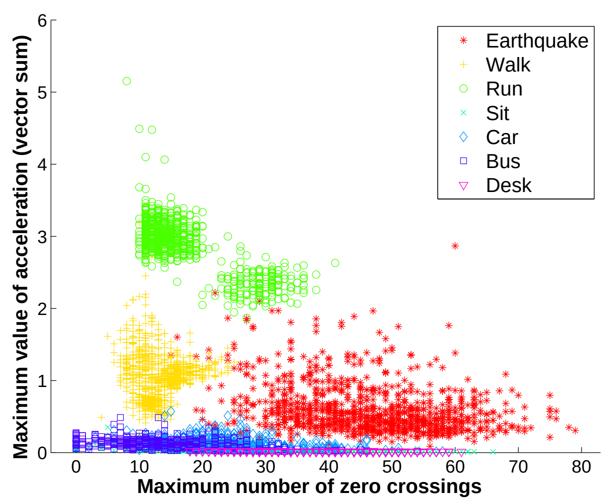

Figure 2.45: Maximum value of acceleration vs maximum number of zero crossings

24.5 Conclusion and Future Work

This initial study shows the potential of using smartphones to detect earthquakes. By using multiple phones in the future, we can achieve higher accuracy. A network

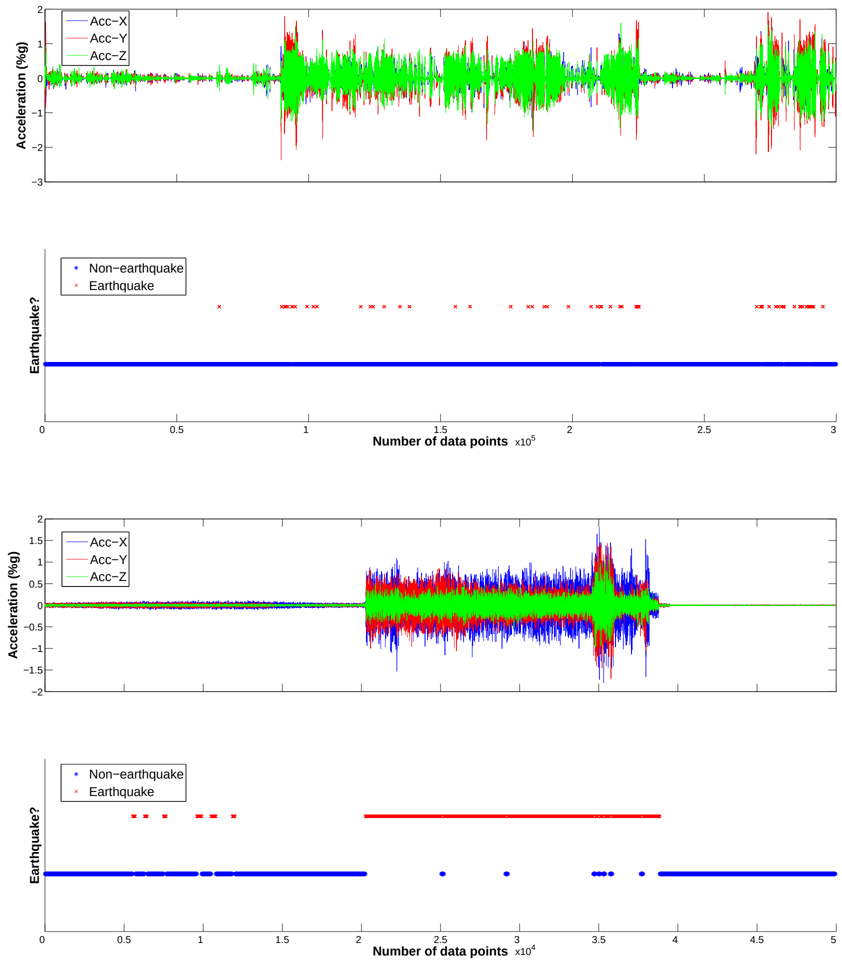

Figure 2.46: Algorithm Test: Figures show the detection of non-earthquakes and earthquakes using the artificial neural network model developed. The upper two panels show the waveform and the detector output for an accelerogram recorded for different random activities. This random record consisted of various activities within about two hours, including walking, running, jumping, riding in a vehicle, and so on. In 97% of cases, the windows were classified correctly as non-earthquake signals. The lower two panels show the detection using data recorded by the phone when it was placed on a shake table. Once the shake table starts to move, the algorithm correctly classifies most of the movement as an earthquake.

consisting of these smartphones may work as a supplemental network to the current traditional network for scientific research and real-time applications.

24.6 Acknowledgements

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24.7 References

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