Smartphone-based Networks for Earthquake Detection

Qingkai Kong*, Young-Woo kwon†, Louis Schreier‡, Steven Allen*, Richard Allen*, and Jennifer Strauss*

*Seismology Laboratory
University of California, Berkeley
{kongqk,syallen,rallen,jastrauss}@berkeley.edu

†Dept. of Computer Science
Utah State University
young.kwon@usu.edu

‡Innovation Lab in Silicon Valley
Deutsche Telekom
louis.schreier@telekom.com

***Abstract*—To enhance current earthquake early warning (EEW) systems, emerging technologies, including social and mobile computing, have been the focus of much attention. As smartphones have benefitted from significant development over the last few years, it is now possible to capture various kinds of motion using a smartphone's sensors, (e.g., accelerometer, GPS, etc.) including earthquake motion. To that end, we developed smartphone software to capture and backend analytics to determine whether the motion captured by a smartphone is caused by an earthquake or by human motion. In so doing, our goal is to establish a new type of seismic network using smartphones which enhance traditional seismic networks. In this paper, we evaluated the use of smartphones as detection devices; collected both human and simulated earthquake data using the smartphones, and developed an algorithm to distinguish earthquakes from human activities. Our results show that using our algorithms, a smartphone can not only be used as a recording instrument, but also a highly accurate earthquake detection tool. As a result, creating networks of seismic sensors based on smartphones will enhance the safety of communities vulnerable to earthquakes, world-wide.**

I. Introduction

Mobile phones, and smartphones in particular, have achieved significant penetration world-wide. Although there's no shortage of consumer and business oriented applications, only a relatively few applications have been and are being developed for community service and fewer still fully make use of the on-board sensors, rich networking and the aggregate power of smartphones when they're networked.

One application of smartphones which takes advantage of their individual and aggregate capabilities is being developed by the University of California Berkeley, Seismology Laboratory and Deutsche Telekom, Silicon Valley Innovation Center. This application, *MyShake*, captures sensor data from smartphones and uses an Artificial Neural Network to classify that data. The project's goal is to setup an end-to-end smartphone seismic network and enhance current earthquake early warning (EEW) systems. Creating networks of seismic sensors based on smartphones can enhance the safety of communities vulnerable to earthquakes, world-wide.

The rest of this paper is structured as follows. Section II introduces related work and defines the problem that our approach aims at solving. Section III details our approach and discusses how we evaluated our approach. Section IV concludes this paper.

II. Background

In this section, we first present the state-of-the-art technologies and research for community services using smartphones and special case studies in seismology. Then, we discuss the problem that we are trying to solve through fundamental research questions.

A. Related Work

Next, we present several recent technologies to detect human activities and disasters as well as community services using smartphones.

978-1-4673-7328-9115/$31.00 ©2015 IEEE

1) Human Activity Recognition: Smartphones, even the lower priced models, boast significant network, processing, memory, and communication capabilities. Their OSes support multithreading and allow applications to access on-board sensors including accelerometers, magnetometers, and GPS, enabling sophisticated software to be developed for a wide variety of applications. Thus, smartphones have become a powerful device for human activity recognition.

Consumer smartphones can be programed to capture the movements of the phone in three dimensions (x, y, and z axis) for every preset time interval. Assuming that a smartphone is attached to a human being (e.g., in the back pocket of one's pants), various human activities such as running, walking, standing, sitting, lying down, and going up and down the stairs, can be recognized by analyzing the captured time series data [1], [2], [3].

The usual process starts from creating a training set which consists of multiple labeled feature vectors. For example, several volunteers perform a given activity while the smartphones in their pocket record the acceleration data. Various features are extracted from this acceleration data, and then labeled with the given activity. After training a classifier using this training set, various human activities can be detected simply by classifying the new acceleration data into one of the activity categories. Sun et al. trained a Support Vector Machine classifier, which performed well with an F-1 score reaching between 91.5 and 93.1% in a natural setting (e.g., a phone was put in the hip or the front pocket of jeans in different orientation). The F-1 score increased to 94.8% if a fixed pocket position was used [1]. Bayat et al. trained five classifiers and compared their performance of activity classification. The overall accuracy rate was 91.15% [3]. These human activity recognition technologies can be used to improve the accuracy of earthquake detection.

2) Community Services using Smartphones: Today, consumer smartphones and their applications are being used to enhance our communites' quality of life. For example, in Europe, there are two mobile apps for community service that include a Paris-based startup, Tinbox [4], which is focused on charity donation, and foodloop.net [5], a German startup, whose application is aimed at minimizing food waste.

In the US, emergency support, disaster readiness and response applications include e.g., MAPS [6] and FiRST [7]. Sonoma County, California publishes a list [8] of community service/emergency support applications, and there's even at least one medical flight emergency support application [9] among the mix.

Again, in the US, the Association of Public-Safety Communications Officials (APCO) International, in cooperation with FirstNet and the Department of Commerce organized a workshop to begin to specify public safety mobile application security requirements. A link to the workshop summary is given below [10].

a) Disaster Early Warning: Although it is difficult to predict natural catastrophes or man-made disasters before they occur, many technologies, which detect and warn of these disasters, have recently received much attention. By analyzing Twitter messages about disaster events, for example, it is possible to find warning signs of imminent earthquakes or typhoons [11], [12]. Furthermore, due to the significant development of mobile hardware and software technologies, a smartphone has become an important device for detecting and warning such disasters [13], [14].

In the following discussion, we further present three closely related projects: *Quake-Catcher* [15], Community Seismic Network [16], and *iShake* [17], which inspired our project *MyShake*.

b) The (Inspired) Model for Using SmartPhones as Seismic Sensors: The *Quake-Catcher* [15] and *Community Seismic Network* [16] are the most recent efforts to detect earthquakes by utilizing low cost MEMS accelerometers as seismic sensors. In these efforts, volunteers are asked to host these sensors at residential buildings across California, and around the world. *iShake* [17] is a project that initiated at Berkeley which was based on iPhones and provided the first proof of principle that smartphone sensors, accelerometers in particular, have the ability to capture earthquake motion. Berkeley Seismological Lab continued this project to the Android phones, and Deutsche Telekom joined the project following that first proof of principle and developed *Droidshake* (the previous version of MyShake), the android version of the mobile application.

B. Fundamental Research Questions

While it's far easier to develop a purpose-built seismic sensor than to try and marshal the power of off-the-shelf smartphones, the sheer number and global penetration of smartphones and the relative costs of the devices raises the following compelling questions:

Given that smartphones have sophisticated operating systems, the requisite on-board accelerometers, magnetometers, and GPS, as well as powerful multi-network capabilities, *1) can we develop a robust, reliable and accurate application for earthquake quick detection, that*

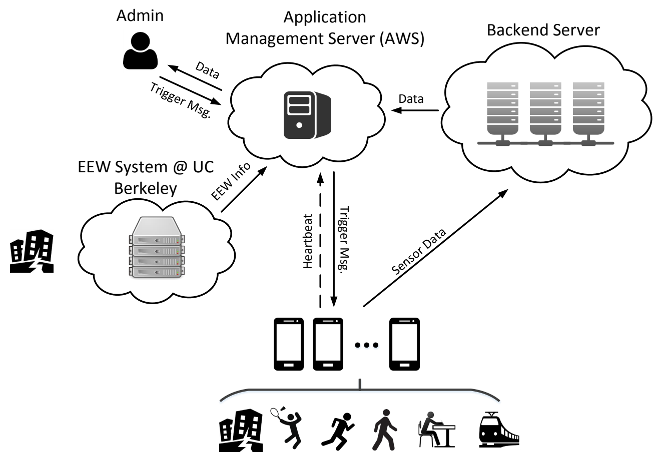

Fig. 1. Approach overview.

won't cripple the user's phone by draining battery or have other negative impacts on the user or her device, and 2) can a smartphone network also support very low latency communication between the smartphones themselves and remote back end processing?

We think the answer is yes. And we set about demonstrating this on Android-based consumer smartphones, without special builds and without constraints on what other applications are installed or also running. In the future, we will look at developing that same functionality on other OSes.

Although using consumer grade smartphones, under the conditions above, makes them black boxes, as it were, it also makes for a diverse sensor network allowing smartphones from most OEMs and Carriers to be used. Redundancy is built in because of the potentially large numbers of the devices and also because of smartphone/network diversity.

III. Approach

In this section, we present our approach with particular emphasis on the analysis of collected sensor data by using *Droidshake* and later *MyShake*[1] software. Specifically, we have evaluated our approach through a series of benchmarks and systematic results analysis. We, then describe some of the implementation details.

A. Approach Overview

Figure 1 gives an overview of our approach. Our MyShake system comprises mainly four components: 1) smartphones, 2) a cloud-based system, 3) an application management system, and 4) an earthquake early warning (EEW) system at UC Berkeley. Next, we briefly explain each component. First, smartphones keep track of tremors and their locations using their sensors including accelerometers, magnetometers, GPS, etc. and records them locally. Second, the recorded sensor data are uploaded to the cloud-based system for further analysis. Moreover, the application management system monitors application usages, triggers detection algorithms, and sets device-specific configurations. Lastly, the EEW system is used as another earthquake detection source. Thus, once the EEW system receives real earthquake warnings from earthquake stations or other sources, it notifies such warnings to the application management server, so that all the smartphones automatically begin to record current tremors. This is a new way to increase the likelihood of collecting earthquake data.

[1]MyShake is the second version of the Android based smartphone application. Droidshake was the initial version for that OS.

B. Experimental Setup

The questions for earthquake detection are whether, and to what degree, can smartphones capture earthquake data from its on-board sensors, and whether we can distinguish earthquakes from human activities. Due to the difficulty of using live data (i.e., difficult to come by because of the unpredictable nature of earthquakes), the Richmond Field Station's Shake Table was used to generate high fidelity earthquake motion for our testing. These shake table tests serves the purpose of both testing the phones' performance under large shaking and also collecting data for training the algorithm.

The Shake Table at the Richmond Field is capable of reproducing earthquake motion in 3 dimensions with very high fidelity in both frequency and amplitude. This allowed the accuracy of the smartphone accelerometers to be measured and tested under realistic earthquake loads and against a reference accelerometer. Smartphones from Samsung, LG, HTC, Motorola etc., running *Droidshake* and *MyShake* software captured the shaking motion for later analysis.

Pictured in Figure 2, are the smartphones being prepared for the shake tests at the Richmond Field Station. We also did noise floor tests to find the minimum noise level of the phone itself. We placed the phones in a quiet place and recorded one month's worth of noise data. This can show the sensitivity of the phones to the smallest movement they can detect. During these tests, we evaluated the sampling reliability and the sensor sample reliability of the phones as well. These reliabilities are key to the data collection process and detection accuracy.

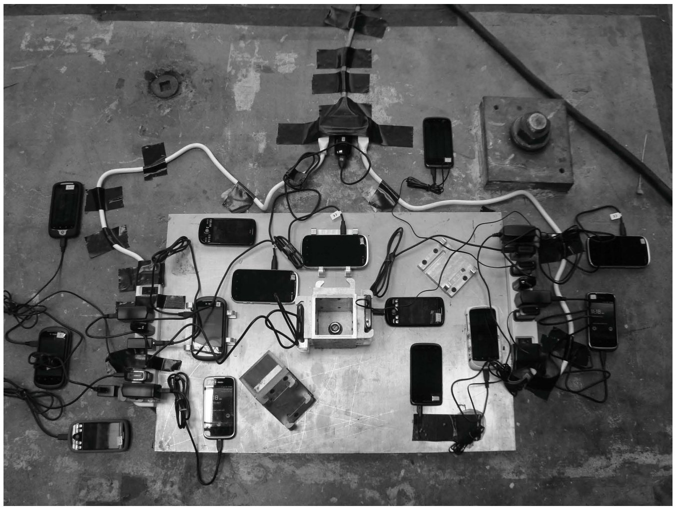

Fig. 2. Smartphones being subjected to Earthquake load at the Richmond Field Station's Shake Table. The silver plate is to hold the phone on the table, other phones not on the plate were placed freely on the table.

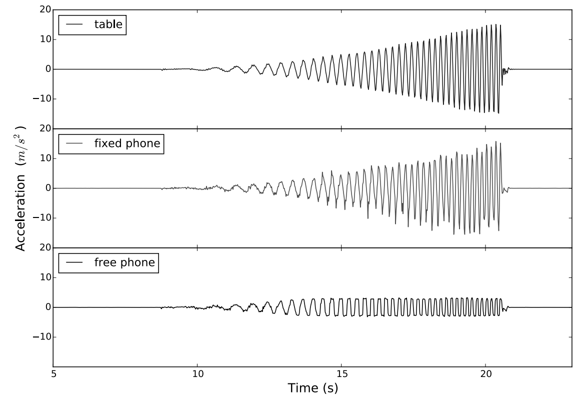

Fig. 3. Smartphone's accelerometer's data and reference accelerometer's data captured on a one-dimensional shake table. The top graph is the recording of the reference accelerometer on the table. The middle and bottom graphs are from the phones fixed and allowed to move freely on the table.

We then had volunteers install our app on their phones and collected daily human activity data when they normally used their phones.

After we collected data, we started to design our artificial neural network classifier to distinguish earthquakes from human motion.

During the time we were analyzing the data, two phones with our app running recorded the 2014 M6.0 Napa earthquake, which we will show in the following section.

C. Experimental Results Analysis

In this section, we describe our experiments and systematically analyze the experimental results, as well as the earthquake data we recorded on our smartphones.

1) Sensitivity Comparison: Pictured above in Figure 3, is a comparison of accelerometer data captured by our phones and compared to a reference accelerometer (the first curve). The second curve was generated by a smartphone that was fixed on the table and resistant to the shaking. The third curve was generated from a smartphone simply placed on the table and allowed to move freely. It was sliding due to the strong shaking motion. Note that all three preserve the frequency content of the shaking wave, although the amplitude of the freely moving phone is clipped at a certain value.

We also compared the smartphones' sensitivity overall against high- and low- earth background noise (The curves labeled HNM and LNM, respectively, at the bottom), analyzed Earthquake data, and a MEMS accelerometer built by HP. This is pictured in Figure 4. The two noise floors recorded from smartphones are average noise floor from phones released before 2013 (Nexus One, Exhibit, Amaze, Double Play, Galaxy S3, Nexus 4) and released after 2013 (XperiaZ, Galaxy S4, MotoX, HTC One, LG G2, Nexus 5), we can clearly see the trend of improvement of the accelerometers in the more recent phones.

The low noise background data represents, in some sense, the sound of the earth at its quietest. The high noise environment represents the sounds of the earth nearer natural phenomena such as ocean waves, without human induced vibrations. The HP MEMS is a sensitive accelerometer developed for seismic imaging applications [18]. Earthquake signals within 10 km are depicted by the dashed lines and labeled with their magnitude.

What the results in Figure 4 indicate is that smartphones' accelerometers are capable of sensing earthquake motion, at a distance of 10km, and above a certain magnitude. Most important, they are sensitive to shaking waves across the frequency range that the earthquake engineering community is interested in, namely: 0.1 Hz to 10 Hz.

2) Sampling Reliability: Also key to the ability of the smartphone to reliably collect data is its clock. Both *DroidShake* and *MyShake* were run hundreds of times for periods varying from several minutes to several hours and overnight. The purpose was to measure the smartphones' ability to maintain a steady sampling rate

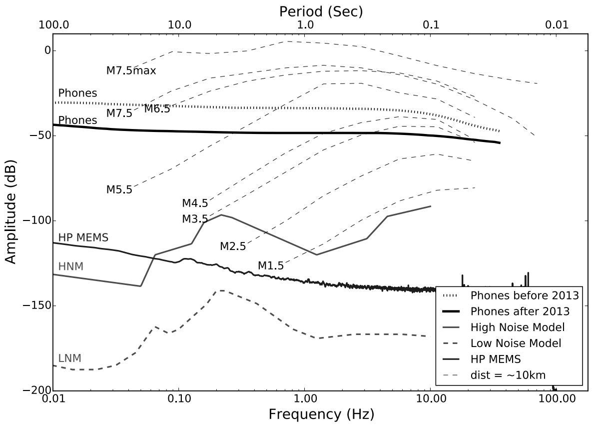

Fig. 4. Accelerometer sensitivity compared against high and low earth background noise, a very high performance HP MEMS, and captured earthquake data.

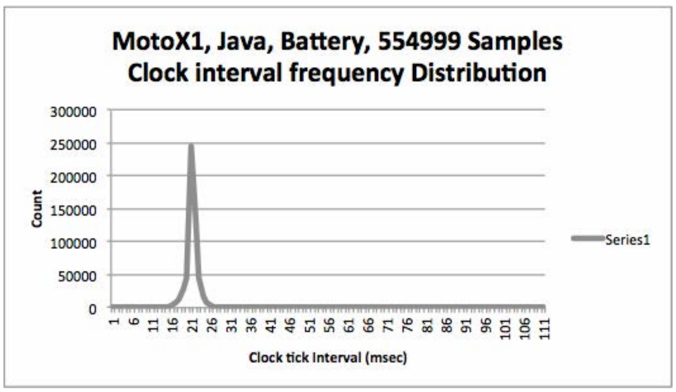

Fig. 5. Distribution of clock intervals around the 20msec sampling rate used to collect data.

around our sampling frequency.

Although not all devices performed as well as the MotoX1 in Figure 5, other smartphones had acceptable stability, with newer devices showing improvement over older ones.

3) Sensor Sampling Reliability: In addition to examining the clock sampling itself, we also looked at the sensor output during times when we observed a small (O (100ms)) jump between sequential time codes.

The plot depicted in Figure 6 shows the relative stability of accelerometer data in terms of its clustering around a small range of values in both the pre and post jump state. By and large, the sensors remained stable over time, yielding highly reliable results.

4) Behavioral Measurements: Using smartphones for earthquake detection requires the ability to distinguish between earthquake and human caused motion. We also recruited student and staff volunteers to carry smart-

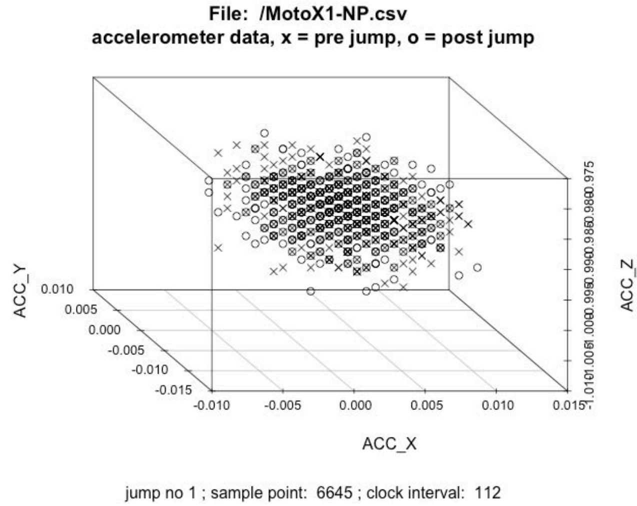

Fig. 6. Accelerometer sample data pre- and post- a 112 msec jump in the sampling interval.

phones, engage in everyday activities including walking, running, riding busses and the like while running *DroidShake* to capture those signals. Figure 7, shows the output of the accelerometers while the volunteers were moving. The figure shows a time slice of the three axial components of acceleration and, as is clear, each activity has different underlying patterns, which can be used as a basis to distinguish earthquakes and human activities.

5) Classifier Results: Data captured by the *DroidShake* and *MyShake* applications are communicated to a back-end server, and then used to train the ANN algorithm developed at UC Berkeley. The ANN is trained on labeled behavioral and seismic data and then unlabeled data are used to determine the degree to which the trained ANN can discriminate and classify. For more details of the algorithm, please refer to a follow up paper (in preparation).

The results of the classification shown in the confusion matrix, Figure 8 were based on an initial dataset from 7 human users and shake table data. The classification success rate is over 99% on the testing dataset.

6) An Opportunistic Event: Although we can't capture earthquake data at will, we were, in some sense, fortunate to have been able to capture the 2014 Napa Valley earthquake shaking on a smartphone running *MyShake*. The smartphone was in Berkeley CA, some 38km distant from the epicenter, and was put freely on a desk on a second floor apartment. The accelerometer data is shown in Figure 9. Figure 10, shows the *MyShake* data and data recorded on a USGS netquake station [19] which was located about 1.2 km away from the

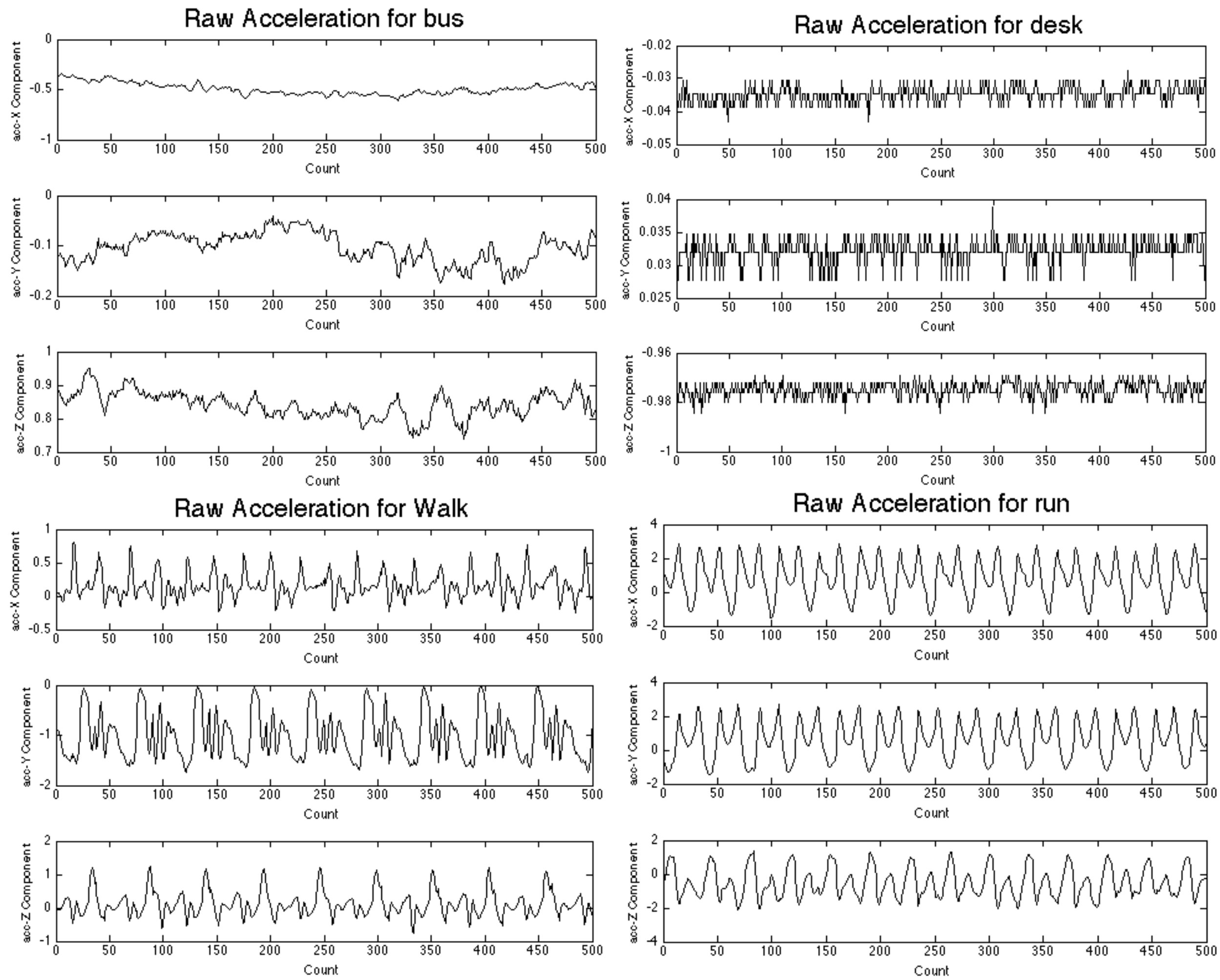

Fig. 7. Examples of accelerometer data captured from human movement.

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

Fig. 8. Confusion matrix for the classifier

smartphone.

D. *MyShake* Implementation

In this section, we present the *MyShake* system architecture that offers an energy-efficient earthquake detection framework.

1) System Architecture: First, *MyShake* keeps track of tremors using accelerometers and GPS sensors and then analyzes such tremors using two-stage triggering algorithm. If the current movement is determined as earthquake-related tremors, its network module sends the recorded data and current data to the cloud-based detection system for further analysis. Furthermore, *MyShake* periodically sends a heartbeat message to the application management system for application usage information.

2) Two-Stage Triggering Algorithm: As energy efficiency becomes an important software design consideration, to reduce the impact of the algorithm on the battery, we adopted a two-stage triggering mechanism.

The first level trigger is a simple STA/LTA (short time average/long time average) algorithm [20]. The STA monitors the sudden change of the signal, and the LTA keeps the background level of noise. This algorithm checks the ratio of the STA over the LTA of the signal,

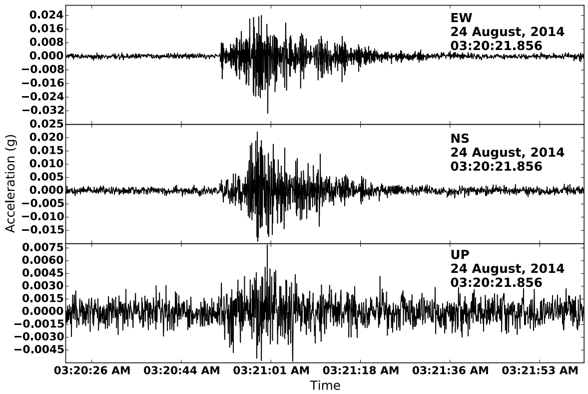

Fig. 9. MyShake accelerometer data recorded from the 2014 Napa Valley, CA M6.0 Earthquake

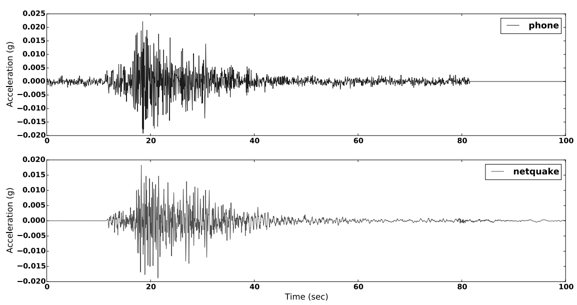

Fig. 10. Netquake station data compare with *MyShake* accelerometer data from the 2014 Napa Valley, CA M6.0 Earthquake, showing here is one horizontal component.

and triggers when the ratio is above certain threshold. It is an efficient and accurate algorithm that reduces the computation of the features for ANN when there is no movement. Since the algorithm does not have any complicated calculations, the real-time detection can be performed in a fast and efficient way. Furthermore, the algorithm is designed to find a sudden signal change that is different from background noises, thereby enabling an accurate detection[20]. The second level trigger algorithm is the ANN we developed, and it only activates to check the incoming data once the STA/LTA triggers. This two level triggering algorithm will run in the background on the users' phones.

IV. Conclusion and Future Work

A. Community-based Service Apps

A significant amount of data collection and analysis have gone into establishing that a *MyShake* smartphone, individually and in aggregate, when coupled with the UCB ANN can be used as part of an EEW system. The advance warning at Berkeley for the Napa Quake was only 5 seconds using the current earthquake early warning system. In the future we envision the advance warning time will be longer when we have a dense smartphone network as a supplement to the current EEW system: sufficient time to find safety, alert hospitals and first responders, begin safety procedures in factories and industrial settings, and provide schools early notice.

In poorer economies whose geographies are prone to seismic events in South America or Asia for example, and whose governments may not be able to afford the very high cost of the traditional seismic stations for EEW, the need for and benefits of a smartphone EEW are that much greater.

Earthquakes are a global phenomenon, affecting millions of people and costing billions of dollars. Smartphones have an additional advantage in addition to those described above: their greatest penetration is in areas of greatest population density, putting them at the center of where early detection would do the most good. And, because we are demonstrating that smartphones can be used for early detection as part of an EEW system, the cost of a seismic network can be significantly reduced, putting seismic detection within the reach of poorer economies.

B. Next Steps

We have currently completed a small 'friends and family' beta test at UC Berkeley to assess the performance of additional smartphones and their ability to provide accurate data and our ability to provide analysis and detection. The data from that are still being analyzed. We are, among other things, implementing the ANN algorithm on the phone itself, so that if the phone senses some movement, the application can decide if the current movement is an earthquake. We are also looking into further improvements to the network protocol to reduce data communication latency to the maximum degree possible.

Acknowledgments

Mr. Qingkai Kong is a PhD candidate at the UC Berkeley, Seismology Laboratory and on whose research and analysis this work is based.

Dr. Young-Woo Kwon is an Assistant Professor at Utah State University. Dr. Kwon developed MyShake based upon the Droidshake app, and also developed the smartphone management application.

Mr. Louis Schreier is the Vice President of Deutsche Telekom's Innovation Lab in Silicon Valley. DT developed the first DroidShake application based upon the iShake application.

Mr. Steven Allen, contributed to the development of the management application software.

Dr. Richard Allen, Mr. Qingkai Kong, Dr. Jennifer Strauss, Mr. Steven Allen are all part of the UC Berkeley Seismology Laboratory. Dr. Allen is its Director. Dr. Strauss is the External Liaison Officer and Science Liaison.

They can each be reached at their respective emails above.

This work was supported by the University of California, Berkeley, as well as grants from the Moore Foundation, the USGS, Google, and Deutsche Telekom, Silicon Valley.

REFERENCES

[1] *Activity recognition on an accelerometer embedded mobile phone with varying positions and orientations*, 2010.

[2] J. Kwapisz, G. M. Weiss, and S. A. Moore, "Activity recognition using cell phone accelerometers," *Explor. Newsl.*, vol. 12, no. 2, March 2011.

[3] A. Bayat, M. Pomplun, , and D. A. Tran, "A study on human activity recognition using accelerometer data from smartphones," *Procedia Computer Science*, vol. 34, pp. 450–457, 2014.

[4] Tinbox. [Online]. Available: http://www.get-tinbox.com/

[5] foodloop. [Online]. Available: http://www.foodloop.net/

[6] Department of Homeland Security, "Mobile applications for public safety." [Online]. Available: http://www.dhs.gov/maps

[7] "FiRST: First responder support tools provides map-based data on hazard standoff, nearby points of concern, and ied damage and injury contours, as well as important reference data and features;) cal fire, flood, first aid." [Online]. Available: http://firstsupporttools.com

[8] "Public safety mobile applications." [Online]. Available: http://sonomacounty.ca.gov/Mobile-Apps/Public-Safety-Mobile-Applications/

[9] "Medflight launches first responder mobile app." [Online]. Available: http://www.woub.org/2015/03/26/medflight-launches-first-responder-mobile-app

[10] M. Ogata, B. Guttman, and N. Hastings, "Public safety mobile application security requirements workshop," NIST, Tech. Rep., 2015. [Online]. Available: http://nvlpubs.nist.gov/nistpubs/ir/2015/NIST.IR.8018.pdf

[11] T. Sakaki, M. Okazaki, and Y. Matsuo, "Earthquake shakes twitter users: real-time event detection by social sensors," in *Proceedings of the 19th international conference on World wide web (WWW '10)*, 2010.

[12] *Chatter on the red: what hazards threat reveals about the social life of microblogged information*, 2010.

[13] F. Graham, "Predicting earthquakes and saving lives with smartphones," July 2013. [Online]. Available: http://www.bbc.com/news/business-23204346

[14] "Mobile4d: A disaster alerting and management system based on smartphones," 2015. [Online]. Available: http://www.capacitylab.org/project/mobile4d

[15] E. Cochran, J. Lawrence, C. Christensen, and A. Chung, "A novel strong-motion seismic network for community participation in earthquake monitoring," *IEEE Inst & Meas*, vol. 12, no. 6, pp. 8–15, 2009.

[16] R. W. Clayton, T. Heaton, M. Chandy, A. Krause, M. Kohler, J. Bunn, R. Guy, M. Olson, M. Faulkner, M. Cheng, L. Strand, R. Chandy, D. Obenshain, A. Liu, and M. Aivazis, "Community seismic network," *Annals of Geophysics*, vol. 54, no. 6, 2012.

[17] J. Reilly, S. Dashti, M. Ervasti, J. Bray, S. Glaser, and A. Bayen, "Mobile phones as seismologic sensors: Automating data extraction for the ishake system," *Journal of IEEE Transactions on Automation Science and Engineering*, vol. 10, no. 2, 2013.

[18] B. D. Homeijer, D. J. Milligan, and C. R. Hutt, "A brief test of the hewlett-packard mems seismic accelerometer," USGS, Tech. Rep., 2014.

[19] USGS, "Netquakes." [Online]. Available: http://earthquake.usgs.gov/monitoring/netquakes/

[20] R. Allen, "Automatic earthquake recognition and timing from single traces," *Bulletin of the Seismological Society of America*, vol. 68, pp. 1521–1532, 1978.