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Seismic Activity Detection Via Smartphone

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Abstract: *The purpose of this study is to depict seismic activity detection via a smartphone. Smartphones are incorporated with sensors such as 3-axis Accelerometer and Locator, the availability of these sensors in mass-marketed communication devices enables us to acquire ample amount of observation data from various locations at once. The accelerometer sensor is used to extract data from various activities occurring around it. The data is processed using a signal processing algorithm and then provided to a classifier algorithm to classify whether the activity is caused by an earthquake. An Earthquake Simulator called as Shake table was used to conduct simulation with smartphones which had our application installed. Once triggered by a mock seismic activity the smartphones alerted the client of an earthquake occurrence and then send a data package to a centralized server for further processing. Thus, seismic activity detection on smartphone provides useful knowledge of seismic energy propagation on an area.*

Keywords: *Accelerometer, Gaussian distribution, Energy propagation, Classification, Earthquake simulator.*

I. Introduction

The key aspect of an Earthquake Warning (EW) system is to detect the seismic activity, such as an earthquake and rapidly transmit warnings to automated systems. Most parts of the world do not receive earthquake warnings mainly due to the cost of building the necessary scientific monitoring network. Also, in current EW mechanism'sa sensor is used to monitor ground motion and transmit this data to an earthquake network center. This center first processes the data and transmits an alert to all the users in that earthquake region. This concludes that this type of system is time consuming and not dependable as an earthquake can occur almost anywhere as well as the earthquake propagation depends on the type of medium it is propagating through; hence the accuracy of such systems is not efficient.In this study we have discuss a unique method where in the user smartphone device identifies seismic activity around it when an earthquake occurs i.e. smartphones act as nodes in gathering seismic activity data. This data is first processed by signal processing algorithm to remove noise and then passed to a classifier algorithm which computes the probability of the seismic activity detected by the node with the seismic activity caused by an earthquake occurrence. The smartphone node uses the services provided by GPS to acquire location of the user and the internet to send the data acquired by the smartphone to a centralize server, also at the same time the smartphone alerts its user about the occurrence of an earthquake.Hence a quick alert and more accurate portrayal of the seismic energy propagation during an earthquake can be provided.

II. Methodology

The accelerometer data recorded by application is in form of a three-valued vector of floating-pointthat represent the individual accelerations of smartphone device on X, Y and Z axes. The accelerometer values are recorded in meters per second squared. Thus, flat on a level surface, the expected output given by the device accelerometer is [0, 0, -9.81].

Application to process a total of 256 accelerometer sampled magnitudes at a time to gain information of the activity been performed by the user, but to remove unwanted noise we consider 272 accelerometer sampled magnitudes. Processing 256 elements to obtain features leads to loss of data and the efficiency of the application on the Smartphone decreases. A solution to this problem we developed is to divide this 272-element block into distinct 4 blocks of 68 elements.

The process of converting the raw accelerometer data into a known activity is expressed in Four Stages as follows:

A. Preprocessing

During this stage, each acceleration vector (X, Y and Z) is combined into a single magnitude and also it consists of an algorithm which allows the removal of noise in the accelerometer data.

The first step in this stage is merging the three-dimensional input signal into one acceleration magnitude. The magnitude of the combine vector acceleration is calculated using a simple Euclidean equation 1.

$$a = \sqrt{(x^2 + y^2 + z^2)}$$

Equation 1

This merger was done to simplify the input given to the next stage, because the activities we needed to recognize did not require any distinction of directional accelerations. However, features from the individual acceleration may be important as some activities require directional information. This drawback can be solved with the use of another sensor called as gyroscope which is inbuilt into smartphones just like accelerometer.

The second step in this stage is removal of sudden spikes i.e. noise in the accelerometer raw data. The Android API only allows the acquisition of acceleration sample on an "onSensorChanged ()" event, which updates every time the accelerometer values changes regardless of how small this change is in the sampled data. Hence there is lot of noise generated in the accelerometer data, the solution to this problem is N-point smoothing algorithm. We considered N to be as 4 therefore we refer to it as 4-point smoothing algorithm. The smoothing algorithm was selected so that the spikes with an observable, steady progression would be preserved while anomalous, sudden spikes would be eliminated. The 4-point smoothing algorithm calculates the average of its 3 nearest neighbors'.

The algorithm is given as follows:

N-point Smoothing: Removes the unwanted noise in accelerometer sampled data.

Require:

W is the accelerometer data points Window
N is total number of points in W
X stores the smoothen data points
Intialize the temp to **null**
for each i value in window W do
    X[temp]= (W[i]+W[i+1]……+W[i+N])
    X[temp]= X[temp]/N
    temp ++;
end for
return X

***B.* Feature Extraction:**

This stage involves the extraction of features from data in Time Domain and Frequency Domain. In Time Domain the individual blocks containing 64 elements which are processed to obtain features such as Mean, RMS, Maximum magnitude and Minimum magnitude, where as in Frequency Domain the feature extraction is not possible using individual blocks containing 64 elements as we cannot conduct a 64 point Fast Fourier Transform (FFT) to convert Time domain elements to Frequency Domain elements i.e. 64 point FFT will consume a lot of processing time. The solution to this problem is dividing each 64-element block into individual 8 element blocks which enables the application to perform 8-point FFT. Once the Time Domain elements are converted to Frequency Domain elements, the application can extract the Frequency Domain features such as Energy and Entropy.

The following features were chosen based on the activity recognition concept which differentiates between various activities [Refer.1]:

a) Mean:

In this feature the mean value is calculated i.e. all the samples are added and divided by the window size. Mean can be calculated by using equation 2 .

$$a_m = \frac{1}{w}\sum_{i=0}^{w} a_i$$

Equation 2

Where a_m is the mean value of all the acceleration signal samples, w is the Window length and a_i is the acceleration samples (i= 0, 1, 2, 3 … w).

b) Maximum Amplitude:
The maximum value of the signal in the window is selected. It returns maximum value attained by a particular motion of an activity.

c) Minimum Amplitude:
The minimum value of the signal in the window is selected. It returns value of least acceleration attained by the motion of an activity.

d) Energy:
Energy is a Frequency Domain Feature, thus the energy of an accelerometer sampled data can be computed as the squared sum of discrete Fast Fourier Transformationcomponent magnitudes of the accelerometer sampled data points. The sum is divided by the window length for normalization.
If X1, X2 ...Xn are the FFT components of the window, which can substitute in the equation 3.

$$E_i = \frac{1}{w}\sum_{i=0}^{w} X_i$$

Equation 3

e) Root Mean Square:
The RootMean Square (RMS) of an accelerometer data sampled x_{RMS}that represents a sequence of ndiscrete values $\{x_1,x_2, \ldots,x_n\}$is obtained using equation4 andcan be associated with meaningful context information.

$$x_{RMS} = \sqrt{\frac{x_1^2 + x_2^2 + \ldots + x_n^2}{n}}$$

Equation 4

f) Entropy:
The entropy metric can be computed using the normalized information entropy of the discrete FFT coefficient magnitudes. Entropy is used to differentiate between accelerometer data samples that have similar energy values but correspond to different activity patterns.

***C.* Classification:**
The Classification stage involves processing of unknown class of accelerometer data samples. The Classification stage uses a modified Naive Bayes Classifier in which it compute's the probability distribution based on the attributes extracted from accelerometer data samples.

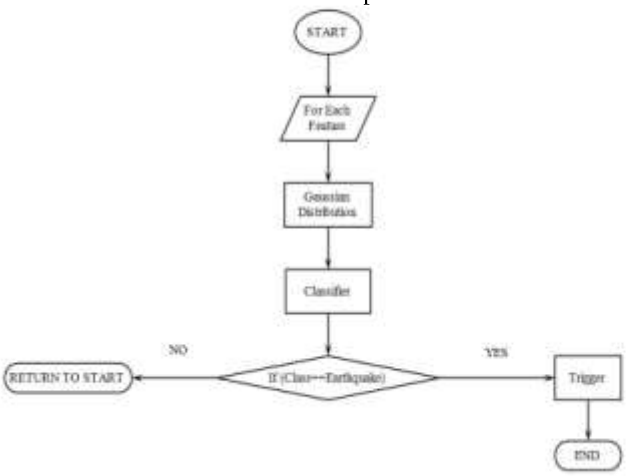

Fig. 1 Gaussian Distribution Conditional Flowchart

As shown in the Flowchart Fig [1] we have used Gaussian distribution [Refer.9] to represent the class-conditioned probability for continuousattributes for each feature. The distribution is characterized by two parameters, i.e. its mean (u) and standarddeviation (σ).
For each classy_j, the class conditional probability for attribute x_i is calculated using equation 5 and 6

$$P(X=x_i \mid Y=y_j) = \frac{1}{(\sqrt{2}\prod)\sigma ij} \exp^{-((z)^{\wedge}2)/2}$$

Equation 5

Where,

$$z = \frac{xi - uij}{\sigma ij}$$

Equation 6

The mean and standard deviation of a normal distribution control how tall and wide it is. The meaning of the probability density function f(z) is that the proportion of observation within an interval of incremental width dz centered on z is f(z)dz.

Gaussian distribution: Represent the class-conditioned probability for continuousattributes.
Require:

i. x[i] are the attributes of an unknown class/activity X.
ii. u[i][j] is mean of elements of a particular attribute belonging to a known class.
iii. σ[i][j] is standard deviation of elements of a particular attribute belonging to a known class.
iv. g is the probability of the unknown class attributes with respect to known class.

Intialize the temp1 and temp2 to **null**
for each j = number of classes
for eachi = number of attributes
temp1 = x[i]-u[i][j]
temp1 = temp1/ σ[i][j]
temp1 = (-0.5) * **Math. Pow** (2, temp1)
temp1 = **Math. Pow** (2.71828182, temp1)
temp2 = 1/ (2.506 * σ[i][j])
g[i][j] = temp2 * temp1
i++
end for
j++
end for
return g

D. Trigger

The Trigger stage is called when Classification stage classifies an activity as an earthquake activity. As shown in Flowchart Fig [2] Trigger stage involves three processes which are performed when an earthquake activity is detected.

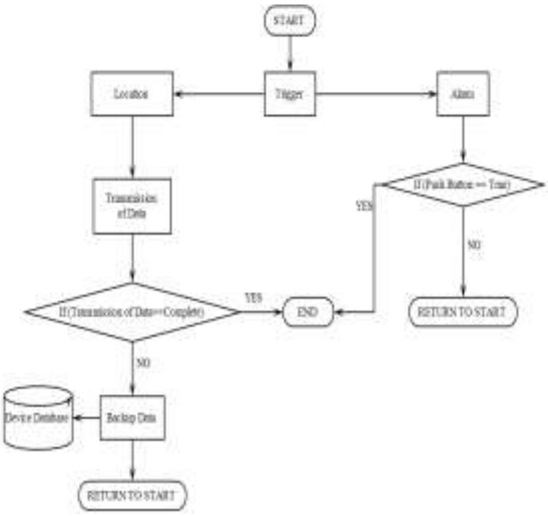

Fig. 2 Classificationalgorithm Flowchart

The three tasks perform by trigger stage are as follows:

a) Location:

This task is performed by Location Manager class which provides access to the system location services. These services allow applications to obtain periodic updates of the device's geographical location. Location is gathered by the smartphone during an earthquake occurrence because this location can be compared with locations of another smartphone giving the same alert. As we know that an earthquake seismic activity propagates on large surface, there is least amount of probability that only a few numbers of smartphones can detect it i.e. we mostly have to focus on the density of the smartphones on a seismic activity region.

b) **Alarm**:

The Alarm system is the most important part of this earthquake detection process as this system notifies and alerts the user of the seismic activity caused by an earthquake occurrence. Additionally, this system acts as a point where the Smartphone sends all the data such as Energy produce by a seismic activity which was detected by the Classifier stage of the system and location of that particular activity.

c) Transmit Data:

The Transmit Data task involves transmitting the data package from the client side i.e. from the smartphone node to the server side i.e. centralized server. The data package consists of the location of the user who is currently in the earthquake activity region, the date and time during which the smartphone had sensed an earthquake activity occurrence, the energy of the earthquake activity and a distinct identity number which is unique to every smartphone. As most of the earthquake detection process is conducted on the client side, the server side is used to collect all the data from smartphone nodes. The Smartphone nodes are plotted on to map using the location data along with energy produced by an earthquake activity hence making it a crowd source system.

III. Shake Table Simulation

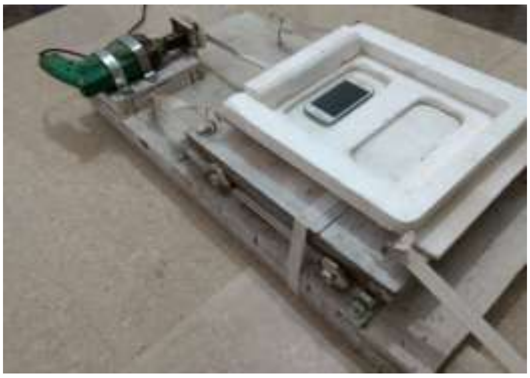

Fig. 3 Shake Table Simulator

An earthquake simulator provides experimental data that leads to better understanding of the behavior of structures and calibration of various numerical tools used for the analysis and design under earthquake activity. There are several different experimental techniques which are referred as Earthquake simulators [Refer 7], one of the widely used earthquake simulator is an Earthquakeshake table**.** The shake table test is the only experimental technique which allows direct simulation of inertia forces on a device or a structure. It can reproduce different types of ground motion such as recorded earthquakes which had occurred in a region. We [Refer 8] have designed a Shake Table where we have tested our project as shown in Fig[3].

IV. Conclusion And Future Scope

The Smartphone Detection for seismic activity is an efficient process of detection as compared to other systems as most of its activity recognition and user alerting system is not dependent on server-end system. The effectiveness of the activity recognition algorithm was tested on a Shaking table i.e. earthquake simulator which gave satisfactory results. This earthquake data along with the Smartphone node location can be used by Seismologist to get more accurate results of the earthquake propagation in an earthquake region as large number of sensors are involved in detecting the seismic activity caused by an earthquake.

Thissystem has many future enhancements which can lead to better earthquake detection and in turn lead to faster response time for alerting the user.

Some future enhancements which can be included are algorithms such as Density Based cluster to determine the density of the smartphone nodes in a particular region which can remove the outlier's and also include more Features in the classification algorithm such that the classification accuracy increases and the relative error decreases.

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