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Algorithms leveraging smartphone sensing for analyzing explosion events

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ALGORITHMS LEVERAGING SMARTPHONE SENSING FOR ANALYZING EXPLOSION EVENTS

by

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ABSTRACT

The increasing frequency of explosive disasters throughout the world in recent years have created a clear need for the systems to monitor for them continuously to improve the post-disaster emergency events such as rescue and recovery operations. Disasters both manmade and natural are unfortunate and not preferred, however monitoring them may be a lifesaving phenomenon in emergency scenarios. Dedicated sensors deployed in the public places and their associated networks to monitor such events may be inadequate and must be complemented for making the monitoring more pervasive and effective. In the recent past, modern smartphones with significant processing, networking and storage capabilities have become a rich source of mobile infrastructure empowering participatory sensing to address many problems in the area of pervasive computing.

In the work presented in this dissertation, smartphone sensed data during disastrous scenarios is extensively studied, analyzed and algorithms were built for participatory sensing to address the problems, specifically in the context of $Explosion-Events$ which are of interest to the current study. This work presents description of the systems for assisting people by detecting, ranging and estimating intensity of the explosion events leveraging multi-modal smartphone sensors. This work also presents various challenges and opportunities in utilizing the capabilities of the sensors in smartphone for building such systems along with practical applications, limitations and future directions.

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1. INTRODUCTION

As a society, we are increasingly being exposed to explosions that are both man-made and naturally occurring. Unfortunately, they can are dangerous to our life and property. In the recent past, a critical component of such dangers is the triggering of explosives (like bombs) intended to harm society [1, 2, 3, 4]. As we are well aware, the shock and blast waves arising as a result of an explosion being triggered, along with the associated debris can cause significant societal scale damages. On the other hand, triggering explosions without malicious intent like those in quarries and construction sites also create vibrations that could cause damages to buildings in their vicinity as has been demonstrated in a number of studies [5, 6], and also affects the human body [7]. If we have systems that monitor explosion events, then they will assist greatly in the scenarios of rescue and recovery operations. Needless to say, devices that can monitor explosion events, along with superior technologies to analyze them are important today.

Traditionally, the standard device that has been used to sense vibrations is a seismometer. While the chief utility of seismometers so far has been primarily for studying earthquakes, they have also been used to analyze the intensity of volcanic activities, vibrations of civil engineering structures, and explosion events. Conventional seismometers comprise of spring and weight and work on the principle of inertia, wherein the motion of the weight is sensitive to the ground vibration causing the motion. Modern seismometers on the other hand, sense ground vibrations using a combination of electronic vibration sensors and amplifiers. They are now equipped with sensors to sense ambient pressure also. This is useful to characterize explosions since the ambient pressure in the vicinity of an explosion rises above the atmospheric pressure due to emanating over pressurization blast waves. Unfortunately though, seismometers are bulky, expensive and not viable for ubiquitous usage.

Smartphones today are becoming both ubiquitous, as well as powerful with significant processing, networking and storage capabilities. In parallel, a critical development in modern smartphones come from the ability to embed multiple sensors in them for fine grained sensing of several phenomena. The sampling rate of such sensors also are very high considering their tiny form-factors as well.

1.1. THE ADVENT OF SMARTPHONES IN SENSING

With advances in MEMS technologies, modern smartphones come with significant sensing power [8]. Most modern smartphones today like the Samsung GALAXY series phone, the iPhone, Google Nexus phone and more, come packaged with various sensors for measuring environmental and human activity parameters. For instance, a Samsung GALAXY S4 smartphone today has built-in sensors that can measure acceleration, ambient temperature, pressure, humidity, light intensity, magnetic intensity, sound intensity, and much more with high sampling rates. The $LIS344ALH$ accelerometer sensor in the Samsung GALAXY S4 phone [9] can consistently sample at the rate of 100 to 110 samples per second, and the sampling rate is programmable. This phone is also equipped with pressure sensor ($LPS331AP$) to measure atmospheric pressure at its location, with a sampling rate of up to 10 samples per second. Furthermore, numerous studies are being conducted today to optimize the performance of smartphone sensors today from the perspective of accuracy, energy efficiency and processing speed [10, 11, 12].

There is a clear and tangible reason for the continued innovation in sensing capabilities of smartphones today, and that lies in numerous innovative and societally useful applications leveraging smartphone sensors. While we discuss important ones in Section 2 in more detail, we find that smartphone accelerometers have been used for monitoring vibrations emanating from earthquakes [13], and for activity tracking of human users [14]. The pressure sensor in smartphones has found applications in indoor localization [15, 16, 17]. Smartphone sensors like ambient temperature, humidity and light intensity have found innovative applications in context-awareness, and pervasive computing applications as well [18, 19, 20].

There is prior research in the areas of monitoring the earthquakes, and building their corresponding alarm systems using smartphone sensing [13], [21]. On the other hand, comparatively fewer studies have been found on monitoring explosive events. There is a need for systems for detecting, ranging and identification of the explosives (in terms of material and intensity) by continuous monitoring. In this context, we did some prior work in [22] on studying temporal and frequency responses of smartphone and seismometer data during explosion events.

The excitation induced by earth quakes and explosions show a significant difference in terms of resultant ground vibrations [23]. In case of explosion, the resulting shock waves propagate through the medium (ground or atmosphere) from the source of explosion to the subject. On the other hand, seismic waves that are result of an earthquake or a volcano are waves of energy that travel through earths layers and imparts low-frequency acoustic energy [24]. Another significant difference is the explosions result in blast wave which results in rise of ambient atmospheric pressure, which is not observed during earthquakes. The spectral differences between the earth quake and quarry explosion blast which is a form of an explosion were explored in recent times to a great extent forming a solid base for classifiers which will uniquely identify the explosions from all its counterparts [25], [26], [27].

In this dissertation, broadly we demonstrate the feasibility of smartphones to detect, range and determine intensity of explosion events. To analyse the explosion events for addressing the problems, we have collected data using smartphone accelerometers and pressure sensors from real-explosion experiments conducted at Explosives Research Lab (ERL), an Experimental Mine located at Missouri University of Science and Technology [28] in May 2014.

First, we attempt to demonstrate the feasibility of leveraging smartphone accelerometer to detect the triggering of explosion events in [29]. To do this, during the experiments we statically emplaced a Samsung Galaxy S4 smartphone at a carefully chosen location right next to a state-of-the-art seismometer, and extracted the accelerometer readings from smartphone and ground truth Geophone data from seismometer, before, during and after blasts. Subsequent processing and comparison of the data, led us to make several insightful contributions. We demonstrate that the temporal and frequency responses of the explosion event readings in the smartphone and the seismometer are highly correlated over multiple blasts. Specifically, an average correlation value of 0.83 was observed for the temporal responses.

Further, we built a model for *ranging* and estimating the *intensity* of explosions using a machine learning approach from accelerometer sensor data in [30]. For this work, we have used 4 Samsung Galaxy S4 smartphones during 4 experiments conducted. We emplaced smartphones at various distances from the source of the explosion during each experiment, and collected the accelerometer readings corresponding to explosion events. We then extracted a number of features from this acceleration data including, mean, median, variance, minimum, and maximum of signal amplitude along with duration of event, dominant frequency and histogram properties. We have used a nonlinear polynomial regression model in our technique and it yielded a high degree of accuracy in ranging the source of explosion events. With the exception of one outlier, an average case error of 12.86% was observed for ranging in our experiments. Subsequently, we also attempted to estimate the intensity of the explosion event, and our results were again highly accurate with an average case error of 11.26%.

Then we tried to demonstrate the feasibility of leveraging multi-modal sensor suites in smartphones for analyzing explosion events. Specifically, we demonstrate how data sensed by the accelerometer (that senses ground vibrations associated with an explosion) and pressure sensor (that senses changes in atmospheric pressure as a result of emanating blast waves) in a state-of-the-art smartphone can be mined for *ranging* (estimating the distance to an explosion source) and estimating the *intensity* (in terms of charge-weight of the explosive material) with high accuracy and consistency. The experiments conducted were similar to that of the previous work [30]. Essentially, this is an extension to our prior work in [30]. With multi modal sensors, we could improve accuracies by achieving an average case error of 11.21% for ranging and 9.4% for intensity estimation.

1.2. MOTIVATION

In the recent past, we have come across explosion blasts at Boston [4], Mumbai [31] and very recently in Paris [1], Nigeria [3] and Turkey [2]. The post-disaster events during these disasters have seen a lot of difficulties for evacuation and also investigation, due to lack of real-time systems monitoring explosion blast events. The time lapse between the occurrence of explosions and the arrival of rescue teams is so precious and become crucial for saving a victim, so the sensing capabilities of the smartphone if better utilized to detect, range and find intensity of the explosions may lead to the effective rescue scenario. This motivates us to study the capabilities of smartphone to turn into a monitoring device during explosions and also similar events like quarry blasts, demolitions of building etc. The signatures from the explosion events are ground vibrations and change in ambient atmospheric pressure, so the building systems will be based on sensing these two primary parameters. A phenomenon of detecting the explosions, ranging them and determining their intensity from participatory sensing may be a valuable input for emergency and rescue teams to plan the evacuation better and can speed up the rescue services.

Modern smartphones are ubiquitously equipped with accelerometer, pressure and microphone sensors. The presence of these sensor-rich-smartphones is most likely in the scenarios of explosion and the sensing capabilities of the smartphone may become a rich source of monitoring, during disastrous scenarios. To evaluate the capabilities of the smartphone during vibration causing disasters, the vibration scenario's can be replicated in the laboratory using simulated testing procedures like "Shake table" [21]. In our work, we have used data-sets from real explosions blasted in a controlled environment at Engineering Research Lab (ERL) [28].

1.3. CONTRIBUTIONS

The goal of this dissertation is to study the feasibility of the smartphone to detect, range and measure the intensity of the explosive events. Explosion monitoring is performed every day in the mining and construction industries [32] using commercial seismic recorders that are equipped with geophones and microphones. With increasing instances of explosions (triggered with or without malicious intent) affecting daily life, there is a clear and tangible need to move beyond seismometers to sense explosions, and therein lies the significance of our contributions. This motivated us to evaluate the capabilities of the smartphone using real data-sets collected from the explosions in mining and other ground vibration causing activities. So we have chosen to analyze the explosion events with data from real explosion experiments. Our initial goal is to demonstrate the feasibility of smartphone accelerometer to detect the triggering of explosion events. Then we used accelerometer in smartphone to range and determine intensity of explosion. Further we demonstrated the feasibility of leveraging multi-modal sensor suites in smartphones for analyzing explosion events for ranging and determining intensity with high accuracy and consistency. In particular, our contributions are below.

- Generating Real Explosion Data-sets: The principle roadblock to overcome for our problem is the access to locations of real explosion events, while simultaneously having such locations controlled enough to obtain real-time data. The Explosives Research Lab (ERL) at Missouri University of Science and Technology is one such environment where explosives are blasted in a controlled underground mine environment for training students [28]. In May 2014, we participated in multiple blasting experiments at ERL, and statically emplaced multiple Samsung GALAXY S4 smartphones at carefully chosen locations in the vicinity of the explosions. The explosive material blasted was *Dynamite with Ammonium Nitrate Fuel Oil* at various intensities. We then collected the data sensed by the accelerometer and pressure sensor from the smartphones during the explosion events for subsequent post processing.

- Identifying Challenges in Processing Smartphone Sensor Data to Establish Stability of the Smartphone: Our approach to detect explosion events requires that the smartphone to stay steady for certain amount of time to eliminate the shakes by man-made external noises while collecting the data. Stability of the phone is to be ensured and it is the important challenge identified. Further, there are other artificial noises which may result in a false-trigger of the system. This requires implementation of frequency filters on the smartphone to eliminate the noise which is subject to the processing capability limitations. To address this challenge, we design a mechanism that in real-time checks the $L2$-norm of accelerometer readings across samples in all 3 directions, to ensure that the smartphone is stable prior to processing accelerometer data to detect explosions.

- Demonstrating the Statistical Similarity of Vibration data from Smartphone and Seismometer: To demonstrate statistical similarities between smartphone and seismometer detected events, sampling rate of the smartphone sensor plays a vital role. For statistical analysis on data-sets, the algorithms are applied on similar number of samples in the data collected from them. But, the sampling rate of the smartphone accelerometer sensor is lower than that of the seismometer. Both of them were brought on to same scale and Pearson correlation analysis is performed for similarity test.

- Algorithm Design to Detect Explosions from Smartphone Accelerometers: The design algorithm is completely dependant on the processing capabilities of the smartphone. The smartphone needs to perform all the processes of the algorithm on a sample and should be completed within one sample period otherwise the incoming sample information might be lost. So the algorithm must be designed in an effective way suiting the smartphone processing capabilities. To address this challenge we designed an algorithm which retains only explosion related samples and filters out the rest. The rationale of the technique is to identify appropriate thresholds for the ratio of sudden spikes in vibration during an explosion to the long term dormant vibration readings in the absence of an explosion.

- Designing a Model for ranging and intensity estimation: While there are some existing works that address the problem of ranging and intensity estimation using measurements from state of the art seismometer sensors [33], they are not practically applicable to the case of smartphone sensors considering the differences in sampling rates, deployment environments, sensing ranges and sensitivities. We accomplished this task of ranging and intensity in two stages. In the first stage, we used only accelerometer sensor data data collected from

4 blasting experiments and built a model based on number of statistical and frequency related features to address the problems namely ranging and intensity estimation. This yielded an average case error of 12.86% for ranging and 11.26% for intensity estimation. In the second stage also, we employ a machine learning approach to solve these problems using data collected from smartphone accelerometer and pressure sensor, from 4 blasting experiments. The number of features extracted in this approach for building model were 45 when compared to 30 in first stage. With this, the accuracies were improved and the average case error was observed to be 11.21% for ranging and 9.4% for estimating intensity of explosion events. We also determine the overall consistency of our model using a number of critical statistical parameters, and results are quite favorable, as we demonstrate later.

- Discussions on practical perspectives: We provide critical perspectives on a number of practical issues including the encoding our algorithms as a storage and energy efficient smartphone apps to sense and analyze explosion events, practical applications of our contributions in this work, and other important issues and challenges when smartphones are leveraged to sense and analyze explosion events. We expect these discussions will help guide practical deployment of our technologies in the near future.

To the best of our knowledge, this is the first work that attempts to leverage smartphones to detect, range and measure the intensity of explosion events. We also present critical perspectives on the practical value of our contributions, and critical directions for future research.

1.4. ORGANIZATION OF DISSERTATION

The rest of the dissertation is organized as follows. In Section 2, related work is discussed. Further, Section 3 details the background of the Explosions along with the underlying physics, seismometers and smartphone sensors. In Section 4, a description of the addressed problems in this work is given along with the challenges. Section 5 presents a detailed description of the experimental setup. In Section 6, analysis on capabilities of smartphone accelerometers to detect explosions is given and Section 7 gives detailed description of the model built to range the explosion and estimate the intensity of explosion using accelerometer data. Section 8 describes about the model built based on accelerometer and pressure sensor with an objective to improve accuracies for ranging and estimating intensity. Further, Section 9 gives an overview of practical relevance, applications, limitations and directions of future work along with open issues and finally Section 10 concludes the work.

2. LITERATURE REVIEW

In this section, we elaborate on important work related to our research in this dissertation from the perspective of leveraging smartphone sensors for innovative societal applications. The field is certainly broad with research works attempting to leverage a smartphone's ability to sense ambient temperature, humidity, magnetic field and light intensity, for innovative applications like sleep monitoring [34], human activity recognition [35, 36, 37, 38], context recognition [39, 40, 41], determining wall layout of a building [42] and much more. In this section we highlight important related work on leveraging smartphone accelerometers and pressure sensors for enabling new applications. First we describe the applications of smartphones in the field of pervasive computing and participatory sensing. Then we describe about leveraging smartphone accelerometers for monitoring ground vibrations from earthquakes, importantly we describe about two systems Community Sense and Response (CSR) System [13] and i-Shake system [21] in this realm. Then we describe about applications leveraging pressure sensors in smartphones for indoor localization.

2.1. USAGE OF SMARTPHONE SENSORS FOR PERVASIVE COMPUTING AND PARTICIPATORY SENSING

There is a clear and tangible reason for the continued innovation in sensing capabilities of smartphones today, and that lies in numerous innovative and societally useful applications leveraging smartphone sensors. The most significant one is emerging in the domain of health-care and well-being. In [43], smartphone accelerometer is leveraged to detect the gait of a subject with applications for fall detection in elder care. The acoustic sensors in smartphones have been leveraged for self-localization of smartphones in [44]. More recently, the pressure sensors in smartphones have been leveraged for context detection in the domain of urban transportation [45], and the magnetometers also available in most smartphones today have been used to detect the presence and shapes of metal pipes or bars embedded behind walls with applications related to building maintenance [42].

While all of the above works focus on applications leveraging a single smartphone, there is another trend of leveraging sensory data from multiple smartphones for societal scale applications. Of these the most significant one so far has been detecting earthquakes from accelerometer readings from multiple smartphones are Community Sense and Response (CSR) system proposed by Faulkner, et. al. [13] and iShake project designed by Jack, et. al. [21] which will be discussed in next section. In other similar work [46], accelerometers of smartphones were used to record the acceleration in real time in order to detect earthquakes.

2.2. LEVERAGING SMARTPHONE ACCELEROMETERS FOR MONITORING GROUND VIBRATIONS FROM EARTHQUAKES

This dissertation work shares similarity with the below discussed systems in the aspect of working with the accelerometer sensors in smartphones to detect ground vibrations, however the focus was on monitoring the earthquakes producing ground vibrations and on sharing the data across the network. Our work differs from them in the sense of analyzing explosive events by the smartphones using continuously sensed accelerometer and pressure sensor data. We first study the feasibility of smartphone for analyzing explosion events. Further a model was built to range the explosion event and estimate its intensity.

There exists a test procedure called Shake-table devised to verify the quality of the accelerometer recordings in the context of earthquake which is simulated in the laboratory by the testing system. The systems discussed below uses this experimental setup for the evaluation of the system while this dissertation deals with the data collected at the real explosive laboratory at Missouri University of Science and Technology.

2.2.1. Community Sense and Response (CSR) System. Community Sense and Response (CSR) system proposed by Faulkner, et. al. [13] leverages accelerometer sensors in smartphones and consumer electronics for monitoring earthquakes. The authors have built a seismic network for the smartphone users to contribute a significant amount of event data to a centralized server. To demonstrate the effectiveness of the system, the authors have used real data-sets collected from 3000 low-cost accelerometers distributed freely in the Los Angeles area, where minor earthquakes are a common phenomena. The CSR system demonstrated that around 50 phones should be enough to detect a nearby magnitude 5 or larger earthquake event with high success rate. The algorithmic challenges of designing, building and evaluating a scalable network for real-time awareness of earthquakes were also presented.

2.2.2. i-Shake Project. The iShake project designed by Jack, et. al. [21] at the University of California, Berkeley resulted in the design of a mobile client back-end server architecture that uses sensor-equipped mobile devices to measure vibrations from earthquakes. iShake provides the general public with a service to contribute a significant amount of data towards earthquake research by automating the data collection and reporting mechanisms via the iShake mobile application. To demonstrate the feasibility, a test procedure called "Shake-table" was devised to verify the quality of the accelerometer recordings in the context of earthquake sensing. The authors have simulated 150 historical ground motion replays for analysis. Two types of mobile devices were used: four 3GS iPhones and three iPod Touches (third generation). The devices were attached to a shaking table that orients the devices at different directions in order to test for biases among axes of the accelerometers. Along with the smart devices, high-quality accelerometers were also attached which served as the ground truth data-set. Results demonstrate the practical feasibility of smartphone accelerometers to detect earthquake events in real-time.

In another work in [46], accelerometer readings from numerous smartphones were collected over a continuous period of time in Berkeley (CA) area, during which time multiple earthquakes affected the area of monitoring. Subsequently human activities were also been recorded using these smartphones and using a classifier algorithm based on neural networks, accelerometer readings associated with earthquakes were distinguished from that associated with activities of human users with very high accuracy.

2.3. LEVERAGING PRESSURE SENSORS IN SMARTPHONES FOR INDOOR LOCALIZATION

In the recent past, pressure sensors in smartphones have been used for indoor localization, which is an important problem. It is well known that atmospheric pressure decreases when altitude increases. With this fact, models have been created to relate altitude or height to pressure. In [15], using the atmospheric pressure determined by the smartphone pressure sensors, floor level of building is determined for indoor positioning. In [47], an integrated framework was proposed to provide ubiquitous and accurate elevation measurement using pressure sensors in smartphones. Experiments were conducted in both indoor and outdoor with different geographical characteristics and it was shown that the system could achieve an error less than 5 meters in estimating elevation in 90% of the cases.

In another work in [48], using pressure sensor values from smartphones, a model was built that can detect floor changes and the mode (elevator, escalator, or stairs) used to change floors. In [17], various characteristics of the pressure sensor data due to door opening/closing events are studied to build a model for recognizing these events. The model could achieve an accuracy of close to 99% based on data collected from smartphones carried by people while entering/exiting in 3 different building environments. The authors claim that it is feasible to build a low-cost ubiquitous door event detection system that enables many in-home monitoring applications without any infrastructure integration which can also work as an augmentation to currently expensive home security systems.

3. BACKGROUND ON EXPLOSION EVENTS, SMARTPHONE SENSORS, AND SEISMOMETERS

Considering the uniqueness of our work in analysing explosion events, this section provides a brief background on explosions, and their underlying physics that guides our work in this dissertation on leveraging smartphone sensors to analyze them. Further a discussion on monitoring devices is given and then a description of smartphone sensors used in our experiments.

3.1. EXPLOSION EVENTS

An explosion is an event that results in extremely high increases in volume and release of energy. Explosions can be caused by cataclysmic nature inspired events like volcanic eruptions, or man made ones like bomb blasts, electrical explosions and fireworks [49, 50]. Man-made explosions of interest to our research can be classified into two types. High-order explosives (HEs) and Low-order explosives (LEs) (discussed in detail in next section). A Low-order explosive is a material that has an explosion velocity* of less than 1000m/s and hence lacks the over-pressurization wave of HE. A low order explosion describes an explosive event where the blast pressure wave moves slowly, displacing objects in its path. Sources of LEs include pipe bombs, gunpowder, and most pure petroleum-based incendiary bombs such as molotov cocktails.

The primary outcome of an explosion is a shock wave that rapidly propagates through the medium creating the vibration impact to the subjects in the vicinity of the explosion. Explosive detonations also create an incident high pressure blast wave,

*Explosive velocity, also known as detonation velocity or velocity of detonation (VoD), is the velocity at which the shock wave travels from a detonated explosive.

characterized by a rise from atmospheric pressure to a peak overpressure [51]. The pressure then decays back to ambient pressure as the intensity of blast wave degrades.

3.1.1. Sources of Explosion. High-order explosives (HE) are more powerful than low-order explosives (LE). HE detonate to produce a defining supersonic over-pressurization shock wave. Several sources of HE include Trinitrotoluene, C-4, Semtex, nitroglycerin and ammonium nitrate fuel oil (ANFO). LE deflagrate to create a subsonic explosion and lack HE's over-pressurization wave. Sources of LE include pipe bombs, gunpowder, and most pure petroleum-based incendiary bombs such a Molotov cocktails or aircraft improvised a guided missiles. HE and LE induce different injury patterns. Only HE produce true blast waves.

3.2. SEISMOMETER

Seismometers are instruments that measure motions of the ground, including those of Seismic waves generated by earthquakes, volcanic eruptions and other seismic sources. Records of seismic waves allow seismologists to map the interior of the earth, locate, and measure the size of these different sources[52].

3.2.1. Conventional Seismometer. Conventional seismometer comprise of spring and weight and it works on the principle of inertia, the weight is sensitive to up-down motions of the earth as shown in Figure 3.1. The relative motion between the weight and the earth provides a measure of the vertical ground motion. If a recording system is installed such as a rotating drum with a paper attached to a frame and a pen attached to the weight, then this relative motion between the weight and earth can be recorded to produce a history of ground motion, called a "seismogram" [53].

3.2.2. Modern Seismometer. Modern Seismometers use electronic sensors, amplifiers, and recording devices that make a record of ground vibrations caused by an earthquake, explosion or other earth-shaking phenomenon. Seismic sensor is

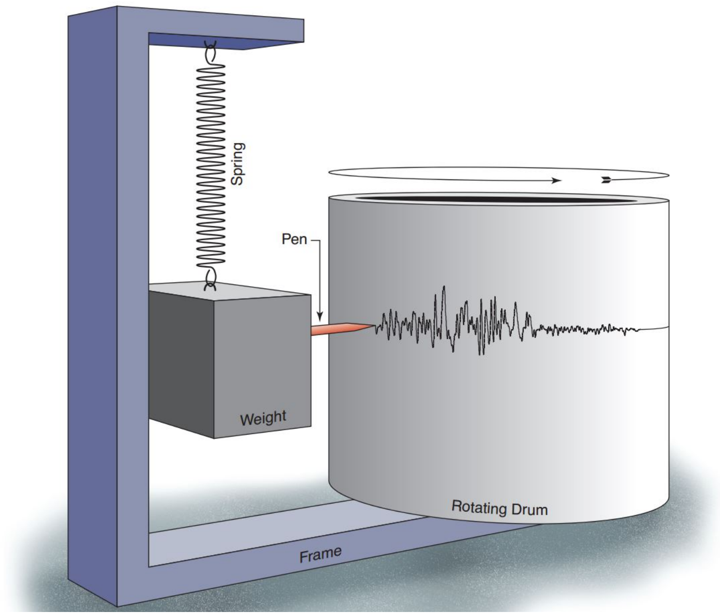

Figure 3.1. Conventional Seismometer With a spring attached to weight and pen for writing the relative motion of the earth on a rotating drum

a part of seismometer that translates ground motion into electrical signal, which are processed and recorded by the instrument based on analog or digital circuits [54].

The two important components contained in a modern seismometer are Geophone and Microphone as shown the Figure 3.2, the Geophone is to measure the voltage generated by the relative motion of the ground whereas microphone senses the changes in atmospheric pressure resulted from the explosion. They use a "triaxial" design, in which three identical motion sensors are set at the same angle to the vertical but 120 degrees apart on the horizontal. Vertical and horizontal motions can be computed from the outputs of the three sensors. Seismometers unavoidably introduce some distortion into the signals they measure; later the signal measured is processed by data detection algorithms to trigger to an event. The selection of these triggering algorithms depends upon the processing capability of the seismometer to compute the algorithms in real-time.

Figure 3.2. Modern Seismometer with Geophone and Microphone

Modern seismometer detects the triggering of an explosion event by sensing the emanating ground vibrations using geophone sensors. The equipped microphone sensors senses changes in atmospheric pressure resulted from explosions. In this dissertation, we leverage the accelerometer and pressure sensors in modern smartphones to sense explosion events, and subsequently estimate their range and intensity.

3.3. SMARTPHONE SENSORS

The sensors used in modern day smartphones are manufactured using MEMS technology(Micro-Electro-Mechanical-Systems) making them miniaturized and powerful. These sensors include sensing element and an IC interface able to take the information from the sensing element and provide the data samples to external world.

The modern-day smartphone is equipped with low-power three-axis linear accelerometer which measures acceleration(in meters per $second^2$) in Linear, Transversal and Vertical directions. The maximum sampling rate that a smartphone accelerometer could give is currently 200 samples per second. However it varies over various phone platforms, 100 samples per second is observed to be consistent sampling rate which is guaranteed in almost all the smartphones across the platforms. On the other hand smartphones are also equipped with a pressure sensor which senses atmospheric pressure in its location, which is a scalar value and its consistent sampling rate is observed to be 10 samples per second across all the phones.

Most of the modern smartphones are observed to contain sensors manufactured by ST Micro electronics with models $LIS344ALH$ and $LPS331AP$ are most prominently used accelerometer and pressure sensors respectively.

Sensitivity is essentially ratiometric to supply voltage that is increasing or decreasing the voltage supply will result in the increase or decrease linearly and the calibration level is $\pm 8\%$ [55]. The readings outputted by the smartphone sensor should be calibrated to obtain the actual acceleration and the calibration depends on the sensitivity of the sensor.

4. PROBLEMS ADDRESSED

Broadly, this dissertation addresses the problem of leveraging smartphones for detecting, ranging and estimating intensity of explosion events. In this section, we first define the formal problem statements, and critical assumptions we make, followed by a brief description of the associated challenges.

4.1. PROBLEM STATEMENT

The primary goal of the dissertation is to demonstrate the feasibility of leveraging smartphone accelerometers (when the phones are static) to detect explosion events. Within this context, there are two sub-problems that we address. The first one is to statistically compare the similarity of accelerometer readings from the smartphone with the ground truth, which in this case comes from a state-of-the-art seismometer when both devices are sensing the vibrations emanating as a result of an explosion. Should the detected events from both devices demonstrate similarity, the next problem is to design an algorithm that can be implemented on a smartphone (as an app) to detect the triggering of an explosion in real-time, while also being efficient in storage and energy consumption.

Further, we want to build a model that takes as the input raw accelerometer readings from a stationary smartphone that senses an explosion, and estimates the *range* (distance from smartphone to an explosion source). Secondly, we want to *intensity* (in terms of charge-weight of explosive material) from the sensed accelerometer readings.

As a next step, we want to demonstrate the utility of multi-modal smartphone sensing capabilities to analyze explosion events. Within this broad context, the specific goals are to determine the *range* (distance from smartphone to an explosion source) and *intensity* (in terms of charge-weight of explosive material) of an explosion event with an improvised accuracies when compared from the previous attempt.

4.2. ASSUMPTIONS WITHIN THE SCOPE OF THE RESEARCH

Considering the scope of the problems, we make certain assumptions. First, we assume that the environment wherein we are collecting real experimental data is actually an operational underground mine. We also assume that the explosive material blasted is known in advance (in our experiments, it is Dynamite) *. However, we do understand that for other types of blasting material, the parameters for detecting, ranging and intensity estimation identified in this work may not directly apply, although the overall methodology, sensing modalities, and algorithmic techniques will still apply.

Another issue to point out is that the smartphones deployed are static. However, our ensuing contributions are still practically useful, since smartphones are not mobile all the time, and they are actually static for a significant duration in real-time. The issue of experimenting with mobile smartphones (emplaced in a mobile human) requires much more careful planning to also ensure subjects safety, and is part of our future work based on contributions of this dissertation.

Finally, we assume that there are no energy/storage issues affecting the sensing and recording of associated vibrations. We also point out that there are many other

*We point out that Dynamite (Unimax-TT) with Ammonium nitrate fuel oil (ANFO) is commonly used in real explosions [56], so it is a good blasting material to study for the context of our work. The issue of detecting the type of explosion material, and investigating potential changes in vibrations sensed as a result of multiple explosion material is out of the scope of the current work, and is part of our ongoing work.

issues emanating as a result of limited network bandwidth, trust, security and privacy of data when numerous smartphones sense and transmit data in real-time for sensing explosions at societal scales. However, these aspects are secondary to the problems addressed, namely, detecting, ranging and estimating the intensity of an explosion event, hence these ancillary issues are out of the scope of this work.

4.3. CHALLENGES

Processing of sensor readings from smartphones for analyzing explosion events can be challenging. In this section, we highlight the most critical challenges in this realm which are described below:

- Availability of real data-sets: Explosions are difficult to be studied for the fact that, they are often inaccessible and difficult to be replicated in the physical environment. Needless to say, it is challenging to gain access to environments where blasts take place. Furthermore, it is even more challenging to have the environment controlled enough to be able to place smartphones in and around the vicinity of an explosion, and simultaneously obtain high quality ground truth data for subsequent analysis of explosion events. Fortunately, we had access to the Explosives Research Lab (ERL) at Missouri University of Science and Technology (Missouri S&T) where explosions are blasted to train students majoring in the Explosives Engineering Program offered there. Specifically, the blasting experiments for the purposes of this research were conducted in an underground experimental mine at Missouri University of Science and Technology as part of experiments conducted by the Explosives Research Lab. The experimental mine is actually a functional limestone mine that serves also as an experimental facility for students training on mine constructions, operations, safety and rescue. Numerous other blasting experiments are conducted regularly there. To the best of our knowledge, such a facility is unique in college campus environments, and provided us with a controlled environment, wherein we could place smartphones to derive an extremely rich source of data-sets to devise techniques to address our problems.

- Stability of the smartphone: Smartphone accelerometers being highly sensitive, generate noise (even when the phone is static) that needs filtering. To address this challenge, we design a mechanism that in real-time checks the $L2$-norm of accelerometer readings across samples, to ensure that the smartphone is stable prior to processing accelerometer data to detect explosions. For the Samsung Galaxy S4 phone we have used in our experiments, we have conducted a series of experiments to determine the appropriate stability thresholds and time-window.

- Retaining only explosion related data in smartphones to save the storage: While the energy consumed during sensing activities in modern smartphones is quite minimal (less than 200mJ per second), the issue of continuously collected sensory readings overloading the storage in the smartphone can become problematic. In case of the smartphone accelerometer in Samsung galaxy S4 when programmed to continuously sense at fastest sampling rate which is 200 samples per second could maintain a history of its observations by storing them in memory produces 25 Gigabytes of raw data per month. This is a large volume of data to store and analyze. The core challenge here is how to design techniques that enable the smartphone to continuously sense the ambient environment for vibrations, but retain only those readings within a time window that correspond to an explosion, while filtering out the rest. So with much less storage the detection of events is made possible by implementing triggering algorithms like the seismometers do [54, 57]. Based on this, we have designed algorithm in [29] to make this goal feasible. The rationale of the technique is to identify appropriate thresholds for the ratio of sudden spikes in vibration during an explosion to the long term dormant vibration readings in the absence of an explosion. Leveraging our findings in [29], we implemented an algorithm and installed it as an app on the smartphones to retain only those accelerometer readings corresponding to an explosion, while filtering out the rest. This dramatically improves storage efficiency.

- Lack of practical models to range explosion sources: As mentioned earlier, the challenge in obtaining ground truth data during explosives blasting, has meant that there is very little body of work in attempting to range explosion sources. While there is some existing work in this realm in [33, 58], they all address this problem using measurements from seismometer sensors only. However, there are clear differences between sensors used in seismometers and smartphones in terms of sampling rates, energy consumption, sensing ranges and sensitivities, which necessitates new techniques for addressing the problems defined in this dissertation. In this dissertation, we adopt a machine learning approach. In our approach, we partitioned the data-sets into two categories: $Training - set$ and $Testing - set$. We then extracted a number of features that are distinct for the accelerometer and pressure readings, and also novel features that integrate them together. Using a technique based on nonlinear regression, we then attempt to build a model to determine the range and intensity of explosion events by learning from $Training - set$, and subsequently validating the model on the $Testing - set$.

- Designing a smartphone app for ranging and estimating intensity of explosion events: After demonstrating the feasibility of leveraging smartphone sensors to estimate the range and intensity of explosions, the issue of designing smartphone apps becomes a practical one. However, this aspect is quite challenging from numerous fronts including energy and storage efficiency. In our research, we report our findings on designing smartphone apps to sense and analyze explosion events, that we believe will provide critical guidelines for practical deployments in the future.

- Other challenges outside the scope of this dissertation: We point out clearly that there are many other challenges in the realm of network bandwidth, trust, security and privacy of data when numerous smartphones in real-time sense and transmit data for detecting explosions at societal scales. Other challenge is identifying the type of explosive material which can be made possible by embedding chemical sensors in smartphones for which the research is still on-going and also explosion data-sets from several type of explosion materials. Another challenge is sampling frequency differences encountered from diversity of modern smartphones. Different smartphones come with different sampling frequencies for sensors. For instance LG Nexus-3 has a sampling rate of 50Hz, while the Samsung Galaxy Note-2 has a sampling rate 80Hz, and the the Samsung Galaxy-S4 has a higher sampling rate of 100Hz for acceleration sensor. However, typical seismometers has a much higher sampling rate of 500Hz, with superior consistency in the sampling rate. To demonstrate correlations of data generated between these two diverse sources requires down-scaling the data from the seismometer for fair comparison. Note that in real-life scenarios where there are numerous smartphones with numerous and possibly inconsistent sampling rates, this challenge is further exacerbated, the addressing of which is out of the scope of this work.

5. EXPERIMENTAL SETUP AND DESCRIPTION OF SMARTPHONES

In this section, we discuss the experimental set-up to address our problems on detecting explosion events, ranging (estimating the distance to the source of an explosion event), and estimating the intensity of the explosion (in terms of charge-weight of explosive). First we discuss the experimental set-up from the perspective of smartphone selection and blasting environment. We point out that the team assembled to collect data went through numerous training procedures prior to visiting the blasting site, in order to ensure safety of all participants in the experiments.

5.1. SMARTPHONE SELECTION

Accelerometer and pressure sensors used in the smartphones are manufactured using MEMS (Micro-Electro-Mechanical Systems) technology making them miniaturized and powerful. Smartphone accelerometers today are tri-axial sensors sensing acceleration in linear, transversal and vertical axis corresponding to x, y, and z directions in vector space in $\frac{\mathrm{m}}{\mathrm{sec}^2}$. The pressure sensor in smartphone outputs a scalar value which is the atmospheric pressure sensed in hectaPascals (hPa).

For the purposes of our research, the chief criterion in choosing a smartphone was clearly the performance of the accelerometer and pressure sensors, which is primarily determined by the sampling rate of the sensor, the consistency and sensitivity. After reading a number of research blogs, and performing limited experiments with a number of smartphone models, we have chosen the Samsung GALAXY S4 phone for our experiments, since its sensitivity, sampling rate, consistency and processing power were among the best *. Critical specifications of Samsung GALAXY S4 are shown in Table 5.1.

Table 5.1. Details of smartphones used during the explosion experiments

Smartphone brand	Samsung GALAXY-S4
Model no.	Samsung-SGH-I337
Operating system	Android-4.4(KitKat)
Accelerometer	STMicroelectronics LIS344ALH
Pressure sensor	STMicroelectronics LPS331AP
Sampling rate of Accelerometer sensor	$100 - 110$Hz
Sampling rate of Pressure Sensor	10Hz

5.2. BLASTING TYPE AND ENVIRONMENT

Figure 5.1 depicts the experimental mine environment. The explosive material used for each explosion was Dynamite (Unimax TT) with Ammonium Nitrate Fuel Oil (ANFO). In each experiment, a different charge-weight (in lb) was used for the ANFO material, which determines the intensity of explosion. The explosive material was kept in holes drilled into the mine's surface to trigger the blasts. The location of the source of the blasts was 25ft underground. Table 5.2 presents more specs on the explosive material blasted in our experiments †.

A total of four different blasting experiments were conducted for the purposes of this research. We denote them as $E1$, $E2$, $E3$, $E4$. Also, four different smartphones we used in the experiments, denoted by $P1$, $P2$, $P3$, $P4$. A critical aspect to note here is the number of blasts in each experiment (the third column in Table 5.3). Each blasting experiment typically occurs with a different charge weight and a certain number of charges. The number of charges indicates the actual number of

*Note that our techniques proposed in this dissertation are general, and are independent of the type of smartphone.

†Some more details on the experimental design are presented in the Appendix also.

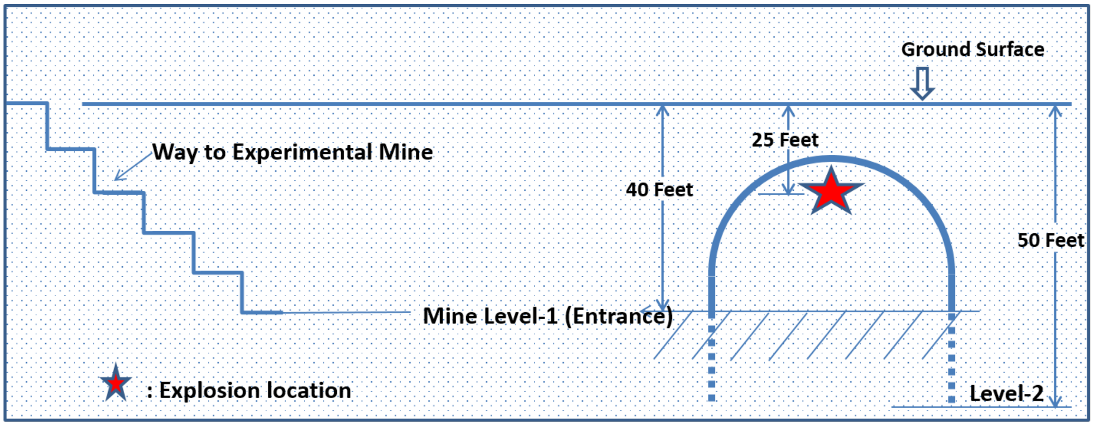

Figure 5.1. Experimental setup

blasts during an experiment. Each blast typically lasts for 250ms with a delay of 1 second duration between each blast. In our experiments, the number of charges set up were 8, 2, 5 and 2 for each experiment, and the corresponding intensities (in lb of the charge weight) were 16.05, 8.05, 11.83 and 8.25 respectively. For each of these experiments, the number of phones emplaced were 2, 4, 4 and 4 respectively to collect data. The phones were all emplaced at multiple distances in each experiment in the vicinity of an explosion event, as shown in Figure 5.2. The distances from the smartphones to the explosion source were measured using a laser-distance-measurer for superior accuracy. Critical details of the experiment are presented in Table 5.3.

Table 5.2. Details of the Explosive material used for Experiments at Explosives Research Laboratory (ERL)

Type of explosive	Dynamite with ANFO
Material blasted	Dolomite Lime
Charge weight	$8.05 - 16.05$ (in lb)
No of charges	$2, 5, 8$
Detonating cord	$25 - 50$ grains/foot

With the above settings, we were able to generate multiple data-sets to develop a model for estimating the range and intensity of the explosion events. Specifically, the number of blast event data-sets from Experiment-1 was 16 (8 charges and 2 phones), Experiment-2 was 8 (2 charges and 4 phones), Experiment-3 was 20 (5 charges and 4 phones) and Experiment-4 was 8 (2 charges and 4 phones). This resulted in a total of 52 blast event data-sets for all the experiments combined.

Table 5.3. Details of the Explosion Experiments at ERL

Experiment	**Intensity (lb)**	**No of blasts**	**Smartphone**	**Distance (feet)**
E1	16.50	8	P1	45
			P2	35
E2	8.05	2	P1	35
			P2	40
			P3	43
			P4	55
E3	11.83	5	P1	26
			P2	50
			P3	60
			P4	61.5
E4	8.25	2	P1	26
			P2	35
			P3	48
			P4	55

5.3. SENSING, FILTERING AND STORING OF EXPLOSION RELATED DATA

In each phone, the acceleration and pressure readings were continuously sensed and recorded by the phone before, during and after the explosion events. The output file is stored in the SD card of the smartphone device in the form of raw-data. After the blasts were completed, the team assembled subsequently collected all the phones for

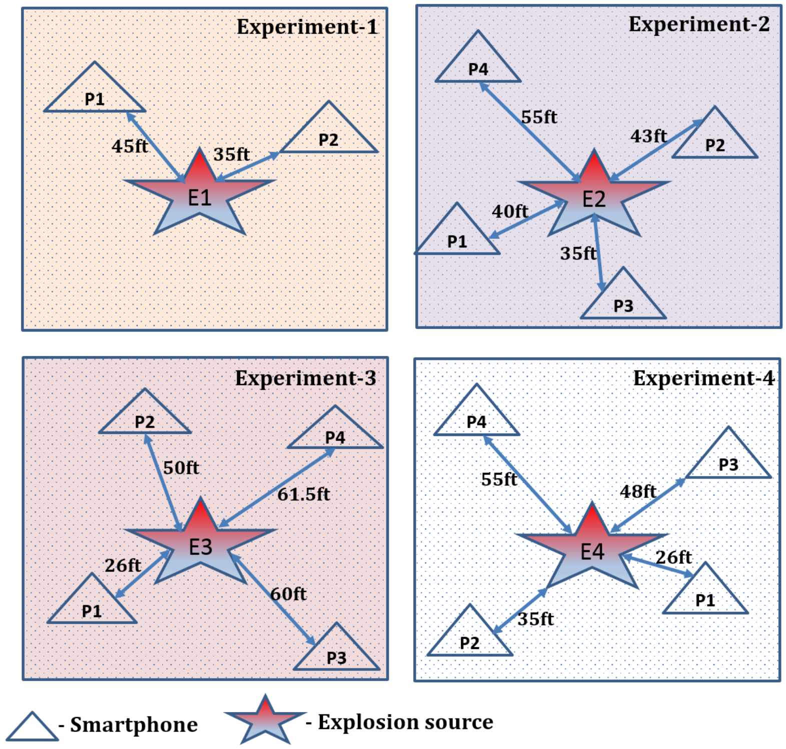

Figure 5.2. Layout of phones during various experiments

post processing. Subsequently, the values are tagged with the time-stamp information and recorded to a Comma Separated Value (.csv) file. Critical specs of the GALAXY S4 smartphone are shown in Table 5.1.

6. CAPABILITY OF SMARTPHONE ACCELEROMETER TO DETECT EXPLOSION EVENTS

In this section, we investigate the feasibility of leveraging the accelerometer in modern smartphones to detect the triggering of explosion events [29]. By emplacing a static smartphone and a state-of-the-art seismometer in the vicinity of real explosion blasts (conducted at an Explosives Research Lab in a university setting), and comparing their detected event readings, we make several insightful contributions. We find that readings from events in the smartphone and the seismometer are highly correlated in the temporal and frequency domain. We then demonstrate the feasibility of designing an algorithm in the smartphone (executing as an app) to detect the triggering of an explosion based on comparing short term sudden spikes in vibrations due to an explosion event, and long-term dormancy in vibration readings (in the absence of an explosion).

6.1. PROBLEM STATEMENT

Broadly speaking, the overall goal of this work is to demonstrate the feasibility of leveraging smartphone accelerometers (when the phones are static) to detect explosion events. Within this context, there are two sub-problems that we address in this work. The first one is to statistically compare the similarity of accelerometer readings from the smartphone with the ground truth, which in this case comes from a state-of-the-art seismometer when both devices are sensing the vibrations emanating as a result of an explosion. Should the detected events from both devices demonstrate similarity, the next problem is to design an algorithm that can be implemented on a smartphone (as an app) to detect the triggering of an explosion in real-time, while also being efficient in storage and energy consumption.

6.2. COMPARISON RESULTS FROM STATISTICAL ANALYSIS

In this section, we present results from analyzing the ground vibration from the blasts as measured by the accelerometer in the Galaxy S4 smartphone and geophone in seismometer. The Geophone basically outputs the velocity of ground movement. We converted these velocity readings to acceleration by finding the rate of change of velocity ($a = (v_2 - v_1)/t$) to bring both the events on to same scale. We wish to reiterate that the detonation consisted of five blasts, each lasting for 250ms with a delay of 1 second duration between each blast as discussed in section 5.

6.2.1. Comparison of Temporal Responses. Figures 6.1 and 6.2 demonstrate the accelerometer response for the five blasts, where the Y-axis denotes the absolute resultant value of the linear accelerations in x, y, z directions and X-axis denotes the time. As can be seen visually, the accelerometer in the smartphone correctly detects spikes in ground vibration due to blasts almost exactly when the seismometer detects it. It also can be seen that the absolute values of the smartphone accelerometer and the one in the seismometer are different, with the seismometer recording higher amplitudes of ground vibration. While this can be explained as a result of calibration issues, our investigations also revealed some insights into the calibration. The output from the smartphone accelerometer is raw sensor data initially and it is ratiometric with respect to the phone's prefixed input voltage. As such, they need to be calibrated to obtain the accurate acceleration reading. However, the results of our work are directly applicable even if the phone is not calibrated. The calibration effort is part of our on-going work.

To further quantify the fidelity of temporal responses between the accelerometer readings from both instruments, we attempted to correlate them using statistical measures. Unfortunately, doing this is not so straightforward. Most of the correlation algorithms are applied on same number of samples of two given signals. But, we have

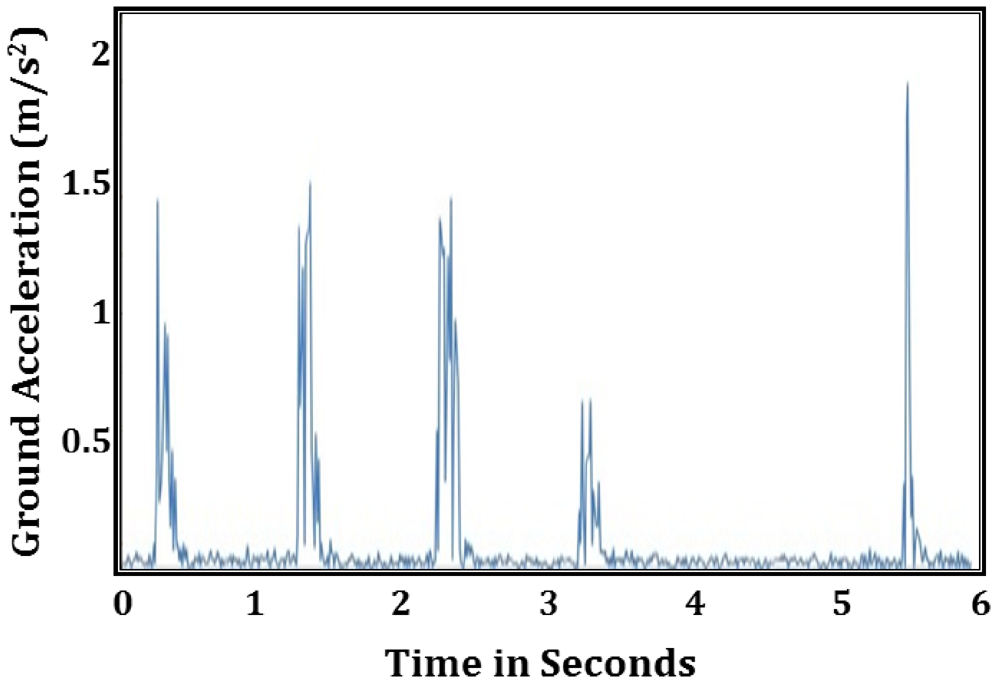

Figure 6.1. Temporal response of smartphone

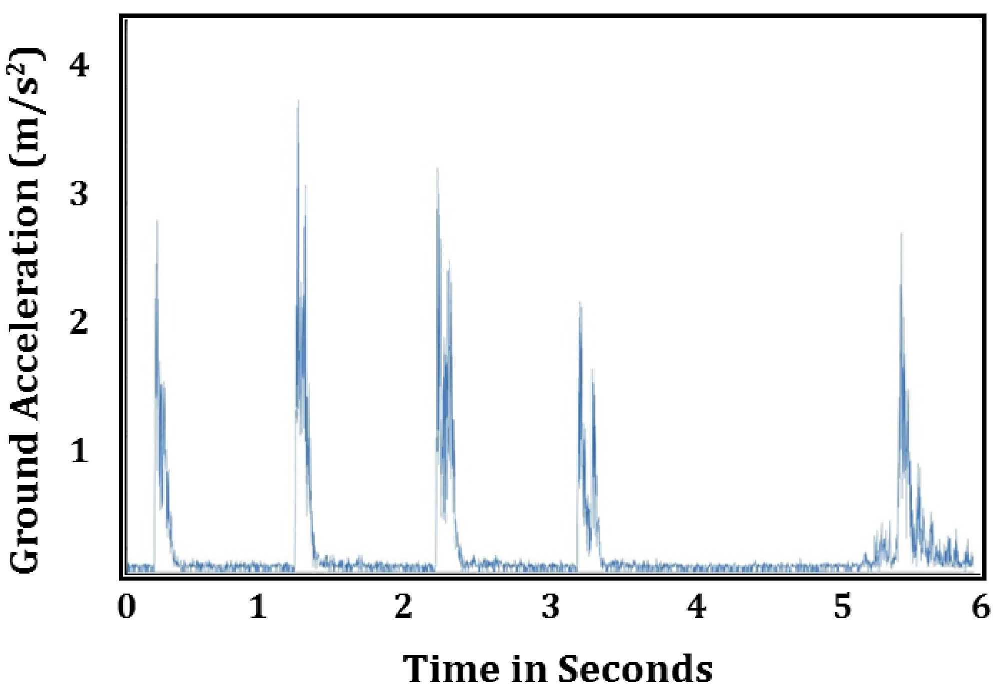

Figure 6.2. Temporal response of seismometer

different sampling rates from smartphone (100Hz) and the seismometer(500Hz). So we had two options to bring seismometer and smartphone on to same scale. One approach is to up-sample the smartphone data and other being down-sampling the seismometer data. If we up-sample the smartphone data by introducing fabricated sample points into the existing signal, then the comparison would be between genuine seismometer data and modified smartphone data which may not give a reliable analysis of correlation. Considering this, we have chosen the latter approach of down-sampling the seismometer data to make the comparison more viable. Recall that duration of an explosion blast is 250ms, which needs to be captured. So even though data from seismometer is down-sampled from 500Hz to 100Hz, we get a sample every 10ms which ensures the capture of explosion trigger, which is of interest to this work. The down-sampled temporal representation of events from smartphone and seismometer are seen in Figure 6.3.

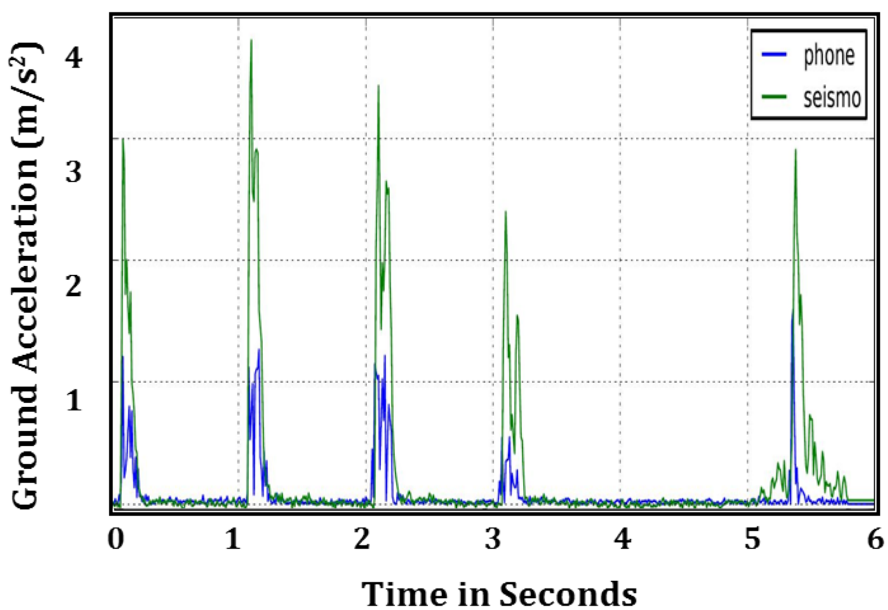

Figure 6.3. Temporal representation of smartphone and down-sampled seismometer readings

Correlation analysis was done on the down-sampled data of the seismometer and the smartphone corresponding to the durations of recording of individual blasts. We have used Pearson product-moment correlation method shown in Equation (6.1), to determine the correlation coefficient,

$$r = \frac{\sum(x_t - \overline{x})(y_t - \overline{y})}{\sqrt{\sum(x_t - \overline{x})^2 \sum(y_t - \overline{y})^2}}, where \tag{6.1}$$

x_t: smartphone sample at time t,

y_t: seismometer sample at time t,

$\overline{x}$: sample mean of the smartphone data,

$\overline{y}$: sample mean of the seismometer data.

From the analysis of correlation for the duration of the explosion events, the correlation coefficient was observed in the range 0.62 to 0.92 as shown in Figure 6.4 with the average correlation being 0.83. Furthermore, to study correlations when the blasts are not taking place (i.e., when the smartphone and seismometer are sensing background noisy vibrations), we also compared accelerometer readings from both devices. We found that the correlations between the two devices when blasts are not taking place is quite poor due to advanced noise filtering algorithms in the seismometer unlike that in the smartphones. This itself does not change any results in our work, but is nevertheless an interesting insight.

6.2.2. Comparison of Frequency Responses. To further derive insights on fidelity of data between the smartphone and seismometer, we also compared their frequency responses. Frequency-domain analysis also helps determine the spectral capability of the smartphones (and the seismometer as well) to determine the significant frequency component of the explosions. Time-domain data is converted to frequency-domain using Fast Fourier transform (FFT) algorithm to analyze the data from frequency perspective. It can be seen that vibrations corresponding to the peak

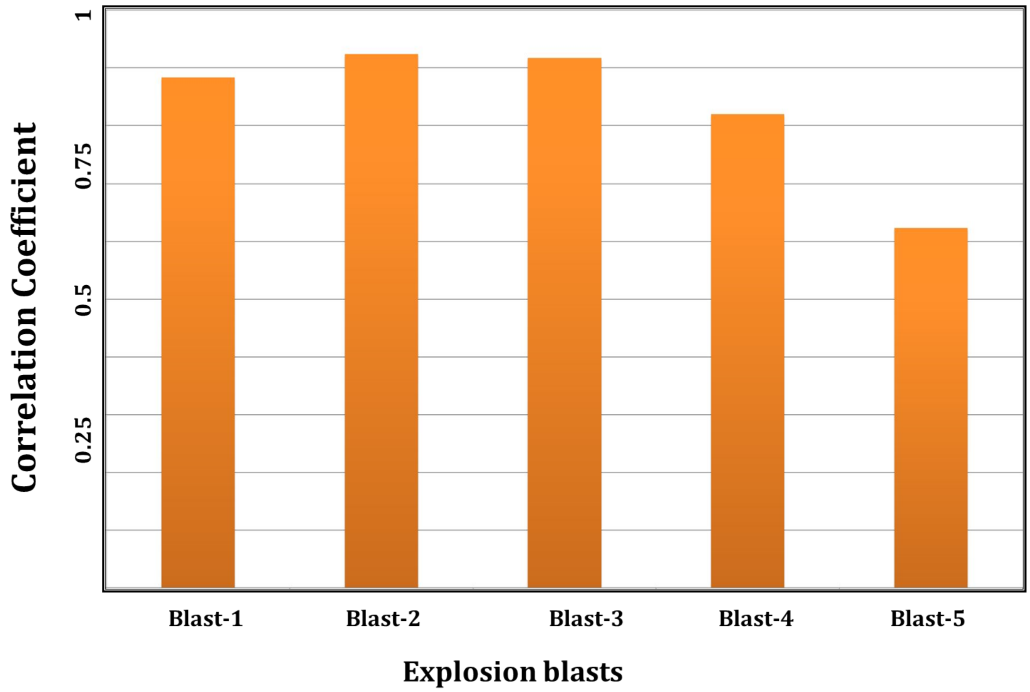

Figure 6.4. Correlation of individual blasts

amplitudes in seismometer and smartphone events occurred at 83Hz and 74.6Hz respectively as seen in Figures 6.5 and 6.6.

However, the quality of the data from the smartphone accelerometer has more noise when they sense background vibrations, which is relatively easy to fix with filtering algorithms, and is out of scope of the work.

6.3. DESIGN, DEPLOYMENT AND VALIDATION OF A SMARTPHONE ALGORITHM TO DETECT EXPLOSIONS

Motivated by the positive results discussed in the earlier section, we now present our contributions in the design, deployment and validation of a smartphone algorithm that can execute in real-time to detect the triggering of explosion events.

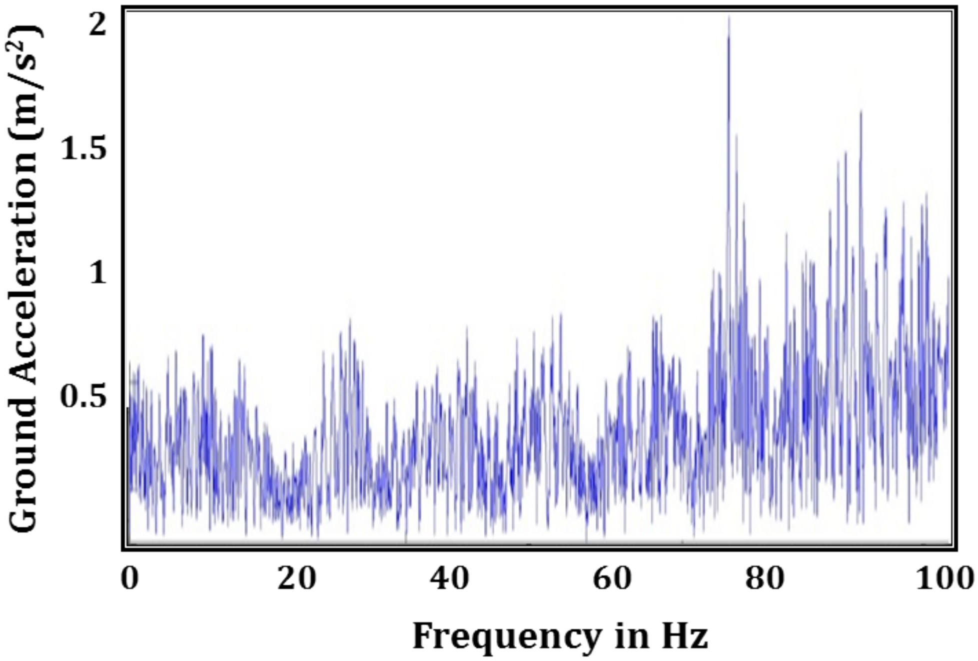

Figure 6.5. Frequency response of smartphone

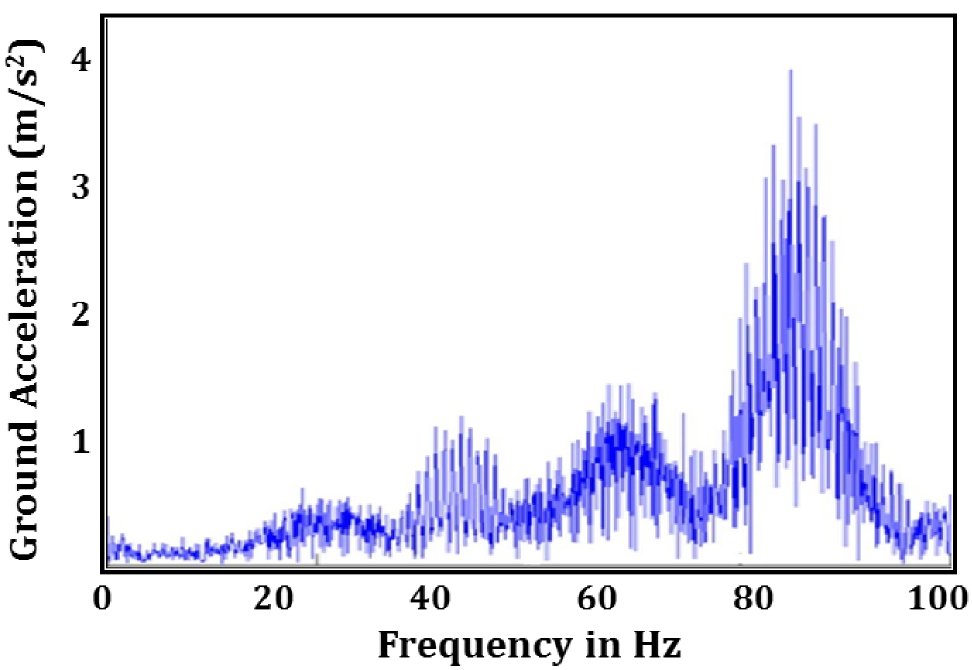

Figure 6.6. Frequency response of seismometer

We first present the motivation of the proposed algorithm. We then present some design challenges, followed by the actual algorithm, its operation, and validation.

6.3.1. Overview of the Algorithm. An explosion is an event that results in extremely high increases in volume and release of energy. Such an event typically results in the ground vibrations generating high pressure waves, due to the deposition of a large amount of energy in a very small localized volume. The proposed algorithm we design to detect explosion events relies on this principle. Specifically, we take into account, and integrate two critical characteristics of explosion events. The first one is the long term dormancy in vibration readings sensed before and after an explosion event, and the second is the sudden increase in vibrations during the brief explosion event. There have been some prior works focused on this principle for detecting earthquakes and volcanic events using seismometers [59, 60, 61]. However, we are not aware of any work that tailors this methodology to be used in smartphones for explosion detection. A significant challenge is to ensure that any algorithm designed and implemented to be executed on smartphones for detecting explosions must do so with minimal latency (i.e., in near real-time). Ideally, it should execute within the time window between two accelerometer samples sensed by the sensor. This ensures that any incoming data (all of which are critical) is not ignored. Critical other challenges to overcome are ensuring the stability of the phone to prevent false negatives and positives, determining right thresholds for triggering and de-triggering of the event, and ensuring efficient processing of incoming data streams in the realm of storage and energy efficiency, all of which are elaborated when we discuss our proposed algorithm next.

6.3.2. Work-flow and Design of the Algorithm. Algorithm 1 shows the pseudo code of our detection strategy. There are three phases of operation: Sensing, Triggering and Event Recording. In the Sensing phase, the smartphone will execute tasks related to sensing of ground vibrations, with the core challenge being ensuring the stability of the phone from ambient noise, prior to data processing. In the Triggering phase, the algorithm will execute tasks related to detecting the triggering of an explosion, based on set parameters explained below. Finally, in the Event Recording phase, the phone will perform tasks related to recording of the explosion event, and getting ready to sense again.

1. Sensing phase: When device starts running the detection algorithm, this is the initial phase it enters into. In this phase, the incoming samples of the accelerometer are processed to ensure the stability. Since the goal of this work is to demonstrate the feasibility of leveraging static smartphones for detecting explosions, it is reasonable to conclude that the accelerometer readings sensed by the sensor in the phone will be stable (due to lack of motion). However, our experiments revealed something different. Considering that the phones are small in form factor and weight, they are quite easy to be displaced even with minimal amount of external stimuli. Such movement, even though minor can cause changes in accelerometer readings which can corrupt values sensed under explosion events. As such, we have designed a simplistic model that ensures the stability of the phone prior to executing our algorithm to make sure that any values sensed as a result of ground vibrations during explosions are minimally corrupted by noise.

   As soon as the smartphone starts monitoring, for each sample the algorithm determines the $L2 - Norm$ of the difference of acceleration vector from its previous known to its current sample value. We call it as s_d and is shown in Equation (6.2).

$$s_d = (a_t^x - a_{t-1}^x)^2 + (a_t^y - a_{t-1}^y)^2 + (a_t^z - a_{t-1}^z)^2, where \tag{6.2}$$

t: time of arrival of current sample,

$t-1$: time of arrival of previous sample,

$a_t = (a_t^x, a_t^y, a_t^z)$: acceleration vector at time t.

Ideally $s_d = 0$, if the device is absolutely stable, which happens when $a_t^x = a_{t-1}^x$, $a_t^y = a_{t-1}^y$ and $a_t^z = a_{t-1}^z$. Unfortunately, the case of perfect stability cannot be achieved in practice, and reaching acceptable stable levels also takes time. If s_d is found to be less than the threshold value for a pre-defined time interval, then we declare the smartphone to be stable. Further, the current average values of the tri-axial acceleration readings in their respective moving windows, denoted as $\overline{x}$, $\overline{y}$, $\overline{z}$ are sent for processing in the next phase of algorithm operation. Figure 6.7 illustrates an instance of the phone reaching from an unstable to a stable state after 6 seconds with a constant shaking further. Numerous experiments for the Samsung Galaxy S4 phone were conducted and we set the threshold for s_d below which we considered the smartphone to be stable as 0.01. Note that to demonstrate the feasibility and for the sake of simplicity, our algorithm does not correct any stabilization errors, but rather ignores any ground vibrations sensed in an unstable state.

2. Triggering phase: The algorithm will move into this phase after the device is confirmed to be stable. This is phase in which the smartphone detects the actual triggering of an explosion event if it meets the criteria for the explosion as discussed below.

   The algorithm processes each incoming signal in multiple steps. When an accelerometer sample is received, each component of the measurement vector x, y, and z are processed separately. In the first step, the samples x, y, z are corrected as $(x - \overline{x})$, $(y - \overline{y})$, $(z - \overline{z})$ respectively, using the correction factors evaluated in the sensing phase to measure the absolute change in acceleration. Then, the

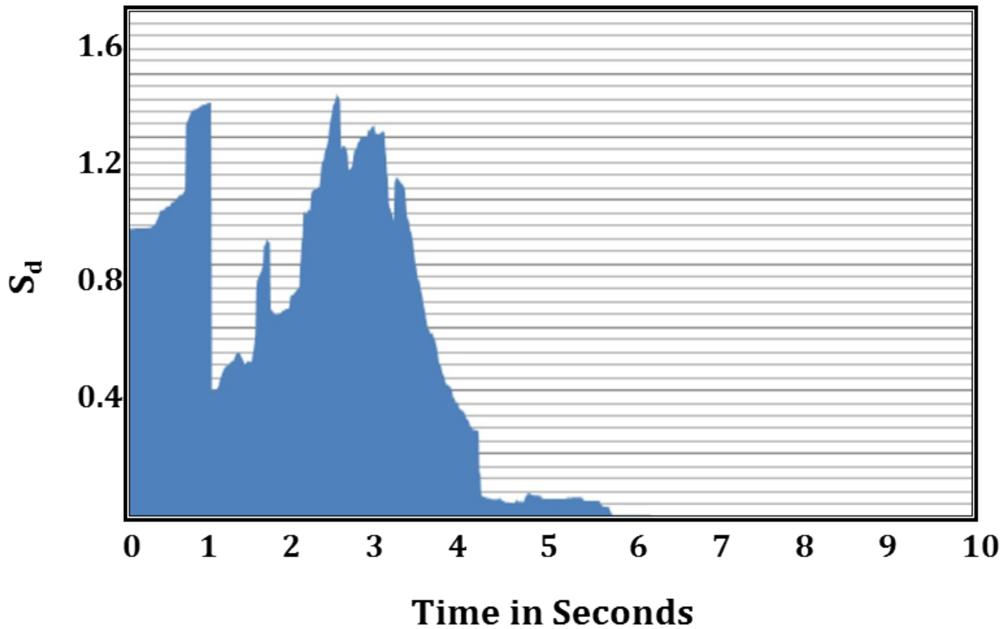

Figure 6.7. Time taken for the smartphone to stabilize

next step is processing these acceleration values to detect the triggering of an explosion event.

Our idea again here is to leverage the long term dormancy in vibration readings sensed before and after an explosion event, and the second is the sudden increase in vibration readings during an explosion event. To implement this strategy, the acceleration readings from the phone are stored in two separate and sliding time windows in our design. The first window is called the Short Term Averaging (S_{TA}) window, and the second one is called the Long Term Averaging (L_{TA}) window. Essentially, these parameters quantify the durations in which the the rapid increase ground vibrations are sensed during an explosion event, and for how long the increased spikes last until they go down. Let us denote S_a and L_a as the average of the acceleration readings computed in the S_{TA} and L_{TA} windows, and R_a as the ratio of their values, i.e., $R_a = \frac{S_a}{L_a}$.

The algorithm computes the ratio upon every sample received, while sliding the windows. If R_a exceeds a pre-set threshold (TR_{th}), then the algorithm triggers an explosion event. Also the end of event is declared when R_a falls below a de-trigger threshold (DTR_{th}). We point out that in practice, these parameters are sensitive to a number of characteristics of an explosion event, including the chemical composition, duration and intensity of an explosion. As such, setting these parameters in a generalized sense is very challenging and requires significantly more experiments and data sets. To demonstrate the feasibility, and within the context of this work, we tailor these parameters specifically to the context of explosion event whose properties are listed in Table 5.2.

Our experiments revealed that an S_{TA} window of 0.1 seconds, an L_{TA} window of 10 seconds, $TR_{th} = 1.75$ and $DTR_{th} = 1.5$ provides the best discriminator for triggering and de-triggering of an explosion event and can be seen in Figure 6.8.

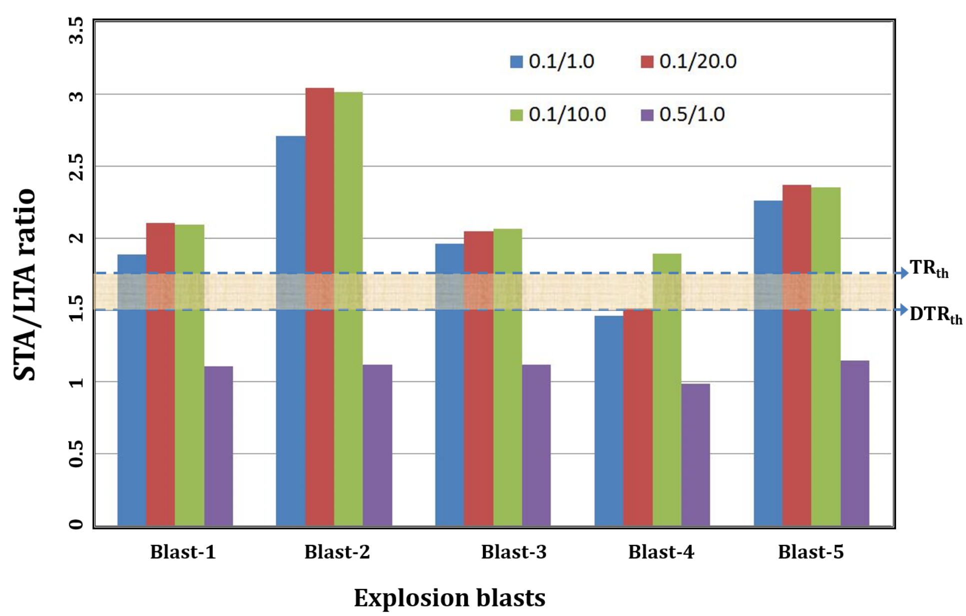

Figure 6.8. STA/LTA ratios for various combinations of STA and LTA values chosen

3. Event recording phase: The final phase of the operation of the algorithm is the Event Recording Phase. This phase is executed when the phone detects the triggering of an explosion event, and its subsequent de-triggering. When that happens, the accelerometer samples are recorded on to the phone along with the pre-event memory as an Event (E). Note that all readings are recorded until the de-triggering condition is met. The phone then returns to the sensing phase and the cycle repeats.

All the phases discussed above are summarized in the algorithm shown below:

Algorithm 1 Pseudocode to Detect Triggering of Explosions

Input: STA Window(S_{TA}), LTA Window (L_{TA}), a_x, a_y, a_z
Output: Triggering status of the accelerometer samples processed

Sensing Phase:
while $True$ **do**
    Compute s_d **(as in Equation** (6.2)**)**
    if $s_d < 0.01$ **then**
        goto $TriggeringPhase$
    end if
end while

Triggering Phase:
$x = (x - \overline{x})$, $y = (y - \overline{y})$, $z = (z - \overline{z})$
Compute S_a, L_a **for time windows** S_{TA}, L_{TA}
if $\frac{S_a}{L_a} > TR_{th}$ **then**
    goto $EventRecordingPhase$
else
    Return *to* $TriggeringPhase$
end if

Event Recording Phase:
while $\frac{S_a}{L_a} < DTR_{th}$ **do**
    Add x, y **and** z *into* E
end while
Store E **on Phone**
Return *to* $SensingPhase$

6.3.3. Deployment and Validation of the Algorithm on a Smartphone. To validate feasibility, we created an Android application (app) that executes our algorithm in real time and it was deployed during another round of blasting experiments (same parameters as Table 5.2). The phone was placed at a location similar to the one placed earlier for the training phase, and it successfully triggered to the explosion event. The application consumes 331KB of memory, 0.173 joules of energy per second and a typical sample processing time of 4ms which is quite minimal.

7. RANGING OF EXPLOSIONS AND INTENSITY ESTIMATION LEVERAGING SMARTPHONE ACCELEROMETERS

In this section, we address the problem of ranging explosion events from sensing corresponding accelerometer readings from stationary smartphones [30]. First, we statically emplaced a number of smartphones with built-in accelerometers at various locations in the vicinity of real explosions (conducted at a university training facility). An app was installed in 4 off-the-shelf smartphones to collect accelerometer readings continuously, and effectively retaining only those readings that correspond to an explosion event (while filtering out the rest). As a result, a total of 52 data-sets from 4 individual explosion blast-experiments (with Dynamite acting as the explosive charge) were collected. Using these data-sets, we developed a non linear regression model to estimate the distance of the source of an explosion event, and the intensity of the explosion (measured in terms of charge weight of the explosive material) based on extracting a number of statistical features from the accelerometer sensor readings in three dimensions (lateral (x), longitudinal (y), and vertical (z) directions) from smartphones. We are able to range the explosion event, with an average case error of 12.86% in our experiments. We were also able to estimate the intensity of the explosion event with a high accuracy, with an average case error of 11.26%.

7.1. PROBLEM STATEMENT

The problem statement is two fold. First, we want to build a model that takes as the input raw accelerometer readings from a stationary smartphone that senses an explosion, and estimates the distance to the source of the explosion event. Secondly, we want to estimate the intensity of the explosion (as a notion of charge weight of the explosive material) from the sensed accelerometer readings.

Considering the scope of the problem, we make certain assumptions. First, we assume that the arrangement where the explosion happens is a controlled underground mine environment. We also assume that the explosive material blasted is known (in our experiments, it is Dynamite) *. Finally, we assume that the smartphones are all stationary, and there are no energy/storage issues affecting the sensing and recording of associated vibrations. We also point out that there are many other issues emanating as a result of limited network bandwidth, trust, security and privacy of data when numerous smartphones sense and transmit data in real-time for sensing explosions at societal scales. However, these aspects are secondary to the problem in this work, namely, estimating the distance and intensity of an explosion event, hence these ancillary issues are out of the scope of the work.

7.2. OUR TECHNIQUE FOR ESTIMATING THE DISTANCE AND INTENSITY OF EXPLOSIONS

In this section, we describe the design of a model for estimating the distance and intensity of an explosion event. Subsequently, the model is validated and results are presented.

As pointed out earlier in Section 4.3, the lack of practically applicable models in the literature related to explosion events mean that we employ a machine learning approach, wherein we leverage a portion of the real experimental data that we collected to train the system to design a model, while using the remaining collected data for testing. For ease of reading, we point out that the parameters we want to estimate are the distance (d) and intensity (i) of an explosion event, and these two are called

*We point out that Dynamite (Unimax-TT) with Ammonium nitrate fuel oil is commonly used in real explosions, so it is a good blasting material to study for the context of our work. The issue of detecting the type of explosion material, and investigating potential changes in vibrations sensed as a result of multiple explosion material is out of the scope of the current work, and is part of our future work.

world-states. The inputs we have are the raw measurements from the smartphone accelerometers in lateral (x), longitudinal (y), and vertical (z) directions.

In this work, our efforts on building a model, and validating its efficacy in the context of estimating the distance (ranging) and intensity of an explosion event comprise of following steps as illustrated in Figure 7.1:

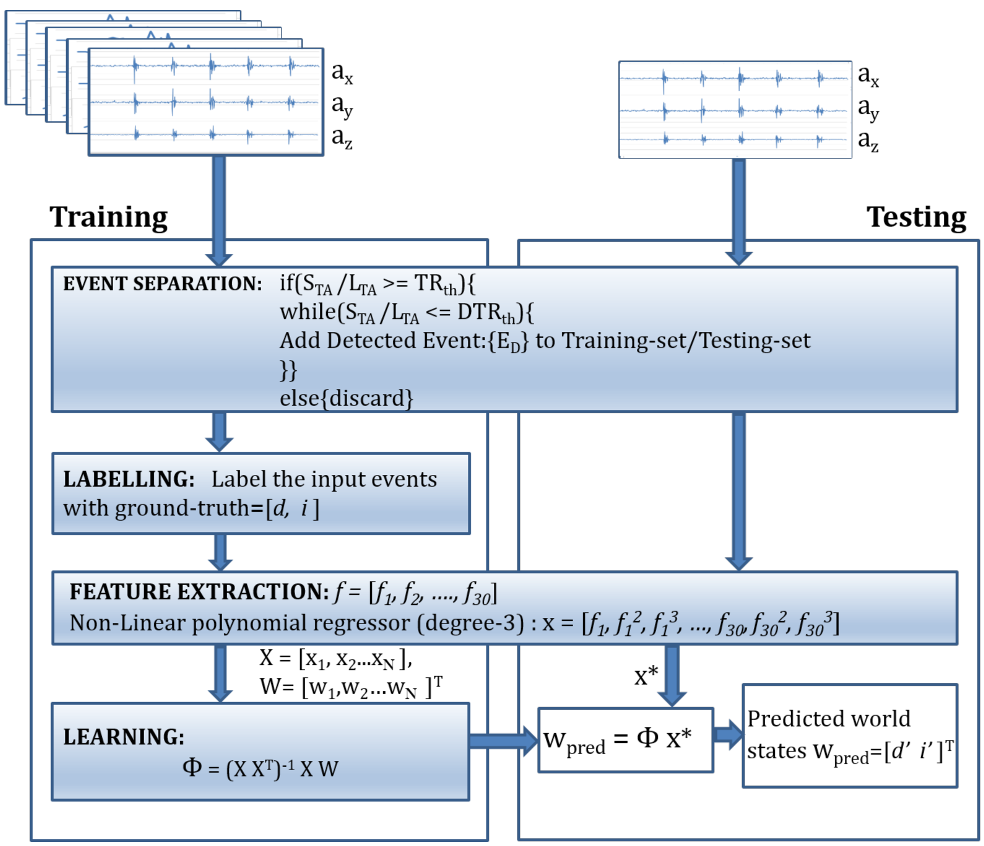

Figure 7.1. Flow of the designed estimation technique

1. Event separation: This is a pre-processing step of training. Recall that if a smartphone continuously senses ambient vibrations and stores all readings, then the storage overhead will be significant. As such, in real-life scenarios, we need a technique that will allow the phone to retain only those vibration readings that correspond to an explosion while filtering out the rest. We implemented

a technique that runs in real-time on the phone as an app. The core rationale of our technique is to compute in run-time, the ratio of averages of vibration readings within a short-term sliding window (denoted as S_{TA}) to the long term sliding window (denoted as L_{TA}). In our prior work in [29], we have identified the triggering threshold (denoted by TR_{th}) and de-triggering threshold (denoted by DTR_{th}) for this ratio that provide the best discriminatory power as $TR_{th} = 1.75$ and $DTR_{th} = 1.5$ and with window sizes of $S_{TA} = 0.1$ second and $L_{TA} = 10$ seconds for the explosion parameters.

In our experiments, the phone will only retain accelerometer readings that meet the above criteria, while deleting all other readings †. Only the retained accelerometer readings are leveraged for post-processing to develop the model which will be discussed in the next step. A total of 52 individual blast event data-sets were obtained as a result of this step (following the above procedure), and the corresponding distances and intensities (ground-truth values) from the experiments were also recorded for subsequent training and testing.

2. Labeling: With experimental data-sets obtained, we are ready to proceed with designing the model. Clearly, the first step to do in this regard is labeling the data-sets appropriately based on ground truth. The distance and intensity are denoted as world-states, which we aim to estimate. Formally,

   The world-states are:

   - d - distance of a smartphone from the explosion source.
   - i - intensity of the explosive material blasted.

   The inputs available for a detected event are:

† Note that our app consumed 331KB of memory, and power consumed was 0.173 joules per second, both of which are quite minimal.

- a_x - ground acceleration in lateral (x) direction.
- a_y - ground acceleration in longitudinal (y) direction.
- a_z - ground acceleration in vertical (z) direction.

3. Feature extraction: After labelling each event with ground-truth data, the next step of training is feature-extraction. Note that we have the accelerometer readings from the smartphones in lateral (x), longitudinal (y), and vertical (z) directions, and we could attempt to build a model between these values and the world-states. However, such a model will be limited to only three sources of readings. In order to make the model more accurate, we attempt to extract several statistical features in the temporal domain, and also features in the frequency domain from the input readings. The features extracted are

   (a) mean

   (b) median

   (c) variance

   (d) minimum

   (e) maximum

   (f) duration of event

   (g) dominant frequency

   (h) time-domain histogram properties: a) The first highest, b) The second highest, c) The third highest occurrences of the samples in a bin.

   Now we have these 10 features evaluated for each dimension resulting in a feature-vector (f = $[f_1, f_2, ..., f_{30}]$) containing 30 features for three dimensions of accelerometer readings. The next thing to do is deciding on a regression technique for estimation (of distance and intensity) which takes the extracted feature-vector as the input. We did a preliminary relationship study to select a suitable regression model. Figures 7.2 and 7.3 illustrates the plot of distance and intensity with respect to resultant of ground acceleration values in 3 dimensions for a single phone respectively. Our observation (also true across all phones) is that the relationship is nonlinear. As such, instead of attempting linear regression techniques that suffer from fitting problems, we employ a nonlinear regression approach.

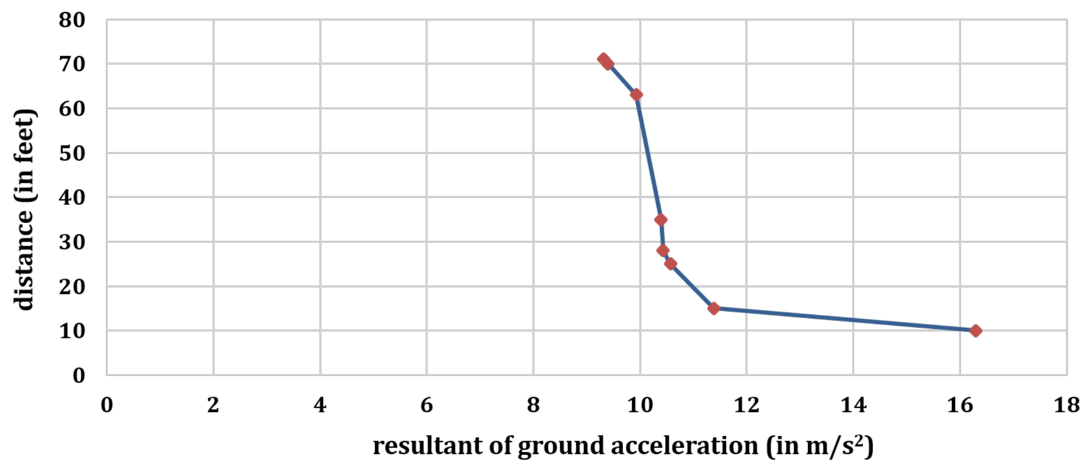

Figure 7.2. Relationship between resultant of ground acceleration (input-state) and distance (world-state)

4. Learning: As discussed above we have 52 individual blast-event data-sets recorded from up to four smartphones across four separate experiments. As is standard in machine learning, we split the data-sets into *Training-Set* and *Testing-Set*. The data-sets in the *Training-Set* is used to build a model between the world-states (i.e., distance and intensity) and the input features extracted, and the model is validated on the *Testing-Set*. We have employed the standard *Leave One Out Strategy* for the validation. In this approach, a *Testing-Set* will include the data-sets from one phone during an experiment, and data-sets from

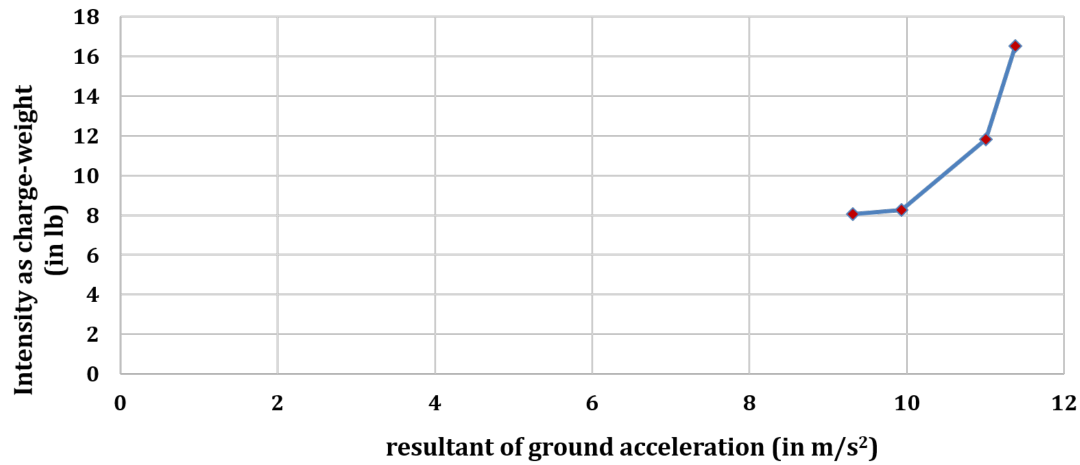

Figure 7.3. Relationship between resultant of ground acceleration (input-state) and intensity (world-state)

all the others form *Training-Set*, and we repeat the process for each phone. For instance, the 8 blast event data-sets sensed by Phone *P1* during Experiment *E1* will form a *Testing-Set-1* (as seen in Table 7.1), while the 8 blast event data-sets sensed by Phone *P2* from the same experiment (*E1*) along with data-sets from all the phones in *E2*, *E3* and *E4* results in a total of 44 data-sets which will form a *Training-Set*. This process is repeated for all phones, and as such, we have a total of 14 *Testing-Sets* to build and test the model as shown in Table 7.1.

We have implemented a nonlinear polynomial regression model on the $Training-set$ to extract a parameter ϕ that will be a result of the learning step. We will use this parameter for estimation which will be discussed in the next step. A nonlinear polynomial regressor can have a degree 2 or higher. Initially, we have tried implementing with degree-2. Further to better-fit the data, we checked with higher order degrees. Note that the increase in the degree of nonlinearity will increase the size of feature-vector and hence the computational complexity.

We have found that after a degree 3, a negligible increase in estimation accuracy was observed. Hence we have set a degree of nonlinearity of 3 for our model. This resulted in the final feature-vector size growing to 90 for 30 features extracted. For each data-set, a 90 dimensional feature-vector x is extracted along with a 2 dimensional world-state vector w (ground-truth distance and intensity) as shown in Equation (7.1).

$$x = [f_1, f_1^2, f_1^3, ..., f_{30}, f_{30}^2, f_{30}^3]^T; w = [d, i] \tag{7.1}$$

If a $Training - set$ has N data-sets in it, then at the end of training, we have

$$\boxed{X = [x_1, x_2, ...x_N] \text{ and } W = [w_1, w_2, ...w_N]^T}$$

where N is the size of $Training - set$, each x is a 90 dimensional vector and each w is a 2 dimensional vector. We define the cost function as

$$O(\phi) = ||X^T\phi - W||^2 \tag{7.2}$$

Solving the cost function shown in Equation (7.2) leads to the estimated parameter ϕ as shown in Equation (7.3).

$$\phi = (XX^T)^{-1}XW \tag{7.3}$$

The parameter ϕ is a vector of size 90 $\times$ 2, where each column corresponds to a world-state. This parameter will be used for estimating the world-states for a $Testing - set$ which will be shown in the next step.

5. Inference: Recall from the previous step that individual blast data-sets corresponding to a single phone during each blast experiment form a $Testing - set$ and data-sets from the rest of the phones form a $Training - set$. The number of blasts in a blast-experiment typically determine the size of the $Testing - set$. For each data-set in a $Testing - set$, we do 'Event-separation' and 'Feature-extraction' steps similar to the training (as seen in Figure 7.1), further apply the nonlinear transformation. From this we have a 90 dimensional feature-vector X^* and our aim is to estimate a 2 dimensional world-state vector w_{pred} using parameter ϕ. Formally,

$$w_{pred} = \phi^T X^* \tag{7.4}$$

By plugging in X^* in the Equation (7.4), we get w_{pred} as a result. $w_{pred} = [d' \quad i']^T$, where d' and i' are estimated distance and intensity, respectively. After estimating these values for all the data-sets in a $Testing - set$, we took mean of the estimated values (mean of distance values, mean of intensity values) within each $Testing - set$. This completes estimation of world-state values for one $Testing - set$. We have 14 such $Testing - set$'s from 52 data-sets as seen in Table 7.1. For all the 14 $Testing - set$'s, the estimated world-state values are compared against ground-truth values and a detailed analysis of results are given in the results section.

Table 7.1 details the summary of evaluations of the model. Each row describes a $Testing - set$ with attributes such as its training-size, testing-size along with estimated, actual (ground-truth) and error percentage values for distance and intensity. As can be seen in Table 7.1, we have 14 $Testing - set$'s for which the estimated world-states are compared against ground-truth values. Figures 7.4 and 7.5 shows a comparison of actual (ground-truth) to estimated world-state values of distance (d') and intensity (i') respectively. The error in estimating the distance is

Table 7.1. Evaluation: validation with test data-sets
Note: Train: training size — Test: testing size — Estim: estimated

set	Train	Test	Distance (in feet)			Intensity (in lb)		
			Actual	Estim	Error (%)	Actual	Estim	Error (%)
1	44	8	45	47.572	5.71	16.5	15.592	5.5
2	44	8	35	33.391	4.59	16.5	16.555	0.33
3	50	2	35	27.372	21.79	8.05	10.178	26.44
4	50	2	40	47.036	17.59	8.05	8.014	0.44
5	50	2	43	37.920	11.81	8.05	9.565	18.82
6	50	2	55	41.909	23.80	8.05	7.803	3.06
7	47	5	26	31.709	21.95	11.83	8.590	27.38
8	47	5	50	53.978	7.95	11.83	9.770	17.41
9	47	5	60	56.608	5.65	11.83	12.664	7.05
10	47	5	61.5	57.511	6.48	11.83	13.251	12.01
11	50	2	26	43.706	68.10	8.25	8.457	2.51
12	50	2	35	32.632	6.76	8.25	6.991	15.26
13	50	2	48	38.701	19.37	8.25	8.791	6.56
14	50	2	55	47.414	13.79	8.25	7.022	14.88

quite low, in fact it is less than 15% in a majority of instances. With the exception of one outlier (data-set 11) that has got an error of 68.1%, an average case error of 12.86% was observed for ranging in our experiments. The intensity on the other hand is quite accurate in our estimation with error less than 10% in a large number of instances and with an average case error of 11.26%. To further quantify the estimation performance of the model, statistical parameters including training-error, root-mean-square-deviation (rmsd) and normalized-rmsd (nrmsd) are evaluated from the testing. The statistical analysis of the evaluation are summarized in Table 7.2, and again results are quite favorable.

These results being the first of their kind in the realm of estimating the range and intensity of an explosion event from statically emplaced smartphones, are quite

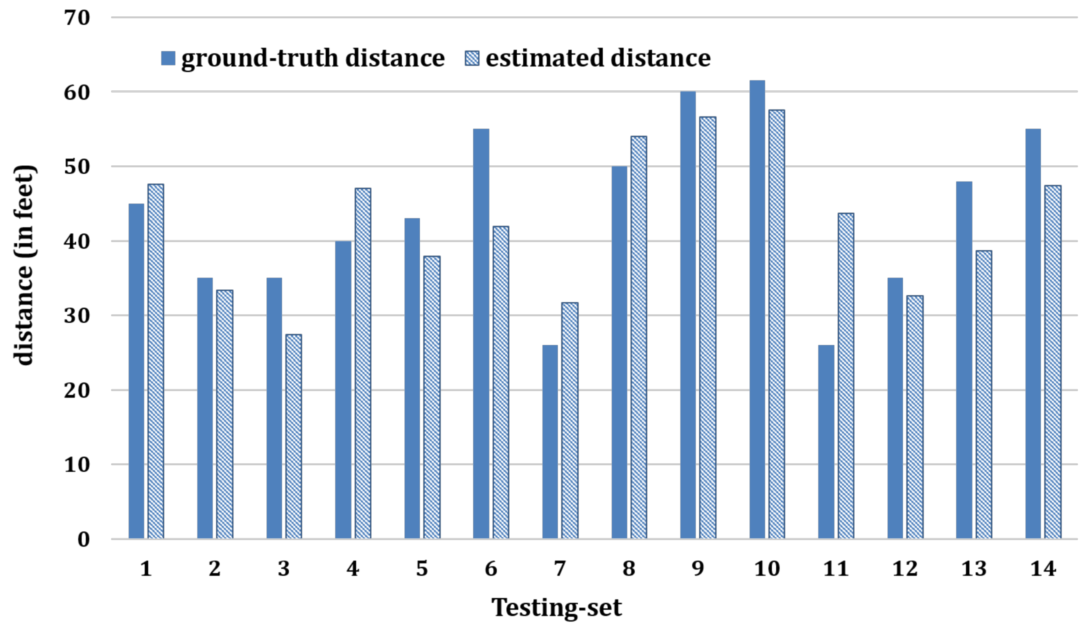

Figure 7.4. Distance estimation

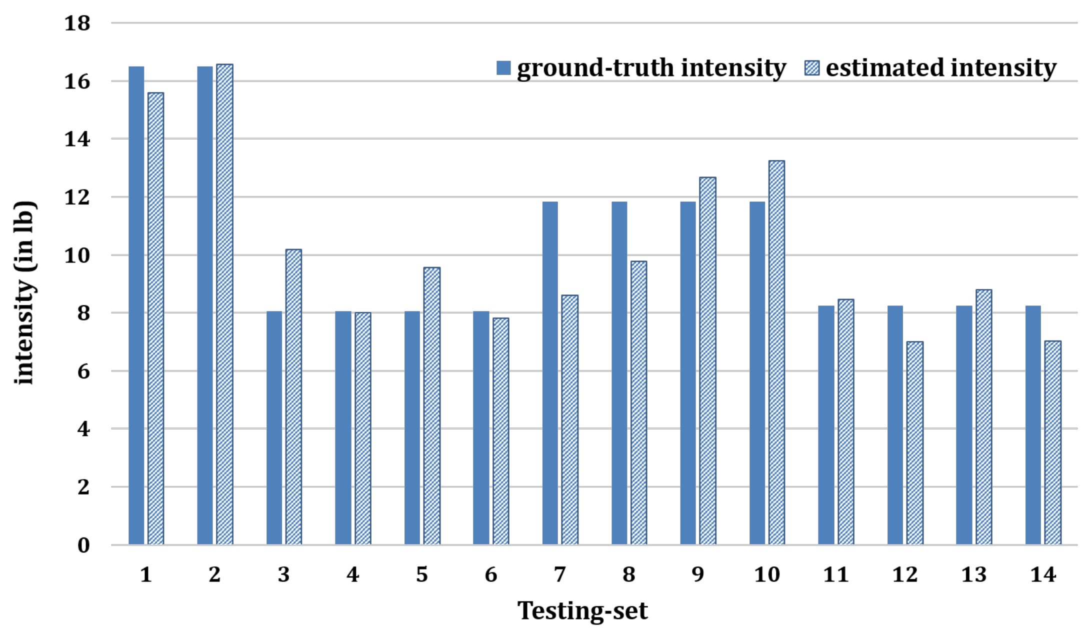

Figure 7.5. Intensity estimation

Table 7.2. Result statistics

	Distance	**Intensity**
Minimum	26 feet	8.05 lb.
Maximum	61.5 feet	16.50 lb.
Range	35.5 feet	8.45 lb.
RMS-deviation (rmsd)	7.805	1.429
Normalised-rmsd (nrmsd)	0.219	0.169
Training error	2.086	0.381

favorable, and demonstrate the clear feasibility for improvement with more experiments. Fusing multiple sensor phenomena like acoustic and pressure sensors, along with vibration sensing, is a part of our future work.

As discussed earlier, we have used a feature-vector of size 90 in our nonlinear regression model. With this feature-vector, the total training took 8.8 seconds on a Windows machine with 32 Gigabytes of RAM and CPU clock speed of 4.6 GHz. A memory footprint of as little as 90 KB was taken for training data since only accelerometer readings corresponding to explosion events were used for processing.

8. LEVERAGING MULTI-MODAL SMARTPHONE SENSORS FOR RANGING OF EXPLOSIONS AND INTENSITY ESTIMATION

In this section, we specifically address the problem of ranging and estimating the intensity of an explosion by leveraging the accelerometer and pressure sensors in the smartphone. To do so, we emplaced a number of (static) smartphones in the vicinity of real explosion blasts conducted at a university mining laboratory, where the material blasted was Dynamite with Ammonium Nitrate Fuel Oil (ANFO). We then collected the corresponding accelerometer and pressure readings sensed by the phone. After appropriately segregating the data into training and testing classes, we extracted a number of novel features, and designed a machine learning algorithmic framework for ranging and estimating the intensity of the explosion event. After extensive validation, we find that our algorithm performs with high accuracy and a high degree of consistency. In fact, the average error in ranging (i.e., estimating the distance to the source of the explosion event) and estimating the intensity of explosive material (in terms of its charge weight) was determined to be 11.21% and 9.4% respectively. We also present perspectives on encoding our algorithm as a smartphone app, identify several critical challenges in processing data from smartphone accelerometers and pressure sensors in the context of explosions, and also identify other practical issues. To the best of our knowledge, our work is pioneering in demonstrating the feasibility of smartphones to analyze explosion events. We believe there are significant societal benefits emanating from our work.

8.1. PROBLEMS ADDRESSED AND ASSOCIATED CHALLENGES

In this section, we give a brief overview of the problems we address in this work. We then identify the critical challenges that need to be resolved.

8.1.1. Problems Addressed and Preliminaries. Broadly speaking, we want to demonstrate the utility of smartphone sensing capabilities to analyze explosion events. Within this broad context, the specific goals of this work are to determine the *range* (distance from smartphone to an explosion source) and *intensity* (in terms of charge-weight of explosive material) of an explosion event with an improved accuracies from proposed model in our previous work [30]. The environment wherein which we are collecting real experimental data is actually an operational underground mine. In this work, to retain scope, we assume that the explosive material blasted is known in advance. For this work, the material is Dynamite with Ammonium Nitrate Fuel Oil. We point out that Dynamite is very commonly used in real explosions [56], and as such it is a very representative material to consider for our problem in this work. However, we do understand that for other types of blasting material, the parameters for ranging and intensity estimation identified in this work may not directly apply, although the overall methodology, sensing modalities, and algorithmic techniques will still apply [*].

Another issue to point out is that the smartphones deployed are static. However, our ensuing contributions are still practically useful, since smartphones are not mobile all the time, and they are actually static for a significant portion of time. The issue of experimenting with mobile smartphones (emplaced in a mobile human) requires much more careful planning to also ensure subjects safety, and is part of our future work based on contributions of this work.

8.1.2. Challenges. We now highlight some of the critical challenges in addressing our problem stated above.

- Availability of real data-sets: Explosions are difficult to be studied for the fact that, they are often inaccessible and difficult to be replicated in the physical

[*]Identifying the type of material blasted is out of scope of the current work.

environment. Needless to say, it is challenging to gain access to environments where blasts take place. Furthermore, it is even more challenging to have the environment controlled enough to be able to place smartphones in and around the vicinity of an explosion, and simultaneously obtain high quality ground truth data for subsequent analysis of explosion events.

Fortunately, we had access to the Explosives Research Lab (ERL) at Missouri University of Science and Technology (Missouri S&T) where explosions are blasted to train students majoring in the Explosives Engineering Program offered there. Specifically, the blasting experiments for the purposes of this work were conducted in an underground experimental mine at Missouri University of Science and Technology as part of experiments conducted by the Explosives Research Lab. The experimental mine is actually a functional limestone mine that serves also as an experimental facility for students training on mine constructions, operations, safety and rescue. Numerous other blasting experiments are conducted regularly there. To the best of our knowledge, such a facility is unique in college campus environments, and provided us with a controlled environment, wherein we could place smartphones to derive an extremely rich source of data-sets to devise techniques to address our problems.

- Lack of practical models to range explosion sources: As mentioned earlier, the challenge in obtaining ground truth data during explosives blasting, has meant that there is very little body of work in attempting to range explosion sources. While there is some existing work in this realm in [33, 58], they all address this problem using measurements from seismometer sensors only. However, there are clear differences between sensors used in seismometers and smartphones in terms of sampling rates, energy consumption, sensing ranges and sensitivities, which necessitates new techniques for addressing the problems defined in this work. In this work, we adopt a machine learning approach. In our approach, we partitioned the data-sets into two categories: $Training-set$ and $Testing-set$. We then extracted a number of features that are distinct for the accelerometer and pressure readings, and also novel features that integrate them together. Using a technique based on nonlinear regression, we then attempt to build a model to determine the range and intensity of explosion events by learning from $Training - set$, and subsequently validating the model on the $Testing - set$.

- Designing a smartphone app: After demonstrating the feasibility of leveraging smartphone sensors to estimate the range and intensity of explosions, the issue of designing smartphone apps becomes a practical one. However, this aspect is quite challenging from numerous fronts including energy and storage efficiency. In this work, we report our findings on designing smartphone apps to sense and analyze explosion events, that we believe will provide critical guidelines for practical deployments in the future.

- Other challenges outside the scope of the current work: We point out clearly that there are many other challenges in the realm of network bandwidth, trust, security and privacy of data when numerous smartphones in real-time sense and transmit data for detecting explosions at societal scales. However, these challenges are currently outside the scope of the current work, and is part of our future work.

8.2. TECHNIQUE FOR ESTIMATING THE DISTANCE AND INTENSITY OF EXPLOSIONS USING ACCELEROMETER AND PRESSURE SENSOR DATA

In this section, we detail out the design and validation of a model and algorithmic framework to estimate the range and intensity of an explosion event from smartphone sensor data. We start with some preliminaries first on smartphone sensitivities, followed by the actual model design and validation.

8.2.1. Preliminaries on the Sensitivity of Smartphone Sensors to Explosion Events. As discussed earlier in Section 2, we have done prior work comparing the statistical similarity of accelerometer readings from a smartphone to that of a state-of-art seismometer. Our results in [29] indicate that there is a high degree of statistical similarity in the temporal and frequency responses of the accelerometer readings in both the smartphone and the seismometer.

To illustrate a bit further, we show show a comparison of the sample explosion events from both smartphone and seismometer during one explosion experiment which consisted of 5 charges (i.e., Experiment 3 in Table 5.3). Figure 8.1 shows the temporal responses of acceleration in lateral (a_x), longitudinal (a_y), and vertical (a_z) directions, along with the pressure readings (p) sensed by one Samsung GALAXY S4 phone for five explosive blasts. Figure 8.2 shows the temporal responses of velocity in lateral (v_x), longitudinal (v_y), and vertical (v_z) directions sensed from its geophone sensor, along with pressure readings (s) sensed from its microphone sensor. The perpendicular dotted lines in the figure indicate the time-stamp of individual blast. As seen from the Figures 8.1 and 8.2, the smartphone accelerometer is clearly sensitive to the blasts correlating with the seismometer during each blast relatively independent of the others.

Recall from Section 3, the atmospheric pressure in the vicinity of an explosion event is sensitive to the emanating blast waves. Specifically, the blast wave causes a rise in the atmospheric pressure to a peak overpressure. As the intensity of blast wave degrades, atmospheric pressure decays back to ambient pressure, and a negative pressure phase occurs that is usually longer in duration than the positive phase. The pressure sensor on the smartphone captures this phenomenon, as we see in Figure 8.1. It can also be observed that, the pressure excitation is delayed when compared to that

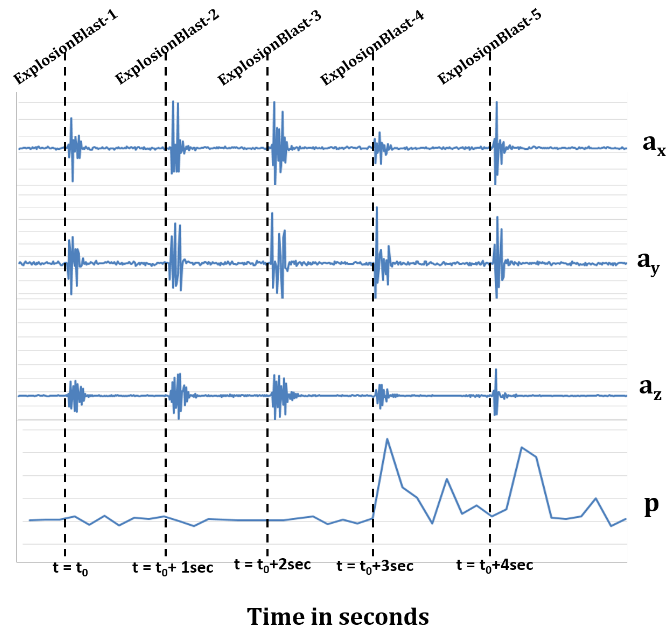

Figure 8.1. Sample explosion event detected by a smartphone from accelerometer and pressure sensor data

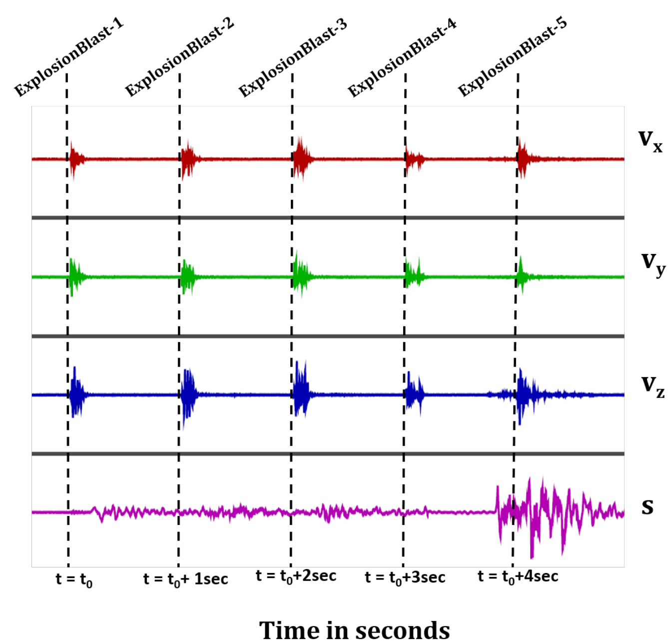

Figure 8.2. Sample explosion event detected by a seismometer from geophone and microphone sensor data

of both acceleration (in Figure 8.1) and velocity (in Figure 8.2) excitations. This is because, the blast waves induced by explosions (that affect the ambient pressure) travels slower than the shock waves (that cause ambient vibrations). Similar trends of sensitivity were demonstrated for all other phones as well. These trends serve as our foundation in leveraging smartphone accelerometers and pressure sensors for designing our model.

8.2.2. Design of a Model for Ranging and Intensity Estimation of an Explosion. As pointed out earlier in Section 8.1, the lack of practically applicable models in the literature related to explosion events means that we employ a machine learning approach, wherein we leverage a portion of the real experimental data that we collected to train the system to design a model, while using the remaining collected data for testing. Recall that the parameters we want to estimate are the distance (d) and intensity (i) of an explosion event, and these two are called world-states. The inputs we have are the raw measurements from the smartphone accelerometers in lateral (x), longitudinal (y), and vertical (z) directions along with the pressure sensed (p). There following are the steps involved in designing the model as detailed below, and illustrated in Figure 8.3.

1. Event separation: This is a pre-processing step during training. As we know the duration of explosion events is very small. But in our blasting experiments, the phones were sensing the readings for an average time of about 65 minutes from the time they were placed statically (before the start of the experiment) to the time they were collected (after the blasting experiments). This is due to safety standards at the laboratory, wherein we are required to place smartphones well before the experiment and allowed to collect them only after confirmation that blast impacts are no longer present. The smartphones are pre-programmed to sense the ambient vibrations and atmospheric pressure readings. This itself

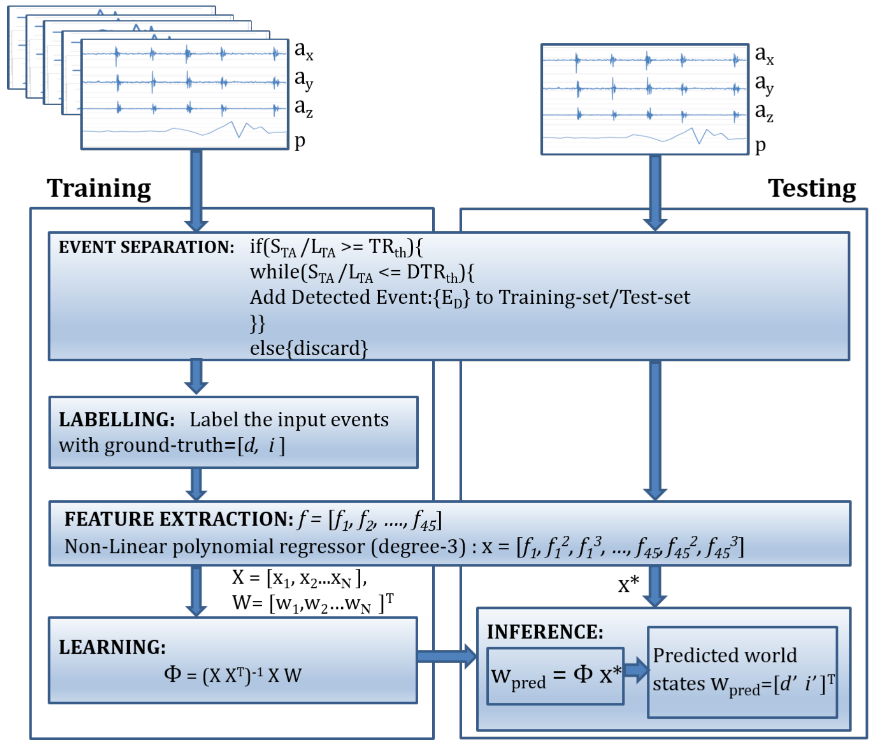

Figure 8.3. Flow of the designed estimation model

consumes very limited energy, and we found it to be 0.26 Joules per second. But because of high sampling rates, the storage overhead grows dramatically. In real-life scenarios, we hence need a technique that will enable a smartphone to continuously perform sensing activities, while being smart enough to filter unnecessary readings, but retain only those that pertain to an explosion event to save storage.

We implemented a technique that can run in real-time on the phone towards the above objective. The core rationale of our technique leverages the fact that when an explosion event happens, there is a sudden spike in the sensed vibrations, compared to the long-term dormancy in vibrations sensed by the smartphone in the absence of any explosion event. Leveraging the above insight we compute on the smartphone in run-time, the ratio of averages of accelerometer readings within a short-term sliding window (denoted as STQ) to the long term sliding window (denoted as LTQ). In our prior work in [29], we have identified the triggering threshold (denoted by TR_{th}) and de-triggering threshold (denoted by DTR_{th}) for this ratio that provide the best discriminatory power to isolate an explosion event as $TR_{th} = 1.75$ and $DTR_{th} = 1.5$ and with window sizes of 0.1 second for STQ and 10 seconds for LTQ. This ratio provides perfect discriminatory power to detect the triggering of an explosion. In our experiments, the smartphone senses the ambient vibration using its accelerometer continually, but only stores those accelerometer and pressure readings that are sensed between the triggering and de-triggering of the explosion event (as identified using the thresholds), while deleting the rest. Only the retained individual blast event data-sets are leveraged for post-processing to develop the model which will be discussed in the next step.

2. Labeling: With our experimental data-sets obtained from explosion events (presented in Table 5.3), we are ready to proceed with designing the model. Clearly, the first step to do in this regard is labeling the data-sets appropriately based on ground-truth. The distance and intensity are denoted as world-states, which we aim to estimate. Formally,

   The world-states are:

   - d - distance of a smartphone from the explosion source.
   - i - intensity of the explosive material blasted.

   The inputs available for a detected event are:

   - a_x - ground acceleration in lateral (x) direction in $\frac{\text{m}}{\text{sec}^2}$.
   - a_y - ground acceleration in longitudinal (y) direction in $\frac{\text{m}}{\text{sec}^2}$.

- a_z - ground acceleration in vertical (z) direction in $\frac{\mathrm{m}}{\mathrm{sec}^2}$.
- p - pressure sensed by the pressure sensor as scalar value in hectaPascals (hPa).

Note that we have recorded the ground-truth values *distance* (from a smartphone to explosion source) and *intensity* (measured in terms of lb of charge weight of explosive material) during each experiment conducted, as described in Section 5. Now, we identify the ground-truth values associated to each data-set and tag them with corresponding labels. To identify them, we have taken into consideration, the fact that each data-set belongs to a smartphone which is placed at a certain distance from the explosion source and also corresponds to a specific intensity (charge-weight) of the explosion blast. With knowledge of the attributes *distance* and *intensity* for each data-set, we subsequently tag the attributes as labels to them.

3. Feature Extraction: After labelling each event with ground-truth data, the next step is feature-extraction. Note that we have the accelerometer readings from the smartphones in lateral (x), longitudinal (y), and vertical (z) directions, along with pressure (p), and we could attempt to build a model between these values and the world-states. However, such a model will be limited to only these sources of readings. In order to make the model more accurate, we attempt to extract several statistical features in the temporal domain, and also features in the frequency domain from the input readings. We first extract features for individual inputs (for both sensors), and also combine them to identify new features in the feature vector. Upon consideration of the explosion impacts to ambient vibrations, and how they impact corresponding accelerometer readings, the following intuitive features were identified in our study for each dimension:

(a) mean

(b) median

(c) variance

(d) minimum

(e) maximum

(f) duration of event

(g) dominant frequency

(h) histogram properties: a) The highest, b) The second highest, c) The third highest occurrences of the samples in a bin.

Now we have these 10 features identified for each dimension resulting in 30 features for three dimensions of accelerometer readings.

The next issue is extraction of relevant features from pressure readings sensed by the smartphone. Before we discuss feature extraction from pressure readings, let us briefly explain the physics relating changes in atmospheric pressure as a result of an explosion. Pressure waves emanating from an explosion propagates much slower than that of ground vibration [51, 62]. The blast pressure wave in air typically travels at 330 meters per second while shock waves carrying vibrations travels in the order of $10,000$ meters per second in solid medium [†]. These studies coupled with our analysis of the experimental data sensed for both sensing modalities, helped us make three key observations:

- The arrival times of the excitations caused due to the pressure and acceleration are different, from the perspective of the smartphone.

[†]Note though that there are some variations based on properties of the medium through which they propagate.

- The smartphone senses the acceleration excitation caused due to blast earlier when compared to when it senses pressure excitation.
- The delay between the arrival times of acceleration and pressure excitation due to explosion blast increases with the distance between the smartphone and explosion blast as shown in Figure 8.4.

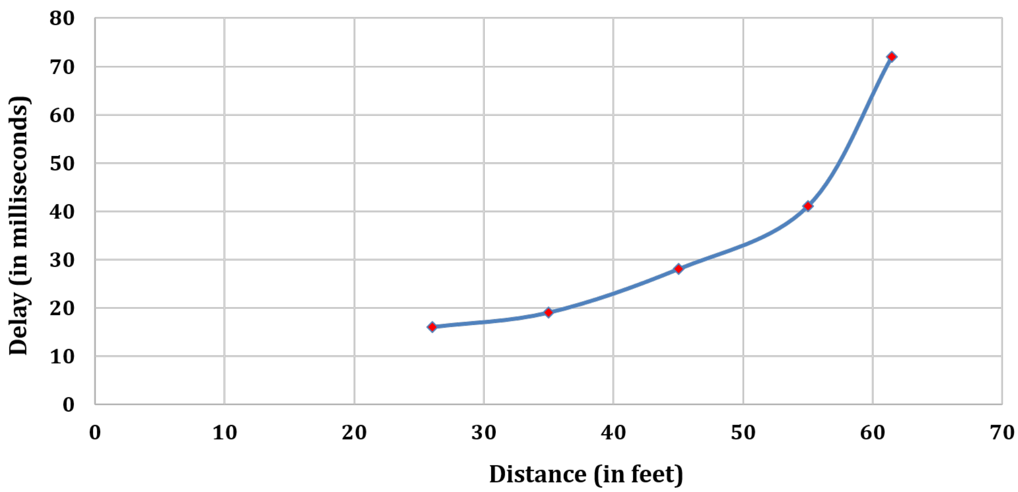

Figure 8.4. Delay vs. Distance

Using the insights from the above observations, we extracted a total of 6 intuitive features from pressure readings towards building our model. Note that the pressure sensor outputs the samples only in one dimension unlike the accelerometer sensor. The features we extracted are:

(a) Delay between arrival times of acceleration and pressure excitation due to explosion blast

(b) maximum

(c) mean

(d) variance

(e) time-domain histogram properties: a) The highest, b) The second highest occurrences of the samples in a bin.

To enhance the feature vector, we then worked on extracting more meaningful features with an objective of improving accuracy by combining both sensing modalities. The most intuitive feature in this realm is the product of accelerometer readings and pressure sensor readings. In this work, we identify a total of 9 additional features as a result of combining features these two sensing modalities which are identified below:

(a) product of acceleration maximum in x dimension and pressure maximum.

(b) product of acceleration maximum in y dimension and pressure maximum.

(c) product of acceleration maximum in z dimension and pressure maximum.

(d) product of highest occurrence in time-domain histogram for accelerometer in x dimension and pressure.

(e) product of highest occurrence in time-domain histogram for accelerometer in y dimension and pressure.

(f) product of highest occurrence in time-domain histogram for accelerometer in z dimension and pressure.

(g) product of second highest occurrence in time-domain histogram for accelerometer in x dimension and pressure.

(h) product of second highest occurrence in time-domain histogram for accelerometer in y dimension and pressure.

(i) product of second highest occurrence in time-domain histogram for accelerometer in z dimension and pressure.

From the above, we can see that for any given data-set with accelerometer and pressure readings from the smartphone, we now have 45 features in total resulting in a feature-vector of size 45 (f = $[f_1, f_2, ..., f_{45}]$). The next thing to do is deciding on a regression technique for estimation (of distance and intensity of the explosion event) which takes the extracted feature-vector as the input. We did a preliminary relationship study to select a suitable regression model. Our observation is that a change of acceleration and pressure measured by a smartphone during an explosion has a nonlinear relationship to the measured distance from the smartphone to the source of an explosion and also to its intensity (which is also true across all phones). As such, instead of attempting linear regression techniques that suffer from fitting problems, we employ a nonlinear regression approach.

4. Learning: Recall that have 52 individual blast-event data-sets recorded from multiple smartphones across four separate experiments. We have have a total of 45 features extracted from the acceleration and pressure readings from each phone. As is standard in machine learning, we split the data-sets into *Training-Set* and *Testing-Set*. The data-sets in the *Training-Set* is used to build a model between the world-states (i.e., distance and intensity) and the input features extracted, and the model is validated on the *Testing-Set*. We have employed the standard *Leave-K-Out-Strategy* for the validation and the value of K is decided by the size of the *Testing-set* (K = size of *Testing-set*). In this approach, a *Testing-Set* will include the data-sets from one phone during an experiment, and data-sets from all the others form the *Training-Set*, and we repeat the process for each phone. For instance, if we see in Table 8.1, the 8 blast event data-sets sensed by Phone *P1* during Experiment *E1* will form the *Testing-Set-1*, while the 8 blast event data-sets sensed by Phone *P2* from the same experiment

(*E1*), along with data-sets from all the phones in *E2*, *E3* and *E4* (a total of 44 data-sets) will form the *Training-Set*. Note that the value of K is 8 in this case. This process is repeated for all phones, and as such, we have a total of 14 *Testing-Sets* to build and test the model.

We implemented a nonlinear polynomial regression model on the $Training-set$ to extract a parameter ϕ that will be a result of the learning step. We will use this parameter for estimation which will be discussed in the next step. A nonlinear polynomial regressor can have a degree 2 or higher. Initially, we tried implementing with degree-2. Further to better-fit the data, we checked with higher order degrees. Note that the increase in the degree of nonlinearity will increase the size of feature-vector and hence the computational complexity. We have found that after degree 3, the increase in estimation accuracy is negligible. Hence, we set the nonlinearity degree as 3 for our model. This resulted in the final feature-vector size growing to 135 for 45 features extracted. For each data-set, a 135 dimensional feature-vector x is extracted along with a 2 dimensional world-state vector w (ground-truth distance and intensity) as shown in Equation (8.1) below

$$x = [f_1, f_1^2, f_1^3, ..., f_{45}, f_{45}^2, f_{45}^3]^T; w = [d, i]. \tag{8.1}$$

If a $Training - set$ has N data-sets in it, then at the end of training, we have

$$\boxed{X = [x_1, x_2, ...x_N] \text{ and } W = [w_1, w_2, ...w_N]^T.}$$

where N is the size of $Training - set$, each x is a 135 dimensional vector, and each w is a 2 dimensional vector. We define the cost function as

$$O(\phi) = ||X^T\phi - W||^2. \tag{8.2}$$

Solving the cost function shown in Equation (8.2) leads to the estimated parameter ϕ as shown in Equation (8.3) below

$$\phi = (XX^T)^{-1}XW. \tag{8.3}$$

The parameter ϕ is a vector of size 135 $\times$ 2, where each column corresponds to a world-state. This parameter will be used for estimating the world-states for a $Testing - set$ which will be shown in the next step.

5. Inference: Recall from the previous step that individual blast data-sets corresponding to a single phone during each blast experiment form a $Testing - set$ and data-sets from the rest of the phones form a $Training - set$. The number of blasts in a blast-experiment typically determine the size of the $Testing - set$. For each data-set in a $Testing - set$, we do 'Event-separation' and 'Feature-extraction' steps similar to the training (as seen in Figure 8.3), and further apply the nonlinear transformation. From this, we have a 135 dimensional feature-vector X^*, and our aim is to estimate a 2 dimensional world-state vector w_{pred} using parameter ϕ. Formally,

$$w_{pred} = \phi^T X^*. \tag{8.4}$$

By plugging in X^* in the Equation (8.4), we get $w_{pred} = [d' \quad i']^T$, where d' and i' are estimated distance and intensity, respectively. After estimating these values for all the data-sets in a $Testing - set$, we took mean of the estimated values (mean of distance values, mean of intensity values) within each $Testing - set$.

This completes estimation of world-state values for one $Testing - set$. We have 14 such $Testing - set$s from 52 data-sets as seen in Table 8.1. For all the 14 $Testing - set$s, the estimated world-state values are compared against ground-truth values and a detailed analysis of results are given next.

Table 8.1. Evaluation: validation with test data-sets
Note: Train: training size — Test: testing size — Estim: estimated

set	**Train**	**Test**	**Distance (in feet)**			**Intensity (in lb)**		
			Actual	Estim	Error (%)	Actual	Estim	Error (%)
1	44	8	45	48.21	7.13	16.5	16.32	1.09
2	44	8	35	34.12	2.51	16.5	15.55	5.75
3	50	2	35	29.23	16.48	8.05	8.91	10.68
4	50	2	40	44.23	10.57	8.05	8.78	9.06
5	50	2	43	40.36	6.13	8.05	10.03	24.59
6	50	2	55	43.22	21.41	8.05	7.12	11.55
7	47	5	26	24.22	6.84	11.83	9.63	18.59
8	47	5	50	54.22	8.44	11.83	10.64	10.05
9	47	5	60	55.35	7.75	11.83	12.22	3.29
10	47	5	61.5	58.34	5.13	11.83	12.37	4.56
11	50	2	26	38.73	48.96	8.25	7.93	3.87
12	50	2	35	33.78	3.48	8.25	7.06	14.42
13	50	2	48	52.27	8.89	8.25	9.12	10.54
14	50	2	55	53.26	3.16	8.25	7.96	3.51

Training Time of Our Model: Recall that our feature-vector was of size 135 in our nonlinear regression (degree-3) model. We implemented our model in Matlab environment. With this feature-vector, the total training took 11.2 seconds on a Windows machine with 32 Gigabytes of RAM, and CPU clock speed of 4.6 GHz.

8.3. RESULTS AND ANALYSIS

In this section, we present evaluations of the model by comparing estimated world-state values with ground-truth values, and we also quantify the performance of the model using well established statistical metrics. We also compare our results in this work using multi-modal sensors with our prior work in [30] that leverages accelerometer sensors only. We also present some critical specs on the complexity of model training. Finally, we present detailed analysis on designing a smartphone app to estimate the range and intensity of an explosion event, and also present important performance specs.

8.3.1. Performance of Our Model. Table 8.1 details the summary of their performance of our model. Each row describes a $Testing - set$ with attributes such as its training-size, testing-size along with estimated, actual (ground-truth) and error percentage values for distance and intensity. As can be seen in Table 8.1, we have 14 $Testing - set$s for which the estimated world-states are compared against ground-truth values. Figures 8.5 and 8.6 show a comparison of actual (ground-truth) to estimated world-state values of distance ($d^{'}$) and intensity ($i^{'}$) for better visualization.

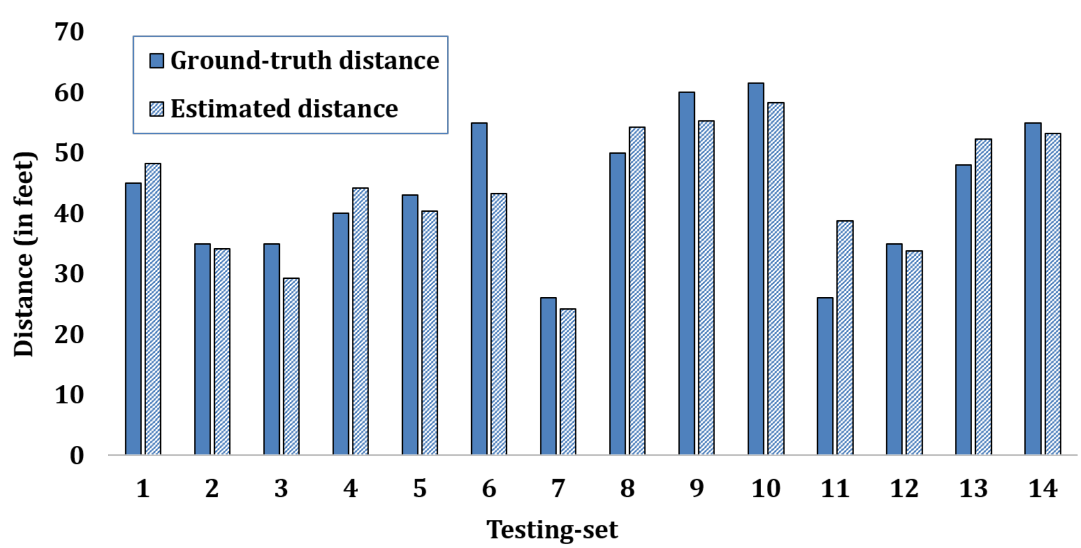

Figure 8.5. Distance estimation

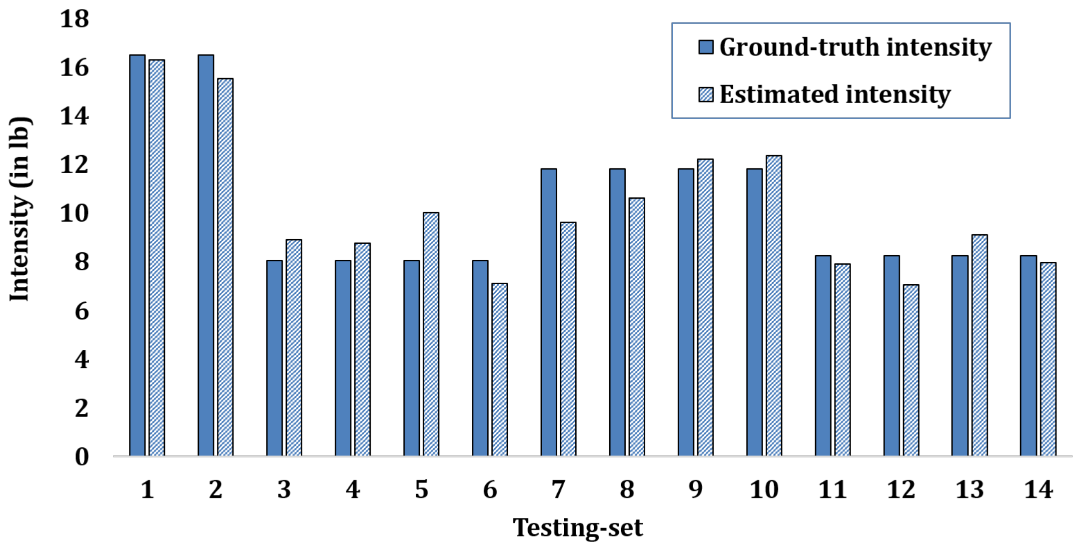

Figure 8.6. Intensity estimation

We observe that the error in estimating the distance is quite low, in fact it is less than 10% in a majority of instances. An average case error of 11.21% was observed for ranging in our experiments. The intensity on the other hand is quite accurate in our estimation with an average case error of 9.4%. These results being the first of their kind in the realm of estimating the range and intensity of an explosion event from statically emplaced smartphones, are quite favorable, and demonstrate clear feasibility for improvement with more experiments.

To further quantify the estimation performance of the model, statistical parameters including training-error, root-mean-square-deviation (rmsd) and normalized-rmsd (nrmsd) are evaluated from the testing. The statistical analysis of the evaluation are summarized appropriately in Table 8.2, and again results demonstrate good consistency, hence validating our model.

As we pointed earlier, in a prior work in [30], we attempted to build a model to estimate range and intensity of an explosion event with only the accelerometer from smartphones. Due to space limitations, we do not discuss too many details on the improvements, but rather show a summary of performance improvements obtained by our model in this work when compared with our prior work in [30]. We do so by comparing the statistical properties of both models in Table 8.2. As we can see the model in the current work that integrates multiple sensors (i.e., accelerometer and pressure), consistently outperforms the model in [30] that leverages data from only one sensor (i.e., accelerometer). This provides us further impetus that the techniques we develop in this work fusing multiple sensing modalities enables our model to learn much better for characterizing explosions.

Table 8.2. Statistical comparison with prior work

Estimated parameter	Statistical metric	**Model using both accelerometer and pressure data in this work**	**Model using only accelerometer data in [30]**
Distance	Average-case error (in %)	11.21	12.86
	RMS-deviation (rmsd)	5.640	7.805
	Normalised-rmsd (nrmsd)	0.158	0.219
	Training error	1.507	2.086
Intensity	Average-case error (in %)	9.4	11.26
	RMS-deviation (rmsd)	1.070	1.429
	Normalised-rmsd (nrmsd)	0.126	0.169
	Training error	0.286	0.381

8.3.2. Designing a Smartphone App. We now report our findings on the feasibility of designing a smartphone app based on our model in this work to estimate the range and intensity of an explosion event. We implemented the application as a two module architecture, as shown in Figure 8.7. The functionality of first module is to detect the triggering of the explosion event and handover the detected event to the second module which estimates the distance and intensity of the explosion. The detailed functionality is described in the following:

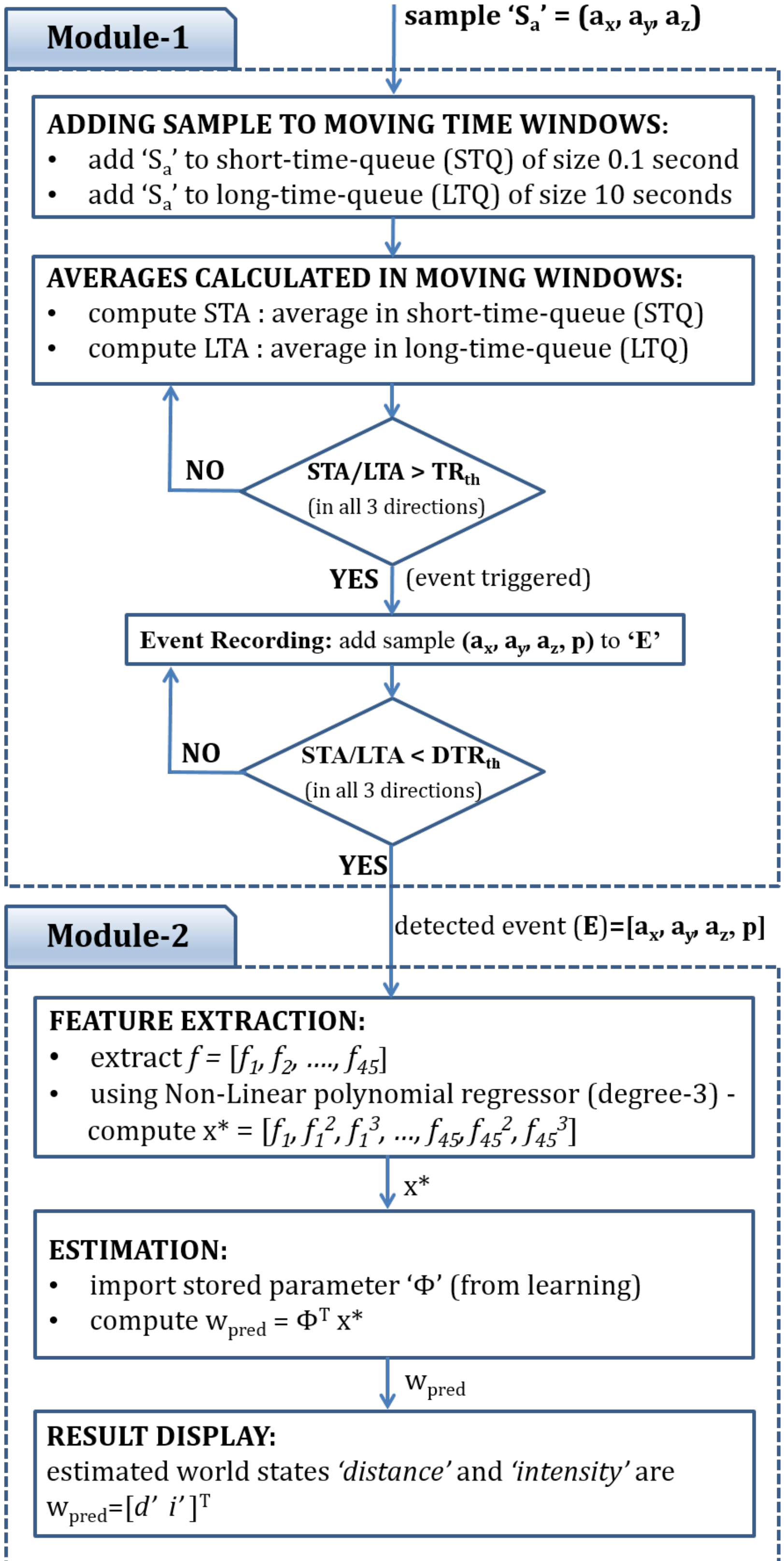

Figure 8.7. Work-flow of our smartphone app

- Functionality of module-1: This module is an implementation of the algorithm proposed in our previous work [29] to sense and retain only explosion events. Note that, in the current implementation we have used time-window values, threshold constants determined in our prior work in [29].

  While the app runs continuously in the background, the smartphone senses and processes the acceleration samples in two moving time windows of different sizes. The sample 'S_a' consists of accelerometer readings available in x, y, z directions. The readings in sample 'S_a' are added to two moving time windows, namely a 'short-time-queue' (STQ) of size 0.1 second and 'long-time-queue' (LTQ) of size 10 seconds (simultaneously for all the 3 directions). Further, averages are calculated in the moving time windows, and their ratio is computed as : *short-time-queue-average/long-time-que-average (STA/LTA)*. This ratio is compared against the trigger-threshold TR_{th} (whose value is 1.75). If the ratio founds to exceed the threshold in all 3 directions, then the algorithm triggers the detection of explosion event and starts recording the explosion event as 'E', by adding accelerometer and pressure sensor readings to it (i.e., 'E' contains readings a_x, a_y, a_z, p). The event is recorded until the ratio value falls below the de-trigger-threshold DTR_{th} (whose value is 1.5), in all 3 directions. This completes the functionality of module-1 resulting in the output 'E' = [a_x, a_y, a_z, p], which are the sensor readings corresponding to the detected explosion event.

- Functionality of module-2: This module is an implementation of the model proposed in the current work for ranging and estimating intensity of explosion event detected.

  As soon as the module receives the event 'E'= [a_x, a_y, a_z, p] from the previous module, the feature-vector f = [f_1, f_2, ..., f_{45}], is extracted for the event. The feature vector is then fed to a nonlinear polynomial regressor of degree-3, which results in a test vector $x^* = [f_1, f_1^2, f_1^3, ..., f_{45}, f_{45}^2, f_{45}^3]^T$. The next step is estimation, where world parameters *distance* and *intensity* are estimated for x^* based on the previous learning. As described in Section 8.2.2, the learning from the training data-sets results in a parameter ϕ. This learnt parameter is a static vector resulted from training process and will be stored in the application, which will be used for estimation of *distance* and *intensity* parameters for a new test vector. The estimation is done as $w_{pred} = \phi^T\ x^*$, resulting in a vector containing estimated *distance* and *intensity*. These parameters are the outputs of the module which are displayed as final output of the application.

- Critical specs of smartphone application: The overall app that contains the algorithms to sense and store only accelerometer/pressure readings pertaining to an explosion, and the algorithm to estimate the range and intensity of an explosion event is of size 4MB. This is well within the limits set by smartphones for apps design. The explosion event is detected and triggered by the smartphone almost instantaneously. The energy consumed by the entire application is 0.350 Joules per second on the average. The average RAM memory in the smartphone consumed by the application for processing accelerometer and pressure readings is 2.4MB which is quite low as well.

9. PRACTICAL RELEVANCE, APPLICATIONS, LIMITATIONS AND FUTURE WORK

In this section, we first describe about practical relevance of our contributions and then briefly highlight some additional perspectives of our work on the feasibility of leveraging smartphones for detecting, ranging and estimate intensity of explosion events. We then describe about limitations and future directions followed by discussion on other open issues.

- Practical relevance of our contributions: We believe that the work presented in this dissertation has practical value to the society. Needless to say, explosion events pose a constant threat to civilian life across the globe, and we believe that participatory sensing based approaches are effective in mitigating ensuing disasters. We also believe that our work makes a critical positive step in this regard by demonstrating the feasibility of detecting, estimating the ranges and intensities of explosion events using stationary smartphones. Our work in its current form is still practical. Note that for a majority of time, a smartphone typically stays static, and hence our results in this dissertation are directly applicable in such cases.

  However, it is also feasible to extend our work to the case of mobile smartphones if appropriate filtering algorithms can be designed to filter out acceleration readings generated as a result of humans moving with the phones. Such algorithms are relatively easy to design with proper training. There are works like [46] that attempt similar objectives. Also, with major initiatives these days across the world on instrumenting buildings and living spaces with "smart sensors", we believe that our work is very timely when our algorithms can be integrated with these smart devices (most of which are static) for explosions detection and analysis also.

- Practical perspectives on app design: Recall that in Sections 6 and 8, we demonstrate the feasibility of designing smartphone apps for detecting and analyzing explosion events for ranging and estimating intensity. While we demonstrated critical specs of the app and its performance, there are some additional issues in practice. In any smartphone today, there are a number of ancillary services like GPS services, application updates, and notification services running in the background in a phone at all times. However, most of these services are pushed in the background depending on priorities and processing costs of more important applications like calling/ messaging. While more experiments are certainly needed from the context of our research, we believe that our application in this work for explosion sensing and analyzing incurs very little processing costs, and hence we expect minimal impact to the execution of its services when more important services are processed by the smartphone.

  Furthermore, as we showed, designing filtering techniques to retain only such kinds of abnormal vibrations are feasible, and also consume minimal overhead. When a number of smartphones send corresponding data to a central server, we believe that significant benefits can result for first responders attempting to range the explosion, and determine intensities. Furthermore, our techniques can also apply to statically emplaced sensors in infrastructures like buildings, bridges, roads etc., with a new application related to ranging explosions.

- Limitations and future directions: Nevertheless, there are some limitations of our work, which naturally leads to the future research directions. Our work in the current form cannot directly apply to the case of mobile phones, since the acceleration sensed as a result of mobility needs to be filtered out from those vibrations related to an explosion. This is part of our on-going work that also relates to activity sensing using smartphones, which is an area of active study today. We are also looking to fuse other sensing modalities like acoustic and magnetometer sensor data for superior accuracies and address problems like detecting type of explosive material. We are also experimenting with heterogeneous smartphones to see how our techniques need to adapt to enhance practical applicability, along with attempts to collect smartphone data arising from blasting other kinds of explosive materials, in other environments.

In this dissertation, we do not address the issue of detecting the type of explosives blasted. In all our experiments, it was Dynamite with Ammonium Nitrate Fuel Oil, and this assumed to be known. However, in practice, we may need techniques to identify the material blasted as well. We believe that is doable today with many prototypes on integrating chemical sensors with smartphones [63, 64, 65]. Such integrations can dramatically enhance the sensing capabilities of smartphones, and they can now perform initial detection of explosives material blasted, following which our algorithms can adaptively attempt to analyze them based on type of material blasted. This will significantly expand the practicality of our proposed techniques, and is part of our future work as well.

Future works of the project include designing algorithms for mobile smartphones, detection of type of explosive material, and to localize explosive events based on multi-modal data sensed from multiple phones. Further testing the design for false triggers in the real-time and further evaluating the full characteristics of the blast using the algorithms designed, also implementing the design in diverse mobile platforms to evaluate the efficiency of the design across the smartphone platforms.

- Other issues: We point out that there are a number of critical open issues that we are addressing currently. These include a) considering readings from acoustic sensors also with accelerometer and pressure sensors for improving the model; b) networking of multiple smartphones in real time to report data to the Cloud; c) understanding diversity in sensor capabilities among multiple smartphones for improved detection at societal scales; d) eliminating false-positives and false-negatives; and finally e) issues related to trust, privacy and integrity of data sensed and shared.

10. CONCLUSIONS

We demonstrate the feasibility of leveraging smartphones to detect the triggering of explosion events. Specifically, we demonstrated the similarity of accelerometer readings from smartphones and ground-truth seismometer readings in the temporal and frequency domains. We also designed an app that can detect explosion events in real-time, and also identified critical performance metrics like energy, storage and execution times. The data-sets collected from the smartphone accelerometers using the application built on it are reliable to be efficient for the detection of explosive event by processing the data using the algorithm design. The design proposed for smartphone based seismometer shows the capability of triggering to the strong motion explosive blasts. By allowing the user to set the parameters based on the blast site conditions, triggering to the typical explosion events was shown possible. The evaluations of frequency and the time-domain responses of the detected events were encouraging and demonstrated the smartphone capable of responding to the explosions by showing the signatures of the explosive events.

Further, we have addressed the problem of estimating the range and intensity of an explosion event using stationary smartphones. Our technique employed a non linear polynomial regression model using data and features extracted from accelerometer sensors in smartphones. Our results are quite favorable, and demonstrate the clear benefit of designing smartphone based participatory sensing networks for the problem of ranging explosion events, and determining their intensities.

Motivated by this, further we designed a model to range and estimate intensity of explosion events leveraging multi-modal smartphone sensors. Our technique employed a non linear polynomial regression model using data, and numerous features extracted from accelerometer and pressure sensors in smartphones. Our estimating results of the model for ranging and estimating intensity using multi-modal sensors have shown an improvement for accuracies from the previous model which was built only on accelerometer data.

To the best of our knowledge, this work is pioneering. Our results are quite favorable, and demonstrate the clear benefit of designing smartphone based participatory sensing networks for the problem of detecting, ranging, and determining the intensities of explosion events. We subsequently provided details and specs of our smartphone app to sense and analyze explosion events. We also provided important discussions that will guide future practical deployments of our technologies proposed in this dissertation.

APPENDIX

In this section, we attempt to give a description of blasting experiments at the experimental mine where we emplaced our smartphones. We expect these discussions to assist future experiments by various stakeholders in this realm.

- Explosion material: The initial step is choosing the type of explosive material. In all our experiments it was Dynamite (Unimax TT) with Ammonium Nitrate Fuel Oil (ANFO). Figure A.1 shows how it looks like. The total explosive material are of different weights, and also have a varied number of charges fixed to it. As mentioned in Section 5.2, the amount of explosive material used determines the intensity of the explosion, and the number of charges determines the number of individual blasts in an experiment.

Figure A.1. Explosive material- Dynamite

- Fixing detonating cords to explosive: After choosing the explosive material, the next step is to connect detonating cords to it. Figure A.2 shows a detonating cord being attached.

Figure A.2. Fixing a detonating cord to explosive material

- Mounting the explosive material: The material to be blasted in the explosion is selected and holes are drilled on the material to exactly fit the explosive material. In our case, the explosion environment is an underground mine, so holes are drilled and explosive material is fixed as shown in Figure A.3.

- Connecting the detonating cords: All the detonating cords are later connected to a single point as shown in Figure A.4. An explosion is detonated from a distance through a long detonating cord which is connected to the junction of cords associated to individual explosive material.

Figure A.3. Mounting the explosive material in to the mines surface

Figure A.4. Connecting individual detonating cords together

- Installing smartphones on the ground: We emplaced a number of smartphones at various distances from the source of the explosion. The smartphones were placed well in advance of detonation, and we were allowed to pick them up only after experts assured us that there were no remnants of the blast. A snapshot of the phone after the blast is shown in Figure A.5. All data stored was fully recoverable for all phones.

Figure A.5. Smartphone emplaced (on the ground) near the explosion site

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