Ranging Explosion Events Using Smartphones

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***Abstract*—In this paper, we address the problem of ranging explosion events from sensing corresponding accelerometer readings from stationary smartphones. 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%. To the best of our knowledge, this is the first work that attempts to range explosion events leveraging sensor readings from smartphones.**

I. Introduction

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. For instance, a modern smartphone like Samsung Galaxy S4 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 [1] can sample up to 200 samples per second, and the sampling rate is programmable. Furthermore, numerous studies have been conducted to optimize the performance of smartphone sensors today from the perspective of accuracy, energy efficiency and processing speed [2].

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 [7], 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 [5]. More recently, the pressure sensors in smartphones have been leveraged for context detection in the domain of urban transportation [10], 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 [12].

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. Community Sense and Response (CSR) system proposed by Faulkner, et. al. [4] leverages accelerometer sensors in smartphones for monitoring earthquakes. The iShake project designed by Jack, et. al. [9] 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 sense earthquakes. In [8], accelerometers of smartphones were used to record the acceleration in real time in order to detect earthquakes.

Contributions of this paper: In this paper, we primarily focus on ranging the source of an explosion event using accelerometer readings obtained from statically placed smartphones in the vicinity of the explosion event, which sense the associated seismic vibrations. A secondary focus is on estimating the intensity of the explosion (as a notion of the charge-weight of the explosive material). Unfortunately, these problems come with significant challenges.

The first (and most significant) challenge is the access to a facility where real explosions take place, while being controlled suitably to place smartphone sensors and obtain corresponding ground truth data (in terms of explosives type, intensity, distance from the smartphones etc). Fortunately, the Explosives Research Lab at Missouri University of Science and Technology is a facility where regular blasts in a controlled facility are carried out to train students. We participated in multiple blasting experiments in May 2014, with a number of smartphones to collect corresponding sensory data (after following appropriate safety procedures) to demonstrate the feasibility of ranging explosion events.

The second major challenge stems from continuously storing and processing accelerometer readings from smartphones. Basically, storing all accelerometer readings and processing

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them continuously to range explosion events is clearly an overkill, from the perspective of storage efficiency. What we need is an effective mechanism to store and process only those readings that correspond to an explosion, while filtering out the rest. In our preliminary work [11], we designed an algorithm to detect the occurrence of an explosion event from accelerometer readings of a stable smartphone. For the current ranging experiments, our algorithm was installed as a smartphone app that continuously processed accelerometer readings from the smartphones, and saved only those readings corresponding to an actual explosion event, while filtering out the rest, hence making our technique storage efficient.

The final challenge is the lack of clear and practically useful models to range explosion events from sensing accelerometer readings from smartphones. While there are some existing works that address this issue using measurements from state of the art geophones [6], they are not practically applicable to the case of accelerometers in smartphones considering the differences in sampling rates, deployment environments, sensing ranges and sensitivities. We hence undertook a machine learning approach to solve this problem using collected data-sets from 4 blasting experiments, in all of which *D*ynamite with ammonium nitrate fuel oil (at multiple intensities) was the material blasted. We used 2 smartphones for initial experiment and then increased to 4 for the rest of the experiments to get more data-sets for the study. We have used Samsung Galaxy S4 smartphones for our experiments and emplaced them 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 non-linear 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%.

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

The rest of the paper is organized as following. Section II presents the problem and associated challenges, while Section III gives a description of experimental set-up. Further Section IV presents a detailed description of our approach to address this problem and a detailed analysis of results. Section V discusses about practical applications and some limitations of the current work with directions of future work and the paper is concluded in Section VI.

II. Problems addressed in the paper and challenges

In this section, we first define the formal problem statement, and critical assumptions we make, followed by a brief description of the associated challenges.

A. *Problem Statement*

Our 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) [1]. 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 smart-phones sense and transmit data in real-time for sensing explosions at societal scales. However, these aspects are secondary to the problem in this paper, namely, estimating the distance and intensity of an explosion event, hence these ancillary issues are out of the scope of this paper.

B. *Challenges*

Attempting to address the problems defined above comes with significant challenges, the most important of which are highlighted below.

- **Availability of real data-sets - Explosions are difficult to be studied for the fact that, they are inaccessible and difficult to be replicated in the physical environment:** The first and most significant challenge comes from the difficulty in obtaining real data-sets to attempt to range explosion sources. 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 in terms of distance and intensities of explosions. Fortunately, we had access to the Explosives Research Lab at Missouri S&T where explosions are blasted to train students majoring in Explosives Engineering. To the best of our knowledge, such a facility is unique in college

[1] 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.

campus environments, and provided us with a controlled environment, and extremely rich source of data-sets to devise techniques to solve our problems.

- **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. 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. We have done prior work in [11] to make this goal feasible. The rationale of our 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 [11], 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 [3, 6], they all address this problem using measurements from geophones that are expensive, bulky and not ubiquitous. Furthermore, there are clear differences between geophones today and smartphone accelerometers in terms of sampling rates, energy consumption, sensing ranges and sensitivities, which necessitates new techniques for addressing the problems defined in this paper. In this paper, we adopt a machine learning approach. In our approach, we partitioned the data-sets into two sets (these are set of data-sets): $Training-set$ and $Testing-set$. Using non-linear regression technique, we attempted to build a model using the $Training-set$, associating distance and intensity of an explosion with accelerometer readings from multiple smartphones. Subsequently, the model was validated using the $Testing-set$ to demonstrate the accuracy of our technique.

III. Experimental Set-up

In this section, we discuss the experimental set-up to address our problems on estimating the distance to the source of an explosion event, and estimating the intensity of the explosion. First we briefly discuss the testing facility, followed by discussions on selecting smartphones for our experiments.

A. Experimental Set-up

The Explosives Research Lab (ERL) at Missouri S&T is a unique facility where students are taught fundamental concepts in Explosives Engineering using practical demonstrations. The blasting is actually done in an underground experimental limestone mine that serves as a facility for student training on explosions, mine constructions, operations, safety and rescue. Figure 1 depicts the mine environment.

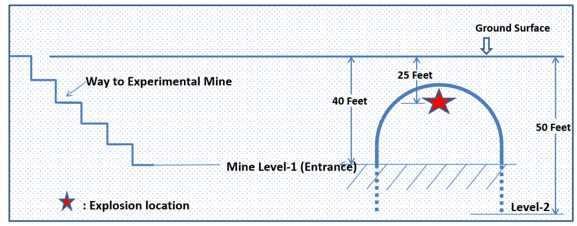


Figure 1. Experimental mine at Explosives Research Lab (ERL)

Table I
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

Table II
DETAILS OF THE EXPLOSIVE MATERIAL USED FOR EXPERIMENTS AT EXPLOSIVES RESEARCH LABORATORY (ERL)

Type of explosive	Dynamite (Unimax-TT)
Material blasted	Dolomite Lime
Explosive sticks	10 - 15 Sticks
No of charges	2, 5, 8
Charge weight	7-17 pounds
Detonating cord	25-50 grains/foot

In May 2014, we participated in several blasting experiments conducted at ERL. Table I presents the parameters of all experiments in which we collected data. As we can see there were a total of 4 experiments (denoted by E1, E2, E3 and E4), each on multiple days. Each explosion was actually composed of multiple blasts, with each blast lasting for about 250ms with a typical one second delay between two blasts.

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. Details of the explosive material are presented in Table II.

B. Smart-phone Selection

Modern smartphones come with a number of sensor arrays including accelerometers, gyroscopes, temperature, acoustic, pressure, humidity sensors and more. For the purposes of this paper, the chief criterion in choosing a smartphone was clearly the performance of the accelerometer, 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 experiments, since its sensitivity, sampling rate, consistency and processing power were among the best[2]. Critical specs of the S4 smartphone are shown in Table III.

Table III
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 model	STMicroelectronics LIS344ALH
Sampling rate	100-110 Hz

After fixing the source location of the explosion in an experiment (denoted by E1, E2, E3, E4), we emplaced smartphones (denoted by P1, P2, P3 and P4) at multiple distances from the source as highlighted in Table I, and shown pictorially in Figure 2. The explosion experiments in the laboratory were conducted in identical environmental conditions with same type of explosive material. Figure 2 shows the layout of the phones during 4 explosion experiments with different intensities. As seen from the figure, we used multiple smartphones placed at various distances from the source to collect data-sets.

The distances from the smartphones to the source were measured using a laser-distance-measurer for superior accuracy. Note that the number of smartphones emplaced in the first experiment was only two due to inherent deployment difficulties. For the second, third and fourth experiments, the number of smartphones was fixed as four. Another critical aspect to note here is the number of blasts in each experiment (the third column in Table I). Each blasting experiment typically occurs with a varied number of explosive sticks and a certain number of charges are placed for each explosive stick. The number of charges indicates the actual number of blasts. In our experiments, the number of charges set up were 8, 2, 5 and 2 for each experiment respectively. As

[2]Note that with appropriate calibration and post data processing, the experiments and results of this paper can be applied to other smartphones as well, and also among a combination of smartphones with appropriate information fusion techniques.

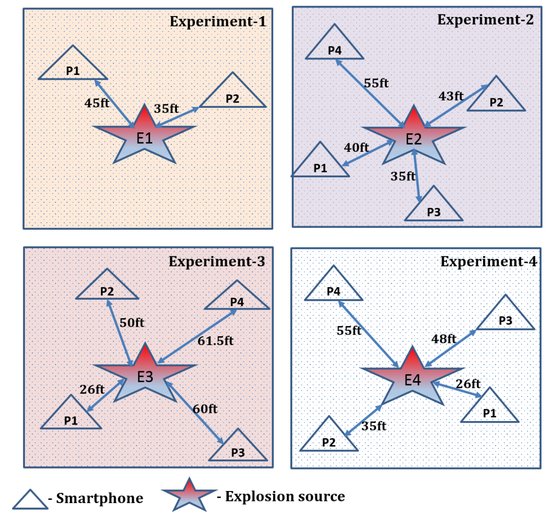


Figure 2. Description of layout of phones during various experiments

such, 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. Figure 3 shows the temporal responses of acceleration in three dimensions (lateral (x), longitudinal (y), and vertical (z) directions) for one smartphone where the number of charges were set as 5. Note that the intensity is determined by the charge-weight of the explosive material in turn depends on the number of explosive sticks used. In our experiments, the intensities (in lb) set up are 16.05, 8.05, 11.83 and 8.25.

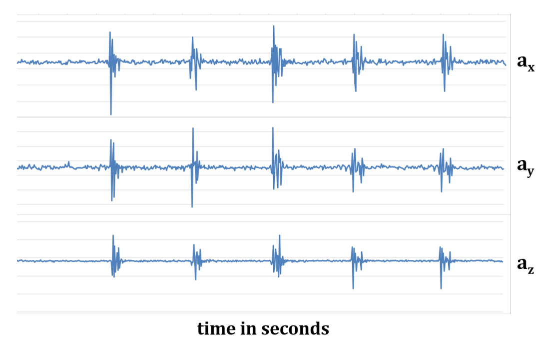


Figure 3. Sample explosion event detected by a smartphone accelerometer

C. Sensing, Filtering and Storing of Explosion Related Accelerometer Data

As mentioned earlier in Section II-B, each phone executed an app that enabled the phone to sense ground vibrations continuously, but retain and store only those accelerometer readings corresponding to an explosion, while filtering out the rest. As soon as the app generates the correct readings related to an explosion event from the accelerometer sensor, it tags the values with the time-stamp information and subsequently writes each time-stamp tagged sample as a record to a Comma Separated Value (.csv) file. 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 post processing (discussed next). Note that the team went through appropriate training procedures prior to visiting the explosives research laboratory.

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

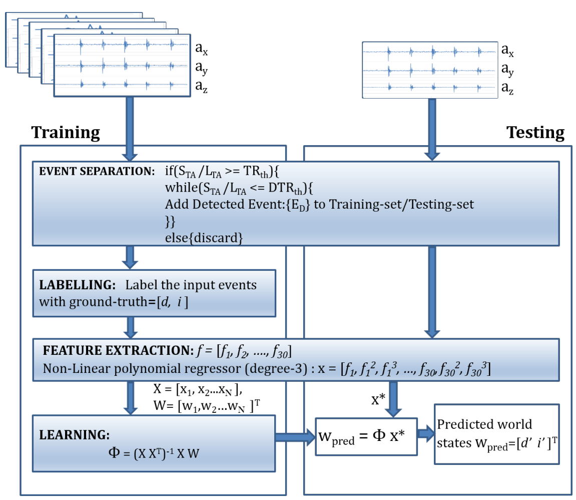


Figure 4. Flow of the designed estimation technique

A. Steps in Building the Model

In this paper, 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 four steps as illustrated in Figure 4.

Step 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 [11], 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 [3]. 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.

Step 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.

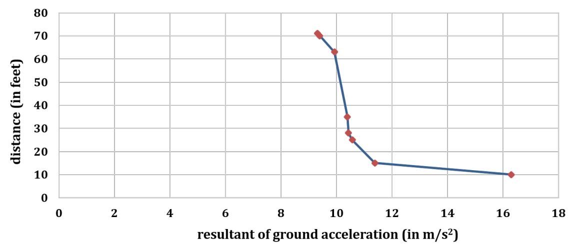
The inputs available for a detected event are:

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

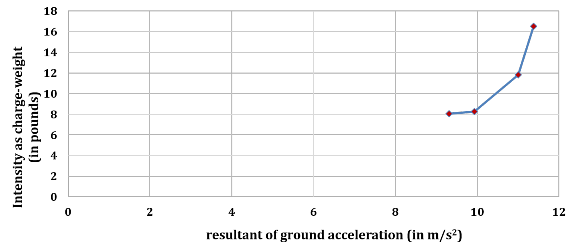
Step 3: Feature Extraction: After labelling each event with ground-truth data, the next step of training is feature-extraction. Note that we have the accelerometer readings from the smartphones in lateral (x), longitudinal (y), and vertical (z) directions, and we could attempt to build a model between 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

1) mean
2) median
3) variance
4) minimum
5) maximum
6) duration of event
7) dominant frequency
8) histogram properties: a) The first highest, b) The second highest, c) The third highest occurrences of the samples in a bin.

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



(a) Relationship between resultant of ground acceleration (input-state) and distance (world-state)



(b) Relationship between resultant of ground acceleration (input-state) and intensity (world-state)

Figure 5. Relationship between the input and world states

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. Figure 5 illustrates the plot of distance and intensity with respect to resultant of ground acceleration values in 3 dimensions for a single phone. Our observation (also true across all phones) is that the relationship is non-linear. As such, instead of attempting linear regression techniques that suffer from fitting problems, we employ a non-linear regression approach.

Step 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 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 IV), 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 IV.

We have implemented a non-linear 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 non-linear 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 non-linearity 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 non-linearity 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 (1).

$$x = [f_1, f_1^2, f_1^3, ..., f_{30}, f_{30}^2, f_{30}^3]^T; w = [d, i] \tag{1}$$

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

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

Solving the cost function shown in Equation (2) leads to the estimated parameter ϕ as shown in Equation (3).

$$\phi = (XX^T)^{-1}XW \tag{3}$$

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.

Testing: 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 4), further apply the non-linear 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,

$$w_{pred} = \phi^T X^* \tag{4}$$

Table IV
EVALUATION: VALIDATION WITH TEST DATA-SETS

Testing-set	Training size	Testing size	Distance			Intensity		
			Actual	Estimated	Error (%)	Actual	Estimated	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

By plugging in X^* in the Equation (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 IV. 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 next subsection.

B. Results and Analysis

In this section, we present evaluations of the model by comparing estimated world-state values with ground-truth values and also quantified the estimation performance of the model using statistical analysis. Furthermore, we present the computational and space complexity of our technique.

Table IV 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 IV, we have 14 $Testing-set$'s for which the estimated world-states are compared against ground-truth values. Figures 6(a) and 6(b) 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 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 V, 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 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.

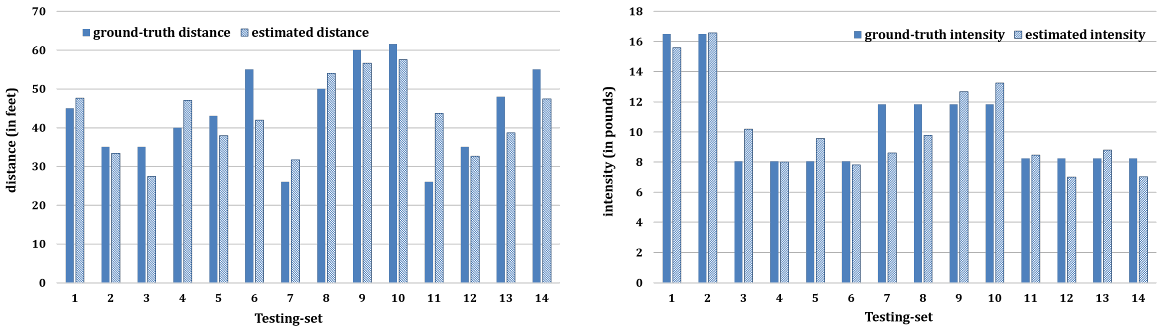
Table V
RESULT STATISTICS

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

As discussed earlier, we have used a feature-vector of size 90 in our non-linear 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.

V. PRACTICAL APPLICATIONS, LIMITATIONS AND FUTURE WORK

We believe that our work in this paper has practical value to the society. Needless to say, explosion events pose a constant threat to civilian life across the globe, and we believe



(a) Distance estimation

(b) Intensity estimation

Figure 6. Evaluation of the estimation model

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 estimating the ranges and intensities of explosion events using stationary smartphones. Our work in its current form is still practical. Smartphones for the most part are actually stationary (when the host is immobile), and hence they can detect abnormal ambient vibrations with minimal noise at most times. 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.

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 sense and fuse multiple phenomena like acoustic, and changes in ambient pressure, along with acceleration to design superior techniques for ranging explosion events. 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.

VI. Conclusions

In this paper, 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. The future work primarily lies in designing new information fusion techniques that integrates multi modal sensor data from smartphones for superior accuracy. We are also looking to extend our techniques to incorporate data from mobile smartphones as well to enhance the practicality of our techniques.

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References

[1] Sensor Specifications of Samsung Galaxy-S4. http://electronics360.globalspec.com/article/94/teardown-what-s-inside-samsung-s-galaxy-s4/.

[2] Y. Chon, E. Talipov, H. Shin, and H. Cha. Mobility prediction-based smartphone energy optimization for everyday location monitoring. In *Proceedings of the 9th ACM conference on embedded networked sensor systems*, pages 82–95. ACM, 2011.

[3] M. Dobrin, R. Simon, and P. Lawrence. Rayleigh waves from small explosions. *Eos, Transactions American Geophysical Union*, 32(6):822–832, 1951.

[4] M. Faulkner, R. Clayton, T. Heaton, K. M. Chandy, M. Kohler, J. Bunn, R. Guy, A. Liu, M. Olson, M. Cheng, and A. Krause. Community sense and response systems: Your phone as quake detector. *Commun. ACM*, 57(7):66–75, July 2014.

[5] M. H. Hennecke and G. A. Fink. Towards acoustic self-localization of ad hoc smartphone arrays. In *Hands-free Speech Communication and Microphone Arrays (HSCMA), 2011 Joint Workshop on*, pages 127–132. IEEE, 2011.

[6] B. C. Johnson, J. B. Jamieson, and R. R. Stewart. Seismic measurement of fracture speed in a weak snowpack layer. *Cold Regions Science and Technology*, 40(1):41–45, 2004.

[7] M. Kangas, I. Vikman, J. Wiklander, P. Lindgren, L. Nyberg, and T. Jämsä. Sensitivity and specificity of fall detection in people aged 40 years and over. *Gait & posture*, 29(4):571–574, 2009.

[8] Q. Kong and R. Allen. Using smartphones to detect earthquakes. In *AGU Fall Meeting Abstracts*, volume 1, page 04, 2012.

[9] J. Reilly, S. Dashti, M. Ervasti, J. D. Bray, S. D. Glaser, and A. M. Bayen. Mobile phones as seismologic sensors: Automating data extraction for the ishake system. *IEEE T. Automation Science and Engineering*, 10(2):242–251, 2013.

[10] K. Sankaran, M. Zhu, X. F. Guo, A. L. Ananda, M. C. Chan, and L.-S. Peh. Using mobile phone barometer for low-power transportation context detection. In *Proceedings of the 12th ACM Conference on Embedded Network Sensor Systems*, pages 191–205. ACM, 2014.

[11] S. Thandu, B. Pratool, L. Malott, and S. Chellappan. On the feasibility of leveraging smartphone accelerometers to detect explosion events. In *Mobile Data Management (MDM), 2015 IEEE 16th International Conference on*, pages 1–6, June 2015.

[12] Y. Zou, G. Wang, K. Wu, and L. M. Ni. Smartsensing: Sensing through walls with your smartphone! In *Mobile Ad Hoc and Sensor Systems (MASS), 2014 IEEE 11th International Conference on*, pages 55–63. IEEE, 2014.