EVENT DETECTION AND LOCALIZATION FOR SPARSELY POPULATED OUTDOOR ENVIRONMENT USING SEISMIC SENSOR

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ABSTRACT

Accurate event detection and localization is one of the key requirements for multiple smart applications. In this paper, we present a framework for event detection and localization using seismic sensors in an outdoor environment. Seismic sensors have been widely used for event detection. This paper extends the application of seismic sensor for localization. We develop a framework using multiple seismic sensors and fuse the information to detect and localize a target. The proposed framework employs regression and property of seismic waves for localization. We develop a prototype system to verify the proposed methods. The event detection module shows the average detection accuracy of 96% whereas localization modules show average localization error 1.37 meters.

Index Terms— event detection, device-free localization, seismic sensors, non-linear regression, seismic wave property

1 Introduction

Researchers and industries are shifting their focus to low-power based microelectromechanical sensors to replace vision-based systems in various real-life applications. These applications include healthcare, security, agriculture, wildlife tracking, and environment monitoring [1].

Sometimes, it is very difficult to associate a device to a target body to monitor a target. The passive systems do not require a target to wear or carry any device. In this article, we focus on passive methodology [2] to develop a framework which can detect [3] and localize [4] a human target in an outdoor environment. There are multiple options available for the passive approach. These options are video, audio, passive-infrared (PIR), wireless (ZigBee, Bluetooth, WiFi) and seismic sensors.

Each modality has some problems associated with it. The wireless technology [2] faces inconsistencies in the measurements made from the different sensors due to the multipath effect. The performance of the audio sensor is compromised in a loud and noisy environment [5]. The performance of a PIR sensor depends on the temperature difference between ambient and a target. A warm gust of wind may cause a PIR sensor to generate a false alarm. Vision-based systems, i.e., CCTV camera-based systems require high storage, more processing power, and colossal processing capability [1, 6]. In this paper, we explore the application of seismic sensors for event detection and localization in an outdoor environment. Seismic sensors offer a number of advantages in terms of low computation, low data rate, and low cost (operation as well as maintenance) [7].

The rest of the paper is structured as follows: Section II describes the related work. In Section III, we formulate the problem and understand the data preprocessing. Section IV discusses the proposed approach. Results, observations, hardware details are included in Section V. Section VI concludes the paper with remarks and future direction of work.

2 Related Work

In this section, we discuss the type of works, which have been addressed using seismic sensors. Researchers have attempted to capture the seismic event to utilize them in various applications. Seismic sensors are widely used for footfall detection and target classification. Succi et al. [8], Anghelescu et al. [6] and Damarla et al. [9] analyzed the seismic events and extracted the statistical features to infer the presence or absence of a target. The statistical features include kurtosis, cadence, span, mean and variance of the seismic signal. Koc et al. [10] used the concept of an adaptive threshold to identify an event. Further, they extended their work to classify the source of the event. Damarla et al. [11] presented a framework based on posterior probability to detect an event using acoustic, seismic, and ultrasonic sensors. Jin et al. [12] proposed a tree-based structure for event detection and target classification. They propose to use symbolic dynamic filtering and probabilistic finite automata. Sundaresan et al. [13] used the joint probability-based copula function for event detection.

The above works deal with either detection or target classification. Xu et al. [14] used a parallel recurrent neural network that uses time as well as frequency domain features to reduce the false alarms in event detection. Audette et al. [15] proposed an adaptive noise cancellation framework to deal with certain types of noise, i.e., tractor to reduce false detec-

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tion alerts.

Pan et al. [16] used a sequence of step events based on energy and timestamp for localization and walking direction detection in indoor scenarios. They also proposed a person identification framework based on the walking style and gait of a person. In this work, we propose a framework for seismic event detection and localization in an unconstrained outdoor environment using three seismic sensors.

3 Data Preprocessing

We consider a two-dimensional physical area of interest $\mathcal{A}$. The area $\mathcal{A}$ is divided into $\mathcal{L}$ discrete locations. The area $\mathcal{A}$ has $\mathcal{M}$ seismic sensors. When a target $\mathcal{H}$ enters into area $\mathcal{A}$, it generates a succession of impacts due to footfalls on the ground. We aim to develop a framework which detects and localizes a human target $\mathcal{H}$ in area $\mathcal{A}$.

Figure 1 shows the components of proposed event-detection and localization module. Now we discuss the details of data preprocessing module.

3.1 Data Denoising

We assume a target stays for duration of $\mathcal{T}$ seconds in the area $\mathcal{A}$ and each seismic sensor has an identical sampling rate, i.e., λ. The number of data collection points will be $\mathcal{P} = \lambda \times \mathcal{T}$ for each sensor. The sensor data contains noise. We use the denoising approach used in the literature [17, 18] where we subtract the average of long term background data from each sensor reading. After denoising, if some readings are negative, they are replaced by zeros.

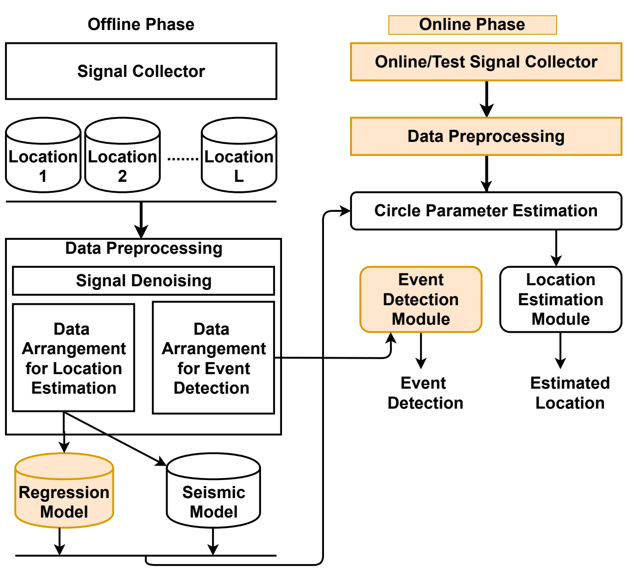


Fig. 1: Proposed Framework for Seismic Sensor-based Event-Detection and Localization.

3.2 Data arrangement

The data arrangement for event detection and localization modules have minor differences. Now we discuss the data arrangement procedure for both modules one by one.

3.2.1 Data Arrangement for Event Detection Module

There are $\mathcal{M}$ sensors and $\mathcal{L}$ discrete data collection points in area $\mathcal{A}$. We divide the data of each sensor into ζ batches where the size of each batch is β. Each sensor has an identical sampling rate and data collection period, thus ζ is a constant value. We horizontally concatenate the batches produced by $\mathcal{M}$ sensors to produce training instances of the effective features for l^{th} discrete location. The size of the training matrix for a location is $\zeta \times (\beta \times \mathcal{M})$. We label the collected data for activity and non-activity class to construct a training matrix.

3.2.2 Data Arrangement for Localization Module

The regression module arranges the offline data in the form of $<$Energy(E)-Distance(D)$>$ pair, where E is the average energy of sensors at distance D. Energy is denoised raw sensor value with respect to a step event. Energy and distance are treated as independent and dependent variable respectively in regression problem. The seismic property based module requires only seismic sensor readings (Energy) for localization.

4 Proposed Approach

Figure 1 shows the system architecture for event-detection and localization. The colored component in Figure 1 indicates the training based modules. We present the details of event-detection and localization modules as follows:

4.1 Event Detection (ED) Module

The sensor reading is different for activity and ambient. Sensor readings for movement in area A have higher energy values than the ambient. We use decision tree classifier [19] to classify seismic signals to solve the binary classification problem, i.e., presence or absence of a target in area A.

4.2 Location Estimation (LE) Module

The LE module is divided into two parts, which are circle parameters estimation and 2-D physical coordinate estimation of an event. The description of these modules is as follows:

4.2.1 Circle Parameter Estimation

We use either non-linear regression or seismic wave property for circle parameter estimation. The details of each approach are discussed as follows:

Non-linear regression-based method (NLRM)- We train a non-linear regression-based model on <Energy-Distance> tuple. The trained regression model takes M sensor readings as input and outputs the distance of the event location for each sensor. The euclidean distance between sensor and event location is termed as the radius of a circle where sensor location is center. In this way, we draw M circles. We estimate the location of an event based on the intersection of M circles.

Seismic property based method (SPM)- The energy of seismic event decays with the increase in distance between sensor and event location. Let (x_{si}, y_{s_i}) be the location of a sensor s_i. The sensor s_i records the reading E_{s_i} due to a seismic event e at distance d_{s_i}. The <Energy-Distance> decay model can be represented as follow [20]:

$$E_{s_i} \propto \frac{1}{d_{s_i}} \tag{1}$$

As there are three sensors, we estimate the circle parameters with the help of two sensors at a time. We pick sensor s_i and s_j, where $i < j$. Let the location of sensor s_i and s_j be (x_{si}, y_{s_i}) and (x_{sj}, y_{s_j}). A seismic event e takes place at an unknown location (x, y). Let the distance of an event e from sensor location (x_{si}, y_{s_i}) and (x_{sj}, y_{s_j}) be d_{s_i} and d_{s_j} with energy values E_{s_i} and E_{s_j} respectively. For event e Equation 1 can be written as follows:

$$\frac{d_{s_i}}{d_{s_j}} = \frac{E_{s_j}}{E_{s_i}} = \alpha \tag{2}$$

$$d_{s_i}^2 = \alpha^2 \times d_{s_j}^2 \tag{3}$$

$$(x - x_{si})^2 + (y - y_{s_i})^2 = \alpha^2 \left[(x - x_{sj})^2 + (y - y_{s_j})^2 \right] \tag{4}$$

on solving the above equation, we get

$$\begin{aligned} &\left[x - \left(\frac{x_{si} - \alpha^2 x_{sj}}{1 - \alpha^2} \right) \right]^2 + \left[y - \left(\frac{y_{s_i} - \alpha^2 y_{s_j}}{1 - \alpha^2} \right) \right]^2 \\ &= \left[\left\{ \left(\frac{x_{si} - \alpha^2 x_{sj}}{1 - \alpha^2} \right) + \left(\frac{y_{s_i} - \alpha^2 y_{s_j}}{1 - \alpha^2} \right) \right. \right. \\ &\quad \left. \left. + \left(\frac{\alpha^2 (x_{s_j}^2 + y_{s_j}^2 - x_{si}^2 - y_{s_i}^2)}{1 - \alpha^2} \right) \right\}^{1/2} \right]^2 \end{aligned} \tag{5}$$

Equation 5 is a circle. The format of center-radius form of a circle is $(x–h)^2 + (y–k)^2 = r^2$, with center (h,k) and radius r. This circle is the result of the joint computation of two sensors s_i and s_j. As there are three circles, there will be $\binom{3}{2}$ circle pairs. Each pair gives a center and a radius. The location of an event is estimated by analyzing the position of circles.

4.2.2 Location Estimation

We now estimate the location of an unknown event e by the intersection of circles where we may get zero or more intersection points; we propose a heuristic for localization. Let us denote a circle as $C_i(c_i, r_i)$ where $i \in \{1, 2, 3\}$. We select two sensors at a time to estimate the location of the event. Each pair of two circles contributes to one effective point. The centroid of $\binom{3}{2}$ effective points is an estimated event location. The heuristic for localization is described as follows:

Case 1: If circle C_i and C_j do not intersect-We identify two closest points $P_i(x_{C_i}, y_{C_i})$ and $P_j(x_{C_j}, y_{C_j})$ on the circle C_i and C_j respectively. The midpoint $\hat{p}_{i,j}$ of the line joining points P_i and P_j constitutes one of the effective points.

Case 2: If circle C_i and C_j intersect- Intersection of circles C_i and C_j give two intersection points P_{ij} and P'_{ij}. We only use one of the intersection points. The intersection point which is closer to third circle C_k contributes to localization. Let us assume that point P_{ij} is closer to circle C_k. The midpoint $\hat{p}_{i,j}$ of line joining point P_{ij} and the closest point on the circumference of circle C_k is one of the effective locations. We repeat the procedure for $\binom{3}{2}$ pairs of circles to get $\binom{3}{2}$ effective points. The centroid of the effective points is estimated event location.

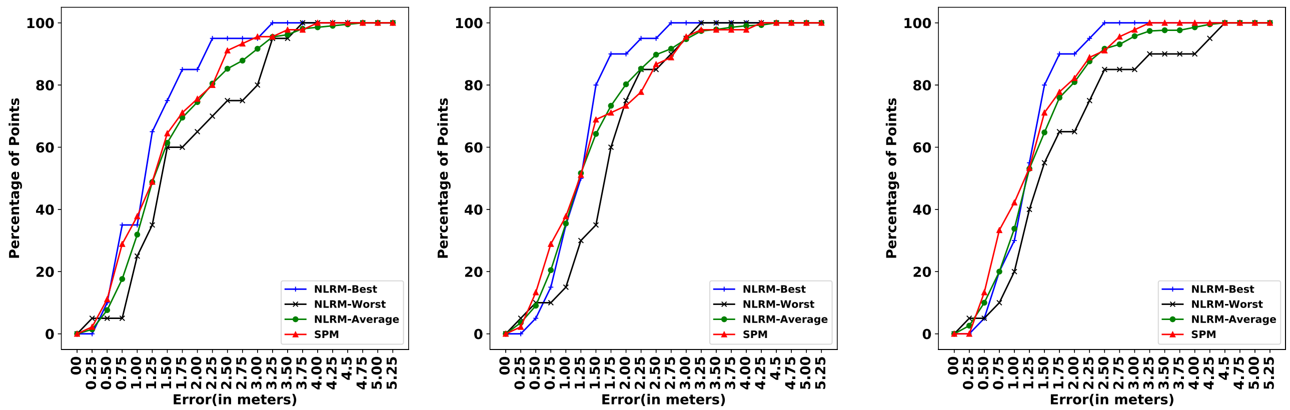
Table 1: Mean Absolute Error on Various Settings

Window Size	NLRM (meters)			SPM (meters)
(seconds)	Best	Worst	Average	-
0.5	1.19	1.7	1.5	1.38
1.0	1.23	1.64	1.39	1.40
1.5	1.22	1.75	1.37	1.26
2.0	1.13	1.73	1.36	1.32
Average	**1.19**	**1.70**	**1.40**	**1.34**

5 Experimental Setup and Results

The experiments were carried out using three SparkFun Geophone - SM-24 1-axis [21] with a sampling rate of 10 Hz. The sensors were buried in the pits of depth 15-16 centimeters. SM-24 geophone was connected to a laptop via Diligent Analog Discovery 2 [22] to sense the earth vibrations. The data was collected at 45 different locations in the lawn of the Department of CSE in IIT Ropar of area $20.25\ m^2$ with sensors at locations $(3.75, 0.1), (1.5, 1.5)$ and $(2.25, 4.45)$. At each location, a target performs foot-drill for 30 seconds.

The ED module uses the Decision Tree (DT) classifier for event detection [19, 23]. An input instance to ED module contains $10 \times 3 = 30$ features which correspond to readings of 1 second duration with sampling frequency 10 Hz of 3 sensors. We conducted our experiments 21 times on different combinations of train and test sets. We use accuracy as the performance measure to evaluate the effectiveness of the



(a) Window Size = 0.5 seconds

(b) Window Size = 1 second

(c) Window Size = 1.5 seconds

Fig. 2: Performance Comparison of Various Approaches

ED module. The accuracy of the ED module is 96.51% and 95.67% on different measures of the quality of a split (entropy and Gini). The maximum depth of DT was set to 6, and the minimum number of sample leaves was set to 2.

We implemented a regression based approach (NLRM) using the scikit-learn APIs library [23]. Since NLRM involves training of data, the NLRM module repeats the experiments 21 times on different combinations of train and test sets to remove bias. It uses 55% and 45% of locations for training and testing respectively.

Figures 2(a), 2(b) and 2(c) show the performance of proposed approaches on different window sizes in the form of cumulative distribution functions (CDFs). As the area to be monitored is of 20.25 m^2, we set the percentage number of points that lie within the error range of 1.5 meters as the performance measure. The NLRM method shows an average error of 1.4 meters. The best, worst, and average performance of NLRM covers 80%, 52.5%, and 64.03% points within the error range of 1.5 meters over all possible scenarios of window size. The SPM approach shows on an average 68.32% of points within an error range of 1.5 meters. We also evaluate the approaches using mean absolute error (MAE). The performance of various approaches can also be seen in Table 1. The mean localization error for SPM is 1.32 meters. We find that the average performance of both modules does not vary too much. The proposed approaches to estimate the target location show a promising localization accuracy.

NLRM needs offline calibration and training; additionally, it needs to be recalibrated if the physical environment is changed. SPM does not require any offline training. We find that the performance of SPM is always better than the average performance of NLRM on referring Figure 2. We also observe that the performance of SPM is comparable to the best performance of NLRM within 1 meter. We have also tested our frameworks on different window sizes. Window size corresponds to the number of samples required for each data point. We can see in Figure 2 that reducing the window size does not affect the average error by a significant amount.

6 Conclusion

In this paper, we propose the use of seismic sensors for event-detection and localization. We validated the use of seismic sensors by developing a framework. The framework uses either decision tree-based regression or property of seismic waves for localization. The framework uses the decision tree algorithm to classify the presence or absence of a target. The results show the efficacy of the proposed framework in event-detection and classification. Our work has proposed a new way of localization of a human target using seismic wave property. In the future, we intend to incorporate more complex features. We also plan to incorporate the functionality of target tracking and activity recognition in the existing framework. We will also analyze the accuracy of the localization framework of the targets of different weight categories.

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