Research Article

Footstep and Vehicle Detection Using Slow and Quick Adaptive Thresholds Algorithm

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Received 15 May 2013; Accepted 4 September 2013

Academic Editor: Adnan Kavak

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An algorithm is developed for footstep, vehicle, and rain detection using seismic sensors operating in a wireless sensor network. Each standalone seismic sensor is coupled with a wireless node, and alarm conditions were evaluated at the sensor rather than at the gateway. The algorithm utilizes slow and quick adaptive thresholds to eliminate static and dynamic noise to check for any disturbance. Duration calculation and filters were used to identify the correct alarm condition. The algorithm was performed on preliminary field tests, and detection performance was verified. Footstep alarm condition up to 8 meters and vehicle presence alarm condition up to 50 meters were observed. Presence of rain did not create any alarm condition. Detection based on kurtosis was also performed and shortcomings of kurtosis especially for vehicle detection were discussed, proposed algorithm has minimal load on the sensor board and its data processing unit; thus, it is energy efficient and suitable for wireless sensor alarm networks.

1. Introduction

Unauthorized human detection is an important and, mostly, an integral part of any security system. In building and perimeter of the building are two essential components of these security systems. In building or immediate vicinity of the structure can be monitored with cameras or security personnel, but perimeter of the building, especially wide open area security systems, requires sensors for intruder detection. Those sensors can be of many different forms ranging from passive and/or active infrared, thermal, seismic, ultrasound, and microphones to electromechanical film. Visually obscured sensors are definitely desired, which makes seismic or acoustic sensors preferable over other sensors. In this study, we used seismic sensors to detect vibrations in the ground to identify and classify human, rain, and vehicle in the prescribed range of the sensor.

Detection methods are usually based on either time or frequency domain. High frequency vibrations decay faster than low frequency vibrations so that the frequency components of a signal can be difficult to differentiate depending on measurement distance. In addition, vibration transmission characteristics are dependent on the soil type and weather conditions. Thus, frequency components of vehicle and footsteps can easily overlap due to vibration transmission characteristics of the soil. Nevertheless, two types of spectrum analyses methods exist for the intruder detection: narrow band and wide band spectrum analyses. Wide band spectrum analyses methods focus on single footstep and vehicle vibration. However, vehicle and footstep vibrations may have frequency components at the same frequency [1, 2]. On the other hand, narrow band spectrum analyses methods focus on several footsteps and vehicle components [3–5]. However, narrow and wide band spectrum analyses require FFT algorithms. Because of the limited memory and power, FFT use is not preferred in wireless sensor network devices. Although FFT may provide promising traffic detection, an alternate analog signal processing may be necessary due to demanding power requirements of FFT evaluation using digital circuits.

Another widely accepted detection method is “kurtosis”, which measures extreme deviations from mean signal [6]. However, detecting intruder movements with kurtosis does not produce clear successful results because vibration of
certain types of noise can easily generate deviations similar to human steps. Another popular intruder detection method is based on “Copula” theory [7, 8]. Copula is in essence full measure of statistical dependence among random variables [7]. However, understanding and quantifying dependence is a challenging task in multivariate statistical modeling. Markov Models are also used in detection of footsteps [9]. Multimodal fusion of sensor data for detection was also proposed in a recent study [10].

The proposed system utilizes wireless communication among sensors that are standalone units and each unit has its own power supply (battery) to operate. All sensor boards are equipped with a wireless unit operating at 2.4 GHz to enable two-way (half duplex) communication between other sensors and the gateway. Geophone sensor SM-24 is used as the seismic sensor and electronic circuit that includes proper filtering and amplification is designed to process analog signal. Filtered and amplified sensor signal is digitized with 12-bit analog-to-digital-converter and processed for alarm conditions. Alarm conditions are communicated to a wireless sensor network (WSN) at 2.4 GHz. WSN board is designed using Texas Instruments tranceiver (CC2420) and microcontroller family (MSP430F1611).

Detection also requires signal processing algorithm where human and vehicle classification can be done. Signal processing algorithm is utilized on the sensor board, and only alarm conditions are broadcasted to the network. The algorithm is designed to eliminate the effects of soil type, environment changes, and ambient noise. Design details of the algorithm are explained in Section 2. Typical scenarios for all types of threats are analyzed for performance evaluation in Section 3. Kurtosis based detection is discussed in Section 4.

2. Detection Algorithm

Detection algorithm works in real time and analyses durations of signals above two adaptive thresholds. The main reasoning behind defining adaptive thresholds is that there are time-dependent noise sources such as elevators, cranes, high power generators, and wind. These types of continuous noise sources generate noise at the same frequency of footsteps and vehicle movement. However, rain is not a continuous noise source, and, because of this, it is defined as a classification object.

Main parts of the algorithms are thresholds, duration calculator, duration filter, classification, and alarm decision as shown in Figure 1.

Two different thresholds are used to determine the durations of the signals: slow adaptive threshold (SAT) and quick adaptive threshold (QAT). SAT is following the noise level with a static and dynamic offset. SAT is designed to eliminate continuous noise effects from the classification by taking the average of the last incoming \( M \) number of sensor data and adding necessary offset values. To determine offset values, a power factor of average (PFA) is defined. PFA is simply a scalar, number and it empirically reflects maximum level of present noise to average noise. For instance, we used a PFA value of 3 in our algorithm to state that maximum noise level is most likely 3 times larger than the average, which is calculated for the last \( M \) data points (10K in our algorithm). Another scale factor called dynamic offset is also defined to account for soil and weather induced noise effects. Static offset is hardware dependent and is based on ambient noise level received by the sensor for the target detection range. SAT is calculated at every data point as follows:

\[
\text{SAT}(i) = \text{StaticOffset} + \text{DynamicOffset} \times \text{PFA} \times \sum_{k=i-M}^{i} \frac{\text{Data}(k)}{M},
\]

where \( \text{Data}(k) \) represents the seismic data. In a single vibration signal, the signal is fluctuating between ground and local maximum. To calculate above-noise durations, QAT is defined. Multiplying the predetermined PFA with the average of the last \( P \) (\( P \) is a fixed memory size in the matlab code) sensor data is equal to the QAT value. With QAT function, amplified signals get smoother and energy of these signals help to execute better classification, especially in the rain conditions:

\[
\text{QAT}(i) = \text{PFA} \times \sum_{k=i-P}^{i} \frac{\text{Data}(k)}{P}.
\]

Duration calculator (DR) counts the number of samples where QAT is higher than SAT. With that, duration of
the intruder vibration signals is determined, and noise is removed from the calculations. DR is calculated as follows:

\[
\text{if } (x) = \begin{cases} 
1, & x \text{ is true,} \\
0, & x \text{ is false,}
\end{cases}
\]

\[
\text{DR}(i) = (\text{DR}(i-1) + 1) \times \text{if } (\text{QAT}(i) > \text{SAT}(i)) .
\]

After calculating the durations, duration filter (DRF) is used to aid classification. DRF parameters are shown in Figure 2. DRF function removes durations in the intervals A, B, and D, but it does not remove several specific durations as stated in Figure 2. It can be expressed as follows:

\[
\text{DRF}(i) = \text{DR}(i) \times \text{if } (\text{DR}(i) \geq \text{DR}(i + 1))
\]

\[
\text{DRF}(i) = \text{DR}(i) \times \text{if } (\text{DR}(i) \geq \text{DR}(i + 1))
\]

\[
\text{DRF}(i) = \text{DR}(i) \times \text{if } (\text{DR}(i) = \text{NFC})
\]

Next step is the classification from filtered duration sizes. Again, intervals and the duration marks in Figure 2 are used. For example, if the filtered duration value is in interval C, then that signal is named as a single footstep. Single alarm (SA) chooses only one signal type which is termed as either “RV” (rain vibration constant) or “FV” (footstep vibration constant) or “CV” (vehicle vibration constant). Hence, SA can be expressed as:

\[
\text{SA}(i) = \text{if } (\text{DR}(i) \times \text{RV})
\]

\[
+ \text{if } (\text{WFC start} < \text{DR}(i) < \text{WFC stop})
\]

\[
\times \text{FV} + \text{if } (\text{DR}(i) > \text{CFC}) \times \text{CV}.
\]

To reduce false alarm rate, repetition of similar type signals is examined by allocating virtual memory slots called “RM” (rain memory), “FM” (footstep memory), and “CM” (vehicle memory) where SA function outcome is constantly monitored and signals are stored in their respective virtual memory slots. At the decision stage, “A” (alarm) function checks these memory slots and counts the signal numbers. If the number of signals in the memories exceeds a threshold value, footstep alarm, rain alarm, or vehicle alarm is generated. Virtual memory slots and alarm are defined as follows:

\[
\text{RM}(i) = \sum_{k=i-RMS}^{i} \text{SA}(k) \times \text{if } (\text{DR}(i) = \text{NFC})
\]

\[
\text{FM}(i) = \sum_{k=i-FMS}^{i} \text{SA}(k)
\]

\[
\times \text{if } (\text{WFC start} < \text{DR}(i) < \text{WFC stop})
\]

\[
\text{CM}(i) = \text{SA}(i) \times \text{if } (\text{DR}(i) > \text{CFC})
\]

\[
\text{A}(i) = \text{RM}(i) \times \text{if } (\text{RM}(i) > 2) + \text{FM}(i) \times \text{if } (\text{FM}(i) > 10)
\]

\[
+ (\text{CM}(i) + 2) \times \text{if } (\text{CM}(i) > 0)
\]

Definitions and values of all these constants are given in Table 1. Algorithm constants was mostly arrived at trial error at the beginning, but, after extensive trial tests, probability of detection and false alarm rates were used to finalize their values for optimum performance.

3. Algorithm Performance

A preliminary test setup is formed to test the algorithm. In all tests, intruders are following a line where sensor is placed in the middle as illustrated in Figure 3. Data were collected with seismic sensors with 250 samples/second. Each seismic sensor is coupled with a wireless node operating in a WSN. Alarm “1” is defined as rain, “2” is footstep, and “5” is vehicle.
Table 1: Definitions of constants in the algorithm.

| Constant Name            | Value | Definition                                                                 |
|--------------------------|-------|---------------------------------------------------------------------------|
| $M$                      | 10000 | Memory size of SAT                                                        |
| $P$                      | 30    | Memory size of QAT                                                        |
| Static offset            | 200   | Static difference between SAT and QAT                                     |
| Dynamic offset           | 1.3   | Proportional difference between SAT and QAT                               |
| PF of average (PFA)      | 3     | The standard ratio between the amplitude of a seismic signal and average   |
| Noise_Filter_Constant (NFC) | 30   | Specific rain vibration duration                                          |
| Walking_Filter_Constant_Start | 35 | Minimum duration of a single footstep vibration                           |
| Walking_Filter_Constant_Stop | 75 | Maximum duration of a single footstep vibration                           |
| Car filter constant (CFC) | 250  | Minimum duration of a single vehicle vibration                            |
| Rain memory (RM)         | 10000 | Memory, which is used in the classification of rain                        |
| Footstep memory (FM)     | 2000  | Memory, which is used in the classification of footstep                   |
| Car memory (CM)          |       | Memory, which is used in the classification of vehicle                    |
| Rain alarm (RA)          | 1     | Classified alarm value of rain situation                                  |
| Footstep alarm (FA)      | 2     | Classified alarm value of footstep situation                              |
| Car alarm (CA)           | 5     | Classified alarm value of vehicle situation                               |

Threshold graphics of noise signal

Duration calculator, duration filter, and alarm results of noise signal

3.1. Noise Performance. Noise data were collected without moving or making any vibration on the ground to test false alarm rate of the algorithm. Raw data with SAT and QAT are shown in Figure 4, and duration calculators and filters are shown in Figure 5. An alarm was not triggered by the algorithm. Also, QAT did not pass SAT at any point of the original signal as expected.

3.2. Footstep Detection. Footstep detection tests were performed in two different test locations. In Test-1, amplification gain of the seismic signal is chosen as 3000 and in Test-2 as 5000. In footstep tests, 30-meter path walked down and 40 footsteps were generated. Original signal for Test-1, its SAT and QAT values, and duration filters with alarm classification are shown in Figures 6, 7, and 8, respectively.

In both tests, 40 steps have been taken and 20 of them have been detected as footsteps. With this, footstep detection range was observed to be close to 8 meters. However, the range can be increased with higher amplification of seismic signals. 32 of 40 footsteps have been detected and 11 of them were classified as a noise. The algorithm produced one false alarm only. Detailed footstep detection test performances are listed in Table 2.

3.3. Vehicle Detection. Vehicle detection tests were executed in two different test locations each having different vehicle
speeds. In Test-1, vehicle speed was 10 Km/hr, and, in Test-2, it was 30 Km/hr. The test setup is illustrated in Figure 9. Original signal for Test-1, corresponding SAT and QAT values, and duration filters with alarm classification are shown in Figures 10, 11, and 12, respectively. In both tests, vehicle presence was detected.

3.4. Rain Detection. Rain detection tests were executed at two different test locations. Original signal for Test-1, corresponding SAT and QAT values, and duration filters with alarm classification are shown in Figures 13, 14, and 15, respectively. In both tests, unwanted signals were detected, but they did not produce any false alarms. Detailed rain detection test performances are listed in Table 3.

4. Detection with Kurtosis

Kurtosis measures the “peakedness” of the real random variable. There are different versions of kurtosis, but we used the most common one for intruder detection:

\[
\text{kurtosis} = \frac{\left(\sum_{i=1}^{N} (X_i - \mu)^4\right) / (N - 1)}{\left(\sum_{i=1}^{N} (X_i - \mu)^2\right)^2 / (N - 1)}. \tag{7}
\]

Kurtosis values are calculated by dividing the data to extracted intervals. The sample number in these intervals is called “N” whereas “μ” is the mean of this interval. It is easy to observe that kurtosis is more sensitive to sudden changes in the data. Therefore, we expect kurtosis to perform better for rain detection and relatively worse for vehicle detection. Kurtosis for different interval samples was analyzed in Figure 16. Kurtosis values of footsteps were varying between 10 and 65. They intersect with noise only in a small interval. Also, the kurtosis values of footstep are increasing with the interval size. However, if the interval size grows a bit more, they will signal several footsteps despite a single footstep. Therefore, interval should contain a number of samples between 80 and 120. It is observed that kurtosis was successful at detecting footsteps and rain; however, for vehicle
detection, kurtosis was not a suitable detection algorithm without any modification.

5. Conclusion

Real-time detection using seismic sensor data was developed to identify the presence of footsteps, vehicle, and rain. Algorithm is based on slow and adaptive quick thresholds with duration calculators and filters. Proposed algorithm was tested on several test scenarios, and its detection and classification success were assessed on several field tests.
Figure 13: Original rain signal (Test-2).

Figure 14: QAT and SAT of rain signal (Test-2).

Figure 15: Duration, filtered duration, and alarm result of rain signal (Test-2).
Footstep detection up to 8 meters and moving vehicle with two different speeds were detected successfully. Kurtosis based algorithm was also developed for comparison, and it was observed that kurtosis was not adequate in classification of all three response types. Although two different test scenarios were implemented, the algorithm needs further verification with extensive field tests.

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