

## Research Article

# Footstep and Vehicle Detection Using Seismic Sensors in Wireless Sensor Network: Field Tests

**Gökhan Koç<sup>1,2</sup> and Korkut Yegin<sup>1,2</sup>**

<sup>1</sup> KoçSistem Information Communication Services Inc., Istanbul 34700, Turkey

<sup>2</sup> Department of Electrical and Electronics Engineering, Yeditepe University, Istanbul 34755, Turkey

Correspondence should be addressed to Gökhan Koç; gokhan.koc@kocsistem.com.tr

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Extensive field tests were carried out to assess the performance of adaptive thresholds algorithm for footstep and vehicle detection using seismic sensors. Each seismic sensor unit is equipped with wireless sensor node to communicate critical data to sensor gateway. Results from 92 different test configurations were analyzed in terms of detection and classification. Hit and false alarm rates of classification algorithm were formed, and detection ranges were determined based on these results. Amplification values of low-intensity seismic data were also taken into account in the analysis. Algorithm-dependent constants such as adaptive thresholds sample sizes were examined for performance. Detection and classification of seismic signals due to footstep, rain, or vehicle were successfully performed.

## 1. Introduction

Seismic sensors are invaluable parts of security systems that focus on perimeter or compound security. Footstep detection is the foremost application of these sensors [1–7]. Fusion of different sensors has also been considered for the same task [8, 9]. Many detection algorithms have been proposed in the past, but some of them place too much burden on computational resources and some of them are simply too complex to be implemented on a wireless sensor network, and yet some of them lack field tests. Field tests compromise of footsteps and vehicles at different ranges of the sensors.

Another critical aspect of footstep detection is the amount of analog signal gain that is applied to seismic data. Low-intensity seismic data require large amounts of amplification before being digitized. On one hand, high amplification is desired for increased range at the expense of increased noise level. On the other hand, low amplification is ideal for suppressing and identifying noise but has limited application range [10, 11]. Any signal processing algorithm must pay attention to amplification level as well as algorithm-dependent variables. In this study, we also study the impact of signal amplification on detection performance by analyzing data with

different amplification values. Seismic data after being processed at the node, has been transferred to other wireless nodes or directly to the gateway to signal alarm conditions. Wireless sensor network nodes, illustrated in Figure 1, were specifically developed for this purpose, utilizing Texas Instruments transceiver and microcontroller family.

## 2. Test Setup

Field tests were performed at Yeditepe University, and test conditions are summarized in Table 1. Test site is shown in Figure 2. Two students with different body weights were chosen for footstep detection. Footstep, vehicle, and combined footstep-vehicle tests were used to test the detection algorithm under various signal amplification conditions.

## 3. Detection Probability and Classification Performance

The detection algorithm was explained previously in [10]. Flowchart of the algorithm is given in Figure 2. The algorithm utilizes slow adaptive threshold (SAT) to identify ambient dynamic noise and quick adaptive threshold (QAT) to detect

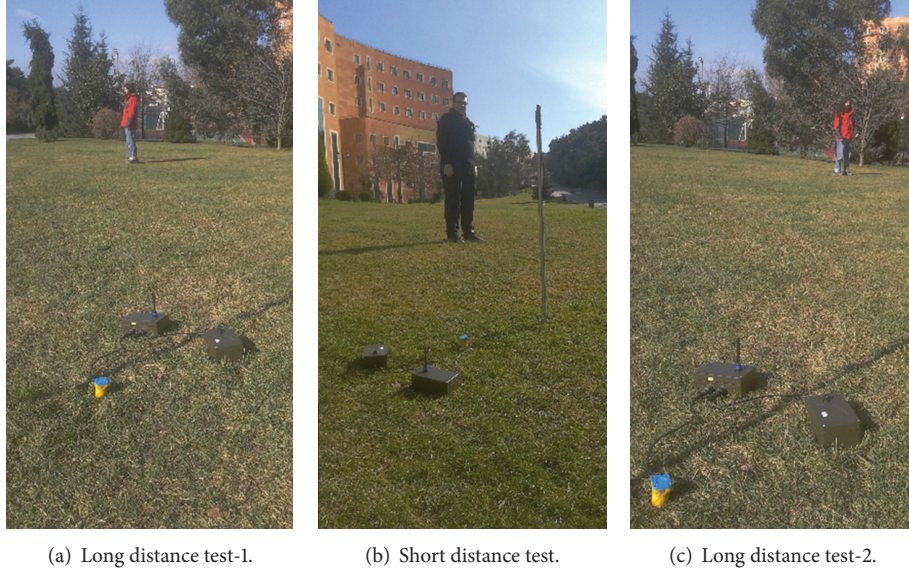


FIGURE 1: Pictures of test setup.

TABLE 1: Field test conditions.

Test conditions	
Test location	Yeditepe University Kayışdağı campus
Weather condition	Dry
Air temperature	9°C
Soil moisture status	Wet
Sampling frequency	250 sample/second
Amplification gain	Different in each Test
Vehicle	Kia Rio GSL EX 1.4
Person A weight	60 kg
Person B weight	120 kg

TABLE 2: Chart for detection performance.

	Detection present	Detection absent
Signal present	True detection (hit)	Missed detection (missed)
Signal absent	False detection (false alarm)	Correct rejection in detection

any disturbance in sensor readings. For field tests, first, noise-only data were collected with different gain values. Signal processing algorithm is expected not to produce any alarm to these noise-only data. Then, a large number of footstep tests were executed to assess the performance of the algorithm. Afterwards, vehicle tests were evaluated, and lastly, vehicle and footstep combined condition were assessed.

First, we define “True Detection”, “False Detection”, “Missed Detection”, and “Correct Rejection” according to Table 2. “true detection” means that the signal type is detected correctly. “Missed detection” refers to the condition that the present signal is not detected. “False detection” refers to incorrect detection; that is, if a vehicle signal is detected in

TABLE 3: Chart for classification performance.

	Classification present	Classification absent
Signal present	True classification (hit)	Missed classification (missed)
Signal absent	False classification (false alarm)	Correct rejection in classification

TABLE 4: Noise-only data (no disturbance).

Gain	Vibration type detection			Classification		
	Footstep	Rain	Vehicle	Footstep	Rain	Vehicle
1000	0	0	0	—	—	—
2500	0	0	0	—	—	—
3500	0	0	0	—	—	—
5000	0	0	0	—	—	—
6500	0	0	0	—	—	—
7500	0	0	0	—	—	—

footstep test, this detection is called “false detection.” “Correct rejection” condition occurs only if there is no signal and no detection.

Since detection is different than alarm, a similar table is formed for alarm conditions in Table 3.

“True Classification” means intruder type is classified correctly. “Missed classification” means intruder type is not classified. “False classification” means signal type is classified incorrectly; for example, if a vehicle signal was classified in footstep test, this classification is called “false classification.” “Correct Rejection in Classification” condition occurs only if there is neither intruder nor any alarm.

Specifying hits and false alarms is sufficient as the others (miss and correct rejection) can be easily extracted; that is, *probability* (Hit) equals to *probability* (Miss).

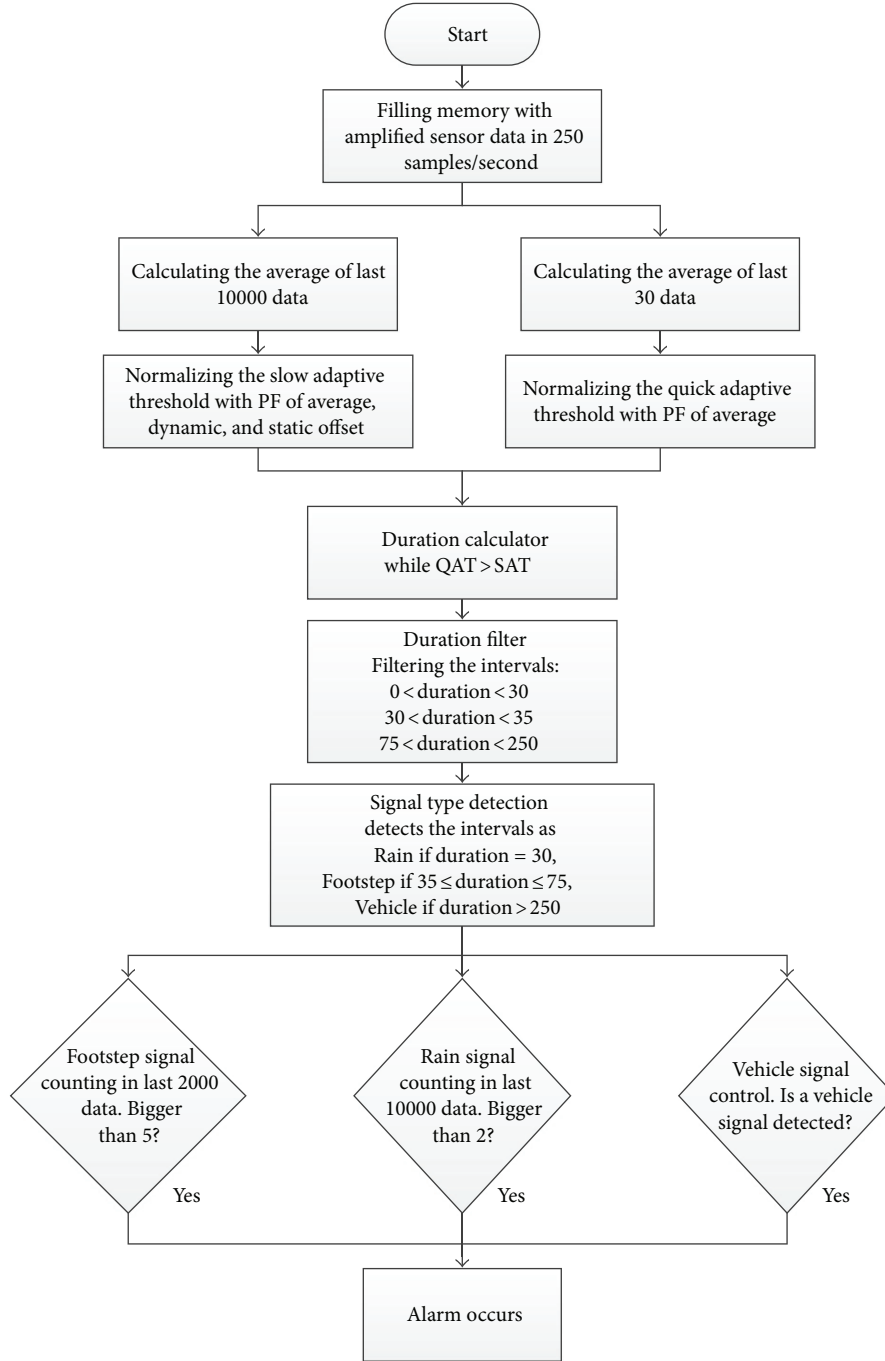


FIGURE 2: The flowchart of the detection and alarm algorithm.

**3.1. Noise-Only Tests.** In noise-only tests, ambient environment is recorded and processed with 20 different gain values in the absence of any movement. Detection and classification results are presented in Table 4. A large range of gain values were tested. Gain values greater than 7.5 K were not tested as noise levels reach full ADC swing.

As it is seen in the Table 4, the signal processing algorithm did not produce any alarm or any vibration detection in noise-only condition at all amplification values.

**3.2. Footstep Tests.** Nine circles concentric to the seismic sensor were traversed by two different persons. The test setup is illustrated in Figure 3. In each test, 60 footsteps were taken (for larger radius circles, only some portion of the circle is traversed.). A total of 72 tests were formed according to Table 5 where combinations of different persons with different amplification values on test circles were evaluated.

The classification result was “true” when only footstep alarm was generated, “false” if rain or vehicle alarm were

TABLE 5: Footstep test configurations.

Distance	Person A				Person B			
	Gain 1 k	Gain 2.5 k	Gain 5 k	Gain 7.5 k	Gain 1 k	Gain 2.5 k	Gain 5 k	Gain 7.5 k
4 m	A-1 k-4 m	A-2.5 k-4 m	A-5 k-4 m	A-7.5 k-4 m	B-1 k-4 m	B-2.5 k-4 m	B-5 k-4 m	B-7.5 k-4 m
6 m	A-1 k-6 m	A-2.5 k-6 m	A-5 k-6 m	A-7.5 k-6 m	B-1 k-6 m	B-2.5 k-6 m	B-5 k-6 m	B-7.5 k-6 m
8 m	A-1 k-8 m	A-2.5 k-8 m	A-5 k-8 m	A-7.5 k-8 m	B-1 k-8 m	B-2.5 k-8 m	B-5 k-8 m	B-7.5 k-8 m
10 m	A-1 k-10 m	A-2.5 k-10 m	A-5 k-10 m	A-7.5 k-10 m	B-1 k-10 m	B-2.5 k-10 m	B-5 k-10 m	B-7.5 k-10 m
12 m	A-1 k-12 m	A-2.5 k-12 m	A-5 k-12 m	A-7.5 k-12 m	B-1 k-12 m	B-2.5 k-12 m	B-5 k-12 m	B-7.5 k-12 m
14 m	A-1 k-14 m	A-2.5 k-14 m	A-5 k-14 m	A-7.5 k-14 m	B-1 k-14 m	B-2.5 k-14 m	B-5 k-14 m	B-7.5 k-14 m
16 m	A-1 k-16 m	A-2.5 k-16 m	A-5 k-16 m	A-7.5 k-16 m	B-1 k-16 m	B-2.5 k-16 m	B-5 k-16 m	B-7.5 k-16 m
18 m	A-1 k-18 m	A-2.5 k-18 m	A-5 k-18 m	A-7.5 k-18 m	B-1 k-18 m	B-2.5 k-18 m	B-5 k-18 m	B-7.5 k-18 m
20 m	A-1 k-20 m	A-2.5 k-20 m	A-5 k-20 m	A-7.5 k-20 m	B-1 k-20 m	B-2.5 k-20 m	B-5 k-20 m	B-7.5 k-20 m

TABLE 6: Footstep classification with 5 K gain.

Footstep classification results with 5 K gain								
Distance (m)	Person A				Person B			
	Footstep	Rain	Vehicle	Result	Footstep	Rain	Vehicle	Result
4	+	−	−	True	+	−	+	False
6	+	−	−	True	+	−	−	True
8	+	−	−	True	+	−	−	True
10	+	−	−	True	+	−	−	True
12	−	−	−	Missed	+	−	−	True
14	−	−	−	Missed	+	−	−	True
16	−	−	−	Missed	+	−	−	True
18	−	−	−	Missed	+	−	+	False
20	−	−	−	Missed	+	+	−	False

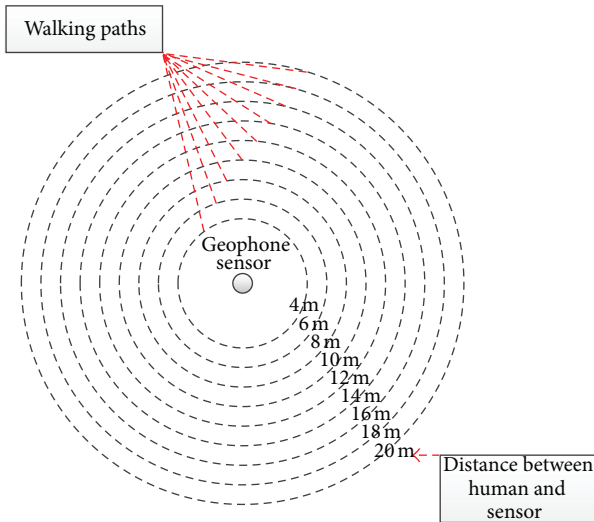


FIGURE 3: Footstep test setup.

triggered, and “miss” if no alarm occurred. The probability of each classification results according to different conditions was evaluated by using data from both persons. The results are presented in Figures 4 and 5 and Tables 6 and 7.

Classification performance can vary depending on gain and range. For >90% true classification rate and less than 10%

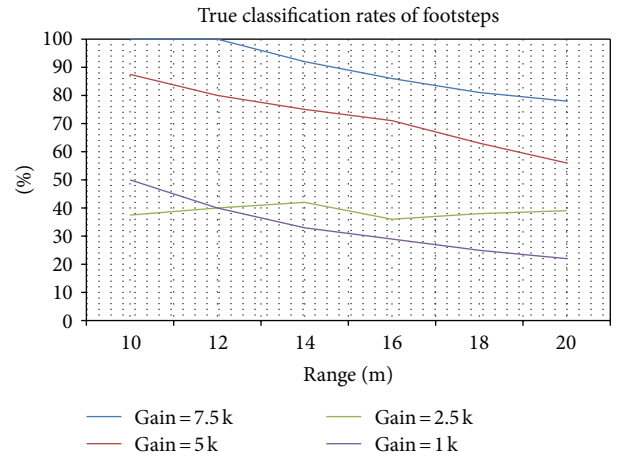


FIGURE 4: True classification rates of footsteps with different gain and range values.

false classification, 7.5 K amplification at 14 m provides best results. However, 7.5 K is still too large for vehicle tests, and if target detection range is lowered to less than 10 m, 5 K gain is as good as 7.5 K gain.

**3.3. Vehicle Tests.** Test setup for vehicle tests is shown in Figure 6. Vehicle tests were executed on a straight line with

TABLE 7: Footstep classification with 7.5 K gain.

Footstep classification results with 7.5 K gain								
Distance (m)	Person A				Person B			
	Footstep	Rain	Vehicle	Result	Footstep	Rain	Vehicle	Result
4	+	−	−	True	+	−	−	True
6	+	−	−	True	+	−	−	True
8	+	−	−	True	+	−	−	True
10	+	−	−	True	+	−	−	True
12	+	−	−	True	+	−	−	True
14	+	+	−	False	+	−	−	True
16	+	−	−	True	+	+	−	False
18	−	−	−	Missed	+	−	−	True
20	−	−	−	Missed	+	−	−	True

TABLE 8: Vehicle tests configurations.

Distance (m)	Gain = 1 K		Gain = 5 K	
	Speed = 20 km/h	Speed = 40 km/h	Speed = 20 km/h	Speed = 40 km/h
10	G1000S20D10	G1000S40D10	G5000S20D10	G5000S40D10
20	G1000S20D20	G1000S40D20	G5000S20D20	G5000S40D20
30	G1000S20D30	G1000S40D30	G5000S20D30	G5000S40D30

TABLE 9: Vehicle classification with different test parameters.

Test ID	Vibration type detection			Classification
	Footstep	Rain	Vehicle	
G1000S20D10	3	1	1	True
G1000S20D20	0	0	0	Missed
G1000S20D30	0	0	0	Missed
G1000S40D10	1	2	1	True
G1000S40D20	3	0	0	Missed
G1000S40D30	1	0	0	Missed
G5000S20D10	8	0	1	True
G5000S20D20	9	0	1	True
G5000S20D30	0	0	0	Missed
G5000S40D10	3	2	1	True
G5000S40D20	4	2	1	True
G5000S40D30	1	1	0	Missed

varying distances from the geophone sensor, 10 meters, 20 meters, and 30 meters. All lines are passed with two different vehicle speeds, 20 km/hr and 40 km/hr. Test IDs were formed as GXXXXSYDZZ, where XXXX represents gain amount, YY represents speed, and ZZ represents distance to sensor. Tests were performed with 1 K and 5 K gains. Although 7.5 K gain produced very good results, we did not use that in vehicle tests due to increased noise levels, which in turn degraded the sensitivity of the system. Particular tests, with corresponding test IDs were given in Table 8, were performed.

Summary of the tests are given in Table 9. There were false vibration type detections. However, these false detections were filtered in the classification processes. Only 1 false classification was observed in 12 tests.

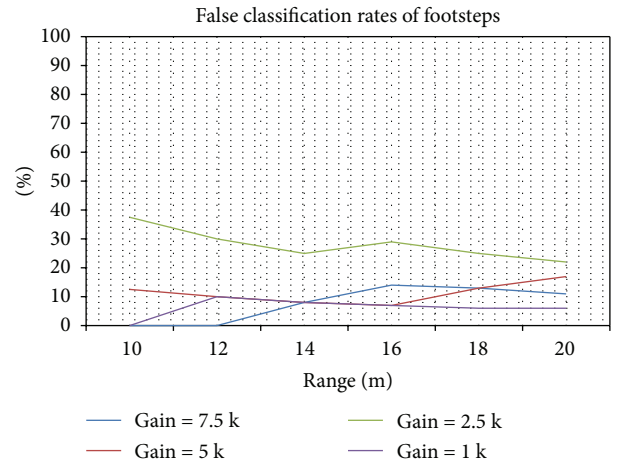


FIGURE 5: False classification rates of footsteps with different gain and range values.

**3.4. Vehicle and Footstep Combined Tests.** The test setup is illustrated in Figure 7. Vehicle with footstep tests were executed on two different lines at the same time. Walking path distance to geophone sensor was 5 meters, and vehicle path distance to sensor is 10 meters. On vehicle path, two different vehicle speeds (20 km/hr and 40 km/hr) were used; all tests were repeated twice.

As before, test ID's were assigned with GXXXXSYTZ where XXXX, YY, and Z represent gain, vehicle speed, and test number, respectively. The tests, all configurations were given in Tables 10 and 8, were performed.

Here, false Alarm was defined as "Rain" alarm, and missed classification was defined as missing any one of

TABLE 10: Vehicle and footstep combined tests.

Test repeat	Gain = 1 K		Gain = 5 K	
	Speed = 20 km/h	Speed = 40 km/h	Speed = 20 km/h	Speed = 40 km/h
First test	G1000S20T1	G1000S40T1	G5000S20T1	G5000S40T1
Second test	G1000S20T2	G1000S40T2	G5000S20T2	G5000S40T2

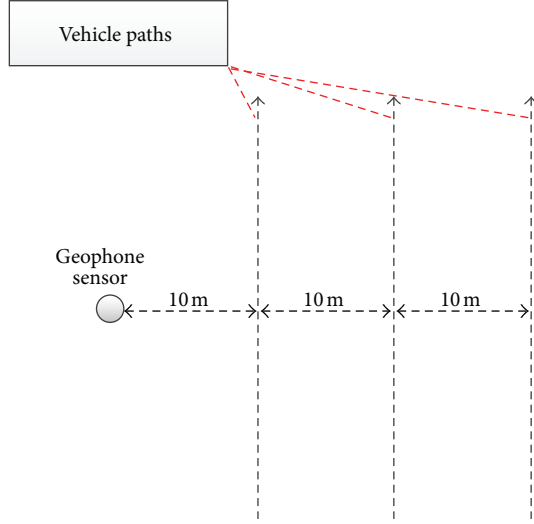


FIGURE 6: Vehicle test paths.

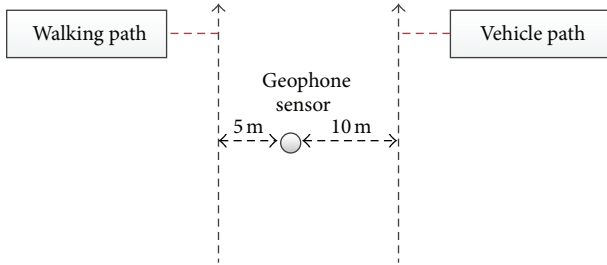


FIGURE 7: Vehicle and footstep combined test configuration.

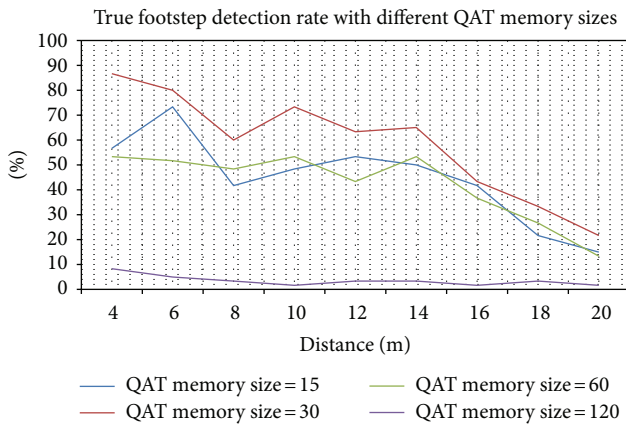


FIGURE 8: True footstep detection rate with different QAT memory sizes.

TABLE 11: Vehicle and footstep classification results.

Test ID	Vibration type detection			Classification
	Footstep	Rain	Vehicle	
G1000S20T1	10	1	1	TRUE
G1000S20T2	8	0	1	TRUE
G1000S40T1	7	0	1	TRUE
G1000S40T2	14	1	1	TRUE
G5000S20T1	9	1	1	TRUE
G5000S20T2	7	1	1	FALSE
G5000S40T1	19	0	1	TRUE
G5000S40T2	11	2	1	TRUE

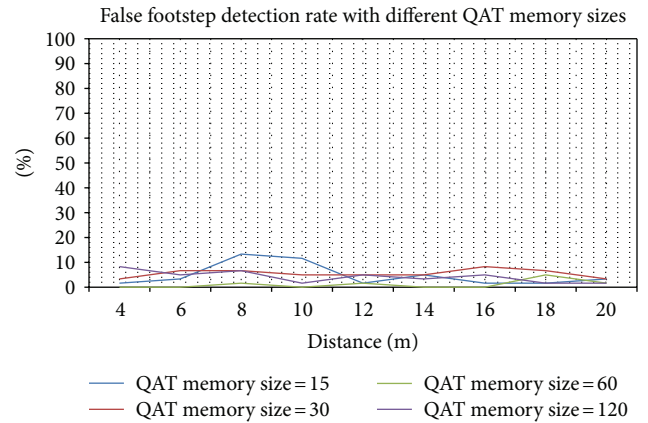


FIGURE 9: False footstep detection rate with different QAT memory sizes.

the two alarms, either vehicle or footstep. Test results were summarized in Table 11.

There were false vibration type detections, but these false detections were filtered in the classification. Only one false classification was observed in eight tests.

#### 4. Algorithm-Dependent Parameters

Detection algorithm heavily relies on QAT and SAT memory sizes, that is, number of samples where moving average is calculated. Thus, we studied detection performance by varying these critical memory sizes. Amplification was set to 5 K for all tests. True, false, and missed detection for various QAT memory sizes as a function of range are shown in Figures 8, 9, and 10. Same analysis was performed for SAT memory sizes and the results are presented in Figures 11, 12, and 13.



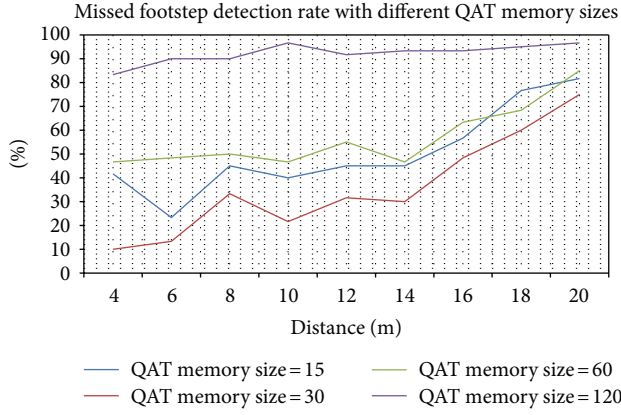


FIGURE 10: Missed footstep detection rate with different QAT memory sizes.

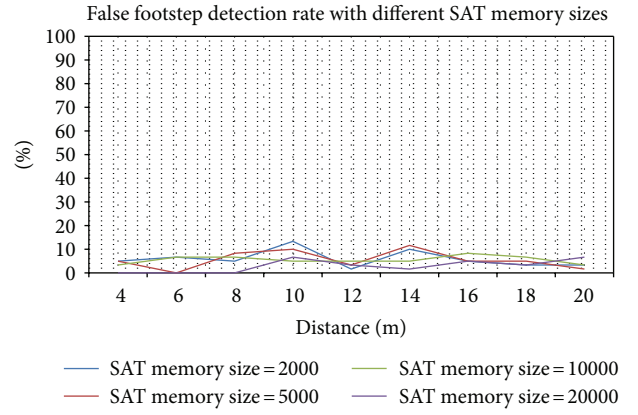


FIGURE 12: False footstep detection rate with different SAT memory sizes.

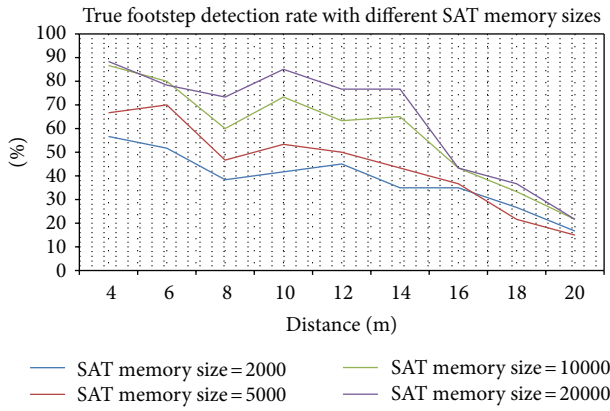


FIGURE 11: True footstep detection rate with different SAT memory sizes.

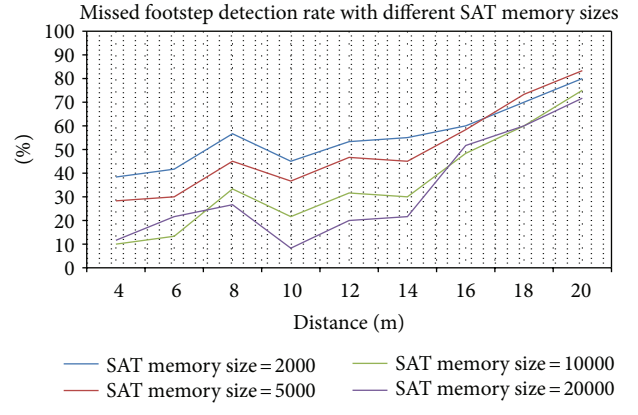


FIGURE 13: Missed footstep detection rate with different SAT memory sizes.

Best performance for true footstep detection was achieved when QAT memory size was 30 samples and SAT memory size was 20000 samples. Lower or higher than 30 samples QAT memory size prevents detection of footsteps due to oscillations in the footstep vibrations. Larger SAT memory sizes provide stability at the intruder movement moments. However, due to memory limitations of WSN, SAT memory size cannot be increased indefinitely.

## 5. Conclusion

Extensive field tests were performed to assess the performance of adaptive thresholds detection algorithm. Over 92 different test scenarios were performed, and results were evaluated in terms of detection performance. Performance tests also included the amplification amount of seismic sensor signals operating in a wireless sensor network. As higher amplification values lead to better detection range, they also increase noise level which, in turn, increases false alarm classification. For detection range under 10 m, 100% footstep classification with less than 5% false alarm rate was observed with 5 K gain. For detection range less than 15 m, 7.5 K gain produced about 95% hit rate and less than 10% false

classification rate. Although the number of experiments with vehicle tests were limited, 5 K gain was also successful (nearly 68% true detection and no false detection). Algorithm-dependent constants such as QAT and SAT sample sizes were analyzed for best performance, and these values were used in detection and classification.

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