Wireless Sensing Without Sensors – An Experimental Approach

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***Abstract*—Motion and intrusion detection are often cited among various Wireless Sensor Network (WSN) applications. A typical configuration comprises clusters of wireless nodes equipped with motion sensors to detect human motion. Currently, the performance of WSN is subject to several constraints, mainly the phenomenon of radio irregularity and finite on-board computation/energy resources. In Radio Frequency (RF) propagation, radio irregularity rises to a higher level in the presence of human activity due to the absorption effect of the human body. In this paper, the feasibility of monitoring RF transmission for the purpose of intrusion detection is investigated. With empirical data obtained from the Crossbow TelosB platform in several different environments, the impact of human activity on the signal strength of RF signals in a WSN is evaluated. This paper offers a novel approach to intrusion detection by turning a constraint in WSN, namely radio irregularity, into an advantage for the purpose of intrusion detection. *Unlike most related work, the "intruders" neither transmit nor receive any RF signals*. By enabling existing wireless infrastructures to serve as intrusion detectors instead of deploying numerous costly sensors, this approach shows great promise for providing novel solutions.**

I. Introduction

A Wireless Sensor Network (WSN) comprises sensor nodes which collaborate to observe some physical conditions such as temperature, pressure and humidity [1]. Deployment of low cost wireless sensors is a useful technique for several applications ranging from early warning systems for natural disasters (like tsunamis and wildfires), ecosystem monitoring, real-time health monitoring, homeland security and surveillance. WSN technology shows great promise for providing novel solutions to various security and intrusion detection applications. By deploying clusters of small, intelligent intrusion detection wireless sensor devices, a large area can be reliably monitored for trespassers. Such a system does not require wiring, can be quickly deployed in a rugged environment, and provides a diligent and automated watch guard against intruders [2].

Currently, security and surveillance applications of WSN are subject to a unique set of resource constraints: finite on-board battery power, limited network communication bandwidth and the phenomenon of radio irregularity. Finite on-board battery requires the deployment of a large number of sensor nodes for redundancy. Besides the wireless transmission hardware, motion detection and other sensing hardware draw down further on the limited power supply. Radio irregularity is a common and non-negligible phenomenon in wireless communications. The variance in the signal path loss is one of the major causes for radio irregularity, which manifests itself in terms of irregularity in radio range and variations in packet loss in different directions. The adverse impact of radio irregularity on the performance of WSN protocols has been studied in [3].

When a signal propagates within a medium, it may be reflected, diffracted, and scattered [4]. Each effect occurs to a different extent in various media, depending on factors such as wavelength and intensity of the wave, thickness and physical composition (permittivity and permeability) of the medium. The human body comprises liquid, bone and flesh, which selectively absorb, reflect or scatter RF signals. Consequently, in the presence of human activity in the network, different components of a signal are absorbed at different time instances, resulting in signal strength fluctuations at the receiver. Thus, in RF propagation, radio irregularity arises to a higher level in the presence of human activity. This correlation provides a theoretical basis for the engineering goal of this research, where we investigate the feasibility of intrusion detection using the phenomenon of radio irregularity in the WSN, instead of the traditional approach of using specialized sensor hardware. **It is important to note that the moving bodies in our study neither receive nor transmit any form of wireless signals**.

In the following section, we briefly discuss related work on motion detection using signal level fluctuations in WSN. In Section III, we describe our experimental approach for monitoring fluctuations in RF transmissions using Crossbow TelosB motes [5] and empirical data collection. This is followed by data analysis and observations in Section IV. We then propose a novel intrusion detection scheme based on our findings in Section V before concluding in Section VI.

II. Related Work

Although specialized sensors and beacons, such as the accelerometer, pedometer or motion sensor, offer precise motion inference [6], they are too expensive and obtrusive for widespread deployments. This prompted efforts to develop alternative motion detection techniques that can be widely deployed for use in today's networks. It has been observed

that multipath fading and shadowing affect the received signal strength and thus embed sensing capabilities into the RF signal which can be exploited in various ways [7]. The authors, through experiments conducted using Mica2 motes, show that node mobility in a network or the motion of objects external to the network leaves a characteristic footprint on signal strength patterns, which they exploit to estimate the velocity of an object.

Existing wireless infrastructures like WiFi and GSM also provide similar opportunities. In [8], the authors show how motion sensing can be achieved by observing WiFi radio signal strength and its fluctuations. Fluctuations in GSM signal levels have also been used for detecting users' motion [9][10]. In [9], the authors adopt a neural network approach to distinguish user motion from GSM signal level changes. However, their scheme requires the neural network to be retrained for different environments. The use of signal traces from GSM network for detecting users' motion is also reported in [10]. Their system achieves an overall accuracy of 85% and is able to extract a set of seven features to classify the user state as either *still, walking,* or *driving*.

From the preceding discussion, we note that most of the work have focused on inferring a node's movement from changes in its received signal levels. Although it has been mentioned in [7] that the motion of objects external to the network also induces signal level changes, there has been no conclusive method to detect foreign objects moving within a network with some level of accuracy. This is because signal fluctuations differ across different environments and conditions, as earlier observed in [9]. In this paper, we propose a means to detect the presence of foreign (non-transceiving) objects moving in a network (in particular, human activity) by analyzing the signal strength fluctuations between communicating network nodes arising from interferences to the signal propagation. In this way, existing wireless infrastructures can be turned into intrusion detection systems without the need to install expensive specialized sensors.

III. Approach

In order to exploit the effects of radio irregularity, we need to be able to characterize the fluctuations and translate them into sufficiently consistent outcomes that correspond to human activity. The first part of our study involves a preliminary investigation to determine the feasibility of motion detection using Radio Signal Strength Indicator (RSSI) readings. Based on the results from this preliminary investigation, we then derive a method to detect motion, and evaluate the success of this method by further experiments.

We begin by deploying pairs of Crossbow TelosB motes in 5 different environments as shown in Table I. We consider (i) *indoor* environments that differ in size and content such as a large multi-purpose hall (A), a 4-person dormitory (B) and a 1-person bedroom (D), (ii) *outdoor* environments such as a sports field (C) and (iii) a *semi-outdoor* large garden (E).

Two motes are placed at a height of 1.5m and spaced between 3m to 5m apart. Over a 15 minute interval, one mote continuously sends packets $p_0, p_1, \cdots$ to the other with an inter-packet interval between 0.25s to 2s; the receiver simply monitors the absolute RSSI, $S(p_x)$, of each received packet, p_x for two scenarios: *with movement* — where a human continuously walks back and forth between the 2 motes — and *without movement*.

Experiment	Description
A	Large multi-purpose hall
B	4-person dormitory room
C	Sports field
D	1-person bedroom
E	Large outdoor garden

TABLE I
Experimental environments

Experiment	No movement		Movement	
	mean	std. dev.	mean	std. dev
A	-39.789	0.413	-44.698	1.445
B	-39.163	0.822	-40.094	0.871
C	-43.073	0.207	-40.050	1.246
D	-70.000	0.018	-73.229	1.612
E	1.509	0.145	-1.376	0.354

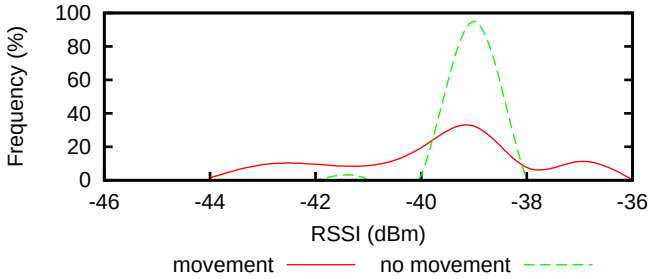
TABLE II
Mean and standard deviation of absolute RSSI values

IV. Experimental results

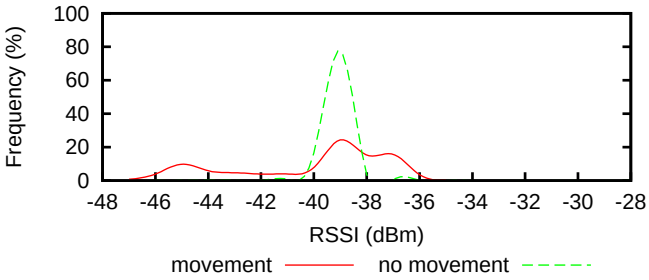
Histograms of the absolute RSSI values are shown in Figure 1 and the mean and standard deviation are shown in Table II. We observe that human movement has marginal impact on the *mean* RSSI measured at the receiver. However, an important observation in all the experiments that we can make is that human movement causes the histogram of the absolute RSSI values to become more *spread*; this is manifested quantitatively as higher standard deviation. However, the standard deviation varies significantly across environments, making it difficult to define a universal threshold to detect movement in terms of these first order statistics.

Nevertheless, by observing the time series of the RSSI values, we note that the RSSI values for successive packets are very stable. Hence, to exploit the observed RSSI spread caused by human movement, while reducing the impact of the environment, we consider the *fluctuation* in signal strength instead. For a given packet p_i, we calculate the RSSI fluctuation as $F(p_i) = S(p_i) - S(p_{i-1})$. For example, a series of RSSI values $\{1,2,4,8,8,6,7,9,8\}$ would produce the corresponding stream of RSSI fluctuation values $\{0,+1,+2,+4,0,-2,+1,+2,-1\}$..

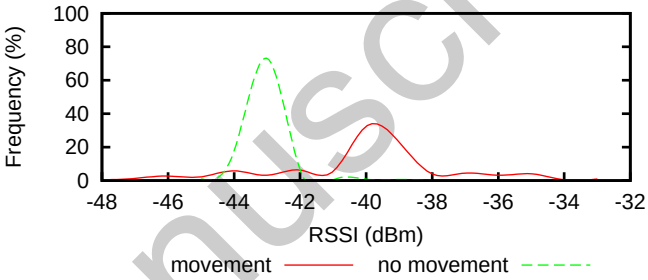
Histograms of the RSSI fluctuation with and without movement are shown in Figures 2 to 6. Comparing with Figure 1, we observe that the spread of the histogram *without* movement is *narrower*, while that *with* movement is *wider*. In fact, the frequency of fluctuation values within [-1, 1] always exceeds 90% when there is no movement and always remains below 65% when there is movement.



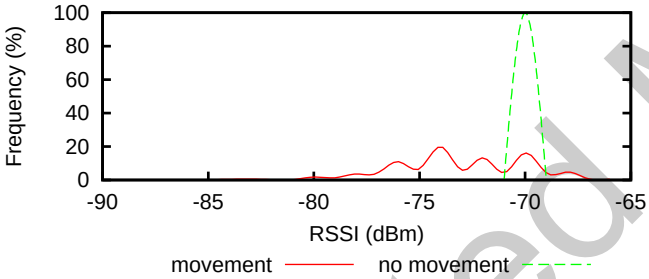
(a) Experiment A



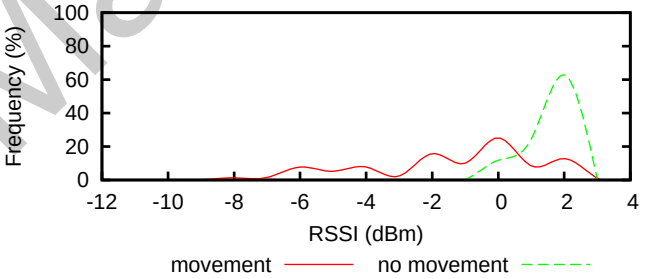
(b) Experiment B



(c) Experiment C

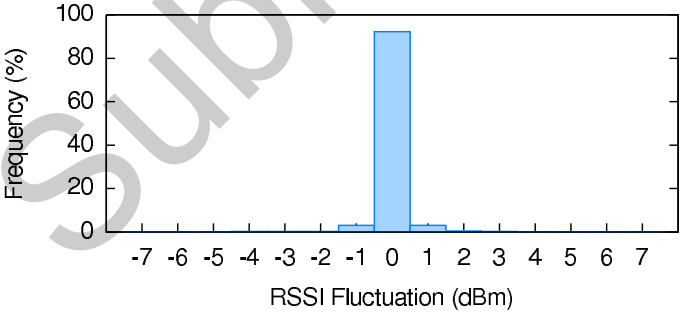


(d) Experiment D

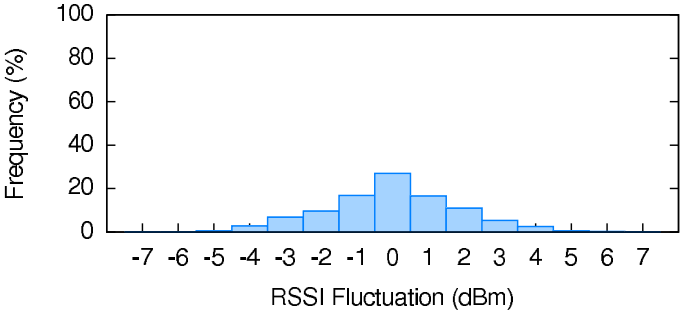


(e) Experiment E

Fig. 1. Absolute RSSI values

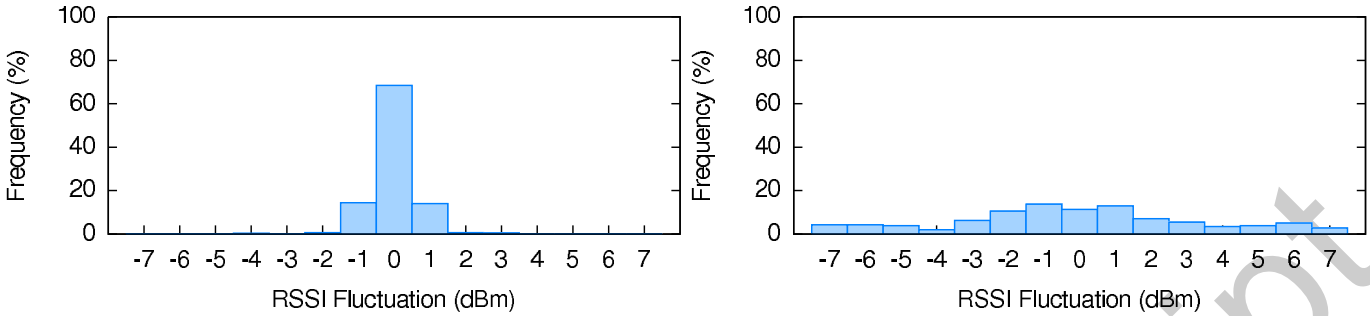


(a) No movement



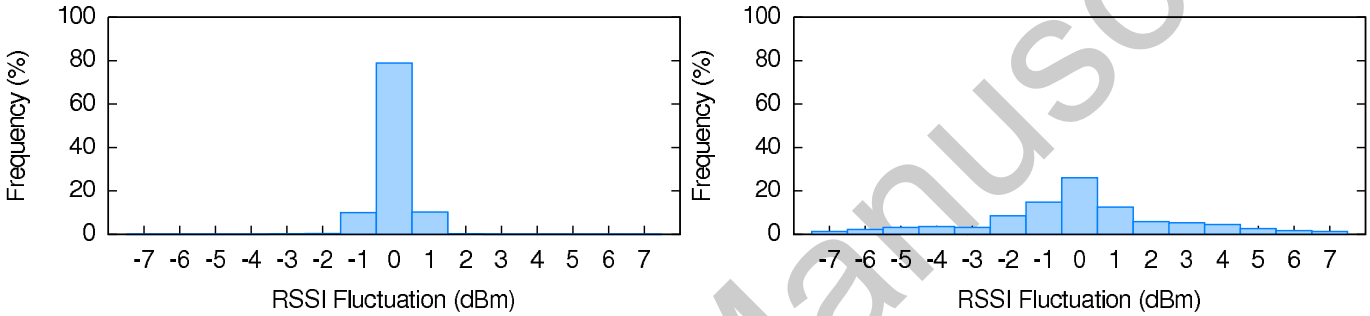
(b) With movement

Fig. 2. Experiment A, large multi-purpose hall



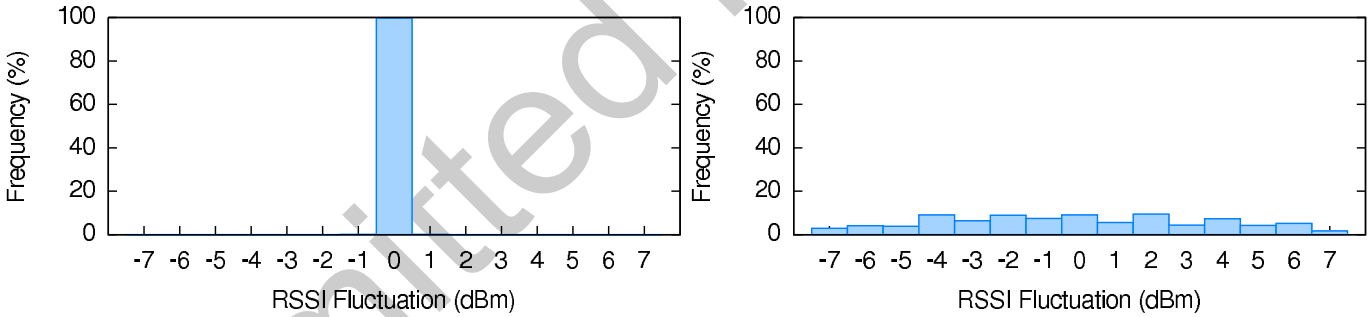
(a) No movement (b) With movement

Fig. 3. Experiment B, 4-person dormitory room with furniture



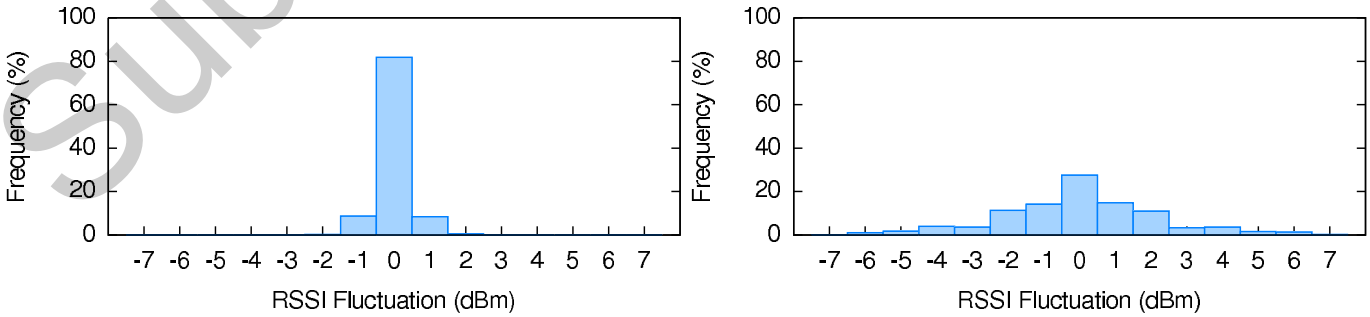
(a) No movement (b) With movement

Fig. 4. Experiment C, sports field



(a) No movement (b) With movement

Fig. 5. Experiment D, 1-person room



(a) No movement (b) With movement

Fig. 6. Experiment E, garden

V. Inferring Human Activity

We propose an algorithm for motion detection that counts the number of fluctuations falling in [-1, 1] over a window of size N packets. The algorithm infers that there is motion if the percentage of such fluctuations falls below $p_{thresh}\%$.

We evaluate the algorithm by running 3 more experiments, conducted in 3 different meeting rooms of sizes about 6m $\times$ 4m. The motes are placed at a height of 1.5m and spaced 4m apart, with inter-packet arrival period of 0.25s. Over a 20-minute period, a human walks between the motes continuously for 30 seconds at the start of minutes $0, 2, 4, \cdots, 18$, for a total of 10 walks. We let $N = 60, 80, 100, 120$ and $p_{thresh} = 65\%$.

A sample run for N = 100, Room 3 is shown in Figure 7, where the normal line represents motion as inferred by the algorithm and the dashed line (- -) represents actual motion. We observe that all 10 walks were successfully detected within 15 seconds of the onset of each walk. In fact, this is observed in every trial.

However, some false positives were detected in Room 1 and 3, where the algorithm inferred motion for a period of 10 seconds or more when there is actually no motion. However, as shown in Table III, the occurrence of false positives may be reduced by appropriate tuning of N. Moreover, in intrusion detection, it is preferable to detect some false positives than to let intrusions go undetected.

N	Room 1	Room 2	Room 3
60	3	0	3
80	3	0	4
100	2	0	3
120	2	0	2

TABLE III
False positives detected by motion detection algorithm

VI. Conclusion

In this paper, we have demonstrated the viability of using wireless sensor motes for motion detection. The absolute signal levels are non-deterministic and highly dependent on the surrounding environment. However, the degree of signal level fluctuations arising from interference by the human body moving in the vicinity of RF transmissions have been shown to be consistent and can be used as a means to detect human activity in the network. We conducted preliminary investigations and proposed a method to detect motion successfully, although with some false positives.

This finding presents a novel approach to intrusion detection by transforming what is typically considered to be a transmission problem into an advantage for the purpose of intrusion detection. This approach is dependent on the fidelity of the wireless transceivers and may not provide the necessary accuracy to perform the task of intrusion detection by itself. However, it can be adopted (at very little additional costs) as a preliminary detection system to trigger other systems such as video surveillance, or alert security personnel to focus on specific CCTV displays. This can provide substantial savings in energy costs and also improve the efficiency of human security operators whose alertness are reduced by observing multiple video surveillance displays over long durations.

References

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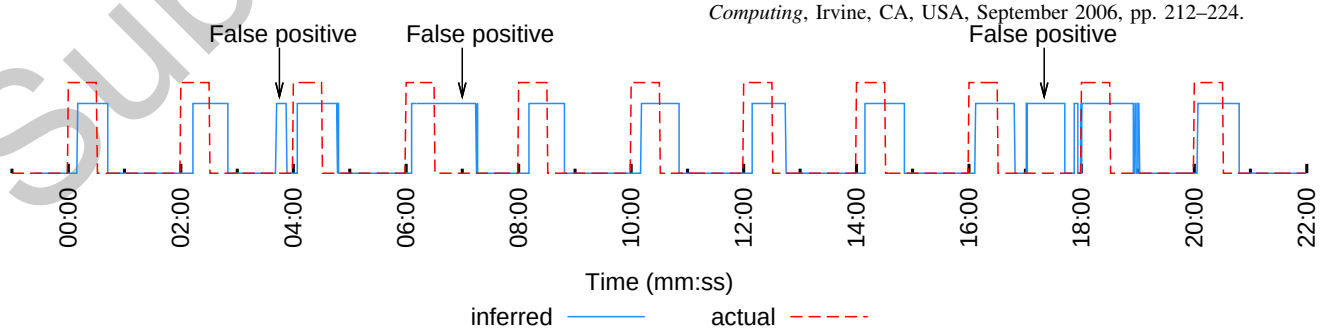

Fig. 7. Motion detection algorithm evaluation, N = 100, Room 3