Your Wireless Network Knows Where You Are! RASID: A Robust WLAN Device-free Passive Motion Detection System

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ABSTRACT

Typical location determination systems require the presence of a physical device that is attached to the person that is being tracked. In addition, they usually require the tracked device to participate actively in the localization process. In this paper, we introduce *RASID*, a device-free passive human motion detection system using the already installed indoor wireless infrastructure. The basic idea is that human presence in an RF environment affects the signal strength, and hence that effect can be used for detecting human presence. This can be useful in a variety of applications including intrusion detection, smart homes, and border protection.

We describe the *RASID* system architecture presenting how it uses statistical anomaly detection techniques to achieve high detection accuracy despite the noisy wireless environment, and how it adapts to changes in the environment. Evaluation in typical environments shows that *RASID* can achieve high detection accuracy while maintaining robust performance over time, enabling a new class of localization applications.

1. PROBLEM AND MOTIVATION

The increasing need for context-aware information and the rapid advancements in communication networks have motivated significant research in the area of location determination systems. These include the GPS system [1], ultrasonic-based systems [2], infrared-based (IR) systems [3], and radio frequency-based (RF) systems [4]. All these systems require the tracked entity to carry a device that participates in the localization process. Thus, we refer to them as **device-based** systems.

In this research, we address the novel problem of device-free passive localization, where we leverage standard WiFi networks to detect and track entities that **do not carry any device nor participate actively** in the localization process.

The basic idea is supported by the observation that the presence and motion of entities in an RF environment affect the RF signals in the environment. Figure 1 gives examples of such effect by comparing the wireless signals of two streams (i.e. RSSI of a single transmitter-receiver pair) in the case of silence (no human presence),

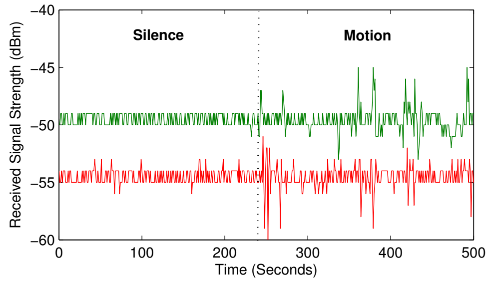
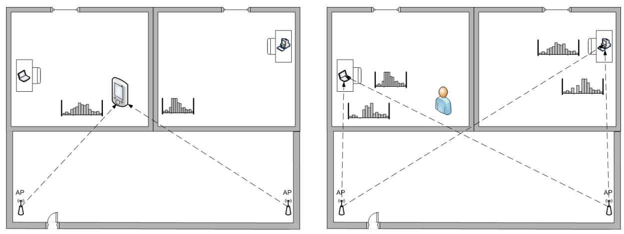


Figure 1: Illustrating the motion effect on wireless signals of two different streams.



(a) Device-based: a device is required for tracking

(b) Device-free: an entity can be tracked without carrying an device

Figure 2: Difference between device-based and device-free localization. Dotted lines present a signal strength stream (RSSI from an AP-MP pair).

and human motion. Our typical deployment consists of signal transmitters (such as standard access points - APs), signal receivers or monitoring points (MPs - such as standard WiFi-enabled devices such as laptops and APs themselves that can hear other APs), and an application server that collects the received signal strength (RSS) from the different streams for processing, detection, and initiating actions (for example sending an SMS or email alert to the concerned people). Figure 2 shows the difference between signal collection in a device-based and device-free setting.

A typical application scenario is that an enterpriser

WiFi network used for data communication during the day can be used during the night, without any extra hardware installation, to detect intruders in a protected area based on the changes in the RSS. Other applications include smart buildings, border protection, sensorless sensing, and low cost surveillance.

2. BACKGROUND AND RELATED WORK

Over the years, there has been significant research on device-based localization systems [1–15]. All these systems share the requirement of tracking a device carried by the user.

On the other hand, intrusion and motion detection systems ***using special hardware*** have been introduced before and even commercial systems are being deployed. Such systems share some drawbacks. For example, camera-based systems (e.g. [16]) and infrared commercial systems are limited to line-of-sight vision and may require a high cost deployment to cover all site regions. Regular cameras may also fail to work in darkness or the presence of smoke. Ultra-wide band radar systems (e.g. [17]) suffer from high complexity. Physical contact-based systems (e.g. [18]), radio tomographic imaging (e.g. [19]), and wireless sensors-based systems (e.g. [20]) are examples of RF based systems. However, all listed technologies share the requirement of **installing special hardware** to handle the device-free functionalities. Moreover, some techniques require high density to provide full coverage like radio tomographic imaging and physical contact-based systems using pressure sensors.

Our proposed RASID system is based on the deployed WiFi networks and hence provides a value-added system to the already-installed WiFi infrastructure without using any extra hardware.

Different techniques for WiFi-based detection [21, 22] and tracking [21, 23–26] were introduced previously by our group. The proposed techniques for the detection capability are either based on time-series analysis, like the moving average and moving variance techniques proposed in [21], or based on classification using the maximum likelihood estimation [22]. These techniques are not robust to changes in the environment. In addition, some techniques require the construction of a human motion profile which is a high overhead process for large-scale environments [22]. Moreover, these techniques were either evaluated in controlled environments, e.g. [21], or in small-scale real environments, e.g. [22].

Our proposed *RASID* system, on the other hand, targets a low deployment overhead, high accuracy despite the noisy wireless channel, and robustness to changes in the environment.

3. APPROACH AND UNIQUENESS

In this section, we present the operation of the *RASID* system and illustrate its unique characteristics. Full details of the system have recently been published in [27].

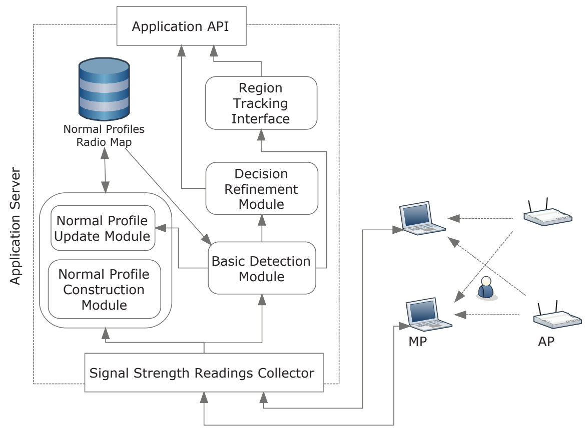


Figure 3: *RASID* system architecture.

3.1 RASID System Architecture and Operation

Figure 3 gives an overview of the system architecture. The modules of the *RASID* system are implemented in the application server. The system works in two phases:

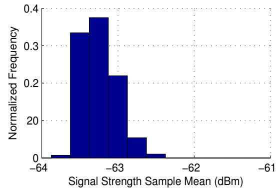
1. An *offline* phase, during which the system studies the signal strength values when no human is present inside the area of interest to construct what we call a normal or silence profile for each stream. This profile stores information about the distribution of the sample variance of the signal strength received during the silence period. Note that the system stores only information about the silence state and does not require storing any motion profiles. This leads to minimal overhead.

2. A *monitoring* phase, in which the system collects readings from the monitoring points and decides whether there is human activity or not based on the information gathered in the offline phase. It also updates the stored normal profile so that it can adapt to environment changes. Finally, a decision refinement procedure is applied to further enhance the accuracy.

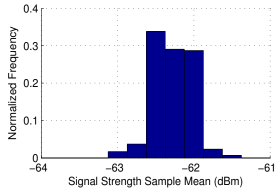
In the following subsections, we provide more details about the system approach and the functionality of its modules.

3.1.1 Feature Selection

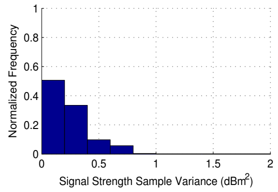
The *RASID* system depends on the RSS variance as the main feature for its operation. As compared to the RSS mean, the variance has two advantages: First, the sample variance as a dispersion measure, can be better used to identify the signal strength fluctuations due



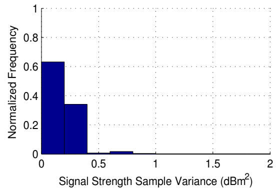
(a) Sample mean silence profile



(b) Sample mean silence profile two weeks later



(c) Sample variance silence profile



(d) Sample variance silence profile two weeks later

Figure 4: Comparison between the sample mean and sample variance silence profiles showing the robustness of the latter. Subfigures (a) and (b) show two-week separated sample mean silence profiles for a wireless stream, while subfigures (c) and (d) show two-week separated sample variance silence profiles for the same wireless stream.

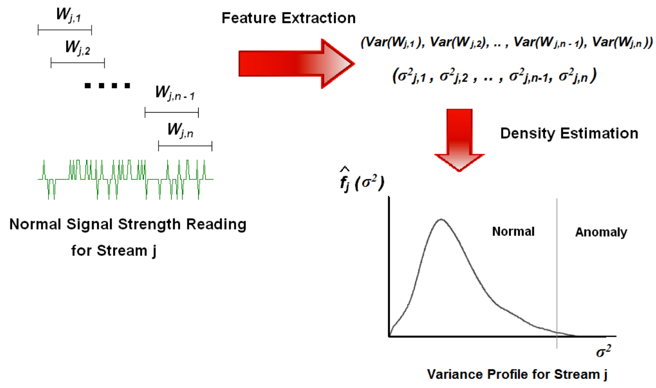
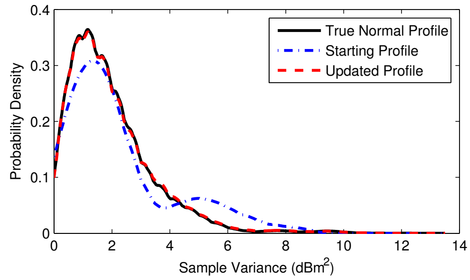
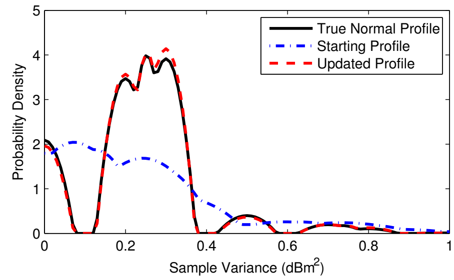


Figure 5: Illustration of the normal profile construction.



(a) Profile Update Example 1



(b) Profile Update Example 2

Figure 6: Comparison between the starting profile, updated profile and the true profile for the sample variance in the case of two different streams. As shown, the updated and true profiles are almost congruent.

to human activity (Figure 1). Second, the variance is a relative measure as it measures difference about the mean. This implies that sample variance profiles will be less affected by the temporal variation shifts that occur in the signal strength histograms, as compared to sample mean profiles (Figure 4), leading to higher robustness [27].

3.1.2 *Normal Profile Construction*

This module constructs the initial silence profiles based on a short offline phase, typically ***two minutes***. The silence (normal) profile of a stream is represented by the PDF of the variance values calculated from a moving sliding window over the training data (Figure 5). The density function of the variance is estimated non-parametrically using kernel density estimation [28]. This is done for each stream independently.

3.1.3 *Basic Detection Procedure*

In the monitoring phase, the *Basic Detection Module* examines each stream and calculates the variance of a moving sliding window over its readings, and then decides whether there is an anomalous behavior or not, based on a significance threshold applied to the variance profile (density) constructed in the offline phase. It also calculates an *anomaly score* for each stream, to express the significance of the generated alarms.

3.1.4 *Adapting to Profile Changes*

To adapt to changes in the environment, the *Normal Profile Update Module* updates the normal profiles constructed in the offline phase while the system is operating in the monitoring phase. This module uses the anomaly scores assigned by the basic detection module, as it mainly updates the variance profiles using groups of readings that have low anomaly scores in average. Figure 6 provides two examples for comparing the starting, updated and true sample variance silence profiles at the end of the experiment discussed in Section 4. It can

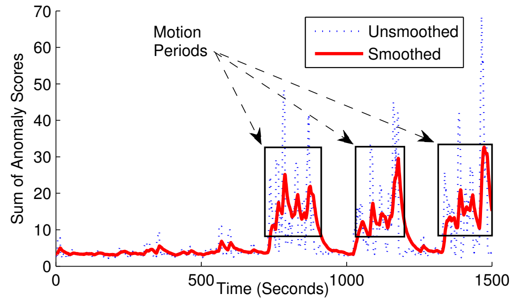
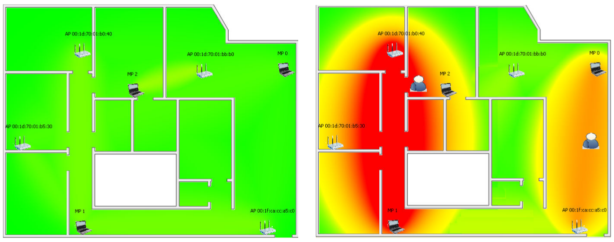


Figure 7: The behavior of the sum of anomaly scores used by the decision refinement module.



(a) Silence State (b) Motion State

Figure 8: A sample output of the Region Tracking Interface.

be noted that the true normal profiles and the updated profiles are almost the same.

3.1.5 Decision Refinement (Noise Effect Reduction)

The *Decision Refinement Module* aims at enhancing the detection accuracy by fusing the states of all streams in the monitoring phase. It studies the behavior of a global anomaly score calculated by summing the individual anomaly scores assigned by the basic detection module to each stream. This module uses exponential smoothing to monitor the global anomaly score in order to reduce the noisy samples. Figure 7 illustrates how the decision refinement procedure works to reduce the noise effect through studying the smoothed sum of anomaly scores. As the figure shows, the human activity effect can be distinguished easily from the curve behavior.

3.1.6 Region Tracking Interface

This module provides an interface that visualizes the output of the above modules. This interface enables the user to identify the regions of the detected events (Figure 8) [1]. This interface mainly uses the anomaly scores values of all streams to produce the heat map shown in the figure.

[1]A video illustrating how this interface responds to human activity in a real experiment is available in [29].

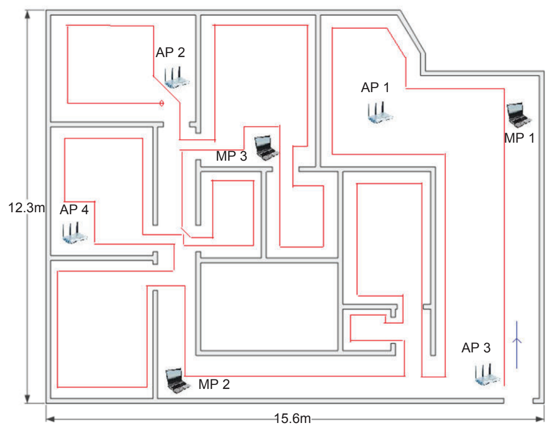


Figure 9: Testbed layout and motion pattern.

3.2 Uniqueness

The uniqueness in our research on device-free motion detection is mainly due to providing the following characteristics:

1. *RASID* allows the detection of entities without requiring them to carry any devices in standard WiFi networks.
2. Compared to other device-free technologies, such as infrared and camera-based systems, *RASID* uses the already installed WLAN infrastructure (only standard access points and laptops). No special hardware is needed.
3. *RASID* requires minimal training overhead, typically two minutes, to construct its silence profiles.
4. *RASID* continuously changes its profiles to adapt to dynamic changes in the environment providing robust performance.

4. RESULTS AND CONTRIBUTIONS

In this section, we briefly present the results of the system evaluation, and compare its accuracy and robustness to other *DfP* detection techniques: [21, 22]. Then, we discuss the contributions of this work in addition to challenges for future work.

4.1 Evaluation

4.1.1 Testbed and Data Collection

We conducted our experiment in a typical IEEE 802.11b environment in an office of approximately 2000 ft^2 (Figure 9). The testbed was covered with typical furniture. We used four Cisco Aironet 1130AG series access points and three DELL laptops equipped with D-Link AirPlus G+ DWL-650+ Wireless NICs.

For the data collection, sets of normal (silence) state readings and continuous motion readings were collected.

A total of about one hour and 15 minutes of data was collected. This included three motion sets, each covers the *entire area* of the testbed, as shown in Figure 9. The motion sets were collected while there is only one person moving inside the area. The system was trained only with the *first two minutes* of the data collected with the absence of human presence.

To evaluate the robustness of the system profiles, other testing profiles were collected two weeks after conducting the original experiment. This is to show how the system maintains its profiles when the training and testing data sets are time separated.

4.1.2 Evaluation Metrics

To analyze the detection accuracy of the system, we used two metrics: the false positive (FP) rate and the false negative (FN) rate. The FP rate refers to the probability that the system generates an alarm while there is no human motion inside the area, whereas the FN rate refers to the probability that the system fails to detect the motion anywhere in the area. We combine both metrics using the F-measure. It should be noted that the system parameters were adjusted based on the analysis provided in [30], and the overall 90^{th} percentile of detection latency was within one second.

4.1.3 Performance Results

In terms of the detection accuracy, Figure 10 shows the system detection accuracy for the different modules. As shown, using the basic detection module only leads to a high FP rate, since the two-minutes training period is not sufficient for one hour of operation. The profile update module reduced the high FP rate by about 50%, but resulted in some increase in the FN rate. The decision refinement module reduced both FP and FN rates due to the fusion of multiple streams (Figure 7). Overall, the system provided a false negative rate of 4.68%, and a false positive rate of 3.78%, achieving a total F-measure of 0.9574.

In terms of the robustness of the system profiles, Figure 11 shows a comparison with other *DfP* detection techniques in terms of the F-measure. As shown, *RASID* outperforms all the other techniques in both cases considered. In particular, the enhancement introduced by our system is more clear in the case when the testing profiles are separated two weeks from the training profiles. This is due to the robustness of the sample variance profiles that *RASID* maintains, in addition to employing techniques for adapting these profiles to the changes in the environment.

The results of evaluating the system in another testbed in addition to more analysis can be found in [30].

4.2 Contributions

The main contribution of this work is that we have shown that the typical wireless area networks can be used to detect human motion in large-scale areas with a high accuracy. This can provide a low cost solution to many applications including smart environments and intrusion detection. The proposed *RASID* system uses statistical anomaly detection techniques to provide high accuracy detection, while maintaining low-overhead and robustness to changes in the environment.

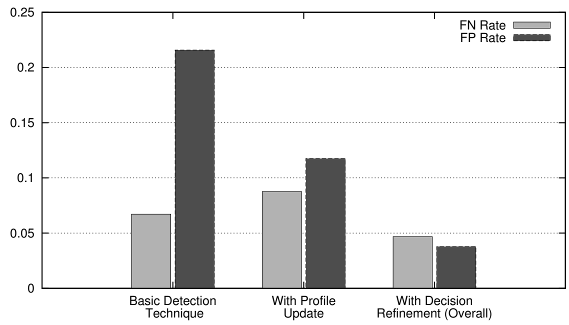


Figure 10: System detection accuracy results. The performance of the system after adding each module.

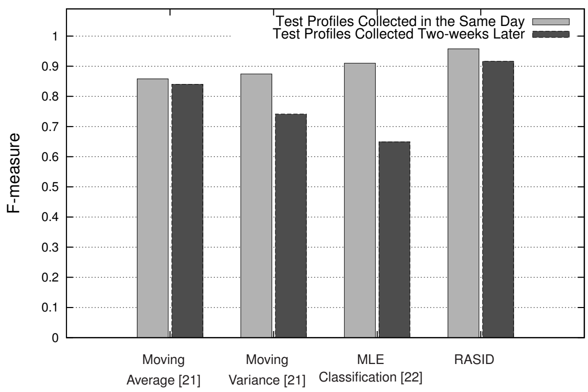


Figure 11: Performance comparison with previous *DfP* detection techniques.

4.3 Challenges

There are different challenges to be addressed in our future work. One challenge is to extend our work to accurately perform device-free tracking. Although the *RASID* system can give information about the regions of the detected entities, we aim to provide more accurate information about the exact locations of those entities. Another major challenge is to identify the characteristics of the detected entities. Such characteristics can include the number, class, name, size and shape of the entities. Other challenges include studying the possible sources of noise in typical wireless environments (e.g. other devices inside or outside the area of interest), and how to reduce their effect. Moreover, the site configuration (i.e. the positions of the APs and MPs) can be studied for optimizing the system performance.

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