MobiCom 2011 Poster: A Robust Technique for WLAN Device-free Passive Motion Detection

Ahmed E. Kosba[†] *ahmed.kosba@alexu.edu.eg*

Ahmed Saeed[‡] *ahmed.saeed@ejust.edu.eg*

Moustafa Youssef[†‡] *moustafa.youssef@ejust.edu.eg*

[†]Dept. of Comp. and Sys. Eng., Faculty of Engineering, Alexandria University, Egypt

[‡]Dept. of Comp. Sc. and Eng., Egypt-Japan Univ. of Sc. and Tech. (EJUST), Egypt

We present RASID: a system capable of detecting passive human motion using the already installed indoor wireless infrastructure. RASID applies a statistical anomaly detection technique to detect motion inside indoor environments by monitoring the changes in the wireless signal strength. The system also adapts to the environment changes and applies decision refinement procedures for enhancing the detection accuracy. Our results show that RASID can achieve an accurate detection capability, reaching 6% miss detection rate and 8% false alarm rate in a typical environment.

I. Introduction

Motivated by the wide use of wireless LANs for indoor communication, we introduced the concept of device-free passive *DfP* localization [1] which enables the localization of entities that do not carry any devices nor participate in the localization process. This concept depends on the fact that the presence and motion of entities in an RF environment affect the RF signals emitted by the wireless signal transmitters and received at the wireless signal receivers.

In this work, we present our research on *RASID*, a system that aims to provide a low-overhead, accurate and robust *DfP* motion detection in large-scale environments. *RASID* uses statistical anomaly detection techniques to detect motion inside indoor environments. It only constructs a profile, for the signal strength readings received at the MPs when there is *no human activity* during a short training phase leading to minimal deployment overhead. The system also employs a technique for adapting to the environment changes and for refining the detection decision. Moreover, it provides an interface through which the regions of the detected events are visualized.

RASID aims to provide a software-only solution on top of the already installed wireless networks and can have multiple applications. These include intrusion detection, sensor-less sensing, low cost surveillance, and smart buildings.

Our research on *RASID* is motivated by several factors: First, the technologies that can be used to provide the desired detection capability (e.g. cameras, IR sensors, radio tomographic imaging, pressure sensors, etc) share the requirement of installing special hardware. In addition, cameras and IR sensors are limited to line-of-sight vision and thus the cost of covering all site regions might be prohibitive. Moreover, regular cameras can fail to work in the dark or in the presence of smoke and they can cause privacy concerns. *RASID* tries to avoid such drawbacks by using the already installed wireless infrastructure without installing any special hardware. It also makes use of the fact that RF waves do not require LOS.

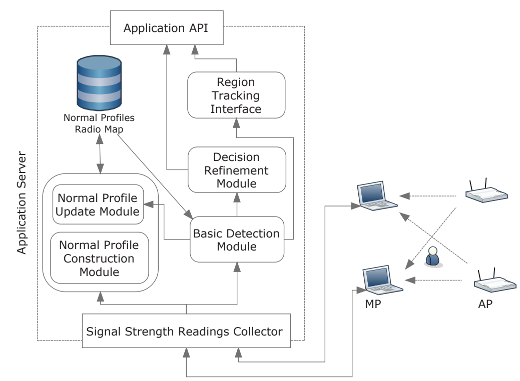


Figure 1: *RASID* system architecture.

From another perspective, the previously proposed techniques for WLAN *DfP* (e.g. [1, 2]) were found to provide good performance under strong assumptions, which may limit their application domain. For example, those techniques are not robust to changes in the environment. That is, they do not adapt to changes like furniture movement and/or humidity and temperature changes. In addition, using the maximum likelihood technique proposed in [2] requires the construction of a human motion profile that requires significant time for calibration when dealing with large-scale environments. This also can require access to private areas of a building, which makes the cost of this technique prohibitive.

RASID aims to avoid the above drawbacks by providing a robust technique that does not require high deployment overhead and has a mechanism to adapt to the environment changes. In Section II, we present *RASID* architecture and discuss its operation. Then, the evaluation of the system is presented in Section III followed by conclusions and future work.

II. RASID System Architecture and Operation

Figure 1 gives an overview of the system architecture. The system consists of signal transmitters, such as access points (APs), signal receivers or monitoring points (MPs), such as standard laptops, and an application server which collects and processes information about the received signals from each MP. 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.

The *Normal Profile Construction Module* constructs the initial silence profiles based on a short offline phase. It extracts the variance values from a moving sliding window over the training data and estimates its distribution (Figure 2). The density function of the variance is estimated using kernel density estimation. This is done for each stream independently.

The *Basic Detection Module* examines each stream in the monitoring phase 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 the variance profile constructed in the offline phase. It also calculates an anomaly score for each stream, to express the significance of the gener-

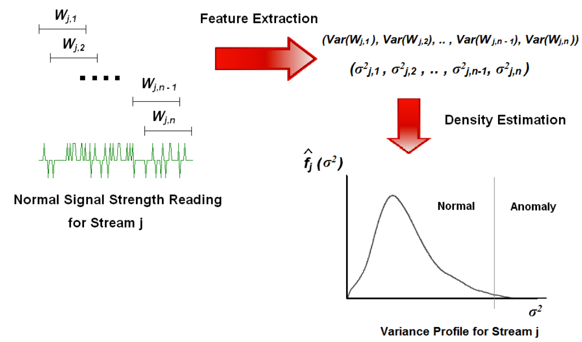
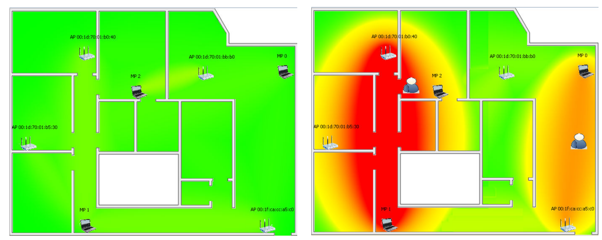


Figure 2: Illustration of the normal profile construction.



(a) Silence State (b) Two Persons Moving

Figure 3: A sample output of the Region Tracking Interface.

ated alarms.

The *Normal Profile Update Module* runs in the monitoring phase. This module updates the normal profiles constructed in the offline phase in order to adapt to changes in the environment. This is done by updating the variance profiles using groups of readings that have low anomaly scores in average.

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 for each stream. This module uses exponential smoothing to monitor the global anomaly score in order to reduce the noisy samples (Figure 5).

The *Region Tracking Interface* 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 3).

III. Evaluation

III.A. Testbed Setup

We conducted our experiment in a typical IEEE 802.11b environment in an office of approximately 2000 ft^2 (Figure 4). The testbed was covered with typical furniture. We used four Cisco Aironet 1130AG

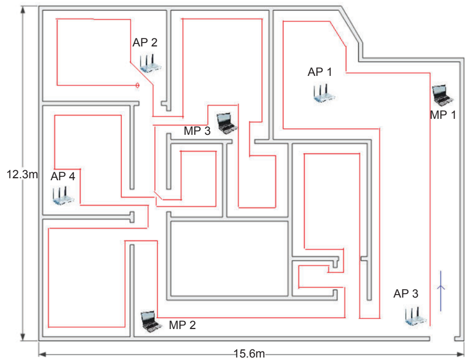


Figure 4: Testbed layout and motion pattern.

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 4. The motion sets were collected while there is only one person moving inside the area. The system was trained with the *first two minutes* of the data collected with the absence of human presence.

III.B. Results

We used two metrics to analyze the detection performance: 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 human motion anywhere in the area. We combine both metrics using the F-measure.

Table 1 summarizes the system performance for the experiment. It also shows the enhancement introduced by each module with respect to the F-measure. As shown, using the basic detection module only resulted in 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 40%, but resulted in some increase in the FN rate. The decision refinement module reduced both FP and FN rates, since it resists noise and makes use of the history of the state of activity inside the area. Figure 5 shows how the decision refinement procedure works.

	Basic Detection Module	Normal Profile Update Module	Decision Refinement Module
FN Rate	0.0611	0.1120	**0.06**
FP Rate	0.3841	0.2270	**0.08**
F-measure	0.8083	0.8397	**0.9227**
Enhancement	-	3.9%	9.8%

Table 1: System performance results.

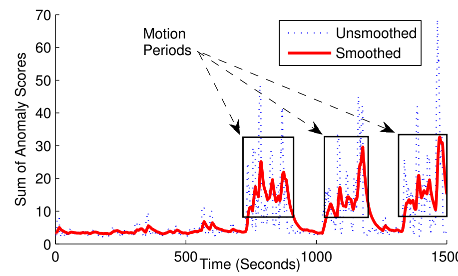


Figure 5: The behavior of the sum of anomaly scores used by the decision refinement module.

IV. Conclusion and Future Work

In this work, we presented the preliminary results of the *RASID* system that aims at indoor device-free passive motion detection using the already installed wireless infrastructure. *RASID* uses statistical anomaly detection techniques to provide the detection capability. Also, it employs a profile update technique to capture changes in the environment and to refine the detection decision. The system was evaluated in a typical office environment achieving a detection capability of 6% miss detection rate and 8% false alarm rate. For future work, we are currently studying noise reduction techniques in order to reduce the system false alarm rate without affecting the detection capability. In addition, we are devising an analytical model for the system operation. Moreover, factors like: site configuration (i.e. the positions of the APs and MPs) and effect of different hardware are to be studied.

References

[1] M. Youssef, M. Mah, and A. Agrawala, "Challenges: Device-free Passive Localization for Wireless Environments," in *MobiCom '07*. ACM, 2007, pp. 222–229.

[2] M. Moussa and M. Youssef, "Smart Devices for Smart Environments: Device-free Passive Detection in Real Environments," in *IEEE PerCom Workshops*, 2009.