Smart Devices for Smart Environments: Device-free Passive Detection in Real Environments

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***Abstract*—Device-free Passive (DfP) localization is a system envisioned to detect, track, and identify entities that do not carry any device, nor participate actively in the localization process. A DfP system allows using nominal WiFi equipment for intrusion detection, without using any extra hardware, adding smartness to any WiFi-enabled device. In this paper, we focus on the detection function of the DfP system in a real environment. We show that the performance of our previously developed algorithms for detection in a *controlled* environments, which achieved 100% recall and precision, degrades significantly when tested in a real environment. We present an alternative algorithm, based on the maximum likelihood estimator (MLE), that has a significant performance increase in a real environment. Our results show that the recall of the system increases by more than 10% when using the proposed MLE without affecting the system's precision.**

I. Introduction

Many location determination technologies have been proposed over the years, including: the GPS [1], infrared [2], ultrasonic [3], and radio frequency (RF) [4]. All these technologies share the requirement for a tracked object to carry a device to be tracked. In addition many of these technologies require the device being tracked to actively participate in the localization process by running part of the localization algorithm. This allows the system to provide the user with its location and other services related to the estimated location [5], [6].

The concept of Device-free Passive (DfP) localization was first introduced in [7]. Unlike most of the known location determination systems, the DfP system does not require the entity being located or tracked to carry any device. Moreover, it does not require it to participate actively in the localization process. The DfP system does not need any special hardware. For example, it can use the WiFi networks already installed for data transmission during the day, for intrusion detection during the night, without using any extra hardware.

The DfP system depends on the fact that RF signals, specially in the ranges of the common wireless data networks, are affected by changes in the environment. It records and analyzes physical quantities of the network, such as the received signal strength or the time of flight, to detect changes in the environment.

Figure 1 shows the different DfP system components. The system consists of signal transmitters, such as access points (APs), monitoring points (MPs), such as standard wireless sniffers, and an application server (AS) to process data and initiate actions as required. Applications of the DfP concept include: intrusion detection and tracking for home and office applications, low-cost and long-range asset protection, and enhancement of traditional security systems, such as motion detection and video surveillance by providing non-line-of-sight detection and lower deployment cost. Therefore, the DfP concept adds smartness to the existing wireless equipment for supporting smart environments.

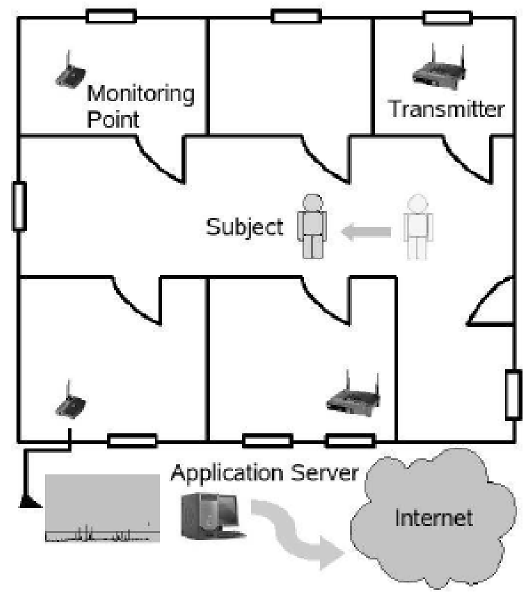

Fig. 1. An example showing the different DfP system components.

This paper focuses on the detection functionality of the DfP system in a ***real environment***. Detection refers to identifying whether there are changes in an area of interest or not. In [7], we presented two DfP detection techniques in a ***controlled environment***: moving average (MA) and moving variance (MV). The moving average technique compares two moving averages of received signal strength indicator (RSSI) with different window sizes. The shorter window size represents the current state, while the longer represents the static environment. An event is detected if the percentage change of the

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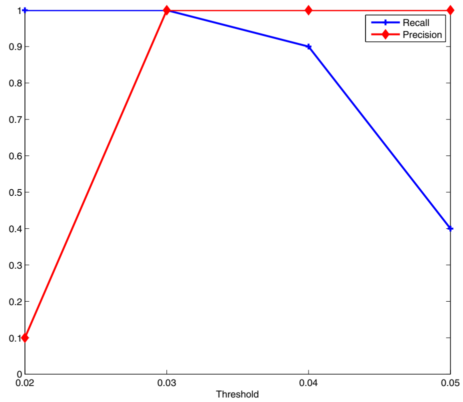


Fig. 2. Effect of changing the threshold on the performance of the moving average technique.

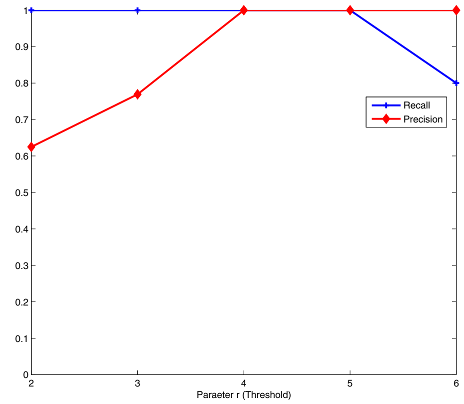


Fig. 3. Effect of changing the parameter r (threshold) on the performance of the moving variance technique.

two averages exceeds a certain threshold. The other technique, the moving variance, compares the moving variance of RSSI to the variance in a silence period. We give more details about the techniques in Section II.

Our evaluation of the two techniques in a controlled environment [7] shows that the two techniques can achieve 100% recall and precision, as shown in figures 2 and 3 for certain parameter values.

However, in a real environment, there are many challenges that need to be addressed to obtain comparable performance. In this paper, we evaluate the performance of the moving average and moving variance techniques in a real environment. We show that their performance degrades in a real environment and propose a new algorithm, based on the Maximum Likelihood Estimator (MLE) that enhances the performance of the DfP system in real environments. Our results show that the performance of the proposed MLE estimator is significantly better than the moving average and moving variance techniques. In particular, the MLE enhanced the recall of the system by more than 10% while maintaining the same precision. This a step toward designing robust device-free passive detection algorithms for real environments.

The rest of the paper is organized as follows: Section II gives a brief background on the previously proposed DfP detection techniques and highlights the need for a new algorithm. Section III describes the effect of the real environment on the system. Section IV presents an alternative algorithm that enhances the DfP performance in real environments. The performance of this algorithm is evaluated in Section V. Finally, Section VI concludes the paper.

II. Background

In this section, we provide a brief background on the moving average (MA) and moving variance (MV) detection techniques we introduced in [7]:

A. Moving Average Technique

In this technique, events are detected by comparing two moving averages of the RSSI of a single stream, with possibly different window sizes. The idea is to compare the long term signal behavior, which represents the static environment, to the short term behavior, which represents the current state, and if there is a significant change, based on a threshold, an event is detected.

More formally, let q_i be a series of raw measurements over time for one raw data stream, i.e. a *single* MP listening to a *single* access point. Let q_i be a series of raw measurements over time for one raw data stream. The averages $\alpha_{l,k}$ and $\alpha_{s,k}$ are defined as follows for time index k:

$$\alpha_{l,k} = \frac{1}{w_l} . \sum_{i=k}^{k+w_l-1} q_i \quad (1)$$

and

$$\alpha_{s,k} = \frac{1}{w_s} . \sum_{i=k+w_l}^{k+w_l+w_s-1} q_i \quad (2)$$

where w_l and w_s correspond to the window length for the two averages $\alpha_{l,k}$ and $\alpha_{s,k}$ respectively.

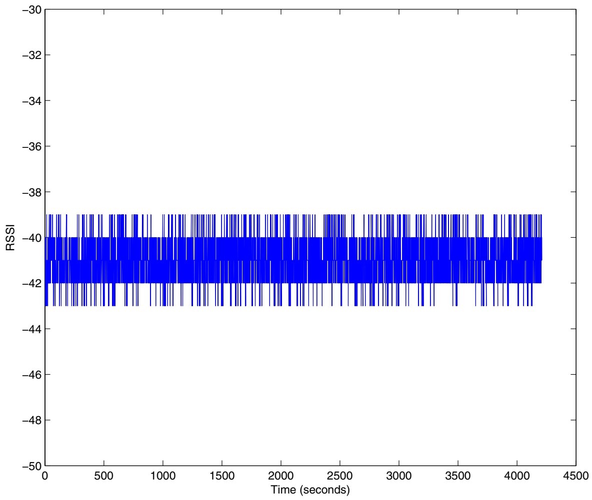
An event is declared when $|\frac{\alpha_{l,k}-\alpha_{s,k}}{\alpha_{l,k}}|$ exceeds a threshold (τ).

B. Moving Variance Technique

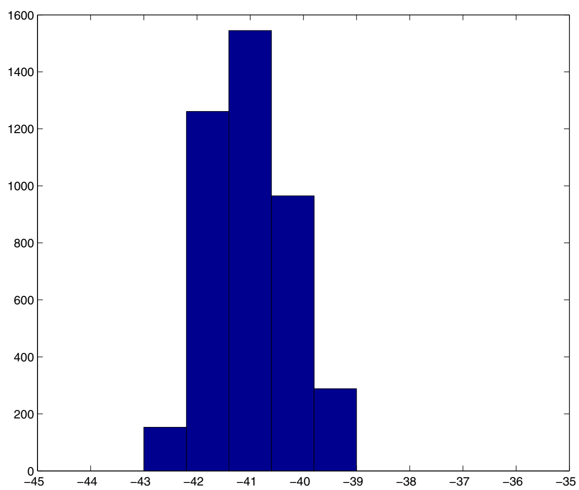
The second detection technique is similar to the first one except that it examines the moving variance of the raw data and compares it to the variance during the silence/static period. Let w be the window size used for calculating the variance. The variance, v_t, is computed as:

$$\overline{q_t} = \frac{1}{w} . \sum_{i=k}^{k+w-1} q_i \quad (3)$$

$$v_t = \frac{1}{w-1} . \sum_{i=k}^{k+w-1} (q_i - \overline{q_t})^2 \quad (4)$$



(a) Raw stream



(b) RSSI histogram

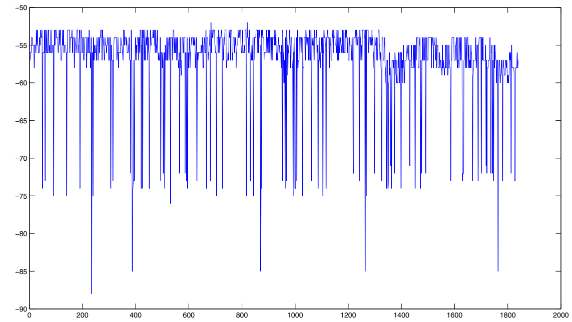
Fig. 4. Signal strength behavior in a controlled environment.

For a training period $[t_{start}, t_{end}]$, the average of the variances $\overline{v_t}$ and the standard deviation of the variance σ_v for the w-sized windows are computed as follows:

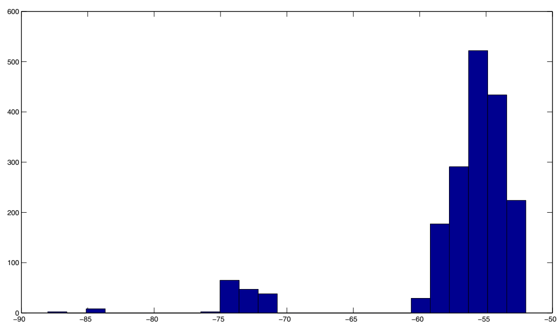
$$\overline{v_t} = \frac{1}{t_{end} - t_{start} + 1} \cdot \sum_{t=t_{start}}^{t_{end}} v_t \tag{5}$$

$$\sigma_v = \sqrt{\frac{1}{w-1} \cdot \sum_{t=t_{start}}^{t_{end}} (v_t - \overline{v_t})^2} \tag{6}$$

An event is declared if $v_t > \overline{v_t} + r.\sigma_v$ for an appropriate value of the parameter r.



(a) Raw stream



(b) RSSI histogram

Fig. 5. Signal strength behavior in a real environment.

C. Performance in a Controlled Environment

Our evaluation of the two techniques in a controlled environment [7] shows that the two techniques can achieve 100% recall and precision for some settings of the parameters, as shown in Figures 2 and 3. The rest of the paper focuses on the performance of the techniques in a real environment and developing better techniques for such environments.

III. Device-free Passive Localization in a Real Environment

A. Effect of the Real Environment

RF signals are affected by changes in the environment, specially in the frequency ranges of the common data networks, such as WiFi. Generally, the signal power level shows clear temporal and spatial variability [8], [9]. Temporal variability is mainly caused by the motion of entities, such as people, while spatial variability is the result of multi-path effects and changes in the distance between the transmitter and the receiver.

Figures 4 and 5 show examples of RSSI stream and its corresponding signal strength histogram in controlled and real environments, respectively, using the same hardware. The results indicate that, as expected, the received power level of the signal is more variable in the real environment. This is shown by the higher variability of the raw data and the wider range of the histogram of the RSSI in a real environment as compared to a controlled environment. This is mainly caused

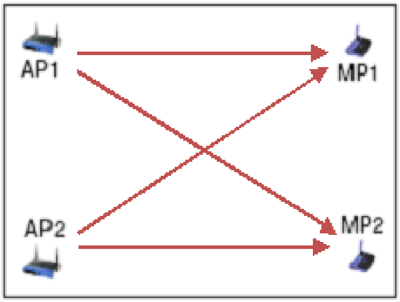


Fig. 6. Experiment setup, showing the four recorded data streams.

by the uncontrolled motion of entities in the environment. These variabilities makes the detection functionality more challenging in a real environment compared to the detection in a controlled environment.

B. DfP Performance in a Real Environment

In this section, we evaluate the performance of the DfP system in a real environment, using the two techniques proposed in [7]: the moving average and the moving variance.

The experiment setup is shown in Figure 6. The experiments were performed in an 802.11b environment, which runs at the 2.4GHz frequency range. Both access points used were standard Cisco APs, model 1130, while the monitoring points were two standard Dell laptops with Orinoco Gold cards. The MPs used the active scanning approach, which is part of the IEEE 802.1 standard [10] to obtain recorded the RSSI from each access point with a sampling rate of 10 samples per second. This setup resulted in four streams of raw data, one stream per each (AP, MP) pair. We performed the experiments during day time, where people were active in the building, in a lab on our university campus. The APs and the MPs were placed at the corners of a 5 m $\times$ 5 m square area, at a height of 1 m from the ground. We define the "event" state as the state when a person enters the area of interest, while the "silence" state is the state where no one is in the area of interest.

To evaluate the performance, we used two metrics: Precision, to evaluate the exactness of the detected events, and Recall, to evaluate their completeness. Precision can be defined as the number of correct events detected, divided by the the number of all events detected. While Recall is the number of correct events detected over the actual number of events in the experiment. Figure 7 shows the performance of the system in a real environment, versus different thresholds, using the moving average technique. Figure 8 shows the performance of the system in a real environment, versus the moving window size, using the moving variance technique. It is clear from the figures that the performance of the system in a real environment is significantly worse than its performance in a controlled environment. This motivates the need for a new approach for detection in a real environment.

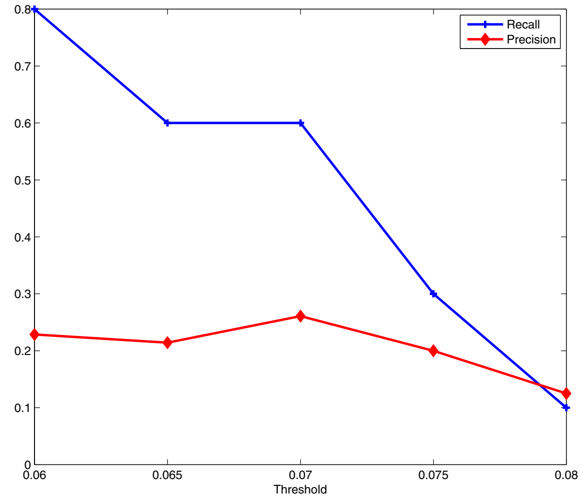


Fig. 7. System performance in a real environment using the moving average technique.

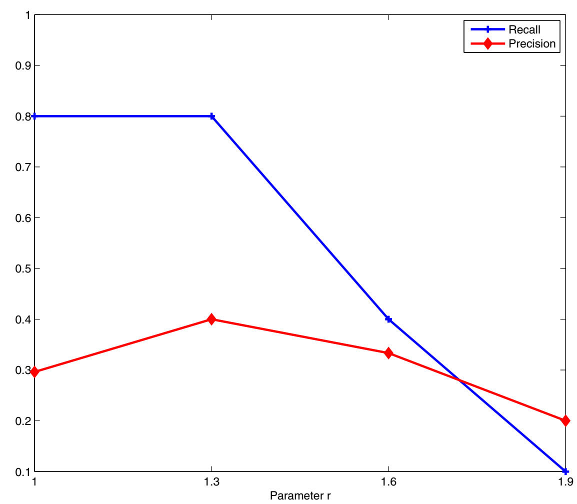


Fig. 8. System performance in a real environment using the moving variance technique.

IV. Improving Detection in a Real Environment

In this section we propose an alternative detection technique, the maximum likelihood, as a better DfP detection technique in a real environment.

A. System Model

We consider a network of n APs and m MPs, giving $n \times m$ raw data streams, each corresponding to an (AP, MP) pair. For each stream, we process a window of samples of size w simultaneously. Let $\bar{s}$ be the vector of observations within a window, i.e. $\bar{s} = [q_0, q_1, ..., q_{w-1}]$. We define two possible hypotheses: H_0 and H_1, representing the silence state and the event state, respectively. The silence state corresponds to the probability distribution $P_0(\bar{s})$ and the event state corresponds to the probability distribution $P_1(\bar{s})$. Thus, we can write:

$$H_0 : \bar{s} \sim P_0(\bar{s}) \tag{7}$$
$$H_1 : \bar{s} \sim P_1(\bar{s}) \tag{8}$$

The system works in two phases: offline phase and online phase.

1) Offline Phase: During the offline phase, the probability distributions $P_0(\bar{s})$ and $P_1(\bar{s})$ are estimated by constructing the two histograms of the collected samples: one representing the silence state and one representing the event state. The offline phase works as a training phase. The system is operated in this phase whenever the silence and event probability distributions are to be updated. For example when the system is first deployed, or when some changes to the environment in which the system is operating occur.

2) Online Phase: In the online detection phase, the system collects w samples $(\bar{s})$ from a single stream and applies the maximum likelihood test to $\bar{s}$. Assuming that the samples are independent, The probability functions are defined as:

$$P_0(\bar{s}) = \prod_{i=0}^{w-1} P_0(q_i) \tag{9}$$
$$P_1(\bar{s}) = \prod_{i=0}^{w-1} P_1(q_i) \tag{10}$$

where $P_0(q_i)$ and $P_1(q_i)$ can be obtained from the histograms of the silence state and event state respectively, constructed during the offline phase.

The likelihood ratio, $\Lambda(\bar{s})$ is given by:

$$\Lambda(\bar{s}) = \frac{P_0(\bar{s})}{P_1(\bar{s})} \tag{11}$$

Thus, the decision rule can be expressed as:

$$\Lambda(\bar{s}) = \begin{cases} \geq 1 & \text{decide } H_0 \text{ is true} \\ < 1 & \text{decide } H_1 \text{ is true} \end{cases} \tag{12}$$

This algorithm is applied to each raw data stream separately. Since each stream is very noisy by itself, we declare an event only if N or more events detects the individual streams concurrently. To account for slight variation of detection time between streams, we use a time buffer parameter b. Therefore, two detections of two different streams are considered concurrent if they occur within a time period b [1].

V. Experimental Results

This section evaluates the performance of the proposed MLE algorithm in a real environment and compares it to the performance of the moving average and moving variance techniques.

[1]Our previous results show that the performance of the system is not sensitive to the time parameter value [7].

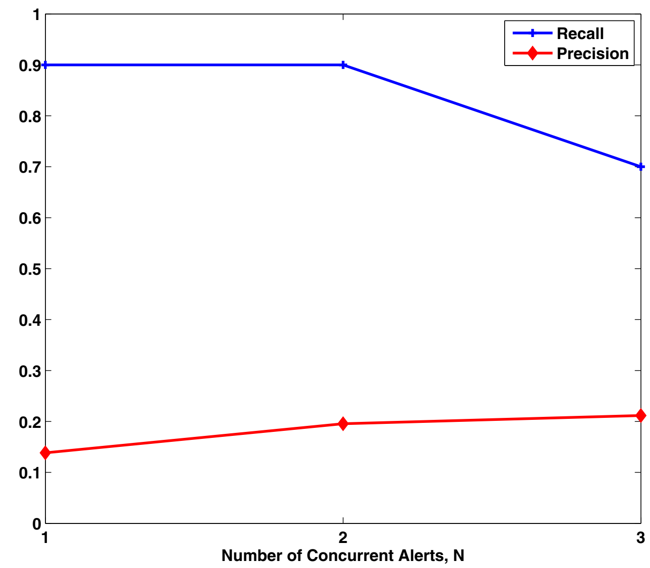


Fig. 9. Performance of the different techniques in a real environment versus the number of concurrent detections, N.

A. Experiment Setup

We used the same experimental setup and metrics as described in Section III-B.

B. Performance Compared to Previous Techniques

In this section, we present the performance of our proposed algorithm in a real environment. Since the different algorithms have different parameters, we present them in different figures. Figure 9 shows the recall and precision of the MLE technique. The results show that the MLE estimator can enhance the recall of the system by more than 10%, while maintaining comparable precision as compared to the moving average and moving variance techniques (shown in figures 7 and 8).

the figure also shows that as the parameter N increases, the recall decreases, since we require more votes to declare a global detection, and precision increases, since the number of false alarms decreases. The MLE can achieve 90% recall. A high recall value is important for applications that require high detection capabilities with minimum false negatives.

VI. Conclusion

In this work, we considered the performance of the Device-free Passive (DfP) detection system in a real environment. We evaluated the performance of the system using our two previously suggested algorithms: the moving average and the moving variance. We showed that although those algorithms gave a 100% recall and precision in a controlled environment, their performance severely degrades when tested in a real environment. We proposed another algorithm, the maximum likelihood estimator, as an alternative. Our experimental results showed that the performance of the DfP system, in a real environment, was significantly improved using the proposed algorithm. Currently, we are working on enhancing the MLE to further enhance the accuracy, especially for increasing the precision of the system. In addition, we are developing algorithms for device-free passive tracking and identification.

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