Challenges: Device-free Passive Localization for Wireless Environments

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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 the concept of Device-free Passive (DfP) localization. A DfP system is envisioned to be able to detect, track, and identify entities that do not carry any device, nor participate actively in the localization process. The system works by monitoring and processing changes in the received physical signals at one or more monitoring points to detect changes in the environment. Applications for DfP systems include intrusion detection and *tracking*, protecting outdoor assets, such as pipelines, railroad tracks, and perimeters.

We describe the DfP system's architecture and the challenges that need to be addressed to materialize a DfP system. We show the feasibility of the system by describing algorithms for implementing different functionalities of a DfP system that works with nominal WiFi equipment. We present two techniques for intrusion detection and a technique for tracking a single intruder. Our results show that the system can achieve very high probability of detection and tracking with very few false positives. We also identify different research directions for addressing the challenges of realizing a DfP system.

Categories and Subject Descriptors

C.2.4 [**Computer-Communication Networks**]: Distributed Systems—*Distributed applications*; H.4 [**Information Systems Applications**]: Miscellaneous

General Terms

Algorithms, Experimentation, Measurement, Security

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Keywords

Device-free localization, passive localization, passive radio map

1. INTRODUCTION

Many location determination technologies have been proposed over the years, including: the GPS [3], infrared [13], ultrasonic [10], and radio frequency (RF) [2]. 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 [6, 16].

In this paper, we introduce the concept of device-free passive (DfP) localization, in which the tracked entity need neither carry devices nor participate actively in the localization algorithm. The idea is to use installed wireless data networks to detect changes in the environment and track the location of entities passively and without requiring any devices to be attached to these entities. The DfP concept relies on the fact that RF signals are affected by changes in the environment, especially for the frequency ranges of the common wireless data networks that are currently deployed, such as WiFi, or envisioned, such as WiMax. By placing monitoring stations that continuously record physical quantities, such as signal strength or time-of-flight, DfP can analyze these signals to detect the changes in the environment and correlate them with entities and their locations.

Figure 1 gives an overview of a DfP system's components. The DfP system we envision consists of signal transmitters, for example access points and stations used in traditional WiFi deployment, monitoring points, for example standard wireless sniffers, along with an application server for processing and initiating actions as needed. Figure 2 shows an example of the measured changes of the environment due to the movement of a person. The time of different events is indicated by $E1$ through $E10$. DfP functions include detecting the presence or absence of entities, tracking entities, and identifying entities.

DfP can be useful in many practical applications including: intrusion detection and tracking for home and office applications, which could enhance the safety of law-enforcement personnel, and low-cost long-range asset protection, e.g. border protection or protecting railroad tracks, thereby increasing the value of data networks. In addition, DfP can be used

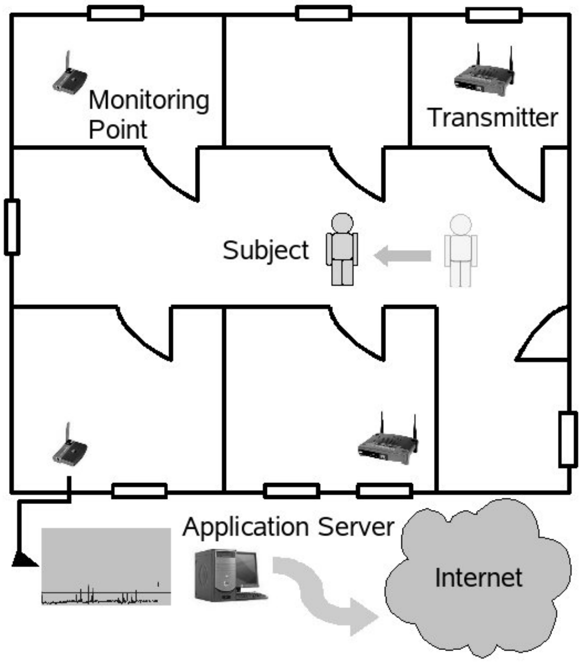


Figure 1: An example of the different components of a DfP system.

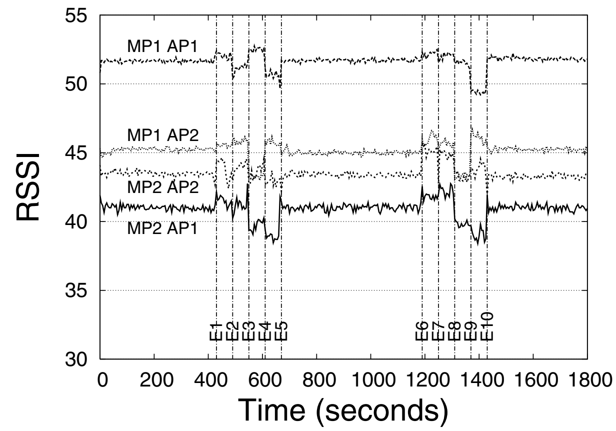


Figure 2: An example of changes in the environment due to the movement of a person (raw data) reported for four different transmitter-receiver pairs. The time of different events, such as movement of a person, is indicated by $E1$ through $E10$.

to enhance traditional security systems, such as motion detection and video surveillance by providing non-line-of-sight detection and lower deployment cost.

Although the concept of DfP looks promising for a number of applications, there are a number of challenges that need to be addressed, These challenges include: handling the noisy physical signal samples to obtain consistent events recognition and tracking, tracking an entity location, and identifying an entity. In this context, we make three contributions is this paper:

- We define the concept of Device-free Passive localization.
- We study the feasibility of DfP. In particular, we seek to find answers to two main questions: (1) by monitoring a physical quantity at one or more locations in an area of interest, where a wireless network is deployed, can we reliably detect changes in the environment? and (2) when we detect changes, can we quantify them? For example, can we determine the number of objects that caused the changes and their location? We present algorithms that can be used for different functions of DfP.
- We identify and discuss several research challenges that exist in realizing both the algorithms and infrastructure support.

The rest of the paper is organized as follows: Section 2 discusses related work. Section 3 introduces the DfP concept and identifies the different subfunctions of a DfP system. Section 4 describes a number of algorithms that address the feasibility of DfP. Section 5 identifies several challenges in realizing DfP in actual environments and finally Section 6 summarizes the paper.

2. RELATED WORK

Many systems over the years have tackled the localization problem including the GPS [3] system, infrared [13], ultrasonic [10], and radio frequency (RF) [2, 8, 16, 21].

All these systems either require the tracked entity to be associated with a device that is being track or requires the device to actively participate in the localization algorithm. Similar to the DfP concept, radar-based techniques, e.g. [11], computer vision based systems, e.g. [7], and physical contact systems, e.g. [9] do not these requirements. However, these systems require specialized hardware and have a limited range and high installment cost, which limits their practical aspects. DfP does not require specialized hardware. In addition it can be considered as an abstraction for such systems.

In summary, the DfP localization concept is unique in detecting, tracking, and identifying entities without requiring any attached devices or active participation in the localization algorithms. In addition, it works with the hardware already installed for the communication network and thus increases the value of the network used for localization.

3. OVERVIEW AND CHALLENGES

The DfP problem can be stated as: given an environment where wireless devices and wireless monitoring stations are installed, we need to detect, track, and identify entities in the environment. By “entity” we mean an object that can cause changes to the environment, such as people and furniture.

The above formal definition is the most general definition for the problem. In this paper, we identify the challenges associated with the DfP problem and study its feasibility. From the definition, we can identify the following three subfunctions for the DfP problem:

1. **Detection** refers to identifying whether there are changes in an area of interest or not. This may also include the detection of the number of entities that caused this change. This can be useful for intrusion detection applications, where automatic alarms can be sent to law enforcement personnel or other interested parties.

2. **Tracking** refers to tracking the position of entities inside the area of interest. This can be for a single entity or multiple entities, with variable complexity. Detecting intruders' positions may reduce the risk of dealing with them.

3. **Identification** refers to detecting the identity of the entities that caused the changes in the physical environment. This can be done at different levels, including detecting the type of entity, its identity, its size, mass, shape, and/or composition.

The DfP concept is based on the fact that RF signals are affected by the presence of people and objects in the environment [5,12]. The extent of the impact depends on the location of the entity relative to the source of the transmitted signal. A DfP system correlates any changes in the physical quantity with the changes to the environment due to object presence.

3.1 Goals

After defining the different subfunctions of the DfP problem, the contribution of this paper is to study the feasibility of the implementing these subfunctions. In addition, we define other research challenges that need to be addressed for the DfP problem to become a practical system.

4. DEVICE-FREE PASSIVE LOCALIZATION APPROACHES

In this section, we provide actual experimental results to demonstrate feasibility of the DfP concepts along with algorithms for solving the detection and tracking subfunctions of the DfP problem. We defer the discussion of the identification function to the next section. We start by listing our assumptions and describing the testbed environment we used to evaluate the proposed algorithms.

4.1 Assumptions and Test Environment

As an example of a typical environment for DfP, our experiment is conducted in an 802.11b environment, which runs at the 2.4GHz frequency range. Although different physical signals can be measured, we use the Received Signal Strength Indicator (RSSI) values reported by the wireless cards for this experiment. In the infrastructure mode of the 802.11 protocol, APs broadcast beacons, usually every 100 ms. In addition, the RSSI values associated with all other frame types can also be extracted. When a frame is received by a card, it not only extracts and supplies data to the higher layers, but also notes the RSSI values which are reported in the header of the link layer frame. Other possible signals that can be exploited are the noise level and time of flight.

Our measurements, taken during the daytime, indicate a significant variability in the RSSI, both temporally as well as spatially. The spatial variability is usually due to the multi-path effects in a typical building and changes of distance between the transmitter and the receiver. The temporal variability is usually due to the movement of entities which affect the 2.4GHz signal. The most common such entities are people, who rarely remain perfectly still. Their movements result in change of the RSSI values. Consider a situation in which we have a quiescent RF environment such that there is no movement or change of any type. Clearly if the beacon frame is sent with the same power every time, the RSSI recorded should also be the same. We confirmed this by making detailed measurements overnight. The variability of the RSSI nearly disappeared from 11 PM to 6 AM when there were no people around. Further controlled experiments confirmed that if a person comes in during the night, the presence can be detected by monitoring the RSSI.

4.2 Testbed

Referring to Figure 1, the access points (APs) represent the transmitting units while the wireless sniffers represent the Monitoring Points (MPs). Our algorithms run on an application server (AS). The AS knows about the topology of the protected area, i.e. the location of the APs and the MPs. All MPs send the measured RSSI along with their IDs and a time stamp to the AS, which is responsible for carrying out the analysis and raising alarms as required. Note that the major components of the experimental system are the APs and the MPs. Any device capable of receiving Wi-Fi signal is capable of operating as an MP. For instance, APs may operate as MPs for other APs. In addition, the client computers in the area of interest can run the software necessary to carry out the MP functions. The Application Server is a dedicated computer. However, the workload of AS is small enough that this functionality can also be provided by executing the AS software concurrently with other tasks.

We use two Cisco Aironet 350 Series APs and two MPs with Orinoco Silver cards in the area of interest. Each monitoring point records the RSSI from each access point's beacons, which broadcast every 100 ms. Both access points were running on the same channel[1]. This gives us four streams of raw data for processing, as shown in Figure 2. More experiments with different placements of APs and MPs can be found in the accompanying technical report [20].

In each experiment the MPs record for approximately 1800 sec. While the MPs are recording, a person walks and pauses for roughly 60 seconds at a series of four positions [2]. Each position is three feet from the previous position. Thereafter the person leaves the room. This process was repeated a second time during each experiment to test repeatability. We have a total of 10 events that can be detected. Figure 3 shows the layout of the experiment.

4.2.1 *Evaluation*

We use three metrics to quantify the performance of the detection and tracking capability of the proposed algorithms:

1. **Probability of detection**: which is the probability that the system will correctly identify events (changes in the environment). This is equal to one minus the probability of false negatives.

2. **Number of false positives**: which is the number of times the system incorrectly identifies a silence period

[1]For multiple channels, the monitoring points can be configured to periodically switch between channels.

[2]We believe that changing the order of locations should not affect the results, as what matters is the person's location and not the history of movement.

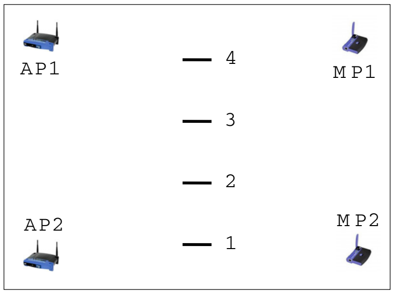


Figure 3: Experiment layout. The numbers represent the location of pauses.

as an event during the entire experiment time (1800 seconds).

3. **Tracking accuracy**: which is the probability of correctly identifying the user location to characterize the tracking performance.

4.3 Detection

Detection refers to identifying whether there are changes in an area of interest or not. This may also include the detection of the number of entities that caused this change. We focus here on detecting that a change occurred.

Consider the case where the AS uses one data stream of a single (MP, AP) pair for detecting events. This may be ambiguous for a reliable event detection. For example, Figure 2 shows that the second raw data stream (MP1, AP2) cannot distinguish the person's movement from the first to the second location (corresponding to events $E1$ and $E2$). In order to reduce this ambiguity, and hence enhance the reliability of detection, we combine different raw data streams to give the overall system detection. We describe two different statistical techniques to detect events. The first technique is based on moving averages and the second is based on the variance.

4.3.1 Moving Average Based Detection

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.

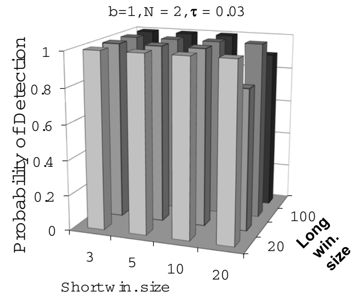
More formally, let q_i be a series of raw measurements over time for one raw data stream[3], i.e. a *single* MP listening to a *single* access point. The averages $\alpha_{l,k}$ and $\alpha_{s,k}$ are defined as follows for time index k:

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

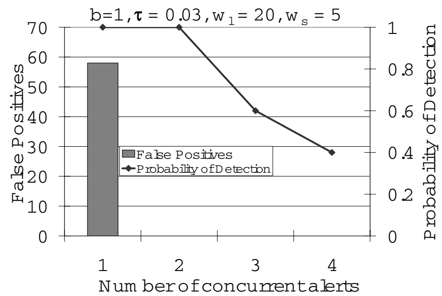
and

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

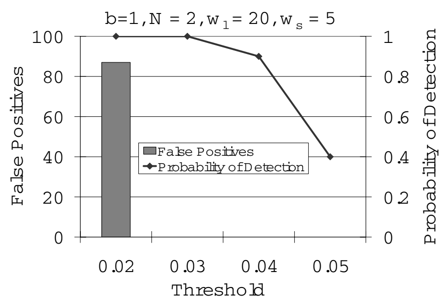
[3]Note that some samples may be missing due to collisions at the MAC layer. In this case, the algorithm works on the latest w_l samples.



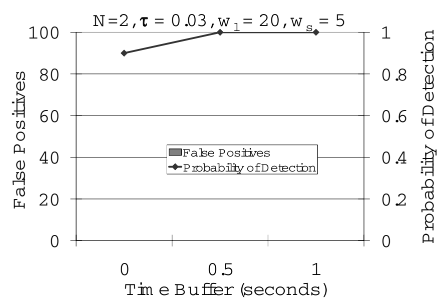
(a) Window size (w_l, w_s)



(b) No. alerts (N)



(c) Threshold (τ)



(d) Time buffer (b)

Figure 4: Effect of different parameters on the moving average technique.

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

When the relative difference between the two averages, $|\frac{\alpha_{l,k}-\alpha_{s,k}}{\alpha_{l,k}}|$, exceeds a threshold ($\tau$), we declare an event detection for the time corresponding to $t = k + w_s$. The AS computes $\alpha_{l,k}$ and $\alpha_{s,k}$ periodically to check for event detection.

As noted before, the system combines a tunable number of these alerts (N) from individual streams that give simultaneous or near simultaneous detections to increase the overall

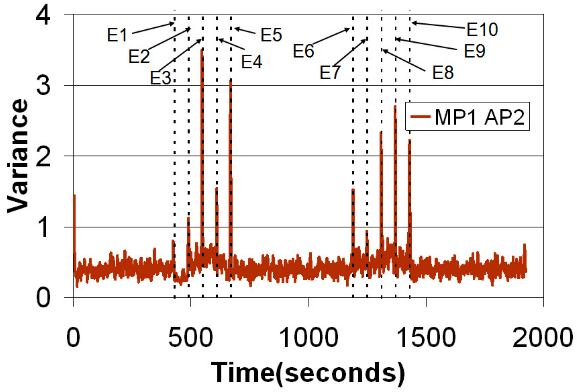


Figure 5: The effect of applying the moving variance technique to the raw data.

system performance. The idea is to declare an event detection if N individual alerts occur within a certain period. We call this period the alert time buffer (b). Figure 4 shows the effect of the different parameters on performance. We can see from the figures that, as expected, increasing either the number of concurrent alerts used for detection (N) or the detection threshold (τ) reduces the probability of detection and decreases the number of false positives. The number of false positives is insensitive to the time buffer duration (b) and the probability of detection increases as the time buffer duration increases. The best values for the parameters are: $(w_l = 20, w_s = 5, N = 2, \tau = 0.03, b = 1)$. This gives a 1.0 probability of detection with zero false positives.

4.3.2 Moving Variance Based Detection

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. We compute the variance, v_t, as:

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

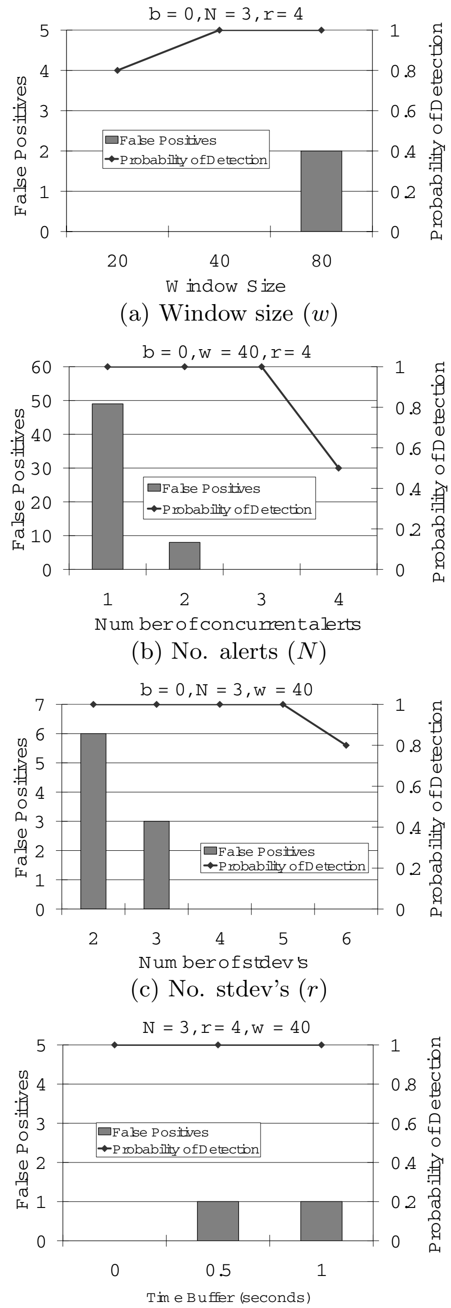
$$v_t = \frac{1}{w-1}.\sum_{i=k}^{k+w-1} (q_i - \overline{q_t})^2 \tag{4}$$

The detection criterion for any series q_i is based on the variance of the training silence/static period. For a training period $[t_{start}, t_{end}]$, we compute the average of the variances $\overline{v_t}$ and the standard deviation of the variance σ_v for the w-sized windows within it.

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

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

The moving variance detection technique of the AS detects an event at time $t + w$ for a single raw stream when $v_t > \overline{v_t} + r.\sigma_v$ for an appropriate value of the parameter r. For a normally distributed variance measurements v_t, values



(a) Window size (w)

(b) No. alerts (N)

(c) No. stdev's (r)

(d) Time buffer (b)

Figure 6: Effect of different parameters on the moving average technique.

above the threshold will be r standard deviations above the mean.

Again, the system combines a tunable number of these alerts (N) from individual streams that give simultaneous or near simultaneous detections, based on a time buffer (b) to increase the overall system performance.

Figure 5 shows the moving variance applied to the (MP1, AP2) stream of the raw data in Figure 2. The figure shows that the system can detect the events, though one stream may not be adequate as it may lead to false positives. Figure

6 shows the effect of different parameters on the performance of the moving variance technique. The results match the intuition: Increasing the variance calculation window (w) increases both the probability of detection and the number of false positives. Increasing either the number of concurrent alerts used for detection (N) or the number of standard deviations (r) reduces the probability of detection and decreases the number of false positives. The probability of detection is insensitive to the time buffer duration (b) and the number of false positives increases as the time buffer duration increases. The best values for the parameters are: ($w = 40, N = 3, r = 4, b = 0$). This gives 1.0 probability of detection with zero false positives.

4.4 Tracking

In order to perform tracking, we need to capture the relation between signal strength and distance. Since the relation between signal strength and distance is very complex in indoor environments [15], due to the multi-path effect and other phenomena, we need to capture this relation at different locations in the area of interest through a radio map. A radio map is a structure that stores information about the signal strength at different locations in the area of interest [16, 17]. This is usually constructed once during an offline phase. This radio map can be constructed automatically, based on signal propagation models [1] or can be constructed manually. We focus in this section on the manually constructed radio map and defer our discussion about the automatic construction to the next section.

4.4.1 Passive Radio Map Construction

For the purpose of a DfP system, we call the radio map a "*passive*" radio map, in contrast to the "active" radio map constructed by the current WLAN location determination systems.

Note that the radio map construction process for a passive radio map is different from the radio construction process for the traditional active radio map. For an active radio map, e.g. as in [2], a person carrying an active device stands at the radio map locations and the signal strength characteristics are recorded based on this device. For constructing a passive radio map, a person stands without carrying any device and the signal strength characteristics are recorded at the MPs as received from the APs. The same difference applies to the automatic construction technique as discussed in the next section.

There are different ways of constructing the radio map. We use the same method in the Horus [14, 16–19] active location determination system where we store at each radio map point the signal strength histograms from different APs. For the passive radio map building, we store at each point of the radio map the signal strength histogram for each raw data stream, where each data stream corresponds to an (AP, MP) pair.

4.4.2 Passive Tracking

Based on the constructed Radio map, we use a Bayesian-inversion based inference algorithm to compare the received signal strength vector, which contains an entry for each raw data stream, to the signal strength at the different radio map points whose signal strength is stored in the radio map.

More formally, given a signal strength vector ($\overline{s}$) for the signal strength readings at different MPs from different APs,

Table 1: Tracking results for two different experiments.

Configuration	Exp. 1 as training	Exp. 2 as training
100% Accuracy	86.3%	89.7%
Average Accuracy	0.685 ft	0.515 ft

with an entry for each pair of (AP, MP), we want to find the location l in the radio map that maximizes the probability $P(l/\overline{s})$. This can be written as:

$$\begin{aligned} \arg\max_l P(l/\overline{s}) &= \arg\max_l P(\overline{s}/l).\frac{P(l)}{P(\overline{s})} \\ &= \arg\max_l P(\overline{s}/l).P(l) \end{aligned} \tag{7}$$

Assuming that all locations are equally probable, the term $P(l)$ can be factored out from the maximization process in Equation 7. This leads to

$$\arg\max_l P(l/\overline{s}) = \arg\max_l P(\overline{s}/l) \tag{8}$$

where $P(\overline{s}/l)$ can be obtained form the constructed radio map.

Table 1 shows the probability of correctly identifying the location of the person and the average accuracy. The two columns represent the case when we used the first experiment as a training data and the second for testing and vice versa. The results show that we can obtain tracking accuracy between 86.3% and 89.7% with simple algorithms.

4.5 Discussion

Experiments in this section, along with the experiments in the accompanying technical report [20], show the feasibility of the DfP concept in the studied environment. We presented two different algorithms for detection and showed that a 1.0 detection probability was achieved with zero false positives. In addition, we introduced the concept of a passive radio map and used it to present an algorithm for passive location tracking. Further experiments may be needed to further show the feasibility of the DfP system in different environments.

5. CHALLENGES

In this section, we describe the different challenges that still need to be addressed to solve the identification problem, multiple person tracking, and ease the DfP system implementation, such as the automatic construction of the passive radio map. In addition, we present different research directions related to the DfP concept.

5.1 Identification Function

One of the main challenges that remains to be addressed is the entity identification problem. This refers to identifying the type or identity/name of the entity being tracked, its size, mass, shape, and/or composition. One approach for addressing this challenge is by constructing a "DfP-profile" for different entities that captures their characteristics and matching them to the profile of identified entities. For example, since different materials have different reflection coefficients, it may be useful to use this property in constructing this profile. Similar ideas have been proposed before for constructing human profiles based on using pressure sensors as in [9]. This opens the possibility for research in this challenging area. Automatic construction of the passive radio map can also help in identifying the features that should be captured by a DfP-profile.

5.2 Handling the Number of Entities

All the experiments performed for this paper were based on a single entity/person. Other challenges are how to detect the number of entities that caused a change in the environment and how to track them. This may not be an issue for events that are spatially separated by a large distance, as the physical signal being monitored may not be affected by far away entities. In this case, this will be treated as separate independent events.

The real challenge lies in handling multiple entities causing changes in the same area. One possibility is to assume that these entities will affect the area sequentially, with close time separation, and try to address them as successive events in time. This will require further research to determine how the environment is affected by simultaneous changes due to more than one entity. Again, automatic construction of the passive radio map can help in identifying and analyzing these effect.

5.3 Automatic Generation of the Passive Radio Map

One of the main technical challenges behind the implementation of the DfP system is to understand the characteristics of the RF signal and how it propagates. In this regard, the localization researchers need to expand an area of research for testing different models of RF-propagation and how they reflect the actual propagation in an RF environment. Different models have been proposed before, e.g. [1], but we believe that none of them is adequate for the DfP problem. What is unique in the automatic generation of the passive radio map is that, not only we need to track the signal in an environment, but also we need to dynamically place entities in the environment and detect the effect of these entities on the received signal at different points in the environment. We have initial results regarding that in [4].

5.4 Positioning of the APs and MPs

Another interesting challenge is to study the effect of the relative position of the APs and the MPs on the accuracy of the DfP system. We believe that there are classes of configurations, i.e. placements of APs and MPs, that have the same performance in capturing changes in the environment. Although we used only one configuration is this paper, we have initial results regarding that in the accompanying technical report [20].

5.5 Using Different Hardware

One requirement for realizing the DfP system is to study the effect of changing the system components hardware on the system parameters. For example, if we use a different NIC card in the MPs, will we need to change the different parameters of the moving variance detection algorithm described in the previous section? Also, a number of the new APs perform automatic power adjustment. In this case, how would this be taken into the design of a DfP system?

5.6 Other Technologies

In this challenge paper we showed the feasibility of the DfP system in an 802.11 environment. Further research is required to test the feasibility in different RF frequency ranges. We believe that we can still detect changes in the environment at other frequency ranges due to the fact that RF signals are affected by reflection, diffraction, absorbtion, and other phenomena for the typical practical frequency ranges.

In addition, we need to investigate the feasibility of the DfP system with other technologies such as ultrasonic and infrared. The problem here may be easier due to the limited range of these technologies.

5.7 Dynamic Changes in the Environment

One of the main challenges to be addressed is how to handle changes in the environment due to the time of day such as temperature, humidity, etc. We believe that the automatic construction of the passive radio map can aid in solving this problem by capturing the effect of these different changes.

A related challenge is how to handle sources of interference in the environment, such as microwave ovens, other WiFi devices, etc, that may affect the measured signal strength. One approach for addressing this would be to use the standard WiFi localization systems for tracking WiFi devices and then compensate for their presence, taking their location information into account. Another possibility is to use other signals, such as time-of-arrival, as a base for the DfP system, which may be less susceptible to some sources of interference.

5.8 User Privacy

Another challenge that needs to be addressed is how to preserve the user privacy in the context of the DfP system. Although this may not fit the goals of the DfP system, the system can be configured to allow the user privacy under some conditions. For example, the system can only be enabled at night to detect intruders in an area of interest. This maintains the privacy of the normal users of the system during the day time.

5.9 Robustness

Although the results presented in the previous section are validated by two sets of independent experiments, the challenge remaining to be addressed is how to ensure robustness of a DfP system under adverse conditions, where an attacker tries to compromise the system. This covers all security aspects of the DfP concept and is a large research area by itself.

6. CONCLUSIONS

In this paper, we introduced the concept of Device-free Passive localization. A DfP system is envisioned to be able to detect, track, and identify entities that do not carry any device, nor participate actively in the localization process. The system works by monitoring and processing changes in the received physical signals to detect changes in the environment.

We described the DfP system's architecture and showed the feasibility of the system by describing algorithms for implementing different functionalities of the DfP system that works with nominal WiFi equipment. We presented two techniques for intrusion detection and a technique for tracking a single intruder. Our results show that the system can achieve 1.0 probability of detection with zero false positives. Moreover, the system can track the intruder's position with more than 86% accuracy.

Our results have established the proof of feasibility of the DfP concept. In order to get it to the point that it can be commercially deployed we have to tackle a number of challenges. We identified different challenges for realizing the DfP system and give directions on how to address them. In particular, we believe that the problem of automatic construction of a passive radio map is an important challenge that needs to be addressed for more understanding of the other DfP challenges and possible solutions. We also believe that research in the DfP challenges identified in this paper, not only will have a major impact on the DfP systems, but also is of value to other localization technologies.

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