A deterministic large-scale device-free passive localization system for wireless environments

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A Deterministic Large-Scale Device-Free Passive Localization System for Wireless Environments

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ABSTRACT

The widespread usage of wireless local area networks and mobile devices has fostered the interest in localization systems for wireless environments. The majority of research in the context of wireless-based localization systems has focused on device-based active localization, in which a device is attached to tracked entities. Recently, device-free passive localization (*DfP*) has been proposed where the tracked entity is neither required to carry devices nor participate actively in the localization process. *DfP* systems are based on the fact that RF signals are affected by the presence of people and objects in the environment.

Previous studies have focused on ***small areas*** with ***direct line of sight*** (LOS) and/or ***controlled environments***. In this paper, we present the design, implementation and analysis of *Nuzzer*, a ***large-scale non-LOS*** DfP localization system, which tracks ***a single entity*** in ***real environments, rich in multipath***. Without any additional hardware, *Nuzzer* makes use of the already-installed wireless data networks to monitor and process changes in the received signal strength (RSS) at one or more monitoring points transmitted from access points. The *Nuzzer* system enables many applications which support the elderly, including smart homes automation which can be used to assist the elderly, and intrusion detection which is used to protect the elderly's homes.

We present deterministic techniques for *DfP* localization and evaluate their performance in a building, rich in multipath, with an area of 750 square meters. Our results show that the *Nuzzer* system gives device-free location estimates with less than 7 meters median distance error using only two monitoring laptops and three access points. This indicates the suitability of *Nuzzer* to a number of application domains.

Categories and Subject Descriptors

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

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General Terms

Algorithms, Experimentation, Measurement, Security

Keywords

Device-free localization, passive radio map.

1. INTRODUCTION

As one of the main context information, location determination has been an active area of research. Recently, we proposed the device-free passive localization (*DfP*) concept [1]. A *DfP* system provides the capability of tracking entities not carrying any devices nor participating actively in the localization process. This is particularly useful in many applications which support the elderly, including smart homes automation which can be used to assist the elderly, and intrusion detection which is used to protect the elderly's homes.

The *DfP* concept is based on the idea that the existence of an entity, e.g. a human, in an RF environment affects the RF signals, especially when dealing with the 2.4 GHz band common in wireless data networks, such as WiFi and WiMax. Since 2.4 GHz is the resonant frequency of water, a person's body absorbs the radio waves in this frequency band.

A typical *DfP* system consists of (Figure 1): (1) signal transmit-

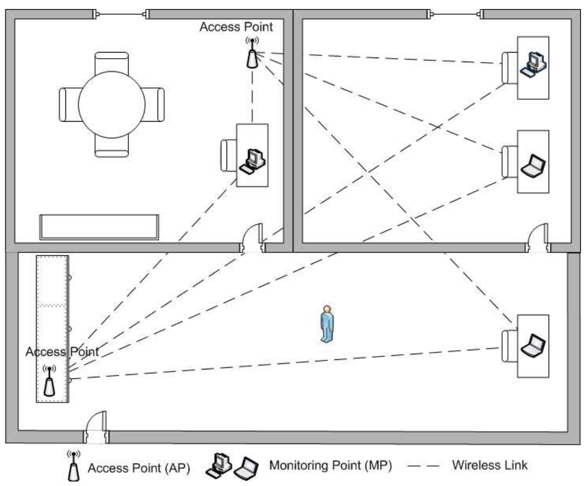
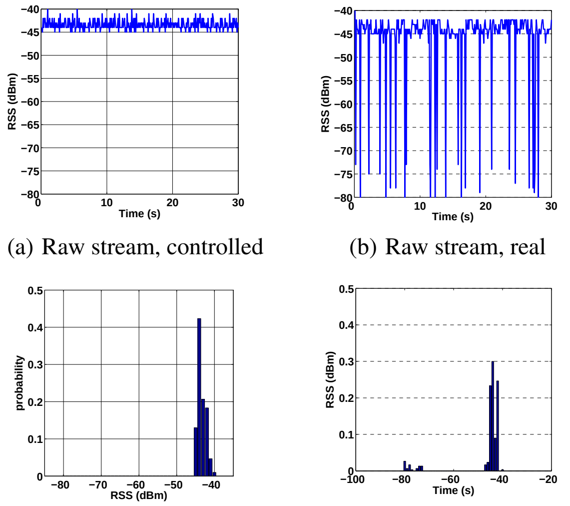


Figure 1: An example of the different components of a device-free passive localization system.APs represent signal transmitters. Standard laptops and wireless-enabled desktops represent MPs. Any device can be used as an application server.



(a) Raw stream, controlled (b) Raw stream, real

(c) RSS histogram, controlled (d) RSS histogram, real

Figure 2: RSS behavior in a controlled versus a real environment.

ters, such as access points (APs) and stations used in typical WiFi deployments, (2) monitoring points (MPs), such as standard laptops and wireless-enabled desktops, along with (3) an application server (AS) for processing and initiating actions as needed.

In this paper, we present the design, implementation and analysis of *Nuzzer*, which can operate in both indoor and outdoor environments. However, we focus in this paper on the indoor environments, in which LOS paths from the transmitters to the receivers are usually obstructed by walls. In addition, indoor environments contain substantial amounts of metal and other reflective materials that affect the propagation of RF signals in non-trivial ways, causing severe multipath effects. Generally, reflection, refraction, diffraction, and absorption of RF signals result in multipath fading, which may either decrease or increase the RSS at the MPs. Moreover, RF signals are also affected by noise, interference from other sources, and interference between channels. Sources of interference include radio-based transmission devices, microwave ovens, cordless phones, and Bluetooth devices. This makes the problem of indoor localization challenging, especially for the *DfP* case.

The *Nuzzer* system aims at achieving specific goals:

Accuracy: Our results show that *Nuzzer*'s accuracy is comparable to active RF-based localization, with a median distance error of 6.74 meters in a typical building.

Ubiquitous Coverage: Since *Nuzzer* works with the standard wireless data networks and does not require any special hardware, it inherits the ubiquity of the technology it works with, such as WiFi.

Scalability: We believe that our study provides the first evaluation of *DfP* systems in a relatively large scale typical environments with non-LOS localization.

Operation in Real Environments: *Nuzzer* addresses *DfP* localization in typical environments. In a typical wireless environment, the signal power level shows clear temporal and spatial variability [2]. Temporal variability is mainly caused by motion of entities, while spatial variability is caused by multipath fading. Figure 2 shows examples of the RSS in controlled and real environments. Raw streams and histograms show that the RSS has a higher variability in real environments. These variabilities make the localization process more challenging in real environments. Note that other systems, such as the proof of concept in [1], can achieve very high accuracy but in a very controlled environment.

Low Cost and Ease of Deployment: *Nuzzer* uses the same hardware installed for the data network to perform *DfP* localization. This enhances the value of the data network.

Privacy Concerns: In many situations, privacy concerns may prevent the deployment of video cameras, which may be a drawback of certain localization systems. *Nuzzer* suits privacy concerns, as it does not use vision-based techniques.

1.1 Approach

In order to perform localization, we need to capture the relation between signal strength and distance. Since this relation is very complex in indoor environments, we do this using a "**passive**" radio map. A radio map is a structure that stores information of the signal strength at different locations in the area of interest . This is usually constructed only once during an offline phase. A passive radio map is similar to the active radio map usually used in device-based active WLAN location determination systems, such as [2–4]. However, in an active radio map, a user stands with a device at the radio map locations and collects samples from all the APs in range. On the other hand, for the passive radio map construction, a user stands at the radio map locations, without carrying any device, and his effect on the different data streams received at the MPs is recorded. Figure 3 demonstrates the difference between active and passive radio map construction.

During the online phase, the *Nuzzer* system uses the signal strength samples received from the APs at the monitoring points and compares them to the passive radio map to estimate the location of the tracked entity.

In the *Nuzzer* system, we propose deterministic techniques to implement *DfP* localization in large-scale real environments. ***We focus on the problem of localization of a single entity and leave the general, and more challenging, problem of multiple-entities localization to a future paper.***

1.2 Paper Organization

Section 2 presents the different algorithms used in the *Nuzzer* system. Section 3 presents the evaluation of the *Nuzzer* system in a large-scaleenvironment and the effect of the different parameters on performance. In Section 4, we discuss the detection problem (detecting the existence of an intruder before localizing it). We discuss different aspects of the *Nuzzer* system in Section 5 and give directions for future work. Section 6 presents a comparison between *Nuzzer* and the relevant related work. Finally, Section 7 concludes the paper.

2. THE NUZZER SYSTEM

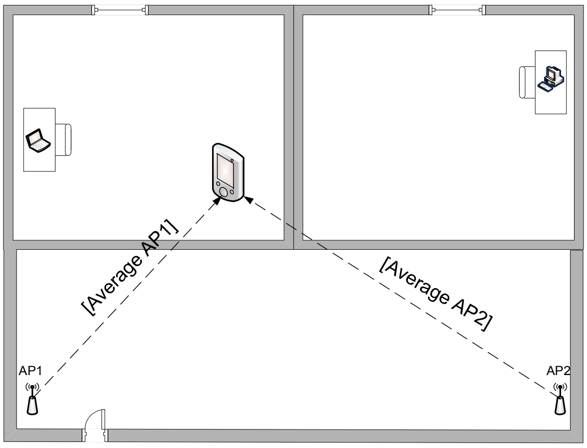
In this section, we present the different algorithms used in the *Nuzzer* system. We start by an overview of the system followed by a description of our algorithms.

2.1 Overview

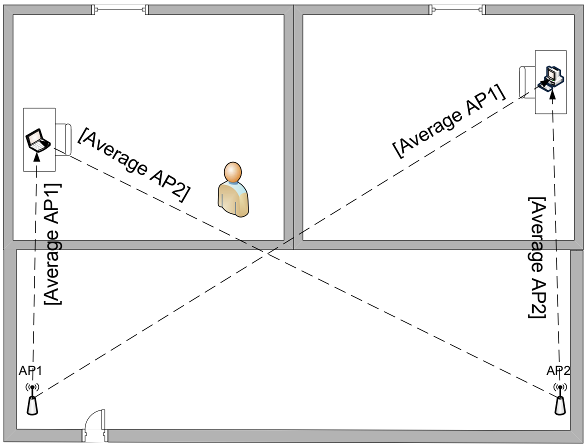
We define two modes of operation for the online phase: The Discrete Space Estimator and the Continuous Space Estimator.

The Discrete Space Estimator module returns the radio map location that has the minimum Euclidean distance given the received signal strength vector from different streams. Therefore, the output of the discrete space estimator must be one of the calibrated locations.

The Continuous Space Estimator works as a post processing step after the discrete space estimator to return a more accurate estimate



(a) Active



(b) Passive

Figure 3: Difference between active and passive radio maps' construction. In a passive radio map, we have a mean value per raw data stream, as compared to a a mean value per AP. Also, a user does not carry any device when constructing the passive radio map.

of the user location in the continuous space. Therefore, if a user is standing between two radio map locations, the continuous space estimator should provide a better estimate than the discrete space estimator.

We start by presenting our mathematical model followed by details of the two modes of operation.

2.2 Mathematical Model

Let $\mathbb{X}$ be a two dimensional physical space. Let q represent the total number of data streams in the system (number of APs multiplied by number of MPs). We denote the q-dimensional signal strength space as $\mathbb{Q}$. Each element in this space is a q-dimensional vector whose entries represent the signal strength readings from different streams, where each stream represents an (access point, monitoring point) pair. We refer to this vector as s. We also assume that the samples from different APs are independent and hence, the samples of different streams are independent. A user standing at any location $x \in \mathbb{X}$ affects the signal received at the different MPs, and hence the equivalent q-dimensional vector.

Therefore, the problem becomes, given a signal strength vector $s(l) = (s_1, ..., s_q)$ at an unknown location l, we want to find the location $x \in \mathbb{X}$ that is closest to l.

In the next section, we assume a discrete space $\mathbb{X}$. We discuss the continuous space case in Section 2.4.

2.3 Discrete Space Estimator

During the offline phase, *Nuzzer* estimates the mean signal strength value for each stream corresponding to the user standing at each radio map location. Therefore, at each radio map location, we store the mean values representing the average signal strength received from each stream when the user stands at this location (Figure 3(b)).

Now, consider the online phase. Given a signal strength vector $s(l) = (s_1, ..., s_q)$ at an unknown location l, containing one entry per stream, *Nuzzer* finds the location $x \in \mathbb{X}$ that minimizes the Euclidean distance in signal strength space, $Euc\_Dist(s(l), s(x))$, where $s(x)$ is the radio map entry at location x. More formally, *Nuzzer* returns the location x that satisfies:

$$argmin_x[Euc\_Dist(s(l), s(x))] \tag{1}$$

$Euc\_Dist(s(l), s(x))$ can be calculated using the radio map constructed during the offline phase as:

$$Euc\_Dist(s(l), s(x)) = \sqrt{\sum_{i=1}^{q} (s(l)_i - s(x)_i)^2} \tag{2}$$

where $s(x)_i$ is the mean signal strength value of stream i calculated during the offline phase at radio map location x. The above equation considers only one sample from each stream for a location estimate. In general, a *number of successive samples*, m, from each stream can be averaged to improve performance.

In this case, $Euc\_Dist(s(l), s(x))$ can then be expressed as follows:

$$Euc\_Dist(s(l), s(x)) = \sqrt{\sum_{i=1}^{q} (\{\frac{1}{m} \sum_{j=1}^{m} s(l)_{i,j}\} - s(x)_i)^2} \tag{3}$$

Where $s(l)_{i,j}$ represents the j^{th} sample from the i^{th} stream at the unknown location l.

Thus, given the signal strength vector, $s(l)$, at an unknown location l, the discrete space estimator applies Equation 3 to calculate $Euc\_Dist(s(l), s(x))$ for each radio map location x and returns the location that has the minimum Euclidean distance in signal space.

2.4 Continuous Space Estimator

The discrete space estimator returns a single location from the set of locations in the passive radio map. In general, an entity need not be standing at one of the radio map locations. Therefore, to increase the system accuracy, *Nuzzer* uses spatial and time averaging techniques to obtain a location estimate in the continuous space.

2.4.1 Spatial averaging

This technique is based on treating each location in the radio map as an object in the physical space whose weight is equal to the probability assigned by the discrete space estimator, normalized so that the sum of probabilities equals one. We then obtain the center of mass of the k objects with the largest mass, where k is a system parameter, $1 \leq k \leq \parallel \mathbb{X} \parallel$. Figure 4 shows an example of using the spatial averaging technique.

More formally, let $h(x)$ be the weight of a location $x \in \mathbb{X}$, i.e., the radio map, and let $\overline{\mathbb{X}}$ be the list of locations in the radio map

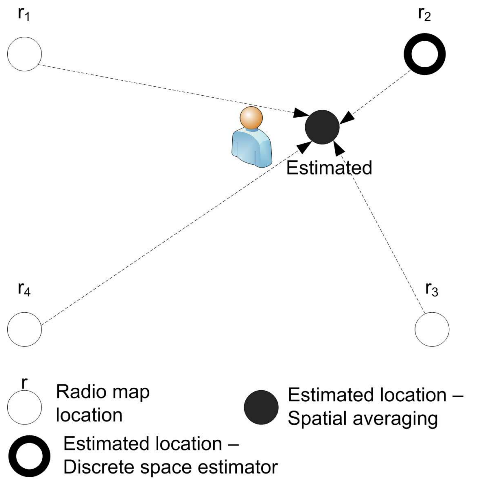


Figure 4: An example of using the spatial averaging technique to enhance accuracy. The discrete space estimator will return the location r_2 as it is the nearest to the actual user location. Using the spatial averaging technique, a better location estimate can be obtained by calculating the center of mass of the top 4 locations ($k = 4$).

ordered in a descending order according to their weight. We assign the weights of the locations to equal the reciprocal of the Euclidean distance in signal space. The center of mass technique estimates the current location x as:

$$x = \frac{\sum_{i=1}^{k} h(\overline{\mathbb{X}}(i)).\overline{\mathbb{X}}(i)}{\sum_{i=1}^{k} h(\overline{\mathbb{X}}(i))} \tag{4}$$

Note that the estimated location *x* needs *not* to be one of the radio map locations.

2.4.2 *Time averaging*

This technique uses a time averaging window to smooth the resulting location estimates. The technique obtains the location estimate by averaging the last w location estimates obtained by either the discrete space estimator or the spatial averaging estimator.

More formally, given a stream of location estimates $x_1, x_2, ..., x_t$, the technique estimates the current location $\overline{x_t}$ at time t as:

$$\overline{x_t} = \frac{\sum_{i=t-min(w,t)+1}^{t} x_i}{min(w,t)} \tag{5}$$

The length of the time averaging window affects the latency and accuracy of the system as discussed in Section 3.

3. PERFORMANCE EVALUATION

In this section, we study the performance of the proposed discrete space estimator and continuous space estimator. We start by describing the experimental setup and data collection, followed by studying the effect of different parameters on the performance of the proposed techniques. We also compare the performance of our system to a random estimator, which is used as a baseline for performance comparison. A random estimator selects a random location in the area of interest as its estimate.

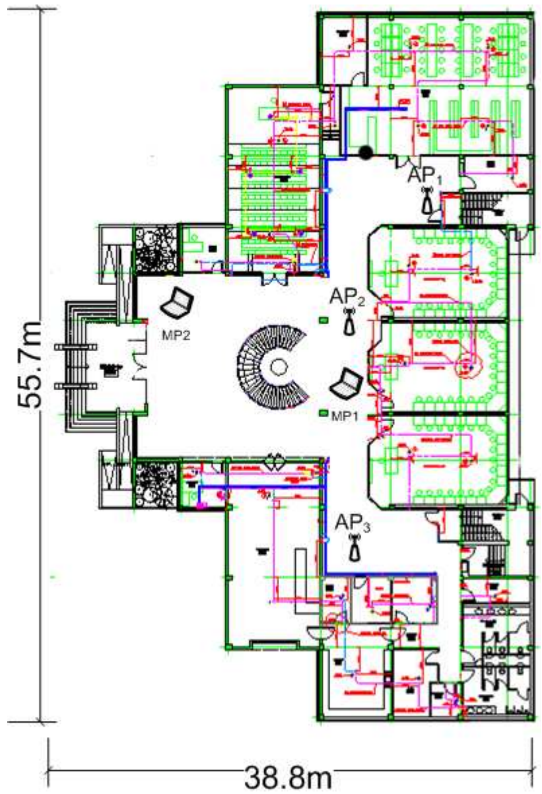


Figure 5: Floor plan of the area where the *DfP* experiment was performed. The environment is rich in multipath, where furniture, plants, and substantial amount of metal exist.The figure also shows the locations of APs and MPs.

3.1 Experimental Testbed

Our experimental testbed is located in the first floor of a two-storeybuilding (Figure 5). The floor has an area of 750 sq. m. (about 8000 sq. ft.). The experiment was carried out in the main entrance and the corridors, where there were furniture, plants, and substantial amount of metal.

Our experiment was conducted in an 802.11b environment. The building had threeCisco APs (model 1130),which cover the first floor[1]. We also used two different laptops; one Dell Latitude D830, and one HP Pavilion ze5600 laptop. The two laptops had Orinoco Silver cards attached to them. APs represent the transmitting units, while laptops represent the MPs. Figure 5 shows the locations of APs and MPs.

3.2 Data Collection

The wireless cards measure different physical signals during the experiment, such as signal strength and noise. We use only the received signal strength indicator (RSSI) values, reported in units of dBm, which is known to be a better function of distance than noise [3]. We collected samples from the access points at the rate of five samples per second.

Each one of the two MPs records samples from the three APs, giving a total of six data streams (one stream for each (MP, AP) pair). During the offline phase, a person stands at each of these

[1]Applications for the elderly's homes can typically include three APs, since APs at neighboring houses can be heard with high RSS.

Table 1: Tunable parameters used in our experiments

Parameter	Default value	Meaning
n	6	Number of processed raw data streams
m	26	Number of consecutive samples to use from one stream per location estimate
k	3	Number of locations to average in the spatial averaging technique
w	5	Size of the time averaging window

Technique	25^{th} $perc.$	50^{th} $perc.$	75^{th} $perc.$
Deterministic	3.86m	8.4m	13.2m
Random	8.8m (2.3×)	14m (1.7×)	18.8m (1.4×)

Table 2: Comparison between the 25^{th}, 50^{th}, 75^{th} percentile values of distance error for different *discrete space* estimator techniques. The table summarizes information in Figure 6. Numbers between brackets indicate the degradation of the random technique compared to deterministic technique.

53 different locations and we record the samples for 60 seconds for each of the six data streams, giving a total of 300 samples per stream.

For testing purposes (online phase), we collected another ***independent*** test set at 32 locations. The test set was collected at a different time from the training set. We use this test set to obtain all figures in this section. Without loss of generality, we consider a fixed orientation for the person being tracked throughout the experiment.

3.3 System Parameters

For the discrete space estimator, we can tune the number of consecutive samples to use from each stream (m). Similarly, we can tune the number of raw data streams to use (n).

For the continuous space estimator, in addition to these two parameters, we can tune the number of locations to use in the spatial averaging (k) and the length of the window to use for time averaging (w). Table 1 summarizes the parameters used in our system. *Unless otherwise specified, we use the default parameters values* ($n = 6, m = 26, k = 3, w = 5$)*, which give the best combined performance.*

3.4 Discrete Space Estimator

Figure 6 shows the cumulative distribution function (CDF) of the distance error using the Discrete Space Estimator. We have a total of six data streams, corresponding to the three APs and two MPs we used. Table 2 summarizes the results of the figure. It lists the 25^{th}, 50^{th}, 75^{th} percentile values of the distance error. We can see from the figure that the median distance error of the discrete space estimator is 1.7 times better than the random estimator. This ratio is even more for the lower percentile values.

The value of the CDF at zero distance error indicates the probability of determining the exact location.

3.4.1 Impact of the number of samples per stream

Figure 7 shows the effect of increasing the number of samples used from each stream per location estimate on the accuracy of the system (parameter m). The figure shows that, as expected, the median distance error decreases as m increases. However, as m increases, the latency, i.e. time required per location estimate, of the system increases as we have to wait till we collect the m samples.

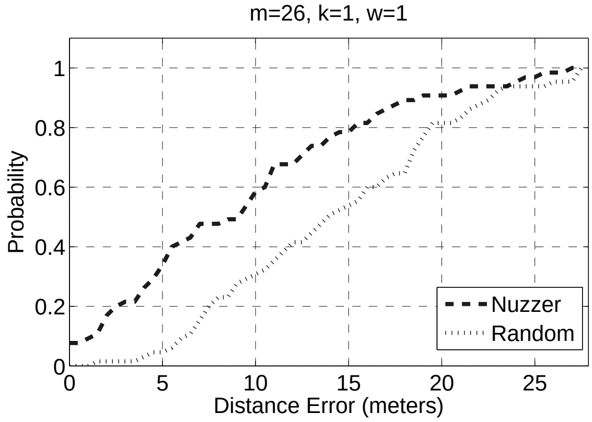


Figure 6: CDFs of the Euclidean distance between actual locations and locations estimated by the *discrete space* deterministic estimator, and the random estimator.

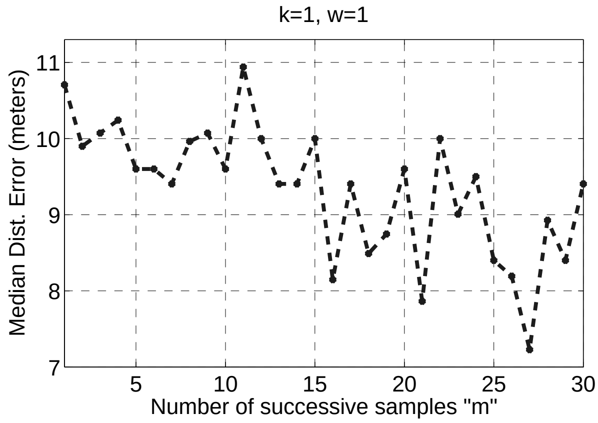


Figure 7: Median distance error of the discrete space estimator for different values of the number of successive samples from each stream per location estimate (m).

Therefore, a balance is required between the accuracy and latency of the system. This depends on the specific deployment environment. Another approach is to use a moving window of m samples, where at each estimate, one new sample is added to $m - 1$ old samples. This removes the requirement of waiting for m samples.

3.4.2 Impact of the number of streams

Figure 8 shows the median distance error versus the number of streams n used in the estimation process. For a specific n, we plot the best result over all possible $\binom{6}{n}$ combinations of streams. The figure shows that as the number of streams increases, we have more information about the environment, and thus we can obtain better accuracy.

3.5 Continuous Space Estimator

Figure 9 shows the cumulative distribution function (CDF) of the distance error using the Continuous Space Estimator for the best values of the parameters. Table 3 summarizes the results of the figure. We can see from the figure that the median distance error of the continuous space estimator is 6.74 meters, 2.1 times better than

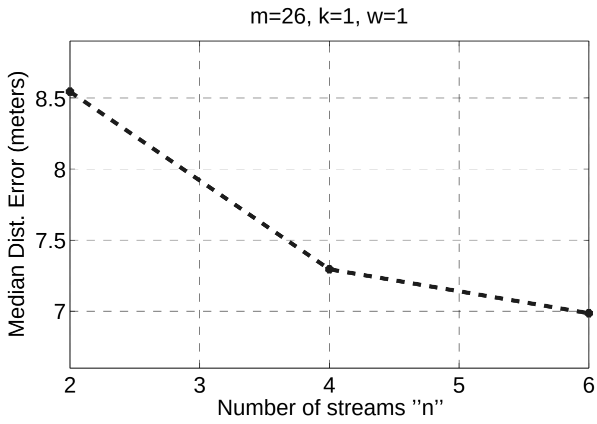


Figure 8: Median distance error of the discrete space estimates versus the number of used raw data streams n. For a given n, the figure reports the best median distance error over all the $\binom{6}{n}$ raw streams combinations.

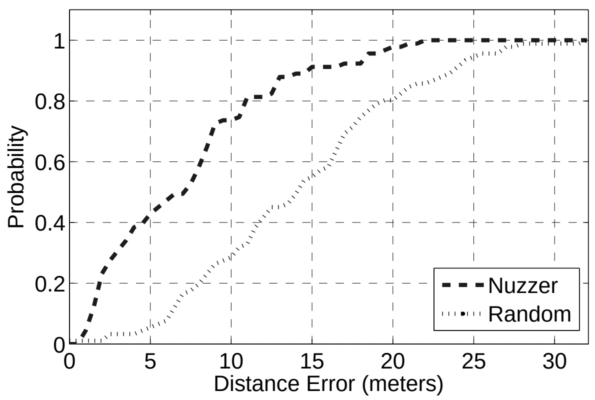


Figure 9: CDFs of the Euclidean distance between actual locations and locations estimated by *continuous space* deterministic estimator, and the random estimator.

the random estimator.

3.5.1 Spatial averaging

We now discuss how the system performance is affected by the number of neighboring locations (k) included in spatial averaging technique. Figure 10 shows the effect of increasing the number of neighbors used in the spatial averaging process (k) on the median distance error. The figure shows an improvement of 30% between $k = 1$ and $k = 3$. When k increases too much, the performance degrades due to the noise introduced by including far locations. A better weighting function can be used to further enhance the spatial averaging technique, which is a subject of ongoing work.

3.5.2 Time averaging

Figure 11 shows the effect of increasing the size of the time averaging window (w) on the median distance error. The figure shows that an improvement of 20% for $w = 5$ as compared to $w = 1$. Again, we have a tradeoff between accuracy and latency. The higher the value of w, the higher the accuracy and the higher the latency.

Technique	25^{th} $perc.$	50^{th} $perc.$	75^{th} $perc.$
Deterministic	2.37m	6.74m	10.6m
Random	8.8m (3.7×)	14m (2.1×)	18.8m (1.8×)

Table 3: Comparison between the 25^{th}, 50^{th}, 75^{th} percentile values of distance error using the *continuous space* estimation technique. The table summarizes information in Figure 9.

3.6 Summary

In this section, we showed that using only six data streams, the *Nuzzer* system provides a *non-LOS DfP* localization system capable of covering large areas, rich in multipath, with a reasonable accuracy; 6.74 meters median distance median distance error.

Comparing the performance of the continuous space estimator to the discrete space estimator, we find that the median distance error in the discrete space is 8.4 meters, whereas in the continuous space, the median is 6.74 meters, 25% better.

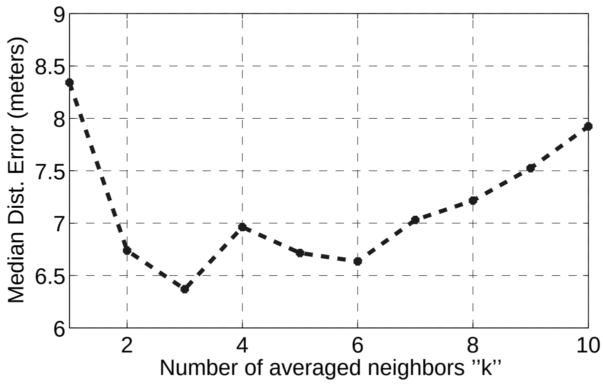


Figure 10: Median distance error of the continuous space estimator versus the number of neighbors used in the spatial averaging (k).

The spatial averaging and temporal averaging techniques are independent and can be used together to further enhance performance. Combining all techniques, leads to the above mentioned accuracy.

The system parameters m, k, and w, which represent the number of samples from each stream, the number of spatially locations averaged, and the time averaging window size respectively, can be tuned to balance accuracy and latency, depending on the deployment environment.

The results also showed that the *Nuzzer* system can provide very good accuracy, even when the number of available data streams is low. This shows the usability of the system in environments with limited hardware installment, such as in homes.

4. DETECTION PROBLEM

Detection refers to identifying if there is a new object in a given area of interest. Once the presence of the object is detected, the tracking system presented in Section 2 can be used to track it. The idea is that the existence of a person in an RF environment affects the radio waves. This effect becomes more significant when a person obstructs the LOS between the transmitter and the receiver. In

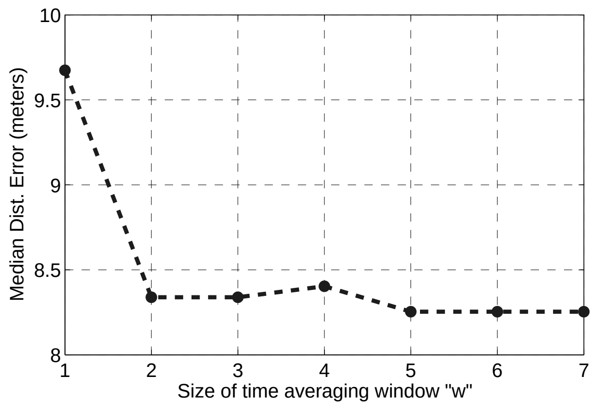


Figure 11: Median distance error of the continuous space estimates versus the time averaging window size (w).

this section, we describe a statistical technique based on the variance of the received signal strength of different streams for detecting new objects in the area interest.

4.1 Relative Variance Technique

Our technique is based on the observation that, for a given stream, the variance of the RSS of the stream during the existence of a person on the LOS (Var_{on}) is higher than the variance of RSS of the stream during his/her absence (Var_{off}). Covering different areas of a building using different streams from APs to MPs, we can detect whether an entity exists in any of the areas of the building based on the relative variance ($\frac{Var_{\text{on}}}{Var_{\text{off}}}$). More specifically, when the relative variance for a given stream, $\frac{Var_{\text{on}}}{Var_{\text{off}}}$, exceeds a certain threshold (τ_{rel}), we declare that a person cuts the LOS between the transmitter and the receiver of this stream.

Since each stream is noisy by itself, we use the average of the relative variance (RV_{av}) of the different streams covering an area as a better metric for detection and compare this average to the threshold τ_{rel}. RV_{av} for a certain area, covered by N streams, is given by:

$$RV_{\text{av}} = \frac{1}{N}\sum_{i=1}^{N}\frac{Var_{\text{on }i}}{Var_{\text{off }i}} \tag{6}$$

4.2 Experimental Results

We conduct our experiment in one corridor of length 18m in order to verify the relative variance technique. Consider a corridor is divided into four zones according to the locations of 2 APs and 3 MPs (As shown on the x-axis of Fig. 12). Thus, we have 6 streams from the 2 APs to the 3 MPs. The RSS for each stream is recorded during an offline phase in order to calculate its variance ($Var_{\text{off}i}$), while no person exists in the corridor. Then, the RSS for each stream is recorded again when a person moves randomly within each of the four zones, in order to calculate ($Var_{\text{on}i}$).

Figure 12 shows the relative variance ($\frac{Var_{\text{on }i}}{Var_{\text{off }i}}$) of the six streams when a person moves in each of the four zones. From the figure, it is clear that setting the threshold value to $\tau_{\text{rel}} = 2$ is reasonable to get a 100% detection probability. Although decreasing the threshold may increase the detection probability, it increases the false alarm probability as well. In case many zones have $RV_{av} > \tau_{rel}$, we assume that a person exists in the zone with the highest RV_{av}.

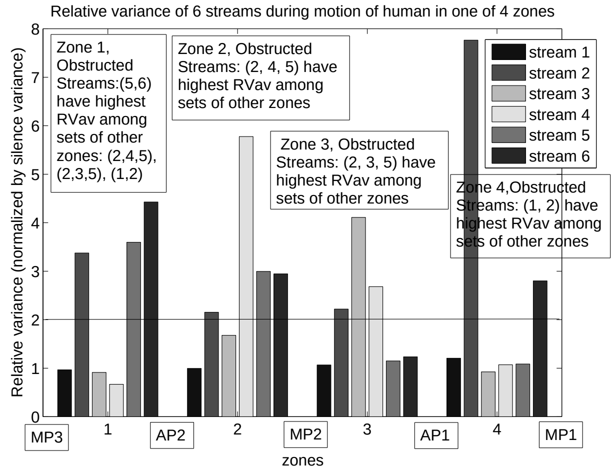


Figure 12: Relative variance ($\frac{Var_{\textbf{on }i}}{Var_{\textbf{off }i}}$) of 6 streams when a person moves in each of the four zones

5. DISCUSSION

In this section, we discuss different aspects of the *Nuzzer* system and our ongoing work on enhancing the system.

5.1 Automatic Generation of the Passive Radio Map

One of the disadvantages of using a radio map is the effort needed to construct it during the offline phase. To reduce this effort, an RF-propagation tool can be used to take as an input the floor plan of the area of interest, objects in the environment, their Rf characteristics, and locations and characteristics of the APs and MPs and based on that generates the radio map automatically.

Such a tool will not be useful only in reducing the ***calibration effort***, but also in understanding the fundamentals of the *DfP* concept and in other functionalities related to tracking such as tracking multiple entities, optimal positioning of APs and MPs, entity identification, as well as dealing with physical size, orientation, and other properties of the passive entity.

5.2 Multiple Entities Tracking

The challenge lies in tracking multiple entities in the same area. The process of radio map construction gets more complicated, in the device-free case, when the number of tracked entities increases, since the radio map needs to take all the combination of the possible tracked entities' locations into account. For example, for a radio map with l locations and a system that wants to track up to n entities, the radio map needs to store information about $\binom{l}{n}$ possibilities. A tool for the automatic construction of the passive radio map can help in identifying and analyzing the effect of multiple entities on a *DfP* system.

6. RELATED WORK

Using video cameras is a traditional way for passive localization of human beings. For example, [5] describes algorithms for detecting and tracking multiple people in cluttered scenes using multiple synchronized cameras located far away from each other. However, video cameras fail to work in the dark and in presence of smoke.

MIMO radar employs multiple transmit waveforms and have the ability to jointly process the echoes observed at multiple receive antennas ([6] and references therein). Elements of the MIMO radar

	MIMO Radar-based Systems	Radio Tomographic Imaging (RTI)	*Nuzzer* System
Measured Physical Quantity	Reflection and scattering	RSS attenuation	Changes in RSS
Range (based on frequency)	Short	Long	Long
Wall penetration	Very high	High	High
non-LOS localization	Yes	No	Yes
Number of deployed nodes (or devices)	Few	Many	Few
Complexity of single node (or device)	High	Low	Moderate
Number of streams	N/A (echo based)	Large (756)	Low (6)
Covering large areas	Limited by its short range (high frequency)	Limited by number of deployed nodes (LOS)	Yes
Accuracy degrades significantly with multipath	No	Yes	No
Handles a number of entities	Yes	Yes	No, Ongoing work
Special hardware required	Yes	Yes	No
Licence-free frequency band	No	Yes	Yes

Table 4: Comparison of different RF-based passive localization systems

transmit independent waveforms resulting in an omnidirectional beampattern. It can also create diverse beampatterns by controlling correlations among transmitted waveforms. In MIMO, different waveforms are utilized and can be chosen to enhance performance in a number of ways. Radar-based systems are able to provide accurate location estimates. However, they require special hardware and their high complexity limits their applications.

The concept of *DfP* localization was first introduced in [1]. Experiments were set up in a highly *controlled* and small environment. Results show that the system can track the entity's position with more than 86% accuracy in this limited controlled environment. These results have established the proof of feasibility of the *DfP* concept.

Another emerging technology is Radio Tomographic Imaging (RTI) [7]. It presents a linear model for using RSS measurements to obtain images of moving objects. The proposed system uses *hundreds* of raw data streams obtained from sensor nodes. The system measures the attenuation in the transmitted signal rather than scattering and reflection. Since this system is based on LOS, its accuracy degrades as multipath components increase. To overcome multipath, a higher density of nodes is used.

The *Nuzzer* system has unique characteristics that differentiate it from the previous systems: It gives high accuracy for large-scale typical environments; it does not require any special hardware; it does not require LOS to operate; and it works with a very low number of raw data streams. However, the current system has two main limitations, which are being addressed in our current work. First, the current system is designed to track a single entity. Second, it needs substantial calibration efforts.

Table 4 summarizes the differences between *Nuzzer* and the recent *DfP* RF-based localization systems.

7. CONCLUSION

We presented the design, implementation, and evaluation of the *Nuzzer* device-free passive localization system. *Nuzzer* uses the standard wireless data networks installed in the environment to monitor and process the RSS at one or more monitoring points leading to estimating the location of entities, without requiring them to carry any devices. It works by constructing a passive radio map during an offline phase, then uses a Euclidian distance-based estimator to determine the closest radio map location, in terms of distance in the signal strength space, to the unknown location. We also presented two post processing techniques: the spatial and temporal averaging to further enhance the accuracy of the basic deterministic technique.

We evaluated the performance of the *Nuzzer* system in abuilding, rich in multipath, with an area of about 750 square meters. We used two laptops and three access points. Our results show that the *Nuzzer* system gives a median distance error of 6.74 meters, 2.1 times better than a random estimator.

We also presented a technique for detecting the intruders based on the variance of the RSS. The proposed technique can provide 100% probability of detection in typical environments.

Currently, we are expanding the system in different directions including: multiple-entities tracking, automatic generation of the passive radio map and optimizing the APs and MPs positions.

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8. REFERENCES

[1] M. Youssef, M. Mah, and A. Agrawala. Challenges: device-free passive localization for wireless environments. In *MobiCom '07: Proceedings of the 13th annual ACM international conference on Mobile computing and networking*, pages 222–229, New York, NY, USA, 2007. ACM.

[2] M. Youssef and A. Agrawla. The horus location determination system. *ACM Wireless Networks (WINET) Journal*, 2007.

[3] P. Bahl and V. N. Padmanabhan. RADAR: An In-Building RF-based User Location and Tracking System. In *IEEE Infocom 2000*, volume 2, pages 775–784, March 2000.

[4] P. Bahl, V. N. Padmanabhan, and A. Balachandran. Enhancements to the RADAR user location and tracking system. Technical Report MSR-TR-00-12, Microsoft Research, February 2000.

[5] J. Krumm et al. Multi-camera multi-person tracking for easy living. In *3rd IEEE Int'l Workshop on Visual Surveillance*, pages 3–10, Piscataway, NJ, 2000.

[6] A. M. Haimovich, R. S. Blum, and L. J. Cimini. Mimo radar with widely separated antennas. *IEEE Signal Processing Magazine*, pages 116Ű–129, January 2008.

[7] J. Wilson and N. Patwari. Radio tomographic imaging with wireless networks. *IEEE Trans. Mobile Computing*, 2009.