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# Device Free Localization with Wireless Networks Based on a Fade Level

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**Abstract—**Device-free localization (DFL) is the estimation of the position of a person or object that does not carry any electronic device or tag. Existing model-based methods for DFL from RSS measurements are unable to locate stationary people in heavily obstructed environments. This paper introduces measurement-based statistical models that can be used to estimate the locations of both moving and stationary people using received signal strength (RSS) measurements in wireless networks. A key observation is that the statistics of RSS during human motion are strongly dependent on the RSS "fade level" during no motion. We define fade level using extensive experimental data that changes in signal strength measurements due to human motion can be modeled by the skew-Laplace distribution, with parameters dependent on the position of person and the fade level. Using the fade-level skew-Laplace model, we apply a particle filter to experimentally estimate the location of moving and stationary people in very different environments without changing the model parameters. We also show the ability to track more than one person with the model.

**Index Terms—**Device-free localization, wireless networks, RF sensors, tracking, through-wall surveillance.

## I. INTRODUCTION

Knowing the location of people is extremely valuable and useful. Global navigation satellite systems, radio frequency identification (RFID), and real-time location systems (RTLSs) have proven their value for locating people and assets with an attached device. Device-free localization (DFL) is the practice of locating people or objects when no tag or device is attached to the entity being located.

DFL technologies are useful in applications where the people being tracked cannot be expected to cooperate with the system. This may be the case because they are intentionally evading the system, because they are physically unable, or because they do not want to be inconvenienced by wearing a tag. In this paper, we investigate a statistical inversion method for DFL in narrowband RF sensor networks, and show its effectiveness in tracking both moving and stationary objects located behind walls.

Various sensor technologies can be used for the purposes of DFL [1], as discussed in Section 4. In this paper, we are particularly interested in DFL systems which use received signal strength (RSS) measurements (RSS-DFL) because RSS can be measured with a variety of widely deployed and inexpensive wireless devices. RSS-DFL can locate motion through building walls [2], in dark or smoke-filled environments, and are not as invasive of privacy as video camera surveillance.

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This statistical inversion method is enabled by a new RSS model presented in this paper for temporal fading on static links. Significant statistical models exist for small-scale fading, but this model represents an advance on two levels. First, the model presented is a function of the current position of a person—whether or not the person is now close to the link. Second, the model presented is a function of the fade level, that is, a quantification of the narrowband fading experienced on the static link prior to the person's appearance in the environment. Fade level is a measurable quantity in RSS-DFL. The new model takes advantage of the uniqueness of each link in the RF sensor network, as quantified by the fade level, rather than assuming each link behaves identically when people are located near a link. We show that links experience drastically different behavior as a function of the fade level.

Our model is based on extensive measurements conducted in two very different environments in which DFL systems are expected to operate. We find that the temporal variation of RSS is well modeled with the skew-Laplace distribution. Our measurements quantify the relation between the parameters of the skew-Laplace distribution to a person's location and a link's fade level.

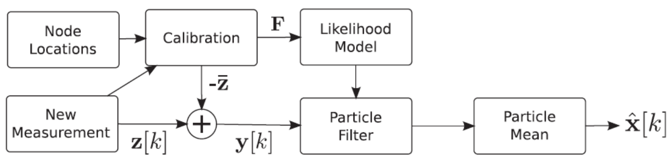


Fig. 1. A flowchart describing the statistical inversion process for device-free localization in wireless networks.

The statistical approach allows us to address some key limitations of previous RSS-DFL systems. Since the new method does not rely on manual site-specific measurements, it can be deployed at multiple sites without the need for offline training. All that is needed is a short calibration period (a few seconds) where the network is assumed to be free from moving objects to determine the means of each link. The training, in essence, has already been performed in the modeling of the statistics. Furthermore, the new method does not require a specific network location geometry or regularity in the environment.

The statistical inversion process is described in detail in Section 2. An overview is provided in Fig. 1. Let M be the total number of links in the network. A M x 1 raw RSS measurement vector z[k] for each link in the network is received at time k at a base station processing unit. Raw calibration measurements are collected during a period during which the network is assumed vacant, or over a long term history. These calibration measurements are combined with knowledge about the node locations to determine the means $\bar{\mathbf{z}}$and fade-levels **F**. During operation, the link means are subtracted from the incoming measurement to determine the change in signal strength y[k] = z[k] - $\bar{\mathbf{z}}$.

The fade-level calibration information is used to determine the statistical likelihood model based on the skew-Laplace distribution, as discussed in Section 2. The likelihood model provides the basis for particle filtering, a nonlinear and non-Gaussian filter for recursive estimation, which is used to infer location results $\hat{\mathbf{x}}[k]$.

## II. STATISTICAL MODELING

### a) Overview

In general, a statistical likelihood model represents the noisy translation from a state space to a measurement space (see Fig. 2). Given a particular state, a certain distribution of measurements will result. This can be thought of as a forward process, defined by likelihood distribution P(Y|X), where X is the state to be estimated, and Y is received or measured data. The inverse problem, therefore, involves taking measured data and estimating the distribution of the state.

The state likelihood is defined by the posterior distribution P(X|Y), found by applying Bayes' theorem

$$P(X|Y) = \frac{P(Y|X)P(X)}{P(Y)}. \quad (1)$$

For DFL applications, the state-space X is the coordinates of device-free entities within a wireless network, and the measurements Y are RSS values of each link in the network. We take the RSS measurements and infer the position of the people by inverting the statistical model through the posterior distribution.

The likelihood function P(Y|X), and the a priori, knowledge of the state described in P(X), describes the statistical model that can be used to invert the problem. We are, therefore, interested in knowing how the position of people affects the resulting RSS measurements, and how those statistics change for different positions of the people. We expect a person standing on the line-of-sight (LOS) of a link to cause significant changes to the RSS measurements, while a person at a distant position away from the LOS will not. The statistics for each link-person geometry are modeled in the likelihood functions.

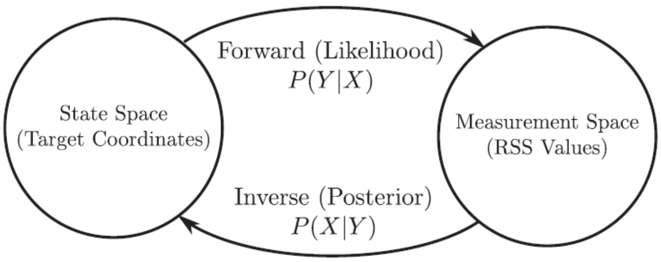


Fig. 2. An illustration showing the role of likelihood and posterior distributions for statistical inversion.

### b) Measurement Collection

To form a likelihood model, an experimental RF sensor network is deployed to capture RSS measurements. The network nodes consist of 34 TelosB nodes from Crossbow, each utilizing the IEEE 802.15.4 protocol in the 2.4 GHz frequency band.

A token passing protocol called Spin, is used to prevent wireless packet collisions while maintaining low data collection latency. Each node is assigned an ID number and programmed with a known order of transmission. When a node transmits, each node that receives the transmission examines the sender identification number. The receiving nodes check to see if it is their turn to transmit, and if not, they wait for the next node to transmit. If the next node does not transmit, or the packet is corrupted, a timeout causes each receiver to move to the next node in the schedule so that the cycle is not halted. A base-station node that receives all broadcasts is used to gather signal strength information and pass it to a laptop computer for processing.

RSS data are gathered as humans walk near and through the networks. The location of each person is carefully tracked by having each person step in a predetermined path defined by markers placed on the ground. To keep each person moving at a constant velocity, an audible metronome is played over a speaker, allowing each person to step to the next marking at the correct time. Using this technique, millions of RSS measurements are gathered, each measurement synchronized with knowledge of the actual positions of each person.

Since our likelihood models are based on changes in signal strength, a calibration process is used for each deployment. During calibration, RSS measurements for each link are taken while the network area is vacant of people. The calibration mean for link l, which we denote $\bar{z}_l$, is set to the average of RSS measurements during this calibration period.

### c) Fading Information

People moving near a wireless link will cause changes in RSS. This temporal variation is different from small-scale or frequency selective fading that occurs due to relative motion between the transmitter and receiver in multipath environments. During motion of a transmitter or receiver, the phase of all multipath components change as the path length changes. In contrast, the presence of the person near the wireless link affects only a subset of multipath components in the link [2], [3].

When the channel is predominantly LOS, such as in an open outdoor area, then a human crossing the LOS will generally cause a drop in signal strength due to shadowing of the LOS path. This phenomenon has been applied to image the attenuation of humans within a wireless network [4].

When an environment is rich in multipath and heavily obstructed, the presence of a human on the LOS of a link causes less predictable changes in RSS. In different cases, the link RSS may decrease, remain unchanged, or increase.

To take advantage of temporal changes in RSS on obstructed links, regardless of the direction of the change, variance-based radio tomographic imaging [2] may be applied. The key weakness of VRTI, however, is that people must remain moving in order to result in measurable temporal variation, and thus be able to be tracked. Stationary people, or those that move very slowly, will not be imaged.

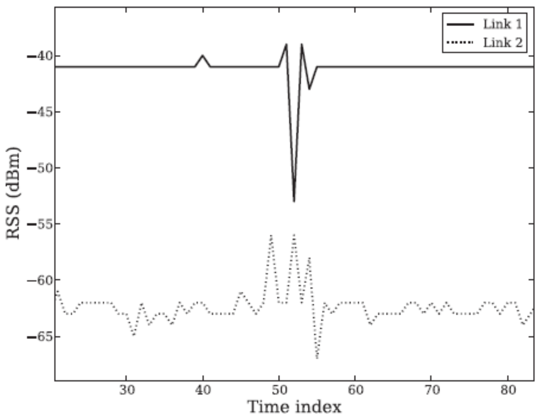


Fig. 5. An example of how the RSS statistics for two links of equal distance and in the same environment are drastically affected by the fade level. Here, a human crosses through the LOS at t = 52. Link 1 is in an "antifade" while Link 2 is in a deep fade.

Note that the steady state of narrowband fading on a link, when there is no person near the link, plays an important role in the statistics of the changes caused when there is a person near the link. We define and describe two extremes of the narrowband fading experienced by a static link.

- **Deep fade.** A link that experiences deep multipath fading (i.e., destructive multipath interference) without the person present is more likely to experience a high variance of RSS when a person enters the area. Further, this link will, on average, measure an increase in RSS due to the person's presence.
- **Antifade.** On the other hand, a link that experiences constructive multipath interference when the person is not present, will vary significantly less due to the person's presence, and further, will measure, on average, a decrease in RSS. We use the term "antifade" to be the opposite of the common term "deep fade."

These observations about temporal fading due to human presence has been verified by simulation [5].

### d) *Quantification of Fade Level*

We now quantify the amount of fading occurring on a static link by defining a "fade level". In a wireless channel, the ensemble mean P(d) (dB) measured by the receiver is dependent on the distance d from the transmitter

$$P(d) = P_T - \Pi_0 - 10\ n_p\ \log_{10} \frac{d}{\Delta_0}, \tag{2}$$

where $P_T$ is the transmitted power in dBm, np is the path loss parameter, and $\Pi_0$ is the loss measured at a short reference distance $\Delta_0$ from the transmitter. For more information on the derivation of this equation and its associated parameters, see [6].

In multipath environments, fading will cause a significant deviation from the ensemble mean in (2). We quantify the fade level as the difference between the path loss prediction and the calibration mean $\bar{z}_l$ in dB for link *l*

$$F_l = \bar{z}_l - P(d_l), \tag{3}$$

Where $F_l$is the lth element of F and dl is the length of link *l*. assuming the locations of each node are known or estimated in a wireless network, it is simple to calculate the fade level for each link. Calibration provides the link mean $\bar{z}_l$, and the path loss model is applied to determine P($d_l$), based on a known path loss parameter and reference powers.

The path loss parameter can be estimated using calibration data. The average signal strength for each link $\bar{z}_l$ is recorded during the calibration phase, and the distance of each link is known since all node positions are known. A least-squares linear fit is used to determine the parameters of (2) that best fit the calibration mean data.

## III. APPLYING THE MODEL: TRACKING WITH PARTICLE FILTERS

### a) *Particle Filtering Algorithm*

There are many frameworks for estimating a posterior distribution using likelihood models. Kalman filtering, in its multiple forms, is by far the most common of these algorithms. For our application, the *particle filter* is an attractive form of posterior estimation, and a simple and brief outline of the particle filter applied in this paper is provided here. The derivation, theory, and variants of the particle filter will not be covered, as this information is widely available in the literature [7]. [8], [9], [10].

There are a number of reasons why particle filtering is attractive for DFL in RF sensor networks. First, particle filters do not make any assumptions on linearity of the measurement process or the dynamics of the state being estimated. Since our likelihood models are dependent on the existence of a person on the LOS path of each link, this is an important flexibility. Furthermore, nonlinear models for person movement can be incorporated directly into the particle framework.

Second, unlike the Kalman filter, the particle filter does not require the likelihood distributions to be Gaussian. This is extremely important for applying our likelihood functions, as they are well modeled as skew-Laplacian. Assuming Gaussian distributions would be suboptimal, and may introduce significant tracking error.

Finally, the particle filter is attractive for real-time processing since incoming measurements can be used to update the posterior estimation without storing a history of previous measurements. As new measurements arrive, the algorithm recursively predicts and updates its estimation in a manner similar to that of the Kalman filter.

The use of a particle filter for DFL is not without disadvantages. The primary weakness of particle filters is the computational complexity required to run the algorithm. The particle filter naturally relies on a high number of particles to achieve accurate results, at the expense of computational resources. There are many forms of the particle filter, including the auxiliary particle filter and the unscented particle filter [9], which aim to increase efficiency and accuracy.

In this work, each particle represents a particular hypothesized location coordinate of a person. Let x[$k$] be the true location of the person at time $k$, and let the set $\{\tilde{\mathbf{x}}^i[k]\}_i$ be the set of particles that represent hypotheses of person position. Let the set $\{\tilde{w}^i[k]\}_i$ be the weights of each particle at time $k$, let y[$k$] be the current difference in RSS measurements for each link from the calibration data, and let $\hat{\mathrm{x}}$[$k$] be the person location estimate. We use the following sampling-importance-resampling (SIR) [7] particle filter to perform our experiments.

1. **Measure.** Receive new measurement vector z[$k$] from each link in the network, then subtract the calibration mean $\bar{\mathbf{z}}$ to obtain y[$k$]. Note that it is not necessary to process every link measurement at each period; a subset of measurements can be used.

2. **Weight update.** For each particle $\tilde{\mathbf{x}}^i$[$k$] and each link RSS measurement, use the measurement vector y[$k$] to determine the updated weights.
   - Determine skew-Laplace parameters $a_l$; $b_l$; and $\Psi_l$ for each link given the current particle $\tilde{\mathrm{x}}^i$[$k$] using Table 1. These are stored in M x 1 vectors a; b, and $\mathbf{\Psi}$.
   - For each link, determine $p(y_l[k]|\tilde{\mathbf{x}}^i[k])$ using the fade-level skew-Laplace likelihood model. Thus,

   $$p(y_l[k]|\tilde{\mathbf{x}}^i[k]) = f(y_l; a_l, b_l, \psi_l)$$

   where $y_l$[k] is the lth element of y[$k$], and $a_l$; $b_l$, and $\psi_l$ are the lth elements of each parameter vector determined in the previous step. Update weights with

   $$w^i[k] = w^i[k-1]p(y_l[k]|\tilde{\mathbf{x}}^i[k]),$$

   and normalize with

   $$w^i[k] = w^i[k] \Big/ \sum_j w^j[k].$$

3. **Resample.** Particles with heavy weights are reproduced, particles with very low weights are eliminated.

4. **Move the particles.** Apply a Markov transition kernel to each particle. In our experiments, we use the Metropolis-Hastings algorithm [11].

5. **Estimate.** Average the particles to obtain the mean of the posterior distribution as the current state estimate.

In this algorithm, we assume that the particle filter proposal distribution $q(\mathbf{x}[k]|\mathbf{x}[k-1], \mathbf{y}[k])$ is equal to the Markov transition $p(\mathbf{x}[k]|\mathbf{x}[k-1])$, which leads to the very simple weight update step. While this assumption makes for easy implementation, the efficiency of the particle filter is drastically reduced, since the current measurement is not used to propose new particle positions. The development and application of more efficient DFL particle filter designs is a topic for future research.

## IV. CONCLUSION

Previous work in the field of RSS-based DFL shows that it is possible to locate humans using only RSS measurements, even through walls. In particular, RTI provides a method for RSS-DFL that does not require exhaustive training information. Previous work in model-based RSS-DFL has been unable to locate stationary or slowly moving people in highly obstructed areas. This paper provides a statistical model and inversion method that can be applied to locate stationary as well as moving people. It can also be applied to track multiple people behind walls and in complex indoor environments, an extension that has not been presented in previous work.

The amount of fading on a static link is an important factor in determining the distribution of RSS when a person enters the area near the link. If the link is already in a deep fade, the disturbance a person causes to the multipath will tend to increase the RSS. Links in deep fades also exhibit more variance, since even slight changes to multipath components can bring the link out of the fade. Links that experience antifades, however, exhibit the opposite behavior. Changes to the environment due to human presence tend to bring signal power down, and variances are significantly lower.

The skew-Laplace distribution is a reasonable representation for the temporal changes in RSS measurements. The mode and decay parameters of the distribution are dependent on the fade level of the link as well as the person's position. When a person is on the LOS path of the link, RSS fluctuations are significantly larger than when the person is away from the LOS. Each parameter, for both the LOS and off-LOS cases, is seen to be linear with the fade level.

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