SAL: SHADOWING ASSISTED LOCALIZATION

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ABSTRACT

Ad hoc networks of inexpensive, low-powered, portable wireless devices have shown enormous potential in emerging applications. Such applications benefit greatly if the nodes can determine their own location. Traditional localization techniques such as GPS may not be available due to design or environmental constraints. Recent works have proposed using received signal strength (RSS) measurements for localization. These techniques suffer from limited accuracy since the RSS measurements are affected by fading and shadowing of the wireless channel.

In this paper we propose the Shadowing Assisted Localization (SAL) algorithm, which employs a model of the shadowing environment to improve localization accuracy. This protocol is unique since it has the flexibility for localization of multi-hop networks in shadowing environments with mobile reference nodes. We show that, in shadowing environments, SAL significantly reduces the mean-squared error (MSE) of node position estimates compared to algorithms that do not consider shadowing.

Index Terms— Localization, Shadowing, Ad-hoc Networks

1. INTRODUCTION

Location awareness can greately enhance the capabilities of ad hoc and wireless sensor networks in a wide range of applications ranging from intrusion detection to environmental monitoring. While, for some of these applications, nodes could be manually placed in surveyed locations, in many cases tedious placement of nodes is impossible, or the nodes may be mobile. For this reason, many applications require nodes in the network to be able to determine their own location. Additionally, nodes capable of self-localization can also be used to offer location-based services or to improve coordination between first-responders at disaster sites or infantry in tactical situations. Traditional localization techniques such as GPS may not be available due to power constraints, obstructions such as buildings, or interference such as that caused by hostile jamming.

Localization techniques generally classify nodes in the network as either reference nodes (also called anchor nodes), which know their location (using GPS or some other external location reference) and floating nodes which do not. Nodes then use angle, distance, delay or received signal strength (RSS) measurements to determine the position of the floating nodes. Systems using RSS measurements do not require specialized measurement hardware, so several techniques have been proposed using algorithms such as extended Kalman filters to [1], Semidefinite Programming [2], and Probability-based Maximum Likelihood Estimation [3]. A problem with RSS measurements is that they are influenced by the wireless channel. Since these methods do not consider the shadowing and fading effects of a realistic wireless channel, they have been shown to have low accuracy [4]. Additionally, recent works [5] have indicated that the correlation from shadowing can be leveraged to further improve location accuracy.

Several works have proposed to use site surveys to improve accuracy when locating a single mobile node. These works [6–9] generally use site surveys to measure the channel from fixed base stations to various locations on site to generate a database of potential locations. Nodes are then located by interpolating between the measured locations. However, these techniques require the base stations to be located in the same position during the survey and localization phases, and can not readily be extended to multi-hop networks.

In this paper we propose the Shadowing Assisted Localization (SAL) algorithm. This technique consists of an initial site survey phase and a localization phase. In the site survey phase, we construct a model of the shadowing environment. In the localization phase, mobile nodes use RSS measurements between themselves and either other floating nodes or anchor nodes to estimate the location of floating nodes in a multi-hop network. The shadowing model is used to along with a particle filter to estimate and track the positions of floating nodes. This technique differs from existing techniques in that it combines all of the following features:

1. Reference nodes can be mobile. Further, nodes can change between being reference nodes and floating nodes dynamically with no communication overhead.
2. Localization occurs over multiple hops, i.e. even floating nodes that do not have any reference nodes as neighbors can be localized.
3. SAL exploits knowledge of shadowing environment to improve localization accuracy.

2. CHANNEL MODEL

We assume a single-path channel between two nodes with both shadowing and path loss. This model can be extended to multi-path channels if only the first arriving path is considered, and the other delayed paths treated as noise. The transmitted signal x is received as:

$$y = hx + u,$$

where h is the wireless channel and u is additive white Gaussian noise (AWGN). The channel h is

$$h = 10^{\frac{\eta}{20}} d^{-\alpha},$$

where d is the distance between transmitter and receiver, α is the path loss exponent (nominally between 2 and 4), and η is the shadowing component.

Under a log-normal shadowing model [10], η for each link would be an i.i.d. Gaussian random variable. In reality the shadowing among adjacent nodes is likely to be correlated. Although numerous models for the spatial correlation have been proposed (e.g. [11, 12]), we have found that the NeSh Model [13, 14] is sufficiently flexible for our application. Under this model the shadowing component is represented as a function of an underlying spatial loss

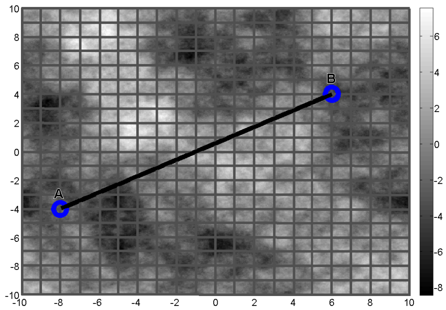


Fig. 1. Shadowing example

field (SLF), $g(\boldsymbol{x})$. The shadowing component η of the link from node i to node j is calculated as the line integral:

$$\eta_{i,j} = \frac{1}{d_{i,j}^{1/2}} \int_{x_i}^{x_j} g(\boldsymbol{x}) \quad d\boldsymbol{x}. \tag{1}$$

The SLF is assumed Gaussian distributed, with a covariance between points separated by a distance $d_{i,j}$:

$$R_g(d_{i,j}) = \frac{\sigma_\eta^2}{\delta} e^{-\frac{d_{i,j}}{\delta}}, \tag{2}$$

where σ_η^2 is the shadowing covariance and δ is a parameter controlling how fast the correlation falls off with distance.

We implement a discretized version of the model, where the field is replaced by a discretized version $\boldsymbol{g} \subset g(\boldsymbol{x})$. The line integral in (1) is replaced by a vector product such that:

$$\eta_{i,j} = \frac{1}{\sqrt{d_{i,j}}} \boldsymbol{b}_{i,j} \boldsymbol{g}, \tag{3}$$

where $\boldsymbol{b}$ is a row vector with elements corresponding to each discrete (x,y) cell in the field $\boldsymbol{g}$. The elements of $\boldsymbol{b}_{i,j}$ are the lengths of the segments of the line from node i to node j that fall within the corresponding cell.

For example, consider Figure 1. The shadowing loss from A to B calculated using (1) is proportional to the line integral along the path. In the discretized version in (3), the vector $\boldsymbol{b}_{A,B}$ contains elements for each grid cell, where only the elements corresponding to cells that the path passes through are nonzero. The shadowing loss is then proportional to the sum of the values of the cells in $\boldsymbol{g}$ the path passes through weighted by the length of the path that falls within the corresponding cell. If the cells are sufficiently small, (1) and (3) should be approximately the same.

We assume the RSS measurements are proportional to the channel estimate. In practical systems the proportionality constant can be determined and eliminated, so without loss of generality we model the RSS measurement $z_{i,j}$ from node i to node j as:

$$z_{i,j} = h_{i,j}(\boldsymbol{g}) + v_{i,j}, \tag{4}$$

where $v_{i,j}$ is AWGN with variance σ_v^2, and the channel $h_{i,j}(\boldsymbol{g})$ is

$$h_{i,j}(\boldsymbol{g}) = 10^{\frac{\boldsymbol{b}_{i,j}\boldsymbol{g}}{20\sqrt{d_{i,j}}}} d_{i,j}^{-\alpha}. \tag{5}$$

3. SHADOWING ASSISTED LOCALIZATION

In this section we present our new algorithm, Shadowing Assisted Localization (SAL). This algorithm consists of an initial site survey phase and an active localization phase. The initial survey phase constructs a model for the shadowing environment using RSS measurements from known locations. The localization phase uses this shadowing model along with RSS measurements from other nodes in the network to determine node locations and track their movements.

3.1. Site Survey

In the site survey phase, a model of the shadowing environment in the network area is constructed. As mentioned in Section 2, we adopt the NeSH shadowing model [13, 14]. This model can be constructed based on theoretical analysis such as ray-tracing the floorplan, or based on empirical measurements from a site survey.

The site survey consists of a series of RSS measurements made from nodes with known positions. These measurements are used to estimate a model for the shadowing in the network. Estimation of the shadowing model can be shown to be a tomography problem, which was examined in [15]. Unlike [15], which focused on imaging only the changing attenuation, we are interested in imaging the static attenuation to build the shadowing model.

This tomographic reconstruction can be found as the solution to the nonlinear least-squares problem:

$$\hat{\boldsymbol{g}} = \arg \min_{\tilde{\boldsymbol{g}}} \frac{1}{2} ||\boldsymbol{h}(\tilde{\boldsymbol{g}}) - \hat{\boldsymbol{z}}||^2,$$

where $\boldsymbol{h}(\boldsymbol{g})$ is a vector of the channel estimates $h_{i,j}(\boldsymbol{g})$ and $\hat{\boldsymbol{z}}$ is the vector containing the corresponding measurements $z_{i,j}$. If the noise is sufficiently smaller than the signal in the measurements $\hat{\boldsymbol{z}}$, we can approximate this problem with the linear least-squares problem:

$$\hat{\boldsymbol{g}} = \arg \min_{\boldsymbol{g}} \sum_{i,j} \left(\frac{\boldsymbol{b}_{i,j}\boldsymbol{g}}{\sqrt{d_{i,j}}} - \tilde{z}_{i,j} \right)^2,$$

where $\tilde{z}_{i,j} = 20 \log_{10} \frac{\hat{z}_{i,j}}{d_{i,j}^{-\alpha}}$. This linear least-squares problem is the same as the one in [15], and can be solved similarly.

3.2. Localization with shadowing

Once the shadowing model has been generated from the site survey, it can be used to track the position of the nodes. We employ a particle filter [16] to track the floating nodes. Each floating node uses an independent particle filter to estimate its own location, and then all the nodes in the network broadcast their most recent position estimate to all of their neighbors. Since the only difference in behavior between the floating nodes and reference nodes is that the floating nodes use a particle filter to estimate their position and reference nodes use an external reference for the location estimate, all nodes need to do to change from reference nodes to floating nodes and vice versa is to change how they obtain their position estimates.

More explicitly, each floating node i independently forms an estimate of its own position $\bar{p}^{(i)}$. Each floating node has P particles which represent samples from its position distribution. Each particle has a position $p_n^{(i)}$ and a weight $w_n^{(i)}$. The weight is proportional to the likelihood of that particle's position being correct. Floating nodes calculate an estimate of their locations $\bar{p}^{(i)}$ as the average of the locations of all of their particles, weighted by the particle weights:

$$\bar{p}^{(i)} = \sum_{n=0}^{P-1} p_n^{(i)} w_n^{(i)} [t+1]. \tag{6}$$

At each measurement interval t, each floating node i receive beacons from each neighbor j containing their neighbor's current position estimate $\bar{p}^{(j)}$. The node also measures the RSS of the beacon as

Algorithm 1 SAL algorithm

At each node i:
Initialize particle positions and weights:
$p_n^{(i)} \sim$ Uniform over network
$w_n^{(i)} = \frac{1}{P}$
for each measurement period t **do**
  if Node i is a floating node **then**
    for each neighbor j **do**
      Receive beacon with $\bar{p}^{(j)}$, $\hat{z}_{i,j}$
      Form expected RSS measurement $\tilde{z}_{p_n^{(i)},j}$ with (7)
      Use $\tilde{z}_{p_n^{(i)},j}$ to adjust weights using (8)
    end for
    Normalize weights
    Calculate effective number of particles N_{eff}.
    if $N_{\text{eff}} < P_{\text{thr}}$ **then**
      Resample Particles:
      $p_n^{(i)} \sim \sum_m N(p_m^{(i)}, \sigma_s^2)$
      $w_n^{(i)} = \frac{1}{P}$
    end if
    Estimate position: $\bar{p}^{(i)} = \sum_n w_n^{(i)} p_n^{(i)}$
  else
    Obtain position estimate from external source
  end if
  Broadcast beacon with position estimate to neighboring nodes
end for

$\hat{z}_{i,j}$. The node then uses this information to calculate the expected measurement $\tilde{z}_{p_n^{(i)},j}$ if the node were at the position of each of its particles $p_n^{(i)}$. The expected measurement is calculated as in (4) using the particles position $p_n^{(i)}$ for the position of node i and the most recent position estimate $\bar{p}^{(j)}$ for the neighboring node j:

$$\tilde{z}_{p_n^{(i)},j} = d_{p_n^{(i)},j}^{-\alpha} 10^{\frac{1}{20}\left(d_{p_n^{(i)},j}\right)^{-\frac{1}{2}}\left(\boldsymbol{b}_{p_n^{(i)},j}\right)\boldsymbol{g}}. \tag{7}$$

The new weight for each particle is then calculated as:

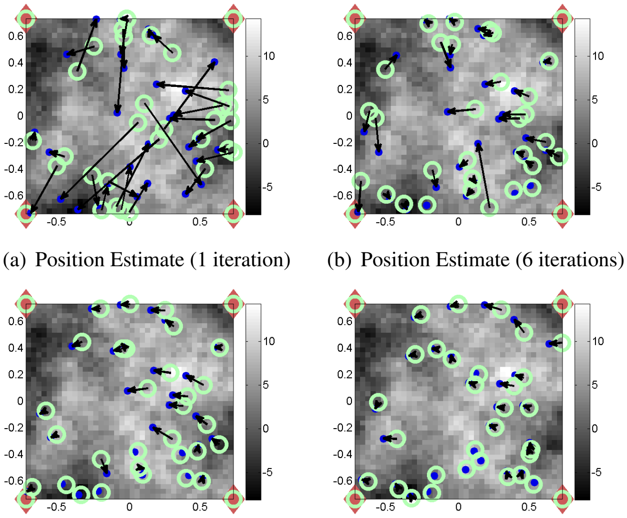
$$w_n^{(i)}[t+1] = w_n^{(i)}[t] \prod_j \Pr\left(\hat{z}_{i,j} = \tilde{z}_{p_n^{(i)},j}\right). \tag{8}$$

Since we assume that the noise is Gaussian, the probability function is simply the Gaussian probability density function:

$$\text{Prob}(\hat{z}_{i,j} = \tilde{z}_{p_n^{(i)},j}) = \frac{1}{\sqrt{2\pi\sigma_v^2}} e^{-\frac{1}{2\sigma_v^2}\left(\hat{z}_{i,j} - \tilde{z}_{p_n^{(i)},j}\right)^2}$$

After all of the measurments have been processed, it is necessary to renormalize the particle weights so that $\sum_{n=0}^{P-1} w_n[t+1] = 1$. Since particle filters require resampling periodically to prevent the weights of the majority of particles from degenerating to 0, each node will periodically resample the particles. During resampling the particles are converted to an approximate probability distribution and random values are then sampled from that distribution to serve as the new particles. We model the probability distribution as a sum of P Gaussians centered on each particle such that the distribution has the probability density function:

$$p^{(i)}(x) = \sum_{n=0}^{P-1} \frac{w_n^{(i)}}{\sqrt{2\pi\sigma_s^2}} e^{-\frac{1}{2\sigma_s^2}\left(x - p_n^{(i)}\right)^2},$$



(a) Position Estimate (1 iteration) (b) Position Estimate (6 iterations)

(c) Position Estimate (18 iterations) (d) Position Estimate (33 iterations)

Fig. 2. SAL Example

where σ_s^2 is a configurable spread parameter. After resampling, all the particles have weight $\frac{1}{P}$ and are random samples from this distribution (i.e. $p_n^{(i)} \sim p^{(i)}(x)$). As in [16], resampling is triggered when the effective number of particles, $N_{\text{eff}} = \left(\sum_m {w_m^{(i)}}^2\right)^{-1}$, falls below a set threshold, P_{thr}.

Initially, the particles are assumed to be uniformly distributed over the field with equal weight. This algorithm continues iteratively as often as necessary to achieve the desired accuracy and for as long as location estimates are required. A summary of this algorithm is shown in Algorithm 1.

3.3. SAL Example

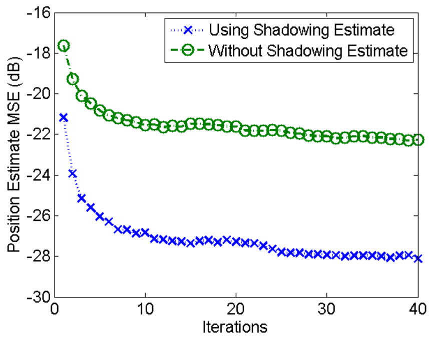
An example simulated network using the SAL algorithm is shown in Figure 2. Snapshots from the first, 6th, 18th and 33rd iterations are shown. The floating node positions from which the measurements were taken are depicted as solid circles, reference nodes as solid diamonds, and the estimated positions as hollow circles. Arrows are drawn from the estimated positions to the true positions for clarity.

Initially, the node locations are completely unknown, so the position distribution for each node is uniform over the entire site, causing the estimated positions to be clustered around the center. After the first iteration (Figure 2(a)), the node's position estimates have shifted towards their true position. As further measurements are made (Figure 2(b), Figure 2(c)), the position estimates become more and more accurate. This process continues as long as location information is desired (Figure 2(d)).

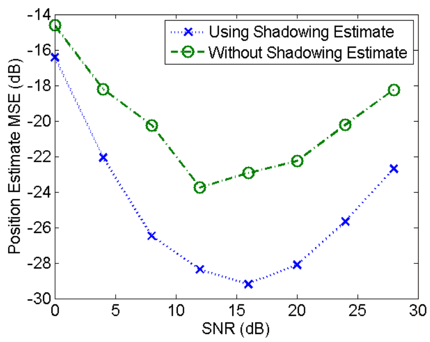
4. SIMULATION RESULTS

In this section we evaluate the performance of the SAL algorithm through Monte Carlo simulations. We evaluate both the steady-state MSE and the convergence rate for the location estimates averaged over 50 random networks. For comparison we also show the MSE and convergence rate when the shadowing is assumed to be its average value (0dB) instead of using the shadowing model.

We simulated a network of 20 mobile nodes and 4 static nodes. The mobile nodes were moved according to a random velocity model



(a) Position MSE at 20dB SNR



(b) Position MSE after 40 iterations

Fig. 3. Simulated Performance

where nodes moved in a random direction at a random speed for a random period of time before changing directions. The shadowing had a shadowing variance of σ_η^2 of 100 dB^2/unit range and correlation parameter δ of 10% of the wireless range. The distance attenuation exponent α was 2. Each node estimated its location using the SAL algorithm with $P = 1000$ particles. We define signal-to-noise ratio (SNR) as the ratio of transmitted power to noise power.

The results are shown in Figure 3. Figure 3(a) shows how the position estimate MSE decreases with each iteration. From the figure it is apparent that the use of the shadowing model does not significantly affect the convergence time of the algorithm, but does significantly reduce the steady-state MSE. The steady-state position estimate MSE is compared for different SNRs in Figure 3(b). From the figure, the use of the shadowing estimate significantly reduces position estimate MSE regardless of SNR. At higher SNRs the position estimate MSE increases because the algorithm is more likely to get stuck in local minima. Since in higher SNR the noise variance σ_v^2 is much lower, the particle position distribution used in (8) is much narrower, restricting the particles to a narrow region consistent with the current estimate of the network as a whole, even if the network is in a local minimum. This effect can be reduced by adjusting the spread parameter σ_s for each SNR, but this optimization is beyond the scope of this paper.

5. CONCLUSION

In this paper we proposed the novel SAL algorithm for node localization in shadowing environments. The SAL algorithm is unique since it is flexible enough to allow for localization of multi-hop networks with mobile reference nodes in shadowing environments. Further, since SAL uses a shadowing model estimated during a site survey, it is able to offer an increase accuracy of location estimates in shadowing environments. We show that the use of the shadowing model significantly reduces location estimate MSE. In the future we will work to combine the shadowing model estimate and localization steps to remove the necessity of the site survey.

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