Localization via the Received Signal Strength Gradient at Lower VHF

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***Abstract*—Localizing a node in complex propagation environments, such as in obstacle-rich indoor scenes, is a challenging task. Conventional approaches employ a dense and/or highly calibrated infrastructure of sensors assisting in the localization process, which is costly and difficult to achieve in ad-hoc situations. In this paper, we propose a minimalistic design based on a small number of access points. Our method uses the received signal strength (RSS) gradient as a direction of arrival (DoA) estimator. Though non-uniform shadowing and multipath adversely affect RSS, these are much less at lower VHF. We show through high fidelity simulations that our approach has promise as a rapidly-deployable localization system.**

I. Introduction

Localization and tracking of targets are critical objectives in a variety of fields, e.g., in radar [1] and mobile robotic systems [2]. Use of global positioning system (GPS) is not always feasible due to cost and/or poor penetration. Many localization techniques rely on time of arrival (ToA), angle of arrival (AoA), or received signal strength (RSS). ToA-based methods based on time-of-flight of a wireless signal suffer from errors due to clock drift and variable processing delays. Classical AoA-based approaches rely on array-processing, requiring multiple synchronized antenna elements per node, and have many challenges [3], e.g. the location estimate is very sensitive to multipath. Classical RSS-based localization approaches attempt to estimate distance-to-source from the received power; this requires estimating various nuisance parameters (e.g., path loss exponent) and in complex scenes, RSS is corrupted by multipath and shadowing [4].

In this work, we take a fundamentally different approach; we use RSS to compute the direction of arrival (DoA) to fixed-location nodes (beacons), and fuse the DoA's to localize the node. This method relies on the basic fact that under ideal propagation, the RSS spatial gradient points towards the source. At microwave frequencies, huge fluctuations in RSS occur over small spatial scales [6] due to small-scale fading. However, these effects are much less prevalent at lower VHF [7]. In addition, we can employ statistical methods to greatly reduce the effect of RSS outliers. Our framework yields point estimates of the DoA as well as uncertainty regions. RSS is easy to measure, does not require an array to process, and since the gradient is a relative measure (a slope), it requires no calibration. Estimation of the RSS spatial gradient does require multiple spatially separated RSS measurements.

II. Model for DoA estimation

Our model for DoA estimation from RSS data is described in [5]. The RSS surface is locally modelled as a linear function of sampling location, and the gradient of the model is a DoA estimate. Notationally,

$$y = X\beta_i + \epsilon \tag{1}$$

where y_i is a $N \times 1$ vector of RSS values of beacon i at N sampling locations, X is a $N \times 2$ matrix of those RSS sampling locations, and $\epsilon \sim N(0, \sigma^2 I_N)$, where I_N is the $N \times N$ identity matrix. We assume the presence of $B \geq 2$ beacons with known fixed locations. Thus, a node seeking to localize itself measures the RSS with respect to each of the B beacons over X.

We adopt a Bayesian model over 1 which enables us to incorporate prior information on σ^2 and to reason probabilistically about the DoA estimate β_i, where i ranges from 1 to B. We can use previous studies characterizing the shadowing variance at lower VHF [8] to derive distributions over σ^2. We use $p(y|X,\beta) = N(X\beta, \sigma^2 I_N)$, a Normal distribution. Using standard statistical theory, we can derive the posterior probability distribution $p(\beta_i|y, X)$ over each β_i.

III. Localization Algorithm

We next combine $\{\beta_i\}_{i=1}^{i=B}$ into a localization estimate. In the general case, the node's orientation θ is unknown (with respect to the global coordinate system). θ is straightforwardly estimated; but for simplicity in the sequel we assume an estimate of it is known (e.g., via compass), so that the β_i are represented in the global coordinate system. Our localization algorithm is presented in Algorithm 1. For each of M Monte Carlo iterations, we sample all B direction vectors from their posterior distributions. We apply a weighted least squares procedure on these DoA's to obtain a point estimate of the node location l based on known beacon locations b_i. M such Monte Carlo runs yield an empirical distribution over node location. We must account for correlations and outliers in the data to ensure the estimates are meaningful. Positive spatial correlation arises when nearby RSS samples encounter correlated shadowing. Without correction, the true uncertainty in the DoA (and hence localization) is underestimated. Outliers arise from fading and non-uniform shadowing, and bias the

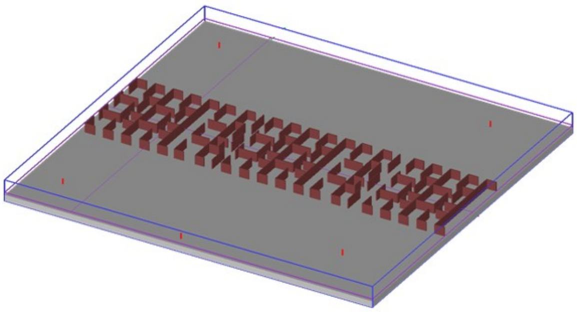

Fig. 1. FDTD simulation of an office building with realistic materials. All nodes are at assumed height of $\frac{\lambda}{10}$ and at center frequency of 40 MHz. The total scene is 122 m $\times$ 115 m. Beacons (red dots) with known locations surround the building.

estimated DoA from the true source direction. We use standard statistical procedures for correcting spatial correlation and outliers; details will be described elsewhere.

Algorithm 1 RSS gradient-based localization

for $m = 1$ to M **do**
  for $i = 1$ to B **do**
    $\beta_i \leftarrow p(\beta_i | y_i, X)$
    $n_i \leftarrow \begin{pmatrix} 0 & -1 \\ 1 & 0 \end{pmatrix} \frac{\beta_i}{||\beta_i||}$
    $w_i \leftarrow ||\beta_i||$
  end for
  $l_m \leftarrow \left(\sum_i w_i n_i n_i^T\right)^{-1} \left(\sum_i w_i n_i n_i^T b_i\right)$
end for

IV. Results and Conclusion

We have conducted high-fidelity simulations at lower VHF using a finite-difference time-domain (FDTD) full wave solver in a complex indoor office environment shown in Figure 1. Figure 2 shows the results; the caption has further details. Note that as the RSS sampling region grows, the typical localization error decreases and the uncertainty ellipses shrink.

We have presented an extremely simple method for localization, requiring a minimum of sensors and no calibration, synchronization, offline training, or array processing. By coupling the benign propagation of lower VHF with rigorous statistical modeling to handle correlations and outliers, we obtain useful point and uncertainty estimates of location. Our approach shows promise as a rapidly-deployable method for tracking and localization in complex scenarios. Further directions include optimizing beacon placement and motion of the mobile agent to improve accuracy.

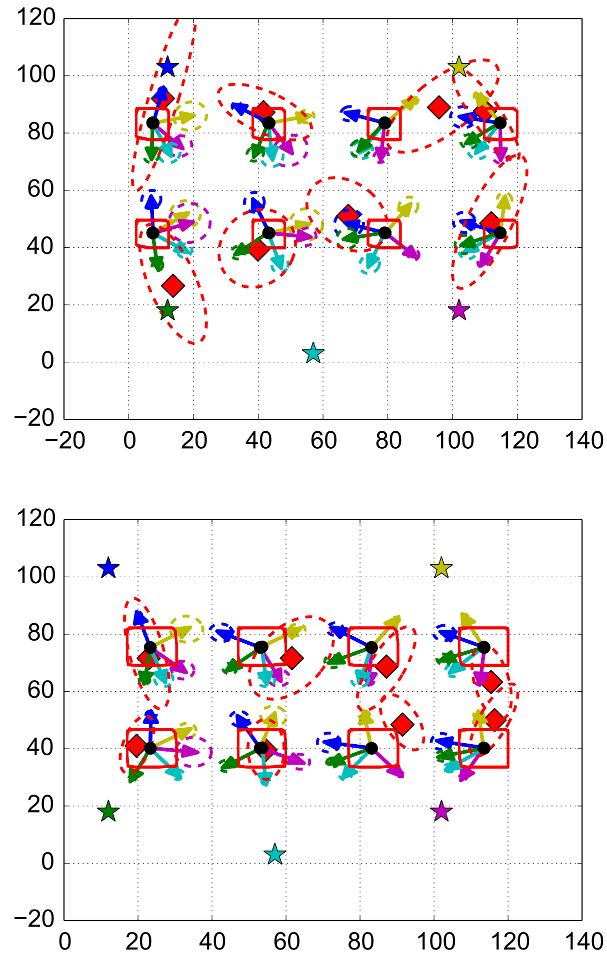

Fig. 2. Localization results for a mobile agent which samples 8 different sampling regions within the office scene in Figure 1 of sizes (top) $\approx$ 10m $\times$ 10m and (bottom) $\approx$ 12m $\times$ 12m. Figure elements: beacon (colored star); estimated DoA based on RSS (arrow colored to match corresponding beacon); DoA uncertainty region (colored dashed ellipse encircling DoA arrow); convex hull of the sampling region (rectangular red region); true location (i.e., centroid of sampling region) (black dot); location estimate (red diamond); location uncertainty ellipse (dashed red ellipse). Top: Median localization error is 10.1 m. Bottom: Median localization error is 7.4 m.

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