NON-COOPERATIVE LOCALIZATION USING DIFFERENTIAL RSS AND LINK LOSS PARAMETER ESTIMATION

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ABSTRACT

Efficient enforcement mechanisms which perform verification of user access information, subsequent localization of non-compliant users, and prompt punitive action to ensure compliance is one of the fundamental requirements of a spectrum sharing system. Fast response time, low computational overhead, and low false alarm rate are some of the desirable characteristics of any practical enforcement system.

Taking these factors into consideration, range based techniques for localization that exploit Received Signal Strength (RSS) provide an economic solution to the problem at hand. We particularly concentrate on methods using Differential RSS (DRSS) and Weighted DRSS (WDRSS) comparing their performance on measured data. The measurement campaign was done in Blacksburg, VA.

In addition a path loss model is proposed which has a single parameter defined as the link loss parameter. The proposed model is motivated by showing the promise of improved location estimation accuracy provided we have sufficiently accurate estimates of the link loss parameters. A joint optimization problem is formulated which simultaneously estimates the location and the link loss parameters. Finally, some initial results of the joint estimation approach are provided, which highlight the challenges of the link loss model approach to localization. Some avenues for further improvement are proposed.

1. INTRODUCTION

Verification of conformance to transmit legitimate requests by a user is one of the essential components of a Spectrum Access System (SAS). The legitimacy of one or more of these requests can often be location dependent, which then necessitates the SAS enforcement mechanism to be equipped with an efficient localization and verification module.

Malicious users may spoof their location to avail themselves of more advantageous transmit capability. The information sent by the user cannot be inherently trusted, so that we have a non-cooperative localization problem. Generally, the localization step is preceded by a verification step which produces a binary declaration as to whether the location information sent by the user is correct or not. If not, a localization step should locate the user and report the location to the enforcement mechanism which in turn will take the necessary punitive action.

In this work, we are focusing on the localization aspect of the problem. It is intuitively clear that high accuracy of the localization algorithm is desired along with speed. It is also desirable that the localization technique incurs low cost, i.e. it utilizes the existing infrastructure to gather the necessary resources. These reasons contribute to the selection of a Received Signal Strength (RSS) based method as our localization technique. A comprehensive summary of other localization techniques can be found elsewhere [1].

The paper is organized in the following way. We start by defining some of the basic terms related to our problem in Section 2. Section 3 describes in brief the measurement campaign [2] which produced the RSS data along with location that is used here. In Section 4 the shortcomings of the existing cost functions are analyzed, and leads to the proposed link loss parameter based model. Section 5 contains the results showing the comparative performance of different models when used on the measured data and is followed by concluding remarks in Section 6.

2. BACKGROUND

The signal power from an emitter located at (x, y) received at (x_k, y_k) suffers a path loss which we assume to be represented by the path loss model [3] shown in (1),

$$P(d_k) = P(d_0) - 10\alpha \log_{10}\left(d_k / d_0 \right) \quad (1)$$

where α is the path-loss component, assumed to range between 2 (Line of Sight (LOS)) and 6, $P(d_0)$ is the signal power measured at a distance d_0 from the emitter, and d_k is the Euclidean distance between the emitter and the receiver given by (2).

$$d_k = \sqrt{(x_k - x)^2 + (y_k - y)^2} \quad (2)$$

The path loss model described in (1) does not take into account the effect due to shadowing. The log-normal shadowing model is given in (3).

$$L(d_k) = P(d_0) - 10\alpha \log_{10}\left(d_k / d_0 \right) + x_k \quad (3)$$

The normal shadowing variable x_k is characterized by

$$X_k \sim N\left(0, \sigma_s^2\right) \tag{4}$$

where σ_s^2 is the variance of shadowing.

The log-normal described in (3) has a parameter $P\left(d_0\right)$ which requires calibration. In order to bypass this parameter a differential RSS (DRSS) model was proposed [4] which is shown in (5).

$$\begin{aligned} L\left(d_i, d_j\right) &= L(d_i) - L(d_j) \\ &= 10\alpha \log_{10}\left(d_j / d_i \right) + \Delta x_{ij} \end{aligned} \tag{5}$$

where

$$\Delta X_{ij} \sim N\left(0, 2(1-\rho_{ij})\sigma_s^2\right) \tag{6}$$

where ρ_{ij} is the coefficient of spatial correlation between the i-th and the j-th anchor points.

For a wireless network with N anchor nodes with known positions, using (5) we can get a total of $N\left(N-1\right)/2$ equations of which $\left(N-1\right)$ are independent. These equations can be utilized to formulate the cost function for the localization problem. The cost function for the DRSS problem [4] is shown in (7).

$$\hat{\boldsymbol{\theta}} = \arg\min_{\boldsymbol{\theta}} \sum_{i=1}^{N-1} \sum_{j=1}^{N} \left(L(d_i) - L(d_j) - 10\alpha \log_{10}\left(d_j / d_i \right) \right)^2 \tag{7}$$

where the argument $\boldsymbol{\theta} = \left[x, y\right]$ gives the location of the emitter. A weighted version of (5) was proposed in [5] and the method was appropriately termed weighted DRSS. The WDRSS cost function is shown in (8).

$$\hat{\boldsymbol{\theta}} = \arg\min_{\boldsymbol{\theta}} \sum_{i=1}^{N-1} \sum_{j=1}^{N} w_{ij} \left(L(d_i) - L(d_j) - 10\alpha \log_{10}\left(d_j / d_i \right) \right)^2 \tag{8}$$

where the weights w_{ij} are given by

$$w_{ij} = \exp\left(-\beta \frac{\left(d_{ij} - d_{\min}\right)}{\left(d_{\max} - d_{\min}\right)} \right) \tag{9}$$

with d_{ij} the distance between the i-th and the j-th anchor nodes, d_{min} the distance between the closest anchor nodes, d_{max} the maximum distance possible once we fix the dimensions of the environment, and β a factor which controls the minimum value w_{ij} can take on. A detailed comparison of the two cost functions described in (5) and (6), with their respective performance on simulated RSS values, can be found elsewhere [5].

3. DATA COLLECTION

A measurement campaign was conducted [2] in Blacksburg, VA, where RSS information was recorded together with location. For the remainder of this paper, the collected dataset will be used to assess the performance of a localization technique rather than simulated values as was done earlier [4, 5].

3.1. Transmitter

The monocone transmit antenna constructed in Virginia Tech's MPRG lab has the exact coordinates of 37.2317543^{o} W and -80.4234772^{o} N. Figure 1 shows the transmitter block diagram.

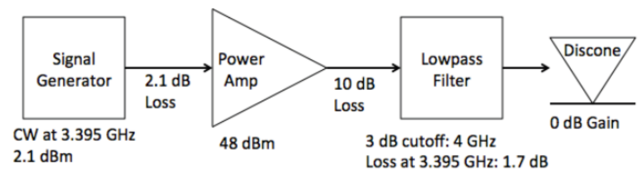

Figure 1: Transmitter Block Diagram.

A continuous wave tone at 3.395 GHz is generated by the signal generator. To verify the non-existence of any co-channel interference the spectrum between 3.3 to 3.5 GHz is measured at various areas of interest. The noise floor is calculated to be -125 dBm over a bandwidth of 1 kHz.

3.2. Receiver

To reduce the cost of the campaign only one sensor was used to measure RSS at different locations under the assumption that the RSS measurements at different locations $\left[X_1 \quad X_2 \quad \ldots \quad X_n\right]$ taken at different times are equivalent to RSS measurements taken at a single time in those same locations $\left[X_1 \quad X_2 \quad \ldots \quad X_n\right]$. The substantiation of this assumption follows from showing that shadowing does not change significantly over a fixed path with time [6].

The receivers used were a Bicone Antenna with 0 dB gain over an isotropic radiator, the EM-6865 manufactured by Electro-Metrics, and a Spectrum Analyzer with a built-in GPS receiver manufactured by Tektronix (SA 2600 RF Hawk). The GPS has a horizontal position accuracy of better than 9 meters. The receiver was mounted either to a car or to a bicycle.

3.3. Measurements

The measurement campaign was conducted across the Virginia Tech campus and the town of Blacksburg. A total of 3,236 RSS measurements was taken with the maximum distance from the transmitter being 1.42 kilometers. Figure 2 shows the heat map of the RSS measurements.

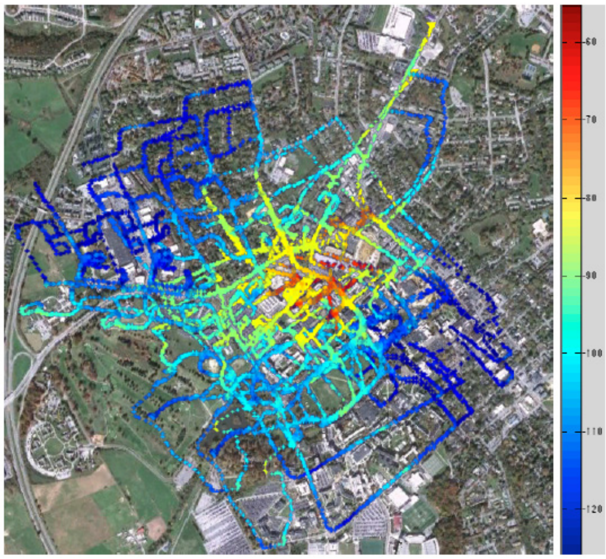

Figure 2: Heat Map of RSS Measurements (in dBm).

The calibration parameter $P(d_0)$ for the transmitter is calculated by placing the receiver at a distance of 3 feet and then progressively moving it to 53 feet. The elevation was maintained throughout. The experimental value of the reference power was found to be -2.85 dBm at a distance of 3 feet (0.9144 meters).

The path loss coefficient α was calculated by minimizing the mean square criterion in (10).

$$\hat{\alpha} = \arg\min_{\alpha} \sum_{i=1}^{M} \left[P(d_i) - P(d_0) + 10\alpha \log_{10}\left(d_i / d_0 \right) \right]^2 \quad (10)$$

where M is the number of measurements taken, i.e. 3,236 in this case. The experimental value of α is calculated to be 3.25.

4. LINK LOSS PARAMETER

4.1 Motivation

The stochastic part of the log-normal shadowing model in (3) can be re-written as:

$$x_k = L(d_k) - P(d_0) + 10\alpha \log_{10}\left(d_k / d_0 \right) \quad (11)$$

From our measured data, we can calculate the stochastic part by substituting in $\alpha = 3.25$, $P(d_0) = -2.85$ dBm, and $d_0 = 0.9144$ m since we know the location of both the emitter and the receiver. Figure 3 shows a histogram of residual RSS.

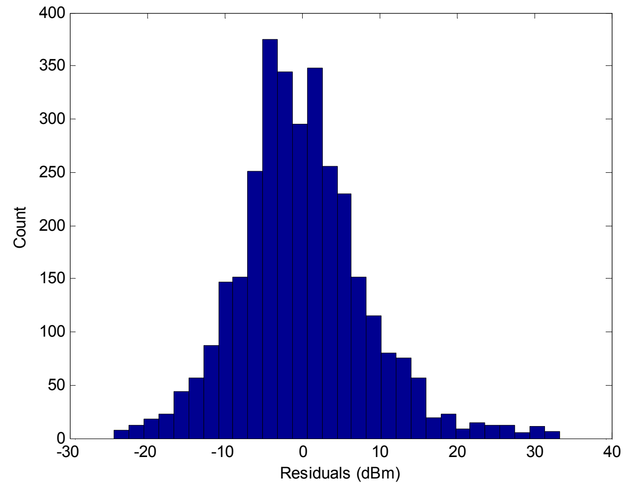

Figure 3: Histogram of residual RSS.

Table 1 shows some of the important statistics of the residual RSS. From Table 1 we observe that the residuals are almost centered on 0, both in terms of mean and median. The spread of the distribution is pretty high as depicted by variance and range. However, the most interesting element is the skewness value which is 0.5482. This indicates that the normality assumption in (4) is not valid.

Table 1: Statistic of the residual RSS.

Statistic	Value
Mean	-6.69×10^{-4} dBm
Median	-0.6610 dBm
Standard Deviation	69.5766 dBm
Range	57.4732 dBm
Skewness	0.5482

A far greater problem arises due to the high variance of the residuals. From (5) and (7) we can conclude that the cost function is formulated based on the assumption that the stochastic component of the log-normal model, i.e. Δx_{ij} is small. The solution set $\mathbf{\theta} = [x, y]$ computed using the cost function in (7) will be close to the actual emitter location if the variance of Δx_{ij} is small, which is possible when either one or both of the following conditions is valid:

i. σ_s^2 : the shadowing variance is small;

ii. ρ_{ij} : the spatial correlation coefficient between the i-th and the j-th anchor node is large (high spatial correlation).

From Table 1 we clearly see that σ_s^2 is not small. The expression for ρ_{ij} is given by [4]:

$$\rho_{ij} = \exp\left(-\frac{d_{ij}}{d_c}\ln 2\right) \tag{12}$$

where d_c is the distance between two nodes for which $\rho_{ij} = 0.5$. A high value of d_c corresponds to a highly spatially correlated environment. The reported value of d_c is 160 meters [2]. With 3236 measurements we have a total of $(3236)(3236-1)/2 = 5234230$ possible pairs of anchor nodes. Among these pairs, the distance between 5024938 pairs (~ 96%) is greater than 160 meters. This implies that for 96% of the cases the spatial correlation coefficient $\rho_{ij} < 0.5$. So it can be concluded that the environment under consideration does not exhibit high spatial correlation. Thus, the assumption under which the cost function (7) was formulated does not hold true.

4.2 Link Loss Parameter

From the discussion in Section 4.1 it is clear that by minimizing the DRSS cost function in (7) the true location of the emitter will be obtained either for environments where the shadowing effect is small (low variance of shadowing) or for environments with high spatially correlated shadowing (high value of ρ_{ij}).

We propose the following log-normal model as an alternative for (3)

$$L(d_k) = P(d_0) - 10\gamma_k \log_{10}\left(d_k / d_0\right) \tag{13}$$

where γ_k is the link loss parameter which accounts for contributions due to path loss as well as shadowing. The corresponding DRSS is given by

$$L(d_i) - L(d_j) = 10\gamma_j \log_{10}\left(d_j / d_0\right) - 10\gamma_i \log_{10}\left(d_i / d_0\right) \tag{14}$$

From (14) it seems that the advantage of DRSS, i.e. the lack of dependence on the calibration parameters, is lost if we use this model since the d_0 term does not cancel out. However, $P(d_0)$ corresponds to the reference power of the transmitter at any arbitrary distance. So without losing generality d_0 can be set to 1 meter.

If we have a priori knowledge of the link-loss parameters γ_k then only the location of the emitter is unknown. In that case the solution set $\boldsymbol{\theta} = [x, y]$ can be obtained by:

$$\hat{\boldsymbol{\theta}} = \arg\min_{\boldsymbol{\theta}} \sum_{i=1}^{N}\sum_{j=i}^{N}\left(\Lambda(i) - \Lambda(j)\right)^2 \tag{15}$$

where

$$\Lambda(i) = L(d_i) - P(d_0) + 10\gamma_i \log_{10}\left(d_i / d_0\right) \tag{16}$$

The exact knowledge of the link loss parameters may not be known all the time. The case in (15) and (16) represents the best case scenario, where the link loss parameters are known completely. Conversely, the worst case scenario takes place when there is no a priori knowledge. For those cases a joint optimization problem is formulated where the cost function used is the one in (15), but the parameter set is expanded to $\boldsymbol{\theta}_1$, as shown in (17).

$$\boldsymbol{\theta}_1 = [x \quad y \quad \gamma_1 \quad \gamma_2 \quad \cdots \quad \gamma_N] \tag{17}$$

From (17) we see that even for the simplest DRSS case with $N = 4$ anchor nodes the dimension of the search space becomes 6. The implications, along with other results, are presented in the next section.

5. RESULTS

Figure 4 shows a comparison of the performance of DRSS and WDRSS in terms of Average Miss Distance (AMD) on the measured data. The cost functions used for DRSS and WDRSS are given by (7) and (8) respectively. For the WDRSS case the tunable parameter β was set to 4.6. All the plotted AMDs were obtained after taking an ensemble average of 5000 independent runs. The interior point algorithm [7] was the algorithm of choice to solve the optimization problem.

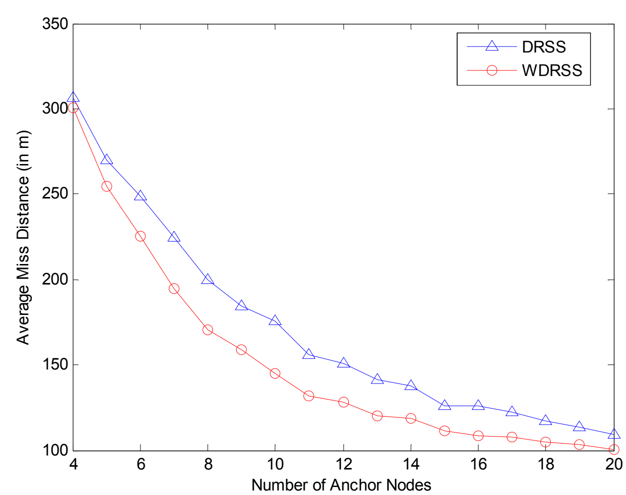

Figure 4: Comparison of DRSS and WDRSS in terms of AMD.

We observe that WDRSS marginally outperforms DRSS in terms of AMD. This result was observed earlier [5]. However, even with 20 anchor nodes we see that the AMD is approximately 100 meters. Neither of the methods is direction sensitive so approximately 100 meters of miss distance translates to an uncertainty area of 0.0314 square kilometers (almost 8 acres). That performance thus shows ample room for improvement.

Next, we assess the performance of our proposed model with link loss parameters on the same dataset used in Figure 4. Figure 5 shows the performance for the best case scenario where we have complete a priori knowledge of the link loss parameters. The cost function described in (15) was used. The dotted lines in Figure 5 represent the localization standard when GPS data is not available [8] for which FCC stipulates the probability of localizing within 100 m and 300 m to be 0.67 and 0.95 respectively. In this problem we are dealing with non-cooperative localization, so that GPS data (even it is supplied) should not be trusted; hence the FCC stipulated localization performance at the 67th and 95th percentile acts as a guideline to assess the performance of the proposed model.

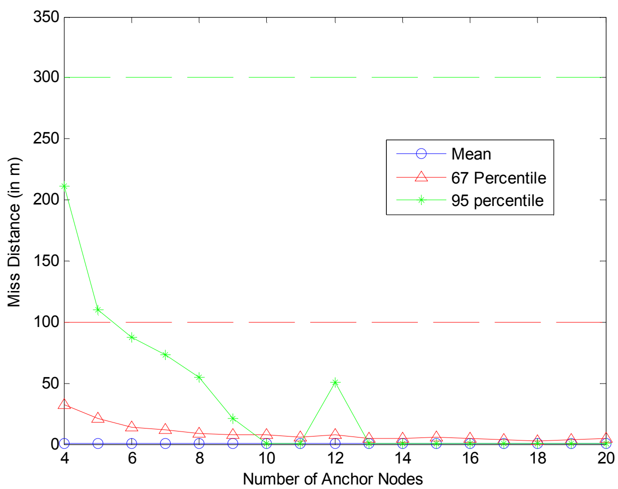

Figure 5: Miss Distance Characteristics for the DRSS Link Loss Model with known parameters.

Figure 5 shows promising results. Not only is the AMD close to zero, the 95th percentile value is close to zero as well, especially for 10 or more anchor nodes used. This shows that the spread of the error distribution is now considerably less.

We notice a curious phenomenon in Figure 5. For twelve anchor nodes the 95th percentile curve shows a spike, which is a deviation from what otherwise was a relatively smooth curve. To investigate this, we show the maximum Miss Distance as a function of the number of anchor nodes in Figure 6. The maximum miss distance in Figure 6 comes from the same ensemble which was used to generate the mean, 67th percentile and 95th percentile plots in Figure 5. We observe that the maximum miss distance is not a smooth function of the number of anchor nodes. In fact we see that for 10 anchor nodes the maximum miss distance is greater than the maximum miss distance corresponding to 12 anchor nodes. However, the 95th percentile point for 10 anchor nodes, in Fig. 5, is almost 0 while it is close to 50 meters for 12 anchor nodes. This indicates that with known link loss parameters, even though the miss distances are negligible for most cases, there might be a few cases where the algorithm converges to an erroneous solution. A large ensemble size is one of the pre-requisites to study these outliers in greater detail, which is not within the scope of the present paper and left for further work.

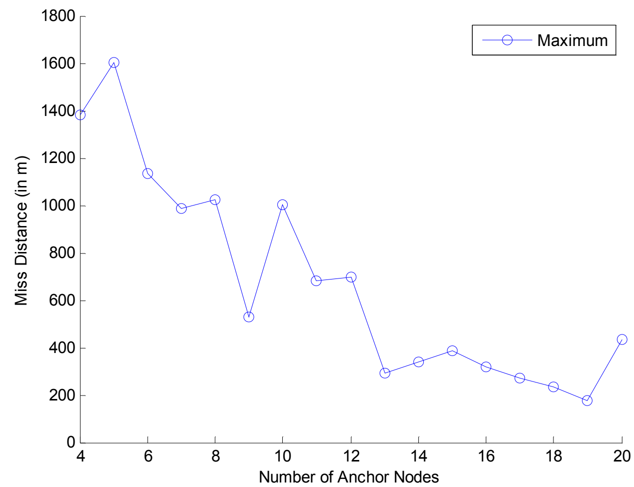

Figure 6: Maximum Miss Distance for the DRSS Link Loss Model with known parameters.

Figure 7 shows the other extreme case where we do not have any knowledge about the link loss parameters. For this case the argument in (17) is used along with the cost function in (15). We see that the performance has deteriorated when compared to the one we see in Figure 4. This deterioration is due to the higher dimensionality of the optimization search space.

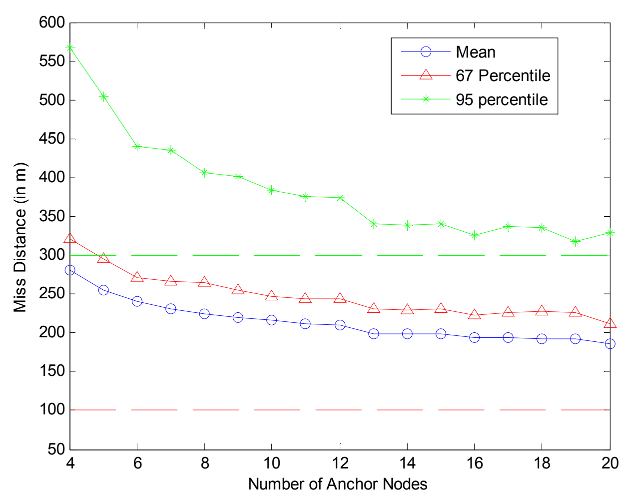

Figure 7: Miss Distance Characteristics for the DRSS Link Loss Model with unknown parameters.

Figure 8 shows the performance of the DRSS Link Loss Model with noisy link loss parameters. Artificial noise was added to the link loss parameters γ_k. Noise came from a uniform distribution over the interval $[-0.2, 0.2]$. We see that AMD, even with these noisy estimates, is less than 50 meters for 10 or more anchor nodes used. The 95th percentile is closing in on slightly higher than 50 meters, signifying the spread of the error distribution is low. This experiment shows that even with relatively noisy estimates location accuracy can be improved substantially.

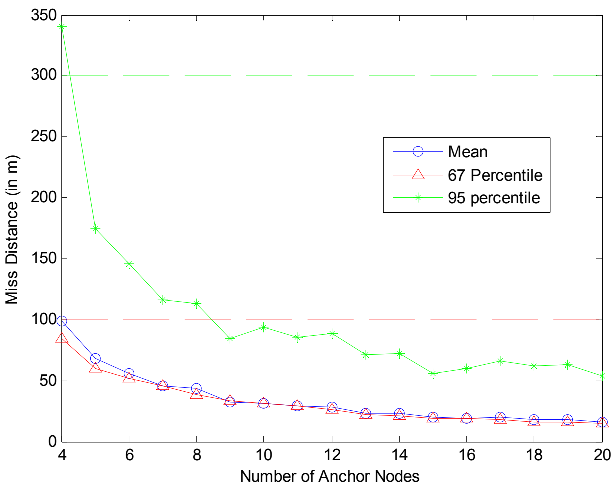

Figure 8: Miss Distance Characteristics for the DRSS Link Loss Model with noisy parameters.

With these results, there can be two possible avenues of further research. Choosing the appropriate heuristic optimization algorithm suited for high dimensional problems can be one path. However, with a more complicated algorithm the computational burden will increase which will adversely affect the time needed to localize. A second avenue to pursue deals with finding an alternate method of measuring the link loss parameters γ_k. The results in Fig. 8 show that even a noisy estimate can result in much improved localization accuracy (AMD of 30 m corresponds to ¾ of an acre).

6. CONCLUSION

In this work we analyzed different cost functions in the light of experimental data and highlighted some of the drawbacks of these cost functions. We proposed a new cost function, and analysis results using measured data, showing that with some a priori knowledge the proposed cost function can lead to substantially improved localization accuracy.

7. ACKNOWLEDGMENT

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