STATISTICAL METHODS FOR FAST LOS DETECTION FOR RANGING AND LOCALIZATION

Monalisa Achalla[1]*,Kevin V. Mack*[1]*,Vanitha M.*[2]*,Harish Krishnamoorthi*[3]*,Mahesh K. Banavar*[1]

[1]Department of Electrical and Computer Eng, Clarkson Center for Complex Systems Science (C^3S^2),
Clarkson University, Potsdam, NY 13699.
[2]School of Information Technology and Engineering, Vellore Institute of Technology, India.
[3]School of ECEE, Arizona State University, Tempe, AZ.

ABSTRACT

Received signal strength indication (RSSI) data is often used for ranging and localization algorithms, where the data may be obtained using Bluetooth Low Energy (BLE) radios. In the BLE protocol, when a device is in advertising mode, it is possible to obtain RSSI values. However, these RSSI values are noisy and can often fluctuate due to multipath effects, which reduces the accuracy and reliability of ranging and localization. Additionally, the effectiveness of RSSI ranging degrades when there is an absence of line of sight (LOS) or when devices are in rich scattering environments. Therefore, the detection of LOS plays a very significant role in indoor localization and room reconstruction.

In this paper, we present algorithms to detect whether there is LOS present between a transmit-receive pair being used for ranging. Our focus in this paper is fast detection with a minimum number of samples. We use measurements such as the energy distance and Mahalanobis distance, and benchmark our results against the Neyman-Pearson detector. Numerical simulations are used to validate our algorithms.

***Index Terms*—** Line of sight (LOS), Neyman-Pearson, Mahalanobis distance, Energy distance, RSSI

1. INTRODUCTION

In most localization problems, the location of a target node at an unknown location needs to be estimated using distance estimates between this target node and several "anchor" devices at known locations. The use of Bluetooth and other wireless signals for obtaining distance estimates has been studied extensively [1–9]. When using this technology in rich scattering environments, there are many challenges that must be overcome to achieve accurate localization. With these environments being reflective and chaotic, there have been many techniques used to mitigate these effects in localization estimates [10–13]. However, few focus directly on methods of determining LOS conditions.

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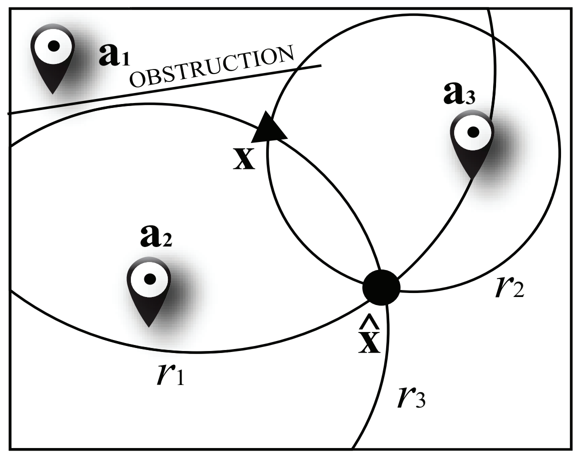

Fig. 1: Ranging error that occurs when there is LOS obstruction. The pins represent the anchors $\mathbf{a}_i$, the triangle is the target node, $\mathbf{x}$, and the circle represents the source location estimate $\hat{\mathbf{x}}$. The noisy ranging estimates are given by r_i. The obstruction causes attenuation in the received power of node $\mathbf{a}_1$, which leads to the overestimation of the distance between the anchor and target for one of the nodes, resulting in localization estimation error.

Common algorithms for solving localization problems are multilateration-based, which are used due to low computational complexity and ease of implementation [12, 14–16]. The same problem can also be posed as an optimization problem [17–20]. Fingerprinting is another popular method due to its ability to perform better in difficult indoor environments [21], but with the caveat that the environment must be mapped extensively to add robustness to the algorithm. Since mapping the environment may not be convenient or possible, other techniques from adaptive filtering have also been widely studied in this area, and include Kalman filtering [1, 2] and neural networks [3]. There are also techniques that use Wi-Fi, accelerometer data, or other sensor data to augment with Bluetooth RSSI measurements [4, 5]. Additionally, dilation algorithms [6] and stigmergic approaches [7] have been used in an attempt to solve the inaccuracy of indoor positioning with Bluetooth. These techniques are designed to mitigate environmental effects such as multipath and fast fading.

While these localization algorithms can be based on ranging information or time information, they rely on there being direct line of sight (LOS) between the transmitter and receiver. Having obstructions, such as walls, in between the transmit-receive pair will lead to reduced RSSI values at the receiver. While this is due to power being absorbed by the obstruction, if LOS is simply assumed, as is the case in the localization algorithms described above, the reduced power is interpreted as a greater distance between the transmitter and receiver, and will consequently lead to errors in localization (Figure 1).

In [2], RSSI sample distributions have been investigated in order to gain information about the statistical properties of RSSI data. The RSSI sample distribution is examined to determine the positioning of devices, or in finger-printing, to obtain a model of the operating environment [10]. In [11], Benedetto *et al*., use packet loss and RSSI in order to extrapolate information about the existence of single-path or multi-path propagation of the Bluetooth signals. Since packet loss information is not available from the Bluetooth API on Android, an approach based solely on RSSI sample distributions is required. This has been attempted in [12, 13]. Specifically, in [13], the authors attempt to determine from RSSI samples, whether or not two devices are in the same room.

In this paper, we consider another scenario which is important to classify: to quickly distinguish between same room line of sight (LOS) and no line of sight (NLOS) conditions of reflective environments. If devices can determine the quality of their line of sight based solely on RSSI, this information can be used to improve ranging estimates and localization. We focus on not only detecting LOS, we investigate methods to perform this task with as few RSSI samples as possible. We use a Neyman-Pearson detector to provide a performance benchmark. Our approaches are validated using numerical simulations.

The rest of this paper is organized as follows. In Section 2, we present the LOS detection problem and present our approaches to solving the problem. In Section 3, we present and discuss our numerical simulations. Finally, in Section 4, we discuss future work and present concluding remarks.

2. LINE OF SIGHT DETECTION

During localization experiments, errors can occur when ranging is performed with the line-of-sight [12, 13] blocked due to obstructions, a common occurrence when localization is attempted in rich scattering environments, such as inside buildings. When the LOS path is blocked, the power that is seen by the receiver is reduced, and it appears that the transmitting device is farther than it actually is. It is therefore important to detect obstructions before performing ranging and localization.

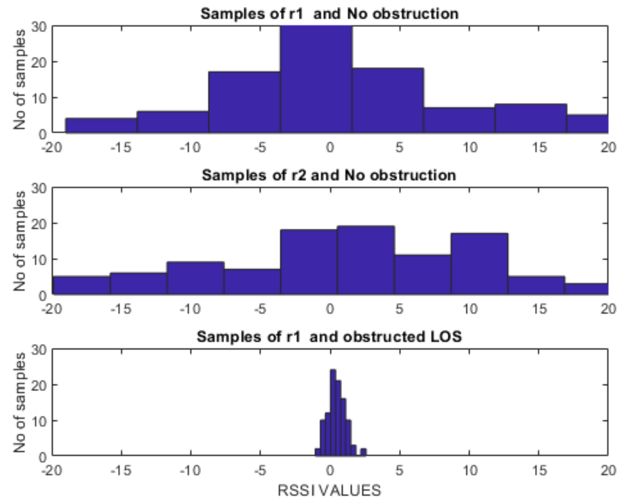

Fig. 2: The results of the line-of-sight tests. Two transmit-receive distances, r_1 and r_2 were used, with $r_2 > r_1$. Each graph represents an RSSI sample distribution. The distributions with several spaced out clusters show line-of-sight paths, as well as reflected paths. This experiment was replicated five times with nearly identical results.

An experiment was conducted to collect RSSI samples between Android devices placed at two different distances with and without barriers in between them, in a rich scattering environment. Histograms of these data are shown in Figure 2. We hypothesize that the structure of data occurs due to the multi-path effects of the signal. Once it is determined that there is no line-of-sight path, range correction between the target node and the anchors can be performed.

A further consideration, is the amount of data, characterized by the number of samples, needed to detect LOS, within some accuracy bounds. This is needed in dynamical environments, where devices may be moving, and the environment will be constantly changing. In order to achieve this, we use instance-based metrics [22], such as the energy distance and the Mahalanobis distance. To verify our results with these methods, we benchmark LOS detection performance using a Neyman-Pearson detector.

2.1. The Neyman-Pearson Detector

Based on our observations from the data collected, we set-up our detection problem with the following hypotheses:

$$\begin{aligned} H_0 &: X \to \mathcal{N}(0, \sigma_0^2), \\ H_1 &: X \to \mathcal{N}(0, \sigma_1^2), \end{aligned} \tag{1}$$

where the data, $x(m)$, is represented using the random variable X, and $\sigma_1^2 > \sigma_0^2$.

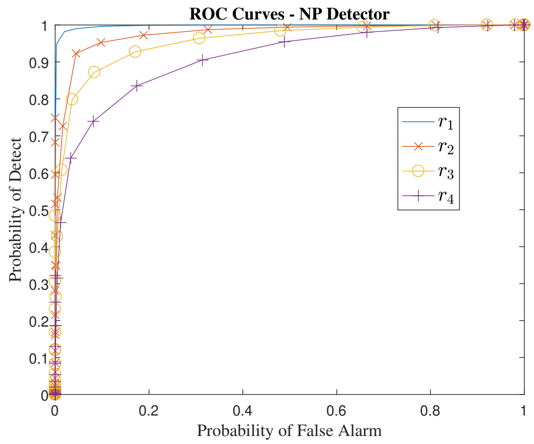

Fig. 3: This figure depicts the ROC curves when the line-of-sight samples are compared to the obstructed samples using a Neyman-Pearson detector and changing transmit-receive distances, with $r_1 > r_2 > r_3 > r_4$.

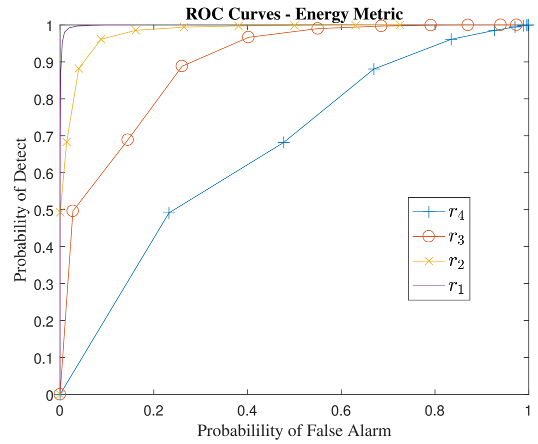

Fig. 4: This figure depicts the ROC curves when the line-of-sight samples are compared to the obstructed samples using the energy distance and changing transmit-receive distances, with $r_1 > r_2 > r_3 > r_4$.

Using the Neyman-Pearson detector [23], the test to declare that the LOS path is present ($\rightarrow H_1$) is given by

$$\frac{1}{M}\sum_{i=1}^{M-1} x[m]^2 > \gamma, \tag{2}$$

where M is the number of recorded samples, $x(m)$ is the value of the m-th RSSI sample, and γ is the detection threshold that can be adjusted based on the desired probability of false alarm.

2.2. Energy Distance

The energy distance metric allows one to quantify the distance between two distributions [24]. Since this is a distance metric, when two distributions are equal, the metric has a value of zero. The energy distance can therefore be used to measure the difference between an empirical distribution constructed from measured samples and a distribution built from a model. For a cumulative distribution function (CDF) of the random variable X, $F(x)$, and an empirical CDF $F_n(x)$, the energy distance is defined as [25]:

$$E(F_n, F) = \int_{-\infty}^{\infty} (F_n(x) - F(x))^2 dF(x). \tag{3}$$

Using the same setup as in Section 2.1, we detect the presence of LOS when

$$E(F_n, F) < \tau, \tag{4}$$

where τ is a varying threshold.

2.3. The Mahalanobis Distance

The Mahalanobis distance is similar to the energy metric and is given by

$$D = \frac{1}{N}\sqrt{\sum_{i=1}^{N}\frac{(\mu_i - x_i)^2}{\sigma_i^2}}, \tag{5}$$

where μ_i, σ_i are the mean standard deviation of the profile for the i-th graph with N shared graphs between the testing set and the profile [26, 27]. The Mahalanobis metric is also multiplied by $\frac{1}{N}$ to control for different numbers of shared graphs between the testing set and the profile. Similar to the above stated statistical methods, we detect the presence of LOS when $D < \tau$, where τ is a varying threshold.

3. RESULTS

In this section, we evaluate the performance of the algorithms we presented, both by comparing them to each other, as well as characterising performance with respect to the number of samples used for detection. We generate synthetic data according to the model described in (1). We generate ROC curves to compare the performance of the algorithms. In order to characterize the speed of detection of each of the algorithms, we plot equal error rates vs. number of samples.

The detection results are benchmarked using the Neyman-Pearson detector. ROC curves are generated for four sets of distances, denoted by r_1, r_2, r_3, and r_4, where $r_1 > r_2 > r_3 > r_4$. From the curves in Figure 3, it can be seen that, as expected, increasing the distance reduces performance. However, error rates are low even for r_4.

Figure 4 shows ROC curves when Energy distance is used for LOS detection for the same distances, r_1, r_2, r_3, and r_4.

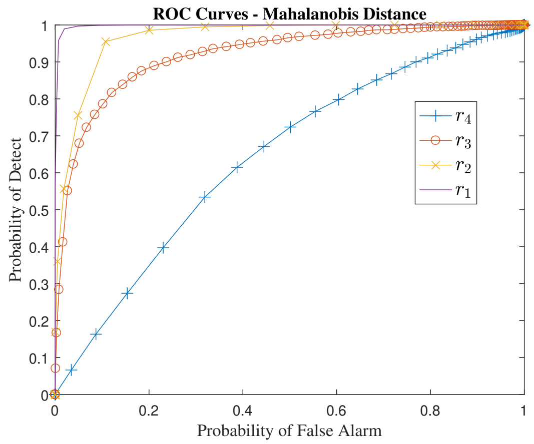

Fig. 5: This figure depicts the ROC curves when the line-of-sight samples are compared to the obstructed samples using the Mahalanlobis distance and changing transmit-receive distances, with $r_1 > r_2 > r_3 > r_4$.

Similar to the NP detector, the performance is best for r_1 and shows low error for r_4. Similarly, ROC curves for the Mahalanobis distance are shown in Figure 5 for the same distances, r_1, r_2, r_3, and r_4. Similar observations can be made.

We have also compared, in Figure 6, ROC curves generated for transmit-receive distance r_1 for each of the three methods.

To compare the three different methods, equal error rates (EERs) are plotted versus number of samples required for testing for each of the three methods, and shown in Figure 7.

It can be seen that for smaller distances all the three methods work almost alike.But as transmit-receive distance increases, the NP detector outperforms the other two.

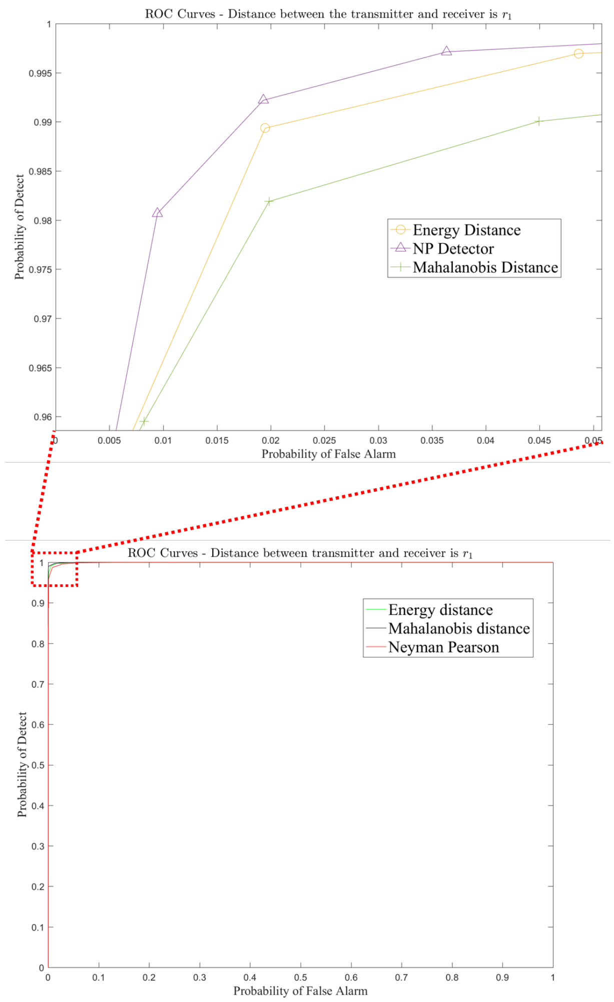

Fig. 6: Comparison of ROC curves generated using NP detector, energy distance and Mahalanlobis distance for transmit-receive distance r_1.

4. CONCLUSIONS AND FUTURE WORK

In this paper, we show that examining RSSI distributions provides us with important information about the localization environment, which can lead to improved ranging and localization. By providing insight into the presence or absence of LOS paths, errors introduced by obstructions can be mitigated. Given the dynamic nature of the operating environment, fast detection needs to be completed.

For fast detection, we have shown the use of the energy distance and the Mahalanobis distance. We have also benchmarked the performance with the Neyman Pearson detector. The importance of using a large number of samples for detection is demonstrated, that is, as the number of samples for detection increases, the equal error rate (EER) decreases significantly.

Future work includes improving ranging in LOS environments by eliminating data collected from reflected paths. This can be done by finding the cluster of RSSI samples with the highest amount of power, after LOS has been confirmed. An algorithm that uses samples only from the LOS path could further improve the localization results, and pave the way to more accurate localization in difficult indoor environments.

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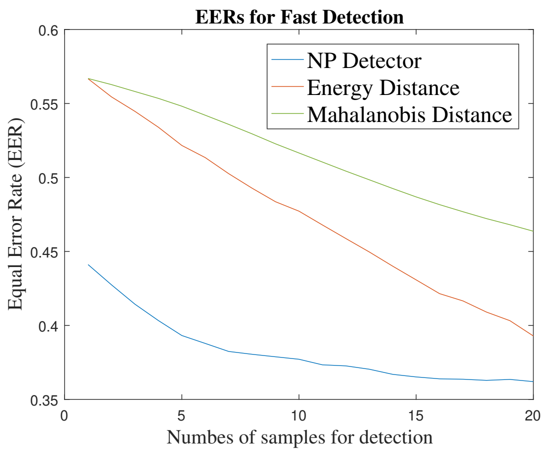

Fig. 7: Plot of equal error rate (EER) vs number of samples for the NP detector, energy distance, and Mahalanlobis distance.

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