ECE 549: Detection and Estimation Theory Spring 2021
Sanyam Jain

NLoS and LoS Link Identification For Improved Localisation

1 Introduction

Localisation is key to various applications such that annotating physical location of sensors with sensors data in wireless sensor network, localising personnel and objects for industrial automation, tracking personnel in working environments, contact tracing for maintaining social distance etc. Ultra-wide band is emerging as one of promising technology for localisation,it is a time-based localisation algorithm. UWB localisation is based on measuring the signal propagation time between a transmitter and a receiver.

Time-difference-of-arrival(TDOA) localisation algorithm requires precise clock synchronisation among all or reference nodes inside system but commonly TWR(Two-way ranging) method is used in UWB localisation as it doesn't require clock synchronisation and thus can be is resource-constrained wireless devices.

UWB pulse radios have ultra-wide bandwidth(typically more than 500MHz) and short transmit pulses offer high temporal and spatial resolutions and great multi-path fading immunity with result in high localisation accuracy and location update rate. However high multi path resolvability alone does not eliminate the effects of multi-path and NLoS (Non-Line of sight) propagation.

TWR based UWB localisation requires a UWB anchor (reference node) network to track tags(node with tracked). TWR is used to calculate range between anchor and tags and then triangulation can be done to have precise location of tag (with reference to anchors).The localisation algorithm will lead to erroneous results when there is large ranging errors between anchors and tag(s). Multi-path propagation and NLoS propagation are primary source of ranging algorithm inaccuracies.

NLoS identification can be used to detect NLoS nodes which can latter be eliminated (or weighted according) from the pool of nodes used of localisation. This is useful when we have a large number of anchor nodes available with many of them with an LoS link to the localized node(s). NLoS and LoS links can be identified based on channel impulse response (CIR) characteristics. A binary hypothesis test, using CIR characteristics, can be formulated to detect NLoS and LoS link.NLoS detection at localized node/localization engine can help eliminate or reduce ranging inaccuracies which can result in more precise and robust UWB based localization system.

2 Problem Statement

Overview of Localisation
A network consists of two types of nodes: *anchors* are nodes with known positions, while *tags* are nodes with unknown positions. Let there be a network with single tag with unknown 2D position $\mathbf{p}(\mathbf{X}, \mathbf{Y})$ surrounded by N anchors with positions, $\mathbf{p_i}(\mathbf{x_i}, \mathbf{y_i})$. The distance between the agent and anchor i is $d_i = \|\mathbf{p} - \mathbf{p_i}\|$.

The tag estimates the distance between itself and the anchors, using a ranging protocol such as Ultra-wide band based Two Way Ranging. Let $\hat{d}_i$ denotes the estimated distanced between the agent and anchor i and $\epsilon_i = \hat{d}_i - d_i$ is the ranging error. Given a set of at least three distance estimate, the tag will be able to determine its position using triangulation. Tag can solve below equation to compute $\mathbf{p}(\mathbf{X}, \mathbf{Y})$.

$$\hat{d}_i = \|\mathbf{p} - \mathbf{p_i}\| \; for \, i = 1, 2, 3... \tag{1}$$

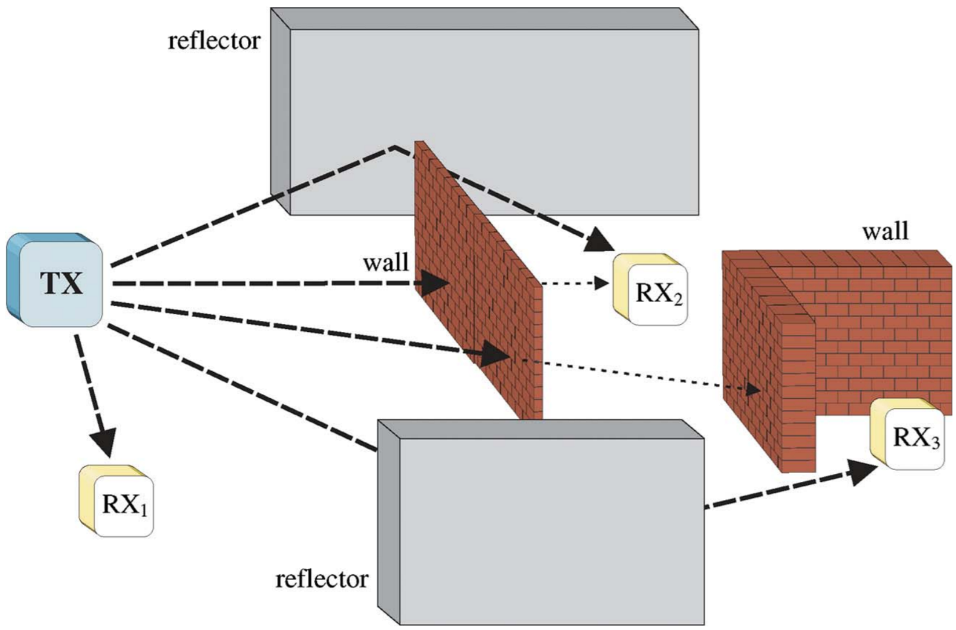

Figure 1: Possible LOS and NLOS conditions from transmitter TX to various receivers. RX1 is in LOS condition, RX2 and RX3 is in NLOS condition

Ranging Error

The triangulation algorithm will lead to erroneous results when the ranging errors are large. In practice the estimated distances are not equal to the true distances, because of a number of effects including thermal noise, multi-path propagation, interference, and ranging algorithm inaccuracies. Additionally, the direct path between requester and responder may be obstructed, leading to NLOS propagation. In NLOS conditions, the direct path is either attenuated due to through material propagation (RX_2), or completely blocked (RX_3). In the former case, the distance estimates will be positively biased due to the reduced propagation speed (i.e., less than the expected speed of light, c). In the latter case the distance estimate is also positively biased, as it corresponds to a reflected path. In NLOS identification nodes (anchors) with NLOS characteristics are identified and distance estimates are not considered for triangulation. Figure 2 is the CDF plot of the ranging error for LOS and NLOS scenario based on the data collected as part of research in [2].In LOS conditions a ranging error below one meter occurs in more than 95% of the measurements. On the other hand, in NLOS conditions a ranging error below one meter occurs in less than 30% of the measurements.

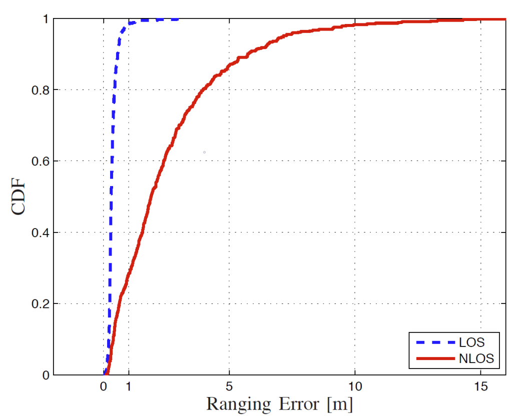

Figure 2: CDF of the ranging error for the LOS and NLOS condition[3]

Channel Impulse Response (CIR) and Channel Statistics

Determination direct path(DP) of arrival is essential requirement for accurate ranging. NLOS and LOS scenarios affect the propagation characteristics, which in turn affects the Channel Impulse Response. Thus, The amplitude and delay characteristics of CIR at receiver can be used to NLOS and LOS identification. UWB channels are able to capture a significant number of multipath components(MPCs). The Saleh-valenzuela model ,widely accepted and popular propagation model, for multipath propagation is given by [2]

$$h(t) = \sum_{l=0}^{\infty}\sum_{k=0}^{\infty} \beta_{kl} e^{j\theta_{kl}} \delta(t - T_l - \tau_{kl}) \tag{2}$$

where $beta_{kl}$ is the gain of the kth ray in lth cluster, θ_{kl} denotes the phase of the kth ray in lth cluster, T_l denotes the arrival time of the lth cluster τ_{kl} time delay of the kth ray in the lth cluster. A naive Hypothesis can be

$$\begin{aligned} H_0 &: d = cT_1 \\ H_1 &: d < cT_1 \end{aligned} \tag{3}$$

where H_0 is the LOS hypothesis, H_1 is the NLOS hypothesis c denotes speed of light, d denotes actual distance between transmitter and receiver.

The amplitude and delay characteristics of CIR can be captured using the kurtosis, the mean excess delay, and the rms delay spread of the CIR.

- Kurtosis(k) - The kurtosis of a certain data is defined as the ratio of the fourth-order moment of the data to the square of the second-order moment(variance) of the data.Kurtosis provides information about the amplitude statistics of the received MPCs, It indicates how "peaky" data is. Thus for a CIR with high kurtosis values, it is more likely that the received signal is under LOS. It is given by[4]

  $$k = \frac{E[(|h(t)| - \mu_{|h|})^4]}{\sigma_{|h|}^4} \tag{4}$$

  $\mu_{|h|})$ and $\sigma_{|h|}$ are the mean and standard deviation of the $|h(t)|$

- Mean excess delay (τ_m) - Mean excess delay characterize delay information of the multipath channel. It is define as the time delay during which multipath energy falls to X dB below the maximum. It is given by[4]

  $$\tau_m = \frac{\int_{-\infty}^{\infty} t|h(t)|^2 dt}{\int_{-\infty}^{\infty} |h(t)|^2 dt} \tag{5}$$

- RMS delay spread(τ_{rms}) - RMS delay characterize delay information of the multipath channel. The RMS delay spread serves as an indicator of the time dispersion of the received signal's energy. It is given by[4]

  $$\tau_{rms} = \frac{\int_{-\infty}^{\infty} (t - \tau_m)|h(t)|^2 dt}{\int_{-\infty}^{\infty} t|h(t)|^2 dt} \tag{6}$$

In [2] B.Silva and G.P. Hancke also mentioned other metrics to characterize CIR and can be used of NLOS and LOS identification.

- Skewness(S) - Skewness is an indicator of the asymmetry of a distribution. It is given by[2]

  $$S = \frac{E[(|h(t)| - \mu_{|h|})^3]}{\sigma_{|h|}^3} \tag{7}$$

  $\mu_{|h|})$ and $\sigma_{|h|}$ are the mean and standard deviation of the $|h(t)|$

- Peak-to-lead delay:(PLD) - The PLD is the time difference(in nanoseconds) between the first(τ_f) and strongest(τ_s) MPCs. Typically the larger the difference, the more severe the NLOS condition. It is given by[2]

$$PLD = \tau_f - \tau_s \tag{8}$$

- Power difference(P_D) - It is define as the difference between total power P_T and the power of the first path P_{FP} in the CIR.

$$P_D = P_T - P_{FP} \tag{9}$$

- Power ratio(P_R) - It is define as the ratio the power of the first path P_{FP} in the CIR to of total power P_T .

$$P_R = \frac{P_{FP}}{P_T} \tag{10}$$

To determine whether a certain measurement is either LOS or NLOS, a binary hypothesis test based on the probability distribution(PDFs) for both hypotheses can be employed. Let H_0 denotes the LOS hypothesis and H_1 denotes the NLOS hypothesis. A binary hypothesis test can be formulated as follows.

$$L = \frac{p_\xi(\xi|H_0)}{p_\xi(\xi|H_1)} \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \lambda \tag{11}$$

where ξ is denotes any metrics previously defined, p_ξ is the conditional PDF for said metric, λ is a threshold, and L is the computed Likelihood ratio.

3 Distributions and Likelihood Ratio

To use the hypothesis test as defined in equation (11) for LOS and NLOS classification a probability distribution for each of the metrics for LOS and NLOS is necessary. Probability distribution for metrics can be obtained either by simulation for NLOS and LOS scenarios or by measurement using experimental setup.

In [4] Ismail et al. uses sample channel realizations from both LOS and NLOS scenarios to obtain PDF of kurtosis(k), mean excess delay (τ_m) and RMS delay spread(τ_{rms}).They did sample channel realizations of the IEEE 802.15.4a standard channel models in order to obtain the histograms of k , τ_m , τ_{rms} for eight different channel models (i.e., CM1 through CM8). Based on simulation they have found that these parameters can be modeled by a log-normal distribution given as follows:

$$p(k) = \frac{1}{k\sqrt{2\pi\sigma_k}} \exp\left[-\frac{(\ln(k) - \mu_k)^2}{2\sigma_k^2}\right] \tag{12}$$

$$p(\tau_m) = \frac{1}{\tau_m\sqrt{2\pi\sigma_{\tau_m}}} \exp\left[-\frac{(\ln(\tau_m) - \mu_m)^2}{2\sigma_m^2}\right] \tag{13}$$

$$p(\tau_{rms}) = \frac{1}{\tau_{rms}\sqrt{2\pi\sigma_{\tau_{rms}}}} \exp\left[-\frac{(\ln(\tau_{rms}) - \mu_{rms})^2}{2\sigma_{rms}^2}\right] \tag{14}$$

where μ_x is the mean and σ_x is the standard deviation of $\ln(x)$. Kolmogorov-Smirnov (K-S) goodness-of-fit hypothesis test at 5% significance level is also measured to analyze how well the log-normal PDF characterizes the data. Figure 3 tabulate the mean, standard deviations and K-S score for the metrics. K-S score shows that the log-normal distribution fits well to the kurtosis of the data for all channel models with more than 90% of passing rates.

Channel model	μ_κ	σ_κ	K-S$_\kappa$
CM1 (residential LOS)	4.6631	0.5770	95.4%
CM2 (residential NLOS)	3.6697	0.4886	94.6%
CM3 (indoor office LOS)	4.4744	0.4579	95.7%
CM4 (indoor office NLOS)	2.8154	0.3459	95.5%
CM5 (outdoor LOS)	4.4509	0.5163	95.5%
CM6 (outdoor NLOS)	4.8886	0.4497	95.5%
CM7 (industrial LOS)	4.2637	0.7447	95.6%
CM8 (industrial NLOS)	2.1141	0.1487	95.4%

	Maximum excess delay			rms delay spread		
Channel model	$\mu_m[ns]$	$\sigma_m[ns]$	K-S$_m$	$\mu_{\mathrm{rms}}[ns]$	$\sigma_{\mathrm{rms}}[ns]$	K-S$_{\mathrm{rms}}$
CM1 (LOS)	2.6685	0.4837	95.7%	2.7676	0.3129	94.8%
CM2 (NLOS)	3.3003	0.3843	95.8%	2.9278	0.1772	95.2%
CM3 (LOS)	2.0993	0.3931	96.2%	2.2491	0.3597	96.2%
CM4 (NLOS)	2.7756	0.1770	95.3%	2.5665	0.1099	95.4%
CM5 (LOS)	3.0864	0.4433	94.6%	3.3063	0.2838	94.6%
CM6 (NLOS)	4.6695	0.4185	94.9%	4.2967	0.3742	95.7%
CM7 (LOS)	1.3845	0.9830	98.9%	1.9409	0.7305	93.9%
CM8 (NLOS)	4.7356	0.0225	94.7%	4.4872	0.0164	95.9%

Figure 3: The mean and the standard deviation of the log-normal PDF for the kurtosis, Mean excess delay and RMS delay spread of the IEEE 802.15.4a channels[4]

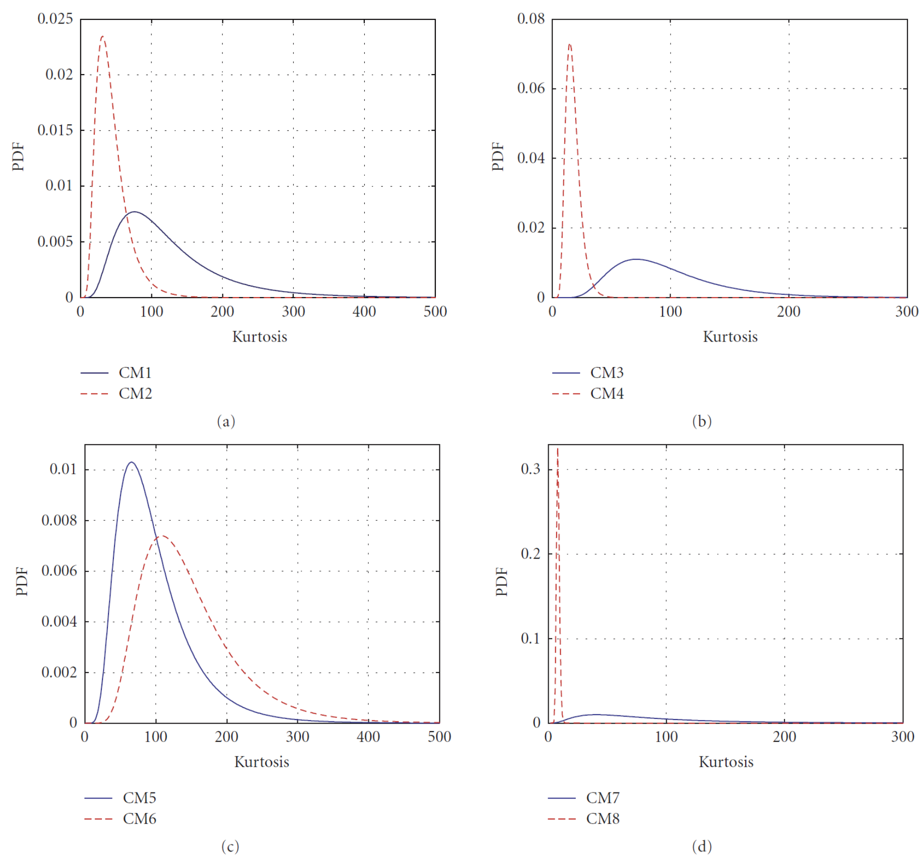

Figure 4: Log-normal PDFs of the kurtosis for CM1 to CM8 of the IEEE 802.15.4a channel models[4]

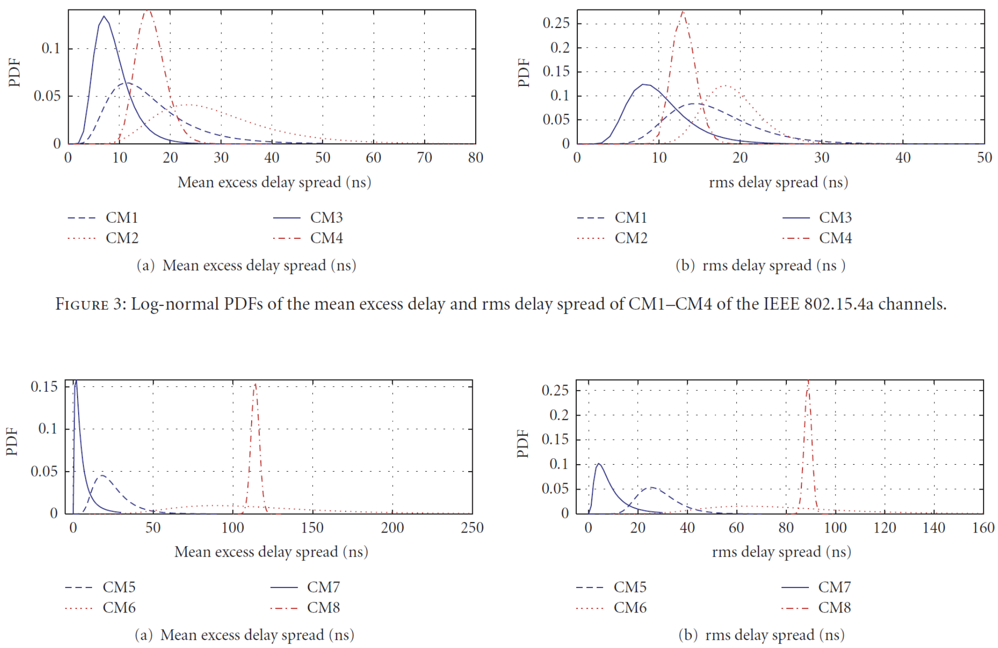

Figure 5: Log-normal PDFs of the mean excess delay and rms delay spread of CM1–CM8 of the IEEE 802.15.4a channels[4]

It can be seen that for indoor residential, indoor office, and industrial environments, kurtosis can provide good information regarding if the received signal is LOS or NLOS. However, for outdoor environment [CH5 – CH8], the PDFs are not distinct thus the amplitude statistics is insufficient to identify the LOS/NLOS scenarios for outdoor environments. Therefore, in order to have a more robust identifier, the delay statistics must be taken into consideration. For delay statistics we observe that as opposed to residential and indoor-office environments [CH1 – CH4], the LOS and NLOS PDFs in outdoor and industrial environments are quite distinct, which implies reliability of the LOS/NLOS identification.

Thus for a given channel realization $h(t)$, three likelihood ratio tests for LOS/NLOS identification of $h(t)$:

$$\frac{p_{k_{LOS}}(k|H_0)}{p_{k_{NLOS}}(k|H_1)} \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} 1 \tag{15}$$

$$\frac{p_{\tau_{m(LOS)}}(\tau_m|H_0)}{p_{\tau_{m(NLOS)}}(\tau_m|H_1)} \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} 1 \tag{16}$$

$$\frac{p_{\tau_{rms(LOS)}}(\tau_{rms}|H_0)}{p_{\tau_{rms(NLOS)}}(\tau_{rms}|H_1)} \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} 1 \tag{17}$$

where, if the likelihood ratio is larger than 1, we choose the LOS hypothesis (H0), and if otherwise, we choose the NLOS hypothesis (H1). Rather than using only the PDFs of individual parameters, hypothesis test using joint PDF of these parameters can also be used.

$$\frac{p_{join_{LOS}}(k,\tau_m,\tau_{rms}|H_0)}{p_{join_{LOS}}(k,\tau_m,\tau_{rms}|H_1)} \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} 1 \tag{18}$$

Since in practice it is very difficult to obtain the joint PDFs as given in (18), a sub optimal approach is proposed by considering k , τ_m , τ_{rms} as independent to each other. There can be correlation between these parameters but for simplicity and using result that correlation factor is small[4] sub optimal detector that considers these parameters independently may still improve the NLOS detection performance and can be given by

$$\frac{p_{join_{LOS}}(k, \tau_m, \tau_{rms}|H_0)}{p_{join_{LOS}}(k, \tau_m, \tau_{rms}|H_1)} = \frac{p_{k_{LOS}}(k|H_0)}{p_{k_{NLOS}}(k|H_1)} \times \frac{p_{\tau_{m(LOS)}}(\tau_m|H_0)}{p_{\tau_{m(NLOS)}}(\tau_m|H_1)} \times \frac{p_{\tau_{rms(LOS)}}(\tau_{rms}|H_0)}{p_{\tau_{rms(NLOS)}}(\tau_{rms}|H_1)} \quad (19)$$

In [2] Bruno Silva et al. conduct CIR measurement for LOS and NLOS scenario is industrial setting using DW1000 802.15.4a IR-UWB transceiver for each transmission CIR data is logged and the kurtosis, peak-to-lead delay, power difference, and power ratio were recorded.

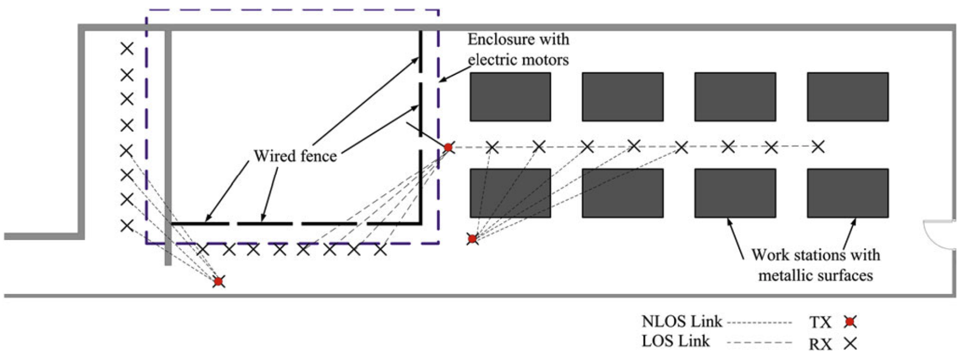

Figure 6: Deployment of nodes for measurement campaign[2]

For both NLOS and LOS the five features (or metrics) from the logged CIRs for all position indices were combined to determine the probability distribution. in contrast to simulation results in [4] using 802.15.4a channel models. Most of the metrics (k Kurtosis, S Skewness, PLD Pe-to-lead delay, P_D Power Difference and P_R Power ratio) were found to have multi-modal distributions, with the exception of LOS P_D and LOS P_R . Figure 7 tabulate model parameters for different metrics, where μn and σn denotes the mean and standard deviations for the individual Gaussian distributions respectively. Similar to [4] using the PDFs for metrics obtained from measurement likelihood ratio tests for LOS/NLOS identification using individual metrics can be formed using equation(11) with $\lambda = 1$

MODEL PARAMETERS (μ_n AND σ_n)

Metric	LOS (μ_1, μ_2)	NLOS (σ_1, σ_2)	LOS (μ_1, μ_2, μ_3)	NLOS (σ_1, σ_2, σ_3)
κ	32.33, 25.44	1.74, 4.01	19.6, 16.4, 18.1	0.28, 0.43, 0.25
S	3.65, 3.93	0.064, 0.043	4.14, 4.75	0.022, 0.014
PLD	3.84, 11.64	0.64, 0.23	2.71, 5.22	0.20, 0.17
P_D	5.45	0.35	3.64, 9.35	0.39, 1.69
P_R	1.06	0.0027	1.094, 1.04	0.025, 0.0038

Figure 7: Model Parameters(μ_n and σ_n) for different metrics[2]

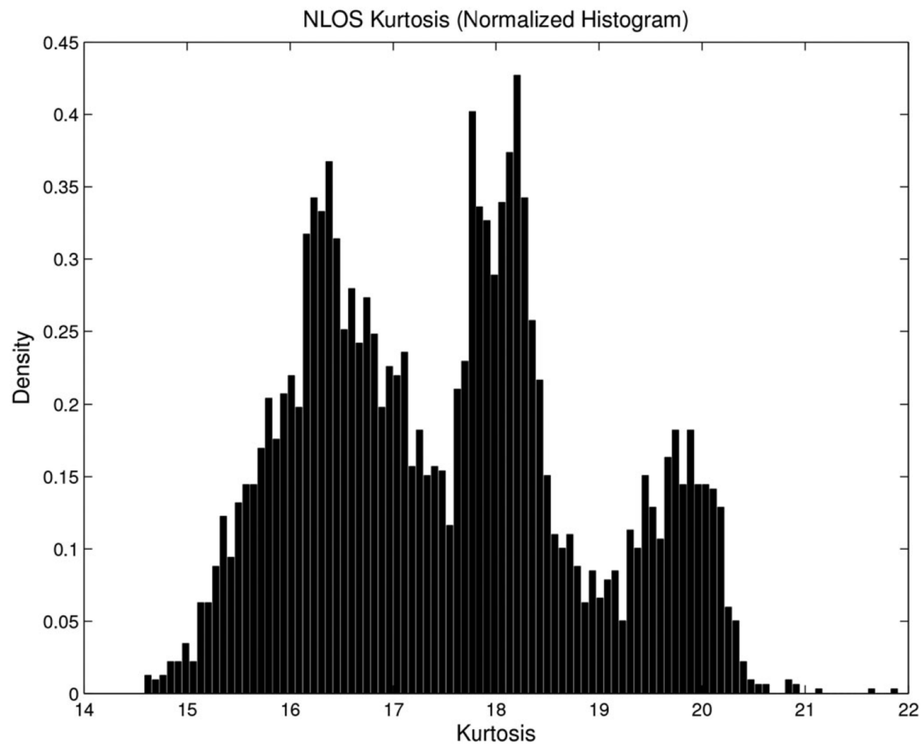

Figure 8: Example of Kurtosis distribution[2]

4 Classification Accuracy

In this section we will discuss the LOS/NLOS identification accuracy for both hypothesis testing using simulation[4] and hypothesis testing using measurement[2].
In[4] for each channel (CH1 - CH8) 1000 channel realizations are generated with channel separation of 494 MHz, central and sampling frequencies of 3.952 GHz, with an over-sampling factor of 8. Results both LOS and NLOS identification are tabulated in Figure 9. It can be seen that using individual metrics may yield high identification percentage only for certain channel models.while the joint approach achieves high identification percentage for most of the channel models.

Channel model	κ	τ_m	τ_{rms}	Joint $(\kappa, \tau_m, \tau_{\text{rms}})$
CM1 (LOS)	78.6%	74.3%	61.7%	81.8%
CM2 (NLOS)	83.2%	77.9%	76.1%	84.3%
CM3 (LOS)	99.0%	88.5%	73.6%	97.9%
CM4 (NLOS)	96.7%	86.3%	89.0%	95.9%
CM5 (LOS)	66.3%	98.2%	93.9%	98.9%
CM6 (NLOS)	71.4%	95.2%	92.7%	97.8%
CM7 (LOS)	98.3%	88.3%	98.3%	88.2%
CM8 (NLOS)	98.4%	100%	100%	99.9%

Figure 9: LOS/NLOS identification percentages.[4]

While simulation done in [4] encompass different transmission environments such as residential, indoor office, outdoor and industrial, measurements done in [4] are specific to harsh industrial environments. To measure accuracy for LOS/NLOS identification for industrial environments data were collected in both LOS and NLOS scenarios for the purpose of classification (approximately 5000 samples for each scenario). Using binary hypothesis described in previous section classification was done. Results are tabulated in Figure 10. The highest accuracy is achieved with Kurtosis and Skewness.The lowest was with power difference and power ratio. As per the result from this research Kurtosis and Skewness are better classification parameters than power difference and power ratio as power difference and power ratio can be similar for NLOS and LOS identification.

CLASSIFICATION ACCURACY

Metric	LOS (%)	NLOS (%)
Kurtosis (κ)	91.8	88.6
Skewness (S)	78.2	98.7
Peak-to-lead delay (PLD)	64.5	54.9
Power difference (P_D)	63.4	57.2
Power ratio (P_R)	54.8	60.7

Figure 10: LOS/NLOS identification percentages.[2]

5 Mitigation Techniques

From previous section we can conclude that hypothesis based on CIR parameters can be successfully used for identification NLOS and LOS scenario but to solve the problem completely i.e to improve localisation accuracy we have to use this classification in location estimation. Extending upon the basic equation(1) to compute tag location, we can form we can form Weighted Least Squares Location Estimator. Here Weights can be used to distinguish between readings (distance observation) from NLOS/LOS scenario in location estimation.

Let θ be the represent the location of tag, $x[n]$ represent the observed data and $s[n]$ represents signal model closet to observed data, then value of θ can be estimated using below equation. Here N represents number of anchor nodes.

$$J(\theta) = \sum_{n=0}^{N-1} w_n (x[n] - s[n])^2 \tag{20}$$

$$s[n] = \theta h[n] \tag{21}$$

Where h[n] is known sequence. Minimising above equation we can get $\hat{\theta}$. In matrix notation we can write above equation as

$$J(\theta) = (\mathbf{x} - \mathbf{H}\theta)^T \mathbf{W} (\mathbf{x} - \mathbf{H}\theta) \tag{22}$$

$$\hat{\theta} = \begin{bmatrix} x & y & R \end{bmatrix}^T \tag{23}$$

$$R = x^2 + y^2 \tag{24}$$

$$\mathbf{W} = \begin{bmatrix} w_1 & 0 & \cdots & 0 \\ 0 & w_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & w_N \end{bmatrix} \tag{25}$$

$$\mathbf{H} = \begin{bmatrix} -2x_1 & -2y_1 & 1 \\ -2x_2 & -2y_2 & 1 \\ \vdots & \vdots & \vdots \\ -2x_N & -2y_N & 1 \end{bmatrix} \tag{26}$$

$$\mathbf{x} = \begin{bmatrix} \hat{d_1} - x_1^2 & -y_1^2 \\ \hat{d_2} - x_2^2 & -y_2^2 \\ \vdots & \\ \hat{d_N} - x_N^2 & -y_N^2 \end{bmatrix} \tag{27}$$

Parameter R is introduced to keep the system solution linear. The estimated position $\hat{\theta}$ of a tag can now be expressed with the WLS estimator using below equation

$$\hat{\theta}_{\mathbf{WLS}} = (\mathbf{H}^T \mathbf{W} \mathbf{H})^{-1} \mathbf{H}^T \mathbf{W} \mathbf{x} \tag{28}$$

Using above equation for location estimation we can form two improvement techniques.

1. Identify and Discard : In this method weights are assigned such that if transmission from a anchor is identified as NLOS weight assigned to that node is 0 else weight assigned to that anchor is 1. Issue with this method is the higher cost of misidentification also this method is applicable only we have high number reference anchors.

2. Weights as per Identification Confidence : In this method weights are assigned such that if transmission from a anchor is identified as NLOS/LOS. Weights are assigned between 0 and 1. Weights are computed from hypothesis result. Weights for the i_{th} measurement can given as follows

   $$w_i = \log_{10}(1 + L_i) \tag{29}$$

   where L_i is result from hypothesis result from i_{th} node. This method is improvement from Identify and Discard method.

6 Simulation to Verify Accuracy

7 Discussion and Takeaways

- Result from research discussed above confirm that we can use CIR characteristics to identify NLOS/LOS scenario.
- One of the major challenge of localization system designed with NLOS and LOS identification is computation overhead. Most of the calculation needs to be at location engine, and is case of decentralise system tags will server as location engine. Thus every tag must have enough computation power to process CIR from transmission of each anchor and apply hypothesis test. Another issue will be latency in location reporting due to these calculation. Thus such a location system needs to be tested rigorously.
- Only two mitigation techniques[4] are discussed here, other more sophisticated location estimation methods can also be used to improve location estimation.
- Identification of features from CIR is essential for developing hypothesis testing. Here some features are discussed and for simplification we have assumed they are independent and their correlation is not significant. But this feature identification problem can be simplified using Machine learning with Neural Networks. Convolution Neural Network based classifier can be designed for NLOS/LOS identification. CIR can be the input to this neural network and neural network will be identify relevant feature itself. Once such system is trained it can be deployed at each tag. Such system is discussed in [5].

8 References

1. D. Dardari, A. Conti, U. Ferner, A. Giorgetti, and M. Z. Win, “Ranging with ultrawide bandwidth signals in multipath environments,” Proc. IEEE, vol. 97, no. 2, pp. 404-426, Feb. 2009.

2. B. Silva and G. P. Hancke, "IR-UWB-Based Non-Line-of-Sight Identification in Harsh Environments: Principles and Challenges," in IEEE Transactions on Industrial Informatics, vol. 12, no. 3, pp. 1188-1195, June 2016, doi: 10.1109/TII.2016.2554522.

3. S. Marano et al., “NLOS identification and mitigation for localization based on UWB experimental data,” IEEE J. Sel. Areas Commun., vol. 28, no. 7, pp. 1026-1035, Sep. 2010.

4. Ismail Güvenç, Chia-Chin Chong, Fujio Watanabe, and Hiroshi Inamura. 2008. NLOS identification and weighted least-squares localization for UWB systems using multipath channel statistics. EURASIP J. Adv. Signal Process 2008, Article 36 (January 2008), 14 pages. DOI:https://doi.org/10.1155/2008/271984

5. K. Bregar and M. Mohorčič, "Improving Indoor Localization Using Convolutional Neural Networks on Computationally Restricted Devices," in IEEE Access, vol. 6, pp. 17429-17441, 2018, doi: 10.1109/ACCESS.2018.2817800.