Measurement Analysis and Channel Modeling for TOA-Based Ranging in Tunnels

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Abstract—A robust and accurate positioning solution is required to increase the safety in GPS-denied environments. Although there is a lot of available research in this area, little has been done for confined environments such as tunnels. Therefore, we organized a measurement campaign in a basement tunnel of Linköping university, in which we obtained ultra-wideband (UWB) complex impulse responses for line-of-sight (LOS), and three non-LOS (NLOS) scenarios. This paper is focused on time-of-arrival (TOA) ranging since this technique can provide the most accurate range estimates, which are required for range-based positioning. We describe the measurement setup and procedure, determine the threshold for TOA estimation, analyze channel propagation parameters obtained from the power delay profile (PDP), and provide statistical model for ranging. According to our results, the rise-time should be used for NLOS identification, and the maximum excess delay should be used for NLOS error mitigation. However, the NLOS condition cannot be perfectly determined, so the distance likelihood has to be represented in a Gaussian mixture form.

Index Terms—tunnels, channel modeling, time of arrival, ultra-wideband, impulse response, ranging, positioning.

I. INTRODUCTION

Accurate positioning can enable many applications including positioning of employees and rescue personnel in industrial environments. For example, knowledge of the last location of the miner, in the aftermath of a mine collapse or explosion, is crucial for search-and-rescue operations. Although there is a lot of available research in this area, little has been done for confined environments such as tunnels. Exceptions are few proposals based on trilateration and fingerprinting techniques, but they are not sufficiently robust against outliers and changes in the environment. Therefore, more research is required to provide accurate channel models, especially for range-based positioning algorithms.

In this paper, we present the result of a measurement campaign in a basement tunnel of Linköping university in Sweden (referred to as the LiU tunnel). Motivated by high temporal resolution of the signals with large bandwidth, we decided to use UWB complex impulse responses for LOS, and three NLOS scenarios, in which the direct path is blocked by a metal obstacle, a person and a tunnel wall. Then, we focus on TOA-based ranging since this technique can provide the most accurate range estimates, which are required for range-based positioning. More specifically, we i) describe the measurement setup and procedure, ii) determine the threshold for TOA estimation using trade-off between false alarms and missed detections, iii) analyze channel propagation parameters obtained from PDPs, and iv) provide statistical model for ranging. According to our results, the rise-time should be used for NLOS identification, and the maximum excess delay should be used for NLOS error mitigation. However, the NLOS condition cannot be perfectly determined due to the overlap in all considered parameters, so the distance likelihood has to be represented in a Gaussian mixture form. Our main contribution is a statistical model that is especially suitable for range-based Bayesian positioning or tracking algorithms, but which can be also used for many other deterministic algorithms.

The remainder of this paper is organized as follows. In Section II we review other indoor measurement campaigns, and NLOS identification and error mitigation techniques. In Section III we describe our experimental setup and measurement procedure. Then, in Section IV we define channel propagation parameters, and select the threshold for TOA estimation. Measurement analysis and channel modeling for TOA-based ranging are performed in Section V. Finally, Section VI provides our conclusions and proposals for future work.

II. RELATED WORK

A. Overview of measurements campaigns

Multipath propagation has been studied and characterized in a multitude of environments, such as residential buildings, indoor offices and mines. The work performed in [6] proposes statistical models for estimating the root-mean-square (RMS) delay spread, path-loss and other relevant propagation parameters. By modeling all parameters as random variables, their models are capable to predict propagation in homes in which the measurements are not performed. In [7], they also provide models for the UWB power-delay profile (PDP) in residential areas. The work in [8] contains a wideband channel characterization of indoor office environments, in which medium levels of RMS delay spread and low levels of path-loss are observed. Similar levels of delay spread are found for UWB channels in an indoor lab environment in [9]. All
TABLE I: Summary of measurements campaigns in different environments with main parameters ($f$ - frequency, $B$ - bandwidth, and $\tau_{RMS}$ - RMS delay spread.). Other relevant parameters can be found in the cited publications.

| Environment     | $f$ [GHz] | $B$ [GHz] | $\tau_{RMS}$ [ns] |
|-----------------|-----------|-----------|------------------|
| Residence [7]   | 5         | 6         | 4.7-8.2          |
| Indoor office [8]| 5.3       | 0.053     | 30-50            |
| Indoor lab [9]  | 4         | 4         | 8-20             |
| Commercial [7]  | 5         | 6         | 5.5-8.2          |
| Steel mill [10] | 1.89      | 0.5       | 298              |
| Paper mill [10] | 1.89      | 0.5       | 23               |
| Subway tunnel [11]| 2.4       | 0.1       | 159-234          |
| Road tunnel [12]| 5.2       | 0.1       | 20-100           |
| Mine tunnel [13]| 1         | 0.2       | 20-50            |
| Mine tunnel [14]| 2.4       | 0.5       | 14               |
| Mine tunnel [15]| 2.4       | 0.2       | 27.4             |
| Mine tunnel [16]| 2.4/5.8   | 0.2       | 1-15             |
| Mine tunnel [17]| 3.5       | 3         | 11-29            |
| Mine tunnel [18]| 2.4       | 0.2       | 1.7              |
| LiU tunnel      | 3.5       | 2         | 4-16             |

These environments [6-9] have delay spread values not higher than 50 ns. On the other hand, industrial environments are characterized as reflective environments with high delay spread values. However, the study performed in [10] distinguished industrial environments with opposite propagation characteristics, i.e., a steel mill and a paper mill, with 298 ns and 23 ns RMS delay spread, respectively.

Regarding previous measurements in tunnels, the work in [11] presents measurements in a subway tunnel, where it is found that delay spread levels can go up to 234 ns due to multiple reflections in the subway station. Analysis of measurements obtained in an arched tunnel [12] showed a waveguide effect, as expected for tunnel-like environments. In this work, the authors separate the multipath components from the different surfaces, and found that scattering from the ground was dominant. In [13], the authors proposed a multimode model for predicting the received power and the PDF in tunnels with pillars. The analysis of measurements performed in wide and narrow iron-mine tunnels [14] show a small delay spread even in NLOS scenarios. The work in [15] analyzed the channel of an underground gold mine, and found that the RMS delay spread is decreasing with distance. Moreover, the same environment is considered in [16], [17], where the authors found that the RMS delay spread is almost uncorrelated with the distance, and in [13], where the authors found that the RMS delay spread can be significantly reduced ($< 2$ ns) using directional antennas. Generally, the studies performed in mine tunnels have found low delay spread levels due to the particular structure of the environment. The multipath rays reflect against the walls, the ceiling and the floor between the transmitter and the receiver, but not from the back of the transmitter and the receiver. Moreover, in contrast to indoor office environments, the delay spread is typically not increasing with distance.

A summary of these measurement campaigns, including the LiU tunnel that will be discussed in next sections, is shown in Table I. For a more detailed overview of measurement campaigns and channel models, we refer the reader to [19–21].

B. Overview of NLOS identification and error mitigation techniques

TOA-based ranging based on NLOS measurements typically leads to positively biased estimates. There are many proposals in literature for how to deal with this problem, which can be broadly classified into two categories [22]: i) NLOS identification, and ii) NLOS error mitigation. The former one attempts to distinguish between LOS and NLOS conditions, while the latter one attempts to reduce the bias caused by an NLOS condition assuming that this NLOS condition is identified.

NLOS identification can be performed by analyzing the variance of the time-series of the range estimates [23]. Since the NLOS measurements typically have much larger variance, the hypothesis testing can be easily performed. However, this approach would lead to high latency since it requires a large number of measurements. An alternative approach is to use channel propagation parameters from the complex impulse response. For instance, in [24] three parameters are jointly used (RMS delay-spread, TOA and RSS) to distinguish between LOS and NLOS scenarios. They found that RMS delay spread is the most useful for this problem, but the combination of these three parameters can improve the probability of correct identification. In [25], the authors found that the kurtosis provides consistent information about NLOS condition, and that using multiple antennas can improve this information. In [26], multiple parameters are considered by using a nonparametric least-square support-vector-machine (LS-SVM) classifier. This approach does not require statistical models, since it directly works with training samples. A nonparametric approach is also used in [27], where the authors use the training samples to construct the kernel of the LOS and NLOS error probability density functions (PDFs). Then, they use Kullback-Leibler (KL) divergence to measure the distance between these PDFs, and set the decision threshold.

Once NLOS identification is performed, the measurement can be discarded but it would lead to unnecessary loss of useful information (especially, if there are no sufficient LOS links). Therefore, NLOS error mitigation is required to make NLOS measurements useful for ranging. Since the distribution of the NLOS error depends on the spatial distribution of the scatterers, the mitigation could be performed by modeling these scatterers [28]. However, this approach is typically not feasible due to the complex shape of the environment, and possible dynamic obstacles. Another way is to model the NLOS error as a function of some channel propagation parameter. For example, in [9], the authors found that the NLOS error is increasing with the mean excess delay and the RMS delay spread. Therefore, a simple polynomial model can be used to significantly reduce this error. Nonparametric regression can be also used to compute the NLOS error as a function of multiple channel propagation parameters. For this purpose, LS-SVM regression has been used in [26], and Gaussian process regression in [29]. Finally, in some cases, it may not be possible to detect an NLOS condition, but...
Fig. 1: Experimental setup: (a) VNA connected to PC, and (b) omni-directional UWB antennas.

TABLE II: Measurement parameters

| Parameter         | Value               |
|-------------------|---------------------|
| Signal power      | 12 dBm              |
| Waveform          | sinusoidal          |
| Center frequency  | 3.5 GHz             |
| Bandwidth         | 2 GHz               |
| IF filter         | 10 KHz              |
| Number of points  | 3001                |
| Sweep time        | 263 ms              |
| Time resolution   | 0.5 ns              |
| Antenna range     | 1.71 - 6.4 GHz      |
| Antenna gain      | 5 - 7.5 dBi         |
| Cable attenuation | 0.65 dB/m           |
| Bandpass filter   | Hann window         |

only its probability. In that case, a soft-decision approach is required, in which NLOS identification and error mitigation are combined into one single step. This approach is proposed in [30], in which the ranging distribution is a mixture of LOS and NLOS models. In addition, this work proposes to use three different models for NLOS errors, depending on how much a priori information is available.

A detailed survey of NLOS identification and error mitigation techniques can be found in [22].

III. EXPERIMENTAL SETUP AND MEASUREMENT PROCEDURE

The measurement setup (see Fig. 1) consists of a vector network analyzer (VNA), two ultra-wide band (UWB) omni-directional antennas and coaxial cables to connect the antennas with the VNA. A PC is used to set the VNA parameters and extract the multiple frequency responses from the instrument. In our case, we use a swept-frequency sinusoidal signal (with 3001 points) to characterize the channel between 2.5 and 4.5 GHz. The power level was set to 12 dBm, and a calibration of the system is performed to compensate for the effect of VNA, cables and antennas (i.e., received power was shifted to 0 dBm when Tx and Rx were placed as in Fig. 1b). Then, the frequency responses are transferred to the PC where a Hann window [31] is used to reduce the out-of-band noise. Finally, by applying the inverse fast Fourier transform, the complex impulse responses are estimated, and subsequently, PDPs are calculated. We summarize the parameters in Table II.

We decided to consider four different scenarios: LOS, and NLOS caused by three different obstacles: a metal sheet, a person, and a tunnel wall (denoted by NLOS-M, NLOS-P, and NLOS-W, respectively). Therefore, we placed the transmitter (Tx) in 6 positions and receiver (Rx) in 30 locations forming the route through the tunnel. Three of the Tx-s have LOS link with the Rx-s, and the rest have NLOS-W links (the direct path is blocked by a thick concrete wall). In addition, the LOS links are obscured by a metal sheet and a person, respectively, placed in front of the appropriate Tx-s. For each of the Rx positions we obtained 10 PDPs, so we obtained 3600 PDPs in total (900 per scenario). All considered scenarios are illustrated in Fig. 2 and the deployment is shown in Fig. 3.
IV. CHANNEL PROPAGATION PARAMETERS AND THRESHOLD SELECTION

Given complex impulse responses of the channel, \( h(t) = \sum_{k=1}^{N_k} a_k \delta(t - \tau_k) \) \((N_k = 3001, \ a_k \in \mathbb{C})\), we can obtain the PDP as \( |h(t)|^2 \) \cite{15}. However, since most of the components of the PDP are caused by thermal noise, we consider only components above a certain threshold \( P_{TH} \) [dBm], i.e.,

\[
p_h(t) = \begin{cases} |h(t)|^2, & \text{if } 10 \log_{10} \left( \frac{|h(t)|^2}{P_0} \right) > P_{TH} \\ 0, & \text{otherwise} \end{cases}
\]

where \( P_0 = 1 \) mW. Then, we consider following channel propagation parameters:

- *Time of arrival (TOA):*
  \[
  \tau_1 = \min \{ t : p_h(t) > 0 \}
  \]

- *Received signal strength (RSS) [dBm]:*
  \[
  P_{RSS} = 10 \log_{10} \left( \frac{\int p_h(t) dt}{TP_0} \right)
  \]

  where \( T = 1.5 \) \( \mu s \) is the observation interval.

- *Maximum received power [dBm]:*
  \[
  P_{MAX} = 10 \log_{10} \left( \max_{t} p_h(t) \right)
  \]

- *Mean excess delay:*
  \[
  \bar{\tau} = \frac{\int t p_h(t) dt}{\int p_h(t) dt}
  \]

- *Maximum excess delay:*
  \[
  \tau_{MAX} = \max \{ t : p_h(t) > 0 \} - \tau_1
  \]

  which is a measure of total delay spread of the PDP.

- *Root-mean-square (RMS) delay spread:*
  \[
  \tau_{RMS} = \sqrt{\int (t - \bar{\tau})^2 p_h(t) dt / \int p_h(t) dt}
  \]

  which is a measure of effective delay spread of the PDP.

- *Rise time:*
  \[
  \tau_{RT} = \arg \max_t p_h(t) - \tau_1
  \]

- *Kurtosis:*
  \[
  \kappa = \frac{1}{\tau} \int \left( \frac{|h(t)| - \mu_{|h|}}{\tau} \right)^4 dt / \left( \frac{1}{\tau} \int \left( \frac{|h(t)| - \mu_{|h|}}{\tau} \right)^2 dt \right)^2
  \]

  where \( \mu_{|h|} = \frac{1}{\tau} \int |h(t)| dt \). Kurtosis is dimensionless metric that quantifies how \( |h(t)| \) matches the Gaussian distribution (larger \( \kappa \) implies stronger non-Gaussianity).

Then, we need to choose the threshold \( P_{TH} \). There are many ways to do it \cite{32}, but since our main goal is robust TOA-based ranging, we decide to choose the value which provides a good trade-off between false-alarm (FA) (when noise is detected instead of the signal) and missed-detection (MD) (when threshold is higher than the strongest path) rates. Therefore, we obtain the FA and MD rate for all reasonable values of the threshold \( P_{TH} \). Taking into account the results in Fig. 4a, we set \( P_{TH} = -43.8 \) dBm. We can see that, according to the thermal noise PDF (Fig. 4p), this value of the threshold is on very right tail of the PDF (i.e., \( P_{TH} = \mu_{\text{noise}} + 3.4 \sigma_{\text{noise}} = -43.8 \) dBm, where \( \mu_{\text{noise}} = -64 \) dBm, \( \sigma_{\text{noise}} = 6 \) dB). Note that the chosen threshold does not minimize the root-mean-square-error (RMSE) in the TOA estimation (\( P_{TH} = -51 \) dBm would achieve it, but it would lead to many false alarms). In principle, this is not a problem since we will in addition perform error mitigation for NLOS range estimates, as will be shown in Section V.C.

In Fig. 5 we show an illustration of TOA estimation for all considered scenarios. We can see that TOA estimates are very accurate for all scenarios, except for NLOS-W in which there is a large positive bias. This behavior is expected due to the high resolution of UWB signal, and its capability to penetrate thin obstacles \cite{5}.

1 We work with calibrated power level since the real power level is not needed for our problem.
V. MEASUREMENT ANALYSIS AND CHANNEL MODELING FOR RANGING

In this section, we first analyze the distance estimation using exclusively TOA. Then, we analyze channel propagation parameters in order to determine the most useful ones for NLOS identification and error mitigation. Finally, we propose a statistical model for distance estimation using TOA and the most appropriate channel propagation parameters.

A. TOA-based ranging

Since TOA measurements based on a UWB signal can provide very accurate range estimates [5] (which will be confirmed in Section V-B), we will focus on TOA-based ranging. We consider the following model:

\[ c\tau_1 = d + \nu \quad (10) \]

where \( d \) is the true distance between Tx and Rx, \( c = 3 \cdot 10^8 \) m/s is the speed of light, and \( \nu \) represents the measurement noise distributed according to \( p_\nu(\cdot) \) (with corresponding mean and variance: \( \mu_\nu \) and \( \sigma_\nu^2 \)).

Since our previous analysis showed that LOS, NLOS-P and NLOS-M behave in a similar way (see Fig. 5), we combine them into one sample set. We also consider NLOS-W (in which the direct path is blocked by a wall), and a combination of all sample sets (LOS, NLOS-P, NLOS-M, and NLOS-W). To simplify notation, the combination of LOS and all soft NLOS scenarios (NLOS-P and NLOS-M) will be referred to as LOS, while NLOS-W will be referred to as NLOS.

The results are shown in Fig. 6. As we can see, the TOA estimates provide very accurate distance estimates in the LOS scenario, but there is a large positive error (up to 11 m) in the NLOS scenario. We also note that there are few false alarms caused by a low threshold, but this problem would not appear if there were no losses in the cables (i.e., a higher SNR would allow to use a higher threshold). According to Fig. 6(d)-(e), the noise PDF can be approximated with a Gaussian distribution in the case of a LOS scenario, and a Gaussian mixture in the case of an NLOS scenario. Therefore, the model in (10) is not good enough, and an error mitigation technique is required to enable more accurate ranging.

B. NLOS identification and error mitigation

We first define a binary variable \( H \in \{ \text{LOS, NLOS} \} \), and assume that TOA measurement noise is given by:

\[ \nu = \begin{cases} \nu_L, & \text{if } H = \text{LOS} \\ \nu_N, & \text{if } H = \text{NLOS} \\ \nu_L + b, & \text{if } H = \text{NLOS} \end{cases} \quad (11) \]

where \( \nu_L \) includes all typical sources of the error in the LOS scenario (i.e., thermal noise, finite bandwidth, non-ideal equipment, etc.), and \( \nu_N \) in addition includes a positive and random bias \( b \) caused by multipath propagation in the NLOS scenario. Since we have available samples of \( \nu_N \), we focus on

\[ Fig. 6: \text{TOA vs. distance and error histograms for: (a), (d) LOS (b), (e) NLOS, and (c), (f) LOS+NLOS scenario. The corresponding means and standard deviations of the ranging error are: } \mu_\nu = -0.27 \text{ m}, \sigma_\nu = 0.16 \text{ m (LOS)}, \mu_\nu = 4.38 \text{ m}, \sigma_\nu = 3.20 \text{ m (NLOS)}, \text{ and } \mu_\nu = 0.89 \text{ m}, \sigma_\nu = 2.58 \text{ m (LOS+NLOS).} \]
mitigation of the total error.

Our goal is to identify the channel state (estimate $H$), and to remove (or at least, reduce) the NLOS error. Thus, we need to choose an appropriate NLOS identification and error mitigation technique. Since we would like to use one single impulse response, to keep the complexity reasonable, and to avoid using the geometry of the tunnel, we will apply the algorithm based on channel propagation parameters (for alternatives, see Section III-B). Although state-of-the-art (e.g., see [9], [24], [25]) already provides parameters that are useful for these problems, they may not be the best for tunnel environment. Therefore, in order to determine which parameters are appropriate, we use the following metrics:

- **Overlap metric** [24] for parameter $\alpha$ ($0 < \xi_\alpha < \infty$):
  \[
  \xi_\alpha = \frac{\sqrt{\sigma_{\alpha L} \sigma_{\alpha N}}}{|\mu_{\alpha N} - \mu_{\alpha L}|}
  \]  
  (12)

  where $\alpha$ can be any of the channel propagation parameters defined in eqs. [2]-[9]. $\mu_{\alpha L}$, $\sigma_{\alpha L}$, and $\mu_{\alpha N}$, $\sigma_{\alpha N}$ represent the means and the standard deviations of PDFs $p(\alpha | H = \text{LOS})$ and $p(\alpha | H = \text{NLOS})$, respectively. They are obtained from an appropriate sample set. A smaller value of $\xi_\alpha$ implies that there is less overlap between the LOS and NLOS distributions, so we can more easily distinguish between the LOS and NLOS states.

- **Correlation coefficient between the parameter $\alpha$ and the true distance $d$** ($-1 < \rho_{\alpha,d} < 1$):
  \[
  \rho_{\alpha,d} = \frac{\text{Cov}(\alpha,d)}{\sigma_\alpha \sigma_d}
  \]  
  (13)

  where $\text{Cov}(\alpha,d)$, $\sigma_\alpha$, and $\sigma_d$ are computed using all available LOS and NLOS samples. For NLOS identification, a smaller $|\rho_{\alpha,d}|$ is preferable since the true distance is unknown.

- **Correlation coefficient between the parameter $\alpha$ and the NLOS error $\nu_N$** ($-1 < \rho_{\alpha,\nu_N} < 1$):
  \[
  \rho_{\alpha,\nu_N} = \frac{\text{Cov}(\alpha,\nu_N)}{\sigma_{\alpha N} \sigma_{\nu_N}}
  \]  
  (14)

  where $\text{Cov}(\alpha,\nu_N)$, $\sigma_{\alpha N}$, and $\sigma_{\nu_N}$ are computed using only the NLOS sample set. A larger $|\rho_{\alpha,\nu_N}|$ implies that the error can be more easily determined from the parameter $\alpha$.

- **Correlation coefficient between the two parameters $\alpha_1$ and $\alpha_2$** ($-1 < \rho_{\alpha_1,\alpha_2} < 1$):
  \[
  \rho_{\alpha_1,\alpha_2} = \frac{\text{Cov}(\alpha_1,\alpha_2)}{\sigma_{\alpha_1} \sigma_{\alpha_2}}
  \]  
  (15)

  where $\text{Cov}(\alpha_1,\alpha_2)$, $\sigma_{\alpha_1}$, and $\sigma_{\alpha_2}$ are computed using all available LOS and NLOS samples. A large value of $|\rho_{\alpha_1,\alpha_2}|$ means that one of the parameters can be discarded.

Note that we will not take into account very small differences between obtained values since we have a limited set of data (2700 LOS and 900 NLOS samples).

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2To find $\bar{b}$, we would need to perform a deconvolution, but it is unnecessary since $b >> \nu_L$ according to Fig. 6.

Estimated results are shown in Tables III. We observe the following:

- $\tau_1$ is strongly correlated with distance, so we can confirm that it is the best parameter for distance estimation (see also Section III-A). Good options are also $P_{\text{RSS}}$, $P_{\text{MAX}}$, and $\bar{\tau}$, but they are strongly correlated with $\tau_1$, and between each other.

- $\tau_{RT}$ provides the lowest overlap, so it is the best parameter for NLOS identification. It is also uncorrelated with the true distance, which means that a simple identification algorithm can be used. One of the parameters, $P_{\text{RSS}}$, $P_{\text{MAX}}$, or $\bar{\tau}$, could be also used since they are uncorrelated with $\tau_{RT}$, but they are strongly correlated with true distance. We also note that $\tau_{\text{RMS}}$ and $\kappa$ are the worst parameters for this problem in contrast to other results in literature (e.g., [24], [25]).

- Due to the strong correlation with the NLOS error, the best parameters for NLOS error mitigation are: $\tau_1$, $P_{\text{RSS}}$, $\bar{\tau}$, $\tau_{\text{MAX}}$, and $\tau_{\text{RMS}}$. However, $P_{\text{RSS}}$ and $\bar{\tau}$ can be discarded since they are strongly correlated with $\tau_1$. Out of the remaining parameters, $\tau_{\text{RMS}}$ and $\tau_{\text{MAX}}$ are the most appropriate due to their lower correlation with the true distance.

We illustrate, in Fig. [7] and Fig. [8] the results for the most competitive parameters.

As we can observe in Fig. [7] $\bar{\tau}$ can be used to (almost) perfectly detect an NLOS condition, but only if we know the distance. A similar problem can be observed for $P_{\text{RSS}}$. These parameters are not preferred for positioning, but would be useful for other applications such as obstacle detection between two objects with a known inter-object distance. Therefore, $\tau_{RT}$ is a unique parameter which is not correlated with the distance and provides relatively good information about NLOS conditions. More precisely, large values ($\tau_{RT} > 20 \text{ ns}$) imply NLOS conditions, but small values lead to ambiguities. In principle, that means that a probabilistic approach should be used, instead of setting a hard threshold.

Regarding NLOS error mitigation (Fig. [8]), none of the parameters can perfectly remove the NLOS error, but $\tau_{\text{MAX}}$ could be chosen since it is slightly better than the rest. The most notable problem is that there are two clouds of samples (corresponding to an error of around 4 m and 10 m, respectively), associated with the same value of the corresponding parameter (the same problem also appears for other parameters). We also note that larger $\tau_{\text{RMS}}$ and $\tau_{\text{MAX}}$ lead to a lower NLOS error, which is consistent with some of the results for tunnels (e.g., [15]), but in contrast to results in indoor environments (e.g., [9]). This can be explained by the fact that that the tunnel is not a very reflective environment, so for large distances (when the NLOS error is also large) many multi-path components will not be detected.

To summarize, along with $\tau_1$ chosen for distance estimation, we choose $\tau_{RT}$ for NLOS identification, and $\tau_{\text{MAX}}$ for NLOS error mitigation. Note that additional refinement (probably, very small) is possible with more than three parameters, but in that case the complexity and communication cost would increase as well.
TABLE III: (a) Estimated $\xi_\alpha$, $\rho_{\alpha,\nu N}$ and $\rho_{\alpha,d}$ for all considered parameters, and (b) estimated $\rho_{\alpha_1,\alpha_2}$ between all pairs of the parameters. High levels of absolute correlation ($> 0.7$) and overlap ($> 2$) are marked with red, while low levels of absolute correlation ($< 0.3$) and overlap ($< 1$) are marked with blue color.

(a) & $\alpha$ & $\xi_\alpha$ & $\rho_{\alpha,d}$ & $\rho_{\alpha,\nu N}$ \\
\hline $\tau_1$ & 1.65 & 0.97 & 0.85 \\
$P_{RSS}$ & 1.10 & -0.81 & -0.73 \\
$P_{MAX}$ & 1.07 & -0.72 & -0.65 \\
$\bar{\tau}$ & 1.07 & 0.93 & 0.81 \\
$\tau_{MAX}$ & 2.12 & -0.68 & -0.84 \\
$\tau_{RMS}$ & 3.08 & -0.55 & -0.81 \\
$\gamma_{RT}$ & 0.58 & -0.14 & -0.42 \\
$\kappa$ & 4.80 & -0.48 & -0.44 \\

(b) & $\tau_1$ & $P_{RSS}$ & $P_{MAX}$ & $\bar{\tau}$ & $\tau_{MAX}$ & $\tau_{RMS}$ & $\tau_{RT}$ & $\kappa$ \\
\hline $\tau_1$ & 1.00 & -0.83 & -0.76 & 0.98 & -0.69 & -0.55 & -0.06 & -0.49 \\
$P_{RSS}$ & - & 1.00 & 0.97 & -0.88 & 0.79 & 0.22 & -0.18 & 0.65 \\
$P_{MAX}$ & - & - & 1.00 & -0.83 & 0.72 & 0.12 & -0.25 & 0.75 \\
$\bar{\tau}$ & - & - & - & 1.00 & 0.31 & 0.03 & 0.45 \\
$\tau_{MAX}$ & - & - & - & - & 1.00 & 0.31 & 0.03 & 0.45 \\
$\tau_{RMS}$ & - & - & - & - & - & 1.00 & 0.41 & 0.11 \\
$\tau_{RT}$ & - & - & - & - & - & - & 1.00 & -0.11 \\
$\kappa$ & - & - & - & - & - & - & - & 1.00 \\

Fig. 7: Channel propagation parameters (a) $P_{RSS}$, (b) $\bar{\tau}$, and (c) $\tau_{RT}$, as a function of true distance. (d)-(f) LOS and NLOS histograms corresponding to samples from (a)-(c).

Fig. 8: NLOS error as function of: (a) $\tau_1$, (b) $\tau_{MAX}$, and (c) $\tau_{RMS}$.
C. Statistical model for ranging

Taking into account previous results, we consider the following model:

\[
ct_1 = \begin{cases} 
    d + \mu_L + \nu'_L, & \text{if } H = \text{LOS} \\
    d + g(\tau_{\text{MAX}}) + \nu'_N, & \text{if } H = \text{NLOS}
\end{cases}
\]  

(16)

where \(\nu'_L\) and \(\nu'_N\) are noise components, \(\mu_L = -0.27\) m is a known LOS bias caused by finite bandwidth and false alarms\(^3\) (see also Fig. 6d), and \(g(\tau_{\text{MAX}})\) is NLOS error. \(g(\cdot)\) is found by fitting the samples to second-order polynomial curve, which provides the best fit out of many analyzed curves. Therefore, we set \(g(\tau_{\text{MAX}}) = p_2\tau_{\text{MAX}}^2 + p_1\tau_{\text{MAX}} + p_0\). As we can see in Fig. 9, the NLOS error after mitigation is significantly decreased, and its PDF is closer to Gaussian. Taking this result into account (and also Fig. 6d), a reasonable model is that \(\nu'_L\) and \(\nu'_N\) follow (approximately) zero-mean Gaussian distribution, i.e., \(\nu'_L \sim N(0, \sigma_L^2)\) and \(\nu'_N \sim N(0, \sigma_N^2)\).

Finally, in order to estimate \(H\), we use Bayes’ rule:

\[
p(H|\tau_{RT}) = \frac{p(H)p(\tau_{RT}|H)p(H)}{\sum_{H \in \{\text{LOS, NLOS}\}} p(\tau_{RT}|H)p(H)}
\]

(17)

where \(p(H)\) is the prior, and \(p(\tau_{RT}|H)\) is the likelihood function. Assuming that the floor plan and the detection range are available, a reasonable choice of prior is:

\[
p(H) = \begin{cases} 
    1 - S_{N,i}/S_{T,i}, & \text{if } H = \text{LOS} \\
    S_{N,i}/S_{T,i}, & \text{if } H = \text{NLOS}
\end{cases}
\]

(18)

where \(S_{T,i}\) is the total detection area of transmitter \(i\), and \(S_{N,i}\) is the part of the area corresponding to NLOS caused by tunnel walls.

The likelihood function \(p(\tau_{RT}|H)\) is approximated with an exponential distribution (see Fig. 7b), i.e.,

\[
p(\tau_{RT}|H) = \begin{cases} 
    \lambda_L e^{-\lambda_L \tau_{RT}}, & \text{if } H = \text{LOS} \\
    \lambda_N e^{-\lambda_N \tau_{RT}}, & \text{if } H = \text{NLOS}
\end{cases}
\]

(19)

where the parameters \(\lambda_L\) and \(\lambda_N\) are found as the inverse of the sample means (from LOS and NLOS samples, respectively). All parameters are summarized in Table IV.

Traditional (deterministic) positioning techniques (see [33] and references therein) require to make decision on \(H\), (e.g.,

\[\hat{\tau}_{RT} = \arg\max_H p(H|\tau_{RT})\], and to obtain a point-estimate of the distance as:

\[
\hat{d} = \left\{ \begin{array}{ll}
    ct_1 - \mu_L, & \text{if } \hat{\tau}_{RT} = \text{LOS} \\
    ct_1 - g(\tau_{\text{MAX}}), & \text{if } \hat{\tau}_{RT} = \text{NLOS}
\end{array} \right.
\]

(20)

However, this approach is highly unrecommended due to the misclassifications (see Fig. 7c and Fig. 10), and would not provide full statistical information about the distance. Therefore, it is much better to provide a likelihood function, which takes into account both hypotheses about the LOS/NLOS condition, i.e.,

\[
p(e|d) = p(H = \text{LOS}|\tau_{RT})N(ct_1 - \mu_L - d; 0, \sigma_L^2) + \\
p(H = \text{NLOS}|\tau_{RT})N(ct_1 - g(\tau_{\text{MAX}}) - d; 0, \sigma_N^2)
\]

(21)

where the vector \(e\) is the set of all available measurements \((\tau_1, \tau_{RT}, \tau_{\text{MAX}})\). The illustration is shown in Fig. 11. This non-Gaussian likelihood can be used for soft-decision (typically, Bayesian) positioning algorithms. A good option is the algorithm in [30], which can provide multiple location estimates from the multi-modal PDF. The detailed analysis of positioning algorithms is beyond the scope of this paper.

VI. CONCLUSIONS AND FUTURE WORK

We presented the results of a UWB measurement campaign performed in a basement tunnel of LiU. More specifically, we analyzed channel propagation parameters, selected a subset of parameters that allow relatively accurate TOA-based ranging, and provided an appropriate statistical model. One main result is that the rise-time should be used for NLOS identification, and the maximum excess delay for NLOS error mitigation. The main problem is that an NLOS condition cannot be perfectly

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determined, so the distance likelihood has to be represented in a Gaussian mixture form. That means that soft-decision algorithms are required for accurate ranging and positioning in tunnels. For the future work, we plan to analyze different positioning algorithms in the presence of NLOS measurements, and find the most appropriate solution for tunnels. In addition, we plan to develop infrastructure-free cooperative localization algorithms, which are crucial for search-and-rescue operations in GPS-denied environments.

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