Nothing Blocks Me: Precise and Real-time LOS/NLOS Path Recognition in RFID Systems

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Abstract—RFID-based localization and activity recognition have attracted much research attention recently. They rely on accurate measurements of signal features, e.g., phase and received signal strength (RSS), in line-of-sight (LOS) condition to estimate the location or activity status of the target objects. However, the LOS requirement might be frequently breached by obstacles between reader and tags in real deployed RFID systems. The resulting non-line-of-sight (NLOS) signal will greatly reduce localization or activity recognition accuracy. How to filter out NLOS in the localization/activity recognition process is therefore practically important for guaranteeing accuracy. In this paper, we propose the first LOS/NLOS path recognition approach to differentiate the signals by LOS path from the ones by NLOS path. The proposed approach is both precise (with precision higher than 0.95) and real-time in nature (with recognition delay less than 400 ms) due to the following innovative designs. First, we design a new metric that can precisely distinguish LOS and NLOS paths by considering the joint variance of phase and RSS. Second, we propose an efficient method to mitigate the negative impacts of phase ambiguity on recognition precision. Third, we sample over a selected subset of channels and use only a handful of readings to perform LOS/NLOS path recognition, which greatly reduces the recognition delay without sacrificing precision. We conducted extensive experiments with commercial-off-the-shelf RFID devices. The results show that our approach achieves high precision and recall in all testing cases, with a precision of up to 0.969 and a recall of up to 0.991. Furthermore, our approach can also distinguish between different types of obstacles with an accuracy as high as 0.93.

I. INTRODUCTION

The past several years witnessed explosive development of Internet of Things (IoT) [1], [2], [3] applications in many fields, e.g., smart factories and smart cities [4]. As one of the most important supporting technologies in IoT, radio frequency identification (RFID) has gained much research attention in recent years [5], [6], [7], [8], [9], [10], [11], [12]. A typical RFID system consists of a set of RFID readers and a large number of tags. The readers are scheduled to read data from and write data to the tags through wireless communications. Compared with traditional techniques like barcodes or two-dimensional codes, RFID can be operated with much larger communication range and can provide more efficient solutions for object identification and localization. Currently, RFID technology has been widely adopted in many market sectors such as warehouse management, logistics, smart libraries, and retail. It is forecasted that the market for RFID will be more than 20 billion dollars by 2027 [13].

RFID-based localization and activity recognition have attracted much research attention in recent years [7], [8], [14], [15], [5], [16], [17], with typical applications such as sorting baggage in airports [7], [18], finding misplaced books in smart libraries [5], [15], mining customers’ behaviors in supermarkets [19], [20], or improving interaction between human and machines [21]. These research works infer the locations or activity status of target objects based on the measured features of received signals (e.g., phase and received signal strength (RSS)) at the reader. Generally, these approaches require the measurement of signal features in line-of-sight (LOS) conditions to achieve high accuracy. As a result, the localization algorithms [7], [15], [5], [17] that use phase measurements to calculate the position of tags will produce large localization error when an obstacle lies between a pair of reader and tag.

This paper studies an important yet unsolved practical problem: How to recognize signals by non-line-of-sight (NLOS) paths to mitigate their negative impacts on localization and activity detection. In RFID systems deployed in a real world, NLOS signal propagation is very common. In smart libraries, for example, the bookshelves and moving people might block the signals transmitted between the reader and tags. In indoor environments, factors like multi-path and reflection will also incur NLOS signal transmissions. If the signal features measured in NLOS cases are treated the same as in LOS cases, they will cause serious accuracy degradation in localization or activity recognition [5]. In order to achieve high localization accuracy, we need to distinguish LOS transmissions from NLOS ones, and drop corresponding NLOS readings or rectify them before feeding them into localization or activity recognition algorithms.

To our knowledge, we are the first to thoroughly study the challenging LOS/NLOS path recognition problem in RFID systems. Although many works have been proposed to classify different obstacle types and sizes (e.g., TagScan[22]), they work under the assumption that obstacles already exist and do not identify LOS/NLOS paths. Moreover, the methods used to recognize LOS/NLOS paths for the wireless-based localization techniques including Wi-Fi [23], [24], Bluetooth [25], and ultra wide band (UWB) [26] cannot be directly adopted in RFID systems. They rely on fine-grained physical
layer information (e.g., channel state information for Wi-Fi [27], [28], [29]) to distinguish between LOS and NLOS paths, which requires high signal bandwidth and complex receiver with high ability. For example, each Wi-Fi channel has a bandwidth of 20 MHz and the bandwidth of UWB is even higher. Compared with them, the signal bandwidth of RFID systems is greatly limited (only 250 KHz per channel) and the receiver tag side is significantly resource-limited.

In this paper, we propose a precise and real-time LOS/NLOS path recognition approach for RFID systems. We propose three innovative designs to enhance recognition precision and reduce recognition delay. First, we propose a clustering-based method to effectively mitigate negative impacts of phase ambiguity and phase discontinuity on LOS/NLOS recognition precision. Second, we design a new metric that considers joint variance scope in phase and RSS, which can discriminate LOS and NLOS paths with high precision. Third, we sample over a selected subset of channels rather than all and use only a handful of readings from each channel, which greatly reduces recognition delay without sacrificing precision. With the combination of these innovative designs, our approach can achieve high recognition precision and low recognition delay. We conducted extensive experiments with the commercial-off-the-shelf (COTS) Impinj Speedway R420 readers and several types of passive tags, under setting of different types of obstacles and different distances between the reader and tags. The experimental results show that with less than 400 ms delay, our approach achieves recognition precision of up to 0.969 and recall of 0.991. Furthermore, our approach can also distinguish various types of obstacles with an accuracy as high as 0.93.

The remainder of the paper is organized as follows. Section II introduces the background of reader-tag communication in RFID systems. Section IV shows how to achieve precise LOS/NLOS path recognition by designing a new discriminative metric and handling phase ambiguity/discontinuity. Section V discusses how to reduce the recognition delay without sacrificing recognition precision. Experimental results are reported and discussed in Section VI. In Section VII, we review related work. Finally, Section VIII concludes the paper with final remarks.

II. PRELIMINARY

A. Communication between the Reader and Tags

In RFID systems, the communication between the readers and tags adopts a reader-talks-first model. When a reader wants to communicate with tags, it first emits a continuous wave signal with two purposes: sending commands/data to tags, and providing energy for tags to backscatter their data to the reader. The (passive) tags harvest energy from the continuous wave signal and modulate the wave to transmit data to the reader. This process is demonstrated in Fig. 1. Since signal attenuation can be caused by many factors including fading and shadowing, the features (e.g., phase and RSS) of the signal backscattered by the tag can be different from those of the signal emitted by the reader. The reader measures features of the backscattered signals, which are used by localization or activity recognition algorithms [7], [15], [21], [16], [30], [18], [31] to infer the location or activity status of the target tags.

When the signal propagates along LOS between a reader and a tag, i.e., there are no obstacles in between, the features of the received signal are mainly affected by the reader-tag distance, denoted by \( d \). The phase of the (backscattered) signal measured at the reader can be modeled as [7]

\[
\phi = (2\pi \frac{2d}{\lambda} + \theta_{\text{div}}) \mod 2\pi,
\]

where \( \lambda \) is the wavelength of the signal and \( \theta_{\text{div}} \) is a diversity term caused by hardware imperfection of the reader and the tag. Similarly, the RSS of the received signal at the reader can be modeled as [32]

\[
P_{\text{rx}} = P_{tx} G_t^2 G_r^2 (\frac{\lambda}{4\pi rd})^2 T_b^2,
\]

where \( P_{tx} \) is the RSS of the backscattered signal at the reader, \( P_{tx} \) is the transmission power of the reader, \( G_t \) and \( G_r \) are the antenna gains at the tag side and reader side, respectively, and \( T_b \in [0, 1] \) denotes the backscatter coefficient of the tag. Currently, many COTS RFID readers can simultaneously report phases and RSS when they successfully interrogate tags. For example, the Impinj R420 reader can report phase of received signals with a resolution of \( \frac{2\pi}{4096} \approx 0.0015 \) radian [7] and report RSS with a granularity of 0.5 dBm.

In order to mitigate the co-channel interference among adjacent readers, COTS RFID systems widely adopt the frequency hopping technology. For instance, the frequency spectrum for communication in RFID systems is between 920.5 MHz and 924.5 MHz. The frequency spectrum is divided into 16 channels, each with a bandwidth of 250 KHz. When communicating with tags, the reader will randomly hop to a new channel about every 200 ms. As shown in Eq. (1) and Eq. (2), when the channel frequency changes, the corresponding RSS and phase values will also change even when all other parameters remain the same, because they are affected by the signal wave length \( \lambda \).

Existing studies [7], [33], [5], [8] show that in ideal cases (i.e., when there is a LOS path between a reader and a tag), the measured signal features coincide well with Eq. (1) and Eq. (2), which form the basis for most existing RFID-based localization and activity recognition algorithms. Thus, by measuring phase and RSS of received signals at the reader side, we can infer the distance between the reader and tags and thus calculate the position of the target tags.

B. NLOS Signal Propagation

To investigate how NLOS propagation will affect the features of the received signals, we conduct an experiment with
COTS readers and tags. In the experiment, we place one tag 2 meters away in front of an antenna, and measure the phase and RSS of the signal received by the reader in two cases: LOS (there is nothing between the reader and the tag) and NLOS (one person stands in the middle of the reader and the tag). For each case we collect data for about 30 seconds, approximately 2 seconds for each channel. All other settings in the two cases are the same.

The experimental results (illustrated in Fig. 2) indicate that the phase and RSS measurements in the NLOS case are greatly different from those in the LOS case. In the LOS case, for most channels the phase values are between 0 and 1.8 radians, while in the NLOS case the measured phase values vary from 4 to 6 radians. Similarly, the RSS measurements in the NLOS case (-64 dBm to -59 dBm) are also greatly different from the LOS case (-46 dBm to -44 dBm). It is clear that such non-negligible deviations in the NLOS case will cause significant localization error. For example, we place a reader and a tag in two cases: (1) the path between the antenna and the tag is LOS with a distance of 4.52m, and (2) the path is NLOS with a distance 2.41m. As shown in Fig. 3, the mean RSS value in the two cases are very similar, -62.8 dBm and -62.9 dBm, respectively. If we use the localization algorithms [33], [31] that do not differentiate these two cases, the inferred distance between the reader and the tag (around 4.5m) for case 2 is actually far deviated from the ground truth (2.41m).

The above experimental results show that it is of great importance to recognize the NLOS transmissions and then to drop or rectify readings in NLOS cases in order to guarantee high accuracy of location or activity recognition. In the following, we study how to recognize LOS paths from NLOS ones only relying on the signal features measured at the reader.

### III. TWO Baseline Approaches

From Fig. 2 and Fig. 3, we observe that in the NLOS case the phase and RSS exhibit much higher variance than in the LOS case. Actually, this is a general phenomenon and can be used to distinguish between LOS and NLOS paths. Motivated by this observation, we design two baseline approaches, *RSS threshold based approach* (RSS-T) and *Phase threshold based approach* (Phase-T), to recognize LOS and NLOS cases. The idea is that we measure the phase and RSS of the signal backscattered from the tag for a period of time, and calculate the average variances of the phase and RSS over all channels. Then we use a threshold-based method to determine whether the signal transmitting path is LOS or NLOS. The details are as follows.

#### A. An RSS Threshold based Approach

In this method, we first calculate the average variance of RSS over all channels, and then use a threshold $T H R_s$ to judge whether the corresponding path is LOS or NLOS. If the average RSS variance is smaller than $T H R_s$, we report the path as LOS. Otherwise, we report the path as NLOS.

The average RSS variance is calculated as following. For the $k$-th channel, we calculate its RSS variance as

$$V S_k = \frac{1}{N_k - 1} \sum_{i=1}^{N_k} (RSS_i^k - \bar{RSS}_k)^2,$$

where $N_k$ is the number of RSS readings in the $k$-th channel, $RSS_i^k$ is the $i$-th RSS reading in this channel, and $\bar{RSS}_k$ is the mean value of RSS readings in the $k$-th channel. After
For the $k$-th channel, the variance of phase readings is

$$V P_k = \frac{1}{N_k - 1} \sum_{i=1}^{N_k} (P S E_{i}^k - \overline{P S E}_k)^2,$$

where $P S E_{i}^k$ is the $i$-th phase reading in the $k$-th channel, and $\overline{P S E}_k$ is the mean phase value in the $k$-th channel. The average phase variance over all channels is

$$V P = \frac{1}{M} \sum_{k=1}^{M} V P_k.$$  

Finally, we use a threshold $THR_p$ to distinguish LOS from NLOS paths: If $V P < THR_p$, we report the path as LOS; otherwise, we report it as NLOS. We use the same data set as in Section 3.1 to evaluate the performance of Phase-T. The precision and $F$-score of Phase-T are plotted in Fig. 5(a) and Fig. 5(b), respectively. Phase-T performs slightly worse than RSS-T. Its balanced precision for LOS and NLOS is about 0.72. The highest $F$-score is about 0.74 for NLOS cases, and is only 0.71 for LOS cases.

C. Discussions

The simple idea of using the variance to distinguish LOS and NLOS paths only achieves a precision of about 0.7. This precision is not enough for many localization and activity recognition applications that require high accuracy. We need to design new metrics and methods to achieve higher precision in LOS/NLOS path recognition. Moreover, another drawback of RSS-T and Phase-T is that they require a relatively long sampling period to achieve high recognition precision, which incurs a large delay. Such a long delay is not acceptable in many real-world applications with realtime requirements. We need to design new mechanisms to speed up the LOS/NLOS path recognition. We will address these two issues in the following sections.

IV. PRECISE LOS/NLOS PATH RECOGNITION

In this section, we present several novel ideas to boost the LOS/NLOS path recognition precision, including a new metric that combines both phase and RSS variances to better discriminate LOS and NLOS paths and a machine learning based method that exploits the new metric and several other features related to frequency hopping to improve the recognition precision.

A. Handling Phase Ambiguity and Phase Discontinuity

Revisiting Fig. 2(a) and Fig. 2(b), we observe two different types of “outliers” in the phase readings. The first type is called “phase ambiguity”, which refers to the phenomenon that the phase readings in the same channel might differ by a shift of around $\pi$. Phase ambiguity can happen in both LOS and NLOS cases and can take place in any channel. Fig. 2 shows that ambiguity happens in 10 and 11 channels in LOS and NLOS cases, respectively. The second type is called “phase discontinuity”, which refers to the phenomenon that the phase readings in the same channel might differ by a shift of about $2\pi$. Different from phase ambiguity, phase discontinuity happens in at most one channel, e.g., channel 14 (light brown) in the LOS case as shown in Fig. 2(a). Actually, it happens only when the phase readings are close to 0 (or $2\pi$). In such cases, the reading would be wrapped by $2\pi$ if the raw report is negative. In RFID systems deployed in real environments, phase ambiguity and phase discontinuity might be more serious than the ones shown in Fig. 2. They dominate the phase variance in both LOS and NLOS cases, making the distinction between LOS and NLOS more difficult.

A simple method to handle the problem is to use some filters (e.g., median filter) to filter out outlier readings. This method, however, does not work well for two reasons. First, sometimes phase ambiguity and phase discontinuity are very
serious and we cannot effectively filter out the outlier readings. Especially for phase discontinuity, the two parts belong to the same channel have nearly the same number of readings (e.g., channel 14 in Fig. 2(a)). Second, if we filter out some readings, the remaining readings might be too few to achieve high precision in LOS/NLOS path recognition.

We propose a clustering-based method that can effectively mitigate the negative effects of phase ambiguity and phase discontinuity, which can also keep all the readings to achieve high recognition precision. For each channel, we use a clustering algorithm (e.g., K-means) to classify a set of phase readings obtained in that channel, denoted as $P$, into two groups $P_1$ and $P_2$ (without loss of generality, $|P_1| \leq |P_2|$). If the distance between the centroids of the two clusters is around $\pi$ (phase ambiguity) or $2\pi$ (phase discontinuity), we shift readings in one group to another group as follows.

For phase ambiguity. If the centroids of the two resulting clusters differ from each other with a drift around $\pi$, we know that there are some readings caused by phase ambiguity. In this case, we shift readings in the small cluster to the large one. Specially, if the centroid of $P_1$ is smaller than that of $P_2$, we add $\pi$ to all the readings in $P_1$; if the centroid of $P_1$ is larger than that of $P_2$, we subtract $\pi$ from all the readings in $P_1$.

**Algorithm 1 Phase Calibration Algorithm**

**Require:**

The phase readings of channel $i$, $P = \{p_1, p_2, \ldots, p_I\}$;

**Ensure:**

The calibrated phase readings of channel $i$;

1. Divide $P$ into two clusters $P_1$ and $P_2$ by using $K$-means clustering algorithm ($K = 2$), $|P_1| \leq |P_2|$;
2. Calculate centroid of $P_1$ and $P_2$, denoted by $c_1$ and $c_2$ respectively;
3. if $|c_1 - c_2| - \pi| \leq \varepsilon_1$ then
   4. //phase ambiguity;
   5. $p_f = c_1 > c_2 - \pi - \pi$;
   6. $\forall p \in P_1, p = p + p_f$;
7. end if
8. if $|c_1 - c_2| - 2\pi| \leq \varepsilon_2$ then
9. //phase discontinuity;
10. $p_f = c_1 > c_2 - 2\pi - 2\pi$;
11. $\forall p \in P_1, p = p + p_f$;
12. end if

**For phase discontinuity.** If the centroids of the two resulting clusters differ from each other with a value around $2\pi$, there are phase discontinuity readings in the current channel. Note that, phase discontinuity happens in only one channel. Similarly, if the centroid of $P_1$ is close to 0, we add $2\pi$ to all the readings in $P_1$; if the centroid of $P_1$ is close to $2\pi$, we subtract $2\pi$ from all readings in $P_1$.

**B. A New Metric**

In this section, we propose a new metric that combines variance in RSS and phase to distinguish LOS and NLOS paths. Actually, the new metric considers the joint variance of phase and RSS and is abbreviated as $VPS$. We use two methods to calculate the $VPS$ of a channel.

**Maximum VPS:** In the first method, we use the maximum variance range of RSS and the maximum variance range of phase to calculate the metric, and denote it by $VPS_{\text{max}}$. For the $k$-th channel,

$$VPS_{\text{max}}^k = (rss_{\text{max}}^k - rss_{\text{min}}^k) \times (\text{phase}_{\text{max}}^k - \text{phase}_{\text{min}}^k),$$

where $rss_{\text{max}}^k$ and $rss_{\text{min}}^k$ are the maximum and minimum RSS readings in the $k$-th channel, and $\text{phase}_{\text{max}}^k$ and $\text{phase}_{\text{min}}^k$ are the maximum and minimum phase readings in the $k$-th channel, respectively. After calculating $VPS_{\text{max}}$ for all channels, we calculate their average value as

$$VPS_{\text{max}} = \frac{1}{M} \sum_{k=1}^{M} VPS_{\text{max}}^k.$$  

**Fitted VPS:** When there are some occasional extreme readings, $VPS_{\text{max}}$ might be also very large for LOS cases, which will impact the recognition precision. Our second method uses the confidence interval of the RSS and phase readings to calculate the metric, which is denoted by $VPS_{\text{fit}}$. In detail, for the $k$-th channel, denote by $[rss_{\text{fit}}^k, rss_{\text{fit}}^k]$ the 95-percentile confidence interval of all the RSS readings, and denote by $[\text{phase}_{\text{fit}}^k, \text{phase}_{\text{fit}}^k]$ the 95-percentile confidence interval of all the phase readings. Then we calculate the metric as

$$VPS_{\text{fit}}^k = (rss_{\text{fit}}^k - rss_{\text{fit}}^k) \times (\text{phase}_{\text{fit}}^k - \text{phase}_{\text{fit}}^k).$$

$$VPS_{\text{fit}} = \frac{1}{M} \sum_{k=1}^{M} VPS_{\text{fit}}^k.$$  

The differences between maximum VPS and fitted VPS lie in the way to calculate the range of phase and RSS. In maximum VPS, the range is calculated as the difference between the maximum reading and the minimum reading among all data. In fitted VPS, the range is calculated as the width of the 95-percentile confidence interval. The fitted VPS is more robust because it might exclude the extremely large or extremely small readings which might be noisy readings. Finally, similar to the cases of RSS-T and Phase-T, we use a threshold-based approach over the new metrics to classify LOS and NLOS paths.

The precision and $F$-score generated by the two metrics are plotted in Fig. 6. Compared with RSS-T and Phase-T, the new metrics greatly improve recognition precision. The balanced precision for LOS and NLOS of using $VPS_{\text{max}}$ and $VPS_{\text{fit}}$ is 0.83 and 0.84, respectively, much higher than 0.74 and 0.72 of using only $V S$ and $V P$. $VPS_{\text{fit}}$ performs slightly better than $VPS_{\text{max}}$ because it can effectively mitigate the effects of some noisy extreme readings. The highest $F$-scores for LOS and NLOS are 0.86 and 0.88 when using $VPS_{\text{max}}$, and are 0.93 and 0.91 when using $VPS_{\text{fit}}$, more than 10 percent higher than that of RSS-T and Phase-T.

**C. Exploiting More Features to Improve Precision**

We find that the recognition precision can be further enhanced by exploiting more features related to frequency hopping. Actually, besides phase variance, RSS variance,
maximum $VPS$, and fitted $VPS$, the following three features can also be used to distinguish LOS and NLOS paths:

- The mean size of 95-percentile confidence interval of phase readings. The size of 95-percentile confidence interval of phase readings differs in LOS and NLOS cases. To obtain this metric, we first calculate the 95-percentile confidence interval for each channel, and then calculate their average size over all channels.

- The average number of phase ambiguity readings. Generally, phase ambiguity happen more often in NLOS cases than in LOS cases. We first determine whether there are ambiguity readings in each channel by using Algorithm 1 described in Section IV-A, and then calculate the average number of ambiguity readings over all channels.

- The variance of reading numbers per channel. We observe that in LOS cases the reading rate (i.e., the number of readings per second) is relatively stable, while in NLOS cases the reading rate varies greatly. We first compute reading rate for each channel and then use the average value as a metric to distinguish LOS/NLOS paths.

We collect a set of test data containing 2330 LOS cases and 2480 NLOS cases, under different settings including different types of obstacles, different distances between the reader and the tag, and different types of tags. We calculate all the aforementioned 7 features of each case and feed them into 4 representative machine learning algorithms, namely RandomForest, Bagging, RandomCommittee, and KStar. The results of 10-fold cross-validation are given in TABLE 1. Compared with the best previous approach that uses $VPS_{fit}$, the precision is greatly boosted by 14 percent (0.98 vs 0.84)! We also observe that RandomForest performs the best in almost all cases, and thus use it as the default classifier in the rest of our experiments.

1\text{The ability in distinguishing LOS and NLOS paths of these three features is weaker than that of phase variance. The recognition precision of using any individual of the three features is lower than 0.65.}

V. Reducing Recognition Delay

Although the machine learning based approach proposed in Section IV-C can achieve high precision, it induces long recognition delay of about 30 seconds because it uses all readings from all channels. In this section, we propose a sampling method that can greatly reduce the delay without sacrificing recognition precision.

A. Discriminative Ability of Individual Channels

One simple idea to reduce the recognition delay is to use measurements of only one channel rather than all the 16 channels to perform the LOS/NLOS path recognition. TABLE III lists the recognition precision of LOS and NLOS cases when using data from different individual channels. It can be observed that the precision of using a single channel lies between 0.89 and 0.93, significantly lower than the precision of using data from all the channels. Actually, the ability of different channels in discriminating LOS and NLOS paths are similar, and there are no optimal channel suitable for both cases in different scenarios.

However, we find that if we randomly select several channels and use their combination to perform LOS/NLOS path recognition, the resulting precision would be close to the precision of using all the data, but the recognition delay can be significantly reduced. In Fig. 7 we plot the recognition precision of LOS/NLOS cases when $K$ (1 $\leq K \leq 16$) randomly selected channels are used to perform LOS/NLOS path recognition. It can be observed that when the number of channels increases from 1 to 3, the recognition precision increases rapidly from 0.93 to 0.97. However, when the number of channels is larger than 4, using more channels can only marginally improve the recognition precision. Actually, when the number of channels is larger than 8, the precision nearly keeps stable. Thus, we can randomly select three channels and collect data on each channel for 2 seconds, and perform LOS/NLOS path recognition with data of the three selected...
A. Experimental Methodology and Metrics

We conducted extensive experiments in a real environment to evaluate the performance of our LOS/NLOS path recognition algorithm. In our experiment, we consider there is a NLOS path between the reader and the tag when there is an obstacle on the line connecting the reader and the tag. When there are no objects between the reader and the tag, we consider there is a LOS path between them. The experiment setup is shown in Fig. 8. We use the Impinj R420 Speedway reader [34] and the Alien ALR-8696-c antenna to communicate with tags. To test the performance of the algorithm for different types of tags, we use 4 different types of passive tags, namely Impinj H-47, Alien AZ-9654, AZ-9634, and AZ-9629. These tags have different sizes and different target applications, and can reflect the performance of our algorithm in different scenarios. We also test the performance of the algorithm with different types of obstacles, including a carton, a cushion, a piece of iron, and a person. For each setup, we repeat the experiments 30 times. Each time we collect data from all the 16 channels, and in each channel we collect data for about 2 seconds. We then use 10-fold cross-validation to evaluate the performance of the proposed algorithm.

B. Sampling Readings over Selected Channels

Actually, we can further speed up the recognition by reducing the number of readings in each channel. To investigate how the number of readings in each channel affects the recognition precision, we randomly sample a subset of readings from 3 randomly selected channels and use them to perform LOS/NLOS path recognition. The results are listed in TABLE III.

From the results given in TABLE III, we observe that when the number of readings in each channel is larger than 20, the recognition precision is nearly not affected. The reason is that all the features used in our approach are statistics, which can be accurately estimated as long as the sampling number is sufficient, e.g., 20. When the number of readings drops below 20, the precision decreases slightly. However, even when the number of readings is as few as 5 per channel, the recognition precision is still higher than 0.95. This requires us to collect 3 * 5 = 15 readings in total. As the reading rate is about 40 readings per second, this corresponds to a recognition delay of about 15/40 = 0.375 seconds. In the following, if not specified explicitly, we use 3 channels and 5 readings for each channel to perform LOS/NLOS path recognition.

VI. EXPERIMENTAL RESULTS

A. Experimental Methodology and Metrics

1) Experimental Methodology: We conducted extensive experiments in a real environment to evaluate the performance of our LOS/NLOS path recognition algorithm. In our experiment, we consider there is a NLOS path between the reader and the tag when there is an obstacle on the line connecting the reader and the tag. When there are no objects between the reader and the tag, we consider there is a LOS path between them. The experiment setup is shown in Fig. 8. We use the Impinj R420 Speedway reader [34] and the Alien ALR-8696-c antenna to communicate with tags. To test the performance of the algorithm for different types of tags, we use 4 different types of passive tags, namely Impinj H-47, Alien AZ-9654, AZ-9634, and AZ-9629. These tags have different sizes and different target applications, and can reflect the performance of our algorithm in different scenarios. We also test the performance of the algorithm with different types of obstacles, including a carton, a cushion, a piece of iron, and a person. For each setup, we repeat the experiments 30 times. Each time we collect data from all the 16 channels, and in each channel we collect data for about 2 seconds. We then use 10-fold cross-validation to evaluate the performance of the proposed algorithm.

2) Metrics: As the LOS/NLOS path recognition problem is actually a classification problem, we use the widely accepted precision and recall as the major metrics to evaluate the performance of the algorithm. The precision is defined as

\[
\text{Precision} = \frac{\#TP}{\#TP + \#FP},
\]

where \#TP is the number of true positive results (e.g., a LOS path is correctly classified as LOS) and \#FP is the number of false positive results (e.g., a NLOS path is incorrectly classified as LOS). The recall rate is defined as

\[
\text{Recall} = \frac{\#TP}{\#TP + \#FN},
\]

where \#FN is the number of false negative results (e.g., a LOS path is incorrectly classified as NLOS). Moreover, we also use the balanced F-score to reflect the overall performance of the algorithm considering both LOS and NLOS cases

\[
F\text{-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}.
\]
**Table III**

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<th>#Readings</th>
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<th>NLOS Recall</th>
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<td>.970</td>
<td>.965</td>
<td>.966</td>
<td>.971</td>
</tr>
<tr>
<td>10</td>
<td>.964</td>
<td>.965</td>
<td>.961</td>
<td>.962</td>
<td>.966</td>
</tr>
<tr>
<td>5</td>
<td>.953</td>
<td>.951</td>
<td>.953</td>
<td>.955</td>
<td>.953</td>
</tr>
</tbody>
</table>

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TABLE IV

<table>
<thead>
<tr>
<th>Tag type</th>
<th>H-47</th>
<th>AR-9654</th>
<th>AR-9654</th>
<th>AR-9629</th>
</tr>
</thead>
<tbody>
<tr>
<td>LOS Precision</td>
<td>0.821</td>
<td>0.982</td>
<td>0.903</td>
<td>0.926</td>
</tr>
<tr>
<td>LOS Recall</td>
<td>0.800</td>
<td>0.949</td>
<td>0.872</td>
<td>0.935</td>
</tr>
<tr>
<td>NLOS Precision</td>
<td>0.950</td>
<td>0.969</td>
<td>0.910</td>
<td>0.970</td>
</tr>
<tr>
<td>LOS Recall</td>
<td>0.956</td>
<td>0.996</td>
<td>0.977</td>
<td>0.967</td>
</tr>
</tbody>
</table>

TABLE V

<table>
<thead>
<tr>
<th>Classification Accuracy of Different Types of Obstacles (CA: Carton; IR: Piece of Iron; CU: Cushion; PE: Person.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CA</td>
</tr>
<tr>
<td>------------------------------</td>
</tr>
<tr>
<td>0.953</td>
</tr>
<tr>
<td>0.024</td>
</tr>
<tr>
<td>0.020</td>
</tr>
<tr>
<td>0.029</td>
</tr>
</tbody>
</table>

Different types of obstacles. The value of the (i,j) entry in the matrix gives the ratio that the i-th type of obstacle is classified as the j-th type of obstacle. We can find that, in general, the classification precision of all the types of obstacles are higher than 0.9, and the average classification accuracy is 0.93. The misclassification rates are all smaller than 0.04, showing the high ability of our algorithm in distinguishing different types of obstacles.

VII. RELATED WORK

A. RFID-based Localization and Activity Recognition

1) RFID-based Localization: RFID-based localization has attracted much research attention in recent years, e.g., [18], [7], [5], [17], [15]. LANDMARC [35] is an early tag localization algorithm that uses reference tags to locate a target tag. Maneesilp et al. [36] offer a tag localization algorithm that uses RSS to calculate the distance between tags and readers, and then uses trilateration to calculate the position of tags. These approaches depend on a LOS-based modeling between RSS and distance, and their accuracy would be greatly degraded if the RSS is measured in NLOS paths.

Due to its high resolution in discriminating distances, phase information has been exploited to perform accurate tag localization in recent years [7], [5], [15]. Tagoram [7] tries to find a position at which the measured phase values best match with the theoretical values. By using differential values rather than absolute values, the proposed algorithm achieves very high accuracy. Liu et al. [18] introduce a hyperbola-based tag localization algorithm, which calculates the position of a tag according to the difference of phase obtained by two different antennas. In [15], [5], the authors present algorithms for relative localization, i.e., determining the relative order of tags rather than calculating their absolute positions.

2) RFID-based Activity Recognition: RFID-based activity recognition has also attracted a lot of research attention in recent years. Han et al. [20] develop a custom behaviour recognition system that uses Doppler effects to detect whether an item is taken by the customers or not. The system then analyzes the behavior of the customers and the relationship among items. Shangguan et al. [19] develop ShopMiner, which identifies the popularity of goods by monitoring their mobility. Ding et al. [37] propose a passive-tag based system to monitor and assess the quality of a person’s gym actions. Xie et al. [38] propose an argument reality system that uses RFID tags to distinguish different objects that belongs to the same category. Li et al. [30] propose several deep learning based activity recognition algorithm.

All these RFID localization algorithms require the measurement of the phase or RSS value in LOS paths; otherwise their accuracy will be greatly affected and degraded. The LOS/NLOS recognition approach proposed in this paper can be used to determine whether the collected data satisfy the LOS requirement and hence can be used to improve their performance.

B. LOS/NLOS Path Recognition in Wireless Systems

Because NLOS signal propagation can greatly affect accuracy of wireless localization algorithms (e.g., those localization algorithms based on Wi-Fi fingerprinting [39], [40], [41]), LOS/NLOS path recognition has also been studied in other wireless systems, including Wi-Fi [23], [24], cellular networks [42], [43], Bluetooth [25], and Ultra-wide-band (UWB) [26]. PhaseU [23] and Li-Fi [24] exploit rich physical layer information that can be obtained on some wireless network interface cards (e.g., Intel NIC 5300) to determine whether a path is LOS or NLOS. In [42], [43] the authors use the error in distance measurement to distinguish LOS or NLOS paths between the mobile terminal and the base station in cellular networks. Mucchi et al. [26] propose a method that uses the kurtosis index of a received signal to recognize LOS and NLOS paths. However, they all rely on the detailed low level physical layer information, which requires very wide bandwidth of the signal. In an RFID system, we cannot obtain such low level information due to its very limited bandwidth, and thus these approaches cannot be used in RFID systems.

VIII. CONCLUSION

LOS/NLOS path recognition is of great importance to achieve high accuracy in RFID-based localization and activity recognition algorithms. In this paper, we propose the first LOS/NLOS recognition approach for RFID systems. Experimental results with COTS RFID devices show that the proposed algorithm can achieve a very high recognition precision with a delay of less than 0.4 seconds. This technique can be used in all RFID-based localization and activity recognition systems that require LOS path signal propagation to achieve high accuracy. In the future, we plan to study how to simultaneously recognize LOS/NLOS paths for multiple tags.

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