Improving RSS-Based Ranging in LOS-NLOS Scenario Using GMMs

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Abstract—Range estimation based on Radio Signal Strength (RSS) has been widely adopted by the indoor localization systems. Many existing works have been devoted to tackle the imprecise and unreliable RSS measurements caused by multipath fading. But there exist only a few works dealing with errors caused by non-line-of-sight (NLOS) radio propagation. In some circumstances, it is common for obstacles (e.g. human movements) to cause NLOS measurements, which could undermine the whole ranging process by introducing significant NLOS errors. In this letter, we propose to use a Gaussian Mixture Model (GMM) to model the distribution of a set of NLOS corrupted range estimations. In the GMM method, the distribution of LOS estimations and the distribution of NLOS estimations are represented by different Gaussian components. Consequently, the ranging quality is improved by employing soft exclusion of those Gaussian components associated with NLOS. An indoor field experiment has been performed to verify the proposed method.

Index Terms—Ranging, NLOS, Gaussian mixture model.

I. INTRODUCTION

RANGING using radio-based measurements has been widely used for target tracking, localization and navigation in radar systems, and recently in wireless sensor networks. Radio Signal Strength (RSS), Time of Arrival (TOA), and Time Difference of Arrival (TDOA) of radio signals are the most common parameters measured in order to estimate the distance between a radio transmitter (Tx) and a radio receiver (Rx) or the difference of distances between a Tx (Rx) and multiple RxTs (TxTs). The common challenges for the radio-based ranging include multi-path fading and non-line-of-sight (NLOS) radio propagation in certain circumstances. In this letter, we will focus on the elimination of the ranging errors due to NLOS and demonstrate the results for a 2.4 GHz narrowband radio system.

II. MEASUREMENT SETUP, RANGE ESTIMATION, AND RANGE ERROR

We consider radio-based ranging in circumstances where the observation of line-of-sight (LOS) signals may be lost from time to time. Although the results have the possibility to be generalized, we mainly consider a short-range low power communication operating at the 2.4 GHz ISM band, which is used by most of the standardized wireless sensor platforms, as well as by WiFi and by Bluetooth. Because a narrowband signal cannot provide fine time resolution, the popular TOA/TDOA-based ranging is not considered. Instead, we consider RSS-based ranging. Although it is challenging to achieve satisfactory accuracy in RSS-based ranging, it has the advantage of simple hardware with certain level of positioning accuracy almost for free.

Consider \( P(r) \) the received signal power (dB) measured at a distance \( r \) and \( P_0 \) be the received signal power measured at a reference distance \( r_0 \). There is a relation between distance and the received signal power (equivalently, the RSS) [1]:

\[
P(r) = P_0 - 10n \log_{10}(r/r_0),
\]

where \( n \) is the path loss exponent. This relation is usually referred to as the log-distance path loss model. By measuring a series of reference powers and distances, we can specify the parameters of this model and use it for RSS-based range estimation.

For TOA-based UWB ranging, range estimation errors have been studied to follow certain kind of mixture models, which incorporate the considerations of multipath effects and NLOS effects [2], [3]. For RSS-based narrowband ranging, there is no similar model. Therefore we propose the following model:

Let \( r \) be the true distance, and let \( \hat{r} \) be the estimated distance. Suppose Tx is located at \((0, 0, 0)\), while Rx is located at \((r, \theta, \phi)\) in a 3D space. We have

\[
\hat{r} = \begin{cases} 
    r + m^{F,OS}_{los}(r, \theta, \phi) + N_{los}, & \text{LOS} \\
    r + m^{F,NO}_{los}(r, \theta, \phi) + N_{nlos}, & \text{NLOS}
\end{cases}
\]

where \( m^{F,OS}_{los} \) and \( m^{F,NO}_{los} \) are respectively the estimation errors due to multipath effects in the case of LOS and in the case of NLOS measurements. The superscripts \( F \) and \( O \) account for the dependencies on radio frequency and obstructions, respectively. In the case of LOS, multipath causes constructive or destructive interference on the received RSS, and the multipath error \( m^{F,OS}_{los} \) is a function of Tx’s and Rx’s locations in the environment. NLOS measurements may be observed when there is an obstruction between Tx and Rx or when the distance is too large such that the LOS signal becomes undetectable. Due to the absence of a dominant LOS signal, the measured RSS from NLOS multipaths will be very weak and will cause large positive NLOS range estimation error \( m^{F,NO}_{nlos} \). Besides the location, the size of an obstruction will affect the propagation of an NLOS signal, and thus has influence on \( m^{F,NO}_{nlos} \). In both LOS and NLOS cases, there are measurement noises, which are represented by \( N_{los} \) and \( N_{nlos} \). Generally, the magnitudes of different errors will have the following relationship: \( |N_{los}|, |N_{nlos}| \ll |m^{F,OS}_{los}|, |m^{F,NO}_{nlos}| \). The noises
usually are neglectable and can be cancelled by multiple measurements. \( m_{los}^F \) mainly exists in an indoor environment, and it can be eliminated by calibrating eq. (1) using a radio map or by applying spatial diversity. In this letter, we purpose to remove \( m_{los}^F \) by implicitly excluding NLOS measurements from range estimation.

III. GAUSSIAN MIXTURE MODEL AND ITS APPLICATION ON RANING

In certain circumstances, the ranging quality suffers from NLOS errors due to the failure of observing LOS signals. Given a set of NLOS corrupted range estimations, it is not straightforward to estimate the true range. In this section, a Gaussian Mixture Model (GMM) is used to describe the distribution of NLOS corrupted range estimations. In the GMM, the distributions of LOS range estimations and NLOS range estimations are represented by different Gaussian components. Because LOS and NLOS range estimations can be separated softly in terms of their different Gaussian components, the ranging quality is enhanced by estimating the true range solely based on the Gaussian component representing the distribution of LOS estimations.

Let \( X = \{x_1, x_2, \ldots, x_N\} \) be the data set of \( N \) sample range estimations. There could be NLOS corrupted range estimations mixed in the \( N \) samples, but there is no a priori information about which samples are NLOS corrupted. For LOS samples, it has been shown that the pdf is Gaussian and is similar to the situation of corruption due to receiver noise [4]. This leads to the pdf being \( f_{los}(x) \sim N(r_{los} + m_{los}^F, \sigma_{los}^2) \), where \( r_{los} \) represents the true range and is always assumed to be a deterministic with an unknown quantity, and \( m_{los}^F \) is defined in eq. (2) and has a fixed value if the measurement environment and settings do not change. Without loss of generality, we set \( m_{los}^F = 0 \) in the following. For NLOS samples, it has been shown that they are also Gaussian distributed [4]. Actually, the rationale for NLOS samples following a Gaussian distribution is also explained by the noise at the receiver if there is a deterministic NLOS error (e.g. if the measuring environment does not change). If the NLOS error is random, the modeling is complicated. If there are a finite number of discrete values for the NLOS error, the NLOS samples associated with different NLOS error situations can be grouped and modelled by different Gaussian distributions. A typical example is that an NLOS situation is always changing or finite possibilities for the NLOS error. In this case, it is not possible to identify a distribution for each possible NLOS situation. Instead, we need to group all NLOS samples together, where the distribution of the whole set of NLOS samples will still follow a Gaussian distribution according to the central limit theorem. In any case, we will have the pdf of a group of NLOS samples, \( f_{nlos}(x) \sim N(r_{nlos} + m_{nlos}^F, \sigma_{nlos}^2) \), where \( r_{nlos} = r_{los} + m_{nlos}^F \), if we refer to the terms in eq. (2).

Without loss of generality, suppose there are \( K \) differentiable NLOS situations and each NLOS sample is associated with one of them (In practice, \( K + 1 \) can be chosen equal to the number of clusters in the sample dataset). According to the above analysis, we can model the pdf of \( X \) using a mixture of Gaussians:

\[
    f(x; \theta) = p_0 f_{los} + \sum_{k=1}^{K} p_k f_{nlos,k} = \sum_{k=0}^{K} p_k g(x;r_k, \sigma_k),
\]

where \( g(x;r_k, \sigma_k) = \frac{1}{\sqrt{2\pi\sigma_k}} e^{-\frac{(x-r_k)^2}{2\sigma_k^2}} \), and \( \theta = (\theta_0, \theta_1, \ldots, \theta_K) = ((p_0, r_0, \sigma_0), (p_1, r_1, \sigma_1), \ldots, (p_K, r_K, \sigma_K)) \) is a \((K+1)\)-dimensional vector containing the mixing probabilities \( p_k \) as well as the mean \( r_k \) and standard deviation \( \sigma_k \) of the \( K + 1 \) Gaussian components in the mixture.

\( r_0 = r_{los} \) represents the true range, and \( r_k > r_{los} \), \( \forall k > 0 \) represents that all NLOS ranges are positively biased. Because each Gaussian function integrates to one and the probability density \( f(x; \theta) \) integrates to one as well, we have \( \sum_{k=0}^{K} p_k = 1 \). (pk ≥ 0).

This GMM method provides a soft clustering for all members in \( X \). With a certain probability, a member in \( X \) belongs to the Gaussian component representing the distribution of LOS samples. With other probabilities, the same member belongs to the other Gaussian components representing the distributions of NLOS samples. In the GMM method, we do not pursue to label each member of \( X \) as LOS or NLOS with 100% confidence. Instead, we try to find the probability density \( f(x; \theta) \) which is most likely to have generated \( X \). Obviously, this problem is equivalent to estimating the vector \( \theta \) given the observation, \( X \).

Due to there is, usually, no a priori knowledge about \( \theta \), the Maximum Likelihood Estimation (MLE) approach can be used to estimate \( \theta \). As of [5], the MLE will lead to three groups of equations for the means, standard deviations, and mixing probabilities:

\[
    r_k = \frac{\sum_{n=1}^{N} p(k|n)x_n}{\sum_{n=1}^{N} p(k|n)}, \quad \sigma_k = \sqrt[2]{\frac{\sum_{n=1}^{N} p(k|n)(x_n - r_k)^2}{\sum_{n=1}^{N} p(k|n)}}, \quad p_k = \frac{1}{N} \sum_{n=1}^{N} p(k|n),
\]

where \( p(k|n) \) is the conditional probability of having the sample \( x_n \) belong to LOS (when \( k = 0 \)) or the \( k \)-th NLOS (when \( k > 0 \)) given that \( x_n \) has been observed. We have \( p(k|n) = \frac{p_k g(x_n; r_k, \sigma_k)}{\sum_{l=0}^{K} p_l g(x_n; r_l, \sigma_l)} \).

Eqs. (4), (5) and (6) are functions of \( p(k|n) \), and \( p(k|n) \) depends on \( r_k \), \( \sigma_k \), and \( p_k \). They are difficult to solve analytically. Therefore, numerical solutions can be found using the Newton's method or the Expectation-maximization method.

Although members of \( X \) are not explicitly labeled as LOS or NLOS in the GMM method, the found probability density \( f(x; \theta) \) and its associated Gaussian components represent the most likely distribution of \( X \). In this case, the Gaussian component with the smallest mean (i.e. \( r_0 \)) has its most support from LOS samples and its mean is an estimate of the true range.
IV. EXPERIMENTAL RESULTS

A ranging experiment is performed in an indoor environment as a proof-of-concept. In this experiment, two TelosB motes with IEEE 802.15.4/ZigBee compliant RF transceiver operating at the 2.4GHz ISM band are placed in the hall of the Electrical Engineering Building, NTNU. The two motes are separated with a distance of 3 meters, and they are 0.715 meters above the ground. One of the motes is acting as Tx and the other one is acting as Rx. Tx periodically sends an empty message at a frequency of 2 Hz. Rx receives each message and measures its received RSS, from which the range between Tx and Rx is estimated according to eq. (1).

In order to collect NLOS corrupted measurements, the experiment is done during rush hour of a busy school day at 12:00-12:45 hrs when many students have just finished their classes. At the peak time, there are about 40 people passing through between Tx and Rx per minute, while there could be as few as a couple of persons per minute at other times. With the message transmission rate of two messages per second, many (although not all) of the people passing by will result in NLOS measurements.

The series of ranges derived by eq. (1) is shown in Fig. 1. It can be seen that many people passing by have caused NLOS range estimations, which can be up to ten times of the true range. In order to estimate the true range, the GMM method is applied to filter noise and NLOS errors. Because people are passing randomly between Tx and Rx, a single Gaussian distribution is used to model the distribution of all NLOS estimations. As a result, there are two Gaussian components in the GMM method. With the range estimation samples observed in a window of five minutes as the input, a single range value is estimated and the results are shown in Fig. 2. As a comparison, the sample mean of the input samples is also used as an alternative estimation method. The reference range shown there is the average value of range samples from a similar experiment performed on a quiet weekend when NLOS measurements are seldom.

From Fig. 2, it can be seen that the GMM method performs much better than the sample mean method (in terms of both the estimation accuracy and the resistance to the amount of NLOS measurements) except for a window when the time elapsed is between 25-30 minutes. This is because the GMM method has the ability of filtering both noise and NLOS errors, while a sample mean calculation can only filter noise. When the time elapsed is between 25-30 minutes, there are much fewer NLOS measurements than there are at other time windows as shown in Fig. 1. Obviously, the GMM method may underestimate the true range if there are few NLOS measurements. This problem can be solved by having only one Gaussian component in the GMM method. By doing this, the GMM method will be equivalent to the sample mean method. An outlier removal program combined with a clustering algorithm can be used to determine the optimal number of components in the GMM method.

V. CONCLUSIONS

A Gaussian Mixture Model (GMM) based method is proposed to enhance radio-based ranging quality when NLOS measurements may corrupt the true range estimation. Experiments have shown that the GMM method has the ability of filtering both NLOS errors and noise from a set of NLOS corrupted range estimations.

REFERENCES