Impact of NLOS Identification on UWB-Based Localization Systems

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Abstract. When considering localization systems, one of the most commonly employed reference parameters is the so-called two-way ranging. To obtain this parameter, technologies such as ultra-wideband (UWB) exploit the signal propagation time between two devices: a target and an anchor. However, this parameter is not immune to propagation phenomena such as shadowing, reflections, and diffractions frequently found in indoor environments, leading to a loss of line-of-sight (LOS) conditions between the target and the anchor (i.e., non-line-of-sight (NLOS) conditions), hence degrading the ranging estimations and, consequently, the performance of the algorithms used for the localization. This work studies how the prior knowledge about LOS and NLOS conditions allows for improving considerably the final position estimations. Results based on UWB measurements are considered to evaluate the performance of different positioning algorithms with and without this prior information.

Keywords: Ultra-wideband · NLOS Identification · two-way ranging.

1 Introduction

Location-based services (LBS) are becoming more popular and demanding with the accuracy of locating users and objects, especially inside buildings, where it is well known that satellite tracking systems have no coverage. The demand for these services requires the use of the so-called sub-meter location systems (i.e., positioning errors below one meter).

Ultra-wideband (UWB) is one of the most used technologies in recent years to achieve sub-meter localization. This technology is based on obtaining the propagation time (time of arrival (ToA) or time difference of arrival (TDoA), depending on the variant of the technology considered) between a reference element (anchor) with a fixed and known location and the target to be located (tag). From such a propagation time, it is possible to determine the distance between the two elements (anchor and tag). Using multiple anchors, trilateration algorithms can be employed to estimate the position of the tag.

Although the propagation times provided by UWB have a much higher precision and accuracy than those obtained by received signal strength (RSS)-based technologies, they are still affected by different propagation phenomena, especially in indoor environments. Multiple and varied obstacles (walls, ceilings, people, furniture, ...), shields and signal blockages, reflections, refractions, and diffractions cause the appearance of multipath propagation between anchors and tags. Each of these paths presents different propagation times, deteriorating the ranging precision and accuracy and, therefore, the tag estimated position.

These phenomena are different depending on the visibility between anchors and tags. Basically, there are two possible path types: line-of-sight (LOS) and non-line-of-sight (NLOS). In the case of LOS, the shortest path is the one that provides a good distance estimation between an anchor and a tag. However, when NLOS appears, the aforementioned phenomena produce secondary paths that predominate over the shortest one, degrading the distance estimation. If the different propagation conditions (LOS or NLOS) between anchors and tags is not taken into account, the positioning algorithms will use noisy or erroneous information that will cause a poor estimation of the final position of the tag.

This work analyzes the benefits of taking into account the propagation conditions (LOS or NLOS) between the tag and each anchor as prior knowledge for the location algorithms. Employing a UWB-based system, we carried out a measurement campaign considering a set of anchors combining LOS and NLOS propagation conditions with respect to a tag. The obtained measurement data are available for public use [1] and were also used to assess the performance of different location algorithms when the propagation conditions (LOS and NLOS) are known compared to the situation in which the location algorithms cannot access such prior information.

The article is structured as follows: Section 2 presents the environment where the measurements have been carried out, explaining how LOS and NLOS propagation conditions are obtained. Section 3 introduces the location algorithms considered to assess the impact of the prior knowledge about the propagation conditions (LOS and NLOS). Section 4 details how the experimental data are used to simulate a more complex scenario. The results are shown and discussed in Section 5. Finally, Section 6 is dedicated to the conclusions.

2 UWB Measurements

To analyse the effect of LOS/NLOS conditions on the performance of a location algorithm, ranging measurements in a real environment with unambiguous identification of these conditions are required. The measurement campaign goal is just to obtain a real distance-measurement database. These measurements were obtained in a campaign carried out inside the Scientific Area building, located in the Campus of Elviña, at the University of A Coruña, Spain.

The hardware used consists of UWB devices manufactured by Pozyx [9]. These devices include a Decawave [2] UWB transceiver and the possibility of being operated through a USB port or using them as Arduino shields. The hardware for the tags and the anchors is identical, varying only the firmware that modifies the behavior according to the desired role. The estimation of the ranging is carried out through the round trip time of UWB signals sent from a tag to an anchor.

To obtain the ranging measurements, an anchor was considered in a fixed and known position, whereas a tag was placed at different known locations. Thus, in the LOS scenario, both the tag and the anchor were placed without obstacles between them. However, in the NLOS scenario, both devices were placed in such a way that it is impossible to find a direct path between them, hence the only path for the UWB signal to reach the receiver is through one or more reflections. The measurements were obtained at different distances between an anchor and a tag, ranging from 3 m to 16 m spaced 0.2 m apart. Therefore, multiple actual ranging measurements between a tag and an anchor were obtained at different distances and with both LOS and NLOS conditions. Notice that the measured data are publicly available in [1] to other researchers, making the results of this work reproducible.

3 Location Algorithms

Pozyx devices are able to obtain an estimation of the distance between a tag and an anchor based on the round-trip ToA of the signal traveling from the tag to the anchor. When there are multiple anchors in fixed positions and one tag in an unknown location, the ranging estimations can be used to estimate the coordinates of this tag:

$$r_{\mathrm{TOA},l} = \sqrt{(x-x_l)^2 + (y-y_l)^2 + (z-z_l)^2} + n_{\mathrm{TOA},l}, \quad l = 1, 2, \cdots, L \tag{1}$$

where $(x, y, z))$ are the coordinates of the tag, (x_l, y_l, z_l) are the coordinates of each anchor, $r_{\mathrm{TOA},l}$ are the ranging measurements between the tag and the anchor l and $n_{\mathrm{TOA},l}$ is an error component modelled as AWGN. If several ranging measurements are available, the previous equation can be used to estimate the location of the tag.

Different location algorithms were chosen to test the effects of considering or not the prior knowledge of the LOS / NLOS condition between a tag and several anchors. The algorithms were selected among the many of them available in the literature taking into account their nature. All of them used the ranging estimations between the tag and the anchors as an information source for their operations. Sections 3.1 to 3.3 describe these algorithms.

3.1 Linear Least Squares

The linear least squares (LLS) algorithm performs the location task in two steps: first, (1) is approximated by means of a linearization and, second, a least squares method is used to find the position that provides the minimum error. There are several methods to approximate the nonlinear equation in (1) such as those described in [7, 8, 12].

3.2 Nonlinear Least Squares

The nonlinear least squares (NLS) is an approach to solve the problem starting from (1) without performing a first linear approximation [6]. Finding this minimum point is not a trivial task, and there are many different techniques to achieve it [10]. In this work, we chose to use the Gauss-Newton method [4]. This is an iterative method that, starting from some given initial point, approximates the solution in each iteration.

3.3 Iterative Extended Kalman Filter

The Kalman filter is a well-known algorithm to estimate the hidden state of a system given some observation variables and is widely applied to positioning problems. The original Kalman algorithm provides an exact solution for this estimation problem in systems where the observations are linear on the state together with Gaussian-distributed noise sources. However, when some of these assumptions do not hold, numerous variations were proposed to overcome these limitations, such as the Extended Kalman filter [3], the Unscented Kalman filter [5], and particle filters [11].

4 Experimental setup

To test the effects of using NLOS measurements in location algorithms, a set of experiments were designed. The aim of these experiments was to study the effect on the final position estimation provided by the algorithms described in Section 3 when using a certain number of anchors with different probability of being in NLOS with respect to the tag. In order to make this study as realistic as possible, we use the ranging measures obtained in the measurement campaign described in Section 2.

Before carrying out the experiments, some common tasks were implemented. Firstly, a method to generate a virtual scenario with an arbitrary number of UWB anchors was considered. In a virtual 3D environment, we placed anchors at different fixed and known spatial positions. The coordinates of each anchor were selected to avoid having two anchors at the same height, whereas the values of x and y coordinates were selected to equally distribute the anchors on the sides of a cube.

Secondly, the movement of a tag inside the scenario along a trajectory was simulated. To perform this task, we used the *waypointTrajectory* method from the *Sensor Fusion and Tracking* toolbox in Matlab™. With this function, we could define a trajectory based on a sorted set of waypoints.

Thirdly, given a position from the tag trajectory, a ranging measurement between the tag and each anchor is produced. Since this data is extracted from a repository obtained from the UWB measurement campaign described in Section 2, not all possible distances are available. Therefore, for each anchor in the virtual environment, we consider the closest distance between the tag and the anchor which is available in the repository. Consequently, in order to maintain the coherence between the distance extracted from the repository and that of the virtual environment, we move the affected anchor slightly around the position initially indicated. For instance, suppose that a tag is located at the position (P_x, P_y, P_z) and the distance between this point and the anchor $A1$, placed at $(A1_x, A1_y, A1_z)$, is 3.16 m. Given that in the ranging measurements repository only distances spaced 0.2 m apart are recorded (i.e., $\cdots$, 3 m, 3.2 m, 3.4 m, $\cdots$), the distance 3.16 m has to be approximated. To solve this problem, we need to round the distance value to the closest one available from the measurements (3.2 m in this case). After this rounding, it is necessary to move the position of the anchor $A1$ around its original position, so that the distance to the tag is consistent with this new distance of 3.2 m (exactly as if the anchor had been placed at a distance of 3.2 m to the tag from the beginning).

Finally, in order to decide if an anchor is in LOS or NLOS with respect to the tag for a given point of the trajectory, we designed a script that returned a LOS or NLOS measurement according to a given probability (note that, for each distance value between the tag and the anchor, there is a LOS and an NLOS ranging measurement). This was done using a randomised process with an appropriate probability distribution.

Once the previous elements were completed, the following experiments were performed:

1. Execution of the algorithms described in Sections 3.1 and 3.2 for the estimation of the positions of a trajectory in a virtual scenario with a fixed number of anchors. Both LOS and NLOS conditions of each anchor, for the different tag positions within the trajectory, were determined according to the given probability. In this experiment, the algorithms consider all ranging estimates from all anchors, regardless of whether they were in LOS or NLOS.
2. Execution of the algorithms as in the previous case, but now the NLOS ranging estimates are discarded. Therefore, for each position of the tag, the number of anchors that provide ranging estimations is variable, depending on the probabilities of having NLOS situations.

5 Results

Fig. 1 shows a comparison of the mean absolute error of the position estimates (with respect to the true position) produced by the three considered algorithms: LLS, NLS, and iterative extended Kalman filter (IEKF). They were tested in a scenario with 8 anchors placed on the sides of a 9 m × 9 m × 9 m cube with the goal of estimating the position of a moving tag that follows a rectangular trajectory at a constant velocity. Each anchor in the scenario has a probability of producing an NLOS measurement according to the values in the abscissa axis of Fig. 1. For instance, if the probability of outputting an NLOS measurement is 0, then the 8 anchors will produce a LOS measurement, whereas if such a probability is 1, all of them will output NLOS measurements.

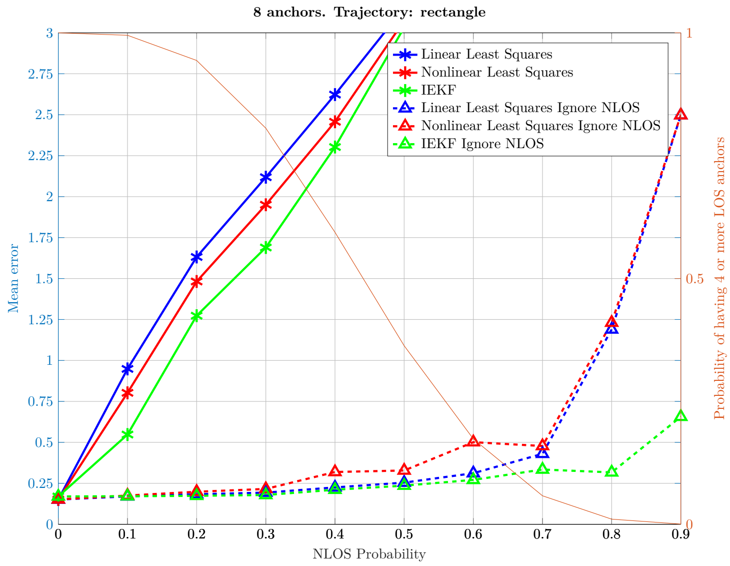

Fig. 1. Mean error of position estimates vs NLOS probability with a rectangular trajectory. Right-hand side ordinate axis: probability of at least four anchors with LOS propagation conditions.

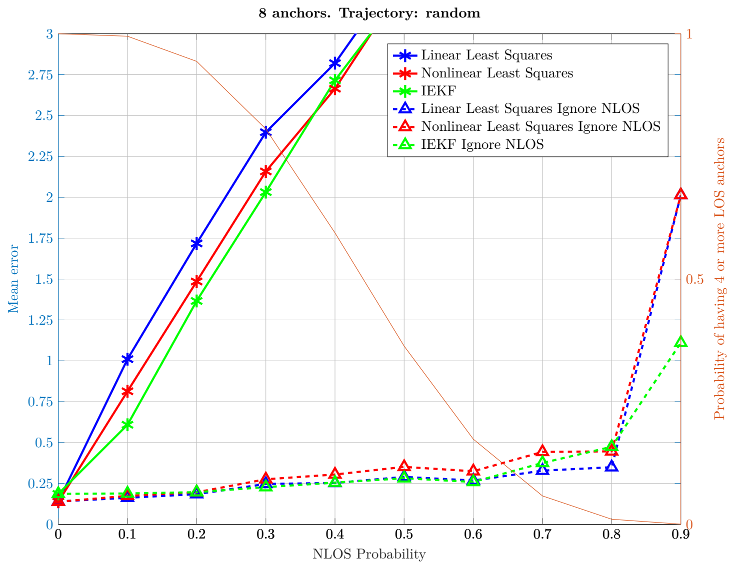

Fig. 2. Mean error of position estimates vs NLOS probability with a random trajectory. Right-hand side ordinate axis: probability of at least four anchors with LOS propagation conditions.

Fig. 1 shows the results corresponding to the first two experiments described in Section 4: considering all the anchors and considering only the anchors with LOS, referred to as "Ignore NLOS" in Fig. 1. Two groups of curves can be observed in Fig. 1. The first group has a very steep slope, with errors starting at 0.25 m in absence of NLOS and quickly growing up to several meters with the NLOS probability. These three curves correspond to the first experiment in which all the measurements were considered by the algorithms. Although we see a slightly improvement when the IEKF algorithm is used, the overall performance is very poor even for low NLOS probability values. Notice that, in this experiment, the IEKF was configured assuming that all the measurements correspond to LOS propagation conditions since, in this experiment, there is no prior knowledge about the propagation conditions. This is why the performance of this algorithm is heavily punished. The second group of curves identified in Fig. 1 exhibits a small slope with an error about 0.5 m. These curves correspond to the second experiment, in which the NLOS measurements, whenever they occur, are ignored by the algorithms. We can see how all the three algorithms exhibit much better results than in the first experiment. Therefore, including only the LOS measurements and disregarding the NLOS ones improves the positioning error significantly for the considered scenario because NLOS propagation conditions yield ranging measurements with a big error. It is important to realize that, for the LLS and NLS algorithms to work, it is necessary to have at least four ranging estimates. Otherwise, the position estimated in the previous point will be used. Note that, in Fig. 1, a curve with the probability of receiving 4 or more LOS measurements is superimposed in order to have a reference with respect to the performance of these algorithm. We can see that, when this probability falls below 0.1 (which corresponds to a NLOS probability value around 0.7 for each anchor), the error in the estimation grows from about 0.5 m to more than 1 m.

Fig. 2 shows the same experiments as in Fig. 1 but now considering a tag moving along a completely random trajectory and at a constant velocity. Whereas the LLS and NLS algorithms exhibit a performance similar to that shown in Fig. 1 for the rectangular trajectory, the IEKF shows a slight deterioration. This is related to the fact that the IEKF considered in this work does not use an inertial measurement unit (IMU) or additional sensors to gather knowledge about the tag movement. Thus, the algorithm can only deduce the velocity of the tag using the ranging measurements. When the tag is moved along the rectangular trajectory, this estimation can be very precise, since only in the corners of the rectangle there is a change in the trajectory. However, in a random trajectory, when the direction of the trajectory is changing all the time, the predictions of the IEKF are degraded because it does not adapt fast enough to such trajectory changes.

6 Conclusions

In this study we have confirmed with measurements captured with real UWB devices how the presence of values obtained from anchors in NLOS can cause large errors in the final estimation of position, and how prior information about the type of propagation condition (LOS or NLOS) can help to improve the performance of the positioning algorithms. In order to do this under practical conditions, a system has been created capable of generating a trajectory in a 3D space and calculating the corresponding ranging estimates from a series of virtually placed anchors around it, but always based on data coming from a real-world measurement campaign. Different classic location algorithms have been considered to analyze how the prior information can be used. Three different experiments were carried out in which the algorithms are fed with 1) the measurements of all anchors without any additional information about the propagation conditions, and 2) only the measurements corresponding to the anchors with LOS propagation conditions.The results show the importance of incorporating the knowledge about LOS/NLOS propagation conditions of UWB ranging measurements before feeding them to the positioning algorithms.

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