An UWB-based communication protocol design for an infrastructure free cooperative navigation

Jianan Zhu and Solmaz S. Kia, *Senior Member, IEEE*
University of California Irvine

***Abstract*—This paper considers the global localization of a pedestrian via an ultra-wideband (UWB) ranging aided inertial navigation system (INS) and aims to address the challenges involved in proper processing of UWB range measurements. Even though UWB offers a decimeter level accuracy in line-of-sight (LoS) ranging, its accuracy degrades significantly in non-line-of-sight (NLoS). This drop in accuracy is due to a significant unknown positive bias in the NLOS range measurements. Therefore, the measurement models used in UWB LoS and NLoS ranging conditions are different, and proper processing of NLoS measurements requires a bias compensation measure. Previous work on bias compensation for UWB ranging that is used to aid an INS based localization assumes that the LoS and NLoS measurements are identified and distinguished from each other with absolute certainty. However, in practice, this assumption is hard to satisfy, and identifiers that determine the type of UWB range measurements deliver their results with only some level of certainty. To take into account the probabilistic nature of the NLoS identifiers, in this paper, we propose an adaptive localization based on the first-order generalized pseudo Bayesian (GPB) method to seamlessly handle the measurement model switching between LoS and NLoS UWB range measurements. The effectiveness of our proposed method is demonstrated via an experiment for pedestrian geolocation using a shoe-mounted INS system aided by UWB range measurements with respect to beacons with known locations.**

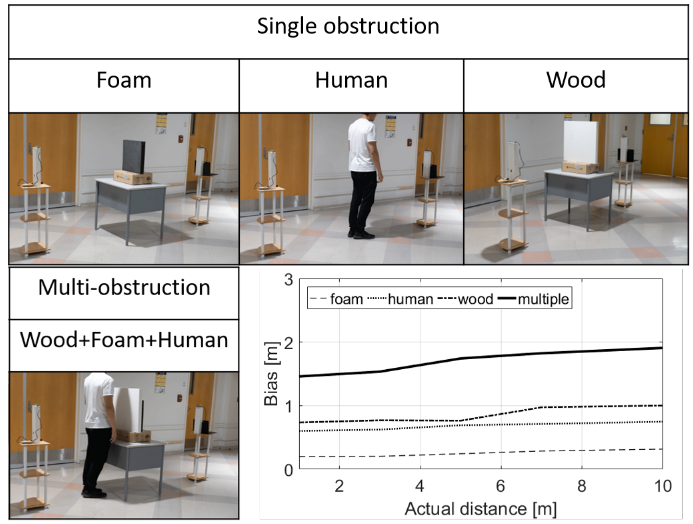

Fig. 1: Bias in NLoS UWB ranging for different obstructions [8]. In the case of multiple obstructions, as expected the bias becomes far more significant.

I. Introduction

Whereabouts of mobile agents including pedestrians is a vital dimension of situation awareness in today's smart operations. Pedestrian tracking and geo-location are in high demand in applications such as monitoring patients in hospitals and senior citizens in nursing homes, detecting miners in underground mines, tracking soldiers in the battlefield, and locating fire-fighters [1], [2]. In this paper, we propose an UWB ranging aided INS based [3] pedestrian geolocation by processing LoS and NLoS measurements with respect to beacons with known locations.

Pedestrian geolocation systems normally use a foot-mounted inertial navigation system (INS) as a self-contained localization solution under Global Navigation Satellite System (GNSS)-denied environments. Therefore, various aiding measures such as processing exteroceptive vision based [4], [5] or wireless radio signal based (e.g., ranging based on time-of-flight or range, angle and velocity measurements using mmWave radar technology) [6]–[8] measurements with respect to beacons with known location or fixed environmental features in case of simultaneous location and mapping are considered. However, the effectiveness of the aiding relies on careful modeling and processing of the measurements collected by the exteroceptive sensors.

In this paper, we consider a global geolocation system via an INS, which is aided by processing UWB range measurements with respect to beacons with known locations. The exteroceptive UWB range measurements with respect to the beacons can be in LoS or NLoS conditions depending on the complexity of the environment. UWB's capability to take NLoS range measurements and its low susceptibility to interfere with coexisting radio signals or UWB signals from other paths have made it an attractive ranging technology for complex environments. However, even though UWB offers a decimeter level accuracy in LoS ranging [9], its accuracy degrades significantly in NLoS, see Fig. 1 for examples. This drop in accuracy is due to a significant unknown positive bias in the NLOS range measurements [10]. Therefore, the measurement models used in UWB LoS and NLoS ranging conditions are different, and proper processing of NLoS measurements requires a bias compensation measure.

The authors are with the Department of Mechanical and Aerospace Engineering, University of California Irvine, Irvine, CA 92697, USA, jiananz1@uci.edu, solmaz@uci.edu. This work was supported by NIST award 70NANB17H192. All the experiments were conducted in the Kia Cooperative Systems Lab, University of California Irvine.

Different approaches have been used in literature to account for the positive bias in the NLoS UWB range measurements. In one set of approaches, to mitigate the effect of the NLoS ranging bias on the localization accuracy, the idea is to identify the NLoS measurements and avoid using them [11]–[13]. Discarding NLoS measurements however limits the effectiveness of the UWB measurement feedbacks in dense and complex environments. An alternative measure to avoid discarding the NLoS measurements is to use machine learning methods to identify and remove the bias [14]–[18]. More specifically, these alternative methods aim to classify the obstruction material by, for example, analyzing the statistics of the channel impulse response. Then, they remove the predetermined bias that is obtained from the training data from the range measurements associated with the material identified. However, as expected and also we have shown in our previous work [8, Fig. 1] these methods lose their effectiveness when there are multiple obstructions in between the ranging sensors. The machine learning techniques also come with a high computational complexity to analyze the channel statistics and they also require collecting a large amount of training data, which make them impractical for real-time online applications. In our previous work [8], [19], we took advantage of the state estimation nature of the UWB aided INS to develop UWB bias compensation methods with a low computational complexity, which does not need prior information as well. In [19], we used the covariance inflation method [20] followed by a constrained Kalman filtering [21] to compensate for bias in UWB range measurements in a cooperative localization algorithm. In [8], we investigated the use of the Schmidt Kalman filtering [22] for bias compensation followed by a novel constrained sigma point based filtering that is used to yield further improvement in the positioning accuracy of an UWB aided pedestrian INS. However, the UWB aided INS system with the bias compensation methods discussed in [8], [19] assume that the LoS and NLoS measurements are identified and distinguished from each other with exact certainty. However, as we demonstrate via an experimental study in Section IV below, in practice this assumption is hard to satisfy, and identification that determines the type of UWB range measurements deliver their results with only some level of certainty, see Fig. 3.

The common UWB ranging is based on time-of-arrival (TOA) algorithms, which measure the propagation time of an impulse that travels from the transmitter to the receiver. The positive bias in the NLoS UWB ranging is due to the extra time that signal takes to travel between the sensor nodes due to the time lost to penetrate through obstructions or traveling a longer non-direct path. The NLoS signal propagation can be distinguished from the LoS signal propagation based on a real-time signal power-based approach without any prior information about the biases [23], [24]. The principle behind the power-based NLoS identification methods emanates from the fact that in the LoS ranging the power of the received direct-path signal constitutes a big proportion of the total received signal power while in the NLoS ranging the direct-path signal is significantly attenuated or even completely blocked, which makes the corresponding signal power smaller. When the difference between total received power and the direct-path power is larger than a threshold value, the range measurement is identified to be NLoS. However, the performance of this method depends crucially on the choice of this threshold value, which specifying its exact value is almost impossible. What is more realistic, and we propose in this paper, is to use a probabilistic approach to indicate the likeliness that the range measurement is taken under LoS or NLoS conditions.

Given the probabilistic nature of the power-based LoS/NLoS identification method, processing the UWB range measurements from beacons to aid the INS system can be modeled as a *dynamic multiple model* problem. As known in the literature [25], [26], optimal estimation of a dynamic multiple model problem requires a set of parallel filters whose number increases exponentially with time. The computational complexity makes the optimal method impractical. To design a practical localization algorithm, we propose a localization algorithm based on the first-order GPB method as a sub-optimal solution that has a computational complexity linear to the number of models. Our choice of the first-order GPB method over other possibilities is motivated by GPB's lower computational complexity, which makes it more suitable for real-time execution over single board computational units used in pedestrian geolocation devices. The effectiveness of our proposed method is demonstrated via an experiment for a pedestrian geolocation using a shoe-mounted INS system aided by UWB range measurements with respect to beacons with known locations.

Notations: The set of real and non-negative integer numbers are, respectively, $\mathbb{R}$ and $\mathbb{Z}^{+}$. The set of $n\times n$ real positive definite matrices is $\mathbb{S}_n^{++}$. The $n\times n$ identity matrix is $\mathbf{I}_n$. The transpose of matrix $\mathbf{A}\in\mathbb{R}^{n\times m}$ is $\mathbf{A}^\top$. For a matrix $\mathbf{A}\in\mathbb{S}_n^{++}$, its matrix square root is $\sqrt{\mathbf{A}}$ which satisfies $\sqrt{\mathbf{A}}\,\sqrt{\mathbf{A}}^\top=\mathbf{A}$. For a matrix $\mathbf{A}\in\mathbb{R}^{n\times n}$, its i^{th} column is indicated by $[\mathbf{A}]_i$. Considering a pedestrian agent, $\mathbf{x}$ is the state, $\hat{\mathbf{x}}$ is its state estimate, and $\mathbf{P}$ is the covariance matrix of its state estimate, where $\mathbf{x}$, $\hat{\mathbf{x}}\in\mathbb{R}^{n_x}$ and $\mathbf{P}\in\mathbb{S}_{n_x}^{++}$, where n_x is the state dimension. We use the term *cross-covariance* to refer to the correlation terms between two estimations. We denote the locally filtered and relatively updated variables, say $\hat{\mathbf{x}}$, at time-step t by $\hat{\mathbf{x}}^{-}(t)$ and $\hat{\mathbf{x}}^{+}(t)$, respectively. We drop the time-step argument of the variables as well as matrix dimensions whenever they are clear from the context.

The organization of the rest of this paper is as follows. Section II defines our problem setting, introduce LoS and NLoS filtering, and gives our objective statement. Section III introduces our proposed multiple model estimator based on the first-order GPB approach to handle the probabilistic switching between LoS and NLoS measurement models in our UWB aided INS based pedestrian geolocation system. Section IV reports on an experimental demonstration study that we used to validate our proposed algorithm. Finally, Section V presents our conclusions.

II. Problem definition and objective statement

Consider a pedestrian equipped with a shoe-mounted strap-down INS [3] and an UWB transceiver. At each time step $t \in \mathbb{Z}^+$, the INS propagates an estimate of the ego state $\hat{\mathbf{x}}^-(t) = f(\hat{\mathbf{x}}^+(t-1), \mathbf{u}(t)) \in \mathbb{R}^{n_x}$ and the corresponding positive definite error covariance matrix $\mathbf{P}^-(t) \in \mathbb{S}^{++}_{n_x}$, in the global earth-fixed coordinate frame with axes pointing north, east and down. The state $\mathbf{x}(t) \triangleq [\mathbf{p}(t), \mathbf{v}(t), \boldsymbol{\psi}(t)]^\top$ includes, respectively, position, velocity and attitude (pitch, roll and heading). Because of inherent noises in the INS self-motion measurements $\mathbf{u}(t)$, as known, relying solely on an INS results in poor estimation accuracy due to error accumulation. To bound the error and improve the state estimation accuracy, processing of range measurements taken by body-mounted UWB ranging sensor with respect to a set of pre-installed UWB sensors as beacons with known locations in the environment is used to correct/update the state estimate to $(\hat{\mathbf{x}}^+(t), \mathbf{P}^+(t))$.

In the UWB LoS ranging, the model of the range measurement with respect to an UWB beacon located at known location $\mathbf{p}_B$ is $z(t) = h(\mathbf{x}(t)) + \nu(t) \in \mathbb{R}$ where

$$h(\mathbf{x}(t)) = \|\mathbf{p}(t) - \mathbf{p}_B\|. \tag{1}$$

The measurement noise $\nu(t)$ is a white zero mean Gaussian noise with $E[\nu(t)^2] = R > \mathbf{0}$. Since the range measurements taken under LoS condition is Gaussian and unbiased, given the prior belief $\text{bel}^-(t) = (\hat{\mathbf{x}}^-(t), \mathbf{P}^-(t))$ obtained from the INS, the UWB range measurement $z(t)$ can be processed using an EKF update via (subscript 1 is used to represent LoS filter)

$$\hat{\mathbf{x}}_1^+ = \hat{\mathbf{x}}^- + \mathbf{K}_1(z - \hat{z}_1), \tag{2a}$$
$$\mathbf{P}_1^+ = (\mathbf{I} - \mathbf{K}_1\mathbf{H}_1)\mathbf{P}^-(\mathbf{I} - \mathbf{K}_1\mathbf{H}_1)^\top + \mathbf{K}_1 R \mathbf{K}_1^\top, \tag{2b}$$

where $\hat{z}_1 = h(\hat{\mathbf{x}}_1^-)$ and $\mathbf{H} = \frac{dh(\mathbf{x})}{d\mathbf{x}}$. $\mathbf{K}_1$ is set to

$$\mathbf{K}_1 = \mathbf{P}^-\mathbf{H}_1^\top(\mathbf{H}_1\mathbf{P}^-\mathbf{H}_1^\top + R)^{-1},$$

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which gives the minimum variance estimate in the first order sense (due to the nonlinearity of (1)). We refer to this update mode for UWB LoS range measurements as mode M_1.

When there are obstructions between the pedestrian and the beacon, however, the UWB range measurement under NLoS condition is modeled with a positive bias as

$$z(t) = h(\mathbf{x}(t)) + b(t) + \nu(t), \quad z \in \mathbb{R}. \tag{4}$$

where $b(t)$ is the additive bias modeled as a Gaussian random variable with mean $\bar{b} > 0$ and variance $\bar{B}$. Under NLoS conditions, an EKF based update is no longer feasible since the stochastic bias will severely degrade the estimation performance and consistency. To compensate for the positive bias, we developed a Schmidt Kalman filtering (SKF) followed by a novel constrained sigma point based filtering in [8]. In our bias compensation method, SKF is first applied to account for the stochastic bias as a variable and the state is updated as (subscript 2 is used to represent NLoS filter)

$$\hat{\mathbf{x}}_2^+ = \hat{\mathbf{x}}^- + \mathbf{K}_2(z - \hat{z}_2), \tag{5a}$$
$$\begin{aligned}\mathbf{P}_2^+ =& (\mathbf{I} - \mathbf{K}_2\mathbf{H})\mathbf{P}^-(\mathbf{I} - \mathbf{K}_2\mathbf{H})^\top - (\mathbf{I} - \mathbf{K}_2\mathbf{H})\mathbf{C}^-\mathbf{K}_2^\top \\ &- \mathbf{K}_2\mathbf{C}^{-\top}(\mathbf{I} - \mathbf{K}_2\mathbf{H})^\top + \mathbf{K}_2 B \mathbf{K}_2^\top + \mathbf{K}_2 R \mathbf{K}_2^\top,\end{aligned} \tag{5b}$$

where $\hat{z}_2 = h(\hat{\mathbf{x}}_2^-) + \hat{b}$, $\mathbf{C}^-(t) = \mathrm{E}[\tilde{\mathbf{x}}^-(t)\tilde{b}]$ is the state-bias cross-covariance and $B = \mathrm{E}[\tilde{b}^2]$ is the covariance of the bias estimation where $\tilde{b} = b - \hat{b}$. The update gain that minimizes the total uncertainty trace$(\mathbf{P}^+)$ is

$$\begin{aligned}\mathbf{K}_2 =& (\mathbf{P}_2^-\mathbf{H}^\top + \mathbf{C}^-\mathbf{H}^\top)(\mathbf{H}\mathbf{P}_2^-\mathbf{H}^\top + \mathbf{H}\mathbf{C}^- + \mathbf{C}^{-\top}\mathbf{H}^\top \\ &+ B + R)^{-1}.\end{aligned} \tag{6}$$

The state and the bias are initially uncorrelated, i.e., $\mathbf{C}^+(0) = \mathbf{0}$. However, the correlation is established after the first update. The state-bias cross-covariance is propagated and updated according to

$$\mathbf{C}^-(t) = \mathbf{F}(t)\,\mathbf{C}^+(t-1), \tag{7a}$$
$$\mathbf{C}^+(t) = (\mathbf{I} - \mathbf{K}_2\mathbf{H})\,\mathbf{C}^-(t) + \mathbf{K}_2 B, \tag{7b}$$

where $\mathbf{F}(t)$ is the state transition matrix of linearized INS. The bias estimate remains the same over time. Next, given that the UWB NLoS bias is inherently positive and dominate the measurement noise $v(t)$ in magnitude [27], in NLoS mode we have $\|\mathbf{p}(t) - \mathbf{p}_B\| \leq z(t)$. This relation can be used as an additional information to correct the updated estimate of the agent via the SKF method discussed above. First, given the updated estimate from SKF as $(\hat{\mathbf{x}}_{2s}^+(t), \mathbf{P}_{2s}^+(t))$, we calculate $2n+1$ sigma points as

$$\hat{\boldsymbol{\chi}}_i = \begin{cases} \hat{\mathbf{x}}_{2s}^+ & i = 0, \\ \hat{\mathbf{x}}_{2s}^+ + [\sqrt{(n+\kappa)\mathbf{P}_{2s}^+}]_i & i = 1, \cdots, n, \\ \hat{\mathbf{x}}_{2s}^+ - [\sqrt{(n+\kappa)\mathbf{P}_{2s}^+}]_{i-n} & i = n+1, \cdots, 2n, \end{cases} \tag{8}$$

where $[\sqrt{(n+\kappa)\mathbf{P}_{2s}^+}]_i$ is the i^{th} column of the matrix square root of $(n+\kappa)\mathbf{P}_{2s}^+$ and $\kappa \in \mathbb{R}$ is the parameter tuning the size of sigma point distribution [28]. The weight associated with each sigma points are $\omega_0 = \kappa/(n+\kappa)$ and $\omega_i = 1/(2(n+\kappa))$, $i = 1, \cdots, 2n$. All the sigma points (8) are passed one by one through constrained correction update

$$\begin{aligned}\hat{\boldsymbol{\chi}}_i^+ =& \underset{\mathbf{x}}{\text{argmin}}(\mathbf{x} - \hat{\boldsymbol{\chi}}_i)^\top \mathbf{W}(\mathbf{x} - \hat{\boldsymbol{\chi}}_i), \\ &\text{subject to } \|\mathbf{p} - \mathbf{p}_B\| \leq z,\end{aligned} \tag{9}$$

where $\mathbf{p}$ is the position component of state x and $\mathbf{W}$ is the positive-definite weighting matrix, which is set to $\mathbf{P}_{2s}^+$. Then, the final constrained corrected estimate and its associated covariance are

$$\hat{\mathbf{x}}_2^+ = \sum\nolimits_{i=0}^{2n} \omega_i \hat{\boldsymbol{\chi}}_i^+, \tag{10a}$$
$$\mathbf{P}_2^+ = \sum\nolimits_{i=0}^{2n} \omega_i (\hat{\boldsymbol{\chi}}_i^+ - \hat{\mathbf{x}}_2^+)(\hat{\boldsymbol{\chi}}_i^+ - \hat{\mathbf{x}}_2^+)^\top. \tag{10b}$$

We refer to this update mode for UWB NLoS range measurements as mode M_2.

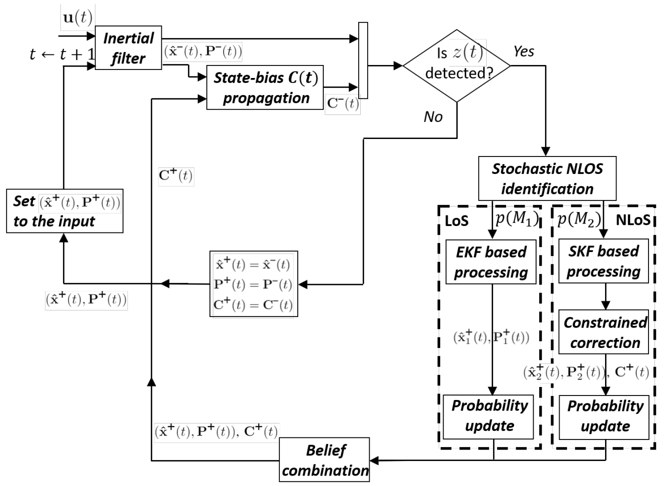

Fig. 2: UWB range measurement corrected localization system with multiple-model estimator combining unbiased LoS filter with bias-compensated NLoS filter.

We use the real-time power-based LoS/NLoS identification method of [23] in our study. Previous work in [8] assumed that using this identification method we can distinguish LoS and NLoS ranging conditions from each other within exact certainty. Then, based on the identification result, [8] chooses the corresponding update mode M_1 or M_2 to process the measurement. However, in practice, the identification methods do not exactly identify the measurement condition with absolute certainty, see the first experiment in Section IV. What the identification methods deliver is a likeliness level about the measurement condition. That is the method assigns a normalized probability that the measurement is in LoS (denoted by M_1) or NLoS (denoted by M_2),

$$p(M(t) = M_i), \quad i \in \{1, 2\}, \text{ where } p(M_1) + p(M_2) = 1. \tag{11}$$

Our experimental results show that using a threshold to assign a measurement type and then a consequent processing using the approach of [8] results in an inferior localization result. In this paper, our objective is to take into account the stochastic nature of the LoS/NLoS identification method when we process the UWB ranging measurements that the pedestrian takes with respect to the beacons. Our proposed UWB aided INS for localization is shown in Fig. 2, and is presented in the proceeding section.

III. GPB-BASED FILTERING TO PROCESS UWB MEASUREMENTS

Given the prior belief $\text{bel}^-(t) = (\hat{\mathbf{x}}^-(t), \mathbf{P}^-(t))$ and an UWB range measurement $z(t)$ with respect to a pre-installed beacon our objective is to process this measurement by knowing only the probability $p(M(t))$, $M(t) \in \{M_1, M_2\}$ of this measurement to belong to LoS (mode M_1) or NLoS (mode M_2). Using a threshold to select only one mode and then proceed with the processing corresponding to that mode results in degradation of the filter performance and consistency; see our second experiment in Section IV.

Given the stochastic nature of the LoS/NLoS identification method, the actual measurement model is unknown. We have two possible measurement models. Therefore, processing UWB measurements with respect to the beacons is a dynamic multiple model problem. Let the update mode history up to time t be

$$M^{t,l} = \{M_{i_{1,l}}, M_{i_{2,l}}, ..., M_{i_{t,l}}\}, \qquad M_{i_{t,l}} \in \{M_1, M_2\},$$

where $M_{i_{t,l}}$ is the update mode at time t. Because there are two possible update modes at each time step then 2^t update mode histories exist at time t, i.e., $l \in \{1, ..., 2^t\}$. There exists a mode-conditioned Gaussian distributed estimation described by probability density function $p(\mathbf{x}(t)|M^{t,l}, \mathbf{Z}_{1:t})$ corresponding to each update mode histories. To obtain the optimal estimation of the state at time t, 2^t filters are needed to estimate the current state based on every possible update mode history. The computational complexity of such a filtering setup grows exponentially with time. The computational complexity makes the optimal estimation impractical. To design a practical localization algorithm, we propose our adaptive localization algorithm as in Fig. 2 based on the first-order GPB method, which is a sub-optimal estimation filter that comes with a computational complexity of $O(1)$ at any time step t.

The first-order GPB-based UWB aid INS proposed in Fig. 2 works as follows. At each time step t, using the self-motion measurement $\mathbf{u}(t)$ and the updated belief $\text{bel}^+(t-1) = (\hat{\mathbf{x}}^+(t-1), \mathbf{P}^+(t-1))$, the INS first provides the prior belief $\text{bel}^-(t) = (\hat{\mathbf{x}}^-(t), \mathbf{P}^-(t))$. Using the prior state estimate $\hat{\mathbf{x}}^-(t)$, we then compute $\mathbf{C}^-(t)$ from (7a). If there is no UWB measurement with respect to a beacon, the updated belief $\text{bel}^+(t) = (\hat{\mathbf{x}}^+(t), \mathbf{P}^+(t))$ is set to the prior belief and is fed back to INS to produce the prior belief of the next time step. We also set $\mathbf{C}^+(t) = \mathbf{C}^-(t)$. If an UWB range measurement $z(t)$ is detected, however, we use our LoS/NLoS identifier to obtain the probabilities $p(M(t) = M_1)$ and $p(M(t) = M_2)$ that indicates the probability of the measurement to be respectively, in LoS and NLoS condition. Then, two update modes, one in mode M_1 and the other in mode M_2, are run in parallel to process the range measurement with respect to the beacon. Mode M_1 delivers $\text{bel}_1^+(t) = (\hat{\mathbf{x}}_1^+(t), \mathbf{P}_1^+(t))$ using (2) and mode M_2 delivers $\text{bel}_2^+(t) = (\hat{\mathbf{x}}_2^+(t), \mathbf{P}_2^+(t))$ using (5)-(10).

Next, we note that the updated beliefs correspond to a Gaussian distribution with probability density function $p(\mathbf{x}|M(t) = M_i, \mathbf{Z}_{1:t})$, $i \in \{1, 2\}$. The mode probability also can be expressed as a Gaussian distribution probability $p(M(t-1)|\mathbf{Z}_{1:t-1})$ conditioned on the measurements in history $\mathbf{Z}_{1:t-1}$. Then, using the Bayes' theorem [29, chapter 2] and law of total probability the updated and prior mode probability distribution are related according to

$$p(M(t)|\mathbf{Z}_{1:t}) = \frac{1}{N} p(z(t)|M(t), \mathbf{Z}_{1:t}) \times \sum_{i=1}^{2} p(M(t)|M_i(t-1)) p(M_i(t-1)|\mathbf{Z}_{1:t-1}), \tag{12}$$

where N is the normalization factor and $p(z(t)|M(t), \mathbf{Z}_{1:t})$ is the mode-conditioned likelihood function of mode $M_i(t)$ given as

$$p(z(t)|M_i(t), \mathbf{Z}_{1:t}) = \frac{\exp[-\tilde{z}_i^2/2S_i]}{\sqrt{2\pi|S_i|}}, \tag{13}$$

where $\tilde{z}_i = z - z_i$ and S_i is the mode-matched innovation and corresponding covariance [30, chapter 2]. Based on the fact the LoS/NLoS measurement condition is irrelevant to the LoS/NLoS measurement condition at previous step, i.e., $p(M(t)|M_i(t-1)) = p(M(t))$, (12) is simplified into

$$p(M(t)|\mathbf{Z}_{1:t}) = \frac{1}{N} p(z(t)|M(t), \mathbf{Z}_{1:t}) p(M(t)). \tag{14}$$

From (14), the model probability is simply the identified probability of measurement condition corrected by the mode-matched likelihood. It is independent of the previous model probability which means there is no need to keep track of this probability iteratively. Once the mode-matched beliefs and mode probabilities are derived, the two mode-conditioned updated beliefs can be combined via

$$\hat{\mathbf{x}}^{+}(t) = \sum_{i=1}^{2} p(M_i(t)|\mathbf{Z}_{1:t}) \hat{\mathbf{x}}_i^{+}(t), \tag{15a}$$

$$\mathbf{P}^{+}(t) = \sum_{i=1}^{2} p(M_i(t)|\mathbf{Z}_{1:t}) (\mathbf{P}_i^{i+}(t) + \bar{\mathbf{P}}_i(t)), \tag{15b}$$

where $\bar{\mathbf{P}}_i(t) = (\hat{\mathbf{x}}_i^{+}(t) - \hat{\mathbf{x}}^{+}(t))(\hat{\mathbf{x}}_i^{+}(t) - \hat{\mathbf{x}}^{+}(t))^\top$. The state-bias cross-covariance is affected by the combination of states and becomes

$$\mathbf{C}^{+}(t) = p(M_2|\mathbf{Z}_{1:t}) ((\mathbf{I} - \mathbf{K}_2 \mathbf{H})\, \mathbf{C}^{-}(t) + \mathbf{K}_2 B).$$

IV. Experimental Evaluations

We demonstrate our results via two experiments that are conducted in the Engineering Gateway Building at the University of California Irvine (UCI) campus. The first experiment demonstrates the performance of the LoS/NLoS identification method [23] in a real-world application that motivates the work of this paper. The second experiment was conducted to evaluate the effectiveness of our proposed estimator in a field test.

First experiment: In the first experiment, we demonstrate the probabilistic nature of the UWB Los/NLoS identification method [23]. In the Los/NLoS identification method [23], the difference between the received power and the first-path power, which is denoted as power metric P_{PM}, is used as a metric to distinguish LoS and NLoS measurements. If P_{PM} is above a certain value, say θ dB, the power-based identification technique of [23] declares the range measurement as NLoS; otherwise the range measurement is declared LoS. However, the value of θ depends on environmental factors and as such the results obtained from this identification are not always absolutely accurate. Instead of specifying a θ to obtain a deterministic identification, we proceed as follows to assign a probability measure of $p(M_1)$ and $p(M_2)$ to the results delivered by the LoS/NLoS identifier. Since $p(M_1) = 1 - p(M_2)$, we focus below on obtaining $p(M_2)$. First, we take UWB range measurements and the corresponding P_{PM} in several different locations of the building where we want to demonstrate our localization performance. Since this is a test, the condition for each measurement is known. At each location we repeat the ranging for M times and record the P_{PM} value for each time. The P_{PM} value read for the experiments in our building fell in the interval of $[0.15, 14.89]$ db. We divided this interval into 30 consecutive subsets with equal size. Next, for each interval, we counted the number of the corresponding experiments and the number of the times the actual condition was in NLoS. Then, by dividing the former by the later we obtained the probability of the measurement being in NLoS condition for the corresponding P_{PM} interval. The results are shown by the o in Fig. 3 for the center of the interval. Then, we fitted a curve to these results and used this curve to obtain the $p(M_2)$ for our localization experiments. This experiment highlights the motivation to use a GPB-based estimator to process UWB range measurements. The second experiment below demonstrates the superiority of our proposed GPB-based approach over a localization method that uses a deterministic LoS/NLoS identifier.

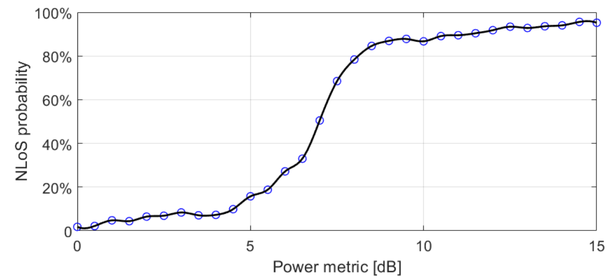

Fig. 3: An experimental result that demonstrates the probabilistic nature of the power-based LoS/NLoS identification.

Second experiment: We evaluate the localization performance of our proposed algorithm in Fig. 2 in an experiment where a pedestrian performs a loop closure along a reference trajectory, which is shown in Fig. 5, in the second floor of the Engineering Gateway Building of UCI campus, see Fig. 4. Three beacons denoted by B1, B2 ,and B3 are placed around the corners such that while the pedestrian is tracing its reference trajectory the UWB range measurements with respect to the beacons are taken under a mixture of both LoS and NLoS conditions. The bottom plot in Fig. 5 shows the probability that the measurements are in NLoS during the test. Four localization

Fig. 4: The experiment setup in the Engineering Gateway Building at UCI campus. The small plots in the right show beacons B2 and B3 that are located in the corners. As we can anticipate from our beacon locations, as the pedestrian walks along the reference trajectory, the collected range measurements with respect to the beacons will vary between LoS and NLoS conditions.

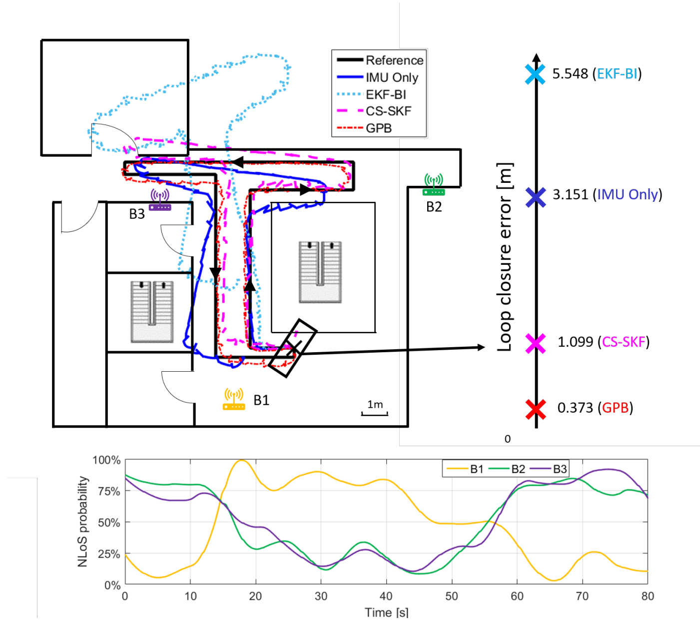

Fig. 5: A loop-closure experiment conducted by a pedestrian who has a foot-mounted INS on and walks along a reference trajectory while taking UWB range measurements with respect to three beacons, denoted by B1, B2, and B3. The top-left is the estimated trajectories, the top-right is the loop closure error and the bottom plot is the probability that the range measurements with respect to the beacons are in NLoS .

filters were tested as described next. The first localization method used the INS only localization (the solid blue plot with corresponding legend as IMU Only in Fig. 5). In this case as we see a major error starts to propagate as the pedestrian takes its second turn. This filter delivers a 3.151 meters loop closure error. The second filter used is the INS aided by UWB where no bias compensation is considered for the NLoS measurements, i.e, the range measurements are processed using the update stage of a regular EKF without any regards to bias in NLoS measurements (the dotted light blue plot with the corresponding legend as EKF-BI in Fig. 5). As we see by ignoring the bias, a performance inferior even to INS only localization is delivered with a loop closure error of 5.548 meters. The third localization filter is the INS aided by UWB where a bias compensation is used for NLoS measurements but the assumption is that we use a threshold method to determine with exact certainly when the measurements are in NLoS and when they are in LoS (the dashed purple plot with corresponding legend as CS-SKF in Fig. 5). As we can see by considering a bias compensation, the localization accuracy improves with a loop closure error of 1.099 meters. The forth localization filter that we consider is our proposed GPB-based method that processes the UWB aiding signals by considering the probabilistic nature of the LoS/NLoS identifier (the dash-dotted red plot with corresponding legend as GPB in Fig. 5). As we can see this filter delivers the best localization result with a loop closure error of 0.373 meters. This experiment highlights the effectiveness of a GPB-based localization algorithm to process UWB range measurements.

V. Conclusions

In this paper, we proposed an UWB ranging aided pedestrian geolocation by processing LoS and NLoS measurements with respect to a set of beacons with known locations. The innovation in our work was to highlight the probabilistic nature of the power-based LoS/NLoS identification and use of the first-order GPB method to seamlessly handle the measurement model switching between LoS and NLoS in the UWB range measurements. We demonstrated the effectiveness of our proposed method via a real-time localization of a pedestrian using an experimental setup. In summary, our proposed GPB-based UWB range measurement processing with respect to beacons to aid the INS system offers the following advantages: (a) it is a practical sub-optimal solution with a low computational complexity, which can be implemented in real-time on a single computing board, (b) it serves as an augmentation atop of the INS in a loose coupling manner, i.e., it only becomes active when there is a UWB range measurement with respect to a beacon.

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