A Recursive NLOS Bias Estimation and Correction Algorithm

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Abstract. The importance of the indoor positioning applications and services in many fields such as health and safety motivated the researchers to develop accurate and cost effective localization systems. In wireless positioning techniques, the position of the mobile node (MN) can be estimated by measuring the distances between the MN and the access points (APs) using ranging techniques such as Time-of-Arrival (TOA), Time-Difference-of-Arrival (TDOA) and Received Signal Strength (RSS). However, due to dense indoor environments, multipath propagation and Non-Line-of-Sight (NLOS) introduce biases to the range measurements causing inaccurate position estimation. This paper proposes a recursive NLOS bias estimator algorithm, which corrects the range measurements by removing the estimated biases. The proposed algorithm is non-parametric and it doesn't require *a priori* information about the environment. Simulation results show that the proposed algorithm has higher positioning accuracy compared to the other state of the art algorithms and it outperforms them by at least 137%.

Keywords: Indoor Positioning · Bias Correction · NLOS · NLOS mitigation.

1 Introduction

Indoor Positioning Systems (IPS) gained a considerable consideration in the last decade due to its important applications in many fields such as military and safety, which require robust and high-accuracy positioning levels [1].

One of the most popular localization systems is the Global Positioning System (GPS) which works very well in outdoor environments since it can provide acceptable accuracy for several applications. However, utilizing GPS for indoor environments may degrade the accuracy of the position estimation due to the lost GPS signal because of propagation through walls and obstacles [2]. Several of indoor positioning systems were proposed such as Inertial Navigation systems, Infrared (IR) and Radio Frequency (RF) positioning systems. RF-based positioning systems include WLAN (Wi-Fi), RFID and Bluetooth [3].

The position of the MN is obtained by measuring the distances between the MN and fixed APs with known locations. The distance can be measured using different ranging techniques such as TOA and RSS [4]. To get an accurate position estimation, there should be direct paths or Line-of-Sight (LOS) between each AP and the MN.

However, due to the obstacles in indoor environments, the direct path of the traveled signal between the AP and the MN might be attenuated or undetected. This will cause the signal to arrive through other paths such as the scattered, penetrated, reflected and diffracted paths. Arriving through these paths will result in increased signal's traveled time. Therefore, the estimated distance between the AP and the MN will contain biases which will lead to an inaccurate position estimation [2, 1, 5]. This problem is called the Non-Line-of-Sight (NLOS).

These NLOS biases are variables and their values depend on the obstacle's profile. Where light objects such as the glass introduce small values of the biases while heavier objects such as metals introduce severe biases in the range estimates [1] that might reach from 10s to 100s of meters. The NLOS biases are random and they need to be estimated and removed from the range estimates in order to obtain accurate position estimation. Therefore, several approaches have been proposed in the literature that estimate and remove the biases such as [6, 2, 7–10]. However, some of these approaches have common assumptions that might not hold in practice such as assuming *a priori* knowledge of the environment and assuming LOS/NLOS identification. In this paper, a low-complexity non-parametric NLOS bias correction algorithm based on a patent [11] is proposed where it recursively estimates and corrects the biases without *a priori* knowledge about the NLOS errors.

The rest of this paper is organized as follows: In section 2, the problem formulation is presented. Section 3 describes the proposed NLOS bias estimator algorithm. Section 4 describes the simulation setup and the results. Finally, the conclusions are drawn in the last section.

2 Problem Formulation

For a general indoor localization scenario and to localize the MN in a $2D$ plane, assume that there are N APs and a MN with a position that needs to be estimated. The range measurement r_i between the AP and the MN at time t_i is given by:

$$r_i = d_i + b_i + n_i, \tag{1}$$

where d_i is the true distance between the MN and the AP, b_i is the positive bias which follows Rayleigh distribution or exponential distribution [12]. n_i denotes the system measurement noise which follows Gaussian distribution with zero mean and σ standard deviation. d_i is given by:

$$d_i = \sqrt{(x_m(i) - x_{ap})^2 + (y_m(i) - y_{ap})^2} \tag{2}$$

where $(x_m(i),y_m(i))$ is the MN's coordinate and (x_{ap},y_{ap}) is the AP's coordinate. The true distance can be estimated by subtracting the estimated biases $\hat{b_i}$ from the range measurements r_i as:

$$\hat{d_i} = r_i - \hat{b_i}. \tag{3}$$

3 Recursive Bias Estimator

In this section, a NLOS bias estimation and correction algorithm is proposed. The algorithm estimates and corrects the biases recursively by using the differential information of the range measurements.

The first-order difference between two consecutive range measurements can be written as:

$$\Delta r_{i,i-1} = r_i - r_{i-1} = \Delta d_{i,i-1} + \Delta b_{i,i-1} + \Delta n_{i,i-1}, \tag{4}$$

By Using Eq.4, the second-order difference can be given by:

$$\Delta\Delta r_{i,i-1} = \Delta r_{i,i-1} - \Delta r_{i-1,i-2} = \Delta\Delta d_{i,i-1} + \Delta\Delta b_{i,i-1} + \Delta\Delta n_{i,i-1}. \tag{5}$$

The second-order bias difference can be defined by $\Delta\Delta b_{i,i-1} = b_i - 2b_{i-1} + b_{i-2}$ and Eq.5 can be re-written as:

$$\Delta\Delta r_{i,i-1} = \Delta\Delta d_{i,i-1} + b_i - 2b_{i-1} + b_{i-2} + \Delta\Delta n_{i,i-1}. \tag{6}$$

The *general form* of the recursive bias estimator can be obtained by rearranging Eq.6 and it is defined by:

$$\hat{b}_i = \Delta\Delta r_{i,i-1} - \Delta\Delta d_{i,i-1} + 2\hat{b}_{i-1} - \hat{b}_{i-2} - \Delta\Delta n_{i,i-1}, \tag{7}$$

In Eq.7, the only available information in practice are $\Delta\Delta r_{i,i-1}$ and $\hat{b}_i$. Where, $\forall i < 2$, $\hat{b}_i = 0$ and $\forall i \geq 2$, $\hat{b}_i$ can be obtained recursively. Moreover, when the sampling interval T_s is small, $\Delta d_{i,i-1} \approx 0$. Thus, the *implementation form* of the bias estimator in Eq.7 can be written as:

$$\hat{b}_i = \Delta\Delta r_{i,i-1} + 2\hat{b}_{i-1} - \hat{b}_{i-2}, \tag{8}$$

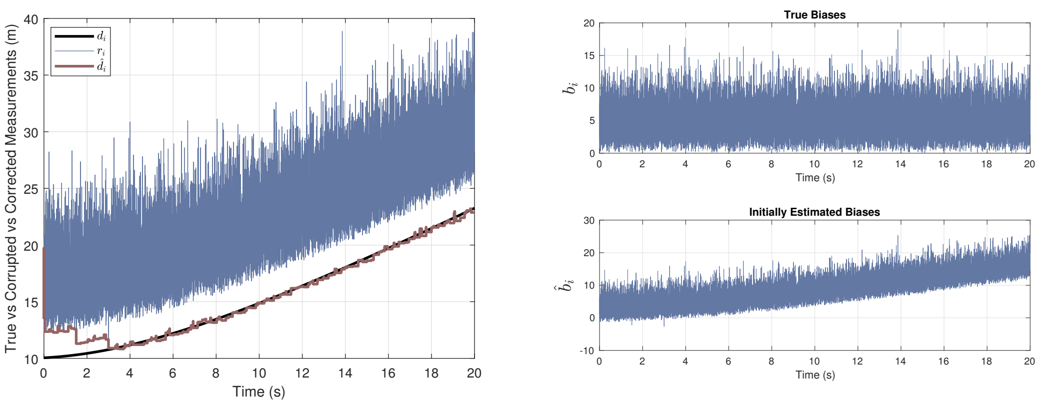
In this work, it is assumed that $\hat{b}_1 = 0$. However, in practice, this assumption might not hold. In case of a nonzero initial bias where $b_1 = \theta$ and $\hat{b}_1 = 0$, $\hat{b}_2$ can be calculated using Eq.8 as follows:

$$\hat{b}_2 = \Delta\Delta r_{2,1} = \Delta r_{2,1} = \Delta d_{2,1} + b_2 - \theta + n_2 - n_1, \tag{9}$$

The above form can be generalized to:

$$\hat{b}_i = \Delta d_{i,1} + b_i - \theta + n_i - n_1. \tag{10}$$

Eq. 10 shows that the estimated biases from Eq.8 undergo skew $\Delta d_{i,1}$ caused by the motion of the MN, and an offset $\theta + n_1$ due to the assumption $\hat{b}_1 = 0$. The proposed algorithm corrects the estimated biases $\hat{b}_i$ by estimating $\Delta d_{i,1}$, θ_i and subtracting them from $\hat{b}_i$. The effect of the biases on the range measurements is shown in Fig. 1a where the true distance d_i and the corrupted range measurements r_i are plotted. The true bias b_i and the estimated biases $\hat{b}_i$ using Eq.8 are shown in Fig. 1b. The true biases are positive since the algorithm is based on the TOA; where time-based ranging techniques such as the TOA produce biases with positive magnitudes that vary depending on the multipath environment.



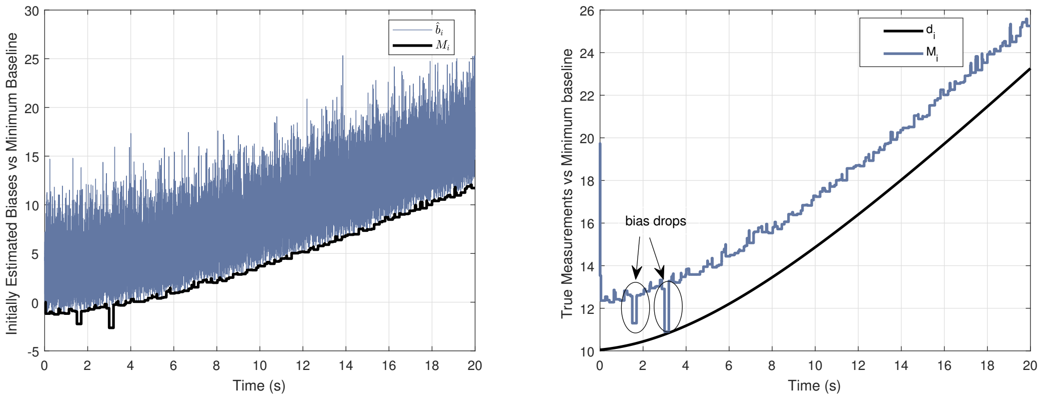
(a) (b)

Fig. 1. (a) True distance d_i, noisy range measurement r_i and corrected measurements $\hat{d}_i$, (b) True biases b_i and bias estimates $\hat{b}_i$ calculated using Eq. 8

$\Delta d_{i,1}$ Estimation Fig. 1b shows the effect of the skew $\Delta d_{i,1}$ on the estimated biases which can be estimated by tracking the minimum (baseline) of the estimated biases $\hat{b}_i$ as follows:

$$M_i = \min_j \ \hat{b}_j : \ j \in [i - W + 1, i], \tag{11}$$

where a controllable sliding window of length W is used to find the minimum value of $\hat{b}_i$ in each window. Fig. 2a illustrates the minimum baseline M_i.



(a) (b)

Fig. 2. (a) Tracking the lower envelope (minimum baseline) of $\hat{b}_i$ using a minimum sliding window $W = 100$, (b) Bias drops in the minimum baseline M_i

$\boldsymbol{\theta}$ Estimation The offset θ in Eq. 10 depends on the channel condition at t_1. If the estimated bias was initialized under a NLOS condition where $\hat{b}_1 = 0$ and $b_1 \neq 0$, a significant offset θ will be added to the estimated biases $\hat{b}_i$. The offset θ can be estimated from the minimum baseline M_i which depends on the propagation environment, as the value of M_i drops when the channel condition improves whether by transitioning from a NLOS condition to a LOS condition or when the obstacle profile changes. Fig. 2b plots the minimum baseline M_i which shows the bias drops resulted from LOS and NLOS transitions. Clearly, M_i and d_i are equivalent at the second bias drop where the magnitude of the bias drop is equal to θ. Therefore, θ is estimated by using the magnitudes of the bias drops. Consider the first order difference of the minimum baseline M_i given by:

$$\Delta M_{i,i-1} = M_i - M_{i-1}, \tag{12}$$

Fig. 3a illustrates $\Delta M_{i,i-1}$ which shows negative impulses at different locations indicating the occurrence of the bias drops. However, due to the measurement noise, $\Delta M_{i,i-1}$ is corrupted by noise that should be filtered as follows:

$$\Delta BD_i = \begin{cases} \Delta M_{i,i-1} & : |\Delta M_{i,i-1}| > \eta \\ 0 & : \text{otherwise} \end{cases} \tag{13}$$

where $\eta > 0$ is a threshold related to the measurement noise intensity. Fig. 3a provides a thresholded impulse train of bias drops ΔBD_i with different magnitudes. Next, to recreate the bias drops presented in the minimum baseline M_i, the impulse train in Fig. 3a should be passed through a running-sum function given by:

$$BD_i = \sum_{k=1}^{i} \Delta BD_i. \tag{14}$$

The offset θ can be estimated by passing the bias drops BD_i through a running minimum as:

$$\hat{\theta}_i = \min_{j} \quad BD_j : \ j \in [1, ...i] \tag{15}$$

The bias drops BD_i and the estimated offset $\hat{\theta}_i$ are shown in Fig. 3b. It is clear from Fig. 3b that the estimated offset $\hat{\theta}_i$ improves when the magnitude of the bias drop increases indicating an improvement in the channel condition. Specifically, a transition from a NLOS condition to a LOS condition. Finally, the *corrected* estimated biases equation is given by:

$$\hat{bc_i} = \hat{b}_i - (M_i - BD_i + \hat{\theta}_i) \tag{16}$$

The true distance d_i and the estimated distance $\hat{d}_i$ are illustrated in Fig. 1a where $\hat{d}_i$ was obtained by:

$$\hat{d}_i = r_i - \hat{bc_i} \tag{17}$$

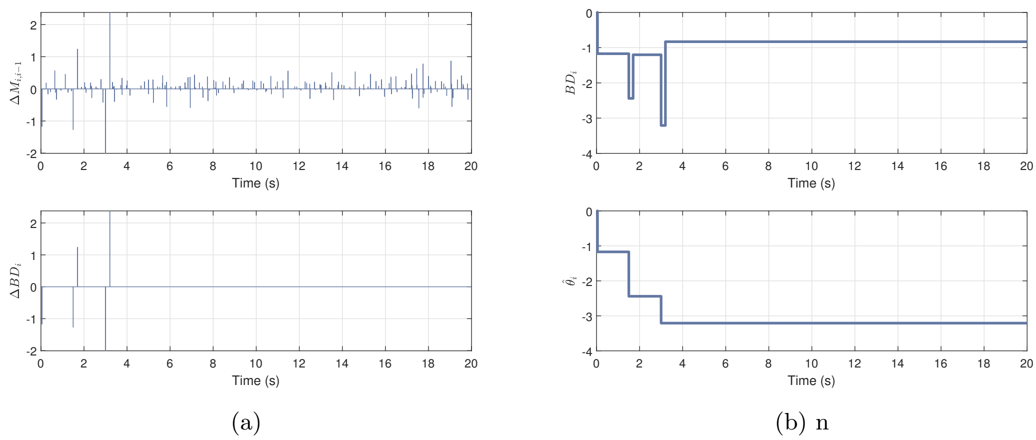


Fig. 3. (a) The noisy first order difference of the minimum baseline $\Delta M_{i,i-1}$ and the filtered first order difference of the minimum base line ΔBD_i, (b) Bias drops extractor waveform BD_i and the estimated offset $\hat{\theta}_i$

4 Simulation Results

4.1 Simulation Setup

Assume an indoor environment of dimensions 23 m x 23 m with 1 MN and 4 fixed APs. The APs: AP1, AP2, AP3 and AP4 are located at (0,0), (0,23), (23,23) and (23,0) respectively and the MN moves in a straight line according to the motion equation given by:

$$\begin{aligned} x_m(i) &= x_m(i-1) + v_x(i)T_s \\ y_m(i) &= y_m(i-1) + v_y(i)T_s \end{aligned} \tag{18}$$

where its initial position starts at (1,10) and $T_s = 0.001s$. Recall that the range measurement between the MN and the AP is modeled by Eq.1. The bias b_i follows Rayleigh distribution [12] with Rayleigh scaling parameter σ_R which determines the harshness of the bias errors i.e, ($\sigma_R = 2$), ($\sigma_R = 4$) and ($\sigma_R = 8$) denote light, moderate and severe NLOS respectively. Higher σ_R means higher NLOS errors. The measurement noise n_i follows Gaussian distribution with zero mean.

4.2 Simulation Analysis

In this section, the state of-the-art algorithms [7] and [10] and the recursive bias estimator are analyzed and evaluated based on their bias correction performance.

The algorithms are simulated in a dynamic random environment where the MN moves with different speeds and mixed NLOS errors for $20s$ as it is shown in Fig. 4 which plots the time evolution of the true and the corrupted range measurements relative to AP1. The MN's velocity was $1m/s$ for the first $10s$ and $0.2m/s$ for the next $10s$. The performance of the algorithms was evaluated by calculating the absolute distance error as follows:

$$e_i = |d_i - \hat{d}_i| \tag{19}$$

where d_i denotes the true distance and $\hat{d}_i$ is the distance estimate obtained by the algorithms. Then, the error samples are used to plot the empirical CDFs to evaluate the performance of the algorithms. Moreover, the mean absolute error is given as:

$$\overline{E} = \frac{1}{N} \sum_{i=1}^{N} e_i \tag{20}$$

where N is the number of samples. In the polynomial fitting algorithm [10], first, the measurements are smoothed by N^{th} order polynomial fitting then the measurement noise is utilized for the correction. This algorithm requires generating fitting by using the range measurements while this step in practice is unattainable. In the PNMC algorithm [7], the measurements are divided by windowing and in each window the NLOS ratio is estimated. Then the measurements are corrected based on the NLOS ratio estimate. This algorithm assumes the NLOS error distribution is known and it was generated by following the same method in [12]. The PNMC algorithm is environment dependent since it depends on the NLOS errors distribution which is unknown in practice. The recursive bias estimator algorithm was simulated by using different fixed window lengths W and the value of W corresponding to the lowest error was selected in the simulation of the recursive estimator. Fig. 5a plots the true and the corrected range measurements. The error CDFs are plotted in Fig. 5b.

Table 1 summarizes the simulation results of the algorithms where the results were obtained after changing the parameters W and σ_R. Moreover, the minimum and the maximum $\overline{E}$ of each algorithm is recorded in the table. The error percentage relative to the minimum recursive estimator is obtained by $((\overline{E}(algorithm) - 0.16) \times 100)$ where 0.16 is the minimum $\overline{E}$ of the recursive estimator.

The mean absolute error $\overline{E}$ of the recursive estimator was obtained after changing the window sizes W. The algorithm achieves the highest accuracy of $0.16m$ when $W = 600$ and it achieves the lowest accuracy when $W = 300$. Moreover, since the PNMC uses windowing and it depends on the NLOS error distribution for the correction, the parameters W and σ_R were changed to obtain $\overline{E}$. The PNMC achieves the highest accuracy of $2.54m$ when $W = 200$ and $\sigma_R = 4$.

Simulation results show that the recursive bias estimator achieved the highest accuracy compared to the polynomial fitting and the PNMC algorithms without *a priori* knowledge of the environment by at least 137%. This is evident from Table 1 where the maximum $\overline{E}$ corresponding to the recursive estimator is much less than the minimum $\overline{E}$ of the other algorithms. In addition, the fitting in the polynomial fitting algorithm was negatively affected by the speed of the MN and the varying NLOS errors.

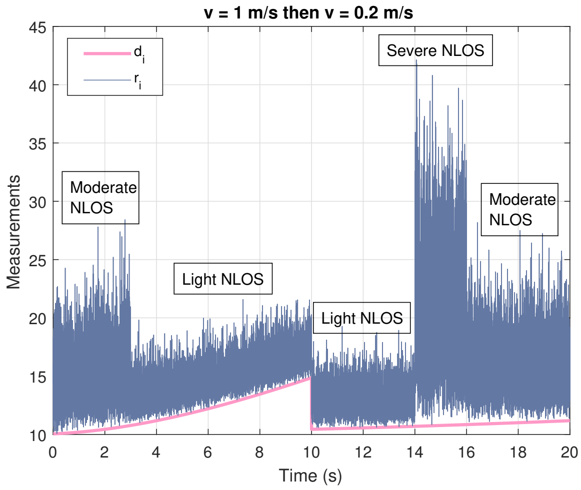
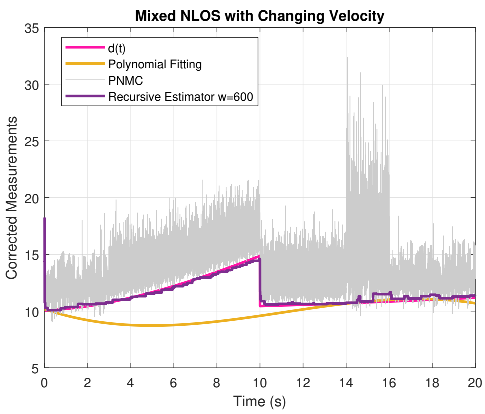
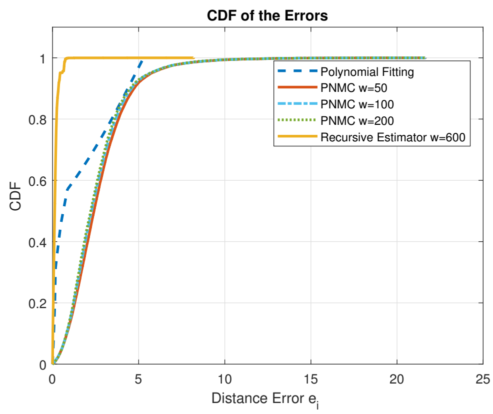


Fig. 4. The true distance d_i and the corrupted range measurements r_i between the MN and AP1



(a) True and estimated distance evolution



(b) Error CDF

Fig. 5. Mixed-NLOS performance evaluation

5 Conclusions

In this paper, a NLOS bias estimator is proposed that estimates and removes the biases recursively based on the range measurements. The algorithm can be implemented in different indoor environments since it is non-parametric and *a priori* information about the channel is not required.

Table 1. Ranging Errors

Algorithm	Parameters		$\overline{E}(m)$	Error % Relative to the minimum Recursive Estimator	Min $\overline{E}(m)$	Max $\overline{E}(m)$
	W	σ_R				
Recursive Estimator	300	-	0.20	4%	0.16	0.20
	600	-	0.16	-		
	900	-	0.18	2%		
PNMC	50	2	2.94	278%	2.69	3.31
		4	2.69	253%		
		8	3.31	315%		
	100	2	2.94	278%	2.58	3.24
		4	2.58	242%		
		8	3.24	308%		
	200	2	2.95	279%	2.54	3.19
		4	2.54	238%		
		8	3.19	303%		
Polynomial Fitting	-	-	1.53	137%	-	-

In addition, the algorithm was compared with two state of the art algorithms in a dynamic random environment where the MN moves with different speeds and experiences different severity of NLOS errors. Simulation results show that the proposed algorithm outperforms the analyzed state of the art algorithms by at least 137%.

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