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Improved NLOS Error Mitigation Based on LTS Algorithm

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Abstract—A new improved Least Trimmed Squares (LTS) based algorithm for Non-line-of-sight (NLOS) error mitigation is proposed for indoor localisation systems. The conventional LTS algorithm has hard threshold to decide the final set of base stations (BSs) to be used in position calculations. When the number of Line of Sight (LOS) BSs is more than the number of NLOS BSs the conventional LTS algorithm does not include some of them in position estimation due to principle of LTS algorithm or under heavy NLOS environments it cannot separate least biased BSs to use. To improve the performance of the conventional LTS algorithm in dynamic environments we have proposed a method that selects BSs for position calculation based on ordered residuals without discarding half of the BSs. By choosing a set of BSs which have least residual errors among all combinations as a final set for position calculation, we were able to decrease the localisation error of the system in dynamic environments. We demonstrate the robustness of the new improved method based on computer simulations under realistic channel environments.

1. INTRODUCTION

New markets for location based services have triggered several new activities in both academia and industry. Indoor localisation is currently being used and developed by companies, such as Google with Indoor Maps, Apple with iBeacons, Nokia with HAIP, etc. In 2012, the Location Alliance was formed by 22 companies to standardize indoor positioning systems [1]. The number of member companies exceeded 45 in mid 2015. This is an example showing how indoor positioning systems have become popular and more widely accepted by industry. Traditional positioning systems such as GPS and cellular network based systems only work in outdoor environments and due to signal propagation properties cannot be directly used in indoor environments [2]. Therefore, standalone indoor positioning systems are required to address challenges unique to indoor environments. Several parameters of the received signal can be used for position calculations such as Time of Arrival (TOA), Time Difference of Arrival (TDOA), Angle of Arrival (AOA), and Received Signal Strength (RSS) [3]. RSS based indoor localisation techniques are more popular among WiFi based systems [4], because WiFi devices cannot directly measure either TOA or TDOA information due to hardware limitations. For AOA based localisation techniques, smart antennas or antenna arrays are required to measure the incident angle of the received signal [5], causing the system to be more complex, cumbersome and more expensive. Time based methods are typically more popular in academia rather than industry. Time based approaches usually can achieve much higher accuracy than the other techniques [6] and sometimes used in "hybrid" systems where they are sometimes used in conjunction with other parameters [7]. However, all these methods suffer from Non-Line-of-Sight (NLOS) propagation issues leading to inaccuracies in localisation values. Indoor environments are unique, categorized by the large number of obstacles in close proximity, and with a wide variety of different materials involved such as concrete, glass, wood, etc. Those peculiarities represent a significant challenge to indoor localisation system. Due to the absence of a clear LOS path

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between transceivers, the transmitted signal is forced to travel some additional distance by reflecting from the obstacles to reach the receiver. The extra distance is the main cause of NLOS error and is difficult to quantify due to multipath effects. NLOS error mitigation is one of the most discussed topics in localisation systems and a significant number of research works have been carried out to address it [3, 8]. As NLOS error mitigation is a fundamental localisation problem, it still represents an open challenge.

The paper is organized as follows. Section 2 describes the system model which is used throughout the paper and discusses the current state-of-the-art methods. A new improved algorithm to achieve accurate localisation is described in Section 3 while the demonstration of the performance is shown in Section 4. Finally, Section 5 gives concluding remarks on the current work.

2. RELATED WORKS

2.1. System Model

For a system model, we consider a real-case scenario in a 2D plane with N BSs located at (x_i, y_i), with $i = 1, 2, \ldots, N$ and a target (which has to be located/tracked) with coordinates (x, y). Using the TOA information we can calculate the estimated distances $\bar{d}_i$ at each BS:

$$\bar{d}_i = c \cdot \bar{\tau}_i = d_i + b_i + n_i, \quad i = 1, 2, \ldots, N \tag{1}$$

where, c is the speed of light, $\bar{\tau}_i$ the measured TOA information at i-th BS, b_i the NLOS bias for the i-th measured distance, n_i the noise for the i-th measured distance, and d_i the real distance between the i-th BS and the target, given by Eq. (2)

$$d_i = \sqrt{(x - x_i)^2 + (y - y_i)^2}, \quad i = 1, 2, \ldots, N \tag{2}$$

The system, described by the equations above can be solved to find the unknown (x, y) coordinates of the target.

2.2. State-of-the-Art in NLOS Indoor Localisation

The NLOS challenge is divided mainly into two parts [8], e.g., channel identification and error mitigation. In the first category, and the received signal is identified and, if corrupted by NLOS error, is discarded. Otherwise, it is used for position calculations. The latter analyses error mitigation caused by NLOS signal propagation, and numerous research works have been published in this area [8]. The NLOS error mitigation techniques are further subdivided into subcategories. One of them is statistics based NLOS error mitigation category. This method of NLOS error mitigation is very popular among researchers because it exploits multiple signal features to combat NLOS error and yields good performance. To improve the position estimation performance of the localisation systems, there have been more complex studies, such as ray tracing based method [9] and subspace separation based methods [10, 11] for NLOS mitigation. Those methods achieve high localisation accuracy at the expense of higher complexity and computational requirements. There are different approaches to localize non-cooperative targets, and one of them is described in [12], here device-free localisation is based on compressive sensing method that relies on multiple transceivers located around the perimeter of the area being localized. Another approach to combat NLOS error is described in [13] where authors used a two-step algorithm with fuzzy based NLOS detection algorithm. The algorithm heavily depends on a membership function based on field measurements which vary from building to building. There are also many less complex methods which are available. To overcome this limitation robust estimator, i.e., the least median of squares (LMS), was proposed by [14, 15] for NLOS error mitigation.

One of the most popular low complexity position calculation methods is based on Least Squares Estimation (LSE) and its variations [16]. LSE based methods are very sensitive to NLOS errors and usually show poor performance when used without NLOS error mitigation. The LSE is based on the following estimation function

$$(x, y) = \text{argmin}_{x,y}\{R(x, y)\} = \text{argmin}_{x,y}\left\{\sum\nolimits_{i=1}^{N} \left(\bar{d}_i - ||(x, y) - (x_i, y_i)||\right)^2\right\} \tag{3}$$

where $R(x, y)$ is the residual error. Authors in [14, 15] proposed a Least Median of Squares (LMS) algorithm in order to exclude NLOS BSs from the set of BSs adopted for the target position calculation. LMS performs very well in mixed environments and where more LOS BSs present. The estimation function of the algorithm is given below

$$(x, y) = \text{argmin}_{x,y}\{R(x, y)\} = \text{argmed}_{x,y}\left\{\text{med}_j\left(\bar{d}_j - ||(x, y) - (x_j, y_j)||\right)^2\right\} \tag{4}$$

LMS relies on the definition of all the possible subsets, m, among the BSs with k BSs in each set (where k is the minimum number of BSs needed for position calculation, i.e., 3 for 2D and 4 for 3D), and searches for the final solution among the calculated m subsets. The LMS algorithm is described in following steps:

(i) All combination of BSs are calculated based on k. Total number of subsets (combinations) are equal to

$$m = \frac{N!}{k!(N-k)!} \tag{5}$$

(ii) Intermediate target locations $L_j = (\bar{x}_j, \bar{y}_j),\ j = 1, \ldots, m$, are calculated for each subset by means of the LSE algorithm as given in (3).

(iii) Based on intermediate locations L_j, residuals are calculated for each subset as

$$R_j = (\bar{d}_i - \tilde{d}_{i1})^2, (\bar{d}_i - \tilde{d}_{i2})^2, \ldots, (\bar{d}_i - \tilde{d}_{ij})^2 \tag{6}$$

with

$$\tilde{d}_{ij} = \sqrt{(\bar{x}_j - x_i)^2 + (\bar{y}_j - y_i)^2} \tag{7}$$

(iv) And the median value for each subset is calculated

$$M_j = \text{med}\{R_j\} \tag{8}$$

(v) The final target position is given by the intermediate position L_j associated with the minimum median value of M_j.

Authors in [17] proposed improvements to the classic LMS algorithm by introducing frequency of BS occurrences. Based on frequent occurrences of BSs in LMS sets, Qiao and Liu tried to find the best combination of BSs. This technique has similar disadvantage to LMS due to large number of combinations (for instance, 120 subsets for 10 BSs) and additional thresholding technique.

In order to reduce the computational cost of the algorithm, we have previously proposed the Least Trimmed Squares (LTS) [18] approach which improved localisation results in NLOS environments.

$$(x, y) = \text{argmin}_{x,y}\left\{\sum\nolimits_{i=1}^{h}(R)_{i:N}\right\} \tag{9}$$

The LTS algorithm is a simple and robust algorithm and can be described in the following steps:

(i) The initial target's position $L = (\bar{x}, \bar{y})$ is calculated by conventional LSE algorithm in Eq. (3) relying on all available BSs.

(ii) Based on intermediate position L, residual values are calculated for each BS.

$$R = (\bar{d}_1 - \tilde{d}_1)^2, (\bar{d}_2 - \tilde{d}_2)^2, \ldots, (\bar{d}_N - \tilde{d}_N)^2 \tag{10}$$

with

$$\tilde{d}_i = \sqrt{(\bar{x} - x_i)^2 + (\bar{y} - y_i)^2} \tag{11}$$

(iii) The squared residuals are sorted from smallest to largest

$$(R)_{1:N} \leq (R)_{2:N} \leq \ldots \leq (R)_{N:N} \tag{12}$$

(iv) And the target's final position is calculated by LSE, in Eq. (3), with only first h of BSs associated with the lowest residuals as in Eq. (12) $h = \frac{N}{2}$.

By excluding large biased NLOS BSs from the final set of position calculations LTS achieves better results than conventional methods in mixed environments.

3. IMPROVED LTS BASED BS SET SELECTION

The conventional LTS algorithm typically uses only half of the available BSs for position calculations, because of the h factor which may force LTS to discard potentially reliable BSs (i.e., BSs that are not under NLOS, or under light NLOS, i.e., minor error). To overcome blind elimination of $N-h$ BSs a new simple method is proposed. The proposed method generates subsets based on ordered BSs according to Eq. (12), and each subset contains one BS less than the previous set until there are $N-3$ BSs left in one set, as 3 is the least number of required BSs for two dimensional localisation. The new algorithm is summarized as following:

(i) The first 3 steps of the conventional LTS are repeated.

(ii) Subsets are generated based on Eq. (12). Each subset size is formed as: $\{N-1\}, \{N-2\}, \ldots, \{3\}$.

(iii) For each subset second intermediate positions are calculated with LSE algorithm.

$$(\tilde{x}_l, \tilde{y}_l) = \text{argmin}_{x,y} \left\{ \sum\nolimits_{i=l}^{N} (\bar{d}_\iota - ||(x,y) - (x_i, y_i)||)^2 \right\}, \tag{13}$$

with $l = 3, \ldots, N$.

(iv) For each subset new residuals are calculated using estimated new distances, $\tilde{d}_{il}$.

$$R_l = (\bar{d}_1 - \tilde{d}_{1l})^2, (\bar{d}_2 - \tilde{d}_{2l})^2, \ldots, (\bar{d}_N - \tilde{d}_{Nl})^2 \tag{14}$$

where

$$\tilde{d}_{il} = \sqrt{(\tilde{x}_l - x_i)^2 + (\tilde{y}_l - y_i)^2} \tag{15}$$

(v) Minimum of normalized residuals is used to find the good BSs set

$$\text{Indx} = \min_l \left\{ \sum\nolimits_{i=1}^{l} \frac{R_l}{l} \right\} \tag{16}$$

(vi) The final position corresponds to the intermediate position associated with the lowest normalized residual set as calculated in Eq. (16).

The new improved LTS algorithm does not relay on any thresholding, which makes it a completely non-parametric NLOS error mitigation solution. The performance of the new method could be further by introducing weighting factors.

4. NUMERICAL RESULTS AND DISCUSSIONS

To evaluate the overall performance of the proposed algorithm extensive numerical simulations have been carried out based on Ultra-Wideband (UWB) technology. We assumed an indoor environment of 50 m by 50 m area with 10 BSs evenly distributed around the periphery of the test environment, and one mobile target randomly placed within the test area. Authors in [19] have extensively carried out indoor and outdoor UWB based measurement campaigns and modeled ranging error distribution in various environments. The measurement system employed consists of an Agilent E8363B vector network analyzer that is used to sweep the frequency spectrum of 3–8 GHz with sampling internal 312.5 kHz and is connected to disccone shaped antennas. The overall measurement system has a dynamic range of 120 dB. According to their findings and NLOS error analysis, the ranging error model was modeled as a lognormal distribution which has 94% passing rate under Kolmogorov-Smirnoff hypothesis test with 5% significance level. This is defined as

$$f(\varphi) = \frac{1}{\varphi\sqrt{2\pi\sigma^2}} \exp\left[-\frac{(\ln\varphi - \mu)^2}{(2\sigma^2)} \right] \tag{17}$$

where φ is normalized ranging error in meters, and μ and σ are the mean and standard deviation (STD) of the ranging error model. We have adopted μ and σ parameters to be equal to -1.59, -1.68, -2.17 and 0.49, 0.88, 0.45 which represents typical office NLOS environments (which correspond to measurements with 500 MHz bandwidth in an indoor-to-indoor scenario) as used in our study. Each parameter is derived from measurements in different buildings. The number of BSs under NLOS was

randomly changed in each simulation loop to simulate the dynamic environment. A comparison of the cumulative distribution functions (CDF) of LSE [16], LMS [15], LTS [18] and proposed improved LTS methods is shown in Figure 1. If the number of NLOS BSs is much larger than the number of LOS BSs, the performance of the LMS algorithm decreases drastically because small number of BSs are used in the second step of position calculation, i.e., k in Eq. (5). The significant decline (red minor dashed line) can be observed from Figure 1. Our previously proposed technique [18], i.e., LTS, proves to be a good solution to mixed LOS and NLOS environments and had overall better results than both the LSE and LMS algorithms.

Conventional LTS used only half of the available BSs in the final set, i.e., h parameter of LTS, while discarding several LOS BSs. Nor it used NLOS BSs which have less NLOS biases. The proposed improved LTS algorithm overcomes those disadvantages by using few subsets of BSs to find position of the target which is least affected by NLOS bias. And it has better than 25 cm localisation error all the time. The statistical parameter of the same simulation environments, such as mean, standard deviation and root mean square errors estimations are compared for LSE [16], LMS [15], LTS [18] and proposed improved LTS algorithms in Figure 2. The new improved LTS shows the lowest error statistics, such as mean excess delay, standard deviation (std) and root mean squares (rms) among all methods, and it is more stable with the lowest std. in dynamic environments. The overall consistency of the results can be observed in Figure 1 and Figure 2 under various building layouts.

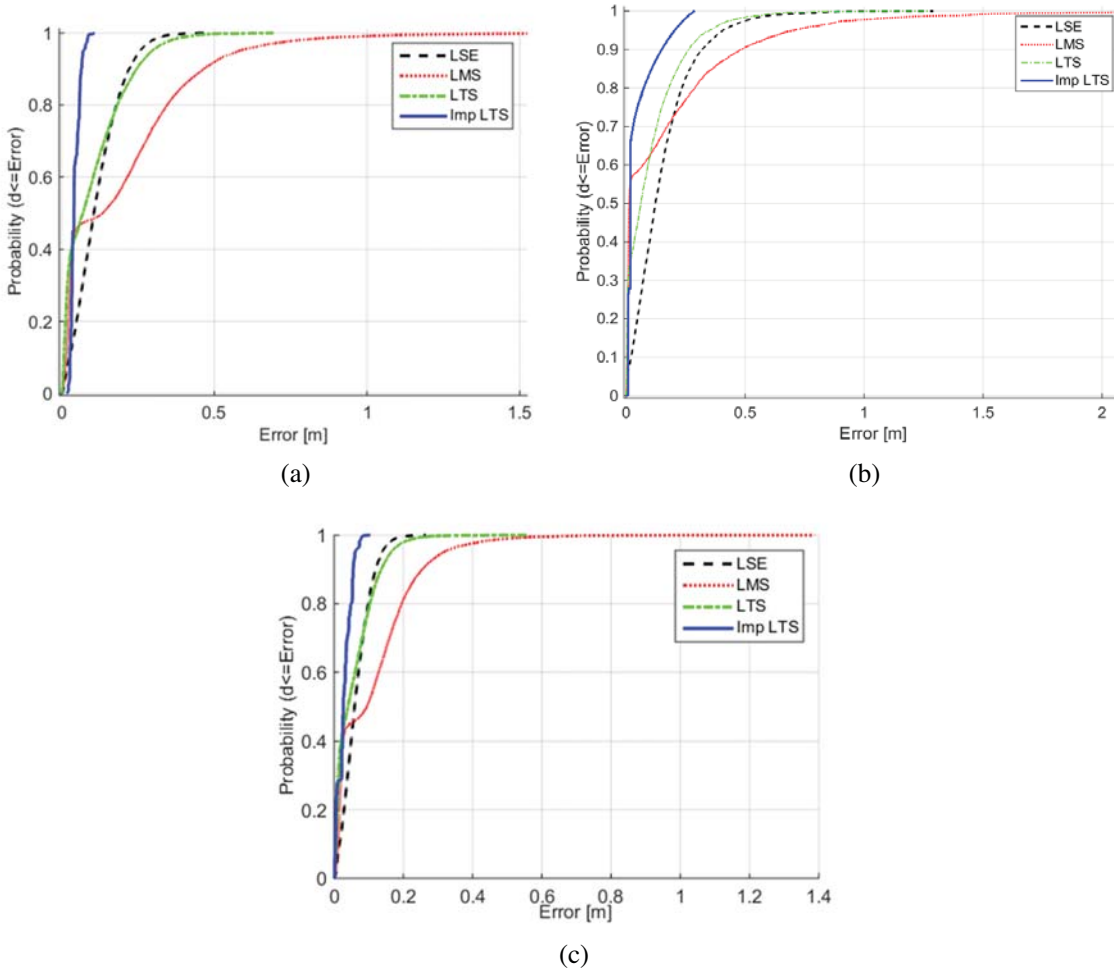


Figure 1. Comparison of CDFs of various methods under three NLOS scenarios. (a) NLOS error model with $\mu = -1.59$ and $\sigma = 0.49$, (b) NLOS error model with $\mu = -1.68$ and $\sigma = 0.88$, (c) NLOS error model with $\mu = -2.17$ and $\sigma = 0.45$.

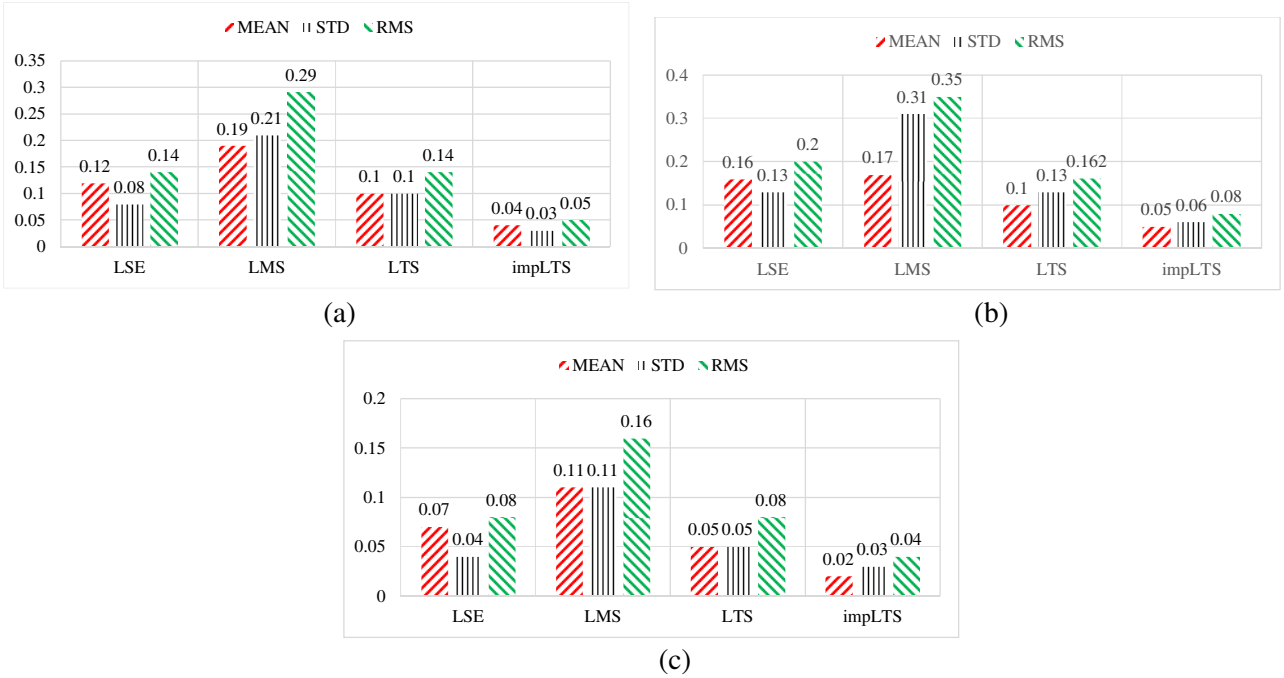


Figure 2. Mean, STD, and RMS comparison of various methods under three NLOS scenarios. (a) NLOS error model with $\mu = -1.59$ and $\sigma = 0.49$, (b) NLOS error model with $\mu = -1.68$ and $\sigma = 0.88$, (c) NLOS error model with $\mu = -2.17$ and $\sigma = 0.45$.

5. CONCLUSIONS

We have proposed an improved LTS based localisation algorithm for dynamic environments. It is based on basic LSE and does not require an extensive computational power. It shows a 50% accuracy improvement compared to conventional accurate localisation methods with little increase in computation complexity. Moreover, unlike LTS, the proposed solution can still achieve better performance under heavy NLOS environments. The new technique as derived from conventional LTS does not require any *priori* information or assumption about the channel. Finally, it does not require any thresholding technique, which makes it an attractive non-parametric solution.

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