PROBABILISTIC BASED OPTIMAL NODE LOCALIZATION IN WIRELESS SENSOR NETWORKS

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ABSTRACT

Localization is one of the most important technologies for many applications in wireless sensor networks (WSNs). Node localization is the process of discovering the exact location of the node. If the number of nodes and network size increase, it becomes very arduous to localize the nodes whose result leads to complexity and path loss. In this paper, we proposed an approach called probabilistic based optimal node localization to obtain the location of node in the WSNs. This approach provides an enhanced channel path-loss model by capturing the features of the additive noise in WSN. In addition, the complexity has been minimized by discovering a lower bound of the non-convex function. The problem of non-convex optimization and subsequent nonlinear is solved with the help of relaxation to achieve a sub-optimal solution. Simulation results show that our proposed localization approach has got better performance for considered scenario settings.

KEYWORDS

Wireless Sensor Networks (WSN), Sensor Nodes (SNs), Node localization, Anchor Nodes (ANs), Root-Mean-Square Error (RMSE).

1. INTRODUCTION

WSN contains a set of reasonable and mini sensors that are semantically distributed over an area to evaluate some physical parameters and monitor different conditions and have several pragmatic implementation areas like target tracking, agriculture, and precision [1-3]. These SNs (sensor nodes) require evaluating their coordinates with fewer resource necessities for most of the applications. The SNs can place their coordinates by utilizing an integrated GPS (Global-Positioning system). Anyways, it’s practically not feasible to incorporate the GPS in entire sensors because of their cost and size. Another method is utilizing the localization algorithm in many ANs (anchor nodes) with incorporated GPS that will not know to define their coordinates.

Node localization is the process of detecting the accurate location of the node. SN’s are deployed randomly with the help of an airplane in an AOI (Area of interest) called a forest. If there any number of anchors are available in a network, the given inputs are anchor locations while other inputs are based on some measurement method, and the process of node localization is shown in figure1. The most significant method is to determine the location of a node in GPS. When a network consists of a larger number of nodes, this technique becomes costliest and power-consuming. Node localization methods [4] for WSNs are based on the measurement of more than one and one physical-parameters of transmitted radio-signal like BNs and RNs. Their parameter types includes RSS (received-signal strength), AOA (Angle of Arrival), TOA (time-of Arrival), and TDOA (time-difference of arrival). There exists a trade-off between the accuracy of localization and complexity of the implementation method and the RSS-based method gives lower cost and easier implementation. Two commonly utilized parameters like LLS (Linearized-least-squares) and ML estimator (Maximum-likelihood) [5-6]. When the measurement error is known, then the estimator of MI is asymptotically optimal. Anyways, localization problems formed as an estimator of ML that has a closed-form solution and an iterative solver is needed. The formed ML-estimator is non-convex and its performance is dependent on the preliminary given for the iterative solver. Afterward, poor initialization leads to a bad estimator. Furthermore, because of non-convexity, discovering ML-estimator is difficult.

Figure 1. Node localization process

A huge number of localization algorithms have been represented to resolve various localization issues [7]. These given algorithms are estimated more flexible so they can work in different diverse outdoor and indoor topologies and scenarios. The localization algorithms are parted into two types range free and range-based algorithms. The location of unidentified nodes is calculated with distance among unknown and anchor SNs. They use range metrics like RSSI (Received-Signal Strength-Indication), angle of arrival, and time of arrival [8-9]. In addition, the algorithms like centroid [10] and Ad-Hoc positioning method [11] generate the utilization of simple techniques related to some connectivity to localize the sensor node. They require the presence of a beacon-signal by AN in a medium. Among all, range based-algorithms are utilized and desired over range free-algorithms [12].

In order to design lower complicated algorithms, different types of bio-inspired algorithms have been introduced for the range-based technique [13], whereas in paper [14], they rendered node-based localization technique that formed on PSO (Particle-swarm-optimization) [15] that limited for swarm optimization to discover the food. This type of algorithm represented better outcomes, but implementation inclined to obtain the local optimum, which outcomes in the convergence of premature. They implemented CS-based node localization in WSNs in [16]. This is due to tuning parameters in the algorithm of CS that ease the computation process. Presently, the modified version of CS was introduced by [17] that improvised the rate of the conventional-CS algorithm. They use to improvise the search process of mutation probability.

This paper mainly intends to node localization algorithm in WSNs that is basically based on a channel-path loss model with GD (Gaussian-Distribution). Anyways, the noise doesn't follow GD because of more than one heterogeneity source [18]. However, the Gaussian model can't represent measured noise which leads to inappropriate node localization algorithms in the WSNs. Based on our knowledge; WSN doesn't find the practical channel of a path-loss model with a non-Gaussian node in node localization. Based on the above assumptions, we introduced an improvised RSS-based node-localization algorithm called the probabilistic-based optimal node localization (PONL) approach to obtain node location in the WSNs. Explicitly; noise is introduced by a non-Gaussian that is followed by the parameter estimator of empirical noise. Afterward, we formulate a node localization algorithm like an optimization problem to obtain the performance of ML. The non-convex and subsequent non-linear optimization problems are resolved with the help of semi-definite to achieve an optimal solution. Lastly, both experimental outcomes and simulation demonstrate the performance of PONLover the other localization algorithms. This paper represents in such a way that section-2 represents a literature survey related to the previous paper based on node localization in WSN, section-3 represents the proposed methodology based on the PSDP model, section-4 represents our experimental outcome that outperforms other existing node localization algorithms, and finally concludes our work.

2. LITERATURE SURVEY

In this section, different localization algorithms have been represented. In paper [19], the author addressed the problem of positioning in WSNs as an adversarial situation. They also proposed a method called VM (Verifiable-Multi-Iteration) for location verification. ANs are called verifiers. This technique secures the confirmation and estimation of unknown location nodes in malicious nodes. They devised a method for securing the positioning in SNs called SPINE. By utilizing this node technique are capable to find it securely. The limitation of this technique has a larger number of verifiers that are required to perform the verifiable multi-literation. Whereas in paper [20], the author improvised a secure node localization method called SLM (secure-localization-method) for a wide range of SNS. The SLM was more robust than the VM but the process of SLM was more sophisticated than the VM that led to more power consumption.

In [21], the author introduced a new method to discover the node localization in a secure way that utilized mobile-BS (base-station) and hidden concepts. Furthermore, by utilizing this technique, one can validate the location of the unknown nodes, whereas [22], emphasized the requirement for node localization and recommended the extension of existing SLM. The novel method is called as secure-based enhanced localization method. This method was the understanding against the attacks of distance reduction but also the attacks of distance enlargement and it gave a more accurate location of nodes.

In paper [23], author introduced a method to minimize the localization problem with the help of the BPSO algorithm for the node localization in the WSN. Each undefined node performs the localization under distance measurement from 3 or more AN. The node achieves localization by utilizing iteration that would be utilized for the other AN. Among BPSO, and PSO of localization methods, modified-BPSO is represented in terms of the localization error. In [24], the author introduced a localization issue in WSN, and to resolve this issue PSO was utilized. In order to improvise the localization precision and efficiency of an algorithm, the author represented the main function based on the distribution of the ranging error and obtains the search space of the particles.

In [25], the author introduced node localization in WSN is very essential due to several applications that need more SNs to know their exact place with a higher precision degree. The optimal path for the mobile anchors was based on the node localization. The introduced path planning technique is defined the exact location of individual SNs with the Mobile-AN. It ensures that the trajectory of mobile-ANs reduced localization problems and ensures all SNs could define their exact locations. Afterward, the PSO algorithm defined the trajectory of mobile-AN. In paper [26], the author introduced applications of SNs that were enhanced for wireless device-location and localization method has been improvised to meet their needs. WSNs prove very useful in several applications such as military surveillance and environmental monitoring.

The author addressed the applications of various PSO and BBO migration-variants algorithms for optimal node localization for deployment sensors [27]. Biogeography is the learning path of biological-geographical particles. This algorithm has novel vigor that is based on biogeography and it employs the migration operator for allocating the data among various habitats and places like problem-solving. The PSO model has faster convergence but also has lower maturity. Hence, the given nodes will obtain localization on repetition as AN and also compared with the performance of PSO and various migration variants of the BBO with any number of localized nodes like computation time and accuracy of localization. In [28], the presented RSSI range-based localization scheme will rely on RSS measurement for evaluation of the distance. The experimental has been shown indoor and outdoor environments for developing the model of path loss.

This paper [29] represents the tracking system based on ARMA (auto-regressive moving-average) method while the distribution in the signal processing framework. This framework act as a peer that is performing the tracking, target detections, classifications, feature extraction in case of the target localization that needed collaboration among WSNs for improving the robustness and accuracy of the networks. Furthermore, the progressive multi-view localization algorithm is prepared in the distributed P2P signals as a processing framework that will assume a trade-off between power consumption and accuracy. Lastly, the real-world tracking experiment has few illustrations. Few outcomes from implementations have represented the target tracking method which is dependent on the P2P signal processing method is generating economic utilization of the scarce energy and communication resources and also obtained the target tracking. In paper [30], the author introduced localization models by utilizing linear intersections and does few concerned experiments for evaluation of the location computation-algorithms. By knowing the locations of the nodes in WSN it becomes most eminent for several useful benefits. The nodes in WSN have many capabilities and exploitation of one and many capabilities that will support resolving the localization issue. They also considered each node in WSN that has the capability of the distance measurement and also represented the allocation of the computation method known as the linear intersections for the node localization.

3. PRELIMINARIES

We begin by representing some notation that is used in this paper.I^s and J^s represent set of s vectors and symmetric matrix $s \times s$. Additionally, any symmetric matrix m, $m \succcurlyeq 0$ means m is the or positive semi-definite.

Let's represent defined coordinates of athanchor-node $\alpha_a = [\alpha_{a1}, \alpha_{a2}]^{\mathbb{T}}(\alpha_a \in I^2, a = 1, \dots, T)$and undefined coordinates of bth target node as $\beta_b = [\beta_{b1}, \beta_{b2}]^{\mathbb{T}}(\beta_b \in I^2, a = 1, \dots, A)$, where A and T are the total number of anchors and the targets. The power is received at bth target from ath anchor node is demonstrated as:

$$\mathbb{P}_{a,b} = \mathbb{P}_0 - 10\gamma log_{10}\frac{di(\alpha_a, \beta_b)}{di} + s_{a,b} \quad (1)$$

$\mathbb{P}_0$ is simplifies transmitted power from the receiver at the di distance, $di(\alpha_a, \beta_b) = \| \alpha_a, \beta_b \|_2$ is Euclidean distance among ath and ath, γ is defined as the exponent of path-loss with common value, $s_{a,b}$ additive noise follows GD (Gaussian-distribution) that shows the shadowing effect of log-normal in the multipath-environments, respectively. One of the issues is addressed in (1). $s_{a,b}$ always not follow the GDs in the real environment. We intend to improvise the channel path of the loss model by taking the features of additive-noise.

3.1. System Model

Here, we introduce noise with the probabilistic model (PM) and resulting in joint PDF (Probability distributed-function) at the detected power vector $\mathbb{P}_b = . \mathbb{P}_{1,b, \dots\dots\dots} \mathbb{P}_{A,b}$ at the target bth:

$\mathfrak{p}(\mathbb{P}_b\|\beta_b) = \prod_{b=1}^{A}\sum_{c}^{C} \mathfrak{t}_{b,c}\mathcal{N}(m_c, v_c^2),$	(2)

Where, $\mathfrak{t}_{b,s}$ is defined as corresponding cluster weight c with v_c^2 variance and m_c mean of noise, and C is defined as the mixture component.

Note: the exponent of path-loss is known and it is fixed in our experiments and simulations in the next section. By using experimental measurements, γ and $\mathbb{P}_0$ can be evaluated as the logarithmic fitting.

3.2. Problem Formulation

Here, mean $m_c$and variance v_c^2 and also $\mathfrak{t}_{b,c}$ are required to be evaluated in the process of node localization. In the criterion of ECM, both variables like mean and variance $v_c^{(n)}$ and $m_c^{(n)}$are evaluated on iteration $n$for informing the position $v_c^{(n)}$ without $\mathfrak{t}_{b,c}{}^{(n)}$ would be equally improved. The iteration index n is not represented.

In the end, in order to design the main objective like node localization algorithm through GM-Semi-definite programming (SDP) is to achieve ML to evaluate v_b^* by discovering the parameter$\mathfrak{t}_{b,c}$. Afterward, the estimator of ML can be expressed:

$\underset{\beta_b,\mathfrak{t}}{\text{maximum}}\, \psi(\beta_b, \mathfrak{t})$ $s.t. \mathbb{K}1: \sum_{c=1}^{C} \mathfrak{t}_{a,c} = 1, \quad \forall_a$ $\mathbb{K}2: 0 \leq \mathfrak{t}_{a,c} \leq 1, \quad \forall_C, a$ $\mathbb{K}3: di(\beta_b, a_a)\forall_C, a$	(3)

Where, $\psi(\beta_b, \mathfrak{t})$ is defined as the function of log-likelihood combined for conditional-pdf in equation (2) such as $\psi(\beta_b, \mathfrak{t}) = ln\, \mathfrak{p}(\mathbb{P}_b|\beta_b)$ and $\mathfrak{t}_{a,c}$ is defined as weights of a mixture, which are constrained to sum-up to 1.

Anyways, the main function of combinatorial-nature in (3) those outcomes in the problem of NP-hard. In order to minimize the complexity, an optimization issue is formulated by discovering the LB function of the non-convex objective. Then, the formulated issue is resolved as the SDP issue through relaxation to get an optimal solution. We begin to resolve an original issue in (3) by getting the sub-optimal solution through the theorem.

Pairs have an optimal solution for the feasible pair $(\beta_b, \mathfrak{t})$ then it will follow optimization issue and feasible pair $(\beta_b, \mathfrak{t})$ is optional for the original issue in (3).

$\max_{\beta_b} \sum_{b=1}^{A} \sum_{c=1}^{C} \mathfrak{t}_{b,c}\mathcal{N}(m_c, v_c^2),$ $s.t. \mathbb{K}1, \mathbb{K}2, \mathbb{K}3.$	(4)

The value of optional β_b is described as $\psi^* = \sup\{\psi(\beta_b, \mathrm{t})\} | \mathbb{K}1, \mathbb{K}2, \mathbb{K}3,$ and the solution of feasible (β_b, t) is defined as $\in -$ optional if $\psi(\beta_b, \mathrm{t}) \geq \psi^* - \in$. Utilizing Jensen's inequity, the objective function of LB-non-convex by (3) is achieved and mentioned by:

$$\psi(\beta_b, \mathrm{t}) \geq \sum_{b=1}^{A} \sum_{c=1}^{C} \mathrm{t}_{b,c} In\, \mathcal{N}(m_c, v_c^2) = \psi_1(\beta_b, \mathrm{t}) \qquad (5)$$

$\psi_1(\beta_b, \mathrm{t})$assists as LB for the parameters of likelihood-function (β_b, t). Anyways, $\in'$exists, afterward, it generates (β_b, t) that satisfies$\psi_1(\beta_b, \mathrm{t}) \geq \psi^* - \in'$. Therefore, (β_b, t) defines $\in'$an as optional issue in (3) and the theorem holds. Moreover, the optimization issue in (3) can be formed as:

$$\underset{\beta_b, \mathrm{t}}{\text{minimum}}\, \psi(\beta_b, \mathrm{t}) \quad s.t. \mathbb{K}1, \mathbb{K}2, \mathbb{K}3. \qquad (6)$$

Where,

$$\psi_2(\beta_b, \mathrm{t}) = -\psi_1(\beta_b, \mathrm{t}) \quad \sum_{b=1}^{A} \sum_{c=1}^{C} \mathrm{t}_{b,c} \left[In\, \sqrt{2v_c} + \frac{(s_{a,b} - m_c)^2}{2v_c^2} \right] \qquad (7)$$

The main objective of (6) is non-convex but its domain $(\beta_b | (\beta_b) \neq \alpha_a$ is not convex-domain and $log_{10} \frac{di(\alpha_a, \beta_b)^2}{2v_c^2}$ is non-convex on the domain of convex. Anyways, it is very difficult to discover the solution of optimal in (6). In order to obtain the estimator of convex in (6), we represent the following Proposition.

3.3. Probabilistic based Optimal Node Localization Approach

Proposition: if $g \in I^s$

Then, we have $\|g\|_\infty \leq \|g\|_2 \leq \sqrt{s}\|g\|_\infty$and $\|g\|_\infty \leq \|g\|_1 \leq \sqrt{s}\|g\|_\infty$.

In order to replaceI_2 in ψ_2 with I_∞ norm like Chebyshev-norm, then we have

$$\frac{(s_{a,b} - m_c)^2}{2v_c^2} \overset{(x)}{\Leftrightarrow} max \left| \frac{1}{v_c} log_{10} \frac{di(\beta_b, \alpha_a)}{\gamma_{i,c}^2} \right| \overset{(y)}{\Leftrightarrow} max \left| \frac{di^2(\beta_b, \alpha_a)}{v_c \gamma_{i,c}^2}, \frac{\gamma_{i,c}^2}{v_c di^2(\beta_b, \alpha_a)} \right| \qquad (8)$$

Where, $\gamma_{i,c}^2 = di_0^2 10^{\frac{\mathbb{P}_0 + m_c - \mathbb{P}_{a,b}}{5\varsigma}}$. In equation (8), (x) outcomes because of 1 in Proposition and (y) outcomes based on$log_{10} g$, which is a strictly monotonic function when maximize all domains$(0, \infty)$. Then, the optimization problem in (6) can be articulated as:

$$\underset{\beta_b, \mathrm{t},, \omega}{\text{minimum}} \sum_{a=1}^{T} \left[\mathcal{T}r\left(t_a \text{ñ}^{\mathbb{T}}\right) + \mathcal{T}r\left(t_a \varpi_a^{\mathbb{T}}\right) \right]$$

$s.t. \mathbb{K}1, \mathbb{K}2, \mathbb{K}3.$ $\mathbb{K}4: \lVert\beta_b - \alpha_a\rVert_2^2 \leq \lambda_{a,c}^2 v_c \varpi_{a,c}$ $\mathbb{K}5: \lVert\beta_b - \alpha_a\rVert_2^2 \geq \lambda_{a,c}^2 {v_c}^{-1} {\varpi_{a,c}}^{-1}, \forall_{a,c}$ Where, $t_a = [t_{a,1}, \ldots\ldots, t_{a,c}]^{\mathbb{T}}$ $\mathrm{n} = [In\sqrt{2\pi} v_c, \ldots\ldots, In\sqrt{2\pi} v_c]^{\mathbb{T}}$ $\varpi_a = [\varpi_{a,1}, \ldots\ldots, \varpi_{a,C}]^{\mathbb{T}}$	(9)

$\lVert v_c - \alpha_a\rVert_2^2 = \mathcal{Tr}(\Psi) - 2{v_c}^{\mathbb{T}}\alpha_a + \lVert\alpha_a\rVert_2^2$. Hence, we write this in the norm as a formulated problem:

$\underset{\beta_b, \mathrm{t},, \omega}{\mathrm{minimum}} \lVert \mathrm{g}\rVert_1 - \lVert \mathrm{h}\rVert_1$ $s.t. \mathbb{K}1, \mathbb{K}2, \mathbb{K}3.$ $\mathbb{K}4: \mathcal{Tr}(\Psi) - 2{v_c}^{\mathbb{T}}\alpha_a + \lVert\alpha_a\rVert_2^2 \leq \lambda_{a,c}^2 v_c \varpi_{a,c}$ $\mathbb{K}5: \mathcal{Tr}(\Psi) - 2{v_c}^{\mathbb{T}}\alpha_a + \lVert\alpha_a\rVert_2^2 \geq \lambda_{a,c}^2 {v_c}^{-1} {\varpi_{a,c}}^{-1}, \forall_{a,c}$ Where, $\mathbb{K}6: \Psi = (\beta_b {\beta_b}^{\mathbb{T}}) =, \Psi \in \mathbb{C}^2$ $\mathbb{K}7: g_i = \mathcal{Tr}(t_a \mathrm{n}^{\mathbb{T}})$ $\mathbb{K}8: h_i = \mathcal{Tr}(t_a \varpi_a^{\mathbb{T}}), \forall_a$	(10)

Anyways, the issue in (10) is not convex, since the similarity constraint is not affine as $\mathbb{K}7$and $\mathbb{K}8$. In order to achieve the problem of convex optimization in (10), $\mathbb{K}6$ is defined as not similarity constraint $\Psi \geq \beta_b {\beta_b}^{\mathbb{T}}$ (semidefinite relaxation) and $\mathbb{K}8$ is defined into $h_i = \sum_{c=1}^{C} \varpi_{a,c}$ like Jensen's inequality. Furthermore, the given constraints $\mathbb{K}5$ and $\mathbb{K}6$ utilizing Schur complement in the linear matrix, which is represented in the optimization problem is:

$\underset{\beta_b, \mathrm{t},, \omega}{\mathrm{minimum}} \lVert \mathrm{g}\rVert_1 - \lVert \mathrm{h}\rVert_1$ $s.t. \mathbb{K}1, \mathbb{K}2, \mathbb{K}3.$ $\mathbb{K}5: \begin{bmatrix} \mathcal{Tr}(\Psi) - 2{v_c}^{\mathbb{T}}\alpha_a + \lVert\alpha_a\rVert_2^2 & \Upsilon_{a,c}/\sqrt{v_c} \\ \Upsilon_{a,c}/\sqrt{v_c} & \varpi_{a,c} \end{bmatrix} \geq 0, \forall_{a,c}$ $\mathbb{K}6: \begin{bmatrix} \Psi & \beta_b \\ {\beta_b}^{\mathbb{T}} & 1 \end{bmatrix} \geq 0, \Psi \in \mathbb{C}^2$ $\mathbb{K}7: g_i \geq \mathcal{Tr}(t_a \mathrm{n}^{\mathbb{T}})$ $\mathbb{K}8: h_i \geq \sum_{c=1}^{C} \varpi_{a,c}, \forall_a$	(11)

Equation (11) is the problem of optimization like convex that can be reconciled with numerical process to achieve the optimal solution β_b^* of the optimization problem, which is defined in (3).

It is very easy to discover PONL estimator variance $\hat{\beta}(\mathbb{P})$ is not biased such as $\mathcal{E}[\hat{\beta}(\mathbb{P})] = \beta(\mathbb{P})$. An estimator's accuracy may be demonstrated by costs that are related to MSE (mean-square-error), or the variance of the estimator for the unbiased estimate. CRB is the FI (Fisher Information) inverse defines LB on estimators of unbiased variance. The variance of the PONL estimator will be:

$$[\hat{\beta}(\mathbb{P}) - \mathbb{P}][\hat{\beta}(\mathbb{P}) - \mathbb{P}]^{\mathbb{T}} \geq \mu^{-1} \tag{12}$$

Where, $|\mu|_{e,f}$ element of μ FIM is described by:

$$|\mu|_{e,f} = \mathcal{E}\left[\frac{\zeta In\mathfrak{p}(\mathbb{P}_b|\beta_b)}{\zeta\beta_{b,e}} \cdot \frac{\zeta In\mathfrak{p}(\mathbb{P}_b|\beta_b)}{\zeta\beta_{b,f}}\right], e,f \in \mathcal{V} \tag{13}$$

Where $\mathcal{V}$ is defined as a set of the dimensions in the coordinated axis. For a localized node in 2D-scenario $|\mathcal{V}| = 2$, we have,

$$|\mu|_{e,f} = \left[\frac{10B}{In\ 10}\right]^2 A_{\mathfrak{n}} \sum_{a=1}^{T} \frac{(\beta_{b,e} - \alpha_{a,f}),(\beta_{b,f} - \alpha_{a,f})}{\|\Phi_b - \alpha_a\|_4^2}, e,f \in \mathcal{V} \tag{14}$$

Where,

$$A_{\mathfrak{n}} = \mathcal{E}\left\{\left[\frac{\Delta_{\mathfrak{n}}\mathfrak{p}(\mathfrak{n})^2}{\mathfrak{p}(\mathfrak{n})}\right]\right\} = \int \frac{[\Delta_{\mathfrak{n}}\mathfrak{p}(\mathfrak{n})^2]}{\mathfrak{p}(\mathfrak{n})} di_{\mathfrak{n}} \tag{15}$$

$$\sqrt{\mathcal{E}(\mathbb{e}^2)} \geq \sqrt{\mathcal{Tr}[\mu^{-1}]} \triangleq CRB(\beta) \tag{16}$$

In equation (15), $\mathfrak{p}(\mathfrak{n}) \sim \sum_{c=1}^{C} \mathfrak{t}_c \mathcal{N}(\beta_c - v_c^2)$ and $A_{\mathfrak{n}}$ is estimated by Monte-Carlo. Furthermore, by describing the location EE (estimator error) as $\mathbb{e} = \|\hat{\beta} - \beta\|_2$. CRB is LB on its MSE (mean-square error) for any type of unbiased-estimator.

4. RESULT AND ANALYSIS

In this section, numerical simulations are conducted to do a performance analysis of our proposed PONL approach. The system configuration; Intel i7 windows-based operating system, 12GB RAM and the complete simulation is done using Matlab 2018a software.

Simulations are conducted to evaluate the performance of our proposed method through comparing with the weighted least squares (WLS) [31] approach, which is referred to as an existing system (ES) incomplete result analysis. In addition, the performance is measured using the Root-Mean-Square Error (RMSE), obtained throughput and Cumulative Distribution Function (CDF). All these parameters are considered, which are computed based on 100 Monte Carlo runs with cell size 10x10 m^2 and 20x20m^2. Therefore, the total numbers of nodes are 104, 112 and 120, the transmitted power at reference distance is -55dB with reference distance of 1 meter, and cluster weight is considered to be 0.37 and 0.63. Table 1 provides the complete parameters details for simulation.

Table 1. Parameters Details for Simulation

Monti Carlo Simulation	100
Cell size	10x10 m^2 and 20x20m^2
Total Number of Nodes	104, 112 and 120
Anchor Nodes	4, 12 and 20
The transmitted power in dB at reference distance	-55
Path-loss exponent in dB	2
Reference distance in meter	1
Cluster weight	0.37 and 0.63

There are two types of scenario has considered with varying the cell size; the first scenario we have a cell size of 10x10 m^2 and in the second scenario we have cell size of 20x20 m^2. Other than that we have the same parameters for both the scenarios and performance evaluation is done using RMSE, obtained throughput and CDF. The assumed noise follows Gaussian distribution/ white noise.

4.1. Scenario-A

In scenario-A, we have considered the cell size of 10x10 m^2, and other than that we have considered various anchor nodes (ANs) 4, 12 and 20. As a validation parameter RMSE provides us information on the variance between the estimated and actual sensor position and it is evaluated through the Monte Carlo runs (i.e., for a number of runs).

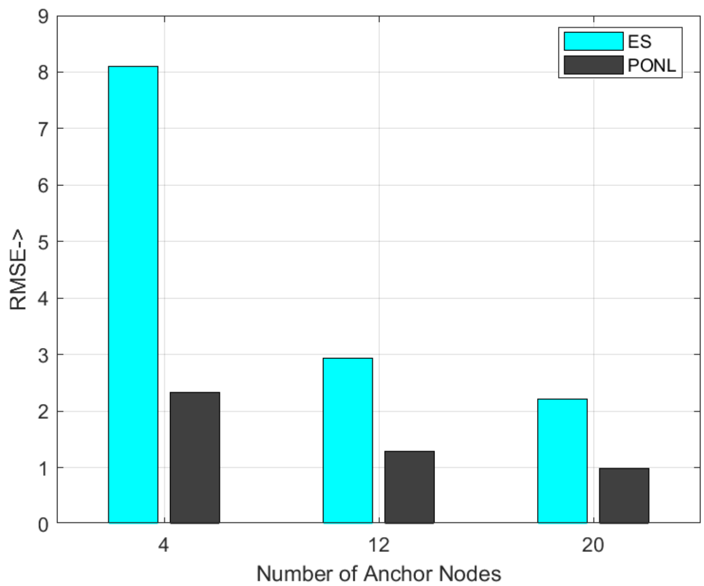

Figure 2. Obtained RMSE w.r.t Anchor Nodes

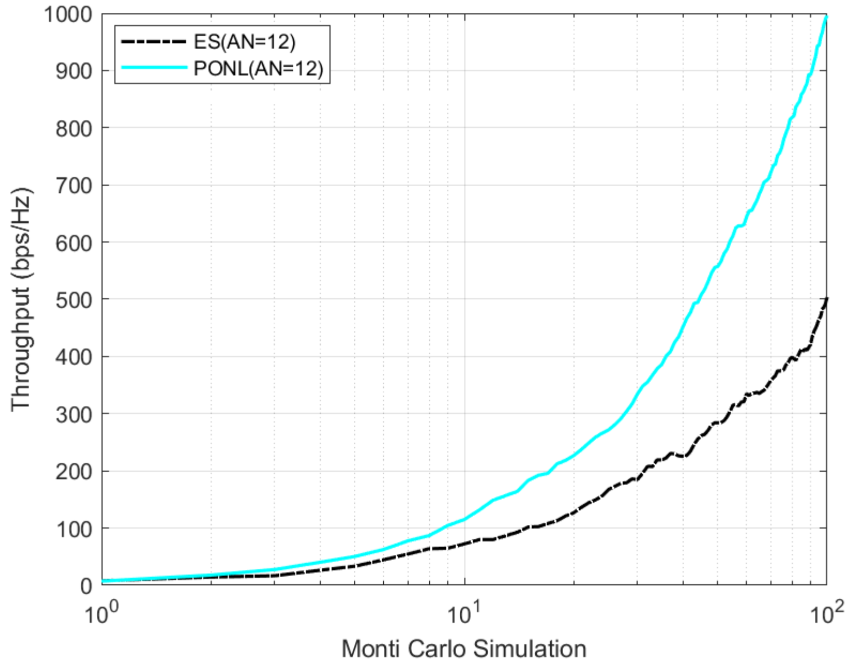

Figure 3. Cumulative throughput with varying Monti Carlo run (Ans=12)

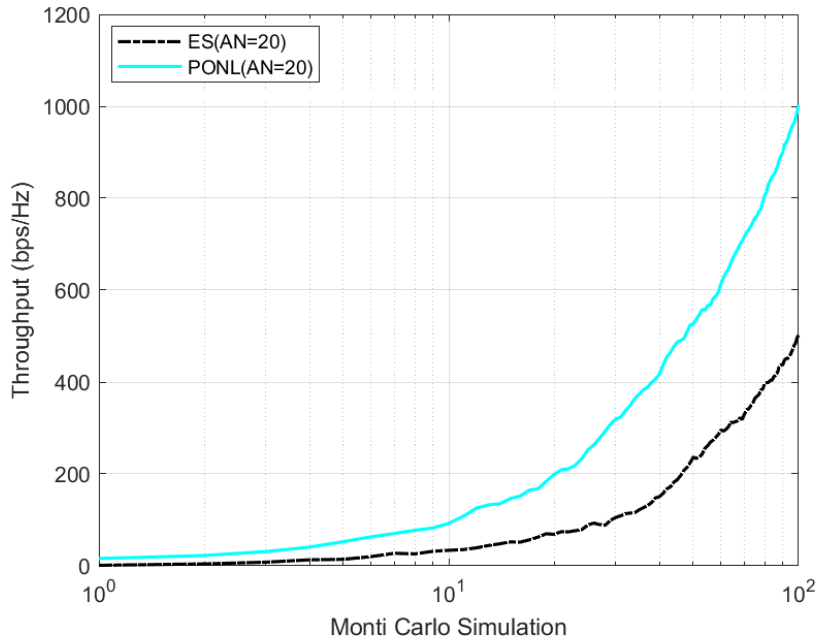

Figure 4. Cumulative throughput with varying Monti Carlo run (Ans=20)

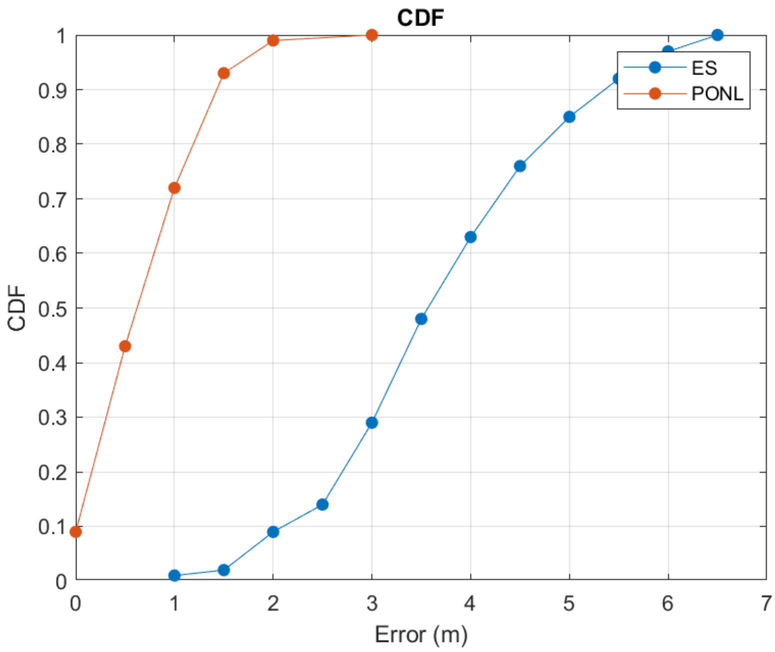

Figure 5. Obtained CDF w.r.t Error (m)

Figure 2 is showing the obtained RMSE with respect to a number of anchor nodes. In each ANs, we have completed the simulation of 100 runs. From figure 2 it is clearly seen that the increasing number of ANs decreases the RMSE value in ES and our proposed system, but PONL approach computed RMSE is very less compared to ES. In 4 ANs, our proposed approach got 2.3m RMSE which is 71% less compared to ES (i.e., RMSE=8.1m). Similarly, when compared at other ANs such as 12 and 20, we observed that our proposed system RMSE is 56% and 55% less compared to the existing system. Further, we also checked with cumulative throughput values that are represented in figures 3 and 4. Having successful node localization, we computed a cumulative throughput, which is increasing as per the Monte Carlo run at ANs 4 and 20. Our proposed model has able to achieve better throughput/successful packet compared to ES. Figure 5 shows the obtained CDF with respect to an error in meter, where our proposed system at 1 meter has got 0.72 increments in CDF, whereas ES has achieved 0.01 CDF value. The 1 CDF value is achieved at 4m using PS and 6.5m using ES.

4.2. Scenario-B

In scenario-B, we have considered the cell size of 20x20 m^2, and rest of the parameters value is same as scenario-A with ANs; 4, 12 and 20.

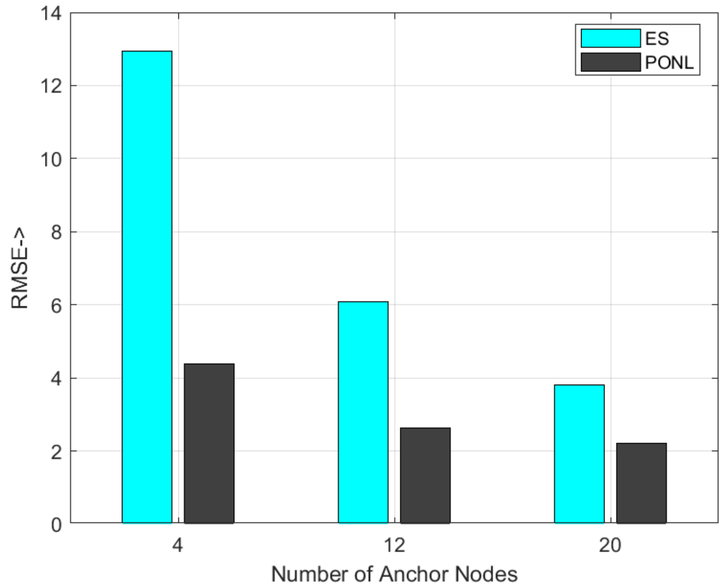

Figure 6. Obtained RMSE w.r.t Anchor Nodes

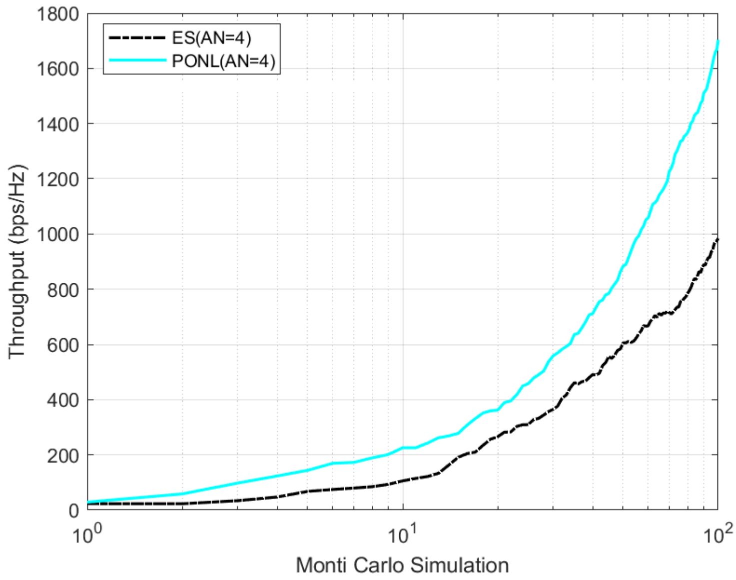

Figure 7. Cumulative throughput with varying Monti Carlo run (Ans=4)

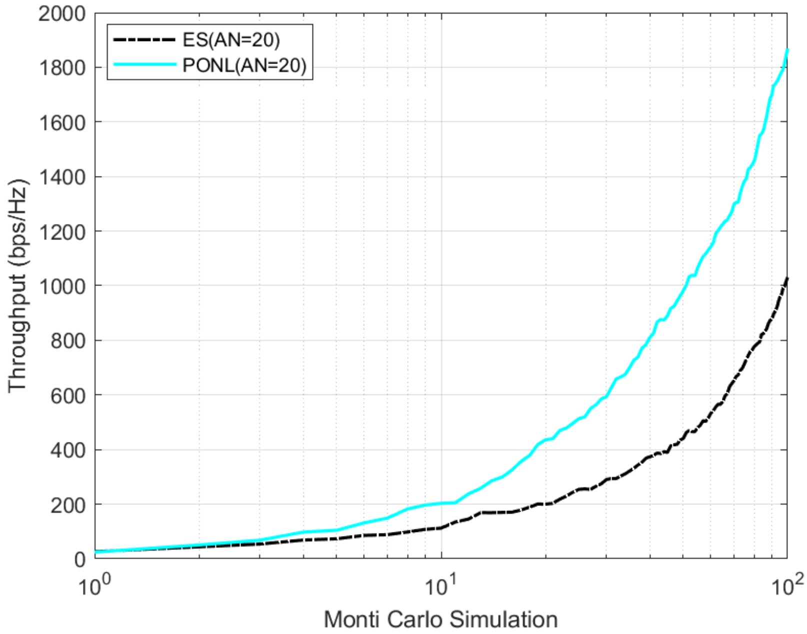

Figure 8. Cumulative throughput with varying Monte Carlo run (Ans=20)

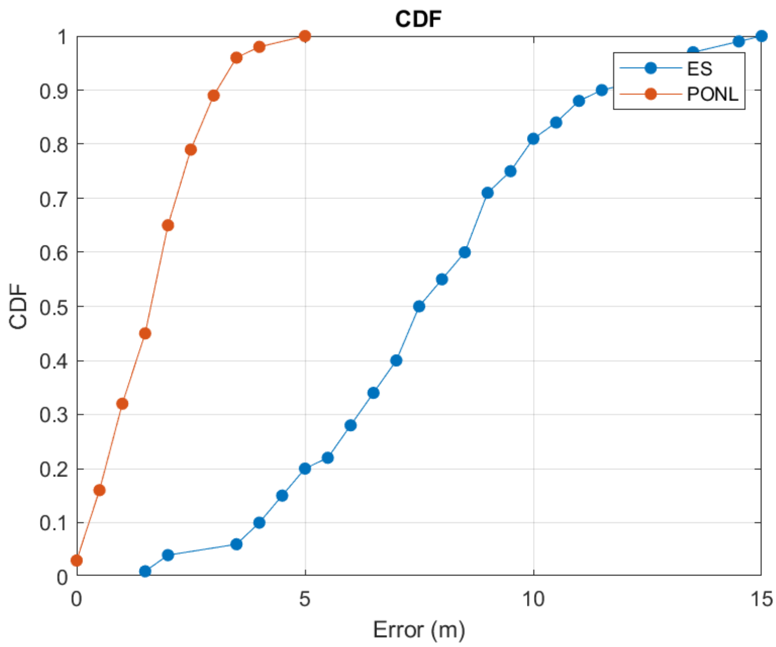

Figure 9. Obtained CDF w.r.t Error (m)

Table 2. Obtained RMSE values with Anchor Nodes at various cell sizes

Cell size	**10x10m^2**		**20x20m^2**	
Methodology	ES	PS	ES	PS
4	8.101673	2.323195	12.93609	4.384795
12	2.939994	1.287258	6.090077	2.624638
20	2.218508	0.992214	3.817957	2.214256

In figure 2 is presenting the obtained RMSE with respect to a number of anchor nodes and for considered ANs we have completed 100 simulation runs. In figure 6 at 4 ANs, our proposed approach got 4.3m RMSE which is 66% less compared to ES with RMSE of 12.9m. Similarly, with considered ANs such as 12 and 20, our proposed system has got 56% and 42% less RMSE compared to an existing system. Therefore, figure 6 shows an increase in number of ANs and decrease RMSE value in ES and our proposed system, but our proposed approach computed RMSE is very less compared to ES. In addition, the cumulative throughput values have shown in figures7 and 8. Our proposed model has got better throughput compared to ES. The obtained CDF with respect to error is shown in figure 9, where our proposed system at 2meters has got 0.65increments in CDF and ES has achieved a 0.04 CDF value.1 CDF value is achieved at 5m using PS and 15 m using ES. The graph shows the significant improvement in CDF values using PONL approach. In addition, more numeric information of the obtained RMSE values with anchor nodes at various cell sizes as shown in table 2.

5. CONCLUSION

WSNs are key components of the cyber-physical systems, the internet of things, etc. and they consisted of a large number of SNs which causes difficulty in node localization. The localization problems formed as ML-estimator is non-convex and its performance was totally dependent on the preliminary given for the iterative solver. Therefore, in this paper; we proposed the improvised RSS-based node-localization algorithm called the PONL approach. The proposed localization approach provides a better and more stable result in considered scenarios. The proposed method was compared through WLS approach incomplete result analysis. The performance is measured using the RMSE, throughput and CDF at two different network scenarios, where our proposed approach had shown significant results as compared to the existing approach.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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