An Improved Group Teaching Optimization based Localization Scheme for WSN

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Abstract

Localization is widely employed in wireless sensor networks (WSN) to detect the present position of the nodes. Generally, WSN comprises numerous sensors, which makes the deployment of GPS in all nodes cost and fails to provide precise localization outcomes in several cases. The manual configuration of the position reference of the sensors is not feasible under dense networks. Therefore, the NL process can be treated as an NP-hard problem and solved by metaheuristic algorithms. In this aspect, this paper presents an improved group teaching optimization algorithm-based NL technique called IGTOA-NL for WSN. The IGTOA technique is derived by integrating the basic concepts of GTOA with the β-hill-climbing technique to improve the overall node localization process. The IGTOA-NL technique can effectually localize the nodes in WSN under varying anchor node count. To showcase the productive outcome of the IGTOA technique, a series of simulations take place under a diverse number of anchors. The resultant values highlighted the proficient NL outcome of the IGTOA technique over the current state of art NL techniques in terms of different measures.

Keywords: Node localization, WSN, Euclidean distance, Metaheuristics, GTOA, Anchor nodes

1. Introduction

Wireless sensor network (WSN) provides several benefits, and they are utilized in several domains as of now [1, 2]. Its localization concept became the focal point of present research and demonstrated its significance in numerous fields such as healthcare, disaster management, etc. It is hard to get the target location of the node without a localization model. As of now, Global Positioning System (GPS) is the well-known localization technique that can precisely find its place [3, 4], yet sensor nodes are restricted by specific features, for example, cost and power utilization; it is challenging to introduce GPS on all nodes, so it isn't utilized in the overall localization model [5, 6]. Node localization dependent on WSN has become an examination area of interest as of late, and an incredible number of researches dependent on it have been contemplated and applied [7].

The concept of node localization can find and track nodes, so the observation is highly significant [8], i.e., information accumulated at BS will be unimportant to the client with no localization data of the nodes in the target area. The localization can be characterized as an assurance of the situation of the obscure sensor nodes called as target nodes utilizing the available place of the nodes called as anchor nodes dependent on the estimation, for example, time distinction of appearance, the season of appearance, point of arrival, triangulation, maximal probability and so on [9-12]. The GPS even doesn't work as expected indoor and submerged. Along these lines, an effective and better option is needed to confine the sensors.

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Different non-GPS-enabled localization models can be utilized [13]. In recent times, node localization in WSNs has been treated as a multi-modal and multi-dimensional advancement issue that can be tackled using metaheuristic algorithms. Numerous metaheuristic models have been utilized to manage the localization issue in WSNs. They endeavor to take care of an enhancement issue by experimentation in which the achievable arrangements are handled, and the closest ideal arrangement is distinguished. Fig. 1 depicts the overview of WSN.

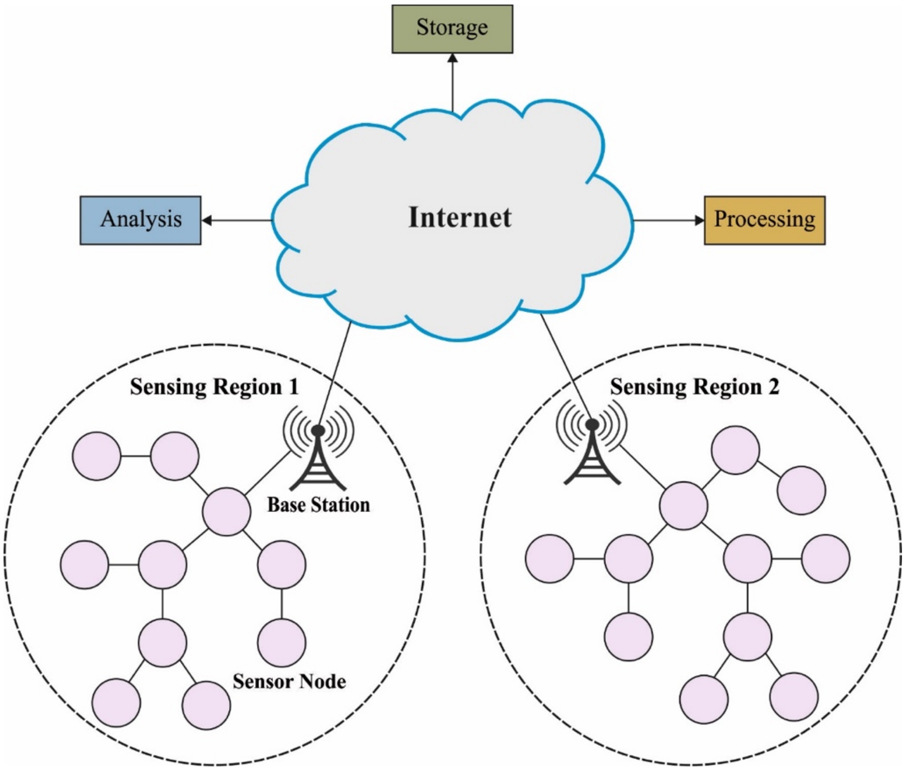

Fig. 1. Example of Clustering Wireless Sensror Networks

Miloud et al. [14] proposed a method for node positioning, i.e., MFOA model. Node is placed by the Euclidean distance, therefore set as an FF in the optimization method. Deploy this method on a huge WSN using thousands of sensors displays better accuracy based on the node positioning. Experimental result shows that MFOA converges fast to the best node location. In [15], a node positioning system is presented according to a current bio-inspired method named SSA model. The presented method is related to a familiar optimization method such as PSO, BOA, FA, and GWO in distinct WSN placements. Hao et al. [16] proposed a node localization method is depending upon a Voronoi diagram and SVM. The fundamental concept of the approach is to split the region to various portions by Voronoi illustration and anchor nodes in the positioning regions. The extent of the first location of the targeted nodes is attained by placing the target nodes in all the regions and later the SVM is employed for optimizing the location of the targeted nodes precisely. The positioning efficiency of the method is examined by the realtime and simulation research.

Lv et al. [17] show that the PSO-BP approach could efficiently evaluate the coordinate of mobile nodes in the indoor 3D region. Estimation accuracy and Convergence speed of the BPNN method enhanced for the PSO are also deliberated. Hybrid GA-PSO-BP algorithms are later introduced. It enhances the BPNN predictive accuracy by enhancing variables like number of neurons for all the hidden layers, the error target, and learning rate of the BPNN. Sekhar et al. [18] design an efficient Meta heuristic based GTOANL method for WSN. The aim is to define the location of the unknown node through anchor node in the WSN with minimal positioning error and maximal positioning efficiency. The method is inspired by the group teaching method also it is employed in the optimization procedure without losing generality. Zhang et al. [19] presented a BASL method for WSN node positioning. In the surveillance that the short routes among 2 nodes having additional nodes nearer the difficulty edge is severely caused by the hole,

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the presented BASL method initially detect edge region node nearer to the hole by examining the network connections.

This paper presents an improved group teaching optimization algorithm based NL technique, called IGTOA-NL for WSN. The IGTOA technique is derived by integrating the basic concepts of GTOA with β-hill climbing technique to improve the overall node localization process. The IGTOA-NL technique has the ability to effectually localize the nodes in WSN under varying anchor node count. In order to showcase the effectual outcome of the IGTOA technique, a series of simulations take place under diverse number of anchors.

2. The Proposed NL Technique

The proposed method is inspired by the group teaching approach. The major goal is to improve the knowledge of the whole class. Based on the differences among learners, it is slightly difficult for group teaching to be performed. For adjusting group teaching, it must be suitable to utilize an optimization technique, initially, it considers as fitness value, decision variable, and population i.e., equivalent to the learner, the subjects which give skill to the learner respectively. The 4 phases are included in the GTOA such as ability grouping, teacher allocation, student, and teacher levels. Without losing generalization, the acquaintance of whole classes is deliberated to be in standard distribution [20, 21] that is represented as follows

$$f(x) = \frac{1}{\sqrt{2\pi\delta}} e^{\frac{-(x-u)^2}{2\delta^2}} \quad (1)$$

Whereas x represents the value in which standard distribution function is required, u indicates the average acquaintance of the whole classes and δ represents the SD that indicates the variance of acquaintance among learners. The maximal value of δ indicates large variances of acquaintance among learners. It represents a learner learns acquaintance from the teacher, which matches the defined 2nd rule. The teachers create different teaching approaches for outstanding and average groups in the proposed method.

Teacher level I: Based on the strong CAK, the teachers uplevel on improving the acquaintance of excellent groups in the proposed GTOA. Precisely, the teachers try to improve average acquaintance of the whole class [21]. Furthermore, the variance of CAK among learners should be considered. Hence, the learners of outstanding groups may attain knowledge by

$$\mathrm{x}_{\mathrm{teacher},i}^{t+1} = \mathrm{x}_i^t + a \times \left(\mathrm{T}^t - F \times (b \times \mathrm{M}^t + c \times \mathrm{x}_i^t)\right) \quad (2)$$

$$\mathrm{M}^t = \frac{1}{N}\sum_{i=1}^{N} \mathrm{x}_i^t \quad (3)$$

$$b + c = 1 \quad (4)$$

Whereas t represents current iteration value, N signifies number of students, x_i^t specifies acquaintance of learner i at iteration t, $\mathrm{x}_{\mathrm{teacher},i}^{t+1}$ indicate acquaintance of learners i with iteration t in learning from teacher, a, b, and c represents arbitrary number in the interval of zero and one. The values of F can be 1 or 2 as generated.

Teacher level II: Assume lower CAK, a teacher give further focuses to average group through excellent groups based on the following order that incline to improve the acquaintance of learner from the perceptions of a person. Therefore, the learners of average group may attain acquaintance by

$$\mathrm{x}_{\mathrm{teacher},i}^{t+1} = \mathrm{x}_i^t + 2 \times d \times (\mathrm{T}^t - \mathrm{x}_i^t) \quad (5)$$

Whereas d represents random value in the interval of zero and one.

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Furthermore, 1 learner could not gain acquaintance by the teacher phase, i.e., consider as (E.g. small issue)

$$\mathrm{x}_{\text{teacher},i}^{t+1} = \begin{cases} \mathrm{x}_{\text{teacher},i}^{t+1}, f\left(\mathrm{x}_{\text{teacher},i}^{t+1}\right) < f(\mathrm{x}_i^t) \\ \mathrm{x}_i^t, f\left(\mathrm{x}_{\text{teacher},i}^{t+1}\right) \geq f(\mathrm{x}_i^t) \end{cases} \quad (6)$$

The student phase involves level I and level II i.e., equal to the specified 3rd rules. In extra periods, a learner may get acquaintance via two distinct ways: self-educated and interact with another student, which can be determined as follows

$$\mathrm{x}_{\text{student},i}^{t+1} = \begin{cases} \mathrm{x}_{\text{teacher},i}^{t+1} + e \times \left(\mathrm{x}_{\text{teacher},1}^{t+1} - \mathrm{x}_{\text{teacher},j}^{t+1}\right) + g \times \left(\mathrm{x}_{\text{teacher},i}^{t+1} - \mathrm{x}_i^t\right), f\left(\mathrm{x}_{\text{teacher},i}^{t+1}\right) < f\left(\mathrm{x}_{\text{teacher},j}^{t+1}\right) \\ \mathrm{x}_{\text{teacher},i}^{t+1} - e \times \left(\mathrm{x}_{\text{teacher},i}^{t+1} - \mathrm{x}_{\text{teacher}.j}^{t+1}\right) + g \times \left(\mathrm{x}_{\text{teacher},i}^{t+1} - \mathrm{x}_i^t\right), f\left(\mathrm{x}_{\text{teacher},i}^{t+1}\right) \geq f\left(\mathrm{x}_{\text{teacher}:j}^{t+1}\right) \end{cases} \quad (7)$$

Whereas e & g denote two random numbers in the range of zero and one, $\mathrm{x}_{\text{student},i}^{t+1}$ indicates acquaintance of student i with iteration t learn from learners phase and $\mathrm{x}_{\text{student},j}^{t+1}$ indicate acquaintance of students j with iteration t learn from the teacher. As a student j $(j \in \{1, 2, \dots, i-1, i+1, \dots, N\})$, randomly selected. In Eq. (7), the second and third items in right indicate learning from other learners and self-educated, respectively.

Based on the defined 4th rules, making a good teacher definition method is highly required to enhance the acquaintance of learners. In GWO, the first 3 optimal results obtained yet are kept, i.e., used to hunt the wolf. Inspired by hunting action in GWO, the teacher establishment in the proposed method could be determined as follows

$$\mathrm{T}^t = \begin{cases} x_{first}^t, & f\left(x_{first}^t\right) \leq f\left(\dfrac{x_{first}^t + x_{second}^t + x_{first}^t}{3}\right) \\ \dfrac{x_{first}^t + x_{second}^t + x_{first}^t}{3}, & f\left(x_{first}^t\right) > f\left(\dfrac{x_{first}^t + x_{second}^t + x_{first}^t}{3}\right) \end{cases} \quad (8)$$

Whereas x^tfirst, $\mathrm{x}_{\text{second}}^t$ & $\mathrm{x}_{\text{third}}^t$ denotes 1st, second, and third optimal learners, respectively. In order to improve the proposed GTOA, outstanding and average groups share the related teacher.

Since the iterative processes continue, the GTOA is related to another Meta heuristic method. Only, it focuses on the procedure of converging to the global optimal and ignores the method of evading the local optimal. While fall to a local optimal, GTOA search could not be continued. This is very fatal while resolving real-world problems. For allowing the methods for escaping from local optimal, the BHC method is presented [22] in the IGTOA. The BHC method could iteratively improve a sequence of arbitrarily estimated solutions. In BHC method, a stochastic approach named the β-operator is used for establishing fine balances among exploitation and exploration through a global search. The IGTOA assists in determining the coordinate points (x, y) of the target node which reduces the localization error. The objective function of NL issue can be determined as the mean square distance, as shown below.

$$f(x, y) = \frac{1}{N}\left(\sum_{i=1}^{N} \sqrt{(x - x_i)^2 + (y - y_i)^2} - \hat{d}\right)^2 \quad (9)$$

where $N \geq 3$ denotes the anchor node count in the communication range. The LE is determined as the mean square of the distance between the estimated node coordinates (X_i, Y_i) and the actual node coordinates (x_i, y_i) as provided below:

$$E_1 = \frac{1}{N_1}\sum_{i=1}^{N} \sqrt{(x_i - X_i)^2 + (y_i - Y_i)^2} \quad (10)$$

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3. Performance Validation

A brief results analysis of the IGTOA-NL technique is performed in this section. Table 1 and Fig. 2 examine the number of localized nodes (NLN) offered by the IGTOA-NL technique with existing techniques under diverse anchors. The results demonstrated the betterment of the IGTOA-NL technique with maximum NLN. For instance, with 10 anchors, the IGTOA-NL technique has offered a higher NLN of 134 whereas the GTOANL, KHANL, PSONL, CSONL, and, GWONL techniques have obtained a lower NLN of 129, 114, 100, 111, and 100 respectively. Also, with 20 anchors, the IGTOA-NL approach has obtainable a superior NLN of 156 whereas the GTOANL, KHANL, PSONL, CSONL, and, GWONL manner have reached a lesser NLN of 141, 128, 103, 117, and 112 correspondingly.

Table 1 Comparative analysis of IGTOA-NL model interms of NLN

Anchor Node count	IGTOA-NL	GTOANL	KHANL	PSONL	CSONL	GWONL
10	134	129	114	100	111	100
20	156	141	128	103	117	112
30	172	163	142	110	135	116
40	179	168	153	117	140	130
50	192	188	167	129	151	137

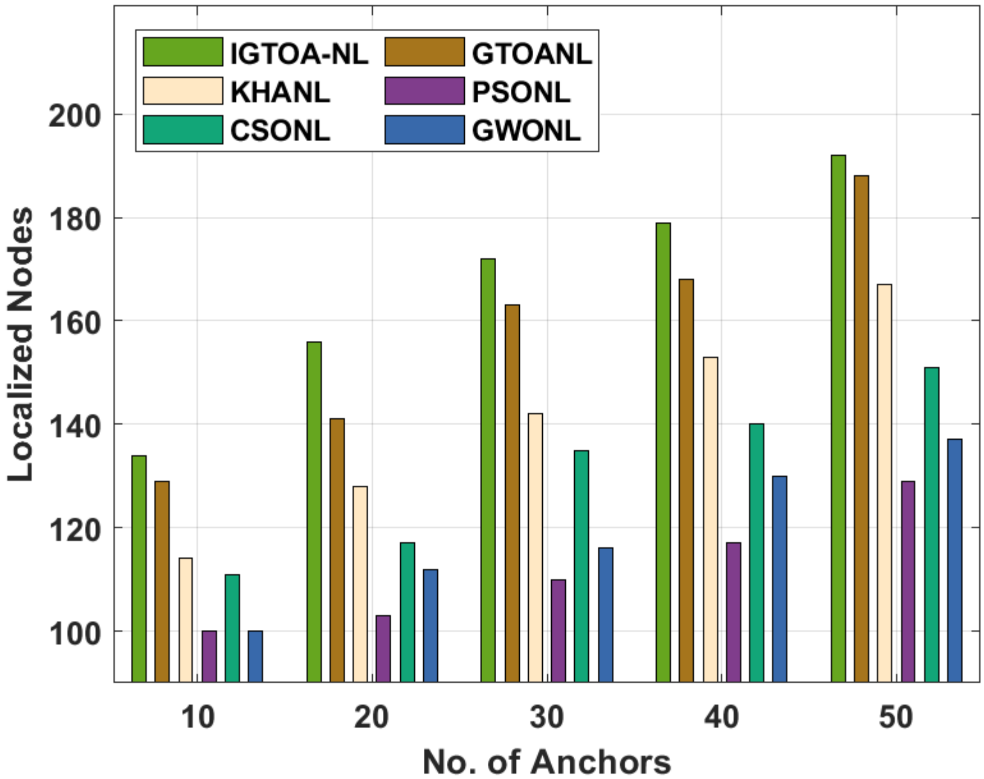

Fig. 2. NLN analysis of IGTOA-NL model with different anchors

Besides, with 30 anchors, the IGTOA-NL algorithm has offered an increased NLN of 172 whereas the GTOANL, KHANL, PSONL, CSONL, and, GWONL techniques have obtained a lower NLN of 163, 142, 110, 135, and 116 correspondingly. Moreover, with 40 anchors, the IGTOA-NL approach has offered a higher NLN of 179 whereas the GTOANL, KHANL, PSONL, CSONL, and, GWONL techniques have obtained a lower NLN of 168, 153, 117, 140, and 130 respectively. Simultaneously, with

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50 anchors, the IGTOA-NL technique has existed a superior NLN of 192 whereas the GTOANL, KHANL, PSONL, CSONL, and, GWONL methodologies have obtained a decreased NLN of 188, 167, 129, 151, and 137 correspondingly.

Table 2 and Fig. 3 inspect the localization error(LE) given by the IGTOA-NL technique with existing techniques under different anchors. The results established the improvement of the IGTOA-NL technique with least LE. For instance, with 10 anchors, the IGTOA-NL technique has provided a reduced LE of 0.33 whereas the GTOANL, KHANL, PSONL, CSONL, and, GWONL approaches have resulted to a raised LE of 0.36, 0.44, 0.72, 0.54, and 0.70 respectively. Likewise, with 20 anchor nodes, the IGTOA-NL technique has provided a lower LE of 0.22 while the GTOANL, KHANL, PSONL, CSONL, and, GWONL manners have gained an enhanced LE of 0.30, 0.40, 0.71, 0.49, and 0.68 correspondingly.

Table 2 Comparative analysis of IGTOA-NL model interms of LE

Anchor Node count	IGTOA-NL	GTOANL	KHANL	PSONL	CSONL	GWONL
10	0.33	0.36	0.44	0.72	0.54	0.70
20	0.22	0.30	0.40	0.71	0.49	0.68
30	0.14	0.24	0.38	0.56	0.47	0.54
40	0.11	0.20	0.35	0.53	0.42	0.58
50	0.04	0.16	0.30	0.50	0.39	0.57

Furthermore, with 30 anchors, the IGTOA-NL technique has provided a reduced LE of 0.14 whereas the GTOANL, KHANL, PSONL, CSONL, and, GWONL methods have obtained an increased LE of 0.24, 0.38, 0.56, 0.47, and 0.54 correspondingly. Simultaneously, with 40 anchors, the IGTOA-NL technique has provided a reduced LE of 0.11 whereas the GTOANL, KHANL, PSONL, CSONL, and, GWONL techniques have gained a higher LE of 0.20, 0.35, 0.53, 0.42, and 0.58 respectively. Concurrently, with 50 anchors, the IGTOA-NL algorithm has provided a reduced LE of 0.04 whereas the GTOANL, KHANL, PSONL, CSONL, and, GWONL methods have achieved a maximal LE of 0.16, 0.30, 0.50, 0.39, and 0.57 respectively.

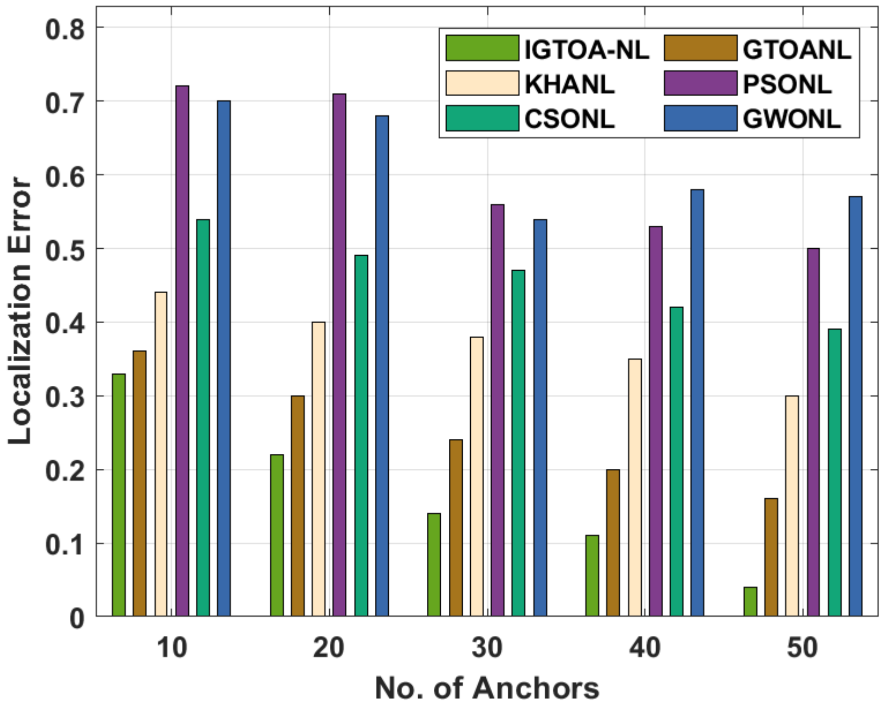

Fig. 3. LE analysis of IGTOA-NL model with different anchors

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The localization rate (LR) obtainable by the IGTOA-NL manner technique with recent algorithms under diverse anchors in Fig. 4 as well as Table 3. The results outperformed the betterment of the IGTOA-NL method with maximal LR. For sample, with 10 anchors, the IGTOA-NL algorithm has offered an increased LR of 0.67 whereas the GTOANL, KHANL, PSONL, CSONL, and, GWONL techniques have obtained a lower LR of 0.645, 0.570, 0.500, 0.555, and 0.500 correspondingly. Likewise, with 20 anchors, the IGTOA-NL technique has offered a higher LR of 0.78 whereas the GTOANL, KHANL, PSONL, CSONL, and, GWONL techniques have obtained a reduced LR of 0.705, 0.640, 0.515, 0.585, and 0.560 respectively. Followed by, with 30 anchors, the IGTOA-NL approach has obtainable a superior LR of 0.86 whereas the GTOANL, KHANL, PSONL, CSONL, and, GWONL techniques have gained a minimal LR of 0.815, 0.710, 0.550, 0.675, and 0.580 correspondingly.

Table 3 Comparative analysis of IGTOA-NL model interms of LR

Anchor node count	IGTOA-NL	GTOANL	KHANL	PSONL	CSONL	GWONL
10	0.67	0.645	0.570	0.500	0.555	0.500
20	0.78	0.705	0.640	0.515	0.585	0.560
30	0.86	0.815	0.710	0.550	0.675	0.580
40	0.90	0.840	0.765	0.585	0.700	0.650
50	0.96	0.940	0.835	0.645	0.755	0.685

Along with that, with 40 anchors, the IGTOA-NL methodology has offered a higher LR of 0.90 whereas the GTOANL, KHANL, PSONL, CSONL, and, GWONL techniques have obtained a lower LR of 0.840, 0.765, 0.585, 0.700, and 0.650 respectively. Eventually, with 50 anchors, the IGTOA-NL manner has accessible a higher LR of 0.96 whereas the GTOANL, KHANL, PSONL, CSONL, and, GWONL algorithms have reached a lesser LR of 0.940, 0.835, 0.645, 0.755, and 0.685 correspondingly.

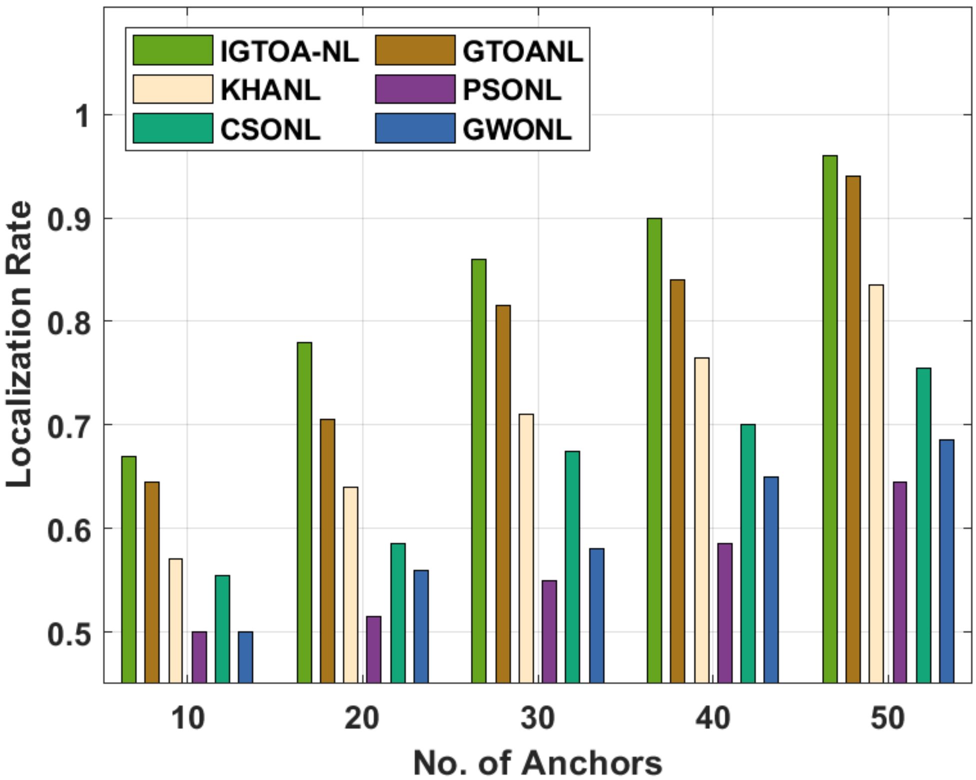

Fig. 4. LR analysis of IGTOA-NL model with different anchors

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4. Conclusion

This paper has presented an effective IGTOA-NL approach determine the location of sensors in the network. The IGTOA technique is derived by integrating the basic concepts of GTOA with β-hill climbing technique to improve the overall node localization process. The IGTOA-NL technique has the ability to effectually localize the nodes in WSN under varying anchor node count. In order to showcase the effectual outcome of the IGTOA technique, a series of simulations take place under diverse number of anchors. The resultant values highlighted the proficient NL outcome of the IGTOA technique over the recent state of art NL techniques interms of different measures.

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