Node Localization in Wireless Sensor Networks using a Hyper-Heuristic DEEC-Gaussian Gradient Distance Algorithm

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## Abstract

In the recent age of technological advancements, wireless sensor networks are an important application for smart modernized environments. In WSNs, node localization has been an issue for over a decade in the research community. One of the goals of localization in a wireless sensor network is to localize sensor nodes in a two-dimensional plane. Localization in wireless sensor networks helps to supply information to aid decision making from the aggregated data that are sent from packets to base stations. Internet of Things with the use of Global Positioning Systems for tracking sensor zones is not a cost-effective means of solution. In the extant literature, there have been a variety of algorithms to identify unknown sensor locations in wireless sensor networks. This research paper aims to address the problem of determining the location of the sensor node at the base station with minimum localization error when the data between the nodes is transmitted wirelessly. To detect the location of an unknown sensor node packets sent to the destinations, the total number of anchor nodes, location error and distance estimation error were considered. The DEEC-Gauss Gradient Distance Algorithm has a lower localization error than the Weighted Centroid Localizations algorithm, Compensation Coefficient algorithm, DV-Hop algorithm, Weighted Hyperbolic algorithm and Weighted Centroid algorithm for the same ratio of anchor nodes and WSN configuration. According to the study's findings, the DGGDEA has an average localization error of 11% for anchor nodes (20-80), and an average localization error of 11.3% for anchor nodes 200-450. Hence, the DEEC-Gaussian Gradient Distance Elimination Algorithm (DGGDEA) showed higher accuracy with comparison to the modern-day approaches.

## Introduction

In recent times node positioning is a new form of technology that has been discussed in the literature on node localization. A sound node localization scheme is central to the accuracy and effectiveness of wireless sensor networks (WSNs) [1-3]. Wireless Sensor Network is a collection of many sensor nodes shared over a geographical area for monitoring the area of interest. In many applications of WSN, the data is meaningless without the accurate location of sensor nodes [4]. While considering the challenges of WSNs and their associated applications, base stations receiving processed data from an unknown source is worthless [5]. This will make the data not useful, therefore, location estimation of the data source is an important area in WSNs. Localization is allied to the fast-paced development in the field of IoT (Internet of Things) [5], with the location of a node determined in a variety of methods [6]. WSNs comprise many rounds, small nodes that are constrained by the limited power and wireless bandwidth. This network has a broad range of applications such as industrial automation usage, area monitoring applications and measuring phenomena. Node localization estimation is of great importance for the Gaussian Elimination Method [7]. WSNs consist of several sensor nodes that are used in transmitting both small and large-scale packets. The growth of electronic technology in WSNs has seen the performance of small and high size sensor nodes applied to system controls, tracking, environmental monitoring, load shedding controls and security applications [8].

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**Figure 1. Node localization estimation processes ([65])**

In this research works the proposed DEEC-Gaussian Gradient Distance Algorithm (DGGDEA) is used to determine the location of a sensor node. The results of this algorithm will be compared to other state of the art algorithms.

Figure 2 presents the novel DGGDEAmethod for node localization for WSNwhich is discussed in the Section of this paper.



**Figure 2. Hyper-heuristic DGGDEA for Node Localization**

Figure 2 shows the combining of the ***Distributed Energy Efficiency Clustering (DEEC) algorithm; the Gaussian Elimination (GAUSS) algorithm and Gradient Distance Algorithm (GDA)***. The novel DGGDEA represents the hyper-heuristic solution for node localization having 20 anchor node and 200 to 450 sensor nodes [78].

## 4. The Study Methodologies

In this work, we contemplate a new approach for node localization using DGGDEA.

We assume that are the sensor nodes are deployed randomly to maintain their static position after they are deployed.

1. Individual sensor node clusters heads of 20 will have a unique identity to be able to spot them from others deployed.
2. We will also assume that the nodes have the same initial energy and power source which cannot be changed but at a different level of significance.
3. We will also assume that the nodes are linked bidirectionally. The parameters used for DEEC-Gauss are P*opt*=0.1 (this is the parameter for period mode). The nodes are randomly deployed from a base station (BS). All nodes are equal with limited energy 0.5J.
4. The probability of error (PoE) is being computed by dividing the localization error with a total number of sensor nodes per round ranging from 200 sensor nodes to 450 nodes calculation is used.

**4.1 Proposed DEEC-Gauss Gradient Distance Algorithm**

The node localization estimation gradient error model helps to dissipate energy to acknowledge data and dispatch the packets sent to the base station within the network size of 100 by 100, we then assume the 10% of the total sensor nodes for the anchor nodes which is tagged to be the cluster heads. The hop-count is set to zero where the *(Xi, Yi)* with the anchor nodes identity *(i)* and $Hop\_{ij}$ is assumed to be the hop count value that is dispatched to the base stations. The proposed DGGDEA as presented in Figure 3 seeks to carry out the proposed solution as follows using the pseudocode process below:

**Step 1**. Set the network model criteria.

**Step 2.** homogeneous energy for all sensor nodes [49]

 using $E\_{Total}= \sum\_{i=1}^{n}E\_{0}\left(1+a\_{i}\right)= E\_{0}\left(\left(n+\sum\_{i=1}^{n}a\_{i}\right)\right)$ (1)

**Step 3.** Start iteration the computation of pi for heterogeneous nodes [66]

 using $p\_{i}=\frac{p\_{opt}N(1+a)E\_{i}(r)}{(N+\sum\_{i=1}^{N}a\_{i})\overbar{E}(r)} $ (2)

 a. Calculate the energy that is needed by the transmit amplifier [67]

$E\_{TX}\left(l,d\right)=\left\{ \begin{matrix}lE\_{elec}+lε\_{f\_{s}}d^{2},&d<d\_{0}\\lE\_{elec}+lε\_{mp}d^{4},&d \geq d\_{0}\end{matrix}\right\}$ (3)

 And the computation of energy needed by the receiver using [67]

 $E\_{RX}\left(l\right)$ using $E\_{RX}\left(l\right)=E\_{elec}$ (4)

**Step 4**. We then calculate [67] ($AvgHopSize\_{i })$ (5)

**Step 5**. The average hop size for the distance between the sensor nodes are

computed with equation 6 [67]

$ AvgHopSize\_{i}=\frac{\sum\_{j=1 j\ne i}^{m}\sqrt{(X\_{J-}X\_{I})^{2}+(y\_{J}-y\_{i})^{2}}}{\sum\_{j=1 j\ne i}^{m}Hopij}$ (6)

**Step 6**. We computed the average size of the Hop, where *u* and *I* are variable and *j* is constant [68] $ d\_{iu}= AvgHopSize\_{j} × hop\_{iu}$ (7)

**Step 7**. The weighted centroid method for the sensor localization as m is determined to be the anchors' nodes for the total sum $\left(X\_{u,}Xy\_{u }\right) , m is the assumed to be the total number of anchor nodes$

$w\_{i}= \frac{1}{mHop\_{ui}}is assumed to be the weighted factor for the i$ and the sensor that are unknown are computed from [69]

 $ X\_{u}=\frac{\sum\_{i=1}^{m}w\_{ix\_{i}}}{\sum\_{i=1}^{m}w\_{i}}$,$, y\_{u}=\frac{\sum\_{i=1}^{m}w\_{iy\_{i}}}{\sum\_{i=1}^{m}w\_{i}}$ (8)

 **Step 8**. The factor of *Wi* for the remote sensor for unknown sensor nodes are localized [70] $w\_{i}= \frac{\sum\_{i=1}^{m}Hop\_{ui}}{mHop\_{ui}}$ (9)

 **Step 9.** We assume the number of anchor nodes to be cluster head as *q*; matrix *A* represents the energy consumption of every node chosen as cluster head and *q* the number of cluster heads. *aij* Denotes the energy consumed by a cluster head *i* which is taken to be a normal nodeif cluster head *j* is its cluster head. Additionally, *bi* denotes the residual energy of cluster head *i*, while *xi* expresses the times that cluster head *i* can become a cluster head [71, 72]. In this way, matrices *B* and *X* are formed, so that *A*·*X* = *B*, as shown in Equation (10) below:

 $\left[\begin{matrix}\begin{matrix}a\_{11}&a\_{12}&a\_{13}\\a\_{21}&a\_{22}&a\_{23}\\a\_{31}&a\_{32}&a\_{33}\end{matrix}&\cdots &\begin{matrix}a\_{1k}\\a\_{2k}\\a\_{3k}\end{matrix}\\\vdots &\ddots &\vdots \\\begin{matrix}a\_{k1}&a\_{k2}&a\_{k3}\end{matrix}&\cdots &a\_{kk}\end{matrix}\right]\left[\begin{matrix}x\_{1}\\x\_{2}\\\begin{matrix}x\_{3}\\\vdots \\x\_{k}\end{matrix}\end{matrix}\right]=\left[\begin{matrix}b\_{1}\\b\_{2}\\\begin{matrix}b\_{3}\\\vdots \\b\_{k}\end{matrix}\end{matrix}\right] $ (10)

The snippet of code is used to calculate the number of rounds within the network and to obtain the optimal number of clusters [ 72 and 73].

|  |
| --- |
| 1. For (k=1; k<m+1; k++)
2. For I\_max:= argmax(i=k…m, abs(A[i,k]));
3. If (A[i\_max,k] = 0)
4. For Error “Matrix is singular!”;
5. Swap rows (k,i\_max);
6. *{Calculate snippet code for packet sent to base station*
7. *Calculate snippet code for the tenth node dead}*
8. For (i=k+1; i<m+1; i++)
9. For (j=k+1; k<n+1; j++)
10. A[i,j]:= A[i,j] – A[k,j] x (A[i,k]/A[k,k]);
11. A[i,k]:=0;
12. end
 |

Step 11. The localization error is computed and the estimated position of the various unknown nodes are estimated [67,74]

 $\frac{1}{n×r}\sum\_{i=1}^{n}\frac{Guass localization error=}{\sqrt{(X\_{ai}- X\_{ui})^{2}+( y\_{ai}-y\_{ui}) ^{2}}}$ (11)

The energy homogeneous is set to 0.5J initiated for every point of the clustering sensors in the entire network connection. The proposed approach with the use of the DEEC-Gaussian Gradient Estimation algorithm provides an adaptive node localization efficient use of energy resources of sensor nodes. The node probability error was determined for 250-450 for benchmarking the DEEC-Gauss to the state-of-the-art algorithm. However, the probability of error (PoE) was computed with the localization error divided by the number of nodes for each full operation during the simulation.

The area of interest is set to m × m meters where m = 100. The base station is present at the centre of the field of the location. The system configuration was Intel Core i7-8650U CPU @1.90GHz, 2.11 GHZ, installed memory (RAM) 8,00GB (7,85 GB usable). System type 64-bit operating system, the x64-based processor running Windows 10. The network consists of n = 200 to 450 nodes just as shown explicitly enough which is summarized.

## 5. Results and Discussion

In this section, we present the simulation results of the proposed novel DGGDEA and the comparison analysis of performance with the state-of-the-art clustering algorithms such as weighted centroid localizations (WCL), DV-Hop, Compensation Coefficient (CC), Weighted Hyperbolic (WH) and Weighted Centroid (WC) approaches. The simulation was carried out in MATLAB 2021 environment, with 20 anchor nodes and varieties of sensor nodes between 200-450 with the random deployment of the nodes and gradient distance were applied to the novel DGGDEA which was run more than 300 times consecutively for the best result to be obtained.

Figures presents the average localization error for sensor nodes between 200 and 450. The results presented show that the DGGDEA outclasses the other algorithms due to the optimization of localized sensor nodes for identifying the most preferred position of sensors.

**Figure 3. The localization error vs the number of anchor nodes**

The results of the localization error vs the number of total sensor nodes between 200 to 450 sensor nodes were presented in Figure 5 consequently, the proposed DGGDEA outperformed all other state of the art algorithms.

**Figure 4. The localization error vs the number of sensor nodes**

Figure 6 shows the true localized position of the 20 anchor nodes. The localized node is represented with the black small circles and the mobile sensor nodes are represented with the small open red circle while the cross symbols represent the mobile true locations at 0.5J energy for sensor nodes between 200 and 450.

Table 1 shows the results of the localization error vs the number of total sensor nodes ranging from 200 to 450 sensor nodes.

**Table 4. The Localization Error vs the Number of Total Sensor Nodes**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Total No. of Nodes | Proposed (DGGDEA) | WCL | CC | WH | DV-Hop |
| 200 | 11.0% | 37.2% | 40.6% | 42.1% | 46.2% |
| 250 | 11.8% | 33.6% | 40.2% | 41.1% | 42.6% |
| 300 | 9.2% | 29.7% | 36.8% | 39.6% | 37.2% |
| 350 | 10.0% | 31.4% | 35.8% | 37.1% | 39.2% |
| 400 | 15.5% | 30.6% | 34.4% | 35.6% | 37.7% |
| 450 | 10.0% | 29.4% | 33.7% | 34.1% | 36.9% |
| Mean | 11.3% | 32.0% | 37.0% | 38.3% | 40.0% |

Table 4 shows that the proposed algorithm outperformed all other algorithms for the total number of nodes from 200 to 450, while the second-best algorithm is WCL followed by CC algorithm, and the worst algorithm is DV-Hop.

The proposed solution has now been able to address node localization and energy efficiency optimising to minimize load shedding error. The proposed solution addresses the first, fourth and sixth Africa's Union's Agenda Goals and priority area 2063 while on the other hand, it addresses the United Nations sustainable development goal seven (SDG 7) and nine (SDG 9) Goals as stipulated, in the table below:

## 6. Conclusions

The novel hyper-heuristic algorithm utilized three meta-heuristic algorithms, namely, Distributed Energy Efficiency Clustering algorithm (DEEC), Gaussian Elimination Algorithm (GAUSS) and Gradient Distance Elimination Algorithms to develop the hyper-heuristic optimization model for node localization in WSNs. The implementation of the novel hyper-heuristic DGGDEA for node localization showed the best performance in comparison to other state-of-the-art algorithms. During the simulation analysis using 20 to 80 sensor nodes and 200 to 450 sensor nodes with 20 static anchors the optimization node localization error and the probability of error (PoE) were determined, with the mean estimation for the locations of sensor nodes in WSNs. The comparative analysis was completed with the state-of-the-art clustering algorithms to determine the performance evaluations using the number of data packets sent to the base station as well as reduction of node localization error and the probability of error. It is evidenced that the performance of the range-free approach of the novel DGGDEA in contrast to traditional state-of-the-art algorithms such as WC, WCL, CC, WH and DV-Hop in the application showed a reduction in the node localisation error for 20 to 80 sensor nodes and a reduction in node localisation error for 200 to 450 sensor nodes. Future work will focus on the performance of the DEEC-Gauss Gradient Elimination algorithm on larger sensor networks.