OPEN ACCESS
The Journal of Engineering and Exact Sciences – jCEC, Vol. 09 N. 04 (2023)
journal homepage: https://periodicos.ufv.br/jcec
eISSN: 2527-1075
ISSN: 2446-9416

Accurate range-based distributed localization of wireless sensor nodes using grey wolf optimizer

Article Info:
Article history: Received 2023-05-05 / Accepted 2023-06-08 / Available online 2023-06-08
doi: 10.18540/jcecvl9iss4pp15920-01e

Nabil Abdelkader Nouri
ORCID: https://orcid.org/0000-0003-1439-0209
Telecommunication and Smart Systems Laboratory, Djelfa university of Algeria, Djelfa, 17000, Algeria
E-mail: nabil.nouri@gmail.com
Abdenacer Naouri
ORCID: https://orcid.org/0000-0002-9327-3643
School of Computer and Communication Engineering, University of Science and Technology Beijing, Beijing, China
E-mail: nacer.naouri@gmail.com
Sahraoui Dhelim
ORCID: https://orcid.org/0000-0002-3620-1395
School of Computer Science University College Dublin
Dublin 4, Ireland
E-mail: sahraoui.dhelim@ucd.ie

Abstract
Various ranging techniques are frequently employed in wireless sensor networks (WSNs) to determine the distance between a node and its neighboring anchor nodes. The distance measurement, as mentioned earlier is subsequently employed to estimate the location of the node whose location is unknown. The present paper presents an Accurate Localization Scheme that utilizes Grey Wolf Optimization (GWO) and is based on the Radio Signal Strength (RSS) ranging technique. The efficiency of our technique has been proved through extensive simulations, showing a consistent improvement in localization accuracy ratios and a decrease in location errors while maintaining cost-effectiveness.
Keywords: Radio Signal Strength. Range-based Localization. Wireless Sensor Networks.

1. Introduction

Nowadays, WSN has been employed for increasing helpful uses cases, such as surveillance systems, military target tracking or, patient monitoring, asset tracking and possibly dangerous exploration. These applications necessitate accurate location services, notably tracking of moving objects. For example, the Global Positioning System (GPS) offers location services using universal methodologies. However, their positioning accuracy is significantly reduced in buildings, indoor environments, and canyons. This makes it challenging to obtain accurate positioning information (Pottie et Kaiser., 2000).

In addition, large-scale, random sensor deployments cannot anticipate clear sensor location information. The problem here is that without knowing the precise location of the sensors, the data gathered for various purposes by these sensors would be irrelevant, and the procedure would be impractical.

Consequently, different WSN location algorithms have been proposed for determining an accurate estimate of the location of sensor nodes. Based on the range measurement, localization algorithms can be subdivided into range-based and range-free methods. Different algorithms, such as maximum likelihood estimation, least squares, triangulation, and trilateration are employed by range-based localization techniques to determine the position of sensors (Mao *et al*., 2007).

In contrast, certain range-free localization algorithms utilize specific data, such as network connectivity and estimated inter-node distance, to achieve positioning. These algorithms comprise the distance vector-hop (DV-hop) positioning algorithm, the centroid algorithm, the approximate point-in-triangulation test (APIT) positioning algorithm, and the convex optimization positioning algorithm (Doherty *et al*., 2001).

Furthermore, based on the data obtained from WSN nodes placed in different locations, localization algorithms can be categorized into centralized and distributed.

Centralized localization methods involve transmitting mobile node data to a central node for position calculation, whereas distributed localization methods rely on information exchange and node coordination. In scenarios involving the localization of multiple mobile nodes, it has been observed that distributed localization methods exhibit greater efficiency and accuracy compared to centralized localization methods. In order to fulfill the need for increased practicality, our research has focused on the *distributed localization of sensor nodes* utilizing the range-based localization method. We aim to enhance the accuracy and efficiency of wireless sensor network (WSN) localization.

The precision of mobile node positioning is contingent upon two factors: the *estimation of anchor node distances* and the *methods employed for position calculation*. Distance estimation in wireless signal propagation is subject to varying degrees of error due to intricate environmental factors, including reflection, refraction, multi-path, environmental interference, and non-line of sight (NLOS) transmission. Simultaneously, the inherent imperfections of wireless sensor networks exacerbate the input inaccuracies, whereby the anchor node may encounter issues pertaining to communication ambiguity, restricted processing capabilities, and inadequate power provision for the sensor node. Consequently, the selection of resilient anchor nodes is crucial for distance estimation and positioning computations in distributed localization systems (Boukerche *et al*., 2007).

This paper, presents a recent bio-inspired metaheuristic for distributed sensors localization. Our work extensively examines the error propagation mechanism in wireless sensor networks (WSN) nodes. Our objective is to improve localization accuracy and system resiliency. Therefore, the minimum mean localization error metric is utilized to identify reliable anchor nodes effectively. Following the selection of anchor nodes, the algorithm is applied to optimize the initial positioning results, resulting in an accurate and definitive position.

The remaining sections of this paper are structured as follows: In Section 2, a comprehensive review of WSN localization is presented. Section 3 will discuss the GWO algorithm, Section 4 will discuss the implementation of GWO for WSN localization, and Section 5 will present and analyze simulation results. Section 6 will end with summarizing remarks and prospective research opportunities.

2. Related Works

On the basis of their goals proposed localization algorithms in the literature can be divided into two categories: range-based and range-free localization. In range-free techniques, network connectivity between the destination node and anchor nodes is essential, whereas in range-based techniques such as time of arrival (TOA), or radio signal strength (RSS) distance estimation between the nodes or tilting effects between the anchor and neighboring nodes is a major concern when running the localization algorithm (Akyildiz *et al*., 2002)

In reference (Niculescu*et al*., 2003), a technique for efficient localization was proposed that utilizes accurate positioning (APS) to extend the capabilities of GPS to non-GPS nodes. In reference (Kang *et al*., 2007), it was observed that systems utilized anchor nodes to disseminate their positional data to neighboring nodes. Subsequently, target nodes employed triangulation techniques to enhance the precision of the location determination process. In order to enhance the accuracy of outcomes, a refinement phase was incorporated into the pre-existing systems (Bulusu *et al*., 2001).

The simultaneous localization of wireless sensor networks (WSN) can be achieved with higher accuracy through the utilization of the Kalman filter, which has been developed based on the least square method. This has been demonstrated in previous research (Savvides *et al.*, 2002). In this method, the localization problem is viewed as a multivariate problem, allowing the gradient search technique to be used for data analysis. The algorithm computes the shortest path distance to enhance the accuracy of localizing unknown nodes. The GFF algorithm proposed by Farid *et al.* (2005), shares standard features with the DV-HOP algorithm, employing the hop counting technique to compute inter-node distances. This algorithm requires a high density of nodes and accurate measurements. A micro genetic algorithm proposed by Tam *et al.*, (2006) where the algorithm worked as a post optimizer into the Accurate Positioning System (APS).

Recently, bio-inspired algorithms have been used to address the problem of localization due to their higher accuracy and faster convergence rates (Yun *et al.*, 2009).

Kannan *et al*l., (2005) proposed a simulated annealing algorithm employing multiple anchor nodes to locate unknown nodes. Using a computational intelligence-based node localization technique, Kumar *et al.*, (2012) determined the optimal placement of nodes. The paper (Zhang *et al.*, 2008) presented a two-phased centralized localization scheme in which both simulated annealing and GA were used to solve the flip ambiguity problem. In order to attain greater precision, a PSO-based algorithm was proposed in (Gopakumar et Jacob. 2008) and an iterative PSO-based scheme was presented in (Chuang *et al.*, 2008) for localizing unknown nodes that are surrounded by three or more known nodes. In (Kulkarni *et al.*, 2009) a novel objective function is introduced to obtain better results and evaluate the fitness value. In (Rencheng *et al.*, 2008), a localization scheme based on Received Signal Strength (RSS) was introduced. The proposed system utilized the RSS values of the anchor nodes and integrated them with the anchor nodes.

3. Grey Wolf Optimizer algorithm

The gray wolf optimizer (GWO) is introduced by Seyedali *et al*, (2014). It is a recent nature inspired population meta-heuristic algorithm

based on the social behavior of grey wolves. The algorithm mimics the leadership hierarchy and hunting mechanism of wolf flock. This algorithm considers four types of wolves: *alpha, beta*, *delta*, and *omega* based on their leadership hierarchy. Moreover, three main steps of hunting, *searching* for prey, *encircling* prey, and *attacking* prey.

To summarize, the search process starts with creating a random population of grey wolves (candidate solutions). Over the course of iterations, alpha, beta, and delta wolves estimate the probable position of the prey. Each candidate solution updates its distance from the prey.

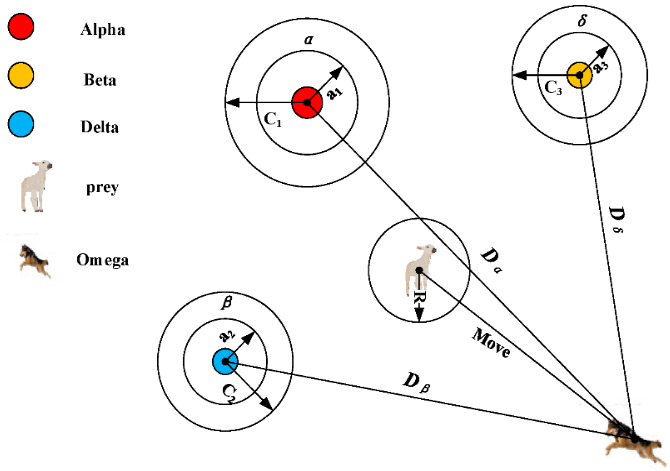

Figure 1 - GWO algorithm concept.

The subsequent equations are given to model this encircling logic.

$$\vec{D} = \vec{C} \times \vec{X}_p(t) - \vec{X}(t) \tag{1}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \times \vec{D} \tag{2}$$

And the hunting process is modeled by following equation:

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{3}$$

where t denotes the current iteration, $\vec{A}$ and $\vec{C}$ are coefficient vectors, $\vec{X}_p$ represents the position vector of the prey, and $\vec{X}$ indicates the position vector of a current wolf. The vectors $\vec{A}$ and $\vec{C}$ are given by:

$$\vec{A} = 2 \times \vec{a} \times \vec{r_1} - \vec{a} \tag{4}$$

$$\vec{C} = 2 \times \vec{r_2} \tag{5}$$

where components of $\vec{a}$ is a temporal parameter and it is decreased linearly from 2 to 0 during the search process by

$$a = 2 - t \times \frac{2}{Max_{Itr}} \tag{6}$$

and r_1, r_2 are vectors uniform randomly chosen between 0 and 1.

The pseudo code of the GWO algorithm is presented in algorithm 1

Algorithm1: Pseudo-code of Grey Wolf Optimizer algorithm

```
Result: Output the global best X_α^{fitness}
Initialize: X_α^{fitness} = 0, X_β^{fitness} = 0 and X_γ^{fitness} = 0
foreach wolf i in the swarm do
    x_i ← initialize the position of the i-th particle
    if f(x_i) > X_α^{fitness} then
        X_α ← x_i
    end
    if f(x_i) > X_β^{fitness} and f(x_i) < X_α^{fitness} then
        X_β ← x_i
    end
    if f(x_i) > X_γ^{fitness} and f(x_i) < X_β^{fitness} then
        X_γ ← x_i
    end
end
while t < Max_{Itr} do
    foreach wolf i in the swarm do
        Update a,A and C
        Update the position of each wolf
    end
    foreach wolf i in the swarm do
        x_i ← initialize the position of the i-th particle
        if f(x_i) > X_α^{fitness} then
            X_α ← x_i
        end
        if f(x_i) > X_β^{fitness} and f(x_i) < X_α^{fitness} then
            X_β ← x_i
        end
        if f(x_i) > X_γ^{fitness} and f(x_i) < X_β^{fitness} then
            X_γ ← x_i
        end
    end
    t ← t + 1
end
```

4. WSN Localization Using GWO

The fundamental objective of Wireless Sensor Network (WSN) localization is to accomplish the localization of the maximum number of unknown nodes through the efficient use of anchor nodes in a technique based on a single hop range. The WSN localization approach involves randomly deploying N nodes within a specified region of interest, with M nodes designated anchor nodes with predetermined geographical coordinates. The transmission range of each node is R. Assuming the presence of M anchor nodes, the number of nodes requiring positioning is equivalent to N - M. At each iteration of the localization procedure, anchor nodes transmit their geographic location. Nodes localized during each iteration will serve as anchor nodes for the subsequent iteration. An unknown node with three or more neighboring nodes within its range will be considered a localizable node. Environmental factors are critical in determining distance in wireless systems, influencing location error. In our case, the environmental impact is assumed to be Gaussian noise n_{noise}, and the distance between nodes and anchors is defined as $\hat{d} = d_i + n_{noise}$, where d_i represents the actual distance and can be calculated using the following equation:

$$d_i = \sqrt{(x - x1)^2 + (y - y1)^2} \tag{7}$$

(x, y) are the target node's coordinates, while $(x_i,\ y_i)$ are *the i-th* anchor node's coordinates. Given the effect of obstacles on RSS measurements, the *log normal shadowing* effect is regarded as noise for distance estimates. In the wireless sensor network distributed localization context, the mean localization error is considered the objective function, whereby the localization problem is formulated as a multimodal optimization problem. Based on this, each localizable node will execute the GWO algorithm to determine its estimated coordinates (x, y).

The objective function of the computed distance is characterized as follows:

$$f(x, y) = \frac{1}{M} \sum_{i=1}^{M} (d_i - \widehat{d_i})^2 \tag{8}$$

Where M is the number of anchor nodes within the transmission range of the node to be localized, note that any unknown node within the range of at least three or more anchor nodes will be localized and then function as a new anchor for the remaining unlocalized nodes.

This process will continue until all unknown nodes with more than two anchors within the region of interest have been located. By minimizing the error function, the GWO algorithm determines the optimal location of localizable nodes (x, y) on each iteration.

Upon locating all the nodes, the localization error shall be determined by utilizing the mean of the squares of distances between the computed coordinates (x_i, y_i) and the coordinates of the true coordinates (X_i, Y_i), where i ranges from 1 to NU. The localization error of unknown nodes is determined using the following equation,

$$EL = \frac{\sum_{i=M+1}^{N} \sqrt{(x - x_i)^2 + (y - y_i)^2}}{NU} \tag{1}$$

NU represents the total number of locations of unknown nodes. Finally, it is important to note that in the next iteration, the nodes that need to be localized could have more anchors.

The pseudo code of our distributed localization algorithm is presented in algorithm 2

Algorithm 2: Distributed localization algorithm

```
Data: Anchors_Nodes_Queue, Unknown_Nodes_Queue and Noise
      standard deviation σ
Result: An estimate for all unknown nodes coordinates
Set GWO algorithm parameters;
T ← 0;
while True do
    if Unknown_Nodes_Queue is empty then
        break;
    Node_To_Localize ← Unknown_Nodes_Queue.Peek();
    if getAnchors(Node_To_Localize) < 3 then
        Node ← Unknown_Nodes_Queue.dequeue();
        Unknown_Nodes_Queue.enqueue(Node);
        T ← T + 1;
        if T = Unknown_Nodes_Queue.Length then
            break;
        continue;
    end
    T ← 0;
    Node_Location ← GWO(Node_To_Localize);
    Unknown_Nodes_Queue.dequeue();
    Anchors_Nodes_Queue.enqueue(Node_To_Localize);
end
```

5. Simulation Results and Discussion

To investigate the efficiency of the Grey Wolf Optimizer (GWO), a series of Matlab 2017b-based experiments were carried out. The characteristics of system parameters are outlined below in Table 1.

Table 1 – Default values of simulation parameters.

Parameters	Default values
The network scale	1000
Transmission range R	200m
Transmission power (dBm)	0 dBm
Path loss exponent α	4
PL($d0$)	-55 dB (d0=1m)
Noise standard deviation σ	2-15
Number of particles k	20

The nodes were randomly distributed within a square area measuring 1000m by 1000m. The deployment consisted of 10 anchor nodes and 90 unknown nodes. It was considered that the nodes' transmission range was 220m and this value remained constant throughout the iterations. The experimental analysis is limited to a maximum of 1500 iterations.

As an example, of the obtained locations of the unknown nodes using GWO, is illustrated in Figure 2, based on the aforementioned considerations and parameters.

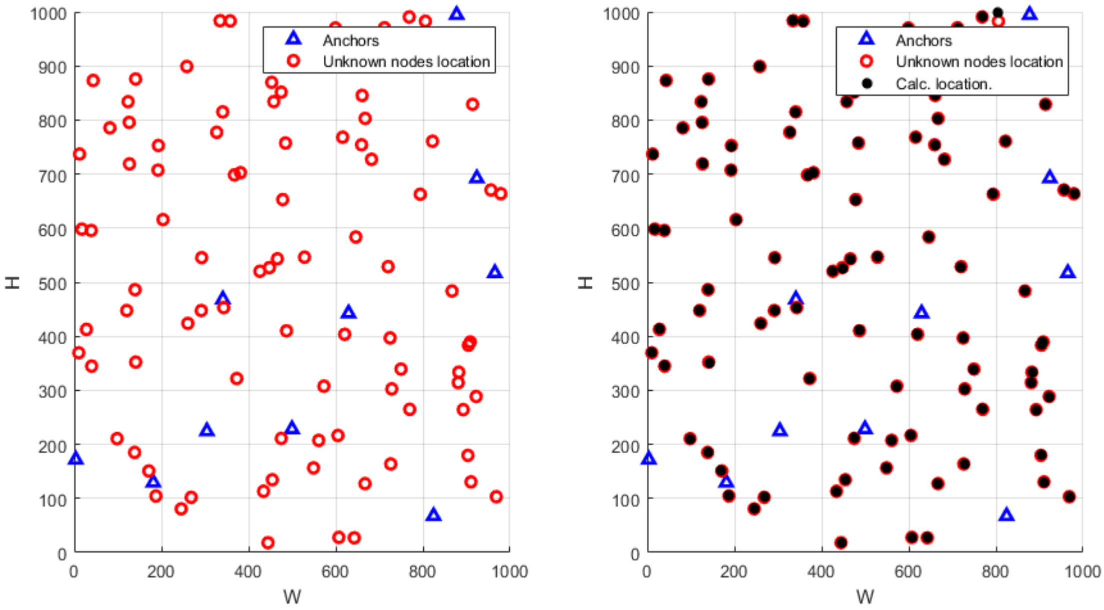

Figure 2 - A localization example obtained using the GWO algorithm.

As illustrated in Figure 3. The mean localization error remains constant at approximately 0.5. In instances where the algorithm becomes trapped in a local minimum, it promptly resolves the issue in the subsequent iteration, thereby demonstrating its efficacy.

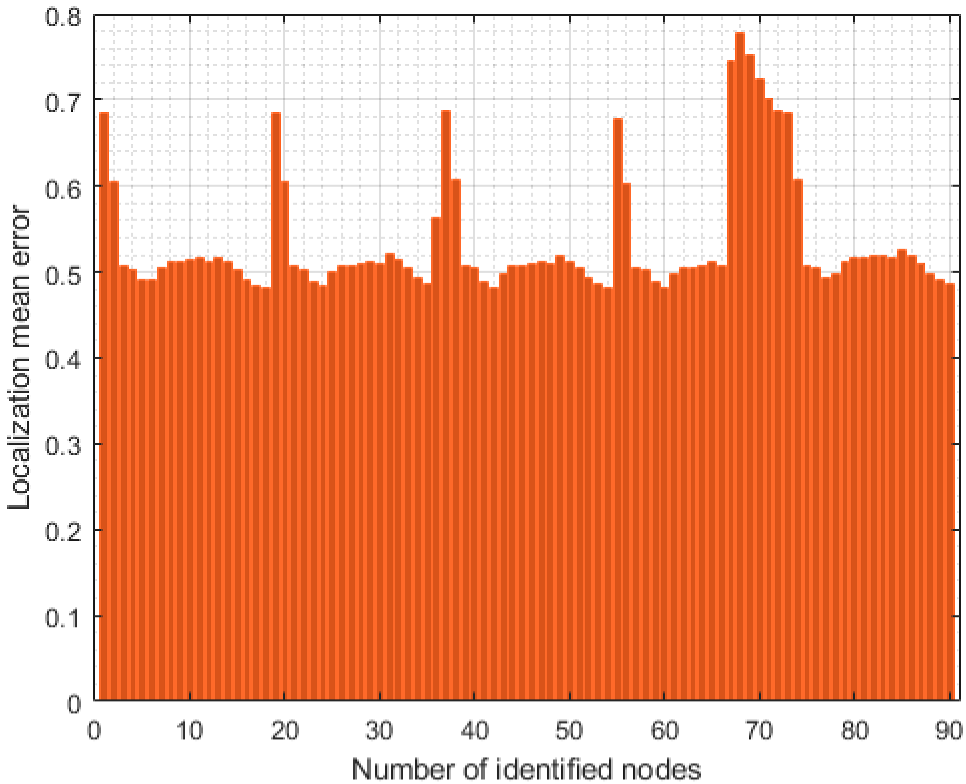

Figure 3 - Localization mean error of unknown nodes obtained using GWO

Serval simulations were carried out to assess the effect of transmission range on wireless sensor nodes localization using GWO algorithm. The noise level was set at $\sigma = 0.5$dBm.

The results shown in Figure 4 suggest that increasing the transmission range can boost localization accuracy. Therefore, transmission range considerably influences wireless sensor nodes' localization, because as the transmission range of sensors increases, there is an associated decrease in localization error. However, this is accompanied by an increase in computational time.

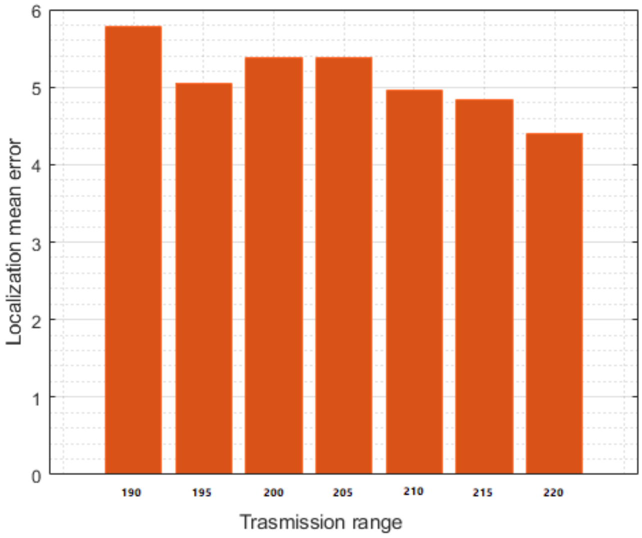

Figure 4 – Transmission range Versus mean localization error

It is impossible to localize an unknown node if its distance from *three or more reference/anchor nodes cannot be calculated or measured*. Increasing the number of anchor nodes becomes necessary under these conditions. numerous simulations are conducted to evaluate the impact of anchor nodes number on localization accuracy. As illustrated in Figure 5, it is evident that increasing the number of anchor nodes decreases the localization error.

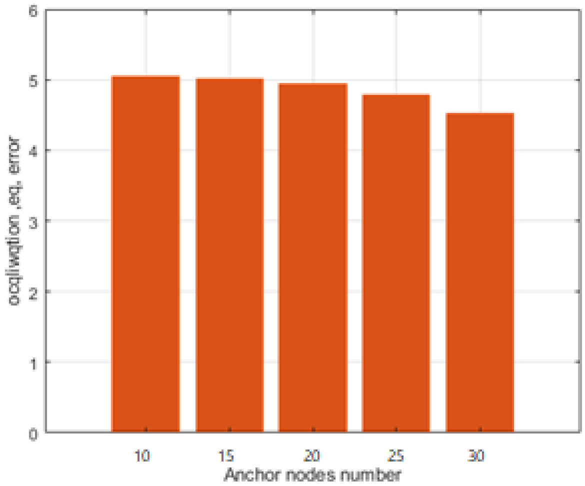

Figure 5 – Anchor nodes number Versus mean localization error

The impact of noise on the estimation of distance based on received signal strength (RSS) is a crucial factor that may significantly impact localization accuracy. A simulation was conducted in order to evaluate the impact of varying levels of noise on the accuracy of localization. The results of this simulation are presented in Figure 6.

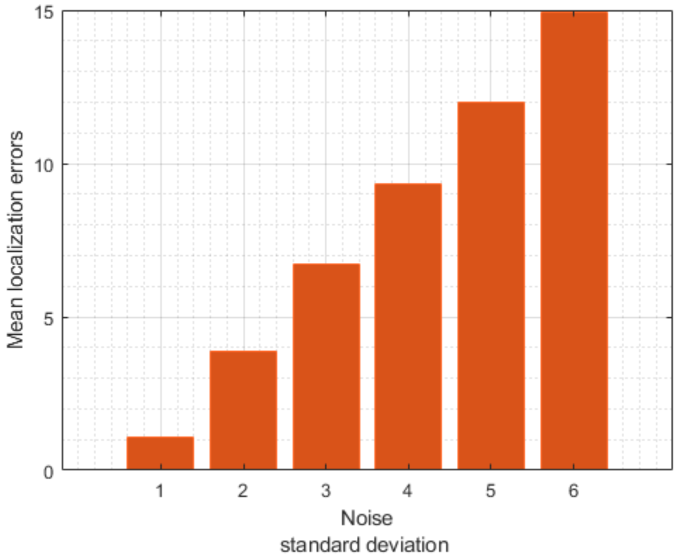

Figure 6 - Noise standard deviation versus mean localization error

The figure demonstrates that an increase in noise level results in a corresponding increase in localization error. This can be associated to the shadowing effect that affects distance calculation, which is a crucial factor in localizing an unknown node using RSS-based localization techniques.

6. Conclusion

Our work introduces a novel node localization approach based on Grey Wolf Optimizer (GWO) to mitigate error accumulation and enhance the success rates of identifying unknown nodes within Wireless Sensor Networks. This scheme involves a modified version of the iterative multilateration approach. This method aims to estimate the position of an unknown node by utilizing location data obtained from remote anchors. Specifically, the closest neighbor anchors of the unknown node are utilized to estimate its position.

References

Akyildiz, I. F., Su, W., Sankarasubramaniam, Y., & Cayirci, E. (2002). Wireless sensor networks: A survey. *Computer Networks*, 38(4), 393–422. https://doi.org/10.1016/S1389-1286(01)00302-4

Boukerche, A., Oliveira, H. A. B. F., Nakamura, E. F., & Loureiro, A. A. F. (2007). Localization systems for wireless sensor networks. *Wireless Communications, IEEE*, 14(6), 6–12. https://doi.org/10.1109/MWC.2007.4407221

Bulusu, N., Estrin, D., Girod, L., & Heidemann, J. (2001). Scalable coordination for wireless sensor networks: Self-configuring localization systems. *In International Symposium on Communication Theory and Applications* (ISCTA 2001) Ambleside, UK.

Chuang, P.-J., & Wu, C.-P. (2008). An effective pso-based node localization scheme for wireless sensor networks. *In Ninth International Conference on Parallel and Distributed Computing, Applications and Technologies*, 2008. PDCAT 2008 (pp. 187–194). IEEE, Piscataway. https://doi.org/10.1109/PDCAT.2008.73

Doherty, L., Pister, K. S. J., & El Ghaoui, L. (2001). Convex position estimation in wireless sensor networks. In INFOCOM 2001. *Twentieth Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE* (Vol 3, pp. 1655–1663). IEEE, Piscataway. https://doi.org/10.1109/INFCOM.2001.916662

Farid. Benbadis, T. Friedman, M. Dias de Amorim, and S. Fdida, (2005) ‘‘GPS-free-free positioning system for wireless sensor networks,’’ in Proc. 2nd IFIPInt. Conf. Wireless Opt. Commun. Netw. (WOCN), Dubai, UAE, ,pp. 541–545. https://doi.org/10.1109/WOCN.2005.1436085

Gopakumar, A., & Jacob, L. (2008). Localization in wireless sensor networks using particle swarm optimization. *In IET International Conference on Wireless, Mobile and Multimedia Networks*, 2008 (pp. 227–230). IET. https://doi.org/10.1049/cp:20080185

Kang, J., Kim, D., & Kim, Y. (2007). RSS self-calibration protocol for WSN localization. *In 2nd international symposium on wireless pervasive computing, ISWPC'07. IEEE*. https://doi.org/10.1109/ISWPC.2007.342597

Kannan, A. A., Mao, G., & Vucetic, B. (2005). Simulated annealing based localization in wireless sensor network. *In The IEEE Conference on Local Computer Networks, 2005. 30th Anniversary, (p. 2). IEEE*, Piscataway. https://doi.org/10.1109/VETECS.2006.1682979

Kulkarni, R. V., Venayagamoorthy, G. K., & Cheng, M. X. (2009). Bio-inspired node localization in wireless sensor networks. *In IEEE International Conference on Systems, Man and Cybernetics*, 2009. SMC 2009 (pp. 205–210). IEEE, Piscataway. https://doi.org/10.1109/ICSMC.2009.5346107

Kumar, A., Khosla, A., Saini, J. S., & Singh, S. (2012) Computational intelligence based algorithm for node localization in wireless sensor networks. *In 2012 6th IEEE International Conference on Intelligent Systems (IS) (pp. 431–438).* IEEE, Piscataway. https://doi.org/10.1109/IS.2012.6335173

Zhang, Q., Huang, J., Wang, J., Jin, C., Ye, J., Zhang, W., & Hu, J. (2008). A two-phase localization algorithm for wireless sensor network. *In International Conference on Information and Automation, 2008. ICIA* 2008. (pp. 59–64). IEEE, Piscataway. https://doi.org/10.1109/ICINFA.2008.4607968

Mao, G., Fidan, B., & Anderson, B. D. O. (2007). Wireless sensor network localization techniques. *Computer Networks*, 51(10), 2529–2553. https://doi.org/10.1016/j.comnet.2006.11.018

Niculescu, D., & Nath, B. (2003). Ad hoc positioning system (aps) using aoa. In INFOCOM 2003. Twenty-Second Annual Joint Conference of the IEEE Computer and Communications. IEEE Societies (Vol 3, pp. 1734–1743). IEEE, Piscataway. https://doi.org/10.1109/INFCOM.2003.1209196

Pottie, G. J., & Kaiser, W. J. (2000). Wireless integrated network sensors. *Communications of the ACM*, 43(5), 51–58. https://doi.org/10.1145/332833.332838

Rencheng, J., Hongbin, W., Bo, P., & Ning, P. (2008). Research on rssi-based localization in wireless sensor networks. *In 4th International Conference on Wireless Communications, Networking and Mobile Computing*, 2008. WiCOM'08 (pp. 1–4). IEEE, Piscataway. https://doi.org/10.1109/WiCom.2008.963

Savvides, A., Park, H., & Srivastava, M. B. (2002). The bits and flops of the n-hop multilateration primitive for node localization problems. *In Proceedings of the 1st ACM International Workshop on Wireless Sensor Networks and Applications* (pp. 112–121). ACM, London. https://doi.org/10.1145/570738.570755

Seyedali Mirjalili, Seyed Mohammad Mirjalili, Andrew Lewis, Grey Wolf Optimizer, *Advances in Engineering Software*, Volume 69, 2014, Pages 46-61, ISSN 0965-9978, https://doi.org/10.1016/j.advengsoft.2013.12.007.

Tam, V.W., Cheng, K., & Lui, K. (2006). Using Micro-Genetic Algorithms to Improve Localization in Wireless Sensor Networks. J. Commun., 1, 1-10.

Yun, S., Lee, J., Chung, W., Kim, E., & Kim, Soohan. (2009). A soft computing approach to localization in wireless sensor networks. *Expert Systems with Applications*, 36(4), 7552–7561. https://doi.org/10.1016/j.eswa.2008.09.064