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A BWO-driven secure localization framework for wireless sensor networks

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Abstract

Accurate node localization remains one of the major research challenges in Wireless Sensor Networks (WSNs), particularly due to environmental noise, irregular deployment structures, and limited anchor nodes. To address these limitations, this study proposes a Black Widow Optimization (BWO)-based localization technique designed to enhance position accuracy through intelligent anchor selection and iterative search refinement. The approach consists of two main phases: a distance estimation stage using RSS-based measurements, followed by an optimization phase driven by the BWO algorithm. The biologically inspired operators—including procreation, cannibalism, and mutation—enable rapid convergence and improved parameter control, ensuring effective exploration and exploitation of the search space. The proposed method is implemented in MATLAB for a random deployment of 50 target nodes within a 100 × 100 m simulation area. Performance is evaluated using Localization Error (LE), Localized Node Percentage (LN), and the number of unlocalized nodes under varying anchor density, transmission range, and iteration count. Results demonstrate that the BWO-based method significantly outperforms Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) in both localization accuracy and robustness. Overall, the findings confirm that BWO is an effective and computationally efficient approach for improving localization performance in WSNs.

Keywords: Wireless sensor networks, BWO, intelligent, localized node percentage, MATLAB

Introduction

Wireless Sensor Networks (WSNs) have become an integral part of modern digital monitoring and intelligent communication systems. They are widely deployed in domains such as environmental surveillance, smart agriculture, military tracking, healthcare monitoring, industrial automation, and smart cities [1].

In most of these applications, the ability of sensor nodes to determine their geographic position accurately is essential because collected data becomes meaningful only when linked to its physical origin. However, achieving accurate localization in WSNs remains a challenging task, especially when nodes are randomly deployed, terrain conditions are irregular, or the network contains obstacles that affect radio signal propagation [2, 3].

Traditional localization techniques such as range-based, range-free methods, centroid localization, and multilateration often suffer from high estimation error due to wireless channel variations, limited anchor nodes, and noisy Received Signal Strength Indicator (RSSI) values [4, 5]. Optimization-based and artificial intelligence-driven techniques have therefore gained increasing attention, offering improved accuracy and adaptability without requiring high-cost hardware [6].

Among emerging optimization techniques, meta-heuristic algorithms inspired by biological intelligence have shown strong potential for solving complex nonlinear problems in WSN localization. The Black Widow Optimization (BWO) algorithm is one such recent approach that demonstrates strong convergence efficiency and enhanced search capability [7]. Inspired by the mating behavior and survival strategies of black widow spiders, BWO integrates reproduction, cannibalism, and mutation mechanisms to refine candidate solutions intelligently [8].

When applied to WSN localization, BWO can adjust node positions iteratively to minimize localization error and optimize network performance. Its balance between exploration and exploitation makes it suitable for complex and noisy sensor environments [9, 10]. Therefore, incorporating BWO into localization frameworks provides new opportunities for achieving higher accuracy, robustness, and computational efficiency in real-world wireless sensor networks [11, 12].

Methodology

BWO Algorithm

The work suggested in this thesis is divided into two phases: the distance measuring phase and the optimization phase. During the first stage, the distance is measured between anchor nodes and nodes still to be identified. In the second stage, the optimization is conducted using the BWO approach (Kaliswaran 2021) to select appropriate anchor nodes to minimize localization uncertainties. The subsequent sections provide a comprehensive explanation of how the location assessments of nodes are conducted by these two stages.

- **Distance Measurement Phase**

This phase introduces range algorithms implemented to calculate the distance between anchor nodes and a destination node. Common metrics used in range methods measurements include Time of Arrival (TOA), Angle of Arrival (AOA), and Received Signal Strength (RSS). These RSS-based distant measurements are regarded to be cost-effective and straightforward. Hence, the equation for the signal attenuation curve, obtained using the RSS approach (Liu Xiaoyang *et al*. 2010), is presented below.

$$p = p_0 + 10\mathrm{nlg}\left(\frac{d}{d_0}\right) + \beth \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1.1)$$

where $d_0$0 represents the reference range of the digital model

The distance d represents the actual distance between the target node and the anchor node.
p_0 represents the RSSI value of the receiving model at a distance of d_0.
$\aleph$ Denotes Cover factor σ and path loss factor n.
According to the following formulation, the RSS value is inversely proportional to the distance between the transmitter and receiver.

$$d = d_0 * 10 \left(\frac{P - p_0 - \beth}{10n} \right) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1.2)$$

- **BWO**

Informed on the reproductive behavior of black widow spiders (Hayyolalam *et al.* 2020), the meta-heuristic algorithm of BWO is developed. This BWO is being compared to other optimization methods characterized by an exclusive process called cannibalism. This phenomenon of cannibalism is employed to get a prompt convergence. In both the conventional Genetic Algorithm (GA) and Particle Swarm Optimisation (PSO), the values of the issue variables must produce a proper structure for the optimal solution, referred to as the "Chromosome" and "Particle position" respectively. To obtain the most optimum solution, each spider processes issue variables repeatedly. This Business Work Order (BWO) is executed by following the many stages outlined below.

Founding population

To address an optimization problem, the values of the problem variables must adopt an appropriate structure as per the present situation. In this approach, the structure of the benchmark functions should be evaluated as an array to provide a solution. A widow spider is an array of dimensions 1 × Nvar that illustrates the solution to a Nvar-dimensional optimization problem. This array is represented as follows:

$$\text{Widow} = [\, x_1 , x_2,,,,,,,,,,,,,,,,,,,,,x_{Nvar} \;] \quad \ldots\ldots\ldots\ldots\ldots (1.3)$$

All variable values (x_1, x_2..., Δx_{Nvar}) are expressed as floating-point numbers. A widow fitness function is derived by applying the fitness function f(widow) on a widow of the interval (x_1, x_2..., x_{Nvar}). Thus

$$f(\text{window}) = f\,(x_1, x_2..., x_{Nvar}) \quad \ldots\ldots\ldots\ldots\ldots... (1.4)$$

To begin the optimization problem, a candidate widow matrix of dimensions Npop × Nvar is generated using the initial population of spiders. Next, the parents are randomly matched to determine and carry out the subsequent reproduction process by mating. This procedure is predicated on the female hunting the male black widow either during or after this last stage.

Procreate

Given the independence of both male and female black widow couples, they will initiate mating to produce a new generation. Similarly, in nature, each pair of mates in the spider web is completely isolated. Each pairing produces around 1000 eggs, from which a small number of spider offspring are more robust and survive. For example, the progeny is produced by the use of alpha (α) using the subsequent equation, where x_1 and x_2 represent the parents, and y_1 *and* y_2 represent the offspring.

$$\left\{ \begin{cases} y_1 = \alpha \times x_1 + (1 - \alpha) \times x_2 \\ y_2 = \alpha \times x_2 + (1 - \alpha) \times x_1 \end{cases} \right\} \quad \ldots\ldots\ldots\ldots (1.5)$$

This process is done for Nvar/2 times, where the numbers are chosen randomly and will not be overlapped. Lastly, both the father and offspring are included in an array and arranged in order of their fitness value. Using cannibalism, a small number of the most exceptional people are included in the newly formed population. These procedures are equally implemented on all pairings.

Cannibalism

Cannibalism is classified into three stages. The first stage is cannibalism when a female black widow spider hunts her spouse after mating. Females and males are distinguished based on their fitness function, and some species engage in sibling cannibalism when the stronger sibling consumes its lesser siblings. To establish the Cannibalism Rating (CR), the number of surviving off spring is calculated. An observed form of cannibalism is the deliberate consumption of the mother by the offspring spiders. Therefore, the measure of fitness is to be assessed by the robust or feeble spiderlings.

Genetic Mutation

The mutations are selected at random from the Mutepop, which includes the number of persons in the population. Every chosen solution undergoes a random exchange of two members inside the array. Hence, the Mutepop coefficient is established based on the mutation rate.

Convergence

This convergence analyzes three stop conditions: (i) a predetermined number of iterations, (ii) the observation that the best widow fitness value remains constant for different iterations, and (iii) achieving high-rated accuracy. This Bayesian Weighted Optimization (BWO) is performed using the benchmark and achieves a high degree of estimated accuracy. Furthermore, the substantial number of iterations is established as a termination criterion.

Configuration of parameters

The suggested BWO algorithm employs the Procreating Rate (PP), Cannibalism Rate (CR), and Mutation Rate (PM) as its fundamental parameters. These criteria are utilized to specify the identification of optimal solutions. The more precise the level of parameter tweaking, the greater the likelihood of finding a local optimum and the greater the capacity for global exploration of the search space. Therefore, the equilibrium between the stages of exploitation and exploration is guaranteed by controlled adjustment of the appropriate number of parameters. The suggested Bayesian Weighted Optimization (BWO) method is endowed with three crucial regulating parameters: PP, CR, and PM. The parameter of reproductive probability (PP) is the proportion of people involved in reproduction that is used to determine the rates of reproduction.
This parameter governs the creation of different offspring, therefore enhancing diversification and creating even more opportunities for investigation of the search space, which is highly valuable. The parameter of the CR controller is the cannibalism operator, which excludes an imprecise number of individuals from the population. Through the adjustment of the appropriate value, it is possible to ensure optimal performance during the exploitation stage by transferring the search agents from the local to the global stage, and vice versa. The metric of PM is used to assess the proportion of

the individual's spider that is affected by mutation. An optimal value can provide equilibrium between the stages of exploitation and exploration. This mechanism is employed to regulate the transmission of search requests from the global stage to local agents and guide them toward the most optimum result.

Results

- **BWO Localization Algorithm**

The comprehensive optimization is depicted in Flowchart 1. The initialization method entails defining M as the number of target nodes and N as the number of anchor nodes, each possessing a transmission range (R).
The distance measuring step assesses the distance between anchor nodes and target nodes.
Each target node is individually analyzed using the BWO algorithm to ascertain its location. The black widows are created from the centroid of the anchor node. Consequently, the transmission range (R) delineates the target node as seen below.

$$(x_e , y_e) = (\tfrac{1}{N} \textstyle\sum_{i=1}^{N} x_i , \tfrac{1}{N} \sum_{i=1}^{N} y_i) \quad \text{................} (1.6)$$

Where N is the total number of anchor nodes, the mean square distance measurement between the target node and anchor node may be expressed as

$$F(x, y) = \tfrac{1}{N} (\textstyle\sum_{i=1}^{N} \sqrt{(x + x_i)^2 + (y - y_i)2} - d_1 \quad \text{................} (1.7)$$

The objective function is employed to minimize the measure of error distance between actual distances and the predetermined distance. Where N ≥ 3 denotes the minimum number of anchor nodes.
The ideal solution is determined via the Bayesian Space Optimization (BSO) algorithm employing generation Equations (4.5) to satisfy an objective function.
Once all the target nodes LN have been accurately identified, the localization error may be assessed by calculating the average square distance between the known node coordinates (X_i, Y_i) and the actual node coordinates (x_i, y_i) provided below.

$$LE = \frac{1}{N_1} (\textstyle\sum_{i=1}^{N} \sqrt{(x + X_i)^2 + (y - Y_i)2} \quad \text{.....................} (1.8)$$

The Localisation Efficiency is calculated using the Localisation Factor (LE) parameters and the quantity of Unlocalised Nodes (UN). The determination of the number of unlocalized nodes is achieved via the equation UN=M-LN. Iterative execution of steps 2 to 5 continues until the minimal values of LE and UN are obtained. The optimal number of anchor nodes is established through iterative processes to enhance the efficiency of localization.

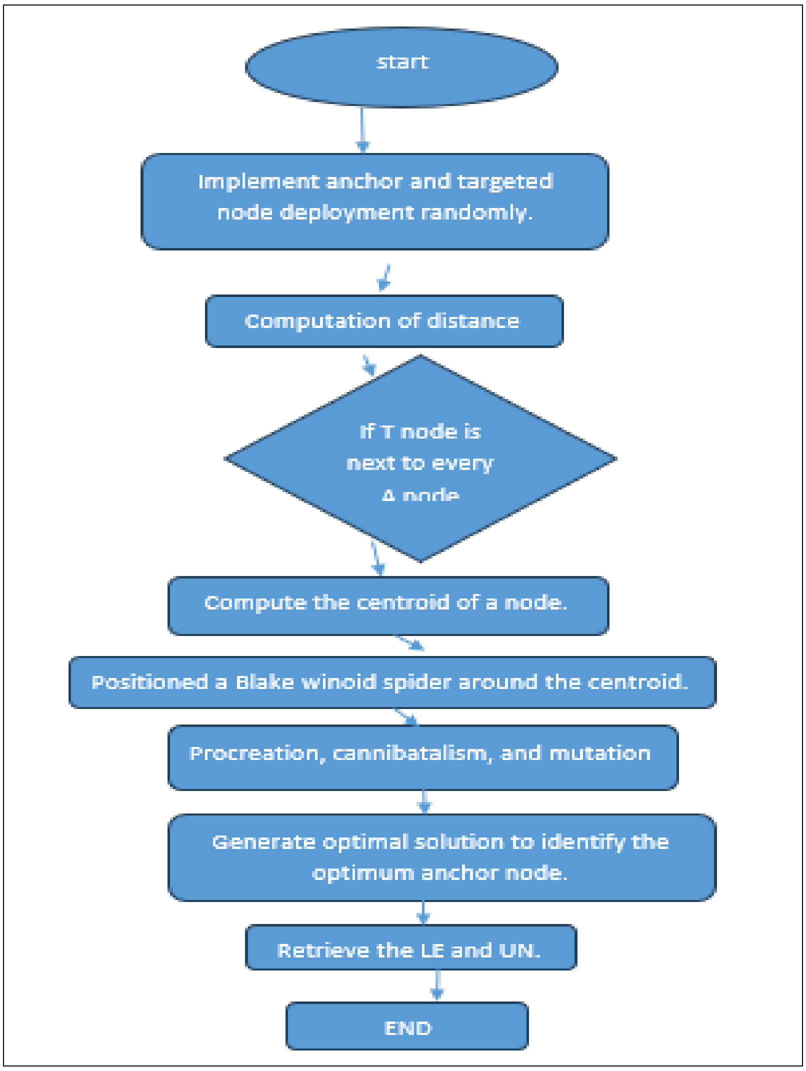

Fig 1: Proposed Anisotropic Optimisation Process

- **Numerical Simulation and its Results**

An implementation of the suggested localization technique using MATLAB.

The total number of target nodes is set at 50 and they are placed in a 100m by 100m region. Each node's position within the border is represented by randomly generated coordinates (x, y). The transmitting range of each anchor node is configured to 30 units.

The population size is set at 30, and the number of generations to 100. The analysis evaluated the proportion of localized nodes under different conditions of node density, transmission range, and the number of iterations. Using a fair comparison, the suggested approach was evaluated against GA and PSO algorithms.

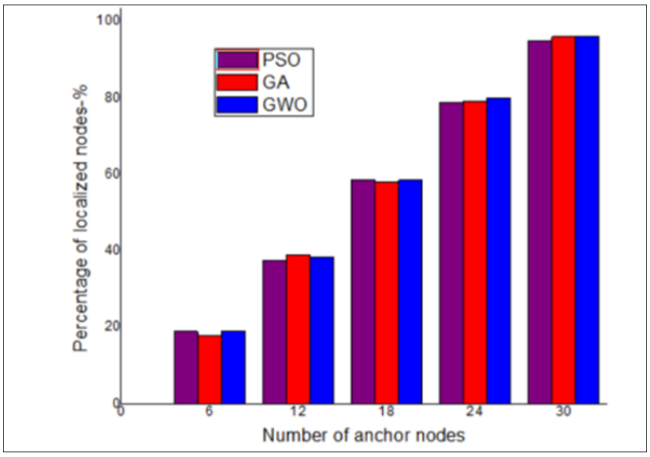

Fig 2: Effects of different quantities of anchor nodes

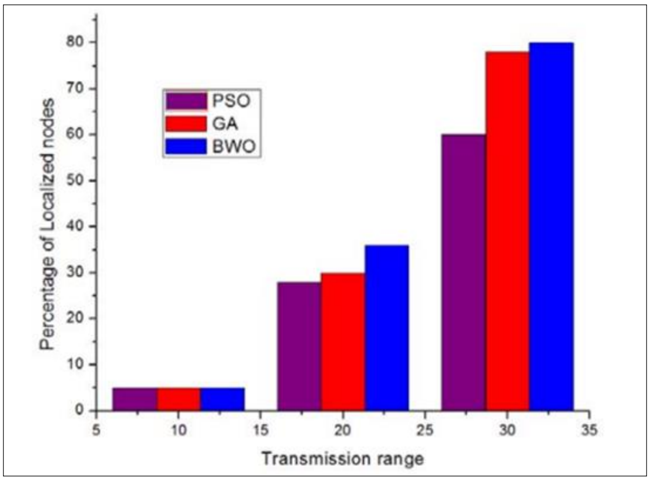

Fig 3: Analysis of the effects of different transmission ranges

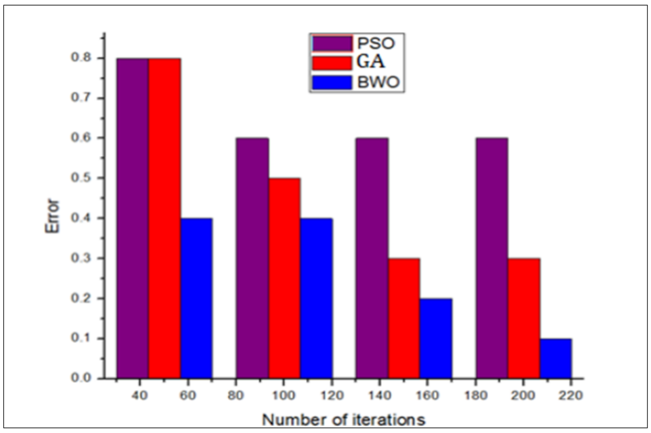

Fig 4: Effect of expanding iterations

It is not feasible to locate the target node if the number of anchor nodes is less than three. As the number of anchor nodes rises, the proportion of localizing nodes also increases. The analysis of Figure 4.4 reveals that the GWO optimization achieves a greater percentage of localization by the appropriate selection of anchor nodes.

The count of localized nodes rose proportionally with the expansion of the coverage or transmission range of the anchor node. The increased coverage prevents intersection issues. The primary factor that fundamentally impacts the accuracy of localization is Gaussian noise. The Gaussian noise in this study is set to zero.

The analysis of Figure 4.5 and Figure 4.6 reveals that the BWO optimization surpasses other approaches in terms of achieving greater localized nodes. Similarly, the augmentation in the number of iterations also served to generate a greater number of localized nodes.

Table 1: Summary of Results

Target node	Anchor node	PSO		GA		BWO	
		LN	LE	LN	LE	LN	LE
20	6	19	0.2567	18	0.799	19.2	0.2245
40	12	37.6	0.4672	39	0.238	38.4	0.362
60	18	58.6	0.486	58	0.290	58.5	0.196
80	24	78.9	0.328	79.2	0.589	80	0.2164
100	30	95	0.6276	96	0.5135	96	0.292

Table provides a summary of the performance of localization error and localized node accuracy. The mean values of LE and LN were obtained after doing 10 experiments. When compared to GA and PSO, the BWO optimization demonstrates superior performance in terms of error and localization rate.

Conclusion

This study presented a BWO-based localization framework for wireless sensor networks, demonstrating its capability to enhance localization performance through adaptive optimization and efficient anchor selection. Simulation results showed that the proposed method consistently achieved a higher percentage of localized nodes and reduced localization error compared to GA and PSO algorithms. The algorithm's biologically inspired operators allowed a balanced trade-off between exploration and exploitation, resulting in faster convergence and improved stability across varying network conditions. The analysis further confirmed that increasing anchor nodes, expanding transmission range, and allowing more iterations directly improved localization performance. Overall, the BWO algorithm provides a computationally lightweight yet highly effective method suitable for large-scale and anisotropic WSN environments. Future extensions may include real-time deployment, hybrid optimization integration, or extension to energy-aware and mobile sensor networks.

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