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Adaptive Node Localization Method in Wireless Sensor Networks based on Mountain Gazelle Optimizer Algorithm

Dhuha Gh. Kadhum, Muntadher Khamees
Computer department, Diyala University, Diyala, Iraq

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Abstract

In wireless sensor networks (WSNs), accurate node localization is critical for ensuring efficient network functionality, as it directly impacts communication, energy consumption, and network management. This paper aims to enhance node localization accuracy by developing a hybrid approach that leverages two bioinspired optimization algorithms: the Mountain Gazelle Optimizer (MGO) and the Crayfish Optimization Algorithm (COA). The research method combines the exploration and exploitation capabilities of these algorithms to optimize the positions of unknown (target) nodes using known (anchor) nodes. The proposed technique was tested across multiple WSN deployment scenarios and compared with traditional optimization methods such as Particle Swarm Optimization (PSO) and Grey Wolf Optimizer (GWO). Experimental results demonstrate that the MGO-based approach achieves superior localization accuracy, reduces computational overhead, and increases the number of accurately localized nodes, highlighting its potential for improving WSN performance.

Keywords: WSN, MGO, COA, metaheuristic algorithm, localization, anchor node, target node.

طريقة توطين العقدة في شبكات الاستشعار اللاسلكية بالاعتماد على خوارزمية الغزال الجبلي

ضحى غضبان كاظم* ,منتظر خميس
قسم علوم الحاسوب، كلية العلوم، جامعة ديالى، ديالى، العراق

الخلاصة

في شبكات الاستشعار اللاسلكية، يعد تحديد موقع العقدة بدقة أمرًا بالغ الأهمية لضمان كفاءة وظائف الشبكة، حيث يؤثر بشكل مباشر على الاتصالات واستهلاك الطاقة وإدارة الشبكة. تهدف هذه الورقة إلى تعزيز دقة تحديد موقع العقدة من خلال تطوير نهج هجين يستفيد من خوارزميتين مستوحاة من علم الأحياء: Mountain Gazelle Optimizer (MGO) و Crayfish Optimization Algorithm (COA). تجمع طريقة البحث بين قدرات الاستكشاف والاستغلال لهذه الخوارزميات لتحسين مواضع العقد غير المعروفة (Target) باستخدام العقد المعروفة (Anchor). تم اختبار التقنية المقترحة عبر سيناريوهات نشر متعددة ومقارنتها بطرق التحسين التقليدية مثل Particle Swarm Optimization (PSO) و Grey Wolf Optimizer (GWO). توضح النتائج التجريبية أن النهج القائم على MGO يحقق دقة تحديد موقع فائقة

*Email: Duha.new7@gmail.com

ويقلل من النفقات الحسابية ويزيد من عدد العقد المحددة بدقة، مما يسلط الضوء على إمكاناته لتحسين أداء WSN.

1. Introduction

In recent years, wireless sensor networks (WSNs) have drawn interest from all over the world, especially with the growth of Micro-Electro-Mechanical Systems (MEMS) technology, which has made the creation of smart sensors easier [1]. A metaheuristic is an advanced process or heuristic that is intended to locate, produce, adjust, or choose a heuristic that could offer an adequate answer to an optimization or machine learning issue [2] [3].

In the past several years, numerous research has been attempted on this issue by the scientific community. It should be noted that the definition of localization is the process of determining an unknown node's position, either by employing connectivity information between the unknown nodes or by utilizing nodes with known positions. Recent research has examined how movement affects localization.[4], [5], [6], real-world applications [7], [8], [9], "Anchor Free" and "Anchor Based" localization techniques [10], " Range Based and Range Free " schemes of localization [11], "Non-Cooperative" schemes—where the target nodes only connect with the anchor nodes—"Cooperative" algorithms—where communication occurs among all nodes[12], and “The centralized” scheme localization and "the distributed" scheme, which uses locally collected information to determine each node's position without central supervision.[13][14]. This paper's primary contribution is the first-ever localization of WSN nodes utilizing the COA and the MGO.

This paper aims to improve node localization accuracy in WSNs by introducing a hybrid localization strategy based on two bioinspired metaheuristic algorithms: the Mountain Gazelle Optimizer (MGO) and the Crayfish Optimization Algorithm (COA). Inspired by the social and adaptive behaviors of mountain gazelles and crayfish, these algorithms offer robust exploration and exploitation capabilities to optimize the localization process. The proposed method employs the MGO and COA to minimize localization errors and enhance computational efficiency by leveraging the unique characteristics of these bioinspired techniques.

To validate the effectiveness of our approach, we conducted comparative evaluations against well-established localization algorithms, including Particle Swarm Optimization (PSO) and Grey Wolf Optimizer (GWO), across different deployment scenarios. The experimental results demonstrate that our MGO-based localization scheme consistently outperforms traditional methods in terms of accuracy, computation time, and the number of successfully localized nodes, providing a reliable and efficient solution for various WSN applications.

The paper's remaining sections are arranged as follows: A selection of the field research projects is covered in Section 2. A brief overview of the several swim algorithms used in this work is given in Section 3. The suggested MGO and COA-based localization techniques are presented in Section 4. The findings analysis and conducted experiments are included in Section 5. The general framework in Section 6, The comparison between schemes in Section 7, The paper is finally concluded in Section 8.

2. Literature Review

Numerous optimization strategies have been used in recent years to solve the node localization issue in WSNs. A brief description and coverage of a few recent pertinent works are provided in this section.

- In 2021, Pudi Sekhar et al.. [15], designed an effective metaheuristic based group teaching optimization algorithm for node localization (GTOA-NL) technique for WSN enabled indoor communication, and the obtained results have ensured the superior performance of the GTOA-NL model over the other compared methods under varying number of anchor nodes, ranging error, and transmission range.

- In 2021, Sana Messous and colleagues proposed an enhanced DV-Hop algorithm to address the high localization error in the original method. By incorporating correction factors, their approach achieved significant reductions in localization error, with accuracy improvements reported up to X% compared to the traditional DV-Hop algorithm. Experimental results confirmed the effectiveness of this modified technique in various network scenarios, achieving greater node positioning accuracy and making it highly suitable for applications like environmental monitoring and asset tracking .
- In 2022, Guo et al. presented an Adaptive Whale Optimization Algorithm for node localization in Wireless Sensor Networks (WSNs). By leveraging the unique search patterns of whales, this adaptive approach enhanced both accuracy and adaptability to dynamic network conditions, improving node positioning precision. Results demonstrated that the Whale Optimization Algorithm outperformed conventional methods in terms of localization accuracy, particularly in environments with fluctuating network parameters, making it a robust choice for complex WSN deployments [17].
- In 2022, Himanshu et al., presented artificial intelligence applications for target node positions in wireless sensor networks using a single mobile anchor node. Particle swarm optimization (PSO), Hybrid PSO (HPSO), and Firefly Algorithm (FA) were used separately to get the optimum positions of the target nodes, and the Simulation results show that the proposed methods perform better in terms of accuracy, energy, scalability, and convergence time as compared to existing techniques [18].
- In 2022, Wenyan Liu et al., proposed a node localization algorithm for wireless sensor networks based on static anchor node location selection strategy to better solve the contradiction between the localization accuracy, localization coverage, and the location of anchor nodes in wireless sensor networks. Simulation results show that the proposed algorithm is superior to the existing typical algorithms in localization accuracy and localization coverage [19].
- In 2023, Baraa Abbas Shahal and Mohammed Najm Abdullah explored the recently proposed localization algorithms and discussed the simulation results for each method used in Software Defined Wireless Sensor Networks (SDWSN) to find the best way to localized nodes with the highest accuracy and lowest energy consumption. Also, they present Software defined networking paradigm and WSNS challenges, which are solved by SDWSNs. The results show that considerable improvement in network performance can be achieved [20].
- In 2023, Yuxiao Cao and Jinbao Xu improved the DV-Hop algorithm accuracy, a DV-Hop-based scheme using optimum anchor nodes subsets (OANS DV-Hop). Simulation results demonstrate that OANS DV-Hop algorithm owns higher localization accuracy compared with the primal DV-Hop and other improved DV-Hop algorithms in various network environments [21].
- In 2023, Rubén Álvarez et al., proposed combined sensor selection and node location optimization for reducing the localization uncertainties in wireless sensor networks to improve the localization accuracy and applicability .The simulation results show that the average positioning error of QABA-2D in 2D space positioning was reduced by 17.22–90.35% compared with other algorithms, and the average positioning error of QABA-3D in 3D space was reduced by 7.79–75.26% compared with other algorithms. Thus, the results show that the proposed QABA not only has excellent performance in the standard function test but also has excellent solution accuracy and applicability in node localization optimization of wireless sensor networks [22].

- In 2024, Yadava et al. introduced a Hybrid Bio-Inspired Optimization approach for node localization in Wireless Sensor Networks (WSNs), combining the Dragonfly Algorithm with Particle Swarm Optimization (PSO). This hybrid approach leveraged the exploration capabilities of the Dragonfly Algorithm and the fast convergence properties of PSO, effectively reducing computation time while enhancing localization accuracy. Experimental results showed that this combination minimized localization errors compared to standalone methods, making it a promising solution for applications requiring high precision in resource-constrained WSN environments. [23].
- In 2024, Arora et al. developed a node localization method for Wireless Sensor Networks (WSNs) using the Butterfly Optimization Algorithm. This approach utilized the butterfly-inspired search technique to enhance positioning accuracy and conserve energy, two critical factors in WSN applications. Experimental results demonstrated that this algorithm achieved significant improvements in localization accuracy while maintaining energy efficiency across various network configurations, making it suitable for energy-constrained environments [24].

3. Intelligent Swarm Algorithms

The collective activities of self-organized systems are the foundation of the intelligence of a swarm. Ant Colony System (ACS), Artificial Bee Colony (ABC), Bacteria Foraging (BF), Stochastic Diffusion Search (SDS), Particle Swarm Optimization (PSO), and other common SI systems are examples. In addition to its applications in traditional optimization problems, SI may also be utilized in controlling robotics and unmanned vehicles, prediction of social behaviors, improvement of communications, computer networks, and more. Swarm optimization can be effectively utilized in several domains, such as engineering and social sciences [25][26]. In this work, we examine a few swarm intelligence techniques for optimization problems, and several comparisons are made between these algorithms.

3.1 Crayfish Optimization Algorithm (COA)

The crayfish has a hard shell and resembles a shrimp. It is a member of the Decapoda, Crustacea, and Arthropoda groups in animal taxonomy. It is typically regarded as an important species for freshwater habitats [27]. The foraging, summertime vacation, and competitive nature of crayfish serve as inspiration for COA. The exploitation stages of COA are the foraging and competitive stages, while the exploration stages are the summer resort stages. At the beginning of the procedure, the crawfish colony X is defined to represent the features of swarm intelligence optimization. The ith crayfish's location, Xi, denotes a solution. ($Xi = \{Xi, 1, Xi, 1, Xi, 1 \ldots Xi, dim\}$, where dim, usually referred to as dimension, is the characteristic quantity of the optimization issue). The function $f(\cdot)$ is introduced by Xi in order to get the fitness value or solution [28].

Temperature, a random constant that reflects the temperature of the environment in which the individual is situated, the temperature controls the exploration and exploitation of COA. COA will go into the competitive or summer resort stage when the temperature gets too high. Update the new solution in accordance with the cave position $Xshade$ and the individual position Xi during the summer resort stage. When the temperature is right, COA will go into the stage of foraging. During the foraging phase, the optimal solution, or best position, is where the food is found. Food size is determined by the optimal solution, fitnessfood (obtained by the optimal solution), and the present solution, fitness (obtained by Xi). Crayfish receive new solutions based on their position (Xi), food intake (constant p), and food position ($Xfood$) update when the food is suitable. When the meal is too big, the crayfish will break it up with its claw foot before eating in turns with its second and third walking feet. We replicated the crayfish's alternating feeding pattern using the sine and cosine formula.

Crayfish have restricted food consumption. The amount of food consumed is decided by demonstrating a positive distribution at room temperature [28].

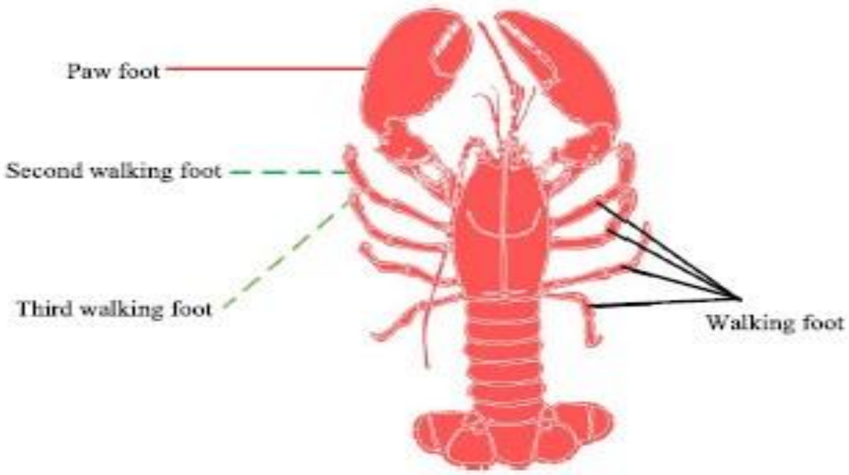

Figure 1: Structure diagram of COA [28]

3.1.1 Initialize population

In the problem of optimization in multi-dimensional, each crayfish is a 1 × dim matrix. A problem's solution is represented by each column matrix. Each variable Xi in a collection of variables ($Xi, 1, Xi, 2, \ldots, Xi, dim$) must fall between the upper and lower bounds. A set of potential solutions X is randomly generated as the COA's initialization in the space. It is suggested that the solution candidate X be used depending on the number of the population N and the dimension of area dim [29]. The initialization of COA scheme is shown in Equation (1).

$$X = [X_1, X_2, \dots, X_N] = \begin{bmatrix} X_{1,1} & \dots & X_{1,j} & \dots & X_{1,dim} \\ \vdots & \cdots & \vdots & \dots & \vdots \\ X_{i,1} & \dots & X_{i,j} & \dots & X_{i,dim} \\ \vdots & \cdots & \vdots & \dots & \vdots \\ X_{N,1} & \dots & X_{N,j} & \dots & X_{N,dim} \end{bmatrix} \quad (1)$$

Where N is the population number, dim is the dimension of the population, and $X_{i,j}$ represents the position of individual i in the j dimension. The value of $X_{i,j}$ is obtained from Equation (2).

$$X_{i,j} = lb_j + \left(ub_j - lb_j \right) \times rand \quad (2)$$

Where $rand$ is a random number and lb_j and ub_j denote the lower and upper bounds of the jth dimension, respectively [30].

3.1.2 Define temperature and intake of crayfish

The crayfish will undergo behavioral changes and go through distinct stages due to the temperature shift. Equation (3) defines temperature. Crayfish will select a cool spot for their summer vacation when the temperature rises above 30 °C. When the temperature is right, crayfish will start to feed themselves. Temperature influences the number of crayfish that feed. Crayfish have a feeding range of 15, 30, and 25 °C, which is ideal. As a result, it is possible to roughly estimate how much Crayfish to feed according to their regular distribution, with temperature having an impact. Because between 20 and 30 °C, crayfish exhibit robust feeding behavior. Accordingly, the COA specifies a temperature range of 20 to 35 °C [28]. Equation (4) displays the crayfish intake mathematical model.

$$temp = rand \times 15 + 20 \tag{3}$$

Where, $temp$, is the temperature of the crayfish's location.

$$p = C_1 \times \left(\frac{1}{\sqrt{2 \times \pi} * \sigma} \times exp\left(-\frac{(temp - \mu)^2}{2\sigma^2} \right) \right) \tag{4}$$

Among them, μ denotes the perfect crayfish temperature, and C_1 and σ are utilized to organize crayfish intake in various temperatures.

3.1.3 Summer resort stage (exploration)

The temperature is too high when it exceeds thirty. This will cause the Crayfish to choose to spend their summertime vacation in a cave [28].

Here is how the cave X_{shade} is described:

$$X_{shade} = (X_G + X_L)/2 \tag{5}$$

Where X_L denotes the optimal position of the current population and X_G is the optimal position reached thus far based on the number of iterations.

Random fights break up between crayfish over caverns. The Crayfish will enter the cave unhindered and be prepared for summer when $rand$ is less than 0.5, meaning no other Crayfish are vying for the cave. Using Equation (6), The crayfish will go into the cave to spend the summer there [31].

$$X_{i.j}^{t+1} = X_{i.j}^{t} + C_2 \times rand \times \left(X_{shade} - X_{i.j}^{t}\right) \tag{6}$$

According to Equation (7), C_2 is a declining curve, where t denotes the iteration number of the current generation and $t + 1$ is the iteration number of the next generation.

$$C_2 = 2 - (t/T) \tag{7}$$

Where T is the maximum number of iterations that can be made.

Crayfish aim to reach the cave, which stands for the best course of action, at the Summer Resort stage. The crayfish will now move towards the cave. This improves the exploitation potential of COA and moves people closer to the ideal solution [32]. Facilitate a faster convergence of the algorithm.

3.1.4 Competition stage (exploitation)

The presence of $rand$ ≥ 0.5 and $temp$ > 30 indicates the interest of other Crayfish in the cave.

They will now engage in a fight to take the cave. Accordingly, the Crayfish uses Equation (8) to compete for the cave [29].

$$X_{i.j}^{t+1} = X_{i.j}^{t} - X_{z.j}^{t} + X_{shade} \tag{8}$$

Where according to equation (9), z stands for the random individual of Crayfish.

$$z = round\left(rand \times (N - 1)\right) + 1 \tag{9}$$

Crayfish compete with one another at the competition stage and Crayfish Xi modifies their position in response to another Crayfish's position (Xz). The position can be changed to increase the search range of COA and improve the algorithm's exploration capability [28].

3.1.5 Foraging stage (exploitation)

The temperature is ideal for Crayfish feeding when it is less than thirty degrees. The crayfish will now start to approach the meal. Once it has been located, the crayfish will measure the size of the meal. If the food is too large, the Crayfish will use its claws to break it up and then use its second and third walking feet to consume it [32]. X_{food} is a food location that is described as:

$$X_{food} = X_G \tag{10}$$

Q represent the food size that is defined as:

$$Q = C_3 \times rand \times \left(fitness_i / fitness_{food}\right) \tag{11}$$

Where the value of the food component, $C3$, is a constant value of 3 and represents the largest food. The fitness value of the ith crayfish is represented by $fitness_i$, and the fitness value of the food location is represented by $fitness_{food}$.

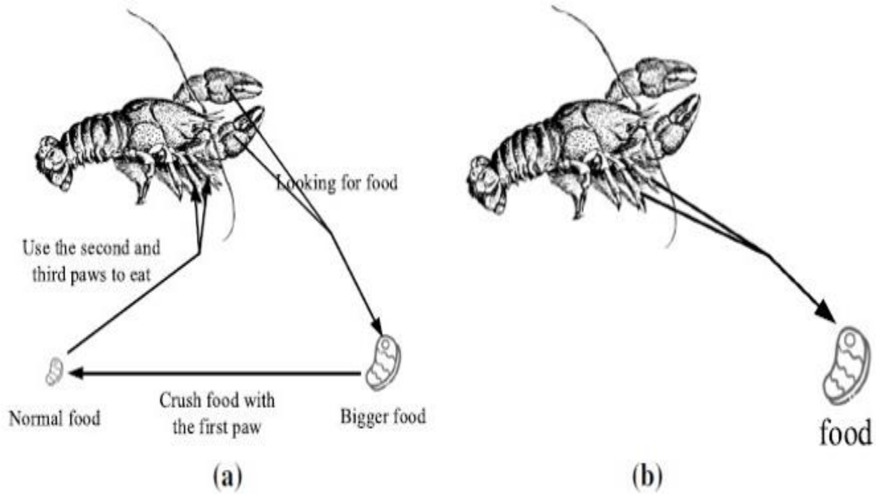

Figure 2: (a) Crayfish shred food before eating. (b) Crayfish eat directly [28]

The Crayfish bases its judgment of food size on the biggest food. $Q > (C_3 + 1)/2$ suggests that the meal is too substantial. Now, in order to break down the food, the Crayfish will use its first claw foot [31]. As shown in figure 2(a). The mathematical equation is as follows:

$$X_{food} = exp\left(-\frac{1}{Q}\right) \times X_{food}, \tag{12}$$

As the meal grows smaller and shreds, the second and third paws will be picked up and placed in the mouth. Using simulation, the alternating process is recreated by combining the sine and cosine functions. As shown in Figure 2(b). Additionally, because Crayfish intake and food availability are correlated, the foraging equation is as follows:

$$X_{i.j}^{t+1} = X_{i.j}^{t} + X_{food} \times P \times (\cos(2 \times \pi \times rand) - \sin(2 \times \pi \times rand)), \tag{13}$$

When $Q \leq (C3 + 1)/2$, the Crayfish just want to move toward the food and eat it right away:

$$X_{i.j}^{t+1} = \left(X_{i.j}^{t} - X_{food}\right) \times P + P \times rand \times, X_{i.j}^{t} \tag{14}$$

Crayfish use a range of feeding strategies during the foraging stage, with food X_{food} being the most effective choice, depending on the size of their meal Q. When the meal is small enough for them to eat, the crayfish will come over. If Q is too big, it means that there is a big difference between the ideal answer and reality. Therefore, X_{food} must be reduced and relocated nearer to the food. COA will go toward the best option during a foraging phase, increasing the scheme's exploitation potential and promoting significant convergence [33].

3.2 Mountain Gazelle Optimizer (MGO)

The innovative meta-heuristic scheme known as the Mountain Gazelle Optimizer (MGO) is inspired by the social and collective behavior of mountain deer in the wild. The social structure and the way of life of untamed mountain gazelles served as inspiration. Based on the four main facets of mountain gazelle life—territorial solitary males, maternity herds, bachelor male herds, and movement in search of food—the MGO system optimizes operations [34].

The essential elements of mountain gazelle life, specifically their grouping and social behaviors, as well as all the variables governing herd communication, breeding, and grazing, are simulated in order to create the MGO mathematical model [35]. This scheme's primary advantage is that it bases its optimization procedures on many factors. The four elements that really formulate such a dynamic procedure are herds of maternity, territorial males, bachelor male herds, migration to grazing zones in search of food, and solitary.
When it is compared to alternative mathematical modeling options, the MGO scheme's study population is chosen to be one to a third of the entire populace, hence lowering costs. This is due to the character of the bachelor group's youthful male members, who are unable to exert dominance over the females in order to reproduce [36].
During the MGO's optimization process, the adult male gazelle in the herd territory is determined to be the overall optimal solution. However, each individual (Gi gazelle) has the option to join the maternity female, the herd of lone males, or the herd of solitary territorial males. Conversely, however, a deer may also give birth. Nonetheless, the MGO algorithm's mechanism allows for the possibility of alternative solutions, which are mostly represented by gazelles in maternity herds.

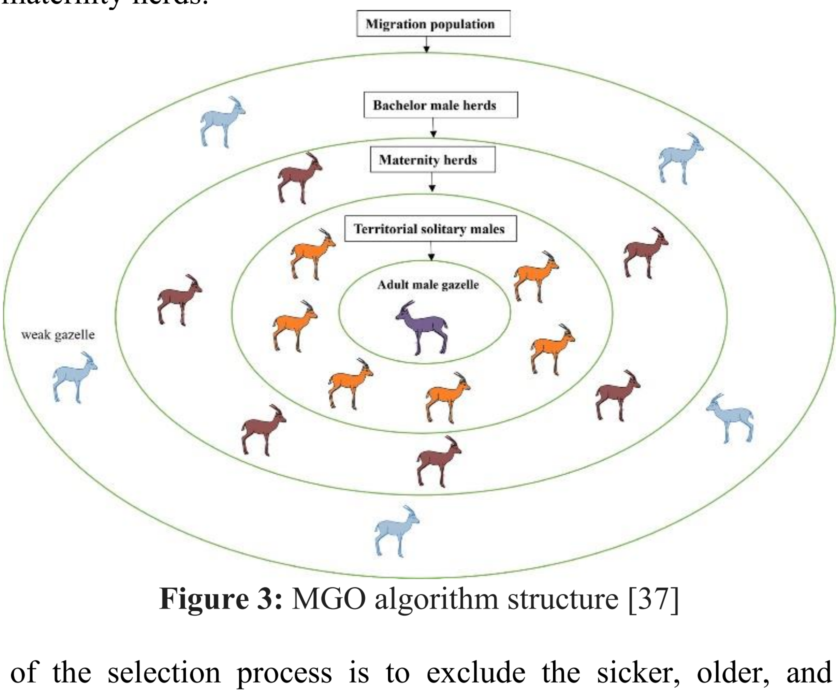

Figure 3: MGO algorithm structure [37]

The goal of the selection process is to exclude the sicker, older, and less valuable gazelles from the population while retaining the healthier, more vigorous members of the population as premium choices.

3.2.1 Territorial Solitary Males

Mountain gazelles are herd animals, including males and females with offspring. By the time they reach adulthood, the male mountain gazelles in their adolescent years possess the strength necessary to assert their dominance and complete their life cycle. The recently matured males now reside in a remote, isolated place. Males battle violently and jostle each other with their horns during the courting or mating season, while adults attempt to defend their domains, and the youngsters strive for possession of the females [35]. One can use Equation (15) to ascertain the adult male's territory.

$$TSM = male_G - |(ri_1 \times BH - ri_2 \times X(t)) \times F| \times Cof_r, \tag{15}$$

The term "$male_G$" in this context denotes the optimal worldwide solution that represents the adult male's position vector. The random numbers ri_1 and ri_2 can be interpreted as either 1 or 2. The young male herd's coefficient vector is denoted by BH. It is roughly represented by:

$$BH = X_{ra} \times \lfloor r_1 \rfloor + M_{pr} \times \lceil r_2 \rceil, ra = \left\{ \left\lceil \frac{N}{3} \right\rceil \dots N \right\} \tag{16}$$

With:

$$ra = \left\{ \left\lceil \frac{N}{3} \right\rceil \dots N \right\} \tag{17}$$

A young male is represented by the random solution X_{ra} in the interval of ra. Random numbers between 0 and 1 make up r_1 and r_2. N is the total number of herd gazelles, and M_{pr} is the average number of randomly chosen search agents $\left\lceil \frac{N}{3} \right\rceil$.

Equation (18) is used to evaluate F in Equation (15).

$$F = N_1(D) \times exp - \left(2 - Iter \times \left(\frac{2}{MaxIter} \right) \right) \tag{18}$$

N_1 is a random number drawn from the standard distribution in accordance with the problem dimensions [37]. The numbers $Iter$ and $MaxIter$ represent the number of iterations that are now in progress and total, respectively.

Moreover, as expressed in Equation (19), the coefficient vector Cof_rthat was first randomly picked is updated in each iteration to improve the search capacity.

$$Cof_r = \begin{cases} (a+1) + r_3, \\ a \times N_2(D), \\ r_4(D), \\ N_3(D) \times N_4(D)^2 \times \cos((r_4 \times 2) \times N_3(D)) \end{cases} \tag{19}$$

In the interval [0, 1], the numbers *rand*, r_3, and r_4 are selected at random. Furthermore, N_2, N_3, and N_4 are fixed at random based on the issue dimensions and the normal range [29]. The expression for the parameter a is:

$$a = -1 + Iter \times \left(\frac{-1}{MaxIter} \right) \tag{20}$$

3.2.2 Maternity Herds

Maternity herds, which produce young, powerful male gazelles to ensure the herd's survival, are the most crucial members in the life cycle of all animals. Equation (21) shows that male gazelles play a major role in the birth of young males who are trying to catch female gazelles [34].

$$MH = \left(BH + Cof_{1,r} \right) + (ri_3 \times male_G - ri_4 \times X_{rand}) \times Cof_{1,r} \tag{21}$$

According to Equation (16), when assessing the impact factor vector (BH) for young males, the coefficient vectors ($Cof_{2,r}$ and $Cof_{3,r}$) are chosen at random using Equation (19). For the current repeat, the adult male designated as $male_G$ is the global solution, and *rand* is the vector location of a randomly selected gazelle. If not, ri_3 and ri_4 are arbitrary integers of 1 or 2.

3.2.3 Bachelor Male Herds

Based on their living circumstances, mountain deer typically have a lifespan of eight years. For males, the breeding process starts at 18 months, and for females, it starts at 12 months. The breeding season usually begins at the first signs of winter. In accordance with sociobiology and zoology, male mountain gazelles reproduce by copulating with multiple females, a behavior known as polygamy, just like many other mammals. The female typically gives birth in April or May once a year. Females pick carefully among the available males in the herd, while males try to entice females and compete with them for mating. In this setting, the establishment of mating relationships is significantly influenced by male dominance [38]. As they get older, juvenile male gazelles start to seize control of new areas, fiercely defend them, and make mating attempts with females. Equation (22), to accomplish these goals, shows an increase in violent behavior between the two male groups during this critical moment.

$$BMH = (X(t) - D) + (ri_5 \times male_G - ri_6 \times BH) \times Cof_r \quad (22)$$

The gazelle vector's position is defined by $X(t)$ during every iteration. As previously stated, $male_G$ is the best answer when ri_5 and ri_6 are arbitrarily chosen to be 1 or 2. Furthermore, a randomly chosen coefficient vector is denoted by Cof_r. Equation (23) is used to establish D [29].

$$D = (|X(t)| + |male_G|) \times (2 \times r_6 - 1) \quad (23)$$

In this case, r_6 is a randomly selected number from the range [0, 1].

3.2.4 Migration to Search for Food

Because they are most active in the early morning and late afternoon, mountain deer spend most of the night sleeping and most of the day awake. These deer are herbivores that graze on grass, leaves, or small shrubs. They are also highly territorial within groups of three to eight . Typically, herds of deer cover enormous distances in search of food and grazing, using their considerable speed for jumping, running, and sprinting as advantages. One of the most significant traits imposed by their habitat is their ability to go extended periods of time without drinking water since they have access to fresh herbs, dew drops, new shoots, and low-lying tree branches, particularly in areas where the acacia tree grows [38]. Equation (24) represents the behavior of mountain gazelles mathematically as follows:

$$MSF = (ub - lb) \times r_7 + lb \quad (24)$$

In this case, lb is the lower limit and ub is the upper limit of the optimization problem that is being tackled. A random number with a range of [0, 1] is called r_7.

Applying the four methods mentioned above guarantees the creation of fresh generations of mountain gazelles, assuming that every generation is equivalent to a repetition. At the end of each era, the addition of a new era to the overall population is also taken into consideration for the classification of all mountain gazelles. The classification is done in ascending order based on the caliber of the answers since the dominant adult male gazelle in the area is regarded as the best gazelle. It is true that only gazelles deemed more cost-effective and promising are retained in the population, with weaker or older individuals being culled [37].

4. WSN Localization Problem Formulation

The problem of localization for wireless sensor network nodes may be defined as a single hop range-based distribution strategy, which involves estimating the target (unknown) nodes'(X, Y) position with the help of the main nodes' coordinates (x, y), which act as the location of the known nodes. Because main nodes come with GPS units, they can figure out where they are on their own. Because GPS is so expensive, the majority of WSN nodes are not outfitted with it. The steps used are shown below to calculate the coordinates of the N target (unknown) nodes.

Step 1: Within communication range (R), randomly establish M anchor nodes and N unknown nodes. Anchor nodes use positional awareness to tell their neighbors their coordinates. The node that settles at the conclusion of each cycle is referred to as the reference node, and it serves as the anchor node.

Step 2: A node is deemed localized if 3 or more main (anchor) nodes are present inside the range of its connection.

Step 3: Assign (x, y) to the target node's coordinates and d_i to the separation between both of target (unknown) and ith anchor (main) node.

$$d_i = \sqrt{(x - x_i)^2 + (y - y_i)^2} \tag{25}$$

Step 4: The localization problem's error is minimized by formulating the optimization problem. The localization problem's objective function is expressed as:

$$f(x, y) = min\left(\sum_{i=1}^{M}\left(\sqrt{(x - x_i)^2 + (y - y_i)^2}\right)^2\right) \tag{26}$$

Where M denotes main nodes that are inside the target node's transmission range.

Step 5: After determining each unknown localized node (N_L), the total error of localization is computed as the mean square of the difference between the predestined and the real coordinates node x_i, y_i, for $i = 1, 2, 3, \ldots N_L$:

$$E_L = \frac{1}{N_L}\sum_{i=1}^{L}(\sqrt{(x_i - X_i)^2 + (y_i - Y_i)^2}) \tag{27}$$

Step 6: Go back to step 2 and repeat through 5 till no more nodes can be located or until all unknown/target nodes have been localized.

5. Experimental Analysis

This section compares the performance of the proposed WSN method with two other algorithms (PSO and GWO) in terms of localization error, calculation time, and number of localization nodes The strategy is assessed under different situations. The calculation of various algorithms was performed using MATLAB R2021b on Intel Core (TM) i5 CPU, Windows10 operating system, and 8 GB RAM. The parameters of the shipping point values are shown in Table 1.

Table 1: The setting of the parameters.

The Parameters	The Values
The target (unknown) nodes	differ on $\sum_{k=1}^{6} \mathrm{k} * 25$
The main (anchor) nodes	differ with increase k=k+5
Range of transmission	30 meters
Space of work	100 meters × 100 meters

For the PSO scheme, the initial values of w_{max} = 0.9, w_{min} =0.2, $c1$ = $c2$ = 2 were recommended for faster convergence after experimental tests. The parameter a for GWO reduces linearly in the interval [2 to 0], and the parameter C linearly increases from 0 to 2 sand r_1, r_2 are random vectors in [0, 1]. For MGO, r_i is a value chosen randomly between 0 and 1.

6. The general framework

In terms of achieving an accurate node localization in WSN, the proposed system is performed in six scenarios where in each scenario, the number of main(anchor) nodes and target or unknown node is different. The number of main nodes is 10, and the target is 25 nodes in the first scenario then it is updated in each scenario five nodes is added to the main node, and 25 nodes are added to the target node until the number of main nodes become 35 and target node become 150 in the sixth scenario. After the environment becomes ready, the PSO, GWO, COA, and MGO algorithms are performed separately in this space. These algorithms are performed in a number of iterations (25,50,75, and 100). Each algorithm is performed ten times, and the average of the result is taken to compare the results of each algorithm. Figure (3) Represents the flow chart of the proposed WSN Localization system.

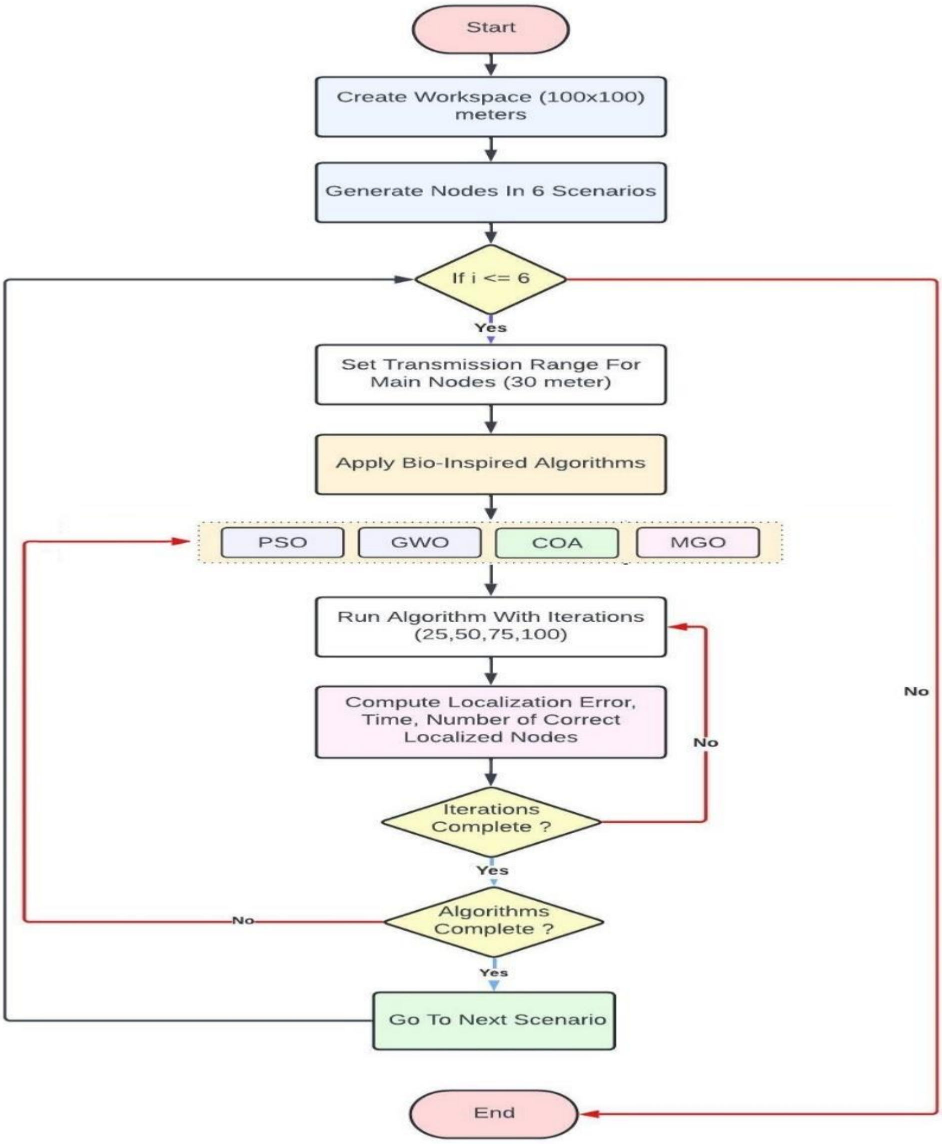

Figure 4: General framework of the proposed WSN Localization System.

7. The comparison between schemes.

In this part, MGO and the other swarm schemes have been examined regarding the number of localization nodes, the time of computation, and the error of localization under various conditions. Table 2 displays the outcomes of the various methods that were obtained.

Table 1- Compression of the various localization schemes'' results.

No. of target nodes	No. of anchor nodes	No. of iteration	PSO			GWO			COA			MGO		
			N_L	*Time (s)*	E_L	N_L	*Time (s)*	E_L	N_L	*Time (s)*	E_L	N_L	*Time (s)*	E_L
25	10	25	22	16	0.039	24	9	0.015	24	27	0.015	24	23	0.015
		50	22	22	0.034	24	19	0.015	24	51	0.015	24	44	0.015
		75	24	30	0.006	24	28	0.015	24	87	0.015	24	67	0.015
		100	21	40	0.058	24	36	0.015	24	114	0.015	24	89	0.015
50	15	25	46	21	0.008	47	20	0.011	47	70	0.011	47	29	0.011
		50	49	43	0.008	47	40	0.011	47	196	0.011	47	57	0.011
		75	48	73	0.013	47	71	0.011	47	299	0.011	47	88	0.011
		100	49	104	0.007	47	75	0.011	47	310	0.011	47	128	0.011
75	20	25	74	36	0.004	74	52	0.008	74	304	0.008	74	42	0.008
		50	75	79	0.014	74	104	0.008	74	555	0.008	74	83	0.008
		75	72	46	0.014	74	144	0.008	74	614	0.008	74	120	0.008
		100	74	206	0.011	74	194	0.008	74	806	0.008	74	161	0.008
100	25	25	99	44	0.004	100	62	0.001	100	284	0.001	100	46	0.001
		50	100	181	0.005	100	87	0.001	100	140	0.001	100	96	0.001
		75	100	281	0.006	100	87	0.001	100	118	0.001	100	137	0.001
		100	99	380	0.006	100	172	0.001	100	184	0.001	100	168	0.001
125	30	25	123	51	0.007	122	46	0.002	122	630	0.002	122	54	0.002
		50	125	93	0.002	122	92	0.002	122	124	0.002	122	113	0.002
		75	123	162	0.002	122	153	0.002	122	212	0.002	122	158	0.002
		100	125	215	0.002	122	326	0.002	122	277	0.002	122	214	0.002
150	35	25	150	69	0.005	150	73	0.005	150	105	0.005	150	79	0.005
		50	150	141	0.005	150	135	0.005	150	191	0.005	150	157	0.005
		75	150	234	0.002	150	204	0.005	150	321	0.005	150	239	0.005
		100	150	315	0.003	150	217	0.005	150	382	0.005	150	317	0.005

It is shown that for all localization strategies, in all cases (the number of the unknown (target) nodes and the number of the main (anchors) nodes), increasing in iteration leads to a reduction in localization error, but an increase in the number of localizations and computation time. This seems to cover the goal, as more iterations equal more calculations and take longer to complete. On the contrary, the greater the number of actions, the more likely we are to reach a better solution. As a result, there are more localized nodes, and the localization error value that explains the location error (E_L) for the relation between these main and unknown nodes. However, as the number of targets and anchors increases, it turns out that MGO outperforms COA, PSO, and GWO in this area. Regarding the computation time, it was observed that increasing the number for both target (unknown) and anchor (main) nodes increases the time of computing for the whole localization's schemes. However, compared with COA, PSO and GWO, the MGO's computation time is better. The next three figures show schematic diagrams of experiments conducted at different scales.

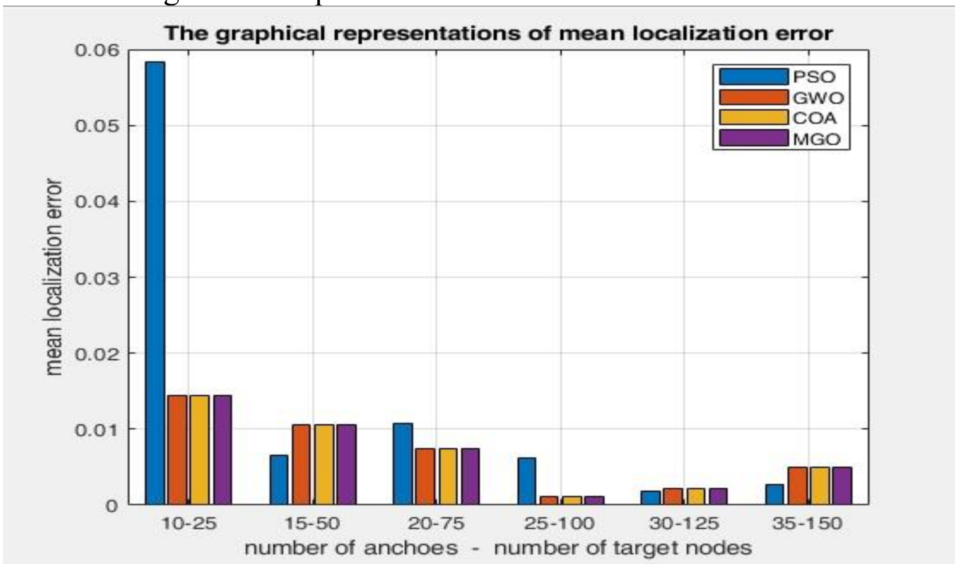

Figure 5: The mean localization error of the localization algorithms across many deployments of wireless sensor networks.

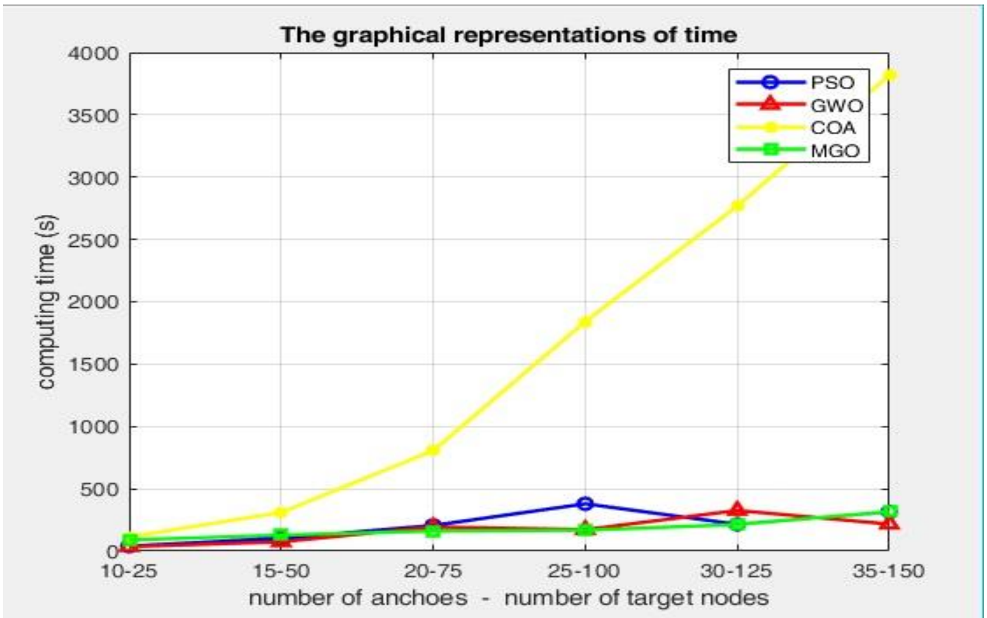

Figure 6: The computation time of various algorithms in various Wireless Sensor Network configurations.

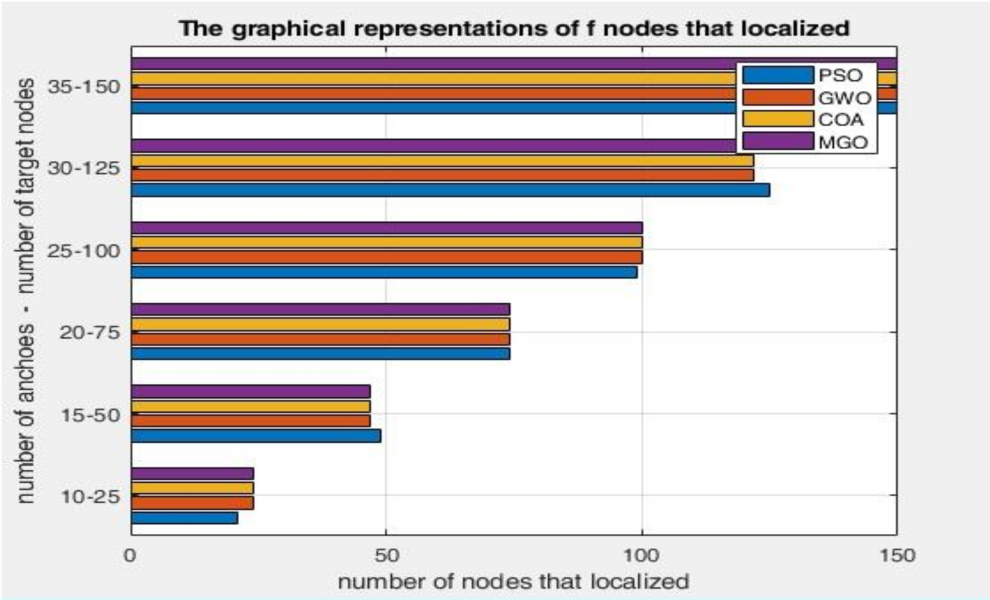

Figure 7: The number of located nodes in various Wireless Sensor Network installations using various localization techniques.

8. Conclusion

Accurate node localization is a significant challenge in Wireless Sensor Networks (WSNs), as precise positioning is essential for optimizing network performance, conserving energy, and ensuring reliable communication. Existing localization techniques often face limitations due to high localization errors, computational demands, and the inability to adapt efficiently in varying network conditions. Addressing these issues, this study introduced a novel hybrid localization method that integrates the Mountain Gazelle Optimizer (MGO) and Crayfish Optimization Algorithm (COA), two bioinspired algorithms with strong exploration and exploitation capabilities.

The proposed method leverages the distinct behavioral strategies of MGO and COA to optimize node positioning by reducing localization errors and enhancing computational efficiency. By accurately estimating the positions of unknown nodes using anchor nodes, the MGO-based approach minimizes computational time while increasing localization precision. Comparative experiments demonstrated that the proposed MGO and COA algorithms outperform traditional approaches, such as Particle Swarm Optimization (PSO) and Grey Wolf Optimizer (GWO), across various network deployment scenarios. This improvement not only reduces localization error but also optimizes resource utilization, making it a highly effective solution for diverse WSN applications.

References

[1] J. Yick, B. Mukherjee, and D. Ghosal, “Wireless sensor network survey,” *Comput. networks*, vol. 52, no. 12, pp. 2292–2330, 2008.

[2] M. Khamees, A. Albakry, and K. Shaker, “Multi-objective feature selection: Hybrid of salp swarm and simulated annealing approach,” in *International Conference on New Trends in Information and Communications Technology Applications*, 2018, pp. 129–142.

[3] M. Khamees and A. A.-B. Rashed, “Hybrid SCA-CS optimization algorithm for feature selection in classification problems,” in *AIP conference proceedings*, 2020, vol. 2290, no. 1.

[4] X. Wang, Y. Liu, Z. Yang, K. Lu, and J. Luo, “Robust component-based localization in sparse networks,” *IEEE Trans. Parallel Distrib. Syst.*, vol. 25, no. 5, pp. 1317–1327, 2013.

[5] S. Salari, S. Shahbazpanahi, and K. Ozdemir, “Mobility-aided wireless sensor network localization via semidefinite programming,” *IEEE Trans. Wirel. Commun.*, vol. 12, no. 12, pp.

5966–5978, 2013.

[6] B.-F. Wu and C.-L. Jen, "Particle-filter-based radio localization for mobile robots in the environments with low-density WLAN APs," *IEEE Trans. Ind. Electron.*, vol. 61, no. 12, pp. 6860–6870, 2014.

[7] C. Wu, Z. Yang, and Y. Liu, "Smartphones based crowdsourcing for indoor localization," *IEEE Trans. Mob. Comput.*, vol. 14, no. 2, pp. 444–457, 2014.

[8] Z. Chaczko and F. Ahmad, "Wireless sensor network based system for fire endangered areas," in *Third International Conference on Information Technology and Applications (ICITA'05)*, 2005, vol. 2, pp. 203–207.

[9] B. Jankuloska, M. Zahariev, A. Mateska, V. Atanasovski, and L. Gavrilovska, "Traffic regulations monitoring using vsns," in *17th Telecommunication forum (TELFOR)*, 2009, pp. 1474–1477.

[10] N. R. Council, *Grand challenges in environmental sciences*. National Academies Press, 2001.

[11] N. B. Priyantha, H. Balakrishnan, E. Demaine, and S. Teller, "Anchor-free distributed localization in sensor networks," in *Proceedings of the 1st International Conference on Embedded Networked Sensor Systems*, 2003, pp. 340–341.

[12] A. Coluccia and F. Ricciato, "RSS-based localization via Bayesian ranging and iterative least squares positioning," *IEEE Commun. Lett.*, vol. 18, no. 5, pp. 873–876, 2014.

[13] H. Wymeersch, J. Lien, and M. Z. Win, "Cooperative localization in wireless networks," *Proc. IEEE*, vol. 97, no. 2, pp. 427–450, 2009.

[14] P. Oğuz-Ekim, J. P. Gomes, J. Xavier, M. Stošić, and P. Oliveira, "An angular approach for range-based approximate maximum likelihood source localization through convex relaxation," *IEEE Trans. Wirel. Commun.*, vol. 13, no. 7, pp. 3951–3964, 2014.

[15] P. Sekhar, E. L. Lydia, M. Elhoseny, M. Al-Akaidi, M. M. Selim, and K. Shankar, "An effective metaheuristic based node localization technique for wireless sensor networks enabled indoor communication," *Phys. Commun.*, vol. 48, p. 101411, 2021.

[16] S. Messous, H. Liouane, O. Cheikhrouhou, and H. Hamam, "Improved recursive DV-hop localization algorithm with RSSI measurement for wireless sensor networks," *Sensors*, vol. 21, no. 12, p. 4152, 2021.

[17] H. Yuan *et al.*, "Improved beluga whale optimization algorithm based cluster routing in wireless sensor networks," *Math. Biosci. Eng.*, vol. 21, no. 3, pp. 4587–4625, 2024.

[18] R. Khanna and A. Kumar, "Artificial intelligence applications for target node positions in wireless sensor networks using single mobile anchor node," *Comput. Ind. Eng.*, vol. 167, p. 107998, 2022.

[19] W. Liu, X. Luo, G. Wei, and H. Liu, "Node localization algorithm for wireless sensor networks based on static anchor node location selection strategy," *Comput. Commun.*, vol. 192, pp. 289–298, 2022.

[20] B. A. Shahal and M. N. Abdullah, "A review of localization algorithms based on software defined networking approach in wireless sensor network," *Meas. Sensors*, p. 100772, 2023.

[21] Y. Cao and J. Xu, "DV-Hop-based localization algorithm using optimum anchor nodes subsets for wireless sensor network," *Ad Hoc Networks*, vol. 139, p. 103035, 2023.

[22] R. Álvarez, J. Díez-González, P. Verde, R. Ferrero-Guillén, and H. Perez, "Combined sensor selection and node location optimization for reducing the localization uncertainties in wireless sensor networks," *Ad Hoc Networks*, vol. 139, p. 103036, 2023.

[23] P. Yadav and S. C. Sharma, "An Efficient Optimal Localization Technique for WSN Using Hybrid Machine Learning Algorithms," *Wirel. Pers. Commun.*, vol. 133, no. 4, pp. 2601–2639, 2023, doi: 10.1007/s11277-024-10892-z.

[24] S. Arora and S. Singh, "Node localization in wireless sensor networks using butterfly optimization algorithm," *Arab. J. Sci. Eng.*, vol. 42, pp. 3325–3335, 2017.

[25] A. Tharwat, E. H. Houssein, M. M. Ahmed, A. E. Hassanien, and T. Gabel, "MOGOA algorithm for constrained and unconstrained multi-objective optimization problems," *Appl. Intell.*, vol. 48, pp. 2268–2283, 2018.

[26] A. G. Hussien, E. H. Houssein, and A. E. Hassanien, "A binary whale optimization algorithm with hyperbolic tangent fitness function for feature selection," in *2017 Eighth International Conference on Intelligent Computing and Information Systems (ICICIS)*, 2017, pp. 166–172.

[27] A. Kouba, A. Petrusek, and P. Kozák, "Continental-wide distribution of crayfish species in Europe: update and maps," *Knowl. Manag. Aquat. Ecosyst.*, no. 413, p. 5, 2014.
[28] H. Jia, H. Rao, C. Wen, and S. Mirjalili, "Crayfish optimization algorithm," *Artif. Intell. Rev.*, vol. 56, no. Suppl 2, pp. 1919–1979, 2023.
[29] Z. Liao, Z. Chen, and S. Li, "Parameters extraction of photovoltaic models using triple-phase teaching-learning-based optimization," *IEEE Access*, vol. 8, pp. 69937–69952, 2020.
[30] S. Carbas, A. Toktas, and D. Ustun, *Nature-inspired metaheuristic algorithms for engineering optimization applications*. Springer, 2021.
[31] N. H. Shikoun, A. S. Al-Eraqi, and I. S. Fathi, "BinCOA: An Efficient Binary Crayfish Optimization Algorithm for Feature Selection," *IEEE Access*, vol. 12, pp. 28621–28635, 2024.
[32] B. Xiao, R. Wang, Y. Deng, Y. Yang, and D. Lu, "Simplified Crayfish Optimization Algorithm," in *2024 IEEE 7th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)*, 2024, vol. 7, pp. 392–396.
[33] H. Jia, X. Zhou, J. Zhang, L. Abualigah, A. R. Yildiz, and A. G. Hussien, "Modified crayfish optimization algorithm for solving multiple engineering application problems," *Artif. Intell. Rev.*, vol. 57, no. 5, p. 127, 2024.
[34] P. Sarangi and P. Mohapatra, "Evolved opposition-based mountain gazelle optimizer to solve optimization problems," *J. King Saud Univ. Inf. Sci.*, vol. 35, no. 10, p. 101812, 2023.
[35] B. Abdollahzadeh, F. S. Gharehchopogh, and S. Mirjalili, "African vultures optimization algorithm: A new nature-inspired metaheuristic algorithm for global optimization problems," *Comput. Ind. Eng.*, vol. 158, p. 107408, 2021.
[36] K. Chandrasekaran, A. S. R. Thaveedhu, P. Manoharan, and V. Periyasamy, "Optimal estimation of parameters of the three-diode commercial solar photovoltaic model using an improved Berndt-Hall-Hall-Hausman method hybridized with an augmented mountain gazelle optimizer," *Environ. Sci. Pollut. Res.*, vol. 30, no. 20, pp. 57683–57706, 2023.
[37] B. Abdollahzadeh, F. S. Gharehchopogh, N. Khodadadi, and S. Mirjalili, "Mountain gazelle optimizer: a new nature-inspired metaheuristic algorithm for global optimization problems," *Adv. Eng. Softw.*, vol. 174, p. 103282, 2022.
[38] R. Abbassi, S. Saidi, S. Urooj, B. N. Alhasnawi, M. A. Alawad, and M. Premkumar, "An Accurate Metaheuristic Mountain Gazelle Optimizer for Parameter Estimation of Single- and Double-Diode Photovoltaic Cell Models," *Mathematics*, vol. 11, no. 22, pp. 1–21, 2023, doi: 10.3390/math11224565.