information

Article

Target Positioning and Tracking in WSNs Based on AFSA

Shu-Hung Lee [1], Chia-Hsin Cheng [2,*], Chien-Chih Lin [2] and Yung-Fa Huang [3,*]

[1] School of Intelligent Manufacturing and Automotive Engineering, Guangdong Business and Technology University, Zhaoqing 526020, China; umaillee@gmail.com
[2] Department of Electrical Engineering, National Formosa University, Yunlin 632301, Taiwan; advcomm@gs.nfu.edu.tw
[3] Department of Information and Communication Engineering, Chaoyang University of Technology, Taichung 413310, Taiwan
* Correspondence: chcheng@nfu.edu.tw (C.-H.C.); yfahuang@cyut.edu.tw (Y.-F.H.); Tel.: +886-4-2332-3000 (Y.-F.H.)

Abstract: In wireless sensor networks (WSNs), the target positioning and tracking are very important topics. There are many different methods used in target positioning and tracking, for example, angle of arrival (AOA), time of arrival (TOA), time difference of arrival (TDOA), and received signal strength (RSS). This paper uses an artificial fish swarm algorithm (AFSA) and the received signal strength indicator (RSSI) channel model for indoor target positioning and tracking. The performance of eight different method combinations of fixed or adaptive steps, the region segmentation method (RSM), Hybrid Adaptive Vision of Prey (HAVP) method, and a Dynamic AF Selection (DAFS) method proposed in this paper for target positioning and tracking is investigated when the number of artificial fish is 100, 72, 52, 24, and 12. The simulation results show that using the proposed HAVP total average positioning error is reduced by 96.1%, and the positioning time is shortened by 26.4% for the target position. Adopting HAVP, RSM, and DAFS in target tracking, the positioning time can be greatly shortened by 42.47% without degrading the tracking success rate.

Keywords: WSNs; target positioning; target tracking; AFSA; region segmentation method

check for updates

Citation: Lee, S.-H.; Cheng, C.-H.; Lin, C.-C.; Huang, Y.-F. Target Positioning and Tracking in WSNs Based on AFSA. *Information* **2023**, *14*, 246. https://doi.org/10.3390/info14040246

Academic Editors: Mohd Nor Akmal Khalid, Hanhan Maulana, Masnizah Mohd, Nursuriati Jamil and Hiroyuki Iida

Received: 13 March 2023
Revised: 6 April 2023
Accepted: 16 April 2023
Published: 18 April 2023

1. Introduction

A wireless sensor network is a network system consisting of one to several wireless data collectors and a big number of sensors, and the communication mode between components is wireless communication. A wireless sensor network is a kind of ad hoc network. It is a distributed network that does not require fixed infrastructure. Each network node communicates directly with other nodes within its range. The packets are forwarded by nearby nodes or other nodes on the path from the source node to the destination node. In the absence of fixed infrastructure and central management, wireless ad hoc networks must be able to establish cooperation between nodes on their own. Network nodes must also be able to adapt to changes in the network and have a dynamic network topology. In other words, we can place any sensor or wireless data collector in the network, which saves considerable deploying costs and is very convenient to use. In the framework of the wireless sensor network, the sensor is designed for saving power, lower costs, being smaller in size, and sensing the environment. The sensor is like a small computer and equipped with simple sensing components, computing, and wireless transmission devices. The sensing elements can detect the things we are interested in in the environment, such as temperature, light source, etc., and after simple calculation processing of the collected data, through the wireless transmission device, the data are sent back to the data collector. Finally, according to the data collected by the data collector, different applications can be developed such as military surveillance, environmental detection, smart home, and target positioning and tracking [1,2].

Wireless sensor network positioning estimates the position of sensors whose initial position information is unknown by using the absolute position information of a few sensors and measuring data such as distance and azimuth between sensors. Generally speaking, the positioning methods of wireless sensor networks can be divided into range-based and range-free types [1]. The former is represented by the global positioning system (GPS). The advantage of GPS is that the positioning accuracy is high, while the disadvantages are that it requires costly construction and that the using scope and its positioning quality are easily affected by factors such as weather or the shelter of buildings. The range-free locating method arranges anchor nodes on the network to assist in the positioning of sensor nodes. It can significantly reduce the cost, but the positioning accuracy decreases. In practical applications, to meet the needs of dynamic events, the sensor must have the ability to move [3–6]. In the target positioning and tracking system, in which each sensor needs to know its position, a lot of target positioning and tracking methods of wireless sensor networks have been proposed, such as received signal strength (RSS), time of arrival (TOA), time difference of arrival (TDOA), angle of arrival (AOA), etc. [7–11]. Sensors communicate with each other to receive signals to the target point to estimate the target position. However, TOA, TDOA, and AOA in these methods require more expensive equipment and higher computational complexity than RSS. In the wireless sensor network, for coping with dynamic network events and dynamic applications, such as the need to send motor vehicles or robots with sensing capabilities to a specific location to perform corresponding tasks, it is necessary to use sensing devices with mobile capabilities. In [12], AFSA was used for target positioning with the least square method. In [13], AFSA and TDOA algorithms were used to locate the sensor. In [14], AFSA combined with visible light communication was used to conduct a high-precision indoor 3D positioning system. Compared with traditional wireless sensor networks, with the rapid development of the Internet of Things (IoT), multiple data collection and computational task wireless sensor networks will face some new challenges. For example: WSN hardware complexity and software computing requirements will increase. Therefore, combining edge computing in the future is crucial for many WSN applications. It can reduce latency and bandwidth usage, although it may lead to higher costs. However, it is helpful to improve overall performance and reduce energy consumption.

This paper proposes the Hybrid Adaptive Vision of Prey (HAVP) method and the region segmentation method (RSM) for the target positioning and tracking methods in the wireless sensor network using AFSA combined with the received signal strength indicator (RSSI) channel model to improve the accuracy of target localization and tracking methods. At the same time, a dynamic artificial fish selection (DAFS) method is proposed for the target tracking system to improve the efficiency of target tracking. In addition, this paper also investigates the impact of the number of sensors on different target positioning and tracking methods.

The rest of this paper is as follows. Section 2 depicts the AFSA and RSSI model, and the system model is introduced in Section 3. Section 4 describes the simulation results, and discussions are made in Section 5. Finally, a conclusion is given in Section 6.

2. AFSA and RSSI Model

2.1. AFSA

The AFSA was proposed by Xiao-Lei Li et al. in 2002 [15,16]. The artificial fish swarm algorithm seeks the best solution by imitating fish behaviors such as foraging behavior, gathering behavior, and following behavior. The artificial fish swarm algorithm has the characteristics of parallelism, simplicity, quick jumping out of the local solution, fast speed of seeking the best solution, and insensitivity to the initial parameters. However, AFSA has the disadvantage that its mathematical theory foundation is relatively weak. The setting of parameters of the algorithm has no exact theoretical basis, and most parameters are set according to experience. Therefore, algorithm parameter setting for different application environments is a very important problem. Based on the basic artificial fish swarm modeling algorithm, many studies have proposed methods to improve the performance of the algorithm [17–19]. The accuracy of the artificial fish swarm modeling algorithm is proportional to the number of artificial fishes. The more artificial fish individuals, the higher the accuracy of the optimal solution but the slower the convergence speed. The authors in [20] introduced the swallowing behavior of fish. If the current individual has small adaptability, it will be swallowed, and new individuals will be randomly generated to reduce the amount of computation and improve the computing speed. A random search and artificial fish jumping behavior were proposed in [21] to improve the efficiency of the algorithm in seeking the global optimal solution. The authors in [22] proposed an adaptive step size and visual range method, which maintains a large step size and visual range for global searching in the initial iteration of the algorithm and reduces the step size and visual range for local search in the later iteration of the algorithm, improving the accuracy of optimization of the algorithm and the speed of seeking the best solution.

2.1.1. Basic Behaviors in AFSA

In bodies of water where the number of fish is the largest is generally the place where the water is rich in nutrients. Fish can swim quickly and agilely in the water to find food, relying on information sharing among fish schools. The artificial fish swarm algorithm imitates the behaviors of a fish swarm, such as praying, swarming, and following, based on this feature and then achieves the purpose of seeking the best solution in the whole domain [23]. An artificial fish (AF) is a virtual version of a real fish that is used to analyze and explain problems. An AF is an entity that encapsulates its data and a series of behaviors. It can receive environmental information through its senses and determines its actions based on it.

In the AFSA, the state of the AFs is expressed as a vector $X = (X_1, X_2, \cdots, X_M)$ where $X_i (i = 1, 2, \cdots, M)$ is the variable to be solved. The food concentration at the current position of the artificial fish can be expressed as $Y = f(X)$, the distance between individual artificial fish is $d_{ij} = \|X_i, X_j\|$, *Visual* is the maximum field of view of the AF, *Step* is the maximum step length of the artificial fish, δ is the crowd factor, and *Try_Number* is the maximum number of tries. Fish do not have the intelligence for complex logical reasoning and comprehensive judgment that humans have. They achieve their goals through simple behaviors of individuals or groups, and their behaviors can be roughly divided into four types, namely preying, swarming, following, and random behavior, as described below.

Preying behavior: Let the current state of ith AF be X_i and randomly select a state X_j within its perception range, being shown as

$$X_j = X_i + Visual + Rand() \tag{1}$$

where *Rand*() is a random number between zero and one. In the problem of finding the maximum value, if $Y_i < Y_j$, move one step forward in this direction; otherwise, randomly select the state X_j in the field of vision again, and after repeated attempts until *Try_Number*, if the condition for advancing is still not satisfied, move one step randomly, which can be expressed as

$$X_i^{t+1} = X_i^t + \frac{X_j - X_i^t}{\|X_j - X_i^t\|} \cdot Step \cdot Rand() \tag{2}$$

where X_i^t is the search for the i-th state at the t-th time, and $\|X_j - X_i^t\|$ is the distance between the current state X_j and the state X_i^t.

Swarming behavior: Let the current state of the AF be X_i, the number of companions in the field of vision is n_f, and X_c is the center position. If $Y_c/n_f > \delta Y_i$ means that there is more food in the partner center and it is not too crowded, move one step towards the X_c

direction as shown in Equation (3). If there is no other AF in the field of vision, the preying behavior will be carried out. Figure 1 is the flow chart of swarming behavior.

$$X_i^{t+1} = X_i^t + \frac{X_c - X_i^t}{\|X_c - X_i^t\|} \cdot Step \cdot Rand() \tag{3}$$

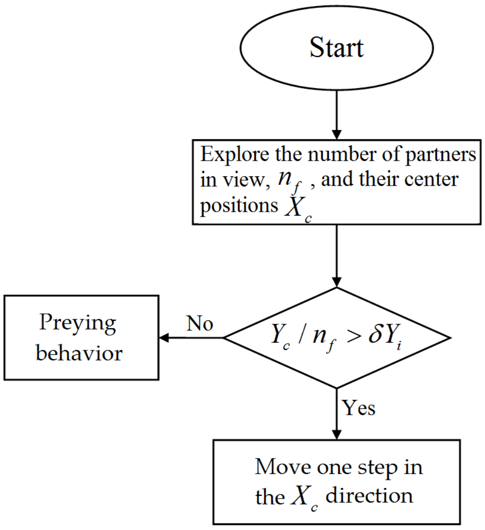

Start
Explore the number of partners in view, n_f , and their center positions X_c
$Y_c / n_f > \delta Y_i$
No
Preying behavior
Yes
Move one step in the X_c direction

Figure 1. Flow chart of swarming behavior in AFSA.

Following behavior: Assume that the current state of *i*th AF is X_i and explore the partner X_j with the maximum fitness value in the visual field ($d_{ij} < Visual$). If $Y_j / n_f > \delta Y_i$, it means that the food concentration of partner X_j is higher and the surroundings are not too crowded, so move forward in the direction of X_j as shown in Equation (4); otherwise, carry out preying behavior. Figure 2 is a flow chart of the following behavior.

$$X_i^{t+1} = X_i^t + \frac{X_j - X_i^t}{\|X_j - X_i^t\|} \cdot Step \cdot Rand() \tag{4}$$

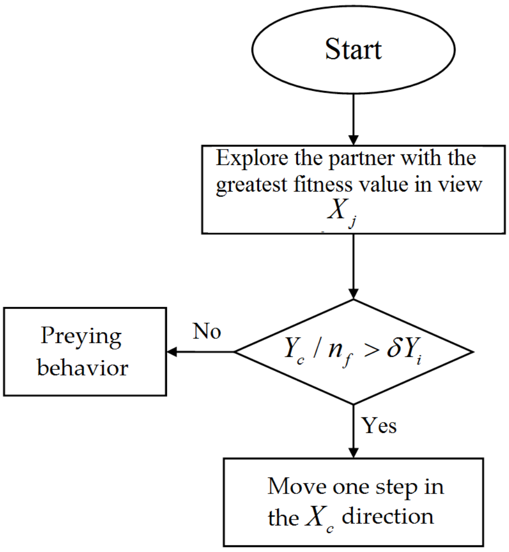

Start
Explore the partner with the greatest fitness value in view X_j
$Y_c / n_f > \delta Y_i$
No
Preying behavior
Yes
Move one step in the X_c direction

Figure 2. Flow chart of following behavior in AFSA.

Random behavior: random behavior is to find a direction randomly in the field of vision and compensate for preying behavior.

2.1.2. Flow Chart of AFSA

According to the previously described behavior, a movement strategy can be formulated. Each AF performs swarming and following behaviors, respectively. If it does not meet the movement requirements of the behavior, it carries out foraging behavior. If the movement requirements of the preying behavior are still not met, it carries out random behavior. After multiple moves to find the best solution in the whole domain, the AFSA process is shown in Figure 3.

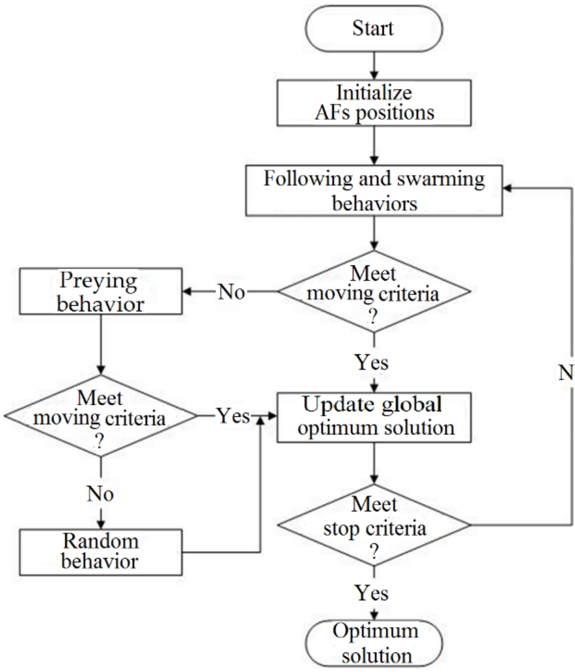


Figure 3. Flow chart of AFSA.

2.1.3. Influence of Algorithm Parameters on System Convergence

The AFSA has five parameters, which are visual range *Visual*, step size *Step*, number of individuals *M*, number of tries *Try_Number*, and crowding factor δ [15–23]. The impact of each parameter on system convergence is summarized as follows:

Visual: When the Visual is small because each individual can see a relatively small number of other individuals in the algorithm at the same time, the ability of the individual to carry out swarming and following behaviors decreases, but the chance of the individual to search the adjacent area will also increase. The chances of individuals performing preying behaviors and random behaviors will also increase at this time. On the contrary, when the Visual is larger, the chances of individuals executing following behaviors and swarming behaviors will increase, while preying and random behaviors will decrease. Overall, the larger the Visual, the easier it is for the individual to find the global optimum solution, but it may also cause oscillations around the global optimum solution.

Step: The step size affects the accuracy and speed of the convergence of the algorithm. If a larger step size is selected, it can help the individual to converge to the extreme value quickly, but it may cause the individual to oscillate back and forth around the global optimum solution in the later stage of convergence, thus affecting the accuracy of convergence. If you choose a smaller step size, the convergence speed will be slower, but its accuracy is relatively better.

M: The larger the number of individuals is, the more information the individuals can exchange, the higher the accuracy of convergence, and the stronger the ability to jump out of the local optimum solution, but the greater the amount of calculation for each iteration of the algorithm. Therefore, in practical applications, on the premise of satisfying stable convergence, the number of algorithm individuals should be reduced as much as possible.

Try_Number: If the number of tries increases, the ability of the individual to perform preying behavior will increase, and the probability of the individual random moving will decrease. However, for problems with prominent local optimal solutions, if there are too many tries, it is easy for the individual to fall into the vicinity of the local optimum solution, thus missing the global optimum solution. Therefore, for general problems, the number of tries can be appropriately increased to speed up the convergence speed. For the problem with prominent local optimal solutions, the number of tries can be reduced to increase the probability of random movement of the individual to avoid falling into the local optimum solution.

δ: The crowd factor affects the results of the individual following and swarming behaviors. By combining the crowd factor with the field of view, it is possible to limit the swarming size of the individuals and further decide whether to perform the following and flocking behaviors. In the follow-up simulation experiments, we will ignore the crowding factor. In other words, as long as the AF X_i explores the state within the field of vision during flocking behavior or following behavior, as long as it is greater than the fitness value of X_i's current position, it will move towards this state position regardless of overcrowding around the state.

2.2. RSSI Model

The RSSI channel model is also known as the Propagation Path Loss Model [24–28]. Under the free space propagation model, the signal intensity received by the receiver is inversely proportional to the square of the distance. When the distance between the transmitter and the receiver is d, the average power $P_r(d)$ received by the receiver is as follows:

$$P_r(d) = \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 d^2 L} = \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 {d_0}^2 L} \cdot \left(\frac{d_0}{d}\right)^2 = P_r(d_0) \cdot \left(\frac{d_0}{d}\right)^2 \tag{5}$$

where P_t is the transmission power, G_t is the antenna gain at the transmitter, G_r is the antenna gain at the receiver, L is the system loss coefficient and represents the hardware signal loss in the communication system, λ is the wavelength, and d_0 is the reference distance. In this study, the antenna gain of the transmitter and the receiver is set as one, which means that the system has no signal loss.

In general, the average loss $\overline{PL}(d)$ caused by the path is proportional to the nth power of the distance. In other words, at any distance between the transmitter and the receiver, the average loss at the receiver is as follows:

$$\overline{PL}(d) = \overline{PL}(d_0) + 10n \times log\left(\frac{d}{d_0}\right) \tag{6}$$

where n is the path loss index, which represents the path loss rate. In the natural environment, the interference received by the signal changes with the environment. Therefore, in the simulation analysis, we can only describe this phenomenon with logarithmic normal distribution, so the average power of the path can be expressed as

$$PL(d) = \overline{PL}(d) + X_\sigma = \overline{PL}(d_0) + 10n \cdot log\left(\frac{d}{d_0}\right) + X_\sigma \tag{7}$$

and the received power can be expressed as

$$P_r(d) = P_t - PL(d) \tag{8}$$

where $\overline{PL}(d)$ is the average path loss at the same distance between the transmitter and the receiver, X_σ is a zero-mean Gaussian random variable with a mean value of zero, and the standard deviation σ is 1 to 10 dBm. At the same distance between the transmitter and the receiver, the more complex the environment and terrain, the greater the fluctuation of the path loss means the larger the standard deviation. The reference distance is 0.5 m in subsequent simulation experiments.

3. System Model

This section will give a complete and detailed description of the AFSA-based wireless sensor network's target positioning and tracking methods. The RSSI channel model is used to estimate the distance between the target point and the individual in the algorithm. Relying on the AFSA to simulate the creature preying characteristics, the highest point of the individual moving to find the food source (RSSI value) is regarded as the estimated point. In addition, this thesis also discusses the impact of sensor arrangement and quantity on the system.

3.1. Target Positioning Method

The AFs (mobile sensors) were arranged on a square plane with an area of 100 m × 100 m. After each AF performs the algorithm behavior, the point with the highest food concentration (RSSI value) is obtained through communication with each AF as the global best solution. After a while, if the current global best solution meets the stop search condition, the corresponding position of the current global best solution is the estimated point, as shown in Figure 4.

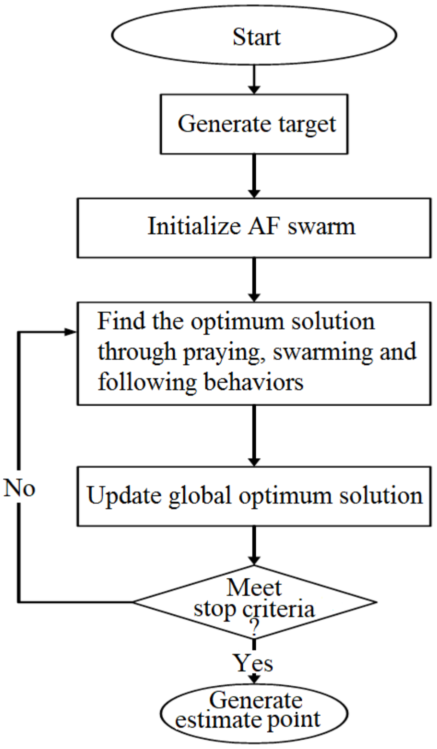

Start
Generate target
Initialize AF swarm
Find the optimum solution through praying, swarming and following behaviors
Update global optimum solution
No
Meet stop criteria ?
Yes
Generate estimate point

Figure 4. Flow chart of AFSA target positioning method.

In Figure 4, N target points are generated randomly. The optimum solution of the current time is obtained through the algorithm's behaviors and compared with the global optimum solution. The bulletin board is a recording matrix with a size of 1 × $T_{\max}$, and $T_{\max}$ is the maximum iteration value. This matrix records the best solution found in each iteration. After multiple iterations, if the stop criteria are met, the last value of the bulletin board is the estimated point.

3.1.1. Adaptive Step Size and Visual Range

Because the step size and field of view of AFSA will affect the performance of the system to find the optimal solution, the method of adaptive step size is proposed in [22] to improve the system performance. Therefore, this paper adds an adaptive step size and field of view method as shown in Equation (9) to the target positioning method and adopts a nonlinear dynamic adjustment of step size and field of view to meet the search requirements at various stages.

$$\begin{cases} Visaul = Visual \times \alpha + Visual_{\min} \\ Step = Step \times \alpha + Step_{\min} \\ \alpha = e^{\left(-30 \times \left(\frac{t}{T_{\max}}\right)^{\zeta}\right)} \end{cases} \tag{9}$$

Here, ζ is the convergence factor and is an integer greater than one, which determines the convergence time of the curve. The larger the value, the later the convergence of the field of vision and step length; *Visual* is the field of vision; *Step* indicates the step size. In general, the initial value of *Visual* is $networkSize/5$ (*networkSize* is the maximum search range). The *Step* is $Visual/8$ [22]; $Visual_{\min}$ is the minimum value of the visual field; $Step_{\min}$ is the minimum step size; t is the number of current iterations; $T_{\max}$ is the maximum number of iterations. This method maintains the maximum value in the initial iteration, enabling the fish swarm to search the entire space approximately, improving the global search ability and convergence speed of the system. In the later iteration, the system changes to local search, keeping the visual field and step size at a low value, so that the region near the optimal solution can be searched for fine.

3.1.2. Hybrid Adaptive Vision of Prey

In this paper, based on the composite adaptive artificial fish swarm algorithm (AAFSA4) in [29], Hybrid Adaptive Vision of Prey (HAVP) is proposed to add a third fixed visual field, so that the method can better meet the needs of the positioning system.

In AAFSA4, the forward mode to the direction with a large fitness value is shown in Equation (10). The forward mode will slow down the search speed. Therefore, this paper takes AAFSA4 as the basis and changes the AF movement mode of the algorithm into a jumping mechanism, that is, when the AF searches for a better position X_j by the AAFSA4 method, the AF moves directly to this position, as shown in Equation (11). On the other hand, the three fields of vision can be searched with again to judge whether the forward condition is met. A search can be performed repeatedly until *Try_number* of times. If the forward condition is not met, one step of movement can be made randomly. In addition, this paper adds a third visual field, *Visual3*, which is the visual field of the fish swarm in the basic AFSA, and its value is a fixed value. The simultaneous random search of the three horizons can improve the efficiency of the system, but inevitably the complexity of the system will also be increased.

$$X_{next} = X + \frac{X_V - X}{\|X_V - X\|} \times Step \times Rand() \tag{10}$$

$$X_{next} = X_j \tag{11}$$

3.1.3. Region Segmentation Method [30]

The region segmentation method (RSM) involves dividing a 100 m × 100 m square wireless sensor network into four equal zones and positioning an anchor node in the center of each zone. The mobile sensor is equally divided into four segments and placed in each region. The anchor nodes of these four regions receive signal strength from the target point, and it is used to determine the approximate location of the target point. The boundaries [X_L, X_U, Y_L, Y_U] are defined, where X_L represents the lower limit of the x axis, X_U represents the upper limit of the x axis, Y_L represents the lower limit of the y axis, and Y_U represents the upper limit of the y axis. These boundaries restrict the movement of the individual particles to a specific range, and the algorithm uses this information to determine which region of the mobile sensor to focus on. Figure 5 is an illustration of RSM region judgment.

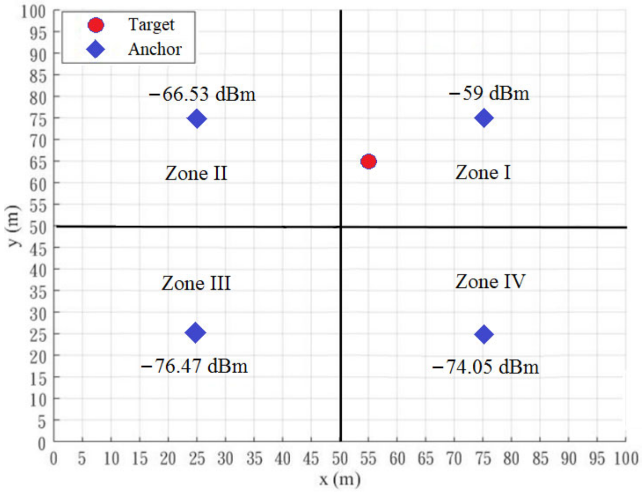


Figure 5. Illustration of RSM region judgment.

3.2. Target Tracking Method

Figure 6 is the AFSA target tracking flowchart [30]. The mobile sensors are deployed in a 100 m × 100 m square wireless sensor network. The AFs will gather in the highest fitness value region through Equation (12) as the estimated point. To avoid the algorithm dropping in a local solution, the global best will be reset to the initial value *GlobalBest_Y* = −100 in each iteration of finding the best one, so the algorithm can start another search.

$$\begin{cases} Yi > GlobalBest\_Y \\ GloblaBest\_Y = Yi \end{cases} \tag{12}$$

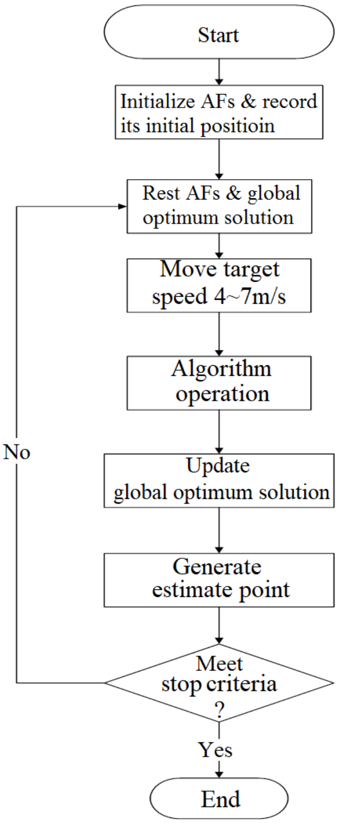
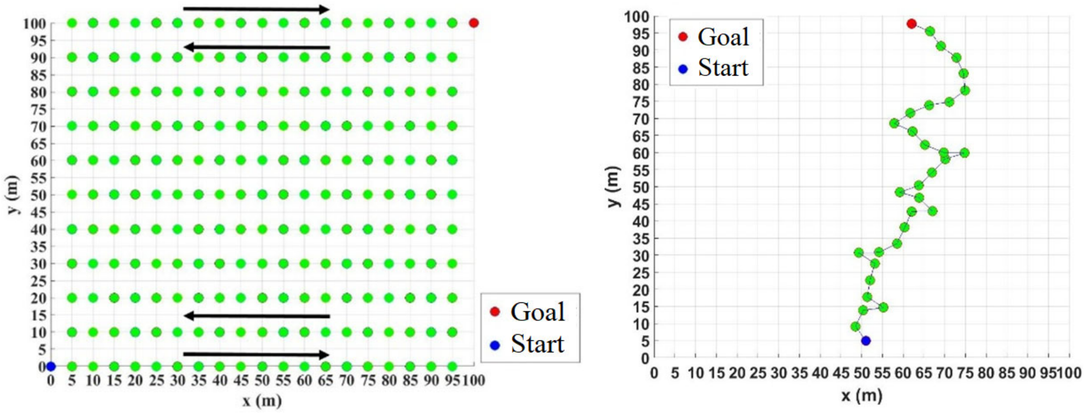

Start
Initialize AFs & record its initial positioin
Rest AFs & global optimum solution
Move target speed 4~7m/s
Algorithm operation
Update global optimum solution
Generate estimate point
Meet stop criteria ?
No
Yes
End

Figure 6. Flow chart of AFSA target tracking.

3.2.1. Tracks Definition

In this paper, two moving tracks, a snake track and a random track of target points, are designed in the target tracking method, as shown in Figure 7a,b. The moving speed is 4~7 m/s, so the students in the algorithm need to find the location of the target point within a limited number of moves. Therefore, the parameter setting of the algorithm is slightly different from the parameters of the algorithm in the target positioning method, such as step size and visual field. How to adjust the parameters in the algorithm so that the AFs can quickly find the target point is one of the problems discussed in this paper.



(**a**) (**b**)

Figure 7. Moving tracks of target points for the target tracking method: (**a**) snake track; (**b**) random track.

3.2.2. AF Movement Restriction in the Algorithm

Due to the moving characteristics of the target in the target tracking system, the target's moving speed is 4~7 m/s. In other words, the AF needs to move as much as possible within one second and reach the set threshold value *alpha*, which affects the system's success rate. If the signal strength received by the AF is greater than or equal to *alpha*, it is considered that the AF has found the target position and ended this search. The information, such as the current estimated point position and fitness value, is recorded in the record matrix for subsequent success rate calculation. On the other hand, the AF can perform the algorithm behavior within one second. If the fitness value of any AF does not reach *alpha* within one second, the AF with the highest fitness value among all AFs in the algorithm is selected as the estimated point. Figure 8 is the flow chart of the movement restriction of AFs in the algorithm. Equation (13) is the definition of success rate.

$$\begin{cases} S = find(Record > alpha) \\ SuccessRate = \left(\frac{S}{Total}\right) \times 100\% \end{cases} \quad (13)$$

Here, S is the number of all estimated points reaching *alpha*. *Record* is the recording matrix, recording the fitness values of all estimated points. *Total* is the number of all estimated points.

3.2.3. Dynamic AF Selection Method

For the AFSA target tracking system, a Dynamic AF Selection (DAFS) method is proposed in this paper to reduce the number of AFs used in the algorithm and reduce the search area to improve the efficiency of the target tracking system. This study assumes the target's moving speed is 4~7 m/s, and the distance between the current and the previous target positions is very close. The DAFS method selects the AFs within 20 m from the last estimate point and starts a new algorithm iteration. If there is no AF in the range of 20 m, the AFs within 30 m are selected. Otherwise, all AFs will be considered in the algorithm. In addition, if the fitness value of the estimated point is less than the correction factor *beta*, all the AFs will be used in the algorithm to prevent error propagation. The DAFS method can reduce the search area and the number of AFs used in the algorithm to improve the efficiency of the target tracking system. Figure 9 shows the procedure of the DAFS method [30].

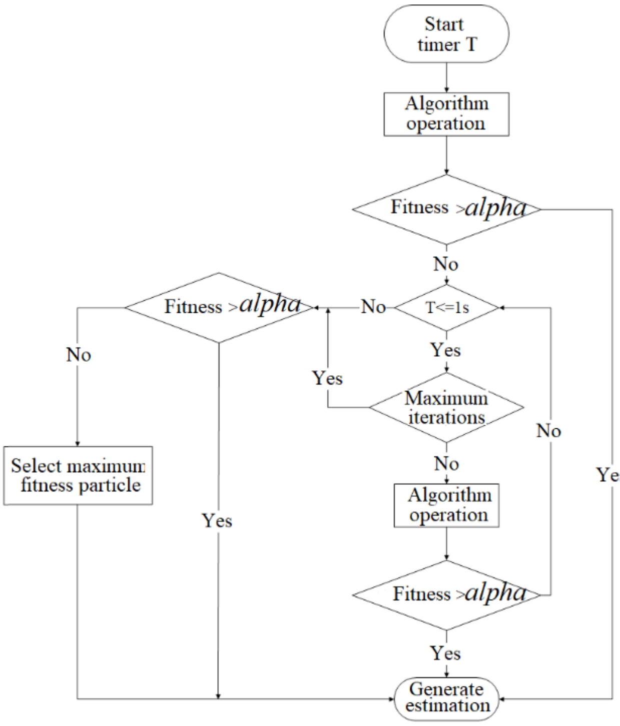


Figure 8. Procedure of AF movement restriction in the algorithm.

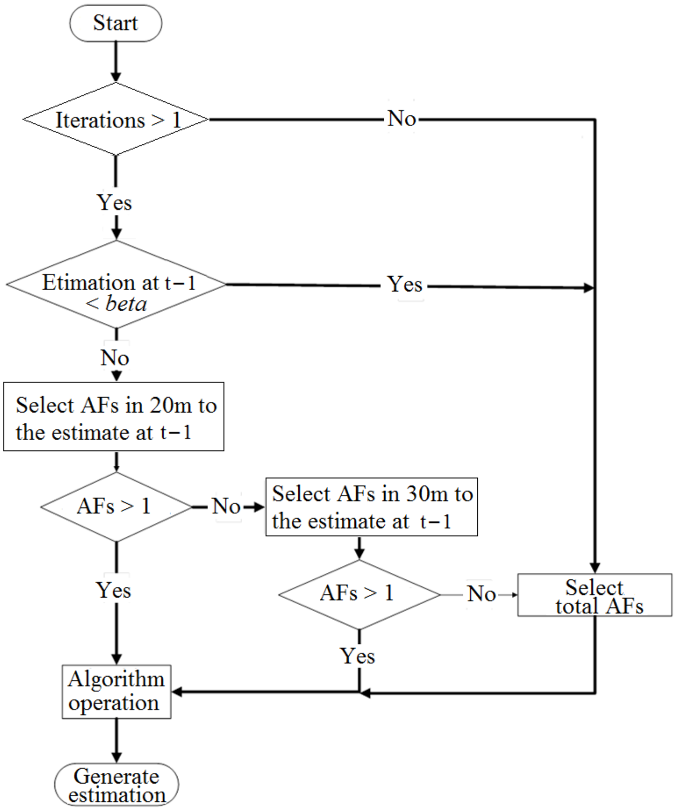


Figure 9. The procedure of DAFS method.

4. Simulation Results

4.1. Simulation Environment

In this study, the hardware and software used for simulations are listed in Table 1 [30]. The wireless sensor network is a two-dimensional area of 100 m × 100 m. The RSSI values will be calculated by substituting the position of each AF and the target point into the target function. The closer the location is to the target, the higher its RSSI value. In the simulation, each AF assumes to know the positions of other AFs. The AFs will move towards the area with the highest fitness value and eventually converge around the global optimum solution after many iterations by the algorithm. Then, the AF with the highest fitness value is selected as the estimated location.

Table 1. Simulation equipment.

Name	Specification
OS	Windows 7 Enterprise 64 bits
CPU	Intel(R) Core(TM) i5-4590 3.30 GHz
RAM	8 GB
MATLAB Edition	R2015a

In this paper, the AFSA was used with different numbers of AF for target positioning and tracking to investigate the impact of the number of AFs on the system. Additionally, the placement of the initial positions of the AFs was random deployment and the numbers of AF used in AFSA are 100, 72, 52, 24, 12, respectively, to address different applications in real-world environments.

The RSSI channel model parameters of the simulation experiment are shown in Table 2 [30], and Table 3 shows the AFSA simulation parameters for target positioning and tracking.

Table 2. Parameters of RSSI channel model.

Parameter	Value
Transmission Power Pt	2 mW
Carrier Frequency f	2.4 GHz
Path Loss Exponent n	4.5
Reference Distance d_0	0.5 m
Antenna Gains G_t, G_r	1
Standard Deviation σ	9 dBm

Table 3. AFSA parameters for target positioning and target tracking.

Parameter	Value	
	Target Positioning	Target Tracking
Network size	100 m × 100 m	
Number of executions	100	
Number of iterations T_{max}	100	
Number of sensors M	100, 72, 52, 24, 12	
Number of targets N	10	1
Try number Try_Number	100	
Initial step $Step$	$Visual/8$ [2]	
Initial visual $Visual$	$networkSize/5$ [2]	
Minimum step $Step_{\min}$	5 [1,2]	
Minimum visual $Visual_{\min}$	50 [1,2]	
Convergence factor S	4 [2]	
Threshold $alpha$	*	−6.5 dBm
Correction factor $beta$	*	−15 dBm

[1] For fixed *step* and *visual*; [2] for adaptive *step* and *visual*; * not applicable.

4.2. Simulation on Target Positioning

In order to calculate the error between the estimated point and the target point obtained by AFSA target positioning, the average error is calculated through Equation (14):

$$e = \frac{1}{N} \sum_{i=1}^{N} \|\hat{X}_i - \hat{X}_i\| \tag{14}$$

where N is the number of target points, $\hat{X}_i$ is the position of the ith estimated point, and X_i is the position of the ith target.

In this study, the performance of the proposed methods, RSM and HAVP, along with the adaptive step and adaptive vision methods, will be analyzed in terms of positioning accuracy. Various analysis modes are shown in Table 4. P1 and P2 are the traditional AFSA methods, and P3 to P8 are the proposed methods in this paper.

Table 4. Analysis modes for target positioning method.

Mode	**Condition**			
	Fixed Step	**Adaptive Step and Vision**	**RSM**	**HAVP**
P1	✓			
P2		✓		
P3	✓		✓	
P4		✓	✓	
P5	✓			✓
P6		✓		✓
P7	✓		✓	✓
P8		✓	✓	✓

Table 5 shows the simulation results of the average error in random deployment, and the average positioning time is shown in Table 6. The average time is the average time required to locate a target point in 100 iterations using the MATLAB software calculation algorithm.

Table 5. Average error of random deployment in target positioning.

Number of AF	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**
100	0.874	0.892	2.516	2.562	0.000	0.000	0.000	0.000
72	1.117	1.113	3.359	3.358	0.000	0.000	0.000	0.000
54	1.614	1.500	4.320	4.418	0.000	0.000	0.000	0.000
24	2.953	2.991	8.370	8.694	0.000	0.000	0.000	0.000
12	5.520	5.341	251.316	231.705	0.121	0.000	11.162	10.247
Average	2.416	2.367	53.976	50.147	0.024	0.000	2.232	2.049

Table 6. Average positioning time of random deployment in target positioning.

Number of AF	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**
100	12.986	13.790	3.406	3.191	9.184	10.018	2.382	2.363
72	8.916	9.613	2.203	2.541	6.546	7.642	1.749	1.650
54	6.634	6.750	1.624	1.787	4.778	4.996	1.362	1.236
24	2.974	3.085	0.860	0.782	2.108	2.236	0.676	0.732
12	1.326	1.352	0.174	0.206	1.049	1.176	0.308	0.290
Average	6.567	6.918	1.653	1.701	4.733	5.214	1.295	1.254

4.3. Simulation on Target Tracking

The methods proposed in this paper, such as RSM, HAVP, and DAFS, are added into the target tracking system, respectively. The analysis modes for the target tracking method are shown in Table 7 to analyze their influence on the system efficiency. In addition, in the simulation experiment, different numbers of AFs are placed in the sensor network for the simulation experiment of each analysis method, and the influence of the number of AFs in the algorithm on the system efficiency is discussed. K1 is a traditional method, and K2 to K8 are the proposed ones.

Table 7. Analysis modes for target tracking method.

Mode	RSM	HAVP	DAFS
K1			
K2	✓		
K3		✓	
K4	✓	✓	
K5			✓
K6	✓		✓
K7		✓	✓
K8	✓	✓	✓

Table 8 shows the simulation results of the average tracking time, and the average tracking success rate is shown in Table 9. The average tracking time is the average time required to track a target point in 100 iterations using the MATLAB software calculation algorithm.

Table 8. Average tracking time of random deployment in target tracking.

Number of AF	K1	K2	K3	K4	K5	K6	K7	K8
100	0.081	0.058	0.076	0.040	0.041	0.032	0.040	0.026
72	0.065	0.041	0.067	0.030	0.038	0.034	0.041	0.028
54	0.061	0.043	0.061	0.033	0.051	0.048	0.040	0.032
24	0.044	0.039	0.046	0.023	0.109	0.098	0.042	0.038
12	0.041	0.064	0.037	0.058	0.123	0.109	0.048	0.044
Average	0.0584	0.049	0.0574	0.0368	0.0724	0.0642	0.0422	0.0336

Table 9. Average tracking success rate of random deployment in target tracking.

Number of AF	K1	K2	K3	K4	K5	K6	K7	K8
100	99%	81%	100%	83%	100%	97%	100%	98%
72	99%	100%	100%	100%	99%	99%	98%	99%
54	100%	100%	100%	99%	95%	96%	97%	96%
24	97%	100%	99%	95%	85%	94%	96%	96%
12	94%	76%	100%	85%	85%	80%	95%	97%
Average	97.8%	91.4%	99.8%	92.4%	92.8%	93.2%	97.2%	97.2%

5. Discussion

5.1. Target Positioning

According to the simulation results in Tables 5 and 6, some discussions for the target positioning system are as follows.

The average positioning error decreases as the number of AFs increases. The results in Table 10 were obtained based on the number of AFs. The average error is minimum at 100 AFs and becomes higher with the decrease in AFs. However, the average positioning time will increase with the increase in AFs because the more AFs there are, the longer the calculation time of the algorithm will be.

Table 10. Total average error and positioning time when the number of AFs is 100, 72, 54, 24, and 12.

Number of AF	Average Error (cm)	Average Positioning Time (s)
100	0.849	7.272
72	1.121	5.081
54	1.467	3.638
24	2.839	1.658
12	66.064	0.741

There is no significant difference between fixed step size and adaptive step size and visual field on positioning efficiency. According to Tables 5 and 6, the values of all methods using fixed and adaptive step size are averaged, respectively, and the results are shown in Table 11. It shows that the simulation results of the fixed step size algorithm or the adaptive step size algorithm have little difference in the average positioning error and positioning time. The reason is that in the simulation environment of the wireless sensor network in this study, when there are a large number of AFs in the algorithm, whether it is a fixed or adaptive step size algorithm can satisfy the need to move AFs in the algorithm to the region of the global optimum solution within 100 iterations. On the contrary, when the number of AFs in the algorithm is fewer, such as reducing to 12, no matter the fixed step size or the adaptive step size, the AFs in the algorithm cannot move around the global optimum solution after 100 iterations.

Table 11. Total average error and positioning time of the fixed and adaptive steps.

Parameter	Fixed Step	Adaptive Step
Average error (cm)	14.589	14.347
Average positioning time (s)	3.587	3.587

RSM will increase the average error but greatly reduce the average positioning time. Table 12 shows the average error and positioning time of using and not using RSM. The average positioning error increases by about 26 cm, but the positioning time is shortened by 74.4%.

Table 12. Total average error and positioning time of using and not using RSM.

Parameter	No RSM	RSM
Average error (cm)	1.185	27.750
Average positioning time (s)	5.866	1.490

The HAVP method effectively improves the positioning error and positioning time. Table 13 shows the total average error and positioning time of using HAVP and not using HAVP. The average positioning error is reduced by about 96.1%, and the positioning time is shortened by 26.4%. If the analysis is carried out on whether to use RSM and HAVP, the results are shown in Table 14. It is obvious that using RSM will effectively improve the positioning time, but the positioning error will become worse. However, if the proposed HAVP is used, not only can the advantages of RSM to improve the positioning time be maintained, but the positioning error will not become worse.

Table 13. Total average error and positioning time of using and not using HAVP.

Parameter	No HAVP	HAVP
Average error (cm)	27.861	1.074
Average positioning time (s)	4.237	3.120

Table 14. Average error and positioning time for methods using and not using RSM and/or HAVP.

Parameter	No RSM + HAVP	RSM	HAVP	RSM + HAVP
Average error (cm)	2.36	53.36	0.01	2.14
Average positioning time (s)	6.76	1.71	4.97	1.27

For target positioning, the proposed AFSA algorithms, P7 and P8, combined with RSM and HAVP have better performance in both average error and average positioning time than the traditional AFSA methods, P1 and P2, in random deployment for target positioning. Especially in P8, the average positioning time is reduced by 81.9% compared with P2.

5.2. Target Tracking

From the simulation results in Tables 8 and 9, the further discussions for target tracking can be depicted as follows.

RSM can use less time to achieve a better tracking success rate when there are many AFs, and the tracking performance of the modes without RSM is better when the number of AFs is fewer. Table 15 shows the total average positioning time and success rate of using RSM and not using RSM, which shows that the average positioning time of the analysis mode with RSM is less than that of the analysis mode without RSM. However, as the number of Afs used decreases, the difference between the average positioning time using RSM and those without RSM is smaller. The reason is that, after using RSM, the number of AFs used at the same time is less than that without RSM, so an AF in the AFSA can obtain less information from other AFs at the same time, so the AF needs to perform more algorithmic actions to reach the global optimal solution. Therefore, when the number of AFs is 12, the average positioning time using the RSM is longer than that without using the RSM.

Table 15. Total average positioning time and success rate of methods using or not using RSM.

Number of AF	Average Positioning Time (s)		Average Success Rate	
	No RSM	RSM	No RSM	RSM
100	0.060	0.039	99.8%	99.5%
72	0.053	0.033	99.0%	99.5%
54	0.053	0.039	98.0%	97.8%
24	0.060	0.050	94.3%	96.3%
12	0.062	0.069	93.5%	84.5%

When the number of AFs is large, using DAFS can shorten the positioning time and maintain a good tracking success rate. Analysis mode K1 without DAFS and K5 with DAFS were used to analyze the impact of DAFS on the performance of the target tracking system, as shown in Table 16. It can be found that the larger the number of AFS, the more data the algorithm needs to process, and the longer the target position estimation time is, and after using DAFS to track the AFSA target, it can be found that the greater the number of AFs used, the shorter the average positioning time. The reason is that when the DAFS method performs the algorithm by selecting the AF around the last estimated point, a larger number of AFs in the algorithm can ensure that there is an AF around the last estimated point and vice versa. The fewer the number of AFs, such as 12, the probability of an AF around the last estimated point is relatively small, so the use of all AFs for algorithm behavior increases, which in turn leads to the average positioning time when the number of AFs is 12. On the contrary, it is longer; in addition, when the number of AFs is greater than 52, DAFS can achieve a good tracking success rate at a faster speed, but when the number of AFs is less than 52, the DAFS method will make the system performance poor.

Table 16. Average positioning time and success rate of modes K1 and K5.

Number of AF	Average Positioning Time (s)		Average Success Rate	
	K1	K5	K1	K5
100	0.081	0.041	99%	100%
72	0.065	0.038	99%	99%
54	0.061	0.051	100%	95%
24	0.044	0.109	97%	85%
12	0.041	0.123	94%	85%

The average performance of the related modes using HAVP is shown in Table 17. It shows that using HAVP alone can improve the tracking success rate without increasing the positioning time. When using both DAFS and RMS for target tracking, the average positioning time of K8 is shorter by 42.47% than that of the traditional one, K1, and the average success rate remains the same as that of K1.

Table 17. Average positioning time and success rate for K1, K3, K7, and K8.

Parameter	K1	K3	K7	K8
Average positioning time (s)	0.0584	0.0574	0.0422	0.0336
Average success rate	97.8%	99.8%	97.2%	97.4%

6. Conclusions

In this paper, AFSA is used to study indoor space target positioning and tracking. The simulation results show that the greater the number of AFs used in algorithm, the better the accuracy of target positioning but the longer the time of target positioning. The HAVP method is proposed to improve the positioning error and positioning time in this paper. The simulation results show that, when using HAVP, the total average positioning error is reduced by about 96.1%, and the positioning time is shortened by 26.4%. In addition, the DAFS method is proposed in the target tracking system to further reduce the number of AFs used in the target tracking system. The simulation results show that when the number of AFs is large, using DAFS can shorten the positioning time and maintain a good tracking success rate. Moreover, HAVP can improve the tracking success rate without increasing the positioning time. If DAFS and RMS are used at the same time, the positioning time can be greatly shortened by 42.47%, and the original success rate of the conventional method can be maintained.

Author Contributions: Conceptualization, C.-H.C. and Y.-F.H.; investigation, C.-H.C., C.-C.L. and Y.-F.H.; methodology, S.-H.L. and Y.-F.H.; software, C.-H.C. and C.-C.L.; supervision, C.-H.C. and Y.-F.H.; writing—original draft, C.-H.C., S.-H.L., C.-C.L. and Y.-F.H.; writing—review and editing, S.-H.L., C.-H.C. and Y.-F.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Ministry of Science and Technology (MOST), R.O.C. grant numbers MOST 111-2221-E-324-018 and MOST-111-2637-E-150-001.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Rajaravivarma, V.; Yang, Y.; Yang, T. An overview of Wireless Sensor Network and applications. In Proceedings of the 35th Southeastern Symposium on System Theory, Morgantown, WV, USA, 16–18 March 2003; pp. 432–436. [CrossRef]
2. Corke, P.; Wark, T.; Jurdak, R.; Hu, W.; Valencia, P.; Moore, D. Environmental Wireless Sensor Networks. *IEEE* **2010**, *98*, 1903–1917. [CrossRef]
3. Suo, H.; Wan, J.; Huang, L.; Zou, C. Issues and Challenges of Wireless Sensor Networks Localization in Emerging Applications. In Proceedings of the 2012 International Conference on Computer Science and Electronics Engineering, Hangzhou, China, 23–25 March 2012; pp. 447–451. [CrossRef]

4. Xu, E.-Y.; Ding, Z.; Dasgupta, S. Target Tracking and Mobile Sensor Navigation in Wireless Sensor Networks. *IEEE Trans. Mob. Comput.* **2011**, *12*, 177–186. [CrossRef]
5. Mesmoudil, A.; Fehaml, M.; Labraouil, N. Wireless Sensor Networks Localization Algorithms: A Comprehensive Survey. *Int. J. Comput. Netw. Commun.* **2013**, *5*, 1–20. [CrossRef]
6. Cheng, L.; Wu, C.; Zhang, Y.; Wu, H.; Li, M.; Maple, C. A Survey of Localization in Wireless Sensor Network. *Int. J. Distrib. Sens. Netw.* **2012**, *8*, 12. [CrossRef]
7. La, H.-M.; Nguyen, T.-H.; Hguyen, C.-H.; Nguyen, H.N. Optimal Flocking Control for a Mobile Sensor Network Based a Moving Target Tracking. In Proceedings of the IEEE International Conference on System, Man, and Cybernetics, San Antonio, TX, USA, 11–14 October 2009; pp. 4801–4806. [CrossRef]
8. Laaraiedh, M.; Yu, L.; Avrillon, S.; Uguen, B. Comparison of Hybrid Localization Schemes using RSSI, TOA, and TDOA. In Proceedings of the IEEE Wireless Conference 2011-Substainalbe Wireless Technologies (European Wireless) 11th Europeanm, Vanna, Austria, 27–29 April 2011; pp. 1–5.
9. Cheng, L.; Wu, C.-D.; Zhang, Y.-Z. Indoor Robot Localization Based on Wireless Sensor Networks. *IEEE Trans. Comput. Electron.* **2011**, *57*, 1099–1104. [CrossRef]
10. Chugunov, A.; Petukhov, N.; Kulikov, R. ToA Positioning Algorithm for TDoA System Architecture. In Proceedings of the International Russian Automation Conference (RusAutoCon), Sochi, Russia, 6–12 September 2020; pp. 871–876. [CrossRef]
11. Ahmed, S.; Abbasi, A.; Liu, H. A Novel Hybrid AoA and TDoA Solution for Transmitter Positioning. In Proceedings of the International Conference on Indoor Positioning and Indoor Navigation (IPIN), Barcelona, Spain, 4–7 October 2021; pp. 1–7. [CrossRef]
12. Xu, C.-X.; Chen, J.-Y. Three-dimentional Sensor Node Localization based on AFSA-LSSVM. *Int. J. Control. Autom.* **2014**, *7*, 399–406. [CrossRef]
13. Yang, X.; Zhang, W.; Song, Q. A Novel WSNs Localization Algorithm Based on Artificial Fish Swarm Algorithm. *Int. J. Online Eng.* **2016**, *12*, 64–68. [CrossRef]
14. Wen, S.; Cai, X.; Guan, W.; Jiang, J.; Chen, B.; Huang, M. High-precision indoor three-dimensional positioning system based on visible light communication using modified artificial fish swarm algorithm. *Opt. Eng.* **2018**, *57*, 106102. [CrossRef]
15. Li, X.-L.; Shao, Z.-J.; Qian, J.-X. An Optimizing Method Based on Autonomous Animats: Fish-swarm Algorithm. *Chin. J. Circuits Syst.* **2002**, *22*, 32–38. [CrossRef]
16. Li, X.-L.; Qian, J.-X. Studies on Artificial Fish Swarm Optimization Algorithm based on Decomposition and Coordination Techniques. *Chin. J. Syst. Eng. Theory Pract.* **2003**, *8*, 1–6.
17. Shan, X.-J.; Jiang, M.-Y.; Li, J.-P. The Routing Optimization Based on Improved Artificial Fish Swarm Algorithm. In Proceedings of the 6th World Congress on Intelligent Control and Automation, Dalian, China, 21–23 June 2006; pp. 3658–3662. [CrossRef]
18. He, S.; Hamam, N.B.H.; Bouslimani, Y. Fuzzy Clustering with Improved Artificial Fish Swarm Algorithm. In Proceedings of the International Joint Conference on Computational Sciences and Optimization, Sanya, China, 24–26 April 2009; pp. 317–321. [CrossRef]
19. Jiang, M.-Y.; Yuan, D.-F.; Cheng, Y.-M. Improved Artificial Fish Swarm Algorithm. In Proceedings of the Fifth International Conference on Natural Computation, Tianjin, China, 14–16 August 2009; pp. 281–285. [CrossRef]
20. Cheng, Y.-M.; Jiang, M.-Y.; Yuan, D. Novel Clustering Algorithm Based on Improved Artificial Fish Swarm Algorithm. In Proceedings of the FSK 09. Sixth International Conference on Fuzzy System and Knowledge Discovery, Tianjin, China, 14–16 August 2009; pp. 141–145. [CrossRef]
21. Fernandes, E.M.G.P.; Martins, T.F.M.C.; Rocha, A.M.A.C. Fish Swarm Algorithm for Bound Constrained Global Optimization. In Proceedings of the International Conference on Computational and Mathematical Methods in Science and Engineering, Asturias, Spain, 30 June–3 July 2009.
22. Zhang, C.; Zhang, F.-M.; Li, F.; Wu, H.-S. Improved Artificial Fish Swarm Algorithm. In Proceedings of the 9th IEEE Conference on Industrial Electronics and Applications, Hangzhou, China, 9–11 June 2014; pp. 748–753. [CrossRef]
23. Neshat, M.; Sepidnam, G.; Sargolzaei, M.; Toosi, A.N. Artificial fish swarm algorithm: A survey of the state-of-the-art, hybridization, combinatorial and indicative applications. *Artif. Intell. Rev.* **2014**, *42*, 965–997. [CrossRef]
24. Fang, Z.; Zhao, Z.; Geng, D.; Xuan, Y.-D.; Du, L.-D.; Cui, X.-X. RSSI Variability Characterization and Calibration Method in Wireless Sensor Network. In Proceedings of the IEEE International Conference on Information and Automation, Harbin, China, 20–23 June 2010; pp. 1532–1537. [CrossRef]
25. Xiong, J.-Q.; Qin, Q.; Zheng, K.-M. A Distant Measurement Wireless Localization Correction Algorithm Based on RSSI. In Proceedings of the Seventh International Symposium on Computation Intelligence and Design, Hangzhou, China, 13–14 December 2014; pp. 176–278. [CrossRef]
26. Barsocchi, P.; Lenzi, S.; Chessa, S.; Giunta, G. A Novel Approach to Indoor RSSI Localization by Automatic Calibration of the Wireless Propagation Model. In Proceedings of the IEEE 69th Vehicular Technology Conference, Barcelona, Spain, 26–29 April 2009; pp. 1–5. [CrossRef]
27. Mahmud, M.I.; Abdelgawad, A.; Yanambaka, V.P.; Yelamarthi, K. Packet Drop and RSSI Evaluation for LoRa: An Indoor Application Perspective. In Proceedings of the IEEE 7th World Forum on Internet of Things (WF-IoT), New Orleans, LA, USA, 14 June–31 July 2021; pp. 913–914. [CrossRef]

28. Yao, L.; Peng, X.; Shi, D.; Liu, B. Design of Indoor Positioning System Based on RSSI Algorithm. In Proceedings of the International Conference on Management Science and Software Engineering (ICMSSE), Chengdu, China, 9–11 July 2021; pp. 145–148. [CrossRef]
29. Hu, X.T.; Zhang, H.Q.; Li, Z.C.; Huang, Y.A.; Yin, Z.P. A Novel Self-Adaptation Hybrid Artificial Fish-Swarm Algorithm. In Proceedings of the 2013 IFAC, Hangzhou, China, 10–12 March 2013; Volume 46, pp. 583–588. [CrossRef]
30. Lee, S.-H.; Cheng, C.-H.; Lin, C.-C.; Huang, Y.-F. PSO-Based Target Localization and Tracking in Wireless Sensor Networks. *Electronics* **2023**, *12*, 905. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.