

WSN Node Based on Adaptive Cuckoo Search Algorithm for Agricultural Broadcast Positioning

Xiaobing Liu, Hunan University of Science and Engineering, China*

ABSTRACT

The node location of wireless sensor networks (WSN) is actually a multi-dimensional constraint optimization problem for measuring distance and range error. A new adaptive cuckoo search algorithm is proposed to solve the problems of the standard cuckoo search algorithm, such as slow convergence rate and easy-to-get-into local optimum. Firstly, the algorithm has a large searching space in the early stage and improves the global searching ability by adjusting the flight step length of Levy. Secondly, dynamic inertial weight and memory strategy are introduced for random swimming; therefore, the algorithm can make full use of historical experience and improve the stability. Finally, simulation results show that the proposed algorithm can effectively improve the positioning accuracy without increasing the hardware cost.

KEYWORDS

Adaptive, Cuckoo Search Algorithm, Levy Flight, Wireless Sensor Network

1. INTRODUCTION

In recent years, with the development of wireless sensor network (WSN), there has been a new trend in the field of agriculture. The field of precision agriculture, such as remote observation, analysis and control management, is related to wireless sensor networks (Ojha, T., Misra, S., & Raghuwanshi, N. S. . 2015). Wireless sensor networks belong to a kind of important wireless networks. They are mainly composed of spatially distributed autonomous sensors, which are used to collect local data and realize mutual communication (Fubao, W., Long, S., Fengyuan, R., 2005; Wang, J., Ghosh, R. K., & Das, S. K., 2010). Sensor node positioning technology is one of the key supporting technologies in many applications of wireless sensor networks. It is an important foundation for technologies such as network topology management, coverage control, and inter-node routing algorithm design. Positioning information will affect the overall performance of the entire network. Therefore, how to effectively improve the positioning accuracy of sensor nodes has become a research hotspot in the field of precision agriculture.

According to whether the actual distance or angle between nodes is measured during the positioning process, the positioning algorithm is roughly divided into a distance-based positioning algorithm and a distance-independent positioning algorithm (Woo, H., Lee, S., & Lee, C. . 2013). Distance-independent algorithms do not require additional hardware configuration and can be located only based on network connectivity (L Yun., J Ming., & C Cheng.,2009) . Therefore, the distance-independent algorithm has the advantages of strong anti-interference and low hardware cost. Typical distance-independent positioning algorithms include centroid algorithm (A Xun., J Ting., Z Zheng.,

DOI: 10.4018/JCIT.295247

*Corresponding Author

This article published as an Open Access article distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0/>) which permits unrestricted use, distribution, and production in any medium, provided the author of the original work and original publication source are properly credited.

2007), convex programming localization algorithm (Z Han., L Feng., 2007), and DV-Hop algorithm (B Feng., J Xiao., & M Hui., 2010) .

The DV-Hop algorithm generally uses the least squares (LS) principle to estimate the coordinates of an unknown node. Although it can reduce the positioning error to a certain extent, the LS algorithm is susceptible to the cumulative ranging error, and the solution speed is slow, which affects the positioning accuracy. Therefore, many researchers consider introducing swarm intelligence optimization algorithm to improve the positioning accuracy (H Zhong., L Jing.,2008). For example, the literature (Y Rong., 6Z Ling.,2011)combines the particle swarm algorithm with the ant colony algorithm for post-optimization. The unknown node position is estimated in the third stage of the DV-Hop algorithm to achieve a minimum distance or minimum error. Literature (W Jin., L Xu., & W Min., 2007) established a mathematical model with unknown node locations as parameters. In addition, genetic algorithm is used to solve the optimal position and improve the positioning accuracy. According to the criterion of anchor node selection, the literature (O Yang., H Jin., & B Hong., 2011) uses the average of the previous generation node and the contemporary node position as the reference node of the next generation target node, thereby reducing the influence of the ranging error. Therefore, an improved particle swarm optimization algorithm is used to optimize the positioning results. In literature (W Ya., Y Jian.,2014), by setting the corresponding constraint fitness function and distance fitness function, the search quantity during positioning is reduced and the convergence speed is accelerated. The introduction of swarm intelligence optimization algorithm improves the accuracy of positioning to a certain extent (Z Shi., S Mei., &T Yi.,2009) .

The cuckoo search (CS) algorithm was first proposed by Yang and Deb(Yang, X. S., & Deb, S. . 2010) . By simulating the nesting and spawning behavior of cuckoos, the algorithm introduces Levy flight mechanism into it, so as to quickly and effectively obtain the optimal solution. CS algorithm can better solve a variety of optimization problems, such as economic scheduling, engineering design, image processing in power, energy and medical fields(Shehab, M., Khader, A. T., & Al- Be Tar, M. A. . 2017).Cuckoo search algorithm (CSA)(X Xiao., L Dan., & T Liu., 2017) has the advantages of simplicity, few parameters, and easy implementation. Moreover, it can efficiently balance the local search and global search of the algorithm(Yang X., Deb S.,2009), which provides a new research idea for optimizing the positioning performance of wireless sensor networks. Researchers have made great achievements in CS algorithm and its application, and put forward corresponding improvement methods.In references (Li, H., D Shuai, Yu, S., Wang, J., & Ke, L. . 2016; Wang, G. G., Deb, S., Gandomi, A. H., Zhang, Z., & Alavi, A. H. . 2016), chaotic cuckoo search algorithm is presented for global optimization, which uses various chaotic maps for randomization.

Considering the shortcomings of cuckoo algorithm, we propose a wireless sensor network node location algorithm based on adaptive cuckoo search algorithm, which By adjusting to the length of the movement, and introducing dynamic inertial weight and memory strategy in this paper.

2. ALGORITHM IMPLEMENTATION

2.1. WSN Localization Theory

Wireless sensor network (WSN) is a group of interconnected micro nodes used to collect data from regions of interest (Akyildiz., Ian.F., Weilian., Sankarasubramaniam., & Yogesh, et al. 2002).The simplicity of wireless sensor network makes it applicable to many applications, including target tracking, health care, disaster, emergency and security applications (Rashid, B., Rehmani, M. H. . 2016). However, wireless sensor networks still face many problems to be considered, such as limited resources, energy efficiency and delay sensitive data transmission (Amjad, M., Sharif, M., Afzal, M. K., & Kim, S. W. . 2016; Pantazis, Nikolaos, A., Nikolidakis, Stefanos, & A., et al. 2013;Akhtar, F., Rehmani., M. H.,2015). In many applications of wireless sensor networks, the location of data collection is very important to locate the monitoring events of interest and respond accordingly

(Patwari, N., Ash, J. N., Kyperountas, S., Hero, A. O., Moses, R.L., & Correal, N. S..2005). For example, when a fire occurs in the field, the location of the fire source and the area where the fire spread are important factors affecting firefighters' planning and response (Mistry, H. P., Mistry, N. H..2015).In other applications such as target tracking and disaster monitoring, location is also very important (Mistry, H. P., Mistry, N. H..2015;Nazir, U., Arshad, M. A., Shahid, N., & Raza, S. H..2012). One way to provide each sensor node with its location is to connect a GPS device to each node. However, due to the limited cost, size and energy of each node, this method is not ideal (Khelifi, M., Benyahia, I., Moussaoui, S., & Nait-Abdesselam, F..2015). Considering these reasons, more and more researchers have presented cheap and efficient localization methods in wireless sensor networks.

The main task of WSN localization is to compute the number of uncertain nodes by exploiting the current nodes in a single hop range based on various algorithm. Using the common method for WSN localization, m nodes are randomly distributed in the region of interest, of which n nodes are identified with geographical coordinates and be called anchor nodes. All nodes have transmission capacity, where the transmission range is calculated as r . With n nodes as anchors, the number of unknown nodes to be localized is $(m-n)$.The anchor node transmits its geographic location in each iteration of the positioning process. The localized node in each iteration will be executed as the reference node for the next iteration. As far as any unknown node is concerned, if it has three or more than three supporting or neighboring nodes within its range will be regarded as a localizable node. Because it is a wireless system, the influence of environment plays an important role in distance calculation, and will eventually affect the positioning error. Considering the cost and power consumption, it is not feasible to equip each sensor node with GPS unit, especially in the environment of large-scale wireless sensor networks. A common method for locating unknown nodes is to use multiple mobile anchors(Ding, Wang, & Xiao, 2010; Campos, Souza, Nakamura, Nakamura, & Rodrigues, 2012), in which GPS units moving between unknown nodes are equipped to locate nearby unknown nodes by broadcasting their current positions regularly, as shown in Figure 1.

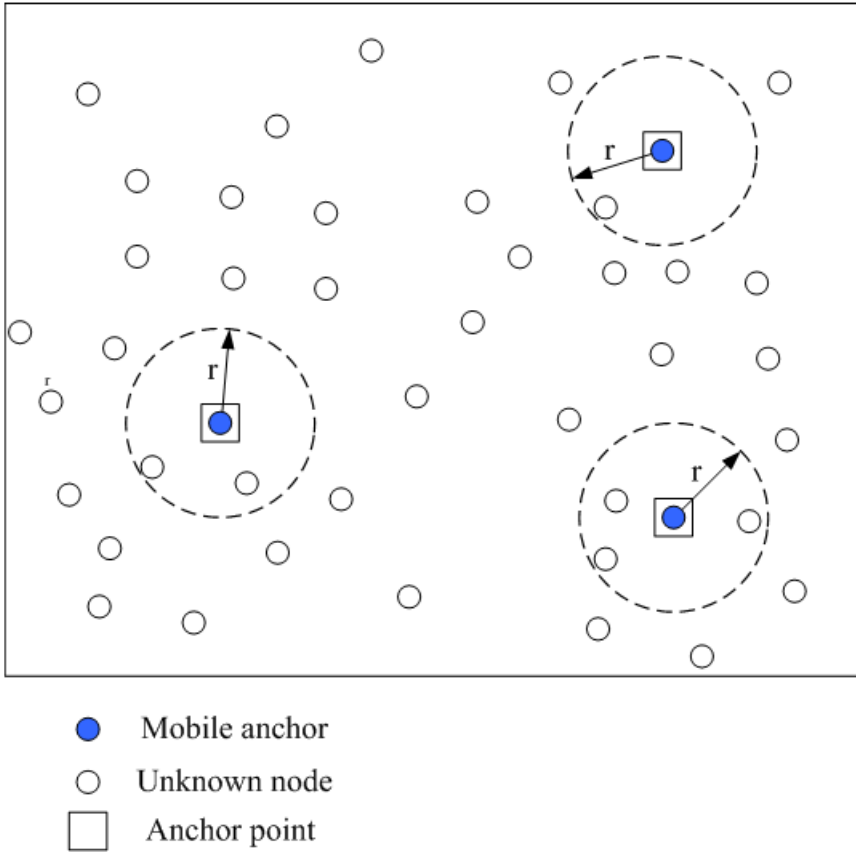
Compared with the unknown node, the mobile anchor node is not affected by energy constraints, and the positioning accuracy can be effectively improved by using the motion trajectory of the mobile anchor. In addition, robots are more conducive to installing GPS than sensors(Ou, C. H., He, W. L. . 2013).The mobile anchor moves between unknown nodes along a given trajectory, and sends its current position signal to the surrounding regularly, so as to locate the nearby unknown nodes, as shown in Figure 2.

From the above Figure 2,we know that the trajectory path is important for mobile anchor to assist node localization. In general, an important factor in determining the mobile path is how to make the mobile anchor work together with different location algorithms. Therefore, using a variety of different location algorithms is very important to study the effectiveness of mobile anchor path planning. When the mobile model and localization scheme can work well together, it shows that the model can be well applied to different scenes and locations.

2.2. Overview of Cuckoo Search Algorithm

Cuckoo search algorithm (CS) mainly includes two aspects: the parasitic breeding mechanism of cuckoo and Levy flight search principle. In general, cuckoos look for nest locations in a random or quasi random way in nature. However, most cuckoos lay eggs in the nests of other birds, not raising their cubs by themselves, but by their owners. The most special habit of cuckoo is parasitic brooding (Winfree, 1999) . Some species of cuckoos sneak their eggs into the host's nest. Since the hatchery's offspring hatch earlier than the host's young chicks, the hatched chicks instinctively destroy other eggs in the same nest (launch the nest) and make a louder sound than the host chicks. Many hosts judge the health of their offspring by the size of the sounds of their offspring. Moreover, healthy offspring get more food, which in turn has a higher survival rate. In some cases, the host will also find strange eggs in the nest. At this point, the host will abandon the nest and choose to re-build the

Figure 1. Mobile anchor applied to assist localization



nest elsewhere. In the constant competition with the host, the cuckoo's eggs and young chicks are moving toward the simulated host to counter the host's evolving resolving power.

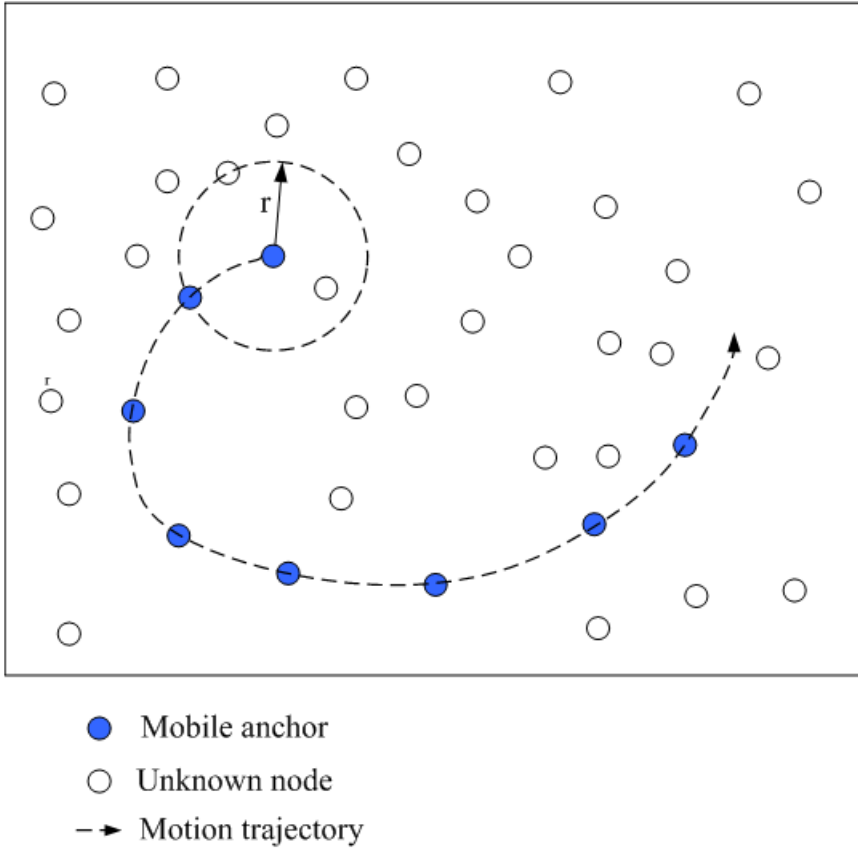
In the cuckoo search algorithm, the parasitic bird nest that the cuckoo chooses to spawn represents a feasible solution. The essence of the algorithm is to replace the previous generation of poor solutions with new and better solutions. Based on the habits and rules of the cuckoo in finding its nest and raising its young, the updated position of the nest in the next generation is expressed as follows:

$$X_i^{t+1} = X_i^t + \alpha \oplus Levy(\beta) \quad (1)$$

where X_i^t represents the i -th solution of the t -th generation. α is the step factor used to control the scope of the random search. $\oplus$ is point-to-point multiplication. The Levy flight described in this equation is a Markov chain, that is, the position of the next generation depends only on the current position. $\alpha \oplus Levy(\beta)$ is the flight step length of Levy, indicating the flight distance from all the nests (feasible solutions) of generation i to the nest of generation $i + 1$.

The probability density function of the power form can be obtained by studying the Levy distribution function, which is denoted as follows:

Figure 2. Node localization process using mobile anchor along a given trajectory



$$Levy(\beta) \sim \mu = t^{-\beta}, 1 < \beta \leq 3 \quad (2)$$

It can be seen from Eq. (2) that the continuous positional change of the cuckoo forms a probability distribution with a heavy tail. It makes the cuckoo algorithm essentially reflect the flight trajectory of cuckoo, that is, the optimization path consists of frequent short jumps and occasional long jumps. This optimization method can make CSA have more search space and more easy to jump out of local optimization. The Levy random number can be expressed as follows:

$$Levy(\beta) \sim \frac{\varphi * \mu}{|v|^{1/\beta}} \quad (3)$$

where μ and v obey standard normal distribution, whereas $\beta = 1.5$.

$$\varphi = \frac{\left(\Gamma(1 + \beta) * \sin(\pi \times \beta / 2)\right)^{1/\beta}}{\Gamma\left(\left(\frac{1 + \beta}{2}\right) * \beta * 2^{(\beta-2)/2}\right)} \quad (4)$$

In order to facilitate the calculation of the Levi flight, the step factor of the literature is used, which is denoted as follows:

$$\alpha = \alpha_0 * (X_i^t - X_b) \quad (5)$$

where $\alpha_0 = 0.01$, X_b represents the current optimal solution.

Combining equation (1) to equation (5), the solution generated by Levy flight can be updated, which is described as follows:

$$X_i^{t+1} = X_i^t + 0.01 * \frac{\varphi \times \mu}{|v|^{1/\beta}} (X_i^t - X_b) \quad (6)$$

When the random number is greater, it means that cuckoo eggs are found. The algorithm enters the preferred random walk, at which point the egg will be eliminated and a new solution will be generated as follows:

$$X_i^{t+1} = X_i^t + v * (X_j^t - X_k^t) \quad (7)$$

Where X_j^t and X_k^t represent two random solutions of the t -th generation. Whereas v is a compression factor, which is uniformly distributed by $[0, 1]$.

2.3. The Adaptive Cuckoo Search Algorithm

The high efficiency of the cuckoo search algorithm comes from the special Levy flight mechanism. In the optimization process, the step factor α is larger, the algorithm exploration ability is stronger, but the high-precision global optimal solution can not be obtained. While the step factor α is always small, the algorithm will pay more iteration when it reaches the target accuracy. The standard cuckoo algorithm has a fixed step factor, and the adaptive adjustment of the step size in the optimization process can not be achieved, and the algorithm converges slowly.

For preferred random swimming, it can be seen from Eq. (6) that the Levy flight mechanism has reduced the search accuracy by one or more orders of magnitude. If the order of magnitude is reduced in random preference swimming, the order of magnitude will jump too fast and the global optimal solution will be missed. In addition, the biologic heuristic algorithm originates from the description of biological behavior habits in nature and has a great randomness.

For the standard cuckoo search algorithm has the disadvantages of slow convergence speed and low precision. In this paper, the global search is performed by the adaptive Levy flight mechanism, and the Levy flight step size is continuously reduced with the iteration. The improved algorithm has a large step factor at the initial stage of optimization, so as to expand the search space in the early stage of the algorithm and improve the global search capability. In the optimization process, the step length decreases and the local search performance of the algorithm is improved.

Based on the above analysis, α_0 in the Eq. (5) can be changes from 0.01 in the standard algorithm to the variable, which can be calculated as follows:

$$\alpha_0 = 0.001 * t_{\max} * \exp\left(-\left(t_i / t_{\max}\right)\right) \quad (8)$$

The improved Levi flight update location is as follows:

$$\alpha_0 X_{g+1,i} = X_{g,i} + 0.001 * t_{\max} * \exp\left(-\left(\frac{t_i}{t_{\max}}\right)\right) * \frac{\varphi \times \mu}{|v|^{1/\beta}} * (X_{g,i} - X_{best}) \quad (9)$$

Where t_i represents the current number of iterations and $t_{\max}$ represents the total number of iterations.

The cuckoo search algorithm approaches the global optimal position by Levy flight. In order to avoid falling into local optimum, the algorithm adopts preference random walk to eliminate some feasible solutions, and generate the same number of new solutions in their vicinity. As far as the magnitude of the solution is concerned, when the value of v in Eq. (7) is small, the eliminated solution (X_i^t) and its offset $(v * (X_j^t - X_k^t))$ will differ by several orders of magnitude, and the local search effect is not significant. As far as the execution of the algorithm is concerned, the update of the cuckoo algorithm to the eliminated bird nest can be expressed as follows:

$$X_i^{t+1} = X_i^t + 0.01 * \frac{\varphi \times \mu}{|v|^{1/\beta}} (X_i^t - X_b^t) + v * (X_j^t - X_k^t) \quad (10)$$

The above formula includes global search and local search. The dynamic inertia improvement strategy is a mechanism to control the ability of population exploration and development. It can effectively improve the search ability of the algorithm and balance the relationship between local search and global search. In this paper, dynamic inertia weights are introduced in the preference random walks to make them adaptive. Dynamic inertia weight ω is denoted as follows:

$$\omega = 1 - e^{(-t_{\max} * 2 / t_i)} \quad (11)$$

Where t_i represents the current number of iterations and $t_{\max}$ denotes the total number of iterations.

This improvement expands the optimization space by setting a large inertia weight in the early iterations, which enhances the global exploration ability of the algorithm. At the same time, in order to ensure the convergence to the global optimal value in the later stage, the local search ability of the algorithm should be continuously enhanced, and the inertia weight is appropriately reduced. Improved preference random walk can be expressed as follows:

$$X_i^{t+1} = X_i^t + \omega * (X_j^t - X_k^t) \quad (12)$$

In addition, the local search update scheme uses a double random solution and can not retain the favorable information of the previous generation, which is not conducive to accurate search. In this paper, the memory strategy is introduced into the preference random walk, which replaces a random bird nest with the position of the previous generation of bird nests, so as to achieve the purpose of making full use of historical experience. Therefore, the updating formula of random preference random walks is modified as follows:

$$X_i^{t+1} = X_i^t + \omega * (X_j^t - X_i^t) \quad (13)$$

The adaptive cuckoo search algorithm focuses on the overall optimization of the algorithm, taking into account improvements in Levy flight and preference for random walks. It can make the algorithm adjust adaptively in the optimization process and improve the convergence speed and accuracy. At the same time, the algorithm can make full use of the current favorable information because of the memory strategy introduced in the local search, and the convergence precision is improved. The diagram of adaptive cuckoo search algorithm procession is shown in Fig. 3.

3. EXPERIMENT AND ANALYSIS

In order to evaluate the algorithm performance, the proposed algorithm is compared with the algorithm of DV-Hop and CSA respectively in the simulation experiment. The normalized positioning error is selected as the performance evaluation index, which is expressed as follows:

$$E = \frac{\sum_{i=1}^n \sqrt{(x_r - x_i)^2 + (y_r - y_i)^2}}{R \times N} \quad (14)$$

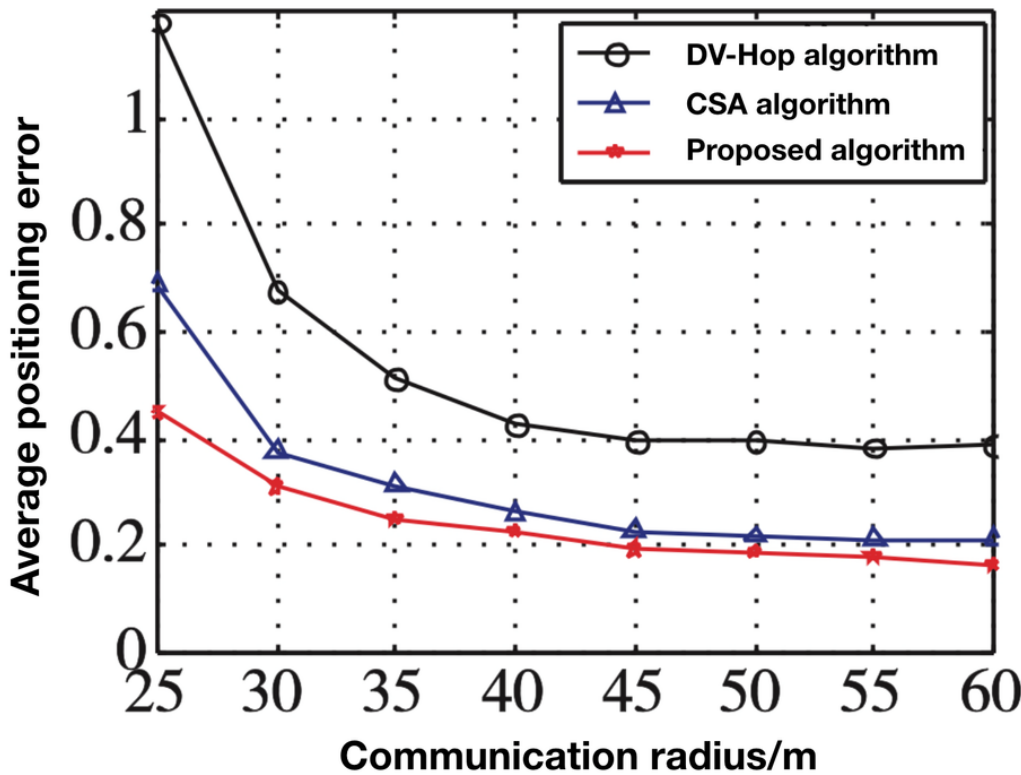
Where (x_r, y_r) represents the true position coordinates of the node to be located whereas (x_i, y_i) denotes the coordinates of the unknown node calculated by the Proposed algorithm. R represents the communication radius of the node, and N represents the number of unknown nodes.

The proposed algorithms, DV-Hop and CSA are simulated and compared under different communication radius and different total nodes. A square with a boundary length of 200 meters is selected as the simulation area. In order to reduce the randomness of the error, the simulation is performed 100 times under the same parameters, and the average positioning error curve is drawn by taking the mean value.

The experiment of different communication radius was performed using the proposed algorithms, DV-Hop and CSA respectively. Fig. 4 shows the average positioning error curves of the three algorithms when the total number of nodes is 200, the number of beacon nodes is 20, and the communication radius is 25 to 60 meters. It can be seen from Fig. 4 that when the total number of nodes and the number of beacon nodes are constant, the average positioning errors of the proposed algorithms, DV-Hop and CSA are gradually reduced as the communication radius increases. Moreover, the proposed algorithm outperforms the other two algorithms at any communication radius. This shows that the advantage of the proposed algorithm is more obvious when the node distribution is sparse. After analysis, the positioning error of the proposed algorithm is reduced by 19.23% and 53.42% respectively, compared with the CSA and the DV-Hop algorithm.

The experiment of different total number nodes was performed. Fig. 5 shows the average positioning error curves of the three algorithms when the number of beacon nodes is 20, the communication radius is 30 meters, and the total number of nodes is gradually increasing from 100

Figure 3. Diagram of the adaptive cuckoo search algorithm process



to 400. It can be seen from Fig. 5 that the positioning errors of the proposed algorithm, DV-Hop and CSA decrease with the increase of the total number of nodes. Moreover, the proposed algorithm outperforms the other two algorithms in any total number of nodes. When the total number of nodes is less than 150, the proposed algorithm has an average positioning error of 60.04% lower than that of the DV-Hop algorithm. This shows that the proposed algorithm performs better and is more practical. After analysis, the positioning error of the proposed algorithm is reduced by 14.74% and 47.07% respectively, compared with the positioning error of the algorithm of CSA and the DV-Hop.

Based on all the above experimental analysis, we can know that the adaptive cuckoo search algorithm is still the best algorithm for improving the node positioning accuracy of wireless sensor networks on all experiments. All in all, the proposed algorithm has better performance compared with other methods.

4. CONCLUSION

In order to improve the node positioning accuracy of wireless sensor networks, a node localization method based on adaptive cuckoo search algorithm is proposed. By adaptively adjusting the Levy flight step size, the algorithm has a large optimization space in the early stage and improves the global search ability. By introducing dynamic inertial weight and memory strategy, the algorithm can make full use of historical experience and improve its stability. Simulation experiments show that the proposed algorithm can effectively improve the positioning accuracy without increasing the hardware overhead.

Figure 4. Average positioning error curve with different communication radius

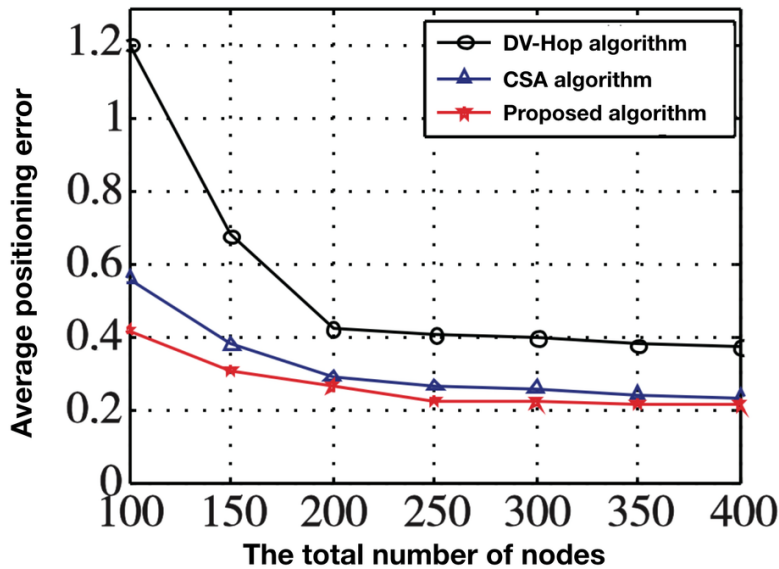
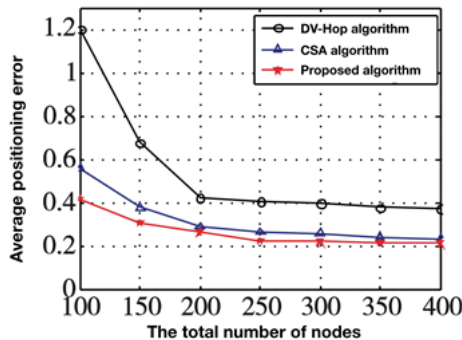


Figure 5. Average positioning error curve with different total number of nodes



Through this research, we have shown that an adaptive cuckoo search algorithm can be used to design and develop a wireless vision sensor network for the field of precision agriculture to improve the node positioning accuracy. In the future, this network will be expanded by using various sensors, so as to develop a low-cost and mature crop monitoring system. The system can not only track the changes of external environmental meteorological parameters, but also monitor weeds and disease insects in crops by using the images obtained by sensors.

REFERENCES

- Akhtar, F., & Rehmani, M. H. (2015). Energy replenishment using renewable and traditional energy resources for sustainable wireless sensor networks: A review. *Renewable & Sustainable Energy Reviews*, 2015(45), 769–784. doi:10.1016/j.rser.2015.02.021
- Akyildiz, I., Weilian Su, , Sankarasubramaniam, Y., & Cayirci, E. (2002). A survey on sensor networks. *IEEE Communications Magazine*, 40(8), 102–102. doi:10.1109/MCOM.2002.1024422
- Amjad, M., Sharif, M., Afzal, M. K., & Kim, S. W. (2016). Tinyos-new trends, comparative views and supported sensing applications: A review. *IEEE Sensors Journal*, 16(9), 2865–2889. doi:10.1109/JSEN.2016.2519924
- Campos, A. N., Souza, E. L., Nakamura, F. G., Nakamura, E. F., & Rodrigues, J. J. P. C. (2012). On the impact of localization and density control algorithms in target tracking applications for wireless sensor networks. *Sensors Journal*, 12(6), 6930–6952. doi:10.3390/s120606930 PMID:22969329
- Ding, Y., Wang, C., & Xiao, L. (2010). Using mobile beacons to locate sensors in obstructed environments. *Journal of Parallel and Distributed Computing*, 70(6), 644–656. doi:10.1016/j.jpdc.2010.03.002
- Feng, B., Xiao, J., & Hui, M. (2010). Research on DV-Hop Algorithm for Wireless Sensor Network. *Computer and Digital Engineering*, 30(2), 34–36.
- Fubao, W., Long, S., & Fengyuan, R. (2005). Self-localization systems and algorithms for wireless sensor networks. *Journal of Software*, 16(5), 857–868. doi:10.1360/jos160857
- Han, Z., & Feng, L. (2007). Optimized localization algorithm for Wireless Sensor Network based on convex algorithm:Convex-PIT. *Chuangang Jishu Xuebao*, 20(5), 1129–1133.
- Jian, W. Ya. Y. (2014). Localization in wireless sensor network based on improved particle swarm optimization algorithm. *Computer Engineering and Applications*, 50(18), 99–102.
- Jin, W., Xu, L., & Min, W. (2007). New Positioning Algorithm for Wireless Sensor Network Ased on Genetic Algorithm. *Jisuan Jishu Yu Zidonghua*, (4), 53–56.
- Khelifi, M., Benyahia, I., Moussaoui, S., & Nait-Abdesselam, F. (2015). An overview of localization algorithms in mobile wireless sensor networks. *International conference on new technologies of distributed systems, NTDS 2015*, 1-6. doi:10.1109/NOTERE.2015.7293510
- Li, H., Shuai, D., Yu, S., Wang, J., & Ke, L. (2016). Chaos-enhanced cuckoo search optimization algorithms for global optimization. *Applied Mathematical Modelling*, 40(5-6), 3860–3875. doi:10.1016/j.apm.2015.10.052
- Mistry, H. P., & Mistry, N. H. (2015). RSSI based localization scheme in wireless sensor networks: A survey. *Fifth international conference on advanced computing communication technologies, ACCT 2015*, 647-652. doi:10.1109/ACCT.2015.105
- Nazir, U., Arshad, M. A., Shahid, N., & Raza, S. H. (2012). Classification of localization algorithms for wireless sensor network: A survey. *International conference on open source systems and technologies, ICOSST 2012*, 1-5. doi:10.1109/ICOSST.2012.6472830
- Ojha, T., Misra, S., & Raghuwanshi, N. S. (2015). Wireless sensor networks for agriculture: The state-of-the-art in practice and future challenges. *Computers and Electronics in Agriculture*, 118, 66–84. doi:10.1016/j.compag.2015.08.011
- Ou, C. H., & He, W. L. (2013). Path planning algorithm for mobile anchor-based localization in wireless sensor networks. *IEEE Sensors Journal*, 13(2), 466–475. doi:10.1109/JSEN.2012.2218100
- Pantazis, N., Nikolidakis, S. A., & Vergados, D. D. (2013). Energy-efficient routing protocols in wireless sensor networks: A survey. *IEEE Communications Surveys and Tutorials*, 15(2), 551–591. doi:10.1109/SURV.2012.062612.00084
- Patwari, N., Ash, J. N., Kyperountas, S., Hero, A. O., Moses, R. L., & Correal, N. S. (2005). Locating the nodes: Cooperative localization in wireless sensor networks. *IEEE Signal Processing Magazine*, 22(4), 54–69. doi:10.1109/MSP.2005.1458287

- Rashid, B., & Rehmani, M. H. (2016). Applications of wireless sensor networks for urban areas: A survey. *Journal of Network and Computer Applications*, 60, 192–219. doi:10.1016/j.jnca.2015.09.008
- Rong, Y., & Ling, Z. (2011). Localization Algorithm for Wireless Sensor Network Based on ACOPSO. *Jisuanji Celiang Yu Kongzhi*, 19(3), 732–735.
- Shehab, M., Khader, A. T., & Al-Betar, M. A. (2017). A survey on applications and variants of the cuckoo search algorithm. *Applied Soft Computing*, 61, 1041–1059. doi:10.1016/j.asoc.2017.02.034
- Shi, Z., Mei, S., & Yi, T. (2009). Gasa-based localization algorithm for wireless sensor networks. *Computer Applications and Software*, 26(10), 189–192.
- Wang, G. G., Deb, S., Gandomi, A. H., Zhang, Z., & Alavi, A. H. (2016). Chaotic cuckoo search. *Soft Computing*, 20(9), 3349–3362. doi:10.1007/s00500-015-1726-1 PMID:26880874
- Wang, J., Ghosh, R. K., & Das, S. K. (2010). A survey on sensor localization. *Journal of Control Theory and Applications*, 8(001), 2–11. doi:10.1007/s11768-010-9187-7
- Winfrey, R. (1999). Cuckoos, cowbirds and the persistence of brood parasitism. *Trends in Ecology & Evolution*, 14(9), 338–343. doi:10.1016/S0169-5347(99)01643-2 PMID:10441306
- Woo, H., Lee, S., & Lee, C. (2013). *Range-free localization with isotropic distance scaling in wireless sensor networks*. IEEE Computer Society.
- Xiao, X., Dan, L., & Liu, T. (2017). Node localization of wireless sensor networks based on cuckoo search algorithm. *Computer Engineering and Applications*, 53(2), 141–145.
- Xun, A., Ting, J., & Zheng, Z. (2007). Centroid localization algorithm for wireless sensor networks. *Computer Engineering and Applications*, 43(20), 136–138.
- Yang, O., Jin, H., & Hong, B. (2011). Constraint Particle Swarm Optimization Algorithm for Wireless Sensor Networks Localization. *Computer Science*, 38(7), 46–50.
- Yang, X., & Deb, S. (2009). Cuckoo search via Levy flights. *Proc of World Congress on Nature & Biologically Inspired Computing (NaBic 2009)*, 210-214. doi:10.1109/NABIC.2009.5393690
- Yang, X. S., & Deb, S. (2010). Cuckoo Search via Lévy flights. In *World Congress on Nature & Biologically Inspired Computing*. IEEE.
- Yun, L., Ming, J., & Cheng, C. (2009). Modified weighted centroid localization algorithm based on RSSI for WSN. *Chuangang Jishu Xuebao*, 23(5), 717–721.
- Zhong, H., & Jing, L. (2008). The Progress of Swarm Intelligence Algorithms. *Techniques of Automation and Applications*, 27(2), 13–15.

Xiaobing Liu received the B.E. degrees at the North University of China, Taiyuan, China, in 2008, and the M.S. degree in control engineering from Guangxi University, Nanning, China, in 2015. He is currently a lecturer in the School of Information Engineering at Hunan University of Science and Engineering, Yongzhou, China.