A Modes Communication of Cat Swarm Optimization Based WSN Node Location Algorithm

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Abstract

Two factors, accuracy and cost, have always plagued the node positing in wireless sensor networks (WSN). If positioning is required to be accurate enough, the cost of equipment required for the location must increase significantly. Conversely, the lower cost will bring some problems like the big bias of positioning. DV-hop is a widely used positioning algorithm due to its low dependence on the device and the low operating cost. Many modified DV-hop algorithms improve the estimation accuracy of the average jump distance and the distance between the unknown and known nodes by adding weights, applying least squares, and using heuristic algorithms. In this paper, a novel algorithm based on the modes communication for the parallel cat swarm optimization is proposed so as to improve the location accuracy of DV-hop.

Keywords: DV-hop, CSO, WSN, Localization

1 Introduction

With the improvement of various technologies, such as energy optimization, fault tolerance, node positioning, clock synchronization, and data Fusion, WSN has been widely in many fields [1-5]. For example, WSN has played a positive role in ecological environment monitoring and forecasting, infrastructure condition monitoring, smart transportation, information appliances, and even the medical system and health care. As one of the key technologies, the location technology of unknown nodes in WSN gradually become the hot spot of scholars' research [6-9]. Positioning algorithms are divided into two categories in general, based on whether they need the precise calculation of the absolute distance between nodes in the progress of positioning. One belongs to the ranging method, which needs additional investment in hardware, increasing the cost burden when the network operating. TOA [10], TDOA [11], RSSI [12], and AOA [13] are classic examples. The other is called non-ranging, which estimates the location of unknown nodes based upon the coordinates of beacon nodes, and it has the superiority in saving consumption and easy deployment. Thus, the latter is more feasible for energy-constrained WSN. For instance, DV-hop [14], APIT [15], and MDS-MAP [16]. DV-hop is a typical representative, widely used non-ranging algorithm. Set up equations through obtaining two quantities, which are the average jump distance and the distance between the unknown and known nodes, and then utilize the maximum likelihood estimation (MLE) to find the location of the unknown node, that is the main idea of the DV-hop. In this method, the average distance of each hop and the estimation distance is inaccurate, resulting in a constant accumulation of errors, which eventually leads to a large positioning error. To reduce this error, and promote the localization more accurately, a novel positioning algorithm is proposed in this work. Some concepts about minimum hop and distance of the DV-hop algorithm are retained. At the same time, a swarm-based heuristic algorithm, an improved cat swarm algorithm, is introduced, and that no longer follows the inherent mathematical calculation model but seeks the optimal solution by imitating intelligent behavior of biological evolution. The experimental results indicate the effectiveness and stability of our proposed positioning method.

2 Modified CSO Algorithm

2.1 CSO Algorithm

The cat swarm optimization (CSO) algorithm is a swarm-based classic heuristic algorithm [17-20]. But it is different from particle swarm optimization (PSO) in that, it has two operation phases inspired by the natural

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behavior of the cat. The first stage is a global search, called seeking mode, which expands the diversity of solutions as far as possible. The second namely tracing mode for local, which improves the convergence speed and accuracy. The solution space tends to be re-located to a region with a high probability of the optimal solution through seeking mode, which makes full preparation for the local search in the next stage. The combination of the two models balances exploration and exploitation. Algorithm 1 shows the pseudo-code of CSO.

Algorithm 1. The pseudo-code of CSO

```
Initialization
While (don't satisfy the termination)
  Seeking mode:
    for i = 1:n_seek
      if Cat(i).cost < gbest.cost
        gbest = Cat(i)
      end if
    end for
  Tracing mode:
   for j = 1:n_trace
     update the velocity
     update the position
     calculate the fitness value
     if Cat(j).cost < gbest.cost
       gbest = Cat(j)
     end if
   end for
 Resetting mode:
   Divide cat swarm into seeking mode and tracing
   mode
End while
Output: gbest
```

2.2 Modes Communication of CSO Algorithm

Although the CSO algorithm has unique competitive advantages of its own, for instance, strong exploration ability and effective solving of complex optimization problems, continuously improving the convergence speed and accuracy is always the motivation and goal of continuous improvement of the optimization algorithm. This section focuses on the improvement of the CSO algorithm. Parallel mode is a common method to speed up convergence. In seeking mode, each candidate will form an independent subgroup and evolve in parallel to get the personal best. And then, the first three best solutions are transmitted to the tracing mode to re-formed solution space around the global optimum. And each candidate solution represents a cat in tracing mode. In our work, the amount of the cat in the tracing mode is set 10 through experimental tests. Finally, using an encircling method, which realized by an inner loop, the global optimum is gradually approached by all cats in tracing mode. The encircling method imitates the hunting behavior of wolves. Encircle the prey, and narrow its activity space gradually until captured [21]. This local search process can assist in increasing the chance of the optimal solution, as well as improve accuracy. To avoid the search falling into local optimum, we proposed a mutation scheme when updating the next generation. The pseudo-code of the improved CSO algorithm shown in Algorithm 2.

Algorithm 2. The pseudo-code of improved CSO

```
Initialization
While (don't satisfy the termination)
  Seeking mode:
   // parallel mode
    for i = 1:population
      seek_Cat(i)generate Group(i)
      select seek_Cat(i).pbest
    end for
    Output. the first three best
        solution Alpha Beta
        and Delta
  Tracing mode:
  // re-formed solution space
   for j = 1:n_trace
     trace_Cat(j) = rand()×(Alpha+Beta+Delta)
     calculate trace_Cat(j).cost
   end for
   update Alpha Beta and Delta
   // encircle mode
   while (don't satisfy the termination)
     for j = 1:n_trace
       update trace_Cat(j) using encircle method
       calculate trace_Cat(j).cost
     end for
     update Alpha Beta and Delta
   end while
   if Alpha.cost < gbest.cost
     gbest = Alpha
   end if
 Update next generation:
   for any dimension, if the value of trace_Cat is less
   than that of gbest and the fitness value after
   exchange is less than gbest.cost, swap values on the
   corresponding dimension
End while
Output: gbest
```

CEC 2013 [22] is a black-box test, including unimodal, basic multimodal, and composition functions. Four algorithms, the basic CSO algorithm, grey wolf optimizer (GWO) [23-25], PSO [26-28], and improved CSO, were tested and compared using it. In the actual test process, to ensure the fairness of the comparison, each algorithm independently runs ten times, and each run time is 30 seconds. Besides, the population size is 30, and the dimension is 10. Table 1 compared the average optimal value of each algorithm. The ICSO represents our proposed algorithm. Values expressed using the bold have higher accuracy than other compared algorithms. For another evaluation index we care about, convergence speed, also has better performance, that there are 22 functions with a faster rate of convergence. Due to the limitation of space, the first two functions of each category selected to show in Figure 1. They are F1, F2, F6, F7, F21, and F22. On the whole, the ICSO algorithm outperforms in both convergence speed and accuracy.

Table 1. The comparison of the average optimal value

F	CSO	GWO	PSO	ICSO
f1	3.3077E+03	1.0796E+04	1.0778E+04	**-1.3991E+03**
f2	2.9796E+07	4.7504E+08	5.0273E+08	**3.0205E+06**
f3	1.3460E+14	9.4670E+14	1.1630E+15	**1.4321E+09**
f4	1.7961E+04	1.4478E+04	1.2291E+04	**-7.1616E+02**
f5	1.9335E+03	2.6804E+04	2.4125E+04	**-9.9465E+02**
f6	-5.9427E+02	-6.3105E+01	-6.2352E+01	**-8.2952E+02**
f7	5.3253E+04	5.3459E+04	4.7467E+04	**-7.5570E+02**
f8	-6.7929E+02	-6.7968E+02	-6.7976E+02	**-6.7978E+02**
f9	-5.8930E+02	-5.8924E+02	-5.8828E+02	**-5.9088E+02**
f10	1.4601E+02	1.2457E+03	1.2958E+03	**-4.8943E+02**
f11	-2.6127E+02	-2.1797E+02	-1.9449E+02	**-3.1189E+02**
f12	-1.7777E+02	-1.5727E+02	-1.3274E+02	**-2.0169E+02**
f13	-6.7175E+01	-3.3155E+01	-2.2530E+01	**-1.2521E+02**
f14	1.7832E+03	1.2318E+03	1.3524E+03	**9.1821E+02**
f15	1.6602E+03	9.6934E+02	1.0623E+03	**9.6672E+02**
f16	2.0230E+02	2.0065E+02	**2.0020E+02**	2.0074E+02
f17	4.2297E+02	4.0307E+02	4.1799E+02	**3.5166E+02**
f18	5.1797E+02	5.0851E+02	5.2896E+02	**4.3315E+02**
f19	2.3018E+03	3.0440E+04	3.0582E+04	**5.0163E+02**
f20	6.0477E+02	6.0500E+02	6.0500E+02	**6.0326E+02**
f21	1.1886E+03	1.3416E+03	1.3421E+03	**1.1005E+03**
f22	3.3592E+03	3.5239E+03	3.5484E+03	**2.3173E+03**
f23	3.3752E+03	2.8817E+03	2.9908E+03	**2.8098E+03**
f24	**1.2328E+03**	1.2653E+03	1.2930E+03	1.3024E+03
f25	1.3298E+03	1.3732E+03	1.3792E+03	**1.3246E+03**
f26	**1.4794E+03**	4.0105E+03	4.0276E+03	1.6451E+03
f27	1.8399E+03	2.0551E+03	2.0558E+03	**1.7036E+03**
f28	2.4507E+03	2.4326E+03	2.4819E+03	**2.3479E+03**

3 Node Location Based on Improved CSO Algorithm

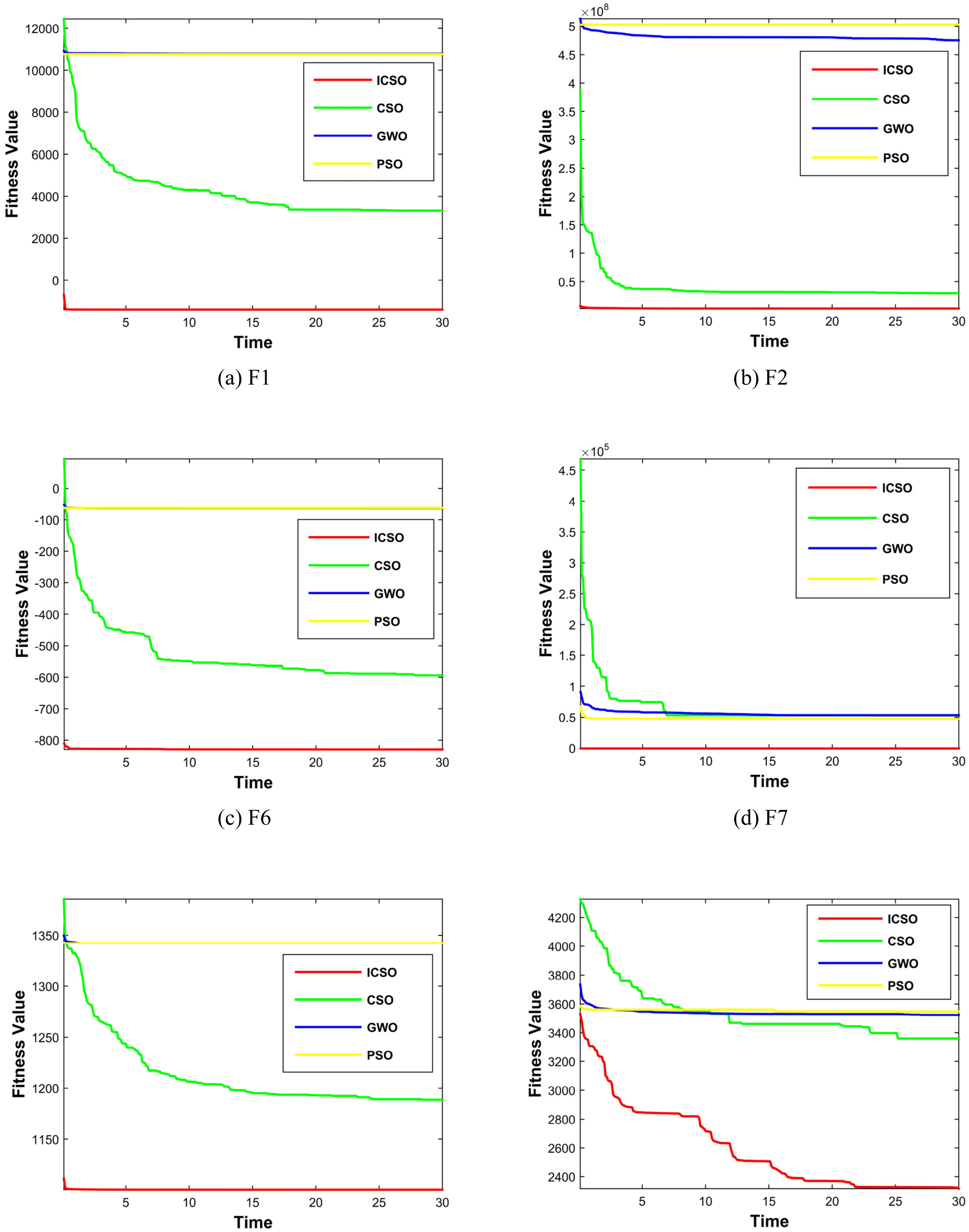
In this part, a novel positioning algorithm is proposed based on an improved CSO algorithm, which gives full play to local optimization-oriented advantages of the group based heuristic algorithm [29-32]. Assuming that all nodes in the WSN have strong information transmission capability, the interference of rugged terrain and some obstacles on signals in the monitoring area can be ignored. In other words, the simulation environment discussed in this paper is a two-dimensional plane. There are two steps in the positioning process. Firstly, the virtual node positioned to the area around the actual unknown node according to some known information about the minimum hops from the unknown node to the beacon node and the coordinates of beacon nodes. And then use the improved CSO algorithm to search the area around the virtual node to obtain the location of the unknown node.

The smaller the minimum hops is, it considers that the closer the distance between two points, that is, the stronger the signal between them, which expressed by the connectivity rate, as shown in Equation (1). The estimated position of the unknown node, also the virtual node, calculated proportionally from the coordinates of the three beacon points with the highest connectivity. That shown as Equation (2).

$$P_{ij} = 1 - \frac{hop_{ij}}{\sum_{j=1}^{m} hop_{ij}} \tag{1}$$

where P_{ij} indicates the connectivity rate from unknown node i to beacon node j, and hop is the minimum hops. m is the count of beacon nodes.

An shown in Figure 2, the green "●" indicates the unknown node, and the blue one is the virtual node. The two '*' indicate beacon nodes with the highest connectivity to the unknown node i. The dotted lines and the solid line indicate the distance between nodes. θ_1 and θ_2 are approximately equal. According to the law of cosines, we can gain Equations (3)-(5). D and E are unknown, and the fitness function of the improved CSO algorithm obtained by deforming Equation (5), as shown in Equation (6). In the local search, the cat swarm is formed by mutation and expansion of the location of the virtual node. Each cat represents the candidate solution of the unknown node coordinate. The unknown node will be found through random searching around the virtual node by cats. The overall flow shows in Figure 3.



(a) F1

(b) F2

(c) F6

(d) F7

(e) F21

(f) F22

Figure 1. The comparison of convergence curves

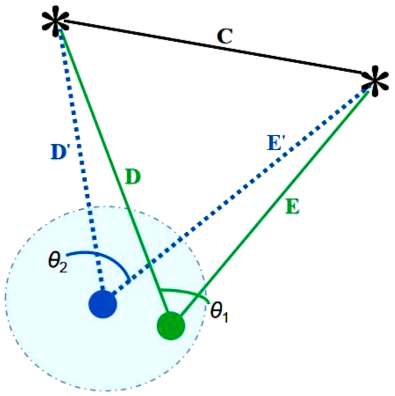


Figure 2. The diagram of nodes relationship

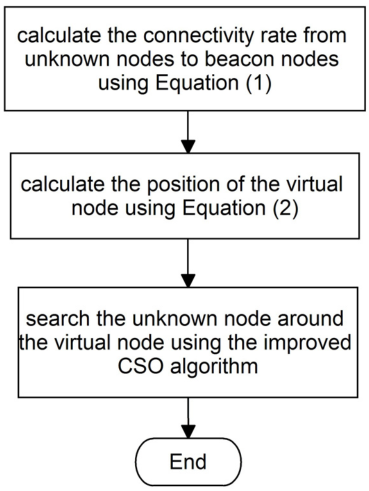


Figure 3. The flow chart of our proposed positioning algorithm

$$VP_i = \sum_{j=1}^{3}\left(B_j \frac{P_{ij}}{\sum_{j=1}^{3} P_{ij}}\right) \tag{2}$$

where the VP_i indicates the virtual node corresponding to the unknown node i and B_j indicates the coordinates of a beacon node.

$$\cos\theta_2 = \frac{D'^2 + E'^2 - C^2}{2D'E'} \tag{3}$$

$$\cos\theta_1 = \cos\theta_2 \tag{4}$$

$$D^2 + E^2 - 2DE\cos\theta_1 = C^2 \tag{5}$$

$$\begin{cases} Fit = \left|D^2 + E^2 - 2DE\cos\theta_1 - C^2\right| \\ D^2 = (w-w_1)^2 + (q-q_1)^2 \\ E^2 = (w-w_2)^2 + (q-q_2)^2 \end{cases} \tag{6}$$

where (w, q) indicates the coordinates of the unknown node. (w_1, q_1) and (w_2, q_2) indicate the position of beacon nodes.

4 Simulation Results and Analysis

To test the effectiveness of the proposed positioning algorithm, we compared it with the DV-hop algorithm, because the latter widely used in practice and its positioning process also related to minimum hops and distance between nodes. We set up a fair simulation environment and made statistics on the positioning errors of the two algorithms under the same conditions. Each algorithm runs independently ten times to avoid mutual interference, obtaining the average value. Specifically, 100 sensor nodes randomly scattered to a square area of 10,000 square meters, and the transmission distance of each node is 20. Comparing the average positioning error in conditions with different count of beacon nodes, and the result shown in Figure 4. The proposed positioning algorithm has an obvious advantage, having smaller positioning errors compare to DV-hop, and it runs stably. And that is also affirmed in Figure 5, comparing the proportion of the unknown nodes whose positioning error is within 15m.

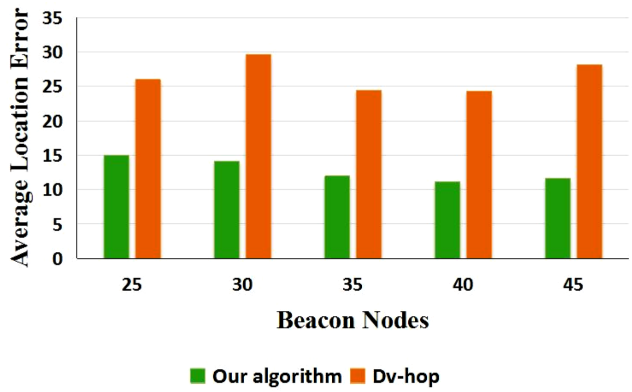


Figure 4. The comparison of average error with different beacon nodes

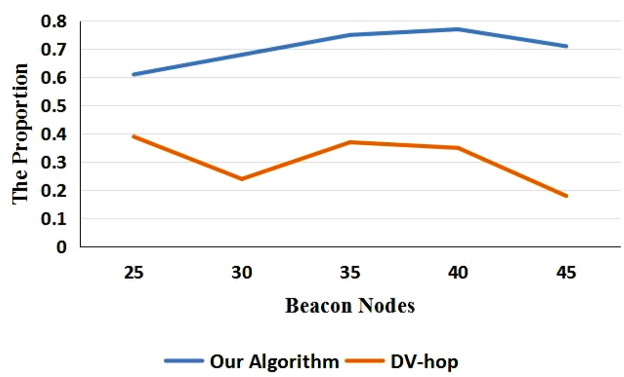


Figure 5. The proportion of unknown nodes with an error within 15m

In the experimental process, through the further comparison of the two algorithms, it is not difficult to find that reducing the accumulation of errors in every step and increasing the accurate information can make positioning more precise. For the DV-hop, the average jump distance of beacon nodes, that of unknown nodes, and the distance between the unknown and known, these three quantities calculated in turn are all estimated values. So there must be errors, which gradually accumulated in the operation process of the algorithm. However, there are only two quantities of the proposed algorithm are the estimated compared with DV-hop algorithm, thus reducing the accumulation effect of errors. And at the same time, the location and distance information of two beacon nodes are utilized in the local search for unknown nodes, which increases the amount of accurate information compared to that in DV-hop, which utilizes one known node. Thus, the positioning accuracy and robustness of the proposed algorithm are improved significantly.

5 Conclusion

In this paper, we optimize the CSO algorithm using the parallel mode, encircling method, and mutation scheme, to speed up the convergence and improve the accuracy. And based on it, a new node localization method is proposed, which utilizes the coordinates of beacon nodes, the law of cosines, and the minimum hops. It not only retains the advantage of a range-free positioning algorithm but also improves the positioning precision compared with the DV-hop algorithm. However, there are still estimated values in the positioning algorithm. So in future work, we will focus on reducing the cumulative effect of errors and several methods may be applied to further improve the locatation accuracy [33-36].

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