Performance Analysis of Improved Glowworm Swarm Optimization Algorithm and the Application in Coverage Optimization of WSNs

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Received: 5 February 2014   /Accepted: 7 March 2014   /Published: 30 April 2014

Abstract: The performance of improved glowworm swarm optimization (GSO) algorithm and its application in coverage optimization of WSNs are analyzed in this paper. The global convergence analysis of basic GSO is made. In order to improve the GSO convergence efficiency, an improved GSO (IGSO) is presented, and it is proved to be guaranteed to the global optimization with probability one. Further, a new coverage optimization algorithm for WSNs, based on IGSO, is presented according to the analysis of GSO. A model of coverage optimization in WSNs is built up by taking node uniformity and network coverage rate as the criterion, and the relationship between node redundancy and network coverage rate and the node dormancy strategy are presented. Then the deployment of nodes is divided into different stages, and the IGSO is used to solve the model in each stage. Through testing classical test functions and optimizing the problems of coverage in WSNs, the simulation results show that the IGSO achieves more reasonable results and can effectively provide the optimal solution of network coverage.

Keywords: Artificial intelligence, Wireless sensor network, Glowworm swarm optimization algorithm, Convergence, Network coverage.

1. Introduction

Particle Swarm Optimization is an evolutionary algorithm based on swarm intelligence, it through the birds, fish simulation presented in 1995 by Kennedy and Eberhart [1, 2]. The algorithm uses the advantage of group provides a new approach for solving complex problems. PSO algorithm has strong global search capability, but has shortcomings of easy to fall into local minima lead to the convergence of low precision and easy to converge to the global optimum.

In a related study, Pang Wei [3] etc. fuzzy matrix to represent the position and velocity of the particle, and redefine its update formula, proposed an improved particle swarm optimization algorithm. Huang Lan, et al [4]. Through introduction of the concept of exchange operator and swap sequence, construction a special particle swarm optimization, and used to solve CICOWSN. Tan Hao, et al [5] put forward a algorithm combination the structure of particle swarm ant characteristics of colony algorithm to solve the algorithm of CICOWSN. Algorithm through selection mechanism of hybrid particle. Using the design of the two kinds of hybrid operator, successfully simulate the exchange and collaboration between different populations of species in the nature, the fertility group strategy and subgroup hybridization between operation into the particle swarm structure, enhance the optimization ability of
genetic algorithm, colony algorithm and the idea of
simulated annealing algorithm, proposed to use
hybrid particle swarm optimization algorithm to
solve CICOWSN.

These improved PSO because of strong spatial
search capabilities, combining with the design of
appropriate operators and the application of local
optimization strategy, the constructed algorithm has
stronger optimal ability and can get the best solution,
but compared to common dynamic programming
algorithm, the optimal benign of execution time and
results of the algorithm largely depends on the design
of the operator, how to design a good operator is
worthy of further research problem.

WSNs are composed of a low cost, limited
processing ability, wireless sensor nodes of energy
resource [7]. Nodes self-organized by certain
deployment method form network, realize effective
target area of monitoring. In recent years, WSNs has
been widely applied in medical treatment, military,
industrial, and other fields. Studies show that
reasonable decorate network node is beneficial to
improve the working efficiency of WSNs, reduce
energy consumption [8]. High density of nodes
deployed can improve the comprehensive
performance of the network, but increased the
redundancy information and channel interference,
caused the waste of energy, so the reasonable
deployment of network nodes and optimize the
network performance has become one of the key
technology of WSNs. Wireless Sensor network
Information Collection ICOWSN is one of the most
basic function of Wireless Sensor network (WSN),
and the whole network energy loss in one of the
biggest part, this paper USES the improved particle
swarm optimization (PSO) algorithm to effectively
study the problem.

2. WSNs Network Signal Acquisition
Model

2.1. Problem Description

Assuming a random deployment of sensor nodes
within a two-dimensional monitoring area, and the
sensor network has the following properties:
1) The sensor node density is large enough, and
there are a lot of redundant nodes.
2) Sufficiently large surveillance area, area
boundary effects are negligible.
3) All sensor nodes have the same sensing radius
$R_s$ and communication radius $R_c$, nodes $s_i$ can
obtain its own position $s_i(x, y)$ in some way, a node
can only communicate within a radius of nodes to
communicate.
4) Nodes using Boolean perception model, the
network did not encourage nodes.

2.2. Definitions

Definition 1, for a node, its perception neighbor
set is defined as:
$$A(j) = \{ k \in \mathbb{K} | |s_k - s_j| \leq 2R_c, j \in \mathbb{K} \neq j \} ,$$
wherein $\mathbb{K}$ is the set of sensor nodes.

Definition 2 For a node $s_a (a \in \mathbb{K}, a \neq j)$, so that
$A(a) = A(j)$, the node is called redundant nodes $o_j$, a
collection of nodes for redundancy is $O = \{ o_j \}$.

2.3. Node Dormancy Strategies

If simply set all the redundant nodes to a dormant
state, possible to reduce the possibility of network
coverage. For example, in Fig. 1, the nodes, coverage
was completely covered, therefore, for the redundant
nodes, if will be set to a dormant state, will appear in
Fig. 2 monitor the presence of the blind spot (shadow), and thus reduce the network coverage, this
paper proposes a kind of redundancy node scheduling
algorithm based on node.

2.4. WSNs Network Routing Model

The entire network of an undirected graph
$G(V, E)$, $V$ in the figure represents the nodes in the
WSNs network, the E represent the edge between the
node and node in the graph. Each sensor node in the
network has a unique network ID, assuming that the
entire network can be connected to each other, no
isolated nodes. Assume that each data collection
information instruction from the Sink node, data
acquisition of the target node is the whole information collected by all the nodes in the network. Less in order to save energy, the entire network routing model will be limited to a number of visits each node, the data need to came back to the Sink node for processing.

3. Dynamic Programming Algorithm

This paper analyzes the factors affecting the performance of the dynamic programming algorithm, introduced the combination resolution of ideas, through placing a ICOWSN sequence split into a number of cluster according to the proposed in this paper one of the five strategies. Then through the improved dynamic programming algorithm to optimize recombine, at last repeat the above two process to get the optimal solution.

3.1. ICOWSN Sequence Split

The problems of ICOWSN often involve hundreds or even thousands of sensor nodes, if from the global dynamic planning, the scale of the problem will lead to time consuming, and may not be able to find out the optimal solution. In order to solve this problem, this article considered from local to global ICOWSN sequence into several sub sequences.

Such as nine ICOWSN problem of sensor nodes can be divided access routes (5-6-2-0-5-6-2-8-4) into three segments, a kind of hypothesis may be broken down into: (5) 6-2-0-3-1[7|8-4] (’ | ' tag truncation point), considering the ICOWSN sequence is cyclic sequences, you can put the 8-4-5, 6 and 7-2-0-3-1 as the corresponding sequence.

In order to ensure the subsequence of the split is relatively reasonable, consider the following five kinds of set truncation in different strategies, which will be make a n sensor nodes ICOWSN split into m(1 ≤ m ≤ n) sequences:

A: in ICOWSN sequence search for m different truncation random.

B: in ICOWSN randomly to look for a sensor node in the sequence, and then set behind a truncation after a sensor of the sensor nodes m node.

C: in a sequence of random search for a sensor node, then of all the sensor nodes to find the sensor node nearest the m- a sensor node, behind find it m a sensor node is set to truncate.

D: find out the long time is not truncated at the resolution of m/2 sensor nodes, and then the back after the truncation is positioned at the cutting position, behind the m/2 sensor nodes before it is truncated at.

E: find out the long time is not truncated at resolution of sensor nodes, then in all sensor nodes in the sensor nodes to find the nearest M-1 sensor nodes, the back of the M sensor nodes to find a truncation point.

3.2. Dynamic Programming

After a split, the solution of the ICOWSN problem simplification to the note sequences into the shortest circuit problem.

Results the local after the split of the overall integration, integration will involve a sequence directional problem. So based on the traditional dynamic programming, this paper introduces a new variable $c_i$ to represent the i sequence direction, if the i sequence is $c_i = 1$ then recorded as positive $c_i = 0$; otherwise according to the sequence of the directional properties.

Because the ICOWSN path is a cyclic path, so the subsequence suppose last access is 0th part series positive. The new state variables $(i, c_i, k)$, representing the current reached the i sub sequences, and the sub sequence direction is $c_i$, k is the subsequence from 0th part series to i sub sequence. In binary it corresponds to the position j is 1 indicates that the sequence has walked in front of the path selection, the 0 indicates not through.

The shortest distance of the definition of $f(i, c_i, k)$ function as state variables $(i, c_i, k)$. You can get the initial state function value $f(0, 0, 0) = 0$, the target state function value $f(0, 0, 2^n - 1)$.

The transfer equation is:

$$f(i, c_i, k) = \min_{i \neq j, k \neq 2^n - 1} \left( f(j, c_j, k - 2^i) + \text{dist}(P(i, c_j), P(j, 1 - c_j)) \right)$$

(2)

Type (2), at the time $c_i = 0$, $P(i, c_i)$ represent the i sequence in the first sensor nodes; when $c_i = 1$ represent the last sensor node in i sequence.

According to (2) type recursive solution can be obtained the optimal value of $f(0, 0, 2^n - 1)$, and according to the optimal path is recorded, all sub sequences form a complete ICOWSN sequence.

3.3. Algorithm

Based on the dynamic programming method, combination and splitting strategy to solve the ICOWSN problem as follows:

Step1: initialization. Set the sequence number (m) $1 \leq m \leq n$ and the maximum running time of $\mathcal{T}$, $N$ and randomly generated a sequence of ICOWSN sensor nodes.

Step2: sequence split. Randomly select a splitting strategy, and according to the selected strategy will be a ICOWSN sequence into m sub sequence.

Step3: dynamic programming.

1) $f(0, 0, 0) = 0$, all other assignment $f(i, c_i, k)$ is infinite, and $k = 0$.
2) Enumerate i, j, c, and \( k/2^{(i+j)/2} = 1 \), \( k/2^{(i+j)/2} = 0 \), according to the type (3-1) update, and record the solution path.

3) If \( k \leq 2^m \), then, and \( k = k + 1 \) returns the 2).

Step4: recombinant sequence \( f(0,0,2^m-1) \).

According to the combination m scripts sequence records for the optimal value of new ICOWSN sequence.

Step5: if the running time is less than T, then jump to the Step2, otherwise the output optimal solution.

### 3.4 Analysis of Complex Algorithm

The main steps of dynamic programming method for solving combinatorial resolution strategy based on sequence reorganization and dynamic programming, the other steps of the complexity with respect to these two aspects can be ignored.

In the sequence of reorganization, the corresponding sequence of 5 kinds of resolution strategies and recombinant sequences are available through sequential enumeration can be achieved, so the time complexity is \( O(N) \); while in the dynamic programming, the state space is \( f(i,j,k) \), to each state space in the calculation and enumeration of M will do next sub sequence transfer, so the time complexity is \( O(m^2 \times 2^m) \), space complexity is \( O(m^2 \times 2^m) \). Therefore an optimization of time complexity is \( O(m^2 \times 2^m + N) \), space complexity is \( O(m \times 2^m + N) \). In realization, the relations of m value and sensor nodes for the scale number N is \( m = \log_2^{N/m} = \log_2^N - 2 \). Through the analysis of the m value, can be derived from each computational complexity is about \( O(N) \).

### 4. Based on Algorithm Particle Swarm Algorithm of Improved Dynamic Programming for Solving the ICOWSN Problem

Particle swarm optimization algorithm PSO is studied based on the foraging habitat, such as birds flying, group behavior modeling and simulation, since the proposed algorithm development soon. As a new type of algorithm, has the following drawbacks in ICOWSN discrete problems: (1) algorithm "premature" (2) the convergence speed is slow and convergence precision is not high (3) operator algorithm is difficult to design and implement.

#### 4.1 Improved Particle Swarm Optimization Algorithm for Solving the ICOWSN Problem

1) The state of a particle.

The state of X particles with a made up of points table remark, he is a N dimensional vector, in X, dimension represents the overall number of sensor nodes, each dimension of the data representation corresponding to the number of sensor. We can use the formula (3) to represent:

\[
X = (x_1, x_2, \ldots, x_j, \ldots, x_N), 1 \leq i \leq N, 1 \leq x_i \leq N, \quad (3)
\]

where N is the number of sensor nodes, the i dimension data \( x_i \), remark sensor node corresponding to the number is \( x_i \), expressed as a whole \( x_i \), will visit the sensor nodes \( x_{i+1} \) in the sensor nodes after visiting \( x_i \), and so on, from the beginning of \( x_i \) to the access \( x_N \), then access the sensor nodes \( x_j \), resulting in the access sequence.

The start of algorithm will be randomly generated M different particle structure particle swarm.

2) The scale-free network topology information to construct guidance method.

In 1999, Barabási and Albert [15] in the dynamic evolution process tracing of the world wide web, accident found that many large complex networks have the ability of self-organization, most complex network node degree is "power-law", any node has k connection probability is directly proportional to \( 1/k \), namely \( p(k) \sim k^{-\gamma} \), \( 2 < \gamma < 4 \), they have the characteristics of the network called scale-free network [19].

This paper use the method in the construction of particle swarm optimization network, the method to construct the scale-free network topology information to guide (Scale-free fully informed network model) [20, 21], in each iteration all the particles to scale-free network topology form a particle swarm to the next step the interpretable exchange of information. Construction method comprises the following steps:

From the original M particles were in front m the highest accuracy of particle.

The M particles form a complete graph, that any two particles have an edge.

One by one the enumeration remaining M-m particles, and then inserted into the original particle, J particle i and the newly inserted in the original with probability \( p_{ij} \) edges, the degree of \( k_i \) probability \( p_{ij} \) and \( j \) particle is proportional to the. With \( p_{ij} \) and \( k_j \) in the formula (4) representation:

\[
p_{ij} = k_j / \sum{k_j}, \quad (4)
\]
3) The information interaction of particles.

According to 2) can get a particle swarm network topology, this chapter according to the known topology relation, information interaction for each particle, so that each particle can convergence precision. On the information interaction practice, we must ensure that in the other particles of the particles is better than that of the particle itself according to the information of self evolution, but also in other particle is better than themselves, according to other particle information to encourage their evolution. In this paper, the design of two kinds of information interaction mode: two information interaction between particles, the evolution of a single particle dynamic programming. The single particle dynamic planning evolution method is 2.1 and 2.2 methods described in this paper.

Information interaction between two particles is: first of all known particles X, based on the topology of the graph to find a particle is connected to the X particles in Y. Secondly, from the particle Y extracted from a Z (z is a random positive number less than 10) of continuous sub vectors such as \( (y_{i+1}, y_{i+2}, \ldots, y_{i+z}) \), and set it as the vector Z. Then according to each element in the Z as a break point, the vector X is divided into Z sections, a section does not contain any element in the Z.

Known as X: (1, 2, 3, 4, 5, 6, 7, 8, 9), Y: (4, 3, 2, 1, 4, 6, 5, 7, 8, 9), and then extracted from Y segment length vector Z= 3 (1, 4, 6), then X is divided into: according to Z (2, 3), (5), (7, 8, 9) three.

Then according to the vector Z sub vector income plus extracted from Y altogether can get Z+1 note vector. The dynamic programming method and finally by the 3.2 reassembled into new particles ’X’.

And then tested for the particles, if the particle relative to the primary particle X convergence, ’X’ will replace the original X particle.

The basic steps of this section for the algorithm:

- Each particle in the particle swarm in the enumeration.
- When the enumeration to the first i particle, then enumerates other particle j in i particles connected, information interaction between two particles of i particle and particle j.
- Enumeration of each particle, and a particle dynamic programming evolutionary operation on the particle.

4) The algorithm flow.

Improved particle swarm algorithm for solving ICOWSN problems as follows:

- Initialization. Set the particle swarm M number and the number of iterations of ds, randomly generated M different particle.
- The scale-free network composition. The network construction of the particles in the swarm into a scale-free network topology information guidance.
- Information switching. According to the information exchange between the particles in the Step2 diagram.

Single particle evolution. For a single particle dynamic programming evolutionary operation for each particle. The iteration number ds minus 1, judge whether the ds is 0, the output is optimal all particles in the solution, or jump to Step2, the next iterative operation.

5. Analysis of Simulation and Results

We selected two groups ICOWSN examples of using improved particle swarm algorithm simulation, the sensor nodes are respectively 783 and 100000, on behalf of the medium scale and large-scale data respectively. The simulation results are shown as follow in Fig. 3:

![Fig. 3. Simulation results.](image-url)
of [17] and improved elastic net algorithm (Improved-EN) [18].

And you can clearly see that the improved particle swarm algorithm and compared with the improved dynamic programming algorithm, a further improvement in the accuracy of convergence, but in time convergence has not. The reason is that: the improved dynamic programming algorithm is a single particle iteration process, the improved algorithm is iterative process of particle swarm multi particle, it is equivalent to the improved particle swarm algorithm is a iterative operation, equivalent to the improved dynamic programming algorithm for particle number and information exchange in a number of operations. So the improved particle swarm algorithm has shortcomings in time convergence. But because of the existence of information interaction between particles, the algorithm runs to the late, particle swarm algorithm is more difficult in the "premature", the final result is improved dynamic programming algorithm convergence of higher.

References


[7]. G. Xu, E. Segawa, S. Tsuji, Robust active contours with insensitive parameters, Pattern Recognition, Vol. 27, Issue 7, 1994, pp. 879-884.


