**ISSN** 1746-7659, England, UK
**Journal of Information and Computing Science**
Vol. 12, No. 3, 2017, *pp*.234-240

# Anycast Routing Algorithm Based on Krill Herd Optimization for Wireless Sensor Networks

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(Received April 26, 2017, accepted June 19, 2017)

**Abstract.** Krill herd optimization is a novel bionic swarm intelligence optimization method, but currently it is mostly used only in the field of engineering optimization. Since node's energy is limited and establishing effective routing is difficult in wireless sensor networks, in this paper, we try to apply krill herd optimization in anycast routing algorithm for wireless sensor networks. The krill are moved to the high fitness area (anycast paths with better energy consumption condition) through induced motion, foraging movement and random diffusion behaviors. Moreover, crossover and mutation operators in genetic reproduction mechanisms are adopted for improving the ability of accelerating optimization speed and breaking away from the local optimum. In comparison with ant colony optimization, simulation experiments results show that the performances of the proposed algorithm are better in terms of convergence speed, optimization results and scalability.

**Keywords:** krill herd optimization, wireless sensor networks, anycast, routing algorithm.

## 1. Introduction

In wireless sensor networks (WSN), node' energy is limited and hard to supply, moreover, communication and computing ability of sensor nodes is very weak. So, table-driven routing protocols such as OSPF (Open Shortest Path traditional table First), are not suitable for WSN. And, on-demand routing protocols such as unlimited flooding, have the disadvantage of huge cost for routing query. Therefore, the focus for WSN is to design an efficient routing algorithm with less energy consumption.

Recently, a bio-inspired swarm intelligence optimization algorithm called Krill Herd Optimization (KH) was for the first time proposed by Gandomi and Alavi in [1]. This algorithm is based on the simulation of the herding of the krill swarms in response to specific biological and environmental processes. The minimum distances of each krill individual from food and from highest density of the herd are considered as the objective function for the krill movement. The aggregation process of krill is the process of finding the optimal solution.

After the introduction of KH, it received a great deal of attention from some scholars. Wang and Gandomi[2] added the crossover and mutation factors of genetic mechanism to KH; for further improving KH' performance, Wang and Gandomi[3] introduced a new krill migration (KM) operator when the krill updating to deal with optimization problems more efficiently and applied the improved algorithm for solving complex optimization tasks; Bulatovic[4] improved the fitness function, food position and crossover factor in KH, and applied the improved algorithm to the optimization design of four-bar linkage; for traditional KH has a deficiency which cannot achieve the excellent balance between exploration and exploitation in optimization processing, Li[5] proposed an improved KH with linear decreasing step; Sultana[6] applied KH to optimal capacitor allocation problem in reconfigured distribution network in order to minimize real power loss of radial distribution systems, the author integrated the opposition based learning (OBL) concept with KH for improving the convergence speed and simulation results; Deng[7] proposed a mobile service sharing community composition approach by utilizing the KH; Rostami [8] proposed an improved KH to moderate the charging effect of PHEVs. For practical economic load dispatch problem has non-smooth cost function with nonlinear constraints which make it difficult to be effectively solved, Mandal [9] proposed a new and efficient KH to solve both convex and non-convex economic load dispatch problems.

KH is a novel bio-inspired swarm intelligence optimization algorithm, and the current research results are mainly focus on engineering optimization field. This paper attempts to apply KH to WSN anycast routing field.

## 2. Problem Description

For saving node's energy and balancing energy consumption, multiple base stations are often deployed in WSN. In this way, sensor nodes can broadcast their monitoring data information to any one or more base station (anycast) according to base stations' circumstances. Therefor, how to find the optimal path between the source node and the base station with the best energy consumption efficiency has become a key problem of WSN anycast routing algorithm.

Some scholars have applied genetic algorithm [10], ant colony algorithm [11], and other intelligent swarm algorithm to solve WSN routing problem. This paper attempts to apply the novel KH to solve the problem.

In this paper, we model a WSN as an undirected connected graph $\mathbf{G}(\mathbf{V},\mathbf{E})$ where wireless nodes are represented by **V** and located in a two-dimensional space. Any directed link between nodes is belongs to set **E**. And, in this paper, we also let *A* be the anycast address; $G(\mathbf{A})$ be the set of anycast communication group members (i.e. base station sets) sharing the same anycast address *A*; $A_i$ be the *i*-th member of $G(\mathbf{A})$; *N* be the number of nodes; *M* be the number of $G(\mathbf{A})$ members.

Different from traditional wired networks, in WSN, one of the most vital policy for routing algorithm is to find the anycast path with the least energy consumption and save the cost for routing queries as possible.

Suppose there are *k* paths between the source node *s* and base station $A_i$, the energy consumption of the path with the least energy consumption is

$$E_i = \min(E_{i1}, E_{i2}, \cdots, E_{ik}) \tag{1}$$

Where, $E_{ij}$ is the total nodes' energy consumption for receiving and transmitting monitoring data packets of all nodes which are belong to path $p_{ij}$, and the path $p_{ij} = p_j(s, A_i)$, that is the *j*-th path between the source node *s* and the base station $A_i$. Thus, we have

$$E_{ij} = \sum_{t \in p_j(s,A_i)} (E_s(t) + E_r(t)) \tag{2}$$

Where, $E_s$ is the energy consumption of node *t* for transmitting data packets; $E_r$ is the energy consumption of node *t* for receiving data packets.

$$E_s = E_{amp} \times d^n \times k + E_{elec} \times k \tag{3}$$

$$E_r = E_{elec} \times k \tag{4}$$

Where, *n* represents attenuation index; *d* represents the physical distance between the sender and the receiver. When sending packets, the sender needs to amplify the signal for transmitting, and we represent the amplifier power parameter $E_{amp}$; in addition to the amplifier, the transmission must also be guaranteed to supply power to other circuits, and we let $E_{elec}$ represent this power.

Therefore, the minimum energy consumption *E* of anycast paths (the source node *s* to any base station) is as follows:

$$E = \min(E_1, E_2, \cdots, E_M) \tag{5}$$

Finding anycast routes with QoS constraint in multi-base-station multi-path WSN is a NP-complete problem [12]. That is, we cannot give a finite polynomial solution. So, in this paper, we attempt to use KH to optimize the WSN anycast QoS routing problem.

## 3. Problem Description

We number each node in WSN with 1 to *N* (the sending node is marked number 1), then create a two-dimensional adjacency 0-1 matrix **W** (in **W**, the element of matrix is either 1 or 0) to represent an anycast path of WSN. While the matrix element $(i,j)$ is 1, that means, in the anycast path there exists the link $(i,j)$; otherwise $(i,j)$ is 0, there dose not exists the link $(i,j)$

For instance, there are sensor nodes $n_1$, $n_2$, $n_3$, base station $A_4$, $A_5$ in WSN connected graph **G**. With regards to the anycast path $n_1 \to n_3 \to n_2 \to A_5$, we have matrix **W** as follows

$$\mathbf{W} = \begin{bmatrix} 0,0,1,0,0 \\ 0,0,0,0,1 \\ 0,1,0,0,0 \\ 0,0,0,0,0 \\ 0,0,0,0,0 \end{bmatrix} \tag{6}$$

Starting from the first row of the matrix **W**, we find $x_{13} = 1$, that means the anycast path there exists the link $n_1 \to n_3$; in the 3rd row, $x_{32} = 1$, there exists the link $n_3 \to n_2$; and so on.

In the KH optimization process, we firstly apply graph depth-first search algorithm to generate $N_p$ krill individuals as the initial population. Each krill individual has its own location (i.e. anycast path). As introduced above, the position of the *i*-th krill individuals can be represented by a two-dimensional matrix of $N \times N$. So, it also can be considered as a *N* dimension vector $X_i = (x_{i1}, x_{i2}, \cdots, x_{iN})$.

In krill populations, the movement of each krill individual is affected by its adjacent krill individuals, the krill individual with the current best position, krill populations, and krill repulsive swarm density. So, we have

$$\frac{\mathrm{d}X_i}{\mathrm{d}t} = N_i + F_i + D_i \tag{7}$$

where, $X_i$ is the position vector of the *i*-th krill individual; $N_i$ is the motion induced by other krill individuals; $F_i$ is the foraging motion, and $D_i$ is the physical diffusion of the *i*-th krill individuals.

Next, we discuss krill individual movement below:

### 3.1. Motion induced by other krill individuals

Krill can luminesce, and luminescence comes from the food the krill get. So, the more food the krill gets, the more luminescence it will create, and the more krill it will induced closely. The behavior is called phototaxis swarming motion, and the motion keeps krill swarm in highest density.

In addition to the attractive effect, the swarm density of krill also has some repulsion effects on krill individuals. For a krill individual, this movement can be defined as:

$$V_i^{new} = \alpha_i V^{max} + \omega_n V_i^{old} \tag{8}$$

where, $V^{max}$ is the maximum induced speed, $\omega_n$ is an inertia weight in the range [0, 1], $V_i^{old}$ is the last change of position of the *i*-th krill individual. $\alpha_i$ is the moving direction vector of the *i*-th krill individual, and it is affected by both adjacent krill individuals and the current best krill individual. Thus, we have

$$\alpha_i = \alpha_i^{local} + \alpha_i^{best} \tag{9}$$

where, $\alpha_i^{local}$ is the local effect provided by the neighbors and $\alpha_i^{best}$ is the target direction effect provided by the current best krill individual. According to theoretical arguments, the krill individuals try to maintain a high density and move due to their mutual effects. The direction of motion induced, $\alpha_i$, is estimated from the local swarm density (local effect), a target swarm density (target effect), and a repulsive swarm density (repulsive effect).

In KH algorithm, krill within specified radius are considered as neighboring individuals. The individual radius $d_{s,i}$ of the *i*-th krill individual is defined as follows:

$$d_{s,i} = \frac{1}{5N_c} \sum_{j=1}^{N} \left\| X_i - X_j \right\| \tag{10}$$

where, $d_{s,i}$ is the sensing distance for the *i*-th krill individual; $N_c$ is the total number of the krill individuals; $X_i$ and $X_j$ are the position of the *i*-th and *j*-th krill individual, respectively.

### 3.2. Foraging motion

The foraging motion is affected by two main parameters. The first one is the current food location, and the second one is the the food location of the last iteration. This foraging motion of the *i*-th krill individual can be expressed as follows:

$$F_i = \omega_x F_i^{old} + V_f \beta_i \tag{11}$$

where, $F_i$ is the position change resulted from foraging; $\omega_x$ is the inertia weight of the last foraging motion and it is in the range [0,1]; $V_f$ is the foraging speed. $\beta_i$ is the foraging direction vector of the *i*-th krill individual, and it is expressed as $\beta_i = \beta_i^f + \beta_i^{best}$. Where, $\beta_i^f$ is the food attractive and $\beta_i^{best}$ is the best fitness of the *i*-th krill individual has experienced so far.

### 3.3. Physical diffusion

In addition to swarm movements and foraging behavior, every krill individual also has itself random motion. This motion can be express in terms of a maximum diffusion speed and a random directional vector. It can be defined as follows:

$$D_i = D^{max}\delta \tag{12}$$

where, $D^{max}$ is the maximum diffusion speed of krill individual, and $\delta$ is a random directional vector.

## 3.4. Position updating

After the above 3 processes, during the interval$[t, t + \Delta t]$, the position of the $i$-th krill individual is updated as follow

$$Z_i(t + \Delta t) = Z_i(t) + \frac{dZ_i}{dt}\Delta t \tag{13}$$

## 3.5. Natural selection

The krill individual with poor fitness and less food will be prey. This eliminating process keep each generation of krill in a good search space. In our optimization process, the path with energy consumption exceeds the prescribed threshold will be discarded through this optimization step.

For further improving performance, genetic reproduction mechanisms are incorporated into the algorithm. The introduced adaptive genetic reproduction mechanisms are crossover and mutation. This improvement can maintain the population diversity, improve the ability of accelerating optimization speed and breaking away from the local optimum.

- **Crossover**

The cross operation process is as follows: according to crossover rate α, we randomly select two krill individuals(two anycast paths) from the krill population, and find all the conjunct nodes in the two krill individuals(two anycast paths); choose one conjunct node as the intersection point at random, create a new krill individuals by exchanging the sub-paths behind the intersection of the two anycast paths; If a loop occurs in the new krill individual, we need to do loop eliminating operation.

- **Mutation**

The mutation plays an important role in evolutionary algorithms for keeping the diversity of krill populations and avoiding falling into local optima. The mutation operation process is as follows: according to mutation rate $\beta$, we randomly select a krill individual (anycast path) in the krill population, then select a sub-path randomly such as $i \rightarrow j$ from the krill individual (anycast path), generate a new sub-path $i \rightarrow j$ instead of the original sub-path by depth first search algorithm. If a loop occurs in the new krill individual, we need to do a loop eliminating operation.

It can be seen that, the krill individual movement is influenced by many factors, such as the density of neighbors, the current best krill individual, food location and the krill individual itself location. Moreover, genetic reproduction mechanisms are incorporated into the algorithm. Thus, the proposed algorithm has a powerful global optimization ability and fast convergence speed.

the proposed algorithm can be introduced by the following steps:

**Algorithm 1** *Krill herd optimization*

**Begin**

***Initialization***: *Network diagram* $\boldsymbol{G} = (\boldsymbol{V}, \boldsymbol{E})$; *maximum iteration times* $I^{max}$; *initial population size* $N_p$; *the energy consumption of sending and receiving k bit data is* $E_s$ *and* $E_r$, *respectively*; *the threshold T*

***Step1***: *Create* $N_p$ *path* $\{p_1, p_2, \cdots, p_{N_p}\}$ *as the initial population by graph depth first search algorithm*

***Step2***: *Evaluate the fitness of krill individual, and select the current best krill individual position* $X^{best}$

***Step3***: *Perform the induced movement according to the neighborhood density, food location and current best krill individual position (formula 8)*

***Step4***: *Perform foraging motion and random motion, then calculate the position changes (formula 11, 12)*

***Step5***: *If a krill individual fitness value < threshold T, perform predatory operations*

***Step6*:** *Perform crossover and mutation operations according to probability α and β, respectively*

***Step7*:** *If a new krill individual (new anycast path) has a routing loop, eliminate the routing loop*

***Step8*:** *Calculate the fitness values of newly generated krill individuals; update the krill individual position in the search space; calculate the new fitness value (formula 13)*

***Step9*:** *If* $I < I^{max}$ $I = I + 1$; *goto* ***Step 2***

**End**

## 4. Simulation experiment and analysis

We use ant colony optimization (ACO) [12] as a comparison algorithm to experimentally evaluate our KH algorithm. Randomly generate $N$=150 nodes, and these nodes randomly distributed in the 150m × 150m rectangular area. Base stations randomly arranged and its number $M$=4; the maximum transmission radius of a sensor node is set to be 30m; every node can adjust its transmit power for communication according to its actual demand, but its maximum transmission radius is set to be 30m; every monitoring data size is 2kB, the data packet size is 512B; crossover rate $\alpha$=0.6; mutation rate $\beta$=0.08; create the initial population by graph depth first traversal algorithm; population size $N_p$=20.

For a routing algorithm, the ability to build an efficient route is the first issue to be considered. In this paper, the performance of each algorithm is evaluated by analyzing the time delay from start until monitoring data packets arrival to any base station. The experimental result is shown in Fig. 1:

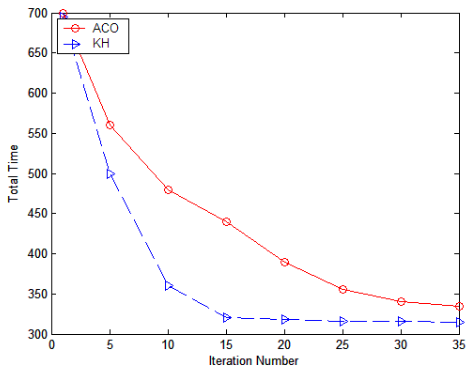


Fig.1 Iterations number and total time delay

As shown in Fig. 1, ACO tends to be stable at about 30 iterations, while KH at about 20 iterations, and the time delay of KH is less. It shows that the performance of KH's searching ability is better, and KH's convergence speed is faster. This is due to, compared with ACO, the designed movement rules in KH are more complex (movement induced by the presence of other krill individuals, foraging activity, and random diffusion) and these movement well express the real movement of krill swarm and krill individuals. Moreover, the crossover and mutation genetic mechanism applied by KH improve the ability of accelerating optimization speed and breaking away from the local optimum [1]. And, KH's fast search convergence ability can greatly reduce routing delay in WSN routing.

In WSN, the most important indicator is energy consumption. Taking the total energy consumption of each node as a measure, and using unlimited flooding and ACO as comparison algorithms, we evaluate the energy consumption performance of KH. The experimental result is shown in Fig. 2.

As in Fig. 2, we can see that, as time elapse, energy consumption of the unlimited flooding has a steep growth; although the energy consumption ACO and KH is growing rapidly at first, they grow slowly in late period. This is because, in early period of this simulation experiment, ACO and KH need to find the optimal path; but in late period, the optimal base station and the optimal anycast path to each node has already been found, and along the found route, ACO and KH only need to transmit monitoring data packets to a base station, maintain nodes' routing information periodically. Moreover, compared to ACO, the energy consumption of ACO are less in any period. Because the optimization ability of KH is stronger than ACO, KH is not easy to fall into the local optimum. Thus, the energy consumption performance of KH is the best of the three.

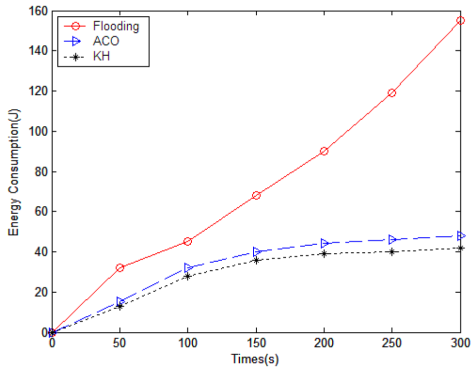


Fig.2 Running time and energy consumption

The monitoring area of WSN is often very large. Therefore, the scalability of routing algorithms is also important for WSN. Adjust network nodes number *N* (150-300), network area and base station number *M* are increased correspondingly according to *N*. The optimization performance of each algorithm under different network sizes are shown in Fig. 3.

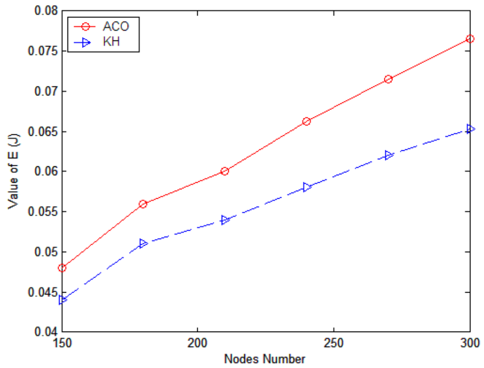


Fig.3 Nodes number and fitness E

As shown in Fig. 3, with WSN network size increases, the fitness values of both ACO and KH thereupon increase. This is mainly due to the corresponding increase in the distance of found anycast paths, and it leads to an increase in energy consumption. However, with the increase of network size, compared with ACO, the optimization result of KH is more satisfactory. The reason is, compared with traditional ACO, KH has a better global optimization ability to solve complex problems [1]; while, traditional ACO is easier to fall into local optimization, thus it affects its optimization performance.

## 5. Conclusion

KH is a swarm intelligence algorithm and it is often applied in engineering problem and so on. In this paper, we try to apply KH to anycast routing problem and propose a WSN anycast routing algorithm. The algorithm uses the bionic features of krill to guide krill to the highest fitness region (anycast path with high energy efficiency) so as to find the optimal anycast path. Since the designed movement rules in KH are more complex and these movement rules well express the real movement of krill swarm and krill individuals. Moreover, crossover and mutation genetic mechanism applied by KH improve the ability a of accelerating optimization speed and breaking away from the local optimum. Experiments data show that, compared to ACO, KH has better performances in terms of search convergence ability, optimization results and scalability.

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