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A target allocation of infrared multi-sensor based on distributed niche genetic algorithm[1]

Tian Min[2,4], Zhou Jie[2,5] ,Lv Xin[3,6]

Abstract. A target allocation of infrared multi-sensor based on distributed niche genetic algorithm is proposed in this paper. This method uses niche selection and distributed genetic algorithm to dynamically adjust targets which are monitored by infrared sensors, so as to global optimize the infrared sensor network. Simulations are conducted for comparison by using distributed niche genetic algorithm, dynamic programming algorithm, and simulated annealing algorithm respectively. Results show that the distribution method proposed in this paper takes advantages of high target detection rate and low energy consumption, etc. It not only improves the search efficiency, but also extends the infrared sensor network's lifetime.

Key words. Infrared sensor, target allocation, distributed genetic algorithms, niche..

1. Introduction

The infrared multi-sensor network utilizing photoelectric effect or pyroelectric technology has been taken more and more attention by researchers with the continuous development of wireless sensor technology [1]. It has a wide range of applications in battlefield information collection, security systems, office automation and target localization speed, etc [2]–[7]. With the improvement of intelligence, size reduction and the decrease of production costs, the number of sensors in infrared multi-sensor network grows exponentially [8]–[10]. There are hundreds to thousands

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[2]College of Information Science and Technology, SHIHEZI University ,Shihezi, Xinjiang 832003, China

[3]The Key Laboratory of Oasis Ecological Agriculture of Xinjiang Production and Construction Group, SHIHEZI University , Shihezi, Xinjiang 832003, China

[4]E-mail: 94662061@qq.com

[5]E-mail: 125101467@qq.com

[6]E-mail: lxshz@126.com

infrared sensors working in the network. In these studies and applications, how to configure the sensor network resources reasonably, to rationally allocate sensors to the multiple detected targets, to save energy and extend the network's lifetime at the same time to ensure the completion of exploration missions, that is a key issue.

Aim at target assignment of multi-sensor network, a target allocation scheme based on topological graph approach is proposed in [11], which prioritize the detected targets according to importance, and find out the better allocation scheme according to distribution efficiency model. However, it does not consider node energy consumption, so it is easy to make the sensors on the better position in a working state for a long time, and then appears the case of node energy depleting, shortened the lifetime of the infrared multi-sensor networks. Paper [12] improves distribution efficiency model on the base of [11], and proposes a new target allocation scheme based on simulated annealing algorithm. It considers both of targets' importance and the nodes' residual energy. So it can effectively reduce the energy consumption of multi-sensor networks at the time of completing target detection. But multi-objective allocation is a NP-hard problem. Its complexities growths exponentially with the number of sensors and targets. The allocation scheme in [12] is only applicable to small-scale networks, which have small amount of infrared sensors, but it is difficult to use in large-scale network because of high complexity. Because the algorithm in [12] has some shortcomings, literature [13] proposes a new one based on particle swarm optimization, which gets a better resource allocation scheme through iteration and then reduce the complexity. However, this program doesn't adjust parameters adaptively in the process of iteration, so convergence is slow, and there is evolutionary stagnation and premature convergence and other shortcomings.

On the basis of above studies, a target assignment of infrared multi-sensor based on distributed niche genetic algorithm is proposed in this paper, and the fitness function is designed at the same time, which combines with distribution efficiency model. It adjusts targets detected by infrared sensors dynamically through the use of heuristic distributed genetic algorithm, and overall optimizes the multi-sensor networks. Through dynamically changing algorithm parameters as well as taking niche options, this program avoids premature convergence and has a faster convergence rate. In the infrared multi-sensor network environment, simulations are conducted for comparison by using distributed niche genetic algorithm, dynamic programming algorithm, and simulated annealing algorithm respectively. Results show that, the distribution program proposed in this paper take advantages of high target detection rate, low algorithm complexity and energy consumption, etc, and with the number of sensors growing in the network, the advantages increase obviously-not only improves the search efficiency, but also extends the infrared sensor network's life.

2. The target allocation model of infrared multi-sensor

Infrared sensors can be divided into photon detectors and thermal detectors in accordance with detection mechanism. Photon detector is radiation detectors by using photoelectric effect. And thermal detectors detect targets' infrared radiation energy through special materials' pyroelectric effect, and then sense targets. Infrared sensors have advantages of fast response, wide frequency band, etc., and take a wide range of usage scenarios in both military and civilian fields. This paper studies a class of infrared multi-sensor network whose nodes distribute randomly. The typical application is shown in Fig. 1.

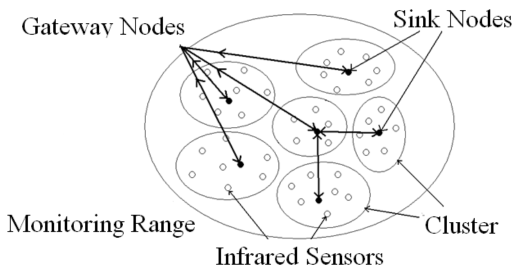

Fig. 1. Architecture of infrared multi-sensor network

As shown, large-scale infrared multi-sensor network is usually clustering structure, and infrared sensor nodes in the monitoring range is divided into multiple clusters, each cluster has a cluster head node which has strong communications and storage capacity. In the uplink transmission phase, the infrared sensor nodes which randomly distributed in the monitoring range sense targets through photoelectric effect or pyroelectric effect, and then converge the results to the cluster head nodes. Cluster head nodes collect the relevant data from sensors in the cluster, and transfer data to the gateway nodes through direct or multi-hop. Gateway nodes gather the data from the sink nodes, and transmit them to the user for further analysis and processing. In the downlink phase, the user downstream releases monitoring tasks through the gateway nodes, and uniformly allocates monitoring objectives and resources; gateway nodes allocate the monitoring tasks to infrared sensor nodes through sink nodes to perform monitoring tasks' allocation.

In order to improve the capabilities of monitoring targets and extend the sensor networks' lifetime, large-scale infrared multi-sensor networks must develop an efficient target allocation to allocate remaining energy and infrared sensing nodes and other resources reasonably. But with the increasing size of the sensor network, the complexity of traditional centralized target assignment algorithm grows exponentially with the number of nodes increasing, so it is difficult to use in infrared multi-sensor networks which has distributed organization and limited energy. In this paper, a new program using niche genetic algorithm takes distributed computing for target assignment of infrared multi-sensor networks, adaptively adjusts parameters in the process of allocation, and dynamically adjusts infrared sensors' detected targets, so as to get real-time solution of infrared multi-sensor target allocation.

3. The target assignment of infrared multi-sensor based on distributed niche genetic algorithm

In the infrared multi-sensor networks, traditional part distributed resource allocation's nodes are short of communication and coordination, so there may be no sensors to detect the nodes on the edge of cluster, but many sensors to detect some ones on better location, resulting in waste of resources within the network and low detection rate. Meanwhile, some sensors which are closer to the nodes are prone to run out of energy as high probability of being selected. The allocation proposed in this paper establishes a mechanism for communication between clusters, which considers target detection rate and nodes' residual energy while ensuring real-time. The main steps are: assessment of targets' priority, individual encoding and initial population generation, design fitness function, selection, crossover and mutation, niche-based cluster interaction, adaptive adjustment of parameters, etc.

3.1. Assessment of targets' priority

Within the scope of monitoring, different nodes take different degree of importance, so the algorithm must priority to allocate resources for important targets to ensure monitoring tasks. Meanwhile, because sensors' working scope and accuracy are limited, so locations of sensors and nodes must be considered at the time of setting target priority, that is improving priority level of nodes closer to the sensor, and setting zero to nodes which are outside of the scope of the sensors' monitoring. At the same time, sensors' residual energy should be considered to avoid some ones' energy running out early, which can lead to unable complete the monitoring tasks and reduce network's lifetime. According to the above principles, in the infrared multi-sensor network which has N targets and L sensors, the priority level of targets can be normalized as (1) as shown in matrix form:

$$\boldsymbol{D} = \begin{bmatrix} d_{1,1} & d_{1,2} & \dots & d_{1,L-1} & d_{1,L} \\ d_{2,1} & d_{2,2} & \dots & d_{2,L-1} & d_{2,L} \\ \dots & & d_{n,l} & & \dots \\ d_{N-1,1} & d_{N-1,2} & \dots & d_{N-1,L-1} & d_{N-1,L} \\ d_{N,1} & d_{N,2} & \dots & d_{N,L-1} & d_{N,L} \end{bmatrix} (d_{n,l} \in [0,1])\,. \qquad (1)$$

In the matrix $\boldsymbol{D}$, $d_{n,l}$ represents normalized priority of nth target to lth sensor. When a target takes high degree importance, more residual energy, and is closer to sensor, $d_{n,l}$ is large; when a target is outside of the scope of the sensors' monitoring $d_{n,l}$ is zero. In this way, infrared multi-sensor network can prior to select sensor with better location to more closely monitor the target which has high-priority, so as to get a more comprehensive target information in the range of monitoring.

3.2. Encoding and generation of initial population

In the infrared multi-sensor networks, the sensor can only monitor and track a limited number targets as processing power, perceived accuracy, direction and other factors; meanwhile, in some specific applications such as three-point positioning and target speed and so on, each target needs a plurality of sensors to complete the monitoring task, so it is need to plan and allocate targets according to specific tasks. In the infrared multi-sensor network which has N targets and L sensors, when the maximum number of targets each sensor can track is M, the sensor's target allocation scheme and constraints can be expressed in matrix form as (2) and (3) shown

$$E = \begin{bmatrix} e_{1,1} & e_{1,2} & \cdots & e_{1,L-1} & e_{1,L} \\ e_{2,1} & e_{2,2} & \cdots & e_{2,L-1} & e_{2,L} \\ \cdots & & e_{n,l} & & \cdots \\ e_{N-1,1} & e_{N-1,2} & \cdots & e_{N-1,L-1} & e_{N-1,L} \\ e_{N,1} & e_{N,2} & \cdots & e_{N,L-1} & e_{N,L} \end{bmatrix} (e_{n,l} \in \{0,1\}) \,, \qquad (2)$$

$$\sum_{l=1}^{L} e_{n,l} \leq M \,, \quad (n \in \{1, 2, ..., N\}) \,. \qquad (3)$$

In (2), $e_{l,n}$ represents that l target monitored by n sensor. If matrix $\boldsymbol{D}$ element is "1", it represents that l target monitored by n sensor; if matrix $\boldsymbol{D}$ element is "0", it represents that l target not monitored by n sensor. (3) limits the maximum number of targets that each sensor can detect.

3.3. Encoding and generation of initial population

In the infrared multi-sensor networks' target allocation scheme, the allocation algorithm must ensure that the network covers the entire scope of monitoring, and complete the monitoring task of key targets, so it is necessary to develop a evaluation criteria for this allocation scheme considering these two factors. Fitness function ofniche-based distributed genetic algorithm can be expressed as (4) as shown

$$\mathrm{Fit}(E) = \sum_{n=1}^{N} \sum_{l=1}^{L} e_{n,l}\, d_{n,l} \,. \qquad (4)$$

In order to complete the monitoring task, when the target requires at least $\boldsymbol{D}$ sensors for monitoring,the constraint can be expressed as (5) as shown

$$\sum_{n=1}^{N} e_{n,l} \geq \boldsymbol{D} \,, \quad (l = l_0) \,. \qquad (5)$$

3.4. Selection, crossover and mutation

In order to ensure a high fitness program has a higher probability to be selected, the probability of selection is proportional to individuals' fitness. Assume that there are T individuals in the population, the selected probability of i-th program is shown as (8) as follows

$$P_{\text{SELECT}}(E_i) = \frac{Fit(E_i)}{\sum\limits_{t=1}^{T} Fit(E_t)} . \tag{6}$$

In (8), the selected probability of is proportional to program's fitness. In order to maintain crossover's uniformity and randomness, crossover takes two-point to reduce agents, and cross-exchange three parts of the individual, and the intersection can't occur in the same gene location, shown in Fig. 2.

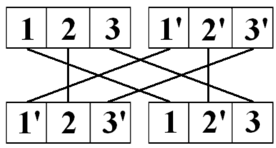

Fig. 2. Process of two-point cross

To speed up the convergence rate, and bring in new genes in the process of computing, the algorithm mutates individual's genes with a certain probability, i.e. individual's non-zero elements turn zero with a certain probability, and zero turns non-zero.

3.5. Niche-based interaction between the clusters

Niche refers to a self-organization feature in specific environment, due to the traditional geneticalgorithm solution is diversifiedin the primary stage, so it is easy to stagnate in later evolution. In order to avoid local optimal solution, niche mechanism divides individuals of the population into several sub-populations, and takes exchange and sharing mechanism to do selection, maintaining population's diversity.

Clusters of traditional distributed resource allocation scheme are lack of communication, so there may be no sensors to detect the nodes on the edge of cluster, but many sensors to detect some ones on better location, reducing the target detection rate and the use efficiency of infrared sensors. Distributed niche genetic algorithm uses niche technology to divide the population into multiple sub-populations, and establish mutual exchange between sub-populations. The sub-populations exchange target distribution schemes regularly, and allocate fringe targets at the junction of multi clusters to specified cluster to be monitored, avoiding the situation of fringe targets' unclear ownership.

3.6. Adaptive adjust the algorithm parameters

In the traditional GA, the mutation probability and crossover probability could greatly affect algorithm performance. If mutation and crossover probability is too small, the convergence rate would be slowed down; and if the crossover and mutation probability is too large,the algorithm would become a purely random search process.

As the value of optimal fitness is constantly changing in the algorithm's running process, so it needs to dynamically and adaptively adjust mutation probability and crossover probability to ensure the algorithm's convergence speed and get rid of local optimum.

The mutation probability and crossover probability of distributed niche genetic algorithm adaptively adjust according to equations

$$P_{\text{cross}} = \begin{cases} k_1 \frac{f_{\max} - f_{\text{high}}}{f_{\max} - \overline{f}}\,, & f_{\text{high}} \geq \overline{f} \\ k_2\,, & f_{\text{high}} < \overline{f} \end{cases}, \tag{7}$$

$$P_{\text{mutation}} = \begin{cases} k_3 \frac{f_{\max} - f}{f_{\max} - \overline{f}}\,, & f < \overline{f} \\ k_4\,, & f \geq \overline{f} \end{cases}. \tag{8}$$

Thus, when the fitness value convergence results local optimum, increasing the mutation and crossover probability could make algorithm get rid of evolutionary stagnation; and when the fitness values have greater difference, reducing the crossover and mutation probability could obsolete some lower fitness individuals to ensure the evolution speed.

4. Simulation and results

In the simulation, the monitoring range is 500 m × 500 m. The targets and infrared sensors randomly distribute within the scope of monitoring. The number of infrared sensors is 400. Monitoring radius is 30 meters. Cluster radius is 100 meters. Each target requires at least three sensors to be monitored simultaneously, and each sensor simultaneously monitor up to four targets. In the niche distributed genetic algorithm, the number of individuals in the population is 400, and $k_1 = 0.95$, $k_2 = 0.5$, $k_3 = 0.12$, $k_4 = 0.005$ and the maximum number of iterations is 100.

Figure 3 shows that in the case of different targets, how the number of detected targets is changing with iterations' number. It can be seen from the simulation results, as the distribution of multi-sensor targets is an NP-hard problem, dynamic programming algorithm cannot come to the optimal solution, whose detected targets' number increases slowly and is unstable with iterations' number. Simulated annealing algorithm performs better than dynamic programming algorithm, rising quickly in the initial running phase. But because it does not adaptively adjust parameters in the running, so it is easy to fall into the evolution stagnation, resulting in low detected number. Distributed niche genetic algorithm takes distributed parallel computing for the target allocation by setting up multiple sub-populations, improving operational efficiency; and dynamically adjusts the algorithm parameters to speed up the algorithm convergence rate, and ultimately gets a higher detected number.

In the case of different targets, Fig. 4 shows the changing of infrared sensors' surviving number with rounds. In the experiment, network's lifetime is defined as

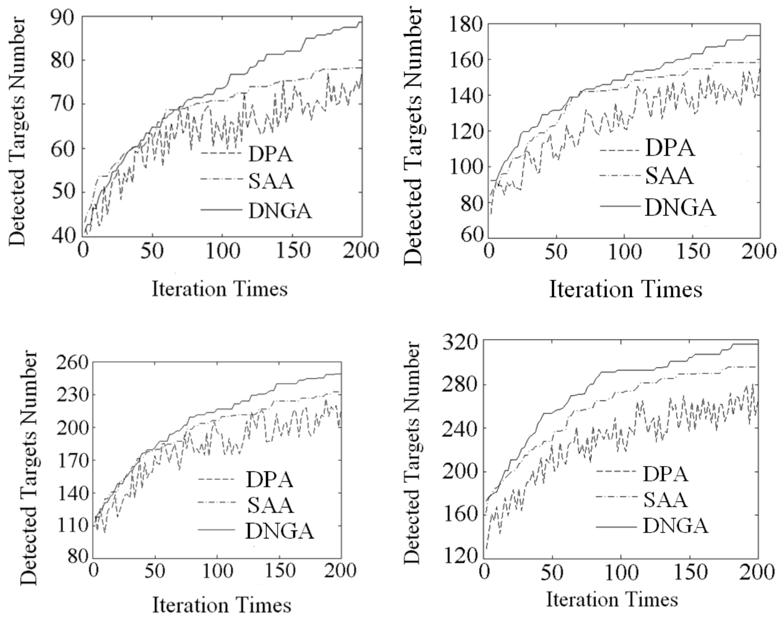

Fig. 3. Changing of detected number with iterations: top left–100 targets, top right–200 targets, bottom left–300 targets, bottom right–400 targets

the death time of the first node. It can be seen from the figure that, dynamic programming algorithm-based allocation scheme doesn't consider node's residual energy during it allocate targets, leading the death round of the first node is smaller and network's lifetime is shorter. Simulated annealing algorithm-based allocation scheme takes dynamic search method, so the network's lifetime is longer than the former one. The distributed niche genetic algorithm-based allocation scheme introduced in this paper considers both of favorable degree of infrared sensors' location and residual energy and other factors, and adaptively adjusts parameters in the running process, so the network's lifetime is extended by 23 % and 16 % respectively compared with dynamic programming algorithm and simulated annealing algorithm in the case of 200 targets, and in the case of 400 goals is extended by 37 % and 25 %.

5. Summary

A target allocation of infrared multi-sensor based on distributed niche genetic algorithm is proposed in this paper. It considers both of favorable degree of infrared sensors' location and residual energy and other factors, and dynamically adjusts infrared sensors' monitoring targets. Compared with traditional solutions based on dynamic programming algorithms and simulated annealing algorithm, this program can improve the detected targets number, and effectively extend the network's lifetime, which has positive significance for further promote multi-sensor monitoring in

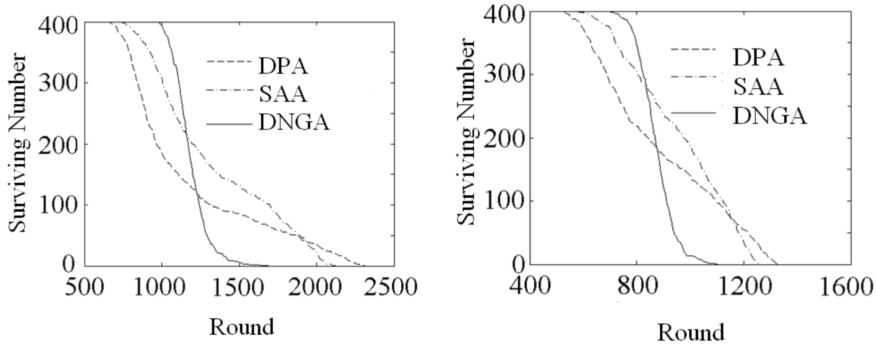

Fig. 4. Changing of infrared sensors' surviving number with rounds: left–200 targets, right–400 targets

the environment of infrared multi-sensors.

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