An Immune Chaotic Niche Genetic Algorithm for Monitoring Distribution Problem in Self-Organizing Wireless Sensor Network

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Abstract. Due to the sensors are restricted in sensing capabilities, monitoring distribution has become a challenging problem in self-organizing wireless sensor network (SOWSN). Micro nodes are self-organized tiny devices with limited sensing capabilities. Careful monitoring distribution scheme can be a suitable optimizing means for achieving the required high target detection rate goals, comprising sensing capacity restrictions. However, the monitoring distribution problem is a typical NP-hard combinatorial stochastic optimization problem. In this study, an immune chaotic niche genetic algorithm (ICNGA) to enhance the target detection rate is explored. Advanced operators such as immune operator and chaotic operator are also incorporated into the ICNGA to increase the explore capacity. The represented immune selection and chaotic generation depending on ICNGA with global search capability can simultaneously optimize multiple variables. Simulation results identify that the proposed algorithm can get a higher target detection rate over SFLA and SA. Besides that, the convergence speed of the presented ICNGA is much higher than that of SFLA and SA. So the proposed method significantly enhanced the efficiency.

Keywords. Self-organizing wireless sensor network, Genetic algorithm, Monitoring distribution

1. Introduction

The technology growth in the field of hardware manufacturing and communication has significantly advanced the applications of low-power and intelligent self-organizing wireless sensor networks (SOWSN). In SOWSN, each sensor made up of five components, including the transmitter component, the information collecting component, the computing component, the data storage component and the power component [1]-[2]. SOWSN have been widely applied in industrial process control, military purposes, tracking, environmental, person locator services, advanced health care delivery, etc [3]-[4].

Target detection is one of the key technologies for applications of SOWSN [5]. Because sensors are restricted in sensing capabilities, it is very important and necessary to exploit new target detection algorithms [6]. In SOWSN, the optimum target detection requires an exhaustive explore over all combinations of the allowed combinations. The computational complexity of an exhaustive explore over all the combinations is too high for large scale SOWSN. Since the monitoring distribution problem is NP-hard, numerous stochastics have been represented to get near ideal solutions in reasonable time [7].
The utilization of Artificial Fish Swarm Algorithm (AFSA) in monitoring distribution problem has been investigated in [8]. AFSA can attain higher target detection rate than Genetic Algorithm (GA). The AFSA techniques have a problem of algorithm convergence and complexity. In [9], authors presented a Shuffled Frog Leaping Algorithm (SFLA) to enhance the target detection rate and also built a system model for the stochastic optimization. This study dedicated to stochastic optimization the network efficiency with network restraints. But it also suffers from an excessive computational time requirement. In [10] a Simulated Annealing (SA) strategy is proposed. The SA method has represented good experiment results in terms of network efficiency and target detection rate. However, The convergence speed of the algorithm is slow.

GA have been investigated in 1979 by H. Holland, from Michigan university. In GA, the simulations are not guaranteed to be the optimum solutions; however, they can be excellent or satisfactory. Since Holland’s paper, evolutionary algorithms have been utilized to several optimization problems for finding their pareto-optimal solutions.

Based on the concept and principles of immune theory, immune operator was introduced in the early 1980s. When compared with other techniques, the immune theory is computationally inexpensive in terms of memory and speed. Thus, in this paper, we propose a novel immune chaotic niche genetic algorithm (ICNGA) to enhance the target detection rate. We first give a formulation of the system model to maximize the target detection rate. By introducing the immune operator and niche operator mechanism into genetic algorithm, the objective function for target detection is designed to optimize the target detection rate. The resulting ICNGA strategy mixes the merits of immune selection and chaotic generation, while controlling the contention for the niche operator. ICNGA has fast exploit speed and low storage requirements. A chaotic generation method is adopted to gain better results and at the same time, avoid local optima.

In the experimental, the effect of ICNGA is compared to those given by heuristic strategies of SFLA and SA for the SOWSN with different sensing radius. Simulation simulations reveal that the proposed algorithm can get a higher target detection rate over SFLA and SA.

2. System Model
In this section we build the system model to demonstrate the monitoring distribution problem with respect to the constraints of monitoring abilities and detecting range. Consider a SOWSN system with $Q$ sensors and $R$ targets in the monitoring area. The distribution relationship can be mathematically formulated by the matrix $C$ in (1):

$$
C = \begin{bmatrix}
    c_{1,1} & c_{1,2} & \ldots & c_{1,R-1} & c_{1,R} \\
    c_{2,1} & c_{2,2} & \ldots & c_{2,R-1} & c_{2,R} \\
    \vdots & \vdots & \ddots & \vdots & \vdots \\
    c_{Q,1} & c_{Q,2} & \ldots & c_{Q,R-1} & c_{Q,R} \\
\end{bmatrix}
$$

(1)

In (1), $Q$ is the number of targets and $R$ is the number of sensors. $c_{q,r} = 1$ means the $q_{th}$ target is within coverage of the $r_{th}$ node, $c_{q,r} = 0$ otherwise.

The monitoring distribution matrix $D$ can be mathematically formulated as (2).

$$
D = \begin{bmatrix}
    d_{1,1} & d_{1,2} & \ldots & d_{1,R-1} & d_{1,R} \\
    d_{2,1} & d_{2,2} & \ldots & d_{2,R-1} & d_{2,R} \\
    \vdots & \vdots & \ddots & \vdots & \vdots \\
    d_{Q,1} & d_{Q,2} & \ldots & d_{Q,R-1} & d_{Q,R} \\
\end{bmatrix}
$$

(2)
In (2), \(d_{q,r} = 1\) means the \(q_{th}\) target is monitored by the \(r_{th}\) node, \(d_{q,r} = 0\) otherwise.

The first constraint (3) states that the successfully monitored target \(e_q = 1\) when the target is monitored by at least \(N\) sensors. \(e_q = 0\) otherwise.

\[
e_q = \begin{cases} 
1 & \sum_{r=1}^{R} d_{q,r} \geq N \\
0 & \sum_{r=1}^{R} d_{q,r} < N 
\end{cases}
\] (3)

The second constraint models the sensing ability. Each sensor node can only monitor \(M\) targets at most, which can be expressed by formula (4).

\[
\sum_{q=1}^{Q} d_{q,r} \leq M (r = 1, \cdots, R) 
\] (4)

The third constraint is the target must be within the monitoring range of the sensor, which can be expressed by formula (5).

\[
d_{q,r} \leq c_{q,r} 
\] (5)

The objective of the monitoring distribution is to search for an optimal distribution that yields higher target detection rate, which can be expressed by formula (6).

\[
\max f(d_{1,1}, d_{1,2}, \cdots, d_{Q,R}) = \sum_{q=1}^{Q} e_q 
\] (6)

3. ICNGA for monitoring distribution problem in SOWSN

In this study, our ICNGA follows the framework of the conventional heuristic methodology, and a new immune way is utilized to handle the monitoring distribution problem. Furthermore, chaotic and niche operators that modify the selection and mutation to diversify the group have been proposed. On the one hand, the new niche operator is to maintain the diversity of a group, which means that the operator has the capacity to avoid the concentration of individuals into a narrow space around local optima. On the other hand, the chaotic operator objectives at increasing the genetic exploit based on a heuristic operator working parallel to the original algorithm, without the further iteration. By this means, ICNGA can get a balance between the convergent speed and the global optimal aim. In addition, the algorithm can provide a good balance between exploitation and exploration.

ICNGA produces a better approximation to the best solution by evolving this group of individuals over successive iterations. It iteratively searches for an ideal individual by based on heuristic operators. The operator of the ICNGA can be briefly discussed as follows.

A) Initialize the system model to imply an initial group over a group of individuals.
B) Select the ideal individuals via the roulette wheel.
C) Using a crossover and mutation operators, develop children, and add them to group.
D) evaluate all objective values for all individuals.
E) update the group by using novel individuals.

3.1. Genetic Representation

In this section, the suggested individual representation will be mentioned. The efficiency of an ICNGA depends on the encoding scheme employed. In ICNGA, every solution is known as an individual. The solution in the target detection region can then be encoded into an individual. In this paper, the individuals are of binary type containing zeros and ones. The operators in the ICNGA are designed depending on the binary encoding technique so that the novel individuals always comply via the scheme. In the search process, ICNGA works on the finite-length strings.
3.2. Chaotic Group Initialization

ICNGA is an overall search technique, which keeps a pool of potential solutions, known as group. In an ICNGA, the candidate solutions within the group are formed such that the combination of the alleles that states the individuals. The group size ought to be selected carefully. ICNGA maintains a group of individuals that evolves over successive iterations. In finding alleles that suit constraints, ICNGA applies a chaotic generator. Starting with an initial pool of group constructed randomly, the individuals in the current group have a certain possibility to reproduce their children. This operator will be utilized repeatedly many times unless the individual becomes feasible.

3.3. Niche Selection

In ICNGA, there is a selection process to remove the poor solutions. There are several niche groups for selection. The selection in ICNGA is the procedure to determine which individuals are selected for the following iteration in terms of their objective value. Larger objective values mean that the individuals have a higher possibility of surviving to the next iteration. The nature of an ICNGA is that good solutions will be more likely to be selected; in the same vein, good recombination of solutions by crossover will be more likely to be picked. There are various parent selection strategies, e.g., proportionate selection and tournament selection. In this paper, two parents are chosen depending on the roulette wheel rule. Fitter individuals have a higher chance to be chosen for reproduction depending on the roulette wheel proportionate selection. In this way, an individual with better possibility of surviving may be selected more than once. It begins its operators as selecting two individuals from a group according to roulette wheel selection after initialization. The algorithm then replaces the inferior solutions with the newly developed superior solutions to gain a better current group. In this way, two parent individuals can swap their alleles to produce two children having features of both parents. The operator selection procedure is random in the ICNGA.

3.4. Crossover

The crossover operator is employed over the individuals that were chosen. Create two children involving two parent individuals. One-point and two-point operators are frequently for modelling. Here, we apply a modified single-point Boolean crossover for crossover process. Crossover is a heuristic operator that exchanges the elements between two different parents to generate novel offspring. A powerful crossover rate at each iteration are important for broadening the search and discovering good solutions. The group is recombined according to a probability of 0.9. The crossover operator can significantly accelerate the explore procedure.

3.5. Immune Mutation

The ICNGA utilize an immune mutation operator to the produced novel solutions. Each individual generated copies proportional to its objective value. The mutation operator inverts one gene of the individual. Mutation operator is an inversion of some bits from whole bit string at very low rate. The operator is used with a low possibility by selecting random individuals and randomly switching one of their alleles. Sometimes a mutation on an unfit individual may develop a very meet individual. Typically, the mutation rate is generally less than 0.1. In ICNGA, mutation is introduced uniformly through the chance of 0.08. In addition, mutation operator leads the explore to attain out of a local optimum.

3.6. Evaluation

ICNGA must decode an individual into a monitoring distribution and evaluate the monitoring distribution for objective value. In ICNGA, while individuals are explicitly represented, monitoring distributions are fixed with the exploit process. The purpose of this paper is to maximize the target detection rate. The new iteration therefore generally possesses higher overall objective value. In ICNGA, a function for evaluating the objective value of an individual is necessary. The objective function measures the quality of a particular solution. For an individual in the ICNGA, its objective
value is calculated depending on the objective function. In this paper, the objective function is placed according to (7). The objective function, quantified by the target detection rate, represents the individuals' capability to survive. In this case, the largest objective value represents the optimal solution. In ICNGA, an elitist selection method ensures that those good individuals are carried on to the next iteration. The best individual in this subset is then chosen as the elite individual.

The ICNGA cycle is then repeated until a desired termination criterion is satisfied. After a particular number of iterations, the algorithm is stopped.

4. Simulation and Results

In this section, the suggested ICNGA is tested with different sensing radius for monitoring distribution in SOWSN. In order to show the ICNGA algorithm capabilities, we also present the simulation results with SFLA and SA. All cases are run by a computer with a Pentium 2.4 GHz CPU. The simulation area is 300m². The objective function applied in the experiments is presented in formula (6). The group size of all three algorithms is defined to be 100.

Fig. 1 and fig. 2 denote the of the target detection rate acquired by ICNGA, SFLA and SA for the monitoring distribution problem with 200 number of sensors and 200 targets. Each sensor can monitor up to 4 targets, and each target needs at least 3 sensors. For every approach, we select solution that yield the best results.

From the figures we can see that the ICNGA performs better in terms of target detection rate. In this case, ICNGA had the optimal simulations 82.76 and 88.31 after 100 iterations. The optimal target detection rates of the SFLA are 72.69 and 76.51 while the target detection rates acquired by the SA are 64.24 and 68.36, respectively. In the beginning, target detection rates of all the stochastics increased. ICNGA perform significantly better than SFLA and SA in terms of convergence rate and target detection rate. After 50 iterations, SFLA and SA maintained a nearly constant result due to its premature convergence. More specifically, ICNGA converges faster than that of SFLA and SA. This is mainly due to the chaotic operator and the niche operator used. Consequently, our ICNGA method is effective and suitable for target detection in SOWSN. The experimental simulations present that the represented ICNGA is qualified to obtain better performance than SFLA and SA schemes, especially for a SOWSN that has large number of sensors and targets.

5. Conclusion

In this study, a new immune chaotic niche genetic algorithm (ICNGA) is proposed to enhance the target detection rate in SOWSN. We first determine a mathematical model for the monitoring distribution problem. By introducing ICNGA into the monitoring distribution, an objective function for evaluating the target detection rate is designed for SOWSN. Simulation experiments demonstrate that the proposed ICNGA method achieves a higher target detection rate than SFLA and SA.
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