Artificial Intelligence Based Sensor Network Congestion Fuzzy Control Algorithm

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Abstract. The topology control of sensor sensor network was studied based on fuzzy control algorithm. Aiming at the dynamic changes of the topology of large-scale and heterogeneous artificial intelligence sensor networks and the incomplete information between nodes, a smart network-based congestion control algorithm for sensor networks was proposed and the performance of fuzzy control algorithms was analyzed. Based on this, a fuzzy control algorithm was designed. The algorithm fully considered the residual energy of nodes and the distribution of nodes in the network. Therefore, the reasonable election of the cluster head can be realized through the game between nodes, which effectively avoided energy holes, made the network energy consumption more uniform, prolonged the network life cycle, and optimized the network topology.

Keywords: Artificial Intelligence, Sensor, Fuzzy Control Algorithm, Bayesian Game

1. Introduction

Based on the power of artificial intelligence sensor nodes and the completion of clustering algorithm, the topology control and optimization of artificial intelligence sensor networks are studied from the perspective of clustering. Aiming at the characteristics of multiple node types and dynamic changes of topological structure in complex dynamic, large-scale and heterogeneous artificial intelligence sensor networks, the game theory is introduced into the clustering control of artificial intelligence sensor networks. Based on the research of Bayesian game clustering model, a fuzzy control algorithm based on Bayesian game for artificial intelligence sensor network is proposed. The algorithm abstracts the cluster head election of artificial intelligence sensor network into a multiple player game process, and realizes the reasonable election of cluster heads in the network through incomplete information static game [1]. Experiments show that because the algorithm design takes into account factors such as the residual energy of the node and the geographical position of the node. Therefore, through the Bayesian game between nodes, nodes with higher energy in the network and less transmission loss between nodes in the cluster can be selected as cluster heads to form a reasonable cluster distribution and optimize the network topology.

1.1. Bayesian game artificial intelligence sensor
Aiming at the practical application environment of artificial intelligence sensor network with heterogeneous network topology and various sensor nodes, a Bayesian game-based artificial intelligence sensor network clustering algorithm is proposed. Through the game between nodes in the case of incomplete information, the cluster heads are reasonably selected to optimize the network topology, realize effective network management, and extend the network life cycle. Different types of sensor nodes are deployed in the hierarchical heterogeneous artificial intelligence sensor network application environment, and each node has different residual energy and different preferences. All the nodes in the network are in a static state. For the convenience of analysis, according to the difference of the remaining energy of the nodes in the network, it is assumed that there are two different types of nodes in the network, namely high energy nodes and low energy nodes. Once deployed, the node enters the ad hoc control mode with no central control node. It is not necessary to set the number of cluster heads and the probability of selection in advance. The nodes in the network forward the data in a broadcast manner, and the neighbor nodes decide whether to apply for the cluster head and whether to forward the data according to information such as their own energy, location and preference. The election of the cluster head is carried out through mutual game between neighbor nodes [2]. Since the election of the cluster head is completed by the game between the sensor node and its neighboring nodes, the number of neighbor nodes of the sensor node determines the number of participants in the game model. To this end, the following theorem is given: For N randomly deployed sensor nodes, assuming that the communication area of the node is A, then within the communication range of node i, the probability that node i has k neighbor nodes approximates the Poisson distribution.

According to the theorem, first consider the case of a one-dimensional coordinate axis, assuming that N nodes are evenly distributed in the range of \([0, x_m]\), and node \(i\) is located at position \(x_i\), therefore, the transmission range of node \(i\) is \([x_i - r_i, x_i + r_i]\). For any node, the probability that a node is randomly located at \([x_i - r_i, x_i + r_i]\) is \(2r_i / x_m\). Therefore, the probability that k nodes are randomly distributed in the range of \([x_i - r_i, x_i + r_i]\) obeys the binomial distribution, and formula (2) is obtained according to formula (1).

\[
p(d = k) = \frac{n!}{k!(n-k)!} \left( \frac{2r_i}{x_m} \right)^k \left( 1 - \frac{2r_i}{x_m} \right)^{n-k}
\]

\[
\lim_{n \to \infty} p(d = k) = \left( \frac{2nr_i}{x_m} \right)^k
\]

(1)

(2)

Because the node density \(\lambda = n / x_m\), and the \(2r_i\) in the formulas (1) and (2) represents the coverage of the node \(i\), the coverage of node \(i\) is \(\pi r_i^2\), the node density is \(\lambda = n / x_m\), and is substituted into formula (2) to obtain the communication range of node \(i\). The probability of having \(k\) neighbor nodes is, as in formula (3):

\[
p(d = k) \left( \frac{\pi r_i^2 \lambda}{k!} \right)^k \cdot e^{-\pi r_i^2 \lambda}
\]

(3)
According to formula (3), the communication range of node $i$ has a probability of having $k$ neighbor nodes as a Poisson distribution.

In the practical application of artificial intelligence sensor networks, the topology is often heterogeneous. In order to perform different tasks, different types of nodes often exist in the network. Due to the dynamic changes of the network topology, the nodes cannot fully grasp the related information of each other, so the full information game cannot be used to solve the Nash equilibrium. Static games for this incomplete information can turn the problem into a complete but imperfect information game by using the Haysani conversion. By introducing a virtual participant naturally, the first action by nature determines the type of participant $i$ [3]. Thus for node $J$, the type of node $i$ becomes completely but imperfect information from incomplete information, as shown in Figure 1:

![Figure 1. Game tree](image)

According to the game tree in Figure 1, the Bayesian Nash equilibrium under incomplete information is analyzed [4]. In the practical application of wireless sensor networks, the topology is often heterogeneous. In order to perform different tasks, different types of nodes often exist in the network. Due to the dynamic changes of the network topology, the nodes cannot fully grasp the related information of each other, so the full information game cannot be used to solve the Nash equilibrium. Static games for this incomplete information can turn the problem into a complete but imperfect information game by using the Haysani conversion. By introducing a virtual participant naturally, the first action by nature determines the type of participant $i$. Thus, for node $J$, the type of node $i$ becomes completely but imperfect information from incomplete information, so that the game tree can be constructed and the Bayesian Nash equilibrium under incomplete information can be analyzed [5].

According to the cluster head direction of the game tree in Fig. 1, the cluster head selection for the static Bayesian game, node $i$ and node $J$ are rational in the game, they will choose the best action to maximize their own income. Therefore, it is concluded that there are two possible choices for node $i$, namely (ND if Rich, ND if Poor) and (D if Rich, ND IF Poor) [6].

1.2. Fuzzy control algorithm

The fuzzy control system is a computer numerical control technology that combines theories of fuzzy sets, fuzzy linguistic variables and fuzzy logic inference. Fuzzy control is the application of fuzzy mathematics in control systems and is a kind of nonlinear intelligent control. At present, fuzzy control, as one of the most practical control methods in the field of intelligence, has solved many problems in the fields of industrial control, power systems, and home appliance automation [7]. The fuzzy control system model is shown in Figure 2.
In Figure 2, the fuzzy controller is the core part of the fuzzy control system. Generally, the control law of fuzzy control is implemented by a computer program. The basic flow of implementing the fuzzy control algorithm is as follows: first, the accurate input value is obtained by sampling, and the fuzzy variable is used to define the input value, that is, fuzzification. Then the fuzzy reasoning is set according to the prior experience, and a fuzzy output value is obtained by fuzzy reasoning. Considering that the actual control object needs precise control object, the fuzzy output value is finally obtained by defuzzifying to obtain the output control value [8].

The eigenfunction $\mu_A(x)$ of a set is not a $\{0,1\}$-value, but a value in the closed interval $[0,1]$. Then $x$ is a function representing the degree to which an object $A$ belongs to the set $A$, and is called a membership function. The most common manifestations of membership functions are: Gaussian membership function, trapezoidal membership function, triangular membership function, etc. [9]. The curve of the trapezoidal membership function is determined by four parameters $a$, $b$, $c$, and $d$. The trapezoidal membership function is shown in equation (4):

$$
f(x,a,b,c,d) = \begin{cases}
0, & x \leq a \\
\frac{x-a}{b-a}, & a \leq x \leq b \\
1, & b \leq x \leq c \\
\frac{d-x}{d-c}, & c \leq x \leq d \\
0, & x \geq d
\end{cases}
$$

In the formula (4), the parameters $a$, $d$ determine the lower corner of the trapezoid, and the parameters $b$, $c$ determine the upper corner of the trapezoid. In matlab, it is: trapmf($x,[a,b,c,d]$);

The following is the graphics of trapmf ($x,[1,5,7,8]$) in matlab [10]. As shown in Figure 3:
2. Experimental results

In order to verify the performance of the traditional algorithm and the fuzzy control algorithm, the following experiment was performed. Loose sensor nodes are randomly deployed in an area with a length and width of 1 km. The communication radius of the node is 18m. In the experiment, the length of the transmission data is set to 125 bytes, the transmission energy consumption is 5 OnJ/bit, and the initial energy of each node is 0.5kJo.

![Trapezoidal membership function graphics](image)

**Figure 3.** Trapezoidal membership function graphics

![Network residual energy distribution](image)

**Figure 4.** Network residual energy distribution

According to the residual energy distribution of the network in Figure 4, the real-time performance of the fuzzy control algorithm can be analyzed, which can be measured by the average number of hops required by the data from the source node to the sink node. As can be seen from Figure 5, after running the fuzzy control algorithm, after 100 simulations, the average hop count of the nodes is between 6 and 7. That is to say, the result of the fuzzy control algorithm operation can ensure the requirements of the network to transmit data in real time. This result is attributed to the reasonable distribution of the cluster head, and also related to factors such as the residual energy of the node and the normalization of the average path loss in the design of the payment function. Obviously, with the change of time, when the number of nodes in the network increases to about 50, the energy consumption of the cluster head in the network is basically stable after running the fuzzy control algorithm [11].

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[Image of the trapezoidal membership function]

[Image of the network residual energy distribution]
Figure 5. Cluster head energy consumption

Figure 5 shows the performance comparison of the total energy consumption of cluster heads in the network after 100 simulations and statistics. As can be seen from Figure 4, the fluctuation of the energy consumption of the cluster head in the fuzzy control algorithm is smaller than that of the traditional algorithm. This is because the traditional algorithm is designed without considering the reasonable distribution of the cluster head, and the data is transmitted to the sink node by a single hop. The traditional algorithm realizes the election and reasonable distribution of cluster heads through the game between nodes. Therefore, the total energy consumption of cluster heads in the network is lower than that of traditional algorithms, and the energy consumption changes relatively smoothly.

The network life is defined as the time when the first node dies, and the network lifetime is investigated under the operation of the CAGB algorithm. Figure 3.7 shows the network lifetime comparison of the cABG algorithm and the LEACH algorithm. As can be seen from the figure, with the CAGB algorithm, the average lifetime of the network is between 50 and 150. With the LEACH algorithm, the average lifetime of the network is between approximately 30 and 90. Compared with the LEACH algorithm, the average lifetime of the network is nearly doubled after running the CAGB algorithm. The main reason is that the LEACH algorithm does not consider the reasonable distribution of the cluster head nodes, the residual energy of the nodes, and the path loss of the nodes. Therefore, the energy consumption of the node is relatively fast, and there is an energy hole in the network, resulting in a relatively short network lifetime. The CAGB algorithm fully considers the residual energy of the node and the path loss of the node in the design of the game model, and realizes the rational distribution of the cluster head by cluster head election through the game between nodes. Therefore, the energy distribution of the entire network is relatively uniform and has a long network life cycle.

3. Conclusion

The fuzzy control algorithm is different from the traditional network. The artificial intelligence sensor network is an energy constrained network, and a suitable emission power can greatly reduce the energy consumption and reduce the internal interference. Power control technology has also become one of the most important key technologies. With the maturity of power control technology in artificial intelligence sensor networks, adaptive node-level power control technology has become a new research hotspot. Therefore, the artificial intelligence-based sensor network congestion fuzzy control algorithm is proposed, and its theoretical rationality is proved by experiments. However, its shortcoming is that it has higher requirements on node distribution density than simple tree structure, and the compatibility of traditional algorithm applications. The structure given in the experiment is only a static result after the topology is established, although it can ensure the advantage over the simple tree structure. However, since the node spreading density and uniformity have great influence
on the sustainability of the backup node strategy, the dynamic quantitative analysis needs to be improved.

Future topology control techniques should explore the use of hybrid approaches to develop a simple and energy efficient topology control scheme. Hybrid approaches refer to a combination of power control models, power regulation models, and clustering algorithms. It is hoped that the HFLTC algorithm will provide some ideas for topology control in a hybrid mode. However, HFLTC still has several shortcomings, such as not considering the movement of nodes, not considering the WSN under the 3D model, and so on. These issues are also the future research trends of topology control technology.

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