Available online at www.sciencedirect.com
SciVerse ScienceDirect
Procedia Environmental Sciences 11 (2011) 55 – 62
Procedia
Environmental Sciences

PSO-FNN-based Vertical Handoff Decision Algorithm in Heterogeneous Wireless Networks

Wang Nan, Shi Wenxiao✉, Fan Shaoshuai, Liu Shuxiang
College of Communication Engineering Jilin University Changchun, China
swx@jlu.edu.cn

Abstract

Aiming at working out the problem that fuzzy logic and neural network based vertical handoff algorithm didn't consider the load state reasonably in heterogeneous wireless networks, a PSO-FNN-based vertical handoff decision algorithm is proposed. The algorithm executes factors reinforcement learning for the fuzzy neural network (FNN) with the objective of the equal blocking probability to adapt for load state dynamically, and combined with particle swarm optimization (PSO) algorithm with global optimization capability to set initial parameters in order to improve the precision of parameter learning. The simulation results show that the PSO-FNN algorithm can balance the load of heterogeneous wireless networks effectively and decrease the blocking probability as well as handoff call blocking probability compared to sum-received signal strength (S-RSS) algorithm.

Selection and/or peer-review under responsibility of the Intelligent Information Technology Application Research Association.

Keywords: Heterogeneous wireless networks; vertical handoff; fuzzy neural network; load balance; particle swarm optimization

1. Introduction

The next-generation wireless networks will be consisted of various mobile and wireless technologies. Given the complementary characteristics of different networks, it is necessary to combine them to provide ubiquitous wireless access for users. The integration of heterogeneous wireless networks requires the design of intelligent vertical handoff decision algorithm to ensure seamless coverage, and provide high quality of service for different applications [1].

Many vertical handoff decision algorithms have been proposed. Fuzzy logic systems and neural network classifiers are good candidates for pattern classifiers due to their non-linearity and generalization capability. In [2], the algorithm uses a neural network to forecast the number of users, and adopts a fuzzy inference system to make a handoff decision. The algorithm achieves better performance in guaranteeing the Quality of Service (QoS). In [3], the fuzzy neural network (FNN) is used to make a vertical handoff decision and the learning target value is set to a constant user satisfaction.

Selection and/or peer-review under responsibility of the Intelligent Information Technology Application Research Association.
doi:10.1016/j.proenv.2011.12.010

The vertical handoff strategies mentioned above had their own advantages, but they did not put attention on the load conditions of the networks, and the allocation of resources is unreasonable.

In this paper, we adopt a Particle Swarm Optimization (PSO) algorithm to train the FNN. The proposed PSO-FNN-based vertical handoff decision algorithm can make reasonable handoff decision intelligently according to the study of network status. This algorithm can reduce the number of unnecessary handoff, avoid Ping-Pong effect, balance the load of networks effectively and decrease the access blocking probability as well as the handoff call blocking probability.

2. PSO-FNN-based Vertial Handoff Algorithm

This paper proposes a PSO-FNN-based vertical handoff decision algorithm, which can adjust the parameters according to the study of network status, so as to achieve the expected performance.

The equal blocking probability of networks indicates that the load conditions of networks are close. So the proposed algorithm executes factors reinforcement learning with the objective of the equal blocking probability of networks, which can make the access blocking probability of the candidate networks close and balance the load of networks effectively.

2.1Flowchart of Vertical Handoff Decision Algorithm

In this paper, we consider a heterogeneous wireless environment with the coexistence of UMTS and WLAN networks. When the average received signal strength reaches the threshold, it triggers a handoff decision. The proposed algorithm is mainly composed of three parts: pre-decision, FNN controller and handoff decision.

As shown in Fig.1, we import the parameters into the pre-decision module. If a handoff decision can be made in the pre-decision module directly, then the FNN control module and the handoff decision module can be skipped. Otherwise, the parameters are imported into the FNN control module. Finally, handoff decision module is used to select the most appropriate network according to the parameter *F*.

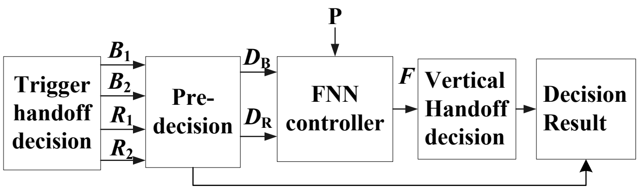

Figure 1 Components of the proposed vertical handoff decision algorithm

Where B_i (i=1,2) and R_i (i=1,2) are, respectively, the available bandwidth (B) and received signal strength (R) of the candidate networks; D_B is the difference of available bandwidth between networks; D_R is the difference of received signal strength between networks; P is the periodical statistics of the access blocking probability.

2.2Handoff Triggering

In order to avoid "ping-pong" effect, we decide whether to execute a handoff or not according to the sum S of the received signal strength in WLAN in a time period T ($T=LT_s$)

$$S = \sum_{k=1}^{K} \overline{\tilde{r}_k} \tag{1}$$

Where K is the times that the received signal strength is higher than the trigger threshold of the handoff R in a time period; $1 \le K \le L$; r_k (k=1,2,···,K) represent the received signal strength in WLAN at time k; L is the times of sampling; T_s is the time interval of sampling.

The handoff triggering has two cases:

1) handoff to UMTS: If the received signal strength is lower than R, then start sampling. If $S<RL/2$, then trigger the handoff decision, otherwise reset S.

2) handoff to WLAN: If the received signal strength is higher than R, then start sampling. If $S>RL/2$, then trigger the handoff decision, otherwise reset S.

2.3Pre-decision Method

The pre-decision method is used to filter the users before importing into FNN controller. We use B and R of the candidate networks to make a pre-decision.

If B_i of the target network is less than the threshold B_T, no handoff happens; if B_i of the target network is larger than the threshold B_T, calculate D_B and D_R, and import the parameters into the FNN controller module. The flowchart of the pre-decision is shown in Fig. 2.

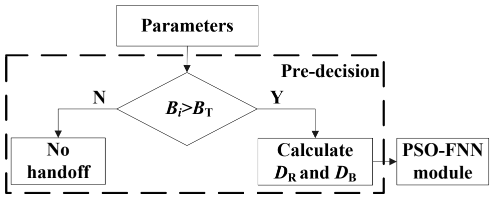

Figure 2 Flowchart of the pre-decision

D_R is calculated as

$$D_R = R_1 - \tilde{R}_2 \tag{2}$$

D_B is calculated as

$$D_B = B_1 - \tilde{B}_2 \tag{3}$$

2.4FNN Vertical Handoff Controller

In this paper, we propose a FNN-based vertical handoff algorithm. This algorithm adopts PSO algorithm to set initial parameters value and executes factors reinforcement learning with the objective of the equal blocking probability of networks.

3) The structure of FNN

A four-layer FNN [4], as shown in Fig. 3, comprises the input (Layer1), membership (Layer2), rule (Layer3) and output layers (Layer4). This type of FNN is good at acquiring rules, recognizing patterns and tuning the membership function shapes [3].

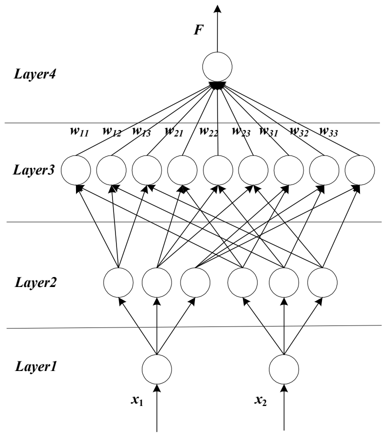

Figure 3 Structure of the four-layer FNN

Layer1: Input Layer

No computation is required in this layer. x_i represents the inputs. $x_1=D_B$ and $x_2=D_R$.

Layer 2: Membership Layer

Each node in this layer transforms the value from Layer1 into the linguistic level using the membership function. The Gaussian function is adopted as the membership function. The membership function μ_{ij} of the node is represented as

$$\mu_{ij}(x_i) = \exp\left(-\left((x_i - c_{ij})/\sigma_{ij}^2\right)^2\right) \quad . \tag{4}$$

Where c_{ij} and σ_{ij} (i=1,2; j=1,2,3) are, respectively, the mean and the standard deviation of the Gaussian function. The total number of the nodes is six.

Layer3: Rule Layer

The nodes in Layer3 are the rule nodes, and the links in this layer perform the precondition matching of the fuzzy rules. Each node represents a single fuzzy rule. This layer performs a fuzzy "AND" operation that sends out the node value according to the incoming membership values from Layer2. Similar to Layers1 and 2, there is no weight to be adjusted in this layer. The value a_{mn} (m=1,2,3;n=1,2,3) of the node is calculated as follows

$$a_{mn} = \mu_{1m} \times \tilde{\mu_{2n}} \quad . \tag{5}$$

Layer4: Output Layer

Each fuzzy rule from Layer3 is given a weight. w_{mn} is the weight of the fuzzy rule a_{mn}.

By the method of weighted mean defuzzification, we convert the vector into a single value F

$$F = \left(\sum_{i=1}^{3}\sum_{j=1}^{3} w_{mn} a_{mn}\right) \Bigg/ \left(\sum_{i=1}^{3}\sum_{j=1}^{3} a_{mn}\right) \quad . \tag{6}$$

4) Ascertainment of the initial parameters

This paper adopts a hybrid training algorithm by combining the PSO and the back-propagation algorithm. The PSO is used to optimize the initial parameters of the FNN, and the back-propagation algorithm is used to implement the self-adaption modulation for the parameters.

In PSO, a group of particles, without quality and volume, fly through a N-dimensional space adjusting their positions in search space according to their own experience. The position of the particle is represented with a position vector $p_i=(p_{i1},p_{i2},\dots p_{iN})$, $i=1,2,\dots,m$ and a velocity vector $v_i=(v_{i1},v_{i2},\dots v_{iN})$. In every time step t, particle i changes its velocity and position according to the following equations [5]

$$v_{ij}(t+1)=\varphi v_{ij}(t)+c_1r_{1j}(t)(p_{ij}(t)-x_{ij}(t))+c_2r_{2j}(t)(p_{gj}(t)-x_{ij}(t)) \tag{7}$$

$$x_{ij}(t+1)=x_{ij}(t)+v_{ij}(t+1) \tag{8}$$

Where i represents the i-th particle; j represents the j-th dimension of speed or location; v_i represents the speed of the i-th particle; c_1 and c_2 represent the study factors; r_{1j} and r_{2j} represent the random numbers among 0 and 1; x_i represents the current location of the i-th particle; φ is the inertial weight; $p_i=(p_{i1},p_{i2},\dots p_{iN})$ is the best personal position of particle i which has been visited during the lifetime of the particle; $p_g=(p_{g1},p_{g2},\dots p_{gN})$ is the global best position that is the best position of all particles in the swarm.

The concrete steps of the PSO algorithm are shown [3]:

Step1: Initialize the positions and velocities of a group of particles randomly.

Step2: Compute every particle's fitness value. The fitness function is defined as $f=M|d_i-o_i|$, d_i represent the realistic value; o_i represent the expect value; M is a positive constant. The d_i and o_i are set as $d_i=y$, $o_i=y^*$. The position with lower fitness value is better.

Step3: Set p_i as the current position of the particle i. And set p_g as the best position of the initialized particles.

Step4: The positions and velocities of all particles are updated according to (7) and (8). Evaluate each new particle's fitness value. If the current fitness value is better than p_i fitness value, replace p_i with the current position. If the best position of all new particles is better than p_g, then p_g is updated.

Step5: Judge the pause conditions. If the conditions are met, stop the iteration, and the positions of particles represented by p_g is the optimal best value. Otherwise, the process is repeated from step4.

Step6: Algorithm ends. Take the coordinates of p_g as the initial parameters of the FNN.

5) Reinforcement Learning Algorithm

To describe the learning algorithm of the FNN using the supervised gradient decent method [6], firstly the error function E is defined as

$$E(t)=\frac{1}{2}(y^*-y(t))^2 \tag{9}$$

Then, the mean c_{ij}, the standard deviation σ_{ij} of the Gaussian function and the weight w_{mn} of the fuzzy rule are updated according to the following equation

$$Z_{ij}(t+1)=Z_{ij}(t)-\eta\frac{\partial E}{\partial Z_{ij}}+\alpha(Z_{ij}(t)-Z_{ij}(t-1)) \tag{10}$$

Where η is the learning rate; α is the momentum rate; Z_{ij} is an universal variable. We can update the parameters by using this method.

2.5 Vertical Handoff Decision

In this phase, we make a vertical handoff decision according to the output parameter F of the FNN. The decision method is defined as:

If F<0.5, handoff to UMTS;

If F>0.5, handoff to WLAN;

If F=0.5, handoff to the network in which RSS is better.

3. Simulation and Analysis

In order to evaluate the performance of the proposed PSO-FNN-based vertical handoff decision algorithm, we compare the performance of PSO-FNN algorithm to sum-received signal strength (S-RSS) algorithm proposed in [7].

3.1Simulation scenario

In our simulation, each UMTS cell overlaps two WLAN cells. Parameter setting is shown in Table 1 .

Table 1 Simulation Parameter Setting

Name	UMTS	WLAN
Bandwidth	2Mbps	11Mbps
Cell size	500m	100m
Transmit power	35dBm	20dBm
Moving speed of users	18km/h	
Threshold to trigger handoff	-100dbm	
Sampling interval	50ms	

3.2Simulation results and discussion

The results of simulation are shown in Fig. 4-Fig. 6.

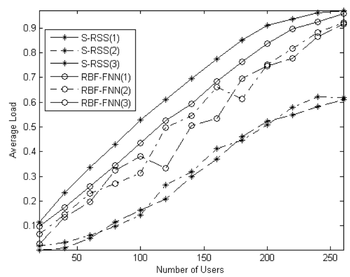

Figure 4 Average load

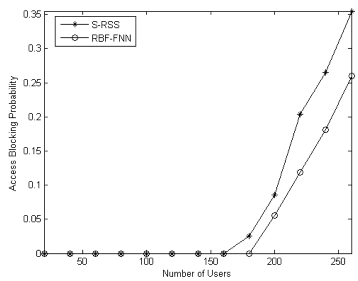

Figure 5 Access blocking probability

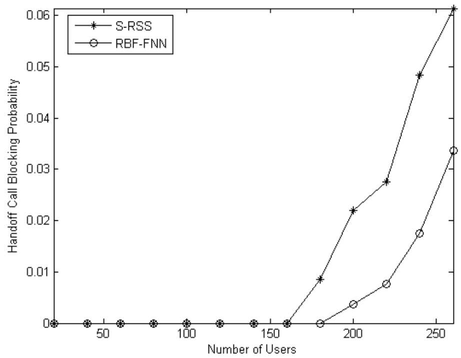

Figure 6 Handoff call blocking probability

Fig. 4-Fig. 6 are the comparisons of PSO-FNN and S-RSS algorithm in one UMTS cell and two WLAN cells repeating coverage area. Fig. 4 is the statistics of the normalized load. We can see that the PSO-FNN algorithm which executes factors reinforcement learning with the objective of the equal blocking probability of networks can balance the load of networks effectively. As the load balancing of networks can increase the usage of the whole network resource and make the overload of a network less possible. Therefore the access blocking probability and handoff call blocking probability will decrease accordingly.

Fig. 5 shows user blocking probability caused by full network load when users initially get access. We can see that the access blocking probability of PSO-FNN algorithm is lower than that of S-RSS algorithm, and when the number of users is greater than 180, the access blocking probability decreases 6.37% in average. Fig. 6 shows handoff call probability caused by full network load when users switch among networks. We can see that the handoff call blocking probability of PSO-FNN algorithm is lower than that of S-RSS algorithm, and when the number of users is greater than 180, the handoff call blocking probability decreases 2.11% in average.

4. Conclusions

This paper proposes a PSO-FNN-based vertical handoff decision algorithm which can make a reasonable handoff decision intelligently according to the study of network status. The proposed algorithm adopts PSO algorithm to set initial parameters value and executes factors reinforcement learning with the objective of the equal blocking probability of networks. Simulation results indicate that the PSO-FNN algorithm can balance the load of heterogeneous wireless networks effectively and decrease the blocking probability as well as handoff call blocking probability.

Acknowledgment

This work was supported by the National Natural Science Foundation of China (No. 60972028).

References

[1]C. Çeken, S. Yarkan, and H. Arslan, “Interference aware vertical handoff decision algorithm for quality of service support in wireless heterogeneous networks,” Computer Networks, vol. 54(5), pp. 726-740, April 8, 2010.

[2]Q. Guo, X. H. Xu, and Y. L. Wang, “Intelligent handoff decision in radio heterogeneous network,” Journal of Harbin Institute of Technology, vol. 4(6), pp. 741-746, December, 2008.

[3]L. Giupponi, R. Agusti, J. Perez-Romero, and O. Sallent, “A fuzzy neural JRRM in a heterogeneous scenario supported by prediction strategies for horizontal and vertical handovers,” IEEE International Conference on Fuzzy Systems, pp. 655–662, 2006.

[4]W. X. Shi, S. S. Fan, N. Wang, and C. J. Xia, “Fuzzy neural network based access selection algorithm in heterogeneous wireless networks,” Journal on Communications, vol. 31(9), pp. 151-156, 2010.

[5]A. B. Hashem and M. R. Meybodi, “A note on the learning automata based algorithms for adaptive parameter selection in PSO,” Applied Soft Computing Journal, vol. 11(1), pp. 689–705, 2011.

[6]R. Ballini and F. Gomide, “Recurrent fuzzy neural computation: Modeling, learning and application,” 2010 6th IEEE World Congress on Computational Intelligence, WCCI 2010, 2010.

[7]X. Liu, L. G. Jiang, and C. He, “An algorithm of vertical handoff for heterogeneous networks,” Journal of Shanghai Jiaotong University, vol. 40(5), pp. 742-746, 2006.