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Handoff Algorithm based on Radial-Basis Function Networks in High Altitude Platform Station Cellular Systems

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Abstract: Handoff algorithm is used in wireless cellular systems to decide when and to which base station to handoff in order that the services can be continued uninterrupted. In this paper, we propose a handoff algorithm based on neural network in a joint system of terrestrial and high altitude platform station (HAPS) cellular systems. Radial-Basis Function network is used for making handoff decision to the neighbor base station. A set of training patterns consists of averaged signal strength receiving from serving and nearby base stations, directions of users, traffic intensities as well. This combined mobile-cell related information improves the handoff algorithm yielding both low number of unnecessary handoffs and decision delay. As a revolutionary wireless system, HAPS base station can supply services for uncovered area improving total capacity of service-limited area by a terrestrial base station. Performance comparisons of the presented method and the conventional Hysteresis rule are given in forms of handoff rate, blocking rate and dropping rate. Simulation results demonstrate that exploiting neural network can reduce unnecessary handoff and call blocking as well as call dropping.

1. Introduction

In mobile communications, the continuity of communication without terminating an ongoing call or blocking new calls is very crucial to enhance high quality of cellular services. Handoff algorithm makes it possible to maintain link quality. In Hysteresis method [1], handoff occurs when the difference of the received signal strength from current and target base stations is more than Hysteresis level. Because of fading effect, the difference can be fluctuated for brief periods of time which results in unnecessary handoff. Such back and forth handoff is known as the ping-pong effect. In addition to network resource waste, calls might be terminated if decision delay is long due to high Hysteresis level.

More recent works have dealt with neural network to improve handoff algorithms. The neural network applied for handoff using received signal strength and traffic intensity is presented in [2]. Neural network is learned to predict the transfer probabilities of a user from the initial state [3]. A new technique to recognize signal patterns of a mobile station using probabilistic neural network is introduced in Rayleigh fading channel [4]. Using statistical pattern recognition of signal strength [5,6] can improve the efficiency of handoff algorithm.

In this paper, we present a handoff algorithm based on radial-basis function network [7] in the high altitude platform station (HAPS) cellular system [8]. The inputs of neural network depend on signal strength, mobile direction and traffic intensity, which are used to make a handoff decision process to the chosen adjacent cell. Figure 1 shows the conceptual model of the joint cellular system, terrestrial and HAPS systems. HAPS cellular system can be considered as a complementary to terrestrial cellular system, to improve and expand the coverage services. As shown in Fig.1, HAPS base station can supply services to the mobile having weak signal from serving terrestrial base station influenced by shadowing and the special case like turning corner as well as being outside the terrestrial coverage.

This paper is organized as follow. Section 2 gives the description of the Hysteresis method. Handoff decision based on radial-basis function network is presented in section 3. The handoff algorithm is proposed and HAPs station improving the call maintenance is shown in section 4. Section 5 illustrates the simulation results followed by conclusions.

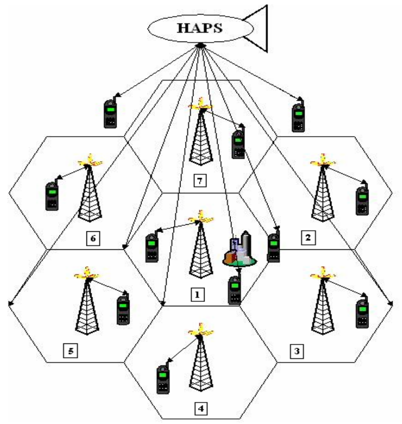

Figure 1. The conceptual joint system model.

2. Hysteresis Method

A traditional handoff algorithm which is known as the Hysteresis method uses relative signal strength as a main component of the handoff decision process. In Fig.2, the mobile is moving from the serving base station to another base station. To have an ongoing call, handoff is needed when the relative signal strength of the target base rise above a hysteresis margin h dB. It corresponds to point C in Fig.2. For GSM mobile system, handoff from one cell to another cell is decided when [1]

$$RSS\_AVG = RSS\_AVG_T - RSS\_AVG_S \geq h \qquad (1)$$

where RSS_AVG is the difference between the averaged received signal strength from an adjacent cell (RSS_AVG_T) and the serving cell (RSS_AVG_S) and h denotes the Hysteresis level. However, the smaller h is, the more frequent the unnecessary handoffs are. In this case, it might result in repeated handoffs between two base stations caused by rapid fluctuations in the received signal or socalled the ping-pong effect. On the other hand, having the larger h, it also increases the decision delay. Call dropping might be happened. There is therefore a tradeoff between the number of unnecessary handoff and decision delay.

Thus, we proposed an improved handoff algorithm based on radial-basis function networks. The input to the neural network is not only the received signal strength, but it also uses the direction of mobile moving to the target cell and the traffic intensities of the neighbor cells. It makes the proposed approach possible to overcome such shortcomings of the Hysteresis method.

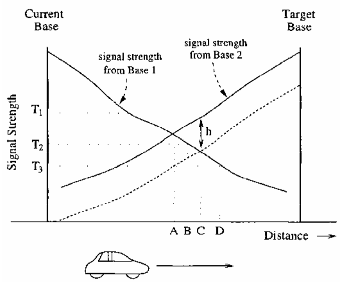

Figure 2. The location of a handoff decision in Hysteresis.

3. The Structure of Neural Network

In this section, we apply neural network with radial-basis function network as depicted in Fig.3. It is suitable for classifying a huge amount of data inlinearly. The basic structure of neural network consists of three layers; input layer, hidden layer and output layer [7]. In the second layers, the number of nodes is 20. We use a nonlinear Gaussian function to connect them to all of the five nodes in the input layer. The output layer consists of two nodes which are y_1 and y_2 obtained by a linearly weighted sum of the outputs of the hidden units. Note that we have two outputs since the iteration of learning processes can be reduced. The outputs of the network in this application are to decide whether the system needs a handoff as follows:
Case 1: If y_1 and y_2 are 00, no handoff will be performed.
Case 2: If y_1 and y_2 represent 11, then the system will handoff the mobile to the chosen base station.

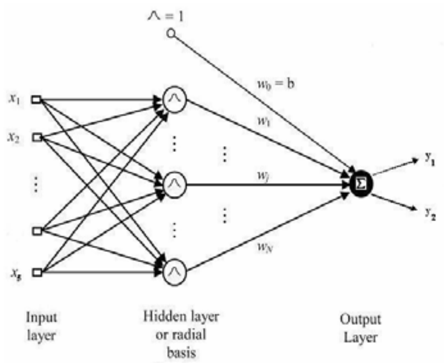

Figure 3. Radial-basis function network.

To find the optimal weight ($w = [w_1, w_2, ..., w_{20}]^T$), the network is learned as the following steps.

1. Set the initial value of center (μ_{ji}) in the hidden layer for the i[th] input node and the j[th] hidden node.
2. Provide the value of span (σ_j) for the j[th] hidden node.
3. Calculate the output of hidden nodes:

$$z = \exp \frac{-\left\|\vec{x} - \vec{\mu}_{ji}\right\|^2}{2\sigma_j^2}$$

where $\vec{x} = [x_1, x_2, ..., x_6]^T$ represents the input vector.

4. Set the initial weight vector which is distributed uniformly between [0, 1].
5. Calculate output of output nodes:

$$y_k = \sum_{j=0}^{M} w_{kj} z_j, \quad k = 1,2$$

where $z_0 = 1$ and $M = 20$.

6. Calculate the error given as:

$$error_k = \text{Target of pattern} - y_k$$

7. Update the weight

$$w_{kj}(n+1) = w_{kj}(n) + \eta_w (error_k) z_j$$

where j =0,1,2,…,20; k =1,2 and η_w is the learning rate of weight.

8. Update the center momentum

$$\mu_{ji}(n+1) = \mu_j(n) + \eta_\mu \frac{z_j}{\sigma_j}(x_i - \mu_{ji}) \sum error_k w_{kj}$$

where η_μ is the learning rate of center.

9. Update the span:

$$\sigma_j(n+1) = \sigma_j(n) - \eta_\sigma z_j \frac{2}{\sigma_j} \ln z_j \sum error_k w_{kj}$$

where η_σ is the learning rate of span.

In our implementation, 6000 samples are used for training the network and 500 samples are used to test the network. For each testing sample, square errors of actual output and desired output are calculated. It is found that the zero errors are achieved within a few of testing samples.

The set of the neural network inputs are the following factors

1. x_1: The directions of the users are divided according to the following angles
   - If $x_2 = 0$, mobile is still in the same cell.
   - If $0 < x_2 \leq \pi/3$, mobile is going to cell no. 2.
   - If $5\pi/3 < x_2 \leq 2\pi$, mobile is going to cell no. 3.
   - If $4\pi/3 < x_2 \leq 5\pi/3$, mobile is going to cell no. 4.
   - If $\pi < x_2 \leq 4\pi/3$, mobile is going to cell no. 5
   - If $2\pi/3 < x_2 \leq \pi$, mobile is going to cell no. 6.
   - If $\pi/3 < x_2 \leq 2\pi/3$, mobile is going to cell no. 7.

This relationship between directions and cell numbers is valid under the assumption that mobile is initially located near base station and its angle is stationary. However, we can use antenna array and MUSIC algorithm to find the direction of arrival which will be our future work.

2. x_2: The signal strength of mobile receiving from the current base station is between -91 to -87 dBm.
3. x_3: The signal strength of mobile receiving from the target base station is greater than -87 dBm.
4. x_4, x_5: The traffic intensities (TI) of serving and target base stations have three levels as:
   - low: TI < 0.58 Erlangs/Channel
   - medium: 0.58 ≤ TI < 0.69 Erlangs/ Channel
   - high: TI > 0.69 Erlangs/Channel

Handoff decision made by our designed neural network as shown in Table 1 depends on both signal receiving strength (RSS) as well as TI of serving and target base stations. NOHO stands for no-handoff.

Table 1: Handoff decision

RSS of Target : Low	RSS of Serving : Low		
TI : T \ TI : S	Low	Medium	High
Low	NOHO	HO	HO
Medium	NOHO	NOHO	HO
High	NOHO	NOHO	NOHO

RSS of Target : High	RSS of Serving : Low		
TI : T \ TI : S	Low	Medium	High
Low	HO	HO	HO
Medium	HO	HO	HO
High	NOHO	NOHO	HO

RSS of Target : Low	RSS of Serving : High		
TI : T \ TI : S	Low	Medium	High
Low	NOHO	NOHO	HO
Medium	NOHO	NOHO	HO
High	NOHO	NOHO	NOHO

RSS of Target : High	RSS of Serving : High		
TI : T \ TI : S	Low	Medium	High
Low	NOHO	HO	HO
Medium	NOHO	NOHO	HO
High	NOHO	NOHO	NOHO

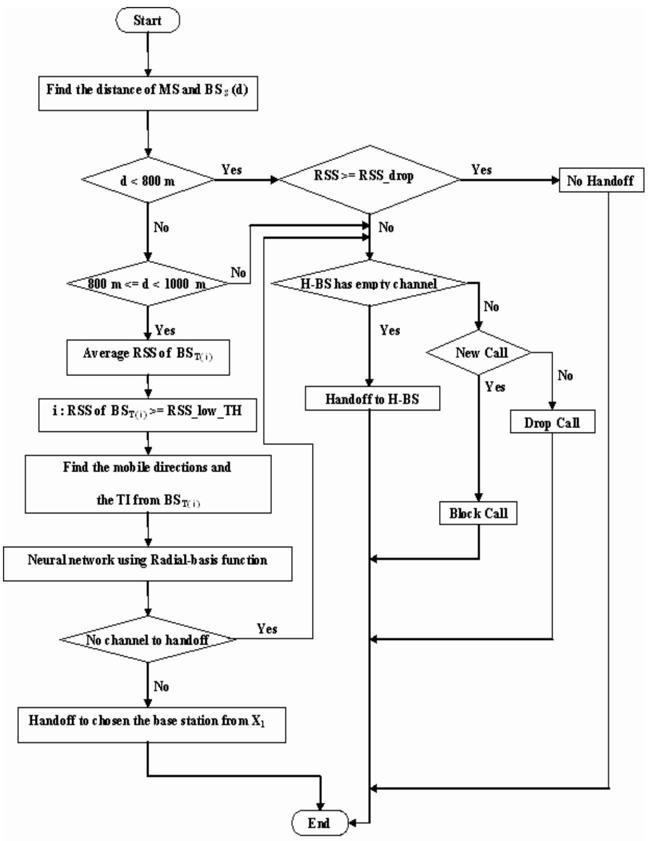

Figure 4. Handoff process using neural network

4. Handoff Decision Using Neural Network in HAPS Cellular Systems

Figure 4 illustrates the proposed handoff method based on radial-basis function network discussed in the previous section. The capacity of the system is more efficient with the goodness of HAPS. First, we check if the mobile is staying in the obstacle position or even at the corners of 3-cell junction by examining the mobile position d plus the received signal strength (RSS). If so, a handoff between the serving terrestrial base station and HAPS base station is necessary to improve the call quality. Additionally, we measure the signal strength of the mobile receiving from the current and adjacent cells every 0.5 sec. In order to decrease variation of the signals, an average of 10 data is calculated. After obtaining the averages signal strength of current and neighbor cells, we can determine which cells are most likely to be the target base stations ($BS_{T(i)}$). Included the knowledge of the mobile directions and traffic intensities of candidate base stations, the process of neural network then makes a decision if the mobile need handoff or not. In the case of handoff happened, the algorithm will assign either case (1) to which base station the mobile will be handoffed or (2) request a channel from HAPS. Note that HAPS gives a priority to handoff calls more than new calls such that call blocking has low probability.

5. Simulation Results

The performance of the handoff algorithm using neural network is illustrated and compared to the conventional handoff algorithm based on the hysteresis rule. Simulations are done for 7 terrestrial cells and 1 HAP station as illustrated in Fig.1. To compute the mobile distance d, we use the initial distance and mobile speed distributed as shown in Table 2. Note that we will apply the concept of timing advance for calculating the mobile station location d in the future work. Hata model is calculated for path loss propagation and given as [9].

$$P_L = 69.55 + 26.16\log f_c - 13.82\log h_b - a(h) + (44.9 - 6.55\log h_m)\log R \quad (2)$$

where f_c is a carrier frequency (MHz).
h_b is the height of antenna at base station (m).
h_m is the height of antenna at mobile (m).
R is the distance between base station and mobile (km)

$$a(h) = 3.26(\log 11.75\, h_m)^2 - 4.97 \text{ for } f_c \geq 400 \text{ MHz}.$$

Accordingly, the strength of signal at a mobile is RSS = P_O - P_L where P_O denotes the power of transmitter at base station and let RSS be the received signal strength at a mobile. In the simulation, 100 trials are run at a fix traffic intensity of serving base station which is cell no. 1 as in Fig.1. The frequency is f_c = 1800 MHz with the power of transmitter in each base station equal to 10 W (40 dBm). The antenna height is 60 m at base station and 1.5 m. at mobile station. The random variables of modeling the users are listed in Table 1 and the parameters of cell environment are fixed as shown in Table 2.

Fig.6 shows the comparison of handoff rate versus traffic intensities between the presented method and Hysteresis method. It is shown that the handoff rate resulting from our method is less than the Hysteresis method since we consider the signal strength, position, direction and traffic intensity to reduce unnecessary handoffs. Blocking rate using our algorithm has a probability lower than the Hysteresis method as plotted in Fig.7. The calls are blocked less because the traffic intensities of adjacent cells are considered to find available channels. Due to unnecessary handoffs, calls are blocked more in the Hysteresis method. We also achieved lower dropping rate than using the Hysteresis method as compared in Fig.8. Due to the reduced unnecessary handoffs, there are more available channels for new calls to access the system. As a result, dropping new calls using the presented handoff algorithm decreases compared to the conventional handoff decision.

Table 2. Mobile Parameters

variable	distribution	interval
initial position in the horizontal	Uniform	[-10,10]
initial position in the vertical	Uniform	[-8,8]
number of users in each cell	Uniform	[100,400]
new call of users in each time	Poisson	1 min
direction of each mobile	Uniform	[0,2π]
average time per call	Exponential	120 sec
average mobile speed	Normal	N(60,10) km/hr

Table 3. Cell Structure Parameters

Parameters	value
cell radius	1000 m
number of channels per call	20 channels
number of channels in HAPS	20 channels
low threshold of received signal strength (RSS_low_TH)	-96 dBm
received signal strength for call dropping (RSS_drop)	<= -82 dBm
Hysteresis level (h)	6 dB

6. Conclusions

We propose a new handoff algorithm based on radial-basis function network in high altitude platform station cellular systems. HAPS system can provide services to the users staying at the corner of cells or at covered area influenced by shadowing. Besides the averaged received signal strength, users position and direction versus different the traffic intensity in the serving base station are inputs for neural network learning. Consequently, handoff rate, blocking rate and dropping rate are reduced compared to the traditional Hysteresis algorithm. In the future work, methods to determine the initial position and directions should be included to obtain more intelligent handoff algorithm. Instead, unsupervised learning method would be done to eliminate the necessity of training runs.

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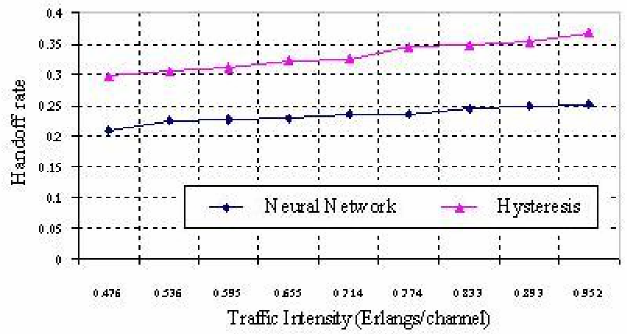

Figure 6. Handoff Rate between NN and Hys.

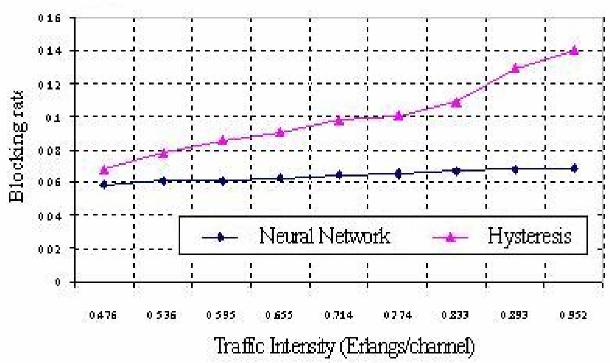

Figure 7. Blocking Rate between NN and Hys.

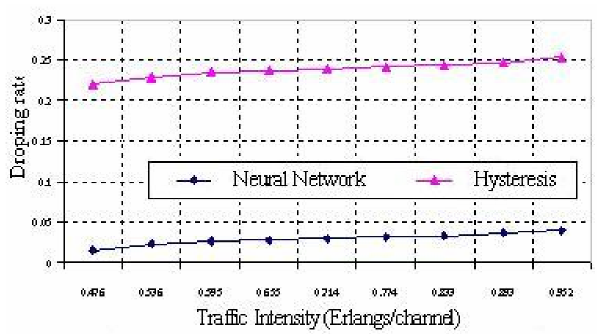

Figure 8. Dropping Rate between NN and Hys.