ADAPTIVE CDMA CHANNEL RESERVATION USING NEURAL NETWORKS

Termsaithong S., Piyatamrong B.

Department of Computer Engineering, Faculty of Engineering
King Mongkut's Institute of Technology Ladkrabung (KMITL), Bangkok 10520., Thailand.
E-mail: dokens@hotmail.com , Email: kpbanjon@kmitl.ac.th

Abstract – In the future wireless networks, resource reservation will be more and more interesting issue because handoff will become more and more frequent in small size cells. So it is not practical to predict the accurate destination of a user. The Transfer Probabilities (The possibilities of user leaving the current cell and entering the neighboring cells) is used to be a statistical strategy for resource reservation in this paper. Movement Model introduced by [4] are implemented to obtain the Transfer Probabilities of a user from the initial states (position, velocity and direction). This paper presents 1.resource reservation algorithm for CDMA network and 2. neural network structure that used to predict the Transfer Probabilities of a user from the initial states. Then the transfer probabilities are used to calculate the amount of reserved resources in each neighboring cell. Simulation results show that the system achieves an acceptable level of Handoff Call Dropping Rate and New Call Blocking Rate.

I. INTRODUCTION

The next generation CDMA cellular networks will support multimedia application. So the network operators must find the way to allow their systems support those applications. One of the most favorite method is to adopt the topology of small sizes cells to increase the system capacity in the future, which will lead to frequent handoffs while users change cells a number of times during their communication sessions. Normally CDMA system gives high priority to more important soft handoff attempts over new call attempts. So during the soft handoff process, resources are reserved and allocated to the handoff user as quickly as possible to avoid possible call dropping or decreasing Qos (Quality of Service). Because of the inherent limitation of the resources in wireless environment and the large requirements of resources in multimedia applications, excessive resource reservation will reduce the capacity of CDMA system. If accurate knowledge about the user's trajectory prior to its movement is known, the system can plan resource reservation most efficiently by reserving only the required resources in the cells along the user's route. However, in the real situation, the user's intended route is generally unknown to the system. The rest of this paper is divided into the following section: Section 2 presents the concept of movement model introduced in [4] used in this paper. Section 3 proposes the back propagation neural network model. Section 4 describes the detailed algorithm for resource reservation. Section 5 shows the simulation results, and finally section 6 draws the conclusion of this work.

II. MOVEMENT MODEL

In the cellular CDMA system with small size cells, the user's movements are more random-like and more likely to cross the cell boundaries frequently. As a result, it is difficult for the system to predict the destination cell, which is dependent on the entire user's path. Many researchers have studied ways to predict the user's routes correctly based on the user's movement pattern. Liu and Maguire Jr. [1] developed a two-layer model, which describes a user's behavior as repetitions of some elementary movement patterns stored in a user's profile. One layer is the regular movement namely the Movement Circle (MC) and the Movement Track (MT), which is based on the assumption that wherever a user moves from, it will eventually return. The other layer is random movement namely Markov Chain Model which only represents the behavior of random parts in the user movement. Simulations have shown that the prediction efficiency is 95% approximately, but it is very sensitive to the random factors, which represents random parts of the movement.

Liu et al [2] suggested another two-layer hierarchy model for the user movement prediction. The top layer is the Global Mobility Model. This is a deterministic model created for inter-cell movements. The bottom layer is the Local Mobility Model. This is stochastic model with dynamically changing state variables (velocity, direction and position) in order to simulate intra-cell movements. The simulations have shown that they obtained accurate results in handoff control and greatly reduced network congestion.

Levine et al [3] proposed a concept of shadow cluster, in which each user has its own specific area called a shadow, which moves along with the user. Each base station in the shadow cluster anticipates the user's arrival and reserves resources for it. The number of base stations that reserve resources will determine the overall system efficiency and Qos guarantee.

These algorithms are useful for reducing the number of reserved resources even in random movements, but almost impossible to implement in general environment because of the associated complexity. The features aren't easy to obtain in the real communications such as call duration time, call dwell time and so on.

This paper implements the work proposed by W.W.H. Yu and Changhua He [4] that constructs a model to describe the user's random movement in small size cells and extract the user's velocity, direction and location as the most important features of its movement, and classify the user's Transfer Probabilities based on these features, which represents the possibilities the user leaving the current cell and entering one of its neighboring cells. Resources are reserved among all its neighbor cells proportional to the value of Transfer Probabilities. And also propose the Back Propagation Neural Networks to approximate the relationship between the user's initial states of soft handoff request and its Transfer Probabilities.

The probability of a user leaving the current cell and entering a neighboring cell is the user's Transfer Probability to this neighboring cell. The Transfer Probability Vector is considered a much better approach to estimating the number of reserved resources in each base station than predicting the user's next destination cell from its current movement pattern because sometimes it's very hard to specify a destination cell from several cells for which a user has almost the same Transfer Probabilities. In order to achieve the relationship between the soft handoff request 's initial states and its Transfer Probabilities, the user's movement pattern and the movement model will be explained as follows. It's very difficult to generate a truly random route to simulate the random nature in reality. An approximation of the user's movement assumes that all the users move with a constant velocity Q_0 and in the direction V_0 for a short time interval τ. After generating a call in a cell at an initial position $P(x_0,y_0)$. At the end of the time interval τ, the user will arrive at a new location $P(x_0,y_0)$. The velocity and the direction at the new location are incremented by d_{v1} and d_{Q1} respectively. The user continues moving with the new velocity $V_1 = V_0 + d_{v1}$ and in the direction $Q_1 = Q_0 + d_{Q1}$ for another time interval τ. The same process repeats in a series of iteration at a time interval of τ. At the end of k^{th} iteration, the total time iteration of travel is $T_k = k\tau$. Figure 1 shows the process of user's movement.

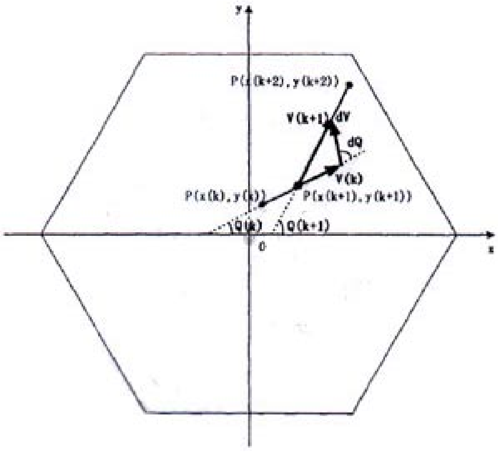

Figure 1: Movement Model proposed by W.W.H.Yu and Changhua He

At time $T_k = k\tau$, the user is at the position $P(x_k,y_k)$. After a time interval τ, or at time interval $T_{k+1} = (k+1)\tau$, it moves to the new position $P(x_{k+1},y_{k+1})$. The speed is changed from (V_k, Q_k) to (V_{k+1}, Q_{k+1}) based on a randomly generated difference (d_v,d_Q) . After another time interval τ, it will move to another position $P(x_{k+2},y_{k+2})$. The relationship between the user 's states at time $T_{k+1} = (k+1)\tau$ and $T_k = k\tau$ can be derived as below:

$$x_{k+1} = x_k + \tau * v_k * \cos Q_k \qquad (1)$$

$$y_{k+1} = y_k + \tau * v_k * \sin Q_k \qquad (2)$$

$$v_{k+1} = \sqrt{v_k^2 + dv^2 - 2 * dv * v_k * \cos(\pi - dQ)} \qquad (3)$$

$$Q_{k+1} = Q_k + \arccos\frac{v_{k+1}^2 + v_k^2 - dv^2}{2 * v_k * v_{k+1}}, 0 \le dQ < \pi \qquad (4)$$

$$Q_{k+1} = Q_k - \arccos\frac{v_{k+1}^2 + v_k^2 - dv^2}{2 * v_k * v_{k+1}}, \pi \le dQ < 2\pi$$

With these equations, the whole route of a user can be obtained in iteration steps based on the initial states and the randomly generated incremental velocity d_v and the angle of the direction d_Q. The length of time interval τ will determine the degree of randomness of the movement. The smaller the time interval is, the more the user's movement resembles a truly random movement in reality.

For users with each set of initial states, it will move according above model for many times, and each route ends when user enters one of its neighboring cells. After thousands of times of iterations for a user with the same initial states, its Transfer Probabilities can be obtained through calculating the times the user enters each neighboring cell respectively. Based on the above model, Back Propagation Neural Networks can be trained to recognize the Transfer Probabilities for a soft handoff user 's initial states.

III. NEURAL NETWORK MODEL

This paper proposed Multi Layer Back Propagation Neural Networks to associate the Transfer Probabilities with the specific user 's initial states. Standard backpropagation is a gradient descent algorithm, as is the Widrow-Hoff learning rule, in which the network weights are moved along the negative of the gradient of the performance function. The term backpropagation refers to the manner in which the gradient is computed for nonlinear multilayer networks. There are a number of variations on the basic algorithm that are based on other standard optimization techniques, such as Variable Learning Rate, Relilient Backpropagation, Conjugate Gradient Algorithms, Levenberg-Marquardt algorithm, Quasi-Newton Algorithms and so on. It is very difficult to know which training algorithm will be the fastest for a given problem. It will depend on many factors, including the complexity of the problem, the number of data points in the training set, the number of weights and biases in the network, the error goal, and whether the network is being used for pattern recognition (discriminant analysis) or function approximation (regression). The chosen algorithm of this work is "Relilient Backpropagation" because from the experiments, the results show that it performs the fastest on pattern recognition problems and The memory requirements for this algorithm are relatively small in comparison to the other algorithms considered [5].

A. Network Structure

The Multi Layer Neural Networks are structured as shown in figure 2

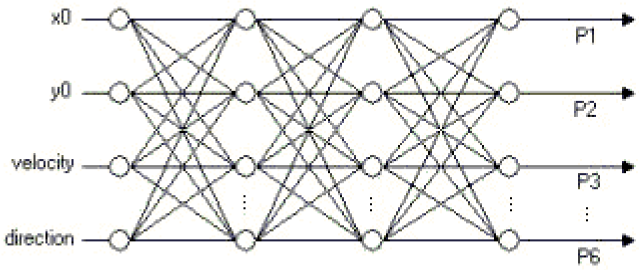

Figure 2: Neural Networks with 2 Hidden Layers

The figure shows that 4 inputs are the user 's initial states and six outputs are the corresponding Transfer Probability Vector. The network has 2 hidden layers, each has 400 nodes and 200 nodes respectively. The non-linear functions of each node are all log-sigmoid transfer functions and the connection weights are all stored in matrix. All the results for Multi Layer Neural Networks with different topologies, say different number of hidden layers and different number of nodes in each hidden layer, are listed in figure 3,4,5,6.

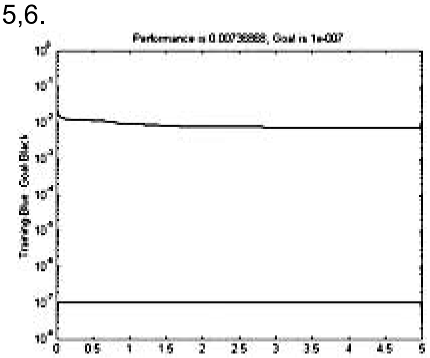

Figure 3: Neural Network with One hidden layer and 20 nodes

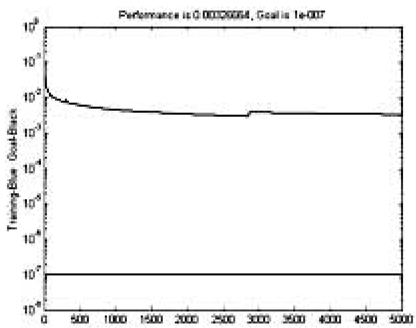

Figure 4: Neural Network with One hidden layer and 100 nodes

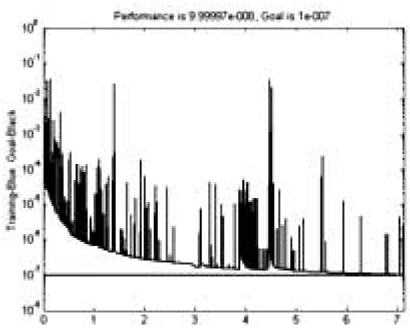

Figure 5: Neural Network with Two hidden layer and 400 x 200 nodes

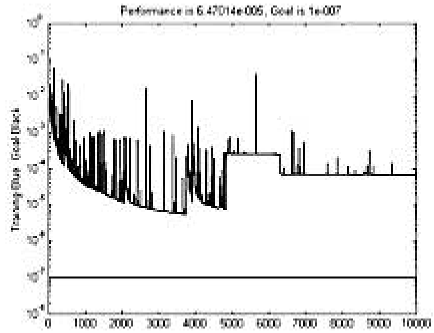

Figure 6: Neural Network with Three hidden layer and 200 x 300 x 6 nodes

The results from the experiments show that 2 hidden layers are enough to achieve a high precision for this problem, and 400 x 200 nodes are best suit considering the precision (*error goal* is 10^{-7}).

In the implementation 1500 samples are obtained from the model in Section 3, among which 1000 samples are used to train the network and 500 samples are used to test the network. For each testing sample, square errors of the actual output and desired output are calculated. The result from the experiments shows the network can achieve rather accurate results about Transfer Probabilities for most input of the initial states in the testing samples. Although the training time is very long for Neural Networks (about 12 hours in the simulation), the execution for each input vector is very fast after training. So we can train the networks off-line, and implement them in the real situation after training. During the simulation, the execute time for each input vector of the network is in the unit of millisecond (*ms*). So it satisfies the requirement of real time communication.

IV. RESOURCE RESERVATION ALGORITHM

To make the algorithm works properly the user 's initial states should be recognized to the system. The position location systems have become a hot issue over the past few years in wireless communications. So far, a number of position location systems have been based on GPS (Global Positioning System) but today we can examine the position location system using IS-95 CDMA networks [6,7,8]. The signal measurements (AOA or TOA/TDOA) are used to determine the signal direction or the propagation time of radio path from/to an MS to/from BSs. As a result, the system can efficiently determine the states of all subscribers in the system. It's not the objective of this paper to provide comprehensive coverage of such position location system and the interested reader is encouraged to refer the detail at any sources by themselves.

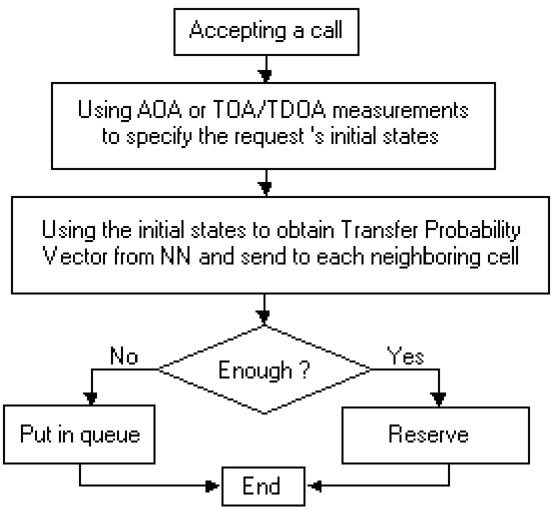

Figure 7: Resource Reservation Algorithm

The flow diagram of the channel reservation is shown in Fig.7. When system accepts a call, its initial states calculated by using position location system (AOA or TOA/TDOA). Then the current base station will use the obtained initial states to calculate the Transfer Probability through Neural Networks and exchange the information with other neighboring base stations. Then, each of the neighboring base station calculates the number of reserved channels according to the equation 5.

$$R(i,j,k,t) = P(i,j,k,t) * r(i,j) \qquad (5)$$

P(i,j,k,t) is the Transfer Probability of the user *j* in the cell *i* to neighboring cell *k* at time *t*, where $k \in S_i$ and S_i is the set of all neighboring cells of the current cell *i*. Assuming *r(i,j)* is the total resources required to achieve Qos guarantee, *R(i,j,k,t)* is the resources reserved in the neighboring cell *k* for such user at time *t*.

After finishing calculate the number of reserved resources, each neighboring base stations will use the result to check whether there are enough resources to be reserved for handoff or not. If enough, each base station add the number of reserved resources for this user to the reservation pool. If not, such user will be placed into queue waiting for enough resources to be reserved from the system. When a handoff request is received, the base station will check the reservation, if there are enough reserved resources for the handoff, it will allocate the required resources to the user from its reservation pool and calculate the Transfer Probability Vector again. Based on such information, its new neighboring base station will recalculate the number of reserved resources for the future handoffs. If there are insufficient resources in the reservation pool, the request will be denied and the call is dropped. When a user breaks connection, the base station will notify all the neighbors to release the resources reserved for it according to its Transfer Probability Vector.

V. SIMULATION

The simulation is performed among a cell cluster of six hexagonal cells and has a “wrap around” topology. That means, when a user exits the cluster boundary, say at the point in the East Side, it will enter the cluster from the related point in the West Side of the boundary. This ensures no user will move out of the cluster and become unknown to the system, and each cell has 6 neighboring cells. Each cell has its own coordinate axis, when a user goes out of the current cell its states will be transformed to the new coordinate axis.

The simulation consists of two control parts: one is call admission control and the other is resource reservation. In this simulation, handoff requests are given higher a higher priority than new call attempts. The parameters used for the simulation are stated as follows.

1. Cell radius *r* = 500 m.
2. All base stations in the system have the maximum queue length of 10.
3. Each call initialized by a user has a normal distribution, which has an average time 30s.
4. The population of new users generated in each cell is a uniform distribution [0,10], and the resources requirement of each user is a uniform distribution in [1,10].
5. New users are generated randomly with the initial positions $P(x_0,y_0)$ uniform distributed in the cell, and the velocity V_0 is a normal distribution with a mean 6 km/h and variance 4 $(km/h)^2$, and direction Q_0 is a uniform distribution in $[0,2\pi]$.
6. Each user moves from the current position to a new position with a constant speed during a short time interval τ = 4s. At the end of the time interval, the speed will change with the acceleration d_v, which is a uniform distribution in [0,2 km/h], and the direction difference d_Q , which obeys a uniform distribution in $[0,2\pi]$.
7. Each user keeps moving by iterate step 5 until it leaves the current cell and enters one of its neighboring cells.
8. At any time interval, all handoff requests and new call requests are managed by the call admission control algorithm, which is not present in this paper. If the requests are accepted, the resource reservation algorithm will be performed to reserve resources in related base stations.

Figure 8 shows the Handoff Call Dropping Rate (HCDR), which is the ratio of the number of failed handoffs to the total number of handoff requests. It shows no handoff drops during the whole simulation time. This is because higher priority is given to handoff attempts over new call attempts

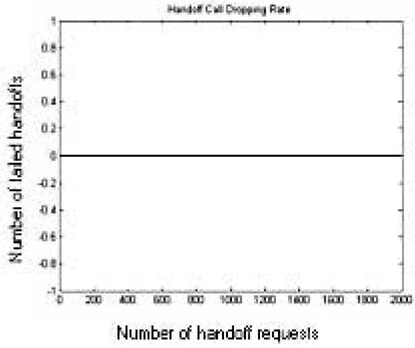

Figure 8: Handoff Call Dropping Rate

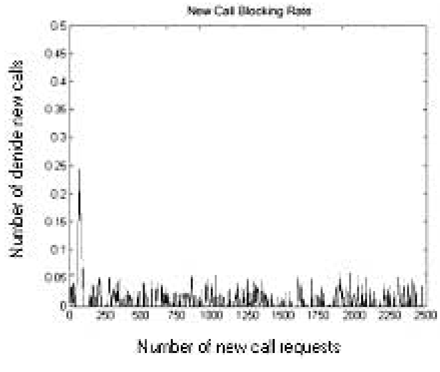

Figure 9: New Call Blocking Rate

Figure 9 shows the New Call Blocking Rate (NCBR), which is the ratio of the number of denied new calls to the total number of new call requests. It shows a little high at the beginning of the simulation, but when the system runs to balance, it kept around 0.05, which is acceptable in a heavy traffic. There is a tradeoff between HCDR and NCBR. When the system cal tolerate higher dropping handoffs, more new call attempts will be admitted to enter the system.

VI. CONCLUSION

The next generation CDMA cellular networks, resource reservation will be more and more important because handoff will occur frequently in small size cells, and the resources will be more and more limited for multimedia applications.

This paper proposes a resource strategy for cellular CDMA system with small size cells. In stead of predicting the destination cell, the Transfer Probability Vector is used to guide reservation. The reserved resources in each base station are proportional to the user's Transfer Probabilities.

And also implement the movement model suggested by W.W.H. Yu and Changhua He to obtain the relationship between the user's initial states and its Transfer Probabilities. And also the structure of Multi Layer Back Propagation Neural Networks model are proposed to approximate the relationship after training with the samples obtained from the movement model.

The simulation result shows that such strategy can achieve successful handoff call dropping rate and acceptable level of new call blocking rate.

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