LOCATION PREDICTION IN CELLULAR NETWORK USING NEURAL NETWORK

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ABSTRACT

The mobility management is an important issue in the cellular network, where it is deal managing of the limited frequency BW, and managing the roaming of mobile station (MS). It consists of two parts, the first called hand-off, which deals with the frequency channel allocation and conserve the call during move between two adjacent cells. The second part called location management (LM), which is deal with how to track an active MS within the cellular network. LM will burden the network with many messages of paging and location update to make the network know the location of MS at any time. Many researchers attempt to improve the LM by using neural networks to perform location prediction.

In this paper, we will use back propagation multilayer neural network to learn the subscriber movement, and then using this trained network to predict the new location of the subscriber. The main aim of this paper is to reduce the total cost of LM by using the prediction of subscriber location instead of using the traditional LM schemes. We get a more than 69% correct prediction for the random walk mobility pattern as will see in the results.

I. INTRODUCTION

The wireless communications exist from the Second World War, but it was limited because of the limited frequency bandwidth (BW). Many researchers try to improve the capacity of the network but the landmark improvement become when the cellular concept developed in Bell laboratories in the 1960s and 1970s [17], [18]. The cellular concept solves the problem of spectral congestion and user capacity, where the service area partitioned into many sub-areas called cells. In this approach the same channels can be assigned to many cells not in the vicinity (frequency reuse). For large network capacity, the cell size must be reduced for more efficient use of the limited frequency spectrum allocation. The main concept in cellular network is the efficient use of the limited frequency spectrum allocated, which is appearing in frequency reuse concept.

The operation of tracking an active MS during his roaming is called mobility management, it consists of two parts, radio mobility, which mainly consist of hand-off process, and network
mobility, which mainly consist of location management[1], [2]. When a MS crossing a cell boundary during a call, it is needed for a new pair of channel in the new cell to conserve the call from dropping, this operation called hand-off.

Location management (LM) consists of two basic operations, location update and paging. We can define the paging process as the operation of searching all possible cells that the MS can be found in it. This operation is done by the network, when a new call request arrives for that MS, the network page all possible cells for that MS, knowing MS location, and then the network delivers the call for that MS. The location update (LU) is done by the user equipment (MS). This operation is summarized by informing the network by the MS location. To perform paging and location update operations, many signals will initiate and received from network to MS and vice versa, this will occupy different network elements and this occupancy of network infrastructure is defined by cost.

There are many schemes for performing LM, location area [5], reporting cell [6], distance, movement, and time based location update [7], profile based [8], and many other schemes. Each of them is to perform the LM with some improvement in the cost.

There is a tradeoff between location update and paging, when the MS is never making location update, the cost of location update will be minimized, but we must search all cells to find a MS, the paging cost will be of maximum value. For the inverse case where the MS make a location update frequently, the network will know the MS at any time where he is, and there is no need to paging for a MS, the cost of paging will at minimum while the location update will be of maximum value. However, the total cost can be reduced or one cost can be reduced by putting a band on the other cost [3], [4].

Other researchers adopt the prediction of the new MS location, instead of the previous schemes. They use the neural network with the user profile to predict the new location of MS, they use the movement history of the MS to train a NN with the subscriber movement and use this trained NN to predict his location. Where each MS has its own mobility pattern depending on itself and the cell it is crossing. In [9], the author assume a network operate with a predetermined location update scheme, and use the history of a subscriber to learn a multilayer perceptron (MLP) network. When a call arrives, and depending on the recent inputs obtained during the last update of the MS, the present location can be predicted using the trained MLP network. The author uses the distance and angular deviation as inputs to MLP network, this input gets it from crossing cell ID, angular deviation, time stamp, and cell residence time. He proposes the origin at the center of the cell of last update or call termination. He shows that 75% of users can be located just in first attempt.

In [12], the authors propose a mixture of experts’ model to predict the precise location of an MS to a suitable base station (BS). Each expert is a neural network trained to work best in a particular region of input vector. The input vector of the expert model contains the user coordinate determined depending on the signal power strength, subscriber identity module (SIM), and timestamp corresponding to each user coordinate. The expert one relies on coordinate to determine the BS identification, whereas expert two to work best on time stamp and SIM of the calling MS to determine BS identification. After training, the test of mixture of experts shows a reduction in cost with them. The authors propose the MS residing at his place (disaster case).

In [10], the author propose a back propagation neural network (BPNN) with time and coordinate (X, Y) as the input vector, the output will be predicted coordinate. They propose a predetermined subscriber movement pattern and then train a BPNN with this pattern, the test results shows the predetermined pattern can predict accurately. However, if there is no definite pattern and the user is visiting places that he has never visited before, the results obtained are not accurate and are off by more than 60%.

IN [11], another signal strength based neural network technique is proposed. Distance estimation is made based on the signal attenuation between MS and the BS. The transmitted power is known and the received power is measured. The propagation model is used to estimate the length of
the radio path. Then using of this data to train MLP neural network using Levenberg-Marquardt back propagation algorithm, the results shows an error in coordinating estimation, the author explains the error because of the smaller training set, and can improve the estimation results by taking a larger set of training readings.

In [14], a user profile learning (UPL) strategy is proposed. By observing the mobile user's daily behavior and training a BPNN this behavior and then can use trained network to predict the new location of MS. This strategy associates to each MS a list of cells where it is likely to be with a given probability in each time interval. The list is ranked from the most likely to the least likely place where a user may be found. When a call arrives for a mobile, it is paged sequentially in each location within the list.

In [15], another use of BPNN to predict subscriber new location, the author proposes an adjacency matrix where the cell number and its adjacency cells numbers are stored. The author proposes a predefined subscriber tracks, after that train a multi layer NN with this track. Each step in the track defined by distance and direction. The simulation results shows that achieved an average of 93% prediction accuracy in uniform movement, 40% to 70% for regular movement and 2% to 30% for random movement patterns of an MS.

In this paper we propose a three imaginary reference point, and calculate the distance between each cell and the three reference points. Another assumption, we are numbering all cells in the topology in an incremental way from the first cell to the last cell, and finally we determine each cell coordinate. All this data are used to train a multi layer back propagation neural network (BPNN). This trained network can be used to predict the new location of MS. Where each MS tend to move in a similar way every day, we take the movement of MS during 24 hours, and the 24 hours divided into 72 time slots, each time slot equal to 20 minutes. The user movement during a day has a stationary point where he stays for a long time, like a house or office. The proposed NN at first classify the movement of a MS, and then use a NN for each class.

We get a very good prediction for a MS location during the day’s hours, this will increase the knowledge of the cellular network with user location at any time, of which serve to reduce the location update operation to a minimum limit.

We will illustrate the location management systems in section II, Our proposed scheme of location prediction based neural network will be discussed in section III. And we will discuss the simulation and results in section IV. Finally the conclusion will be in the last section V.

II. LOCATION MANAGEMENT SYSTEMS

Location management deals with how to keep track of an active mobile station within the cellular network. There are two basic operations involved with location management: locations update (LU) and paging. The paging operation is performed by the cellular network. When an incoming call arrives for a mobile station, the cellular network will page the mobile station in all possible cells to find out the cell in which the mobile station is located so the incoming call can be routed to the corresponding base station. This process is called paging. The number of all possible cells to be paged is dependent on how the location update operation is performed. The location update operation is performed by an active mobile station. The location update and paging will employ the infrastructure of the cellular network, and this occupancy represented as a cost.

For cost calculation, we will consider a movement based location update scheme, where a threshold movement (D) achieved to perform location update operation. In this scheme, when a new call arrives the network will pages all cells with a distance (D) from the last registered location of the called MS. We propose a two dimension topology with hexagonal cells in the same size, the mobility of MS is a random walk [16]. For performance comparison we will rely on this work for cost calculation. Where the probability of moving and the probability of call arrival were taken in cost
calculations. We calculate the cost for a MS moving in two dimension topology with call arrival probability of 0.01, the cost of performing a location update is 100, and the cost of polling a cell is 1. We take the paging delay bounds as one (paging all cells in the location area at one time). And finally we consider the moving probability is varied from 0.001 to 0.5. We make (D=3) to complete the cost calculation. Figure 1-a show the result of total cost, we noted that the cost increase with the probability of moving increase, and figure 1-b show only the update cost.

![Figure 1: (a) total cost, (b) update cost](image)

Figure 2 shows the effect of the threshold distance (D) on the cost in one dimension topology (ring topology) [7], the total cost increase with increasing D.

The cost reduction can be performed by prediction in two ways, the first by prediction the new location instead of threshold distance and this will increase the threshold distance (D) for location update [7], and will reduce the cost. The second reduction by search the predicted cell and if the MS not found the search will include the first and the second tiers of the predicted cell.

![Figure 2: update and paging cost with threshold dis. D](image)
Every subscriber has its mobility pattern and many people during day hours visit the same location, start from home, then move to work place and maybe take a trip to the supermarket and then back home. For this reason when we use an intelligent network that can predict the subscriber location at any time, the location management cost will be reduced obviously.

Depending on the subscriber movement history, we can use a BPNN to learn his mobility pattern, and predict his location when a new call arrives for that subscriber.

We used three layers NN, in the hidden layer we use a sigmoid function (1) as a transfer function, and in the output layer we use a tan sigmoid function or the bipolar sigmoid function (2) [13].

\[
f(x) = \frac{1}{1+e^{-x}} \quad (1)
\]

\[
f(x) = \frac{1-e^{-x}}{1+e^{-x}} \quad (2)
\]

For preparing the input data for NN we use a linear normalization to make the input limit between -1 and 1 as in (3).

\[
y = \frac{2 \times (x - x_{\text{min}})}{(x_{\text{max}} - x_{\text{min}}) - 1) \quad (3)
\]

Where:
- \(y\) = normalized value
- \(x\) = input number
- \(x_{\text{min}}\) And \(x_{\text{min}}\) = the minimum and maximum numbers for this input.

**III. LOCATION PREDICTION BASED NEURAL NETWORK**

We propose a cellular system consist of 19 location area, each location area consist of 3 tiers that is 37 hexagonal cells per location area. All cells in the topology numbered incrementally, also the location area numbers. We define each cell with its number (ID) and its coordinates. After that, a database matrix calculated, this matrix include all topology data, cell number, location area number, cell number with respect to location area, cell coordinates, and the distances of the three reference points. Each row will represent one cell.

We define many tracks, uniform and random tracks, each of them described by the time slot number and cell ID. Figure 4 shows a sample of uniform and random tracks.

Our proposal is defined per user, where each user has its history and then his prediction NN. Before training phase, the inputs of NN collected from a database matrix with respect to track information. We propose a daily movement which it means there is a stationary point where the subscriber will stay for a long time like home or office.

For this reason we divide the user track to many sub tracks, and use a BPNN to train this sub track. The dividing process depending on time slot numbers and the correlation between cells coordinate (figure 3).
Where the stationary points will be a sub-track, the cells with positive correlation will be a sub-track, and finally the cells with negative correlation. Each track will divided at least for three sub-tracks, therefore at least a three NN for any subscriber to predict his location. The first sub-track starts from cell number 44 (the lowest cell in uniform track) and move upward to cell number 660, the second sub-track start of cell number 643 (the highest cell in the uniform track) and move downward to cell number 44, the last sub-track is the stationary part where the subscriber will stay for 23 time slots in this cell. The tables 1 and 2 illustrate the two tracks each with its sub-tracks.

**Figure 3:** Multi neural network

**Figure 4:** proposed topology with tracks, black stars are the uniform track, blue circles are the random track, and the square is the start of each track, the cyanic squares are the start of each track.
IV. SIMULATION RESULTS

After training we take parts from track and feed it to NN and collect the result, the identical percentage calculates as:

\[
\% = \frac{\text{correct predict} - \text{error predict}}{\text{total no.}} * 100\% \quad (4)
\]

We feed the sub-track one by one (table 1), and collect the results. Because of we take the cell center coordinate as a target, we calculate the distance between the target cell center and the predicted cell center to simplify our results, we also calculate the difference between target coordinate and the predicted coordinate.

We start with uniform track part 1, figure 5 show part one of the track (sub-track 1) as the black stars, and the output of the NN as the blue circle, figure 6 show the errors.
We use cell diameter as 2.5 km, the distance between predicted and target cells center must be less than cell radius, (i.e. less than 1.25). From figure 6-a, the predicted coordinate is within the cell (87.5% correct prediction) where just three distances more than 1.25. In figure 6-c, we note 21 prediction results exact as a target, and only three results in the first tier. Finally the identical percentage of this part is 75%.

Figure 7 shows the results of sub-track 2 of the uniform track, here just two results located in the first tier (figure 7-c) where 91.3% of the results were correct and the identical percentage of this part were 82.61%.

We take the random track as in figure 4, this track consists of three sub-track as in table 2, we test the first

Figure 5: sub-track 1 of the uniform track

Figure 6: error of NN for sub-track 1, (a) the distance between predicted and target cells centers, (b) difference between coordinate, and (c) cell location
Figure 7: error of NN for sub-track 2, (a) the distance between predicted and target cells centers, (b) difference between coordinate, and (c) cell location

Figure 8: random track, sub-track 1

Sub-track (as in figure 8) where the tested sub-track with predicted results, the results showed in figure 9.

Figure 9: error of NN results for random track, sub-track 1, (a) the distance between predicted and target cells centers, (b) difference between coordinate, and (c) cell location
From 39 inputs, there are 6 results in the first tier of the target cells, and all other 33 results were exact predicted. Figure 9-a show the distance between target and predicted cells, it is clear the distance is less than 1.25 for all 33 good results. There are 84.6% as an exact prediction and the identical percentage of this part were 69.23%. Finally we test sub-track 2 of the random track, figure 10 show the target and the predicted track. And figure 10 shows the error graphs.

![Figure 10: random track, sub-track 2](image)

In figure 10 we note exact prediction for the whole track, the percentage exact prediction was 100%, and the identical percentage was also 100%. Figure 11 shows the error graphs for this part. In figure 11-c we note all predicted cells matched with the target and error in the distance (figure 11-a) was for all results less than 1.25. Table 3 shows all results for comparison.

![Figure 11: error of NN results for random track, sub-track 2](image)
### Table 3: the results

<table>
<thead>
<tr>
<th>Test</th>
<th>Prediction %</th>
<th>Identity %</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Unif. sub-track 1.</td>
<td>87.5</td>
<td>75</td>
</tr>
<tr>
<td>2. Unif. sub-track 2.</td>
<td>91.3</td>
<td>82.61</td>
</tr>
<tr>
<td>3. Rand. Sub-track 1.</td>
<td>84.6</td>
<td>69.23</td>
</tr>
<tr>
<td>4. Rand. sub-track 2.</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

## V. CONCLUSIONS

In this paper we introduce a subscriber pattern learning strategy using back propagation neural network to reduce the total cost of location management by increasing the accuracy of prediction of subscriber location. The prediction gives the nearest cell to the target; when the network page a MS, it will page a predicted cell, or cells in the first tier instead page all location areas. Obviously the total cost will reduce, the location update cost reduced by prediction, instead periodically location update, and the paging cost will reduce by intelligent paging some cells instead paging all location areas. Another benefit of prediction is the case of zigzag, when the subscriber roaming in the boundary of two adjacent location areas, in location prediction no need for repeatedly location update messages, the cellular network can locate the subscriber at any time.

## REFERENCES


