



APPLICATION OF NEURAL NETWORK TECHNIQUES FOR LOCATION PREDICATION IN MOBILE NETWORKING

Pradeep Bilurkar, Narasimha Rao, Gowri Krishna and Ravi Jain,

Mahindra British Telecom Ltd, Sharada Centre, Erandwane, Pune, India, 411 004

ABSTRACT

Over the last few years, the worldwide cellular communication market has undergone the exponential growth. This can be attributed to several factors like decreasing prices, improved radio coverage, lightweight and compact terminals. In order to accommodate higher subscriber densities, the standard technique used is to reduce the radio cell size. However, reduction in cell size increases signaling for location management procedure, which reduces the effective bandwidth available for the user traffic.

Location management in general and location prediction in particular incorporates procedures with which system can locate particular mobile subscriber at any given time. Number of location prediction algorithms have been developed in the recent past. In this study, a technique of Artificial Neural Network has been used for Location Prediction of a mobile subscriber. In the present paper learning methods like Back Propagation, back propagation with momentum, quick propagation and resilient propagation has been applied. Results are compared with conventional Box Jenkins forecasting technique.

1. INTRODUCTION

In wireless communications network, mobile users receive and place calls through a wireless medium. When a call arrives for a user in cellular network, it is necessary to locate the mobile user correctly and efficiently in order to route the call appropriately. Currently two standard techniques, Paging [1] and Location Update [2] are used for this purpose. In 'Paging', network sends the signal to search the subscriber when call arrives while in 'Location Update' subscriber sends the signal to inform the

network, his current location. In either case, paging is viewed as a fundamental operation. There is a trade off between the frequency of location update and paging costs: if location updates are frequent, there is a less uncertainty about the user's position and fewer calls need to be paged. On the other hand if location updates are infrequent the cost of paging increases.

In wireless network, apart from location management, in order to guarantee quality of service (QoS) to the subscriber, it is necessary to maintain connectivity to the mobile terminal even if the terminal frequently changes its physical location. The QoS can be guaranteed if the system knows, prior to the mobile subscriber movement, the exact trajectory it will follow. With this information the system can determine if there are enough resources available along with the mobiles path for the lifetime of the connection. If such is the case, the system can plan in anticipation the mobile subscriber's demand, and take appropriate steps such as setting up end to end routes from base stations in mobile subscriber's path, reserving resources along these routes and planning quick handoffs between the involved base station. Thus, Location prediction is the key issue to provide quality of service to mobile subscriber.

Several techniques have been proposed to predict the future location of the mobile user based on the available historical data [3-8]. These techniques can be grouped into two. First group of technique uses only mobile subscriber's current time as the basis for prediction of his future location whereas second group relies only on the current state of the mobile user to predict his future location. However, in reality it is found that the location of a subscriber does not depend only on time but also depends on it's current state. Thus, these techniques can not predict the correct location, if the subscriber shows

different movement patterns at different times. Hence it is necessary to develop a location prediction technique that will take care of both the parameters, state and time, into consideration.

Neural Networks (NN) are very sophisticated modeling techniques capable of modeling extremely complex functions. In particular, NN are non-linear. These networks learn by example. NN user gathers representative data, and then invokes training algorithms to automatically learn the structure of the data. NN methodology for location prediction can be applied in two steps. In the first step, suitable NN is trained with observed motion pattern. (It is important to note that prediction is not possible unless some regular subscriber movement patterns are detected and stored in the database.) In the second step the trained NN is used for prediction, the actual movement and time is used to feed to the trained neural network to get the next location.

In the present study we have explored the possibility of using NN technology to predict the mobile users next location prediction based on the information of his current location as well as time.

Conventional statistical techniques that include one of the advanced statistical techniques, like Box-Jenkins have also been explored to predict the mobile subscriber location. Results of the techniques are compared. We have used in house developed software packages for both Neural Network and Box-Jenkins.

2. MOBILE SUBSCRIBER DATA

Mobile subscriber's movement data is usually stored in the form of tables. Mobile subscriber data used in the present study is an emulated one. The assumptions that are used during emulation of the data are as follows:

It is assumed that each cell is square in shape (Usually cells are assumed to be hexagonal in shape) and its location can be represented by its longitude and latitude on the map. This means that with the change in physical location of mobile subscriber, the longitude and latitude are updated in the database. For the simplicity we have referred longitude as x co-ordinate and latitude as Y co-ordinate. We have also assumed that each mobile subscriber sends the signal to the base station in fixed time intervals of 20 minutes. Thus, in 10 hours

time one can have 30 data points per day. Six weeks data for each subscriber has been emulated.

3. NEURAL NETWORK ARCHITECTURE

The multilayer NN architecture used in the present study is shown in the Figure 1.

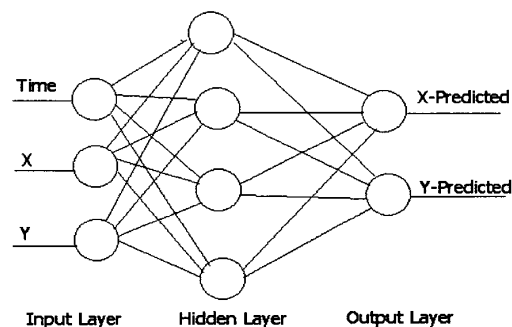


Figure 1: Neural Network Architecture

Back propagation (BP) learning algorithm, which was developed by Rumelhart, et al. in 1986, has been used in the present study. Three inputs in the form of time, X and Y co-ordinates of the cells are fed to NN. X and Y co-ordinates of the predicted cell in next interval of time is obtained from two outputs. In this algorithm, a given input pattern is forward propagated, the error is determined and error is back propagated to update the weights. With enough learning the algorithm converges to a minimum error.

However, it is observed BP has major disadvantage. Depending on the learning rate either convergence is slow or it oscillates around the minimum. Several modifications have been suggested to improve the convergence. BP with momentum, quick propagation and resilient propagation techniques are some of them. In the present study all the three modified learning algorithms have been used. Normalized input data is used during the study, so that values of input as well as output will always lie between 0 and 1. Learning using back propagation is the method of learning by example. During learning phase of the NN, expected output is also fed to the NN along with input. The expected output is the input data shifted with one delta time, (20 minutes in this case). We have also

assumed that location area and the page area are same and one cell corresponds to one location area.

3.1 Box-Jenkins Method

Box-Jenkins is basically time series based forecasting technique. Pre-processing of the input data is an essential step in applying this methodology. Also, it requires a minimum number of data points for predicting next point in the time series. In-house developed Box-Jenkins software package requires minimum 25 data points. The emulated data for ten different users was tested with this technique.

4. NEURAL NETWORK RESULTS

A typical emulated subscriber movement pattern is shown in figure 2. Each square is assumed to be one cell.

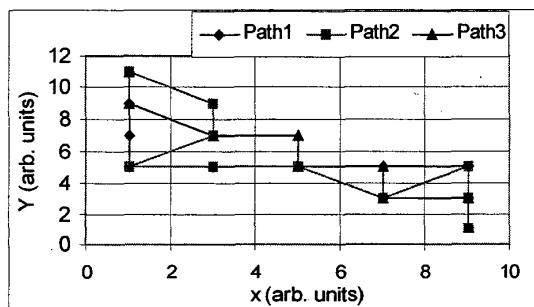


Figure 2. Typical Subscriber Movement Pattern

Note that for every subscriber a separate NN is trained, keeping the architecture and all other parameters same. During learning of the each NN, out of six weeks data, four weeks data is used. One week data is used for validation of learning of NN. After satisfactory learning, remaining one-week data is used for testing.

After applying NN technique for prediction of next location, predicted X and Y co-ordinates are mapped to the corresponding cell. This is mapped to the cell number or to the corresponding longitude and latitude of the cell.

All four learning algorithms are applied. Results show that all four techniques yield promising results but resilient propagation method gives better results. The mean absolute percentage error (MAPE) in case

of the results obtained with BP was found to be ~30% and that in case of BP with momentum it was ~41%. Average MAPE obtained with Resilient Propagation was found to be as low as ~13%. The graphs of best result obtained with Resilient Propagation and BP with Momentum are shown in figure 3 and figure 4 respectively. In both the figures diamonds represent targeted points while squares represent NN predicted point. It can be seen that predicted points closely match with the targeted points, when neural network was trained with resilient propagation technique. Most of the predicted points lie in the same cells in which the targeted points lie.

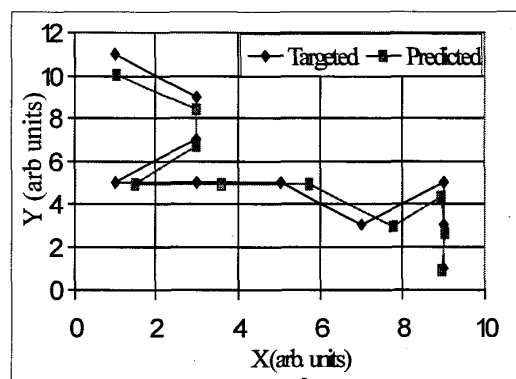


Figure 3. Resilient Propagation Result

In case of BP with momentum, difference between targeted points and predicted points is larger. It can also be more than one cell.

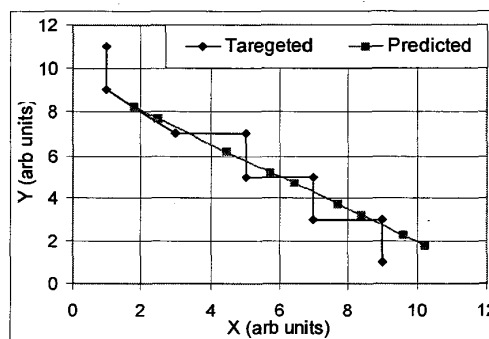


Figure 4. BP with momentum Result

MAPE (Mean Absolute Percentage Error) for ten different users is calculated using the NN output. The results are shown in table 1.

User	X-MAPE	Y-MAPE	Avg. MAPE
A	12.79	13.78	13.29
B	7.46	7.52	7.49
C	9.52	13.69	11.60
D	13.88	15.40	14.64
E	6.48	4.00	5.24
F	7.50	11.29	9.39
G	13.33	16.23	14.78
H	17.17	6.66	11.92
I	9.85	9.90	9.88
J	3.14	16.73	9.94

Table 1. MAPE for Ten Users

It can be seen that, depending on the user travel pattern, MAPE vary between 5% to 15 % approximately.

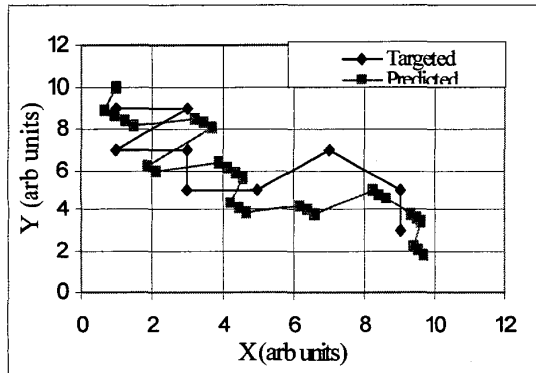


Figure 5. Out put for Near Random Behavior

In order to emulate the travel paths, close to realistic ones, some paths are chosen wherein no definite travel patterns are observed. One can say such mobile user's travel pattern show near random behavior. A typical output obtained from NN is depicted in figure 4. From the figure it is evident that predicted outputs are far off from the expected one.

4.1 Box Jenkins Results

Statistical methods like ARIMA, moving averages and simple exponential are also applied to the emulated data. It is observed that moving average method yields better result with prediction probability more than 50%. Though the Box Jenkins method is advanced forecasting technique and in general it can be applied to any type of data. It requires that the data should be in stationary form. Some intelligent modifications are required in input data to use Box Jenkins technique in predicting the future location of the mobile user.

5. DISCUSSION

As mentioned earlier, figure 3 is one of the best-predicted results. In general it is observed that if a subscriber follows well-defined pattern, NN can recognize the underlying pattern and can correctly predict the next location. 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%. We have also studied the effect of number of hidden neurons on the predicted output. It is found that accuracy of the output increases as numbers of neurons in hidden layer are increased from 2 to 4. After four number of neurons in the hidden layer, the output gets stabilized.

6. CONCLUSIONS

Simple well-established neural network technique with resilient propagation learning methodology yields promising results. Results are close to the expected output for the subscribers that are following well-defined travel pattern. More advanced techniques such as Recurrent Neural Networks and Neuro-Fuzzy should be explored particularly for the travel paths that do not contain defined pattern. Advanced statistical forecasting techniques like an ARIMA method requires more data points, for predictions. Also, some intelligent modification in BJ methodology needs to be explored to use it for location prediction.

7. REFERENCES

[1]. ANSI/EIA/TIA, "Mobile station-land station compatibility specification," EIA/TIA Technical Report 553, 1989.

[2]. R Jain, Y-B Lin, and S Mohan, "Location Strategies for Personal Communication Services", The Mobile Communication Handbook, Jerry Gibson ed., CRP Press, 1996.

[3]. A Bar-Noy, I. Kessler and M Sidi, "Mobile Users: To Update or not to Update?" ACM -Balzar Journal of Wireless Networks, Vol 1, No. 2, pp. 175-186, July, 1994

[4]. I F Akyildiz and J.S.M. Ho, "Dynamic mobile User Location Update for Wireless PCS Networks," ACM-Balzar Journal of Wireless Networks, Vol 1, No. 2, pp. 187-196, July, 1995

[5]. J.S.M.Ho and I F Akyildiz, "Mobile User Location Update and Paging under Delay Constraints,"

ACM-Balzar Journal of Wireless Networks, Vol 1, No. 4, pp. 413-425, December, 1995

[6]. A Hac and Zhou, "Locating Strategies for Personal Communication Networks: A Novel Tracking Strategy," IEEE Journal on Selected Area in Communication, vol 15, no 8, pp. 1425-36, October 1997.

[7]. I.F. Akyildiz, J McNair, J.S.M. Ho Uzunalioglu, and W. Wang, "Mobility Management in Next Generation Wireless System," proc. IEEE, Vol. 87, pp 1347-1384, August 1999

[8]. Ian F Akyildiz, "A Dynamic Location management Scheme for Next Generation Multitier PCS System" IEEE Transactions on Wireless Communications," Vol. 1, No. 1, January 2002