Artificial Neural Network Based Node Location Prediction for Applications in Mobile Communication

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Abstract **- Present generation cellular networks provide different services to the mobile users. The movement of the users is highly dependent on individual characteristics. To offer an uninterrupted service to the mobile users, continuous tracking of its location is very important. This can be achieved by the proper location management schemes. In this paper, a prediction-based location management scheme for locating a mobile station is proposed. A multilayer neural network model for mobile movement prediction is designed to predict the future movement of a mobile host. The model is trained with the data obtained from the past movement pattern of a mobile host. The prediction method is found to give satisfactory results.**

Keywords **- Cellular communication system, location management, movement prediction, multilayer neural network.**

I. Introduction

Location update is an important issue in mobile cellular networks to provide efficient services at low cost. In a cellular communication system, the user movements are normally preplanned and the mobile station (MS) or mobile node (MN) is free to move within the entire service region. On call arrival, the network searches the terminal for call delivery and the process is known as terminal paging [1]. However, the amount of channel bandwidth required for these numerous broadcast signals can be extremely high. To make the paging process easier, every MN informs the network about its location periodically, the process being called location update. Future mobile networks will have to provide efficient and low-cost services to large number of subscribers. So location update has become a major issue to facilitate different services to mobile users.

Location management can be divided into two groups: static location management and dynamic location management. In case of static location managements location updating occur on either periodic intervals or upon every cell change. On the other hand dynamic location management is an advanced concept where the parameters of location management can be modified to be best fitted for individual users and conditions. However, dynamic location management proposals are excessively theoretical and complex, and are difficult to implement on a large scale.

There are two different location management services: location updating & paging. Location update is used to inform the network the location of the mobile device & paging is used to determine the current cell location of a user to route an incoming call.

In mobile networks, location updating and paging generate enormous traffic. Several attempts have been made to reduce traffic load [1-3]. One of the methods is to use mobile station movement behavior and their traffic characteristics to predict the future location of a mobile host. If the location of an MS is known in advance, then no explicit location updation is necessary and paging throughout the geographical area can be avoided, thereby reducing system overload.

In this paper, a prediction-based location management using backpropagation neural network is proposed. The method predicts the future location of a mobile station based on the history of its movement pattern. The network is trained with the data obtained from the history of movement pattern of a MN for making predictions for future movement.

II. Proposed Method For Location Update

The proposed method for mobile movement prediction is based on the MN's history of movement patterns, which has been recorded for a certain time duration. Multi-layer neural network is used to process the mobile movement pattern for accurate prediction of mobile movements.

Movement pattern (M_n) is the history of movement of a mobile station recorded for a period of time T_n, where n is the number of regular time intervals at which the mobile host movements are recorded. The time interval can be minutes, hours, days, etc. The movement pattern M_n can be represented by a data at regular time interval, $t_1, t_2, ...t_n$.

Let the movement pattern $M_n = \{m_1, m_2, ...,m_n\}$ be recorded for an MN, where M_i indicates the movement of a mobile host during time t_i, and we define the movement in terms of distance and direction traveled by the MN during the time interval t_i. Then M_i is represented by a pair (dis_i, dir_i) where dis_i is the distance travelled by a mobile host at i^{th} time interval which may be number of cells, kilometers, meters etc. and dir_i is the possible direction in which a mobile host moves at i^{th} time interval.

For example, if a mobile movement pattern is recorded for two time intervals (n=2) with direction of movements North and East and the distance traveled is 2 and 3 units, then the movement pattern is, $M_2 = \{m_1, m_2\} = \{(dis_1, dir_1), (dis_2, dir_2)\} = \{(2, North), (3, East)\}$. Training data set is the set of subpatterns obtained from the movement pattern m_n by partitioning it into x subpatterns, where x + 1 is the size of each subpattern (x << n). The subpattern is a training data pair with mobile movements for x time intervals as input and the movement for the next time interval as a desired output. For example, the first training subpattern is $m_1, m_2, ..m_x$ as input and m_{x+1} as the desired output.

The parameter x is the prediction order or time window, which is normally chosen based on the movement characteristics of a mobile host and the size of the recorded movement pattern [4 - 5].

In our work, we have considered two mobiles MN1 and MN2 with regular and random movement patterns respectively. Their movement patterns are given in terms of number of cells the mobile has crossed and the direction of movement. The training data sets for MN1 and MN2 are given in Table I and II respectively.

TABLE I: TRAINING DATA SET FOR MN1

dis1, dir1	**dis2, dir2**	**dis3, dir3**	**Output : Dis4, dir4**
(1, NE)	(1, E)	(1, NE)	(1, E)
(1, E)	(1, NE)	(1, E)	(1, NE)
(1, NE)	(1, E)	(1, NE)	(1, E)
(1, E)	(1, NE)	(1, E)	(1, NE)
(1, NE)	(1, E)	(1, NE)	(?, ?)

dis1 and dir1 = MN distance and direction during the first time interval; dis2 and dir2 = MN distance and direction during the second time interval; and so on and dis4 and dir4 = MN distance and direction observed at fourth time interval, i.e. desired output for the given input training data.

The directions are represented as follow –
North – N, East – E, South – S, West – W, North-East – NE, South-East – SE, South-West – SW, North-West – NW.

The table indicates that the MN1 Moves one cell distance in North direction, then one cell distance in North – East direction and so on. The size of subpattern is kept here to be 5. (?, ?) denotes the final output movement to be predicted.

TABLE II: TRAINING DATA SET FOR MN2

dis1, dir1	**dis2, dir2**	**dis3, dir3**	**dis4, dir4**	**Output : dis5, dir5**
(1, E)	(1, SE)	(2, E)	(1, S)	(1, E)
(1, SE)	(2, E)	(1, S)	(1, E)	(1, NE)
(2, E)	(1, S)	(1, E)	(1, NE)	(1, E)
(1, S)	(1, E)	(1, NE)	(1, E)	(2,S)
(1, E)	(1, NE)	(1, E)	(2, S)	(1, W)
(1, NE)	(1, E)	(2, S)	(1, W)	(1, SW)
(1, E)	(2, S)	(1, W)	(1, WS)	(1, W)
(2, S)	(1, W)	(1, SW)	(1, W)	(1, N)
(1, W)	(1, SW)	(1, W)	(1, N)	(?, ?)

By observing the directional changes in the movement pattern, suitable prediction order (k) is considered and the corresponding subpatterns are obtained. Here, the size of subpattern is kept to be 6. The neural network is trained with all the subpatterns to predict the movement (?, ?) of Table 1 and 2. The same data set are then used to predict multiple moves by updating the data set given in Table 1 and 2.

III. DEVELOPMENT OF NEURAL NETWORK MODEL

A mobile cellular environment is considered with rectangular array of cells in which the mobile stations can move freely. The possible direction which a mobile host can move is considered from the direction set D = {North, NorthEast, East, SouthEast, South, SouthWest, West, NorthWest} = {N, NE, E, SE, S, SW, W, NW}. The distance is recorded in terms of the number of cells traveled by a mobile station at each time interval. This distance is taken as the training inputs for our neural network model as shown in Fig.1 [6]. A three layer neural network with 8 hidden neurons was used to develop the model for mobile movement prediction. The training sets are formed from the data for direction of the mobile host in a particular time interval and the corresponding direction of the mobile host in next time interval is taken for output of the training pattern. A gradient decent back propagation algorithm has been used to optimize the weight vectors of the neural network model. A sigmoid function is used as activation function and eight different data sets were used to train the neural network for optimized movement pattern. The trained neural net model is used for direction/ distance prediction after proper learning. The testing of the model has been done with some arbitary data which have not been used in the training process. Multiple prediction results can be obtained from the trained neural network model with successive data sets. The role of the neural networks in this application is to capture the unknown relation between the past and the future values of the movement pattern. This helps in predicting the future location of a mobile host for location management.

The single movement prediction result for MN1 is found to be (1, E) i.e it moves one cell in East direction. Similarly, the predicted movement of MN2 is found to be (2, N) i.e it will move 2 cells in North directions. Then the data of Table 1 and 2 are updated using this predicted movement and the multiple prediction is carried out using the same model as shown in Table 3 and 4 respectively. The predicted output are shown by bold letters.

TABLE III: TRAINING DATA SET FOR MN1 AND PREDICTION RESULTS

dis1, dir1	**dis2, dir2**	**dis3, dir3**	**Output : Dis4, dir4**
(1, NE)	(1, E)	(1, NE)	(1, E)
(1, E)	(1, NE)	(1, E)	(1, NE)
(1, NE)	(1, E)	(1, NE)	(1, E)
(1, E)	(1, NE)	(1, E)	(1, NE)
(1, NE)	(1, E)	(1, NE)	(1, E)
(1, E)	(1, NE)	(1, E)	**(1, NE)**
(1, NE)	(1, E)	(1, NE)	**(1, E)**
(1, E)	(1, NE)	(1, E)	**(1, NE)**
(1, NE)	(1, E)	(1, NE)	**(1, E)**

TABLE IV: TRAINING DATA SET FOR MN2 AND PREDICTION RESULTS

dis1, dir1	**dis2, dir2**	**dis3, dir3**	**dis4, dir4**	**Output : dis5, dir5**
(1, E)	(1, SE)	(2, E)	(1, S)	(1, E)
(1, SE)	(2, E)	(1, S)	(1, E)	(1, NE)
(2, E)	(1, S)	(1, E)	(1, NE)	(1, E)
(1, S)	(1, E)	(1, NE)	(1, E)	(2,S)
(1, E)	(1, NE)	(1, E)	(2, S)	(1, W)
(1, NE)	(1, E)	(2, S)	(1, W)	(1, SW)
(1, E)	(2, S)	(1, W)	(1, WS)	(1, W)
(2, S)	(1, W)	(1, SW)	(1, W)	(1, N)
(1, W)	(1, SW)	(1, W)	(1, N)	(2, N)
(1, SW)	(1, W)	(1, N)	(2, N)	**(1, NW)**
(1, W)	(1, N)	(2, N)	(1, NW)	**(1, W)**
(1, N)	(2, N)	(1, NW)	(1, W)	**(1, W)**
(2, N)	(1, NW)	(1, W)	(1, W)	**(1, W)**

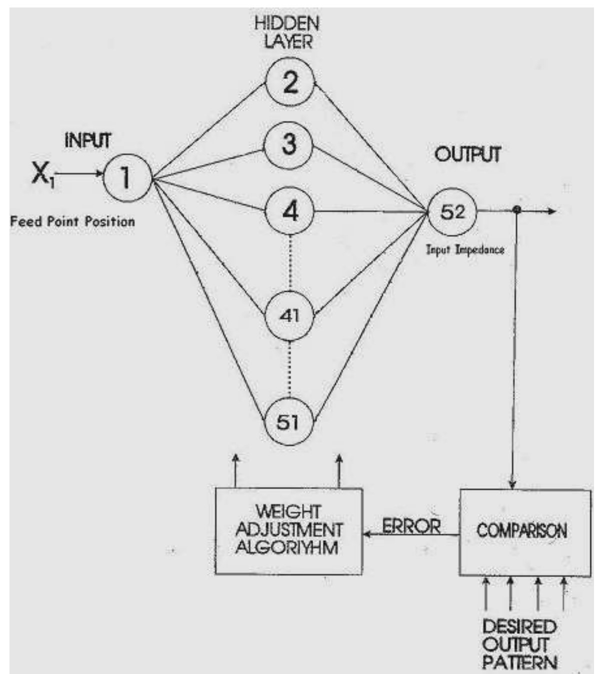

Fig. 1. A general Neural Network Configuration

IV. CONCLUSION

In this work, single and multiple movements of mobile nodes are predicted using artificial neural network which may be used as location update information in mobile cellular networks. The results for user with regular movement pattern show exact prediction. In future, the results for random movement pattern are to be tested and prediction accuracy is to be found out.

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