Prediction-Based Location Management using Backpropagation in Wireless Communication

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Abstract—**In a wireless communication system, wireless location is the technique used to predict the node location of a mobile station. To enhance the accuracy of a mobile station, an algorithm is proposed that utilizes location services to locate the mobile stations for multiple base stations. A multilayer neural network model for mobile movement prediction will be designed to predict the future movement of mobile host. The model will be trained with the data obtained from past movement pattern of a mobile host. Simulation and comparative analysis will be carried in MATLAB for different locations.**

Index Terms— **Cellular communication system, location management, movement prediction, multilayer neural network**

1.INTRODUCTION

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. 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 main stream of this research work is "ARTIFICIAL NEURAL NETWORKS". An artificial neural network consists of a pool of simple processing units which communicate by sending signals to each other over a large number of weighted connections. Location information is the major component in location based applications. This information is used in different safety and service-oriented applications to provide users with services according to their Geolocation. There are many approaches to locate mobile nodes in indoor and outdoor environments.

Our localization method is based on hello message delay (sending and receiving time) and coordinate information of **B**ase **T**ransceiver **S**tation (BTSs). To validate our method across cellular network, we implemented and simulated our method in two scenarios i.e. maintaining database of base stations in centralize and distributed system. Simulation results show the effectiveness of our approach and its implementation applicability in telecommunication systems.

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.Preliminaries

The node location can be done with the location management schemes which uses the various node location mechanisms involved in it. There are two management schemes used for locating the node. The schemes involved are 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. Static location management involves locating the node based on the cells available in the network. Static location is not used often. In the case of 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.

Consider a new dynamic LR area decision scheme, which continuously reflects the regional information and mobile characteristics such that the required number of paging and location updating signals is minimized. The minimization of the use of these two signals will eventually increase the capacity of the cellular system, even if the total usage might be restricted by the service level preserved at each cell. For the modeling of the decision problem, we introduce the two signal costs as follows:

Paging cost=α * #of_ call _arrivals * #of cells in LR area (1)

Updating cost=β * #_of_ updates (2)

where α and βare weights (bits/signal) of paging and updating signals ,respectively.

Note that the updating cost is proportional to the velocity of a subscriber, while the paging cost is proportional to the call arrival rate and the size of the area. If we assume the uniform distribution of subscribers in a region, the LR area size may be defined by either the radius or the length of the side of the area. However, under the nonuniform assumption, the density of subscribers and the moving tendency at each cell are not identical. Thus, the optimization of the LR area must be based on each cell. A cell may or may not be contained in the LR area of a particular subscriber. Now, at each cell included in the LR area of a mobile, a certain service level has to be met. In other words, a prespecified standard *o€* blocking probability has to be satisfied by the forward and reverse control channel between the subscribers and a base station.

III. Location Services

Two types of control signals are needed for paging and location registration. A paging signal from each base station pages a mobile for a call setup. A location updating signal on the other hand requests the telephone switching office to enroll and update the location of the mobile.

A.Location update

Location update is an important issue in mobile cellular networks to provide efficient services at low cost. Location update is used to inform the network the location of the mobile device 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. However, the amount of channel bandwidth required for these numerous broadcast signals can be extremely high.

LR-area Updating Procedure

(1) A subscriber sends an updating signal to a new cell.
(2) The cell sends the LR area updating request to the MTSO for the subscriber.
(3) The MTSO decides the new LR area based on the Dynamic LR-area Decision Scheme.
(4) Cell identifications of the new LR area are updated in the database of the subscriber’s VLR. The MTSO informs cell identifications of the new LR area to the current base station.
(5)The current base station sends the cell identifications of the new LR area to the subscriber

B.Paging

Paging is used to determine the current cell location of a user to route an incoming call. When a mobile telephone switching office (MTSO) receives a call request, it first scans the VLR in which the location of each subscriber is recorded. It decides the location according to the level of the response from each base station. The MTSQ then sends a paging signal to each registered cell of the subscriber.

Paging Procedure

(1) The MTSO that received a paging request scans response of the subscriber
(2) The MTSO sends the paging request to registered LR area cells of the subscriber.
(3) Each cell sends the paging signal and receives the VLR.
(4) If a response returns, each cell sends the response level to the MTSO.
(5) The MTSO decides the location of the subscriber with the response level of each cell.

IV. Neural network Model

Back propagation is a systematic method for training multi-layer artificial neural networks. It is a multi-layer forward network using extend gradient-descent delta-learning rule, commonly known as Back propagation. This provides computationally efficient method for changing the weights in a feedforward network, with differentiable activation functions, to learn a training set of input-output.

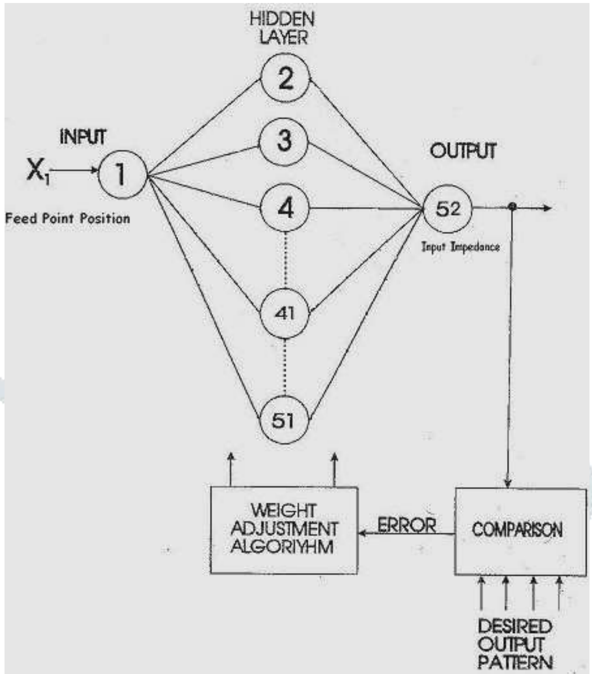


Fig.1:Neural network model

All the weights in the network are modifiable, and the network learns to produce the correct input output mapping by modifying these weights. The back propagation network is an example of supervised learning, the network is repeatedly presented with sample inputs to the input layer, and the desired activation of the output layer for that sample input is compared with the actual activation of the output layer, and the network learns by adjusting its weights until it has found a set of weights that produce the correct output for every sample input.

V.Prediction

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 P_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 P_n can be represented by a data at regular time interval$(t_1, t_2, \dots . t_n)$.

Let the movement pattern $Pn = \{p1, p2, ...,pn\}$ be recorded for a mobile MH, where Pi indicates the movement of a mobile host during time t_i, and we define the movement in terms of direction and distance travelled by an MH during the time interval t_i.

Here P_i is represented by a pair (d_i, d_{is}). d_i is the possible direction in which a mobile host moves at i_{th} time interval. For example, if we consider four possible directions, *North, East, South* and *West*, of movement of a mobile host, then d_i € {*North, East, South, West*}. If a mobile host moves towards North direction at i_{th} time interval, then d_i = *North. dis* is the distance travelled by a mobile host at i_{th} time interval. Here, the distance travelled may be number of cells, kilometers, meters, etc.

TABLE I: TRAINING DATA SET FOR MN1

$d_{is}1$, $d_{ir}1$	$d_{is}2$, $d_{ir}2$	$d_{is}3$, $d_{ir}3$	Output : $d_{is}4$, $d_{ir}4$
(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)	(?, ?)

Training data set

$d_{is}1$, $d_{ir}1$	$d_{is}2$, $d_{ir}2$	$d_{is}3$, $d_{ir}3$	$d_{is}4$, $d_{ir}4$	Output: $d_{is}5$, $d_{ir}5$
(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)	(?, ?)

Training data set is the set of sub patterns obtained from the movement pattern p_n by partitioning it into n - k sub patterns, where k + 1 is the size of each sub pattern (k << n). The sub pattern is a training data pair with mobile movements for k time intervals as input and the movement for the next time interval as a desired output. For example, the first training sub pattern is *p1, p2, ..pk* as input and *pk*+1 as the desired output. The parameter k is the prediction order or time window, which is chosen based on the movement characteristics of a mobile host and the size of the recorded movement pattern.

In general, suppose we have a movement pattern for n time intervals (time-lagged intervals), then for prediction order of k, there are n - k training *sub patterns*. The first training subpattern is *p*1, *p*2, ..*pk* as the inputs and *pk*+1 as the desired output. Similarly, the i_{th} training sub pattern contains *pi, pi*+1, ...,*pi*+*k*-1 as the inputs and *pi*+*k* as the desired output.

VI. Mobile movement prediction

The mobile movement prediction is to find the future movement of a mobile host from the MNN model trained with respect to the training data set. To predict the future movement of a mobile host, we can either go for single or multiple move prediction.

Single move prediction

This predicts the movement (p_{n+1}) of a mobile host at time interval t_{n+1} for the given movement pattern p_n.To carry out single move prediction, input the subpattern $\{p_{n-k+1}, p_{n-k+2}, \ldots . p_n\}$ to the MNN and the output obtained will be the predicted movement p_{n+1} for time interval t_{n+1}, which is the direction d_{n+1} and the distance ds_{n+1} travelled by a mobile host.

Multiple move prediction

This predicts the movement of a mobile host after several time intervals from t_n^{th} time interval ,i.e to predict the movement (p_{n+m}) of a mobile host, where m>1. A recursive method has been designed for multiple move predictions. In this method, the predicted output p_{n+1} is inserted as one of the inputs in subpattern at the extreme right by shifting the entire subpattern to left by one time interval to predict the next movement p_{n+2}.

VII. PREDICTION BASED LOCATION MANAGEMENT

The movement pattern of an MH travelled over a period of time $[0,T_n)$ is recorded and is processed to construct MNN model for mobile movement prediction. If an MH is to be located (or called) at time T_c with $T_c > T_n$, the system calculates the time difference between T_n and T_c to find how many time intervals ahead the prediction is to be carried out, i.e. If $m > 1$, then a multiple move prediction is carried out. [*m*] If $m = 1$, then a single move prediction is to be carried out.

The rationality behind the prediction of location of a mobile host is based on the following. In general, the movement of mobile hosts shows some pattern according to their movement behaviour. If the movement patterns for the previous several hours, days or months are investigated, some periodicity for the patterns will be exhibited . This periodicity is a key to predicting the future location of a mobile host.

Based on the above discussion, the movement patterns of a mobile host may be subdivided into *uniform*, *regular*, *random*, *zigzag* movements, etc. Uniform movements are the ones in which the movement of a mobile host will be in the same direction over a period of time considered.

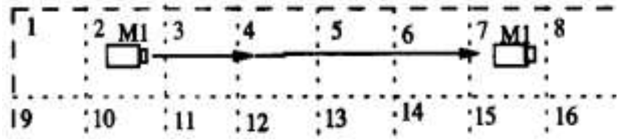
For regular movements the movement pattern will be periodic and deterministic in nature. Selection of neurons is the most important factor to be considered to develop an MNN model of appropriate size for capturing the underlying movement patterns in the training data. The selection of number of input and hidden layer neurons will largely fix the size of the MNN model. There are some thumb rules proposed, whose guidelines are some heuristic methods.

VIII. Model description

The neural network model designed with three layers p: input, hidden and output. The number of input neurons is an important parameter since it corresponds to the length of the sub patterns used to discover the underlying features in a given movement data. Too few or too many input neurons can have significant impact on the learning and prediction ability of the network. In practice, the number of neurons is often chosen through experimentation or by trial and error to have more generalization capability for the MNN model.

Also, while choosing the number of input and hidden layer neurons, care must be taken to avoid any under learning or over fitting of the training data. A set of input layer neurons is selected by experimentation results and correspondingly the length of the input training sub patterns or window size k of the training data that is considered for a given movement pattern.

Movement patterns



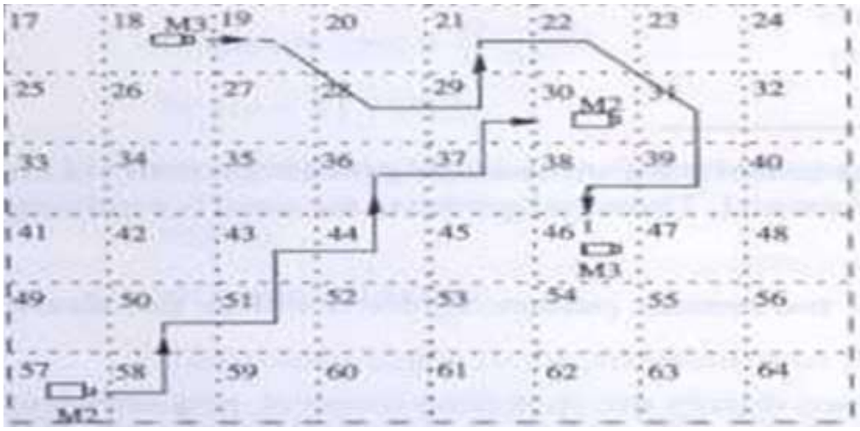


Fig.2: An 8*8 rectangular array of cells

The movement patterns are obtained as:

M1{2,3,5,6,7} for 4 time intervals

M2 { 57, 58, 50, 51 43,44, 36, 37, 29, 30} for 9 time intervals

M3 { 18,19,28,29,21,22,31,39,38,46} for 9 time interval:

From the cell-based movement pattern, we derive the direction and distance by using the adjacency matrix as preprocessing for prediction. The above movement patterns, preprocessed for obtaining the distance and direction of movement pattern using adjacency matrix.

For M1, the movement pattern is

P_4^1 = {(E,1), (E,2), (E,1), (E,1)}, where P_4^1 is the movement pattern of MI for four time intervals.

For M2, the movement pattern is

P_9^2= { (E,1), (N,l), (E,1), (N,l), (E,1), (N,l), (E,1), (N,l), (E,1)}, where P_9^2 is the movement pattern of M2 for nine time intervals.

For M3, the movement pattern is

P_9^3= {(E,1), (SE,1), (E,1), (N,1), (E,1), (SE,1), (S,1), (W,1),(S,1)},where P_9^3 is the movement pattern of M3 for nine time intervals.

The number of neurons in the hidden layer depends on the length of the sub pattern and the number of sub patterns provided for training. The number of output layer neurons depends on the output movement parameters and their representation. We consider direction and distance as the movement parameter; hence, there are two output neurons.

Adjacency matrix

N	NE	E	SE	S	SW	W	NW
57	58	02	10	09	16	08	64
58	59	03	11	10	09	01	57
59	60	04	12	11	10	02	58
60	61	05	13	12	11	03	59
61	62	06	14	13	12	04	60
62	63	07	15	14	13	05	61
63	64	08	16	15	14	06	62
64	57	01	09	16	15	07	63
01	02	10	18	17	24	16	08
02	03	11	19	18	17	09	01
03	04	12	20	21	18	10	02
04	05	13	21	22	19	11	03
05	06	14	22	23	20	12	04
06	07	15	23	22	21	13	05
07	08	16	24	23	22	14	06
08	01	09	17	24	23	15	07

09	10	18	26	25	22	24	16
10	11	19	27	26	25	17	09
11	12	20	28	27	26	18	10
12	13	21	29	28	27	19	11

TABLE III: TRAINING DATA SET FOR MN1 AND PREDICTION RESULTS

$d_{is}1$, $d_{ir}1$	$d_{is}2$, $d_{ir}2$	$d_{is}3$, $d_{ir}3$	Output : $d_{is}4$, $d_{ir}4$
(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

(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)**

$d1$and d_s1 = Mobile host direction and distance during the first time interval, respectively.

$d2$ and d_s2 = Mobile host direction and distance during the second time interval; and so on.

$d4$and d_s4 = Mobile host direction and distance observed at time interval 5, i.e. desired output for the given input training data.

We measure the average learning error and prediction accuracy as follows.

Average learning error=$\frac{1}{100-k}\sum_{i=k}^{100}(p_i - p_i')$^2 (3) where

p_i is the desired output

p_i' is the prediction output

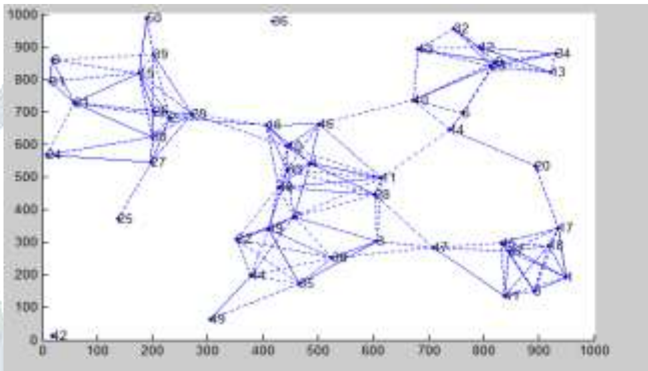
K is the prediction order

IX. Simulation and results

The simulation is done using MATLAB 9.0 and various results are obtained.

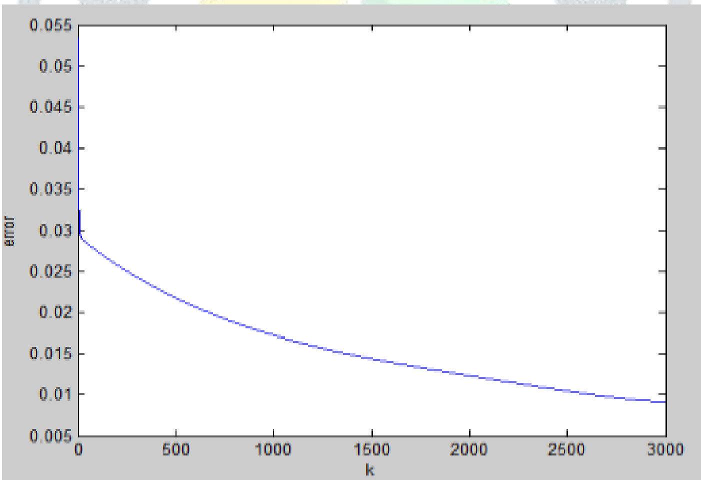
(1) Node location

The various number of nodes is located using node location mechanism involved in it. The node is located using the algorithm and the output is obtained. From this, there are totally fifty(50) nodes present in the network.

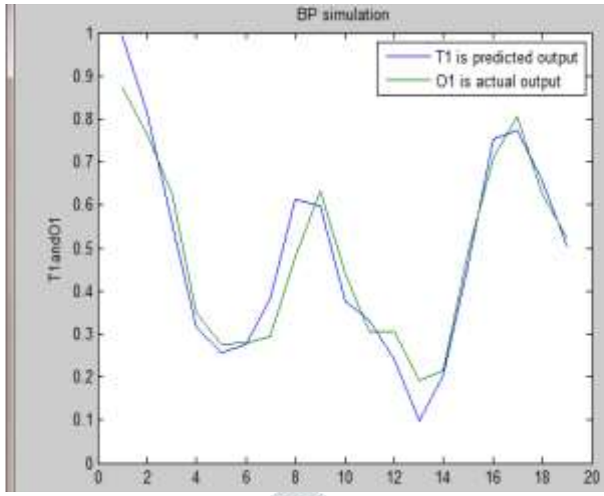


(2) Error performance

As the number of itearations(k) increases, the error gets reduced and performance is obtained.



(3) Predicted vs Desired movement



X.CONCLUSION

In this, a prediction-based location management in a mobile network is used. The approach uses a multilayer neural network to predict the future location of a mobile host based on the history of movement pattern of a mobile host. MNN model for single and multiple move prediction is designed for predicting the future location of a mobile host. The performance of the method has been verified for prediction accuracy by considering different movement patterns of a mobile host and learning accuracy of the MNN model. Simulation is also carried out for different movement patterns (i.e. regular, uniform, random) to predict the future location of a mobile host. The average prediction accuracy was measured and achieved up to 93% accuracy for uniform patterns, 40% to 70% for regular patterns and 2% to 30% for random movement patterns. The proposed method helps in reducing the signaling cost for location management by predicting the future location of a mobile host.

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