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Locomotion Forecast in MANET using MLP and ELM

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ABSTRACT

Modern advances in wireless and mobile processing have prepared for an extraordinary demand development for mobile administrators and applications. These administrators and applications convey and trade data utilizing wireless local area networks (WLAN) and mobile ad-hoc networks (MANET). Nonetheless, new plan challenges arise because of the mistake inclination, self-association and portability nature of these systems. This paper proposes a neural learning-based solution to the issues associated with the mobility of the MANET nodes where future changes in the network topology are efficiently predicted. Here, the correlation between the changes in mobile node location, speed and direction are exposed. The routing table is also predicted to reduce the data exchange of MANET hence the lifetime of nodes are improved. Using synthetic and real-world mobility traces, the proposed predictor achieves higher prediction accuracy by an order of magnitude. The obtained accuracy enables the proposed mobility predictor to enhance the overall quality of service in MANET.

Keywords:- MANET, WLAN

I. INTRODUCTION

Mobile Ad Hoc Networks (MANETs) represent self-organizing and self-configuring multi-hop wireless networks with no consolidated control where wireless connection and extemporaneous interaction take place between mobile nodes in a highly dynamic manner. In the last decade, MANETs have been successfully deployed in both civilian and military environments [1,2] . Their ability to self-organize and self-adapt, without the need for an essential infrastructure, contributed to their rapid deployment in non-predictable scenarios such as tragedy recovery. All MANET nodes have similar functionalities and capabilities with free motion and future locations usually unknown. These nodes can forward packets and sustain routes while having limited communication range. Therefore, these packets are forwarded in multi-hops from source to destination involving a number of transitional nodes in a cooperation mode . In this mode, Global Positioning Systems (GPS) continuously provide location data of the user nodes to the MANET control system. However, this tractability in infrastructure requirements stimulates issues and problems not known in traditional wireless networks. These issues are specifically addressed by scheduling [3] , topology control [4] and routing [5] modules and sub-systems. Efficient scheduling, topology control and routing modules rely on accurate and reliable mobility prediction mechanisms. The goal of this thesis is two- fold: 1) to develop a soft mobility predictor using neural learning machines, and 2) to demonstrate the superiority of the ”predictive ”formulation of future node locations where the inherent interaction between the node mobility patterns is captured and modelled more accurately.

II. MANET

A mobile ad hoc network (MANET) is a continuously self-configuring, infrastructure less network of mobile devices connected wirelessly. Each device in a MANET is free to move independently in any direction, and will therefore change its links to other devices frequently. Each must forward traffic unrelated to its own use, and therefore be a router. The primary challenge in building a MANET is equipping each device to continuously maintain the information required to properly route traffic [1]. Such networks may operate by themselves or may be connected to the larger Internet. They may contain one or multiple and different transceiver between nodes. This results in a highly dynamic, autonomous topology.

MANET is a kind of Wireless ad hoc network that usually has a routable networking environment on top of a Link Layer ad hoc network. MANET consists of a peer-to-peer, self-forming, self-healing network. MANET circa 2000-2015 typically communicates at radio frequencies (30 MHz - 5 GHz).

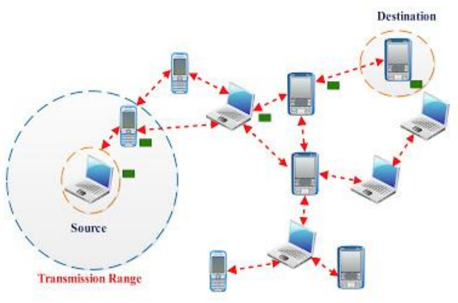

Figure.1. Architecture of MANET

Mobility Prediction Methods and Their Applications

The mobility prediction methods for MANET are classified into three categories as follows:

- Movement history based prediction methods, which predict the future location of a mobile user based on his movement history (i.e., Previous user movement patterns).
- Physical topology based mobility prediction methods, which base their prediction on the use of the characteristics of MANET's physical topology and therefore, require the use of a Global Positioning System (GPS) to obtain exact node location and mobility information.
- Logical topology based mobility prediction methods, which choose a logical topology of the MANET (e.g. A clustering structure) over which they apply their prediction process. On the contrary, to the previous category, they do not require exact location and mobility information and thus they do not make use of a GPS. The estimated values of node location and mobility information may be obtained by other means (e.g., Using signal attenuation versus travelled a distance to estimate Internode distances, or inferring the mobility of each node from how different is the neighbourhood of the node over time).

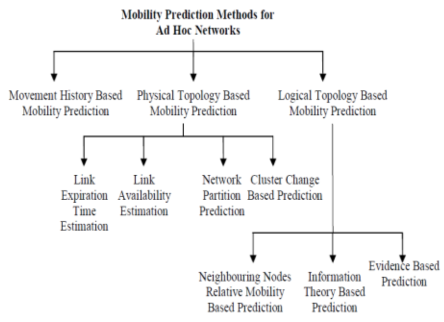

Figure.2 Classification of the mobility prediction methods

Movement History Based Mobility Prediction

A number of motion prediction algorithms mainly for fixed wireless networks, which predict the future location of a mobile user based on the user's movement history (i.e., Previous user movement patterns). The algorithms use different mobility models (e.g., The movement circle model, the movement track model, the Markov chain model) to model the user mobility behaviour, exploiting the fact that the movement of a mobile user consists of a random and a regular movement part. The regularity in human movement behaviour derives from certain activities that are repeated within a defined period of time.

The above methods fail in the case that there are unpredictable changes in user's behaviour. Also, there are additional problems when these methods are applied in MANET because of the nature of those network applications. Due to dynamic topology and nonregular requirements in such applications node mobility prediction based on the movement history is not always feasible and/or efficient.

Physical Topology Based Mobility Prediction

A. Link expiration time estimation

By exploiting the fact that in real world situations, usually, a mobile node's movement is not completely random, but the node travels in a predictable manner, we can predict the future state of the network topology. By predicting the future state of the network topology, the route reconstruction can be done effectively prior to route breaks and without generating excessive control overhead.

B. Link availability estimation

The link availability is defined as the probability that there is an active link between two mobile nodes at time t+Tgiven that there is an active link between them at time t. Note that a link may experience one or more failure and recoveries in the time interval between t and t+T. Note that the metric is not practical as a criterion to select a path between two nodes, because if a link fails, then rerouting should immediately take place rather than waiting for the failed link to become available again. But, the link availability criterion is useful during the clustering process as it can be used by mobile nodes to select more reliable neighbours to form more stable clusters.

III. LOGICAL TOPOLOGY BASED MOBILITY PREDICTION

A. Neighbouring nodes relative mobility based prediction

In clustering scheme, the network is partitioned into clusters of mobile nodes, that are mutually reachable along cluster internal paths which are expected to be available for a period of time t with a probability of at least a. The parameters of this model are predefined. In addition, it is assumed that the movement of each mobile node is random and entirely independent of the movements of other mobile nodes. However, this random walk model cannot always capture some node mobility patterns occurring in practice in MANET.

MAPLE is another clustering algorithm which also infers node mobility from measurements of the received signal strength. In particular, each mobile node belonging to a cluster can estimate its distance from its CH by using the well-known formula of the signal attenuation versus travelled distance. Then, based on past measurements, mobile nodes use a linear model for estimating their future distance from their CH. This helps mobile nodes to proactively join another cluster if they are going to soon leave their current cluster. However, MAPLE does not take node mobility into account during CH election. Specifically, mobile nodes contend for free frames in a single shared broadcast channel during the cluster formation phase and mobile nodes that first reserve the available frames in this phase become CHs. Thus, the election of CHs is mostly a random procedure and it is not based on some CH suitability criteria.

B. Evidence based mobility prediction

The Dempster-Shafer (DS) theory of evidence is an approach that enables combination of different information sources (called evidences) to reach decisions in situations characterized by a high degree of uncertainty. In the DS theory, if a probability p is assigned to an event, then 1-p represents the confidence not assigned to this event. 1-p represents ignorance and uncertainty and it is not necessarily assigned to the opposite event.

The main advantage of the DS theory of evidence is its ability to model the narrowing of a hypothesis with the accumulation of evidences and to explicitly represent uncertainty in the form of ignorance or reservation of judgment. The DS theory provides the possibility of giving to different evidences weights according to their relevance and importance in the final decision

III. EXISTING SYSTEM

In existing system, a neural learning based solution was proposed to the problems associated with the mobility of MANET nodes where future changes in the network topology are effectively predicted. The major objective of this paper was to develop a soft mobility predictor using neural learning machines and to demonstrate the superiority of the predictive formulation of future node locations where the inherent interaction between the node mobility patterns is captured and modelled more accurately.

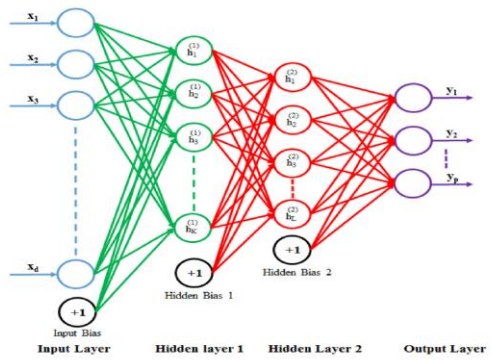

Figure3. Two hidden layer neural learning machine architecture

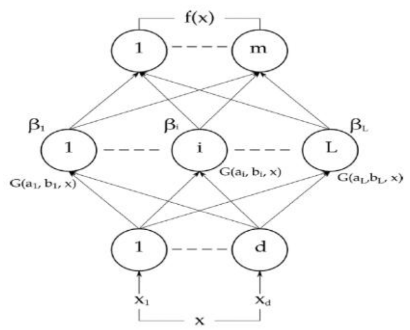

Figure4. Typical architecture of the ELM learning model

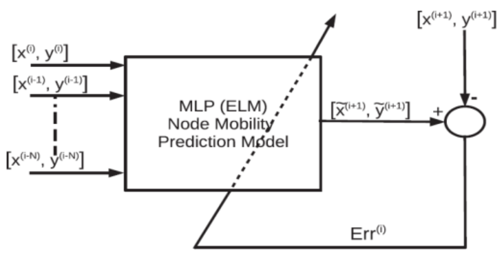

Figure5. Mobility prediction model using MLP and ELM architectures

Mobility predictor model using MLP and ELM architecture

In existing system, both learning machines (MLP and ELM) were used to build the mobility predictor. It should be kept in mind that the design of a soft mobility predictor should neither cause excessive computational requirement nor increased battery usage at the mobile unit level. Therefore, several model parameters and aspects must be inspected carefully during the predictor design stage. For instance, the predictor complexity is characterized by the number of hidden neurons in the MLP- and ELM-based solutions. This complexity is characterized differently in the solutions since the MLP model can have more than one hidden layer. Finding the optimal model complexity will simultaneously keep the computational requirements and the prediction error at a minimum level.

IV. PROPOSED SYSTEM

The proposed system is developed for exposing the correlation between the changes in mobile node location, speed and direction in order to effectively predict its mobility. Also, the life of node battery is improved by predicting routing tables in order to reduce data exchange in MANET. For these purpose, a neural learning based framework is proposed in which the future changes in the network topology are efficiently predicted.

Module

- → Neural learning machines using MLP-based architecture
- → Neural learning machines using ELM-based architecture
- → Mobility predictor

Neural learning machines using MLP-based architecture

Artificial Neural network (ANN) is used as learning algorithm which is more suitable to tackle complex tasks and problems. A typical architecture of neural based learning machine consists of an input layer, one or more hidden layer and an output layer. Each hidden layer extracts the more complex representation for the previous layer such that the last hidden layer would have representation meant to discriminate between the samples of different classes.

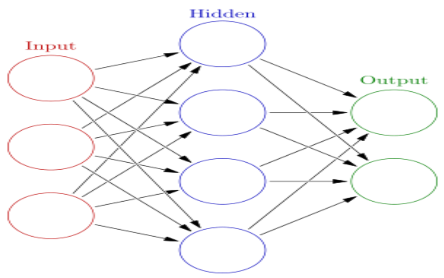

Figure6. ANN architecture

An ANN is typically defined by three types of parameters:

- → The interconnection pattern between the different layers of neurons.
- → The learning process for updating the weights of the interconnections.

In supervised learning a set of samples are obtained $(x, y), x \in X, y \in Y$ and the objective

is to find the function $f: X \rightarrow Y$ in the allowed

class of functions that matches the examples. The cost function is related to the mismatch between our mapping and the data and it implicitly prior knowledge about the problem domain. Mean squared error is commonly used as cost function which tries to minimize the average squared error between the networks output f(x) and the target value y over all the example pairs. When one tries to minimize this cost using gradient descent for the class of neural networks called multilayer perceptrons (MLP), one obtains the common and well-known backpropagation algorithm for training neural networks.

Neural learning machines using ELM-based architecture

Neural learning machine using ELM has three steps such as,

Given training set $N = \{(x_i, t_i) | x_i \in R^n, t_i \in R^m, i = 1, \ldots, N\}$,

activation function g, and the number of hidden nodes L,

- → Assign randomly input weight vectors or centers a_i and hidden node bias or impact factor b_i , i = 1,…, L.
- → Calculate the hidden layer output matrix H.
- → Calculate the output weight β: $\beta = H^T T$.

H^T is the Moore-Penrose generalized inverse of hidden layer output matrix H.

This ELM based learning algorithm is simple tuning-free three-step algorithm and learning speed is extremely fast.

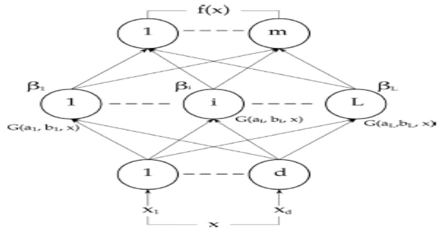

Figure7. ELM learning model

Mobility predictor

The mobility predictor is constructed by both MLP and ELM learning machines. The model parameters are includes mobile node location, speed and direction for exposing the correlation between the mobile nodes. This mobility predictor model achieves higher prediction accuracy than existing system. Here, the routing table is also predicted which is used to improve the lifetime of nodes.

V. PERFORMANCE METRICS

Mean Square Error

The closeness of the predicted to the target pattern, given by the MSE measure, is computed as follows,

$$MSE = \frac{1}{p}\sum_{i=1}^{p}(t_i - y_i)^2$$

In above equation, p represents the number of data points in the mobility trace of node. The i^{th}target and predicted node locations are given by $t_i \, and \, y_i$ respectively.

Mean Absolute Error

MAE is averages the magnitude of the error with the same weight across all *P* samples,

$$MAE = \frac{1}{p}\sum_{i=1}^{p}|t_i - y_i|$$

VI. CONCLUSION

In this paper, a new solution for the prediction of the future node locations in mobile ad-hoc network using neural learning machine-based model is proposed. This framework is based on the architectures of the standard multi-layer perceptron (MLP) and the extreme learning machine (ELM). The ELM does not require any parameter tuning and is unbiased to initial weights also this predictor capture better correlation between Cartesian coordinates of arbitrary MANET nodes leading to more realistic and accurate prediction. Also, the complex-valued representations are achieved to reveal the correlation between the changes in mobile node location, speed and direction. This proposed predictor is also used to predict the routing tables which are used to reduce the data exchange in MANET. This superior performance has been validated against several standard mobility models and real- world mobility data.

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