Mobility Prediction in Mobile Ad Hoc Networks Using Extreme Learning Machines

Lahouari Ghoutia, Tarek R. Sheltami1, Khaled S. Alutaibib

a King Fahd University of Petroleum and Minerals, Dhahran 31261, Saudi Arabia
b University of British Columbia, Vancouver, BC Canada V6T 1Z2

Abstract
Recent advances in wireless technology and computing have paved the way to the unprecedented rapid growth in demand and availability of mobile networking and services coupled with diverse system/network applications. Such advances triggered the emergence of future generation wireless networks and services to address the increasingly stringent requirements of quality-of-service (QoS) at various levels. The expected growth in wireless network activity and the number of wireless users will enable similar growth in bandwidth-crunching wireless applications to meet the QoS requirements. Mobility prediction of wireless users and units plays a major role in efficient planning and management of the bandwidth resources available in wireless networks. In return, this efficiency will allow better planning and improved overall QoS in terms of continuous service availability and efficient power management. In this paper, we propose extreme learning machines (ELMs), known for universal approximation, to model and predict mobility of arbitrary nodes in a mobile ad hoc network (MANET). MANETs use mobility prediction in location-aided routing and mobility aware topology control protocols. In these protocols, each mobile node is assumed to know its current mobility information (position, speed and movement direction angle). In this way, future node positions are predicted along with future distances between neighboring nodes. Unlike multilayer perceptrons (MLPs), ELMs capture better the existing interaction/correlation between the cartesian coordinates of the arbitrary nodes leading to more realistic and accurate mobility prediction based on several standard mobility models. Simulation results using standard mobility models illustrate how the proposed prediction method can lead to a significant improvement over conventional methods based on MLPs. Moreover, the proposed solution circumvents the prediction accuracy limitations in current algorithms when predicting future distances between neighboring nodes. The latter prediction is required by some applications like mobility aware topology control protocols.

© 2013 The Authors. Published by Elsevier B.V. Open access under CC BY-NC-ND license. Selection and peer-review under responsibility of Elhadi M. Shakshuki

Keywords: Mobile Ad Hoc Networks (MANETs), Mobility Prediction, Extreme Learning Machines (ELMs)

1. Introduction
Mobile ad hoc networks (MANETs) represent self-organizing and self-configuring multi-hop wireless networks with no centralized control where wireless connection and spontaneous interaction take place between many mobile nodes in a highly dynamic environment. In the last decade, MANETs have been the focus of interest in several mobile deployments in both civilian and military environments. Such deployments include a network of smart devices carried by members of armed forces in a battlefield, a network of wireless sensors deployed in an oil field (intelligent oil fields), etc. Also, the ability to self-organize and self-adapt without any need for the underlying infrastructure enabled MANETs to be deployed rapidly in...
non-conventional scenarios such as disaster recovery. In such situations, it is difficult (if not impossible) to re-install the infrastructure or provide a wireless access to the backbone network. Moreover, in MANETs all connected nodes are peer nodes (user and agent nodes) having similar functionalities and capabilities which allow them to operate as mobile routers as well. User nodes have free mobility and are their future locations are usually unknown. In MANETs, nodes can forward packets and maintain routes while having limited communication range and packets are therefore forwarded in multi-hops from source to destination involving a number of intermediate nodes. This characteristic mode of message forwarding makes MANETs operate based on node cooperation. In this cooperation mode, global positioning systems (GPS) continuously provide location data of user nodes to the MANET control system. Such information characterizes the user nodes in addition to their wireless connection range and velocity. However, this flexibility in infrastructure requirements comes at a price of issues and problems not known in traditional wireless networks. In fact, with MANETs emerge issues such as self-configuration and adaptive reconfiguration to address the effect of node mobility on the network topology, increased energy constraints and ad-hoc addressing. Moreover, timing constraints are imposed on data traffic calling for proactive routing and maintenance procedures in ad hoc network applications such as collaborative mobile computing and disaster recovery. However, this flexibility in infrastructure requirements comes at a price of issues and problems not known in traditional wireless networks. In fact, with MANETs emerge issues such as self-configuration and adaptive reconfiguration to address the effect of node mobility on the network topology, increased energy constraints and ad-hoc addressing. Moreover, timing constraints are imposed on data traffic calling for proactive routing and maintenance procedures in ad hoc network applications such as collaborative mobile computing and disaster recovery. These issues are cast into scheduling [1], topology control [2] and routing [3] issues.

2. Mobility Models and Prediction Techniques

2.1. Mobility Models

The application of mobility model is of great importance because it describes the movement pattern of mobile users by explaining how their location, velocity and acceleration change with respect to time. It is very much necessary to use the mobility models to follow the movement pattern of targeted real life applications in a realistic way. Every mobility model has different characteristics. We describe the Random Walk, Random Way Point and Gauss-Markov mobility models:

2.1.1. Random Walk Mobility Model

In this mobility model, mobile node (MN) moves from its current location to a new location by randomly choosing both the direction and speed. The new speed and direction are both chosen from ranges defined in advance [speedmin, speedmax] and [0, 2π], respectively. The movement can be calculated in two ways; either with a constant time interval t or with a constant distance traveled d. If the mobile node approaches boundary, it bounces back with an angle determined by the next upcoming direction. This mobility model is memoryless mobility pattern [4], i.e. the next move is totally independent from the previous one.

2.1.2. Random Waypoint Mobility Model

The Random Waypoint Model was proposed by Johnson and Maltz [5]. A model that includes pause times between changes in destination and speed. Firstly, the mobile node chooses a random location and considers it as its destination and then it moves towards its destination with constant velocity, which is uniformly distributed between [minvelocity, maxvelocity]. After arriving at the destination, the MN pauses for a specific time before choosing another random destination. The pause time can have the value zero ‘0’, which means that it will continue its movement without any pause [5, 6, 7]. This mobility model also is Memoryless.

---

1User nodes request network services and agents nodes provide support to ensure best network services possible.
2.1.3. Gauss-Markov Mobility Model

From [8], the Gauss-Markov Mobility Model was planned to achieve randomness via one tuning parameter. Initially each mobile node is assigned a current speed and direction. At fixed intervals of time, $n$, movement occurs by updating the speed and direction of each MN. Specifically, the value of speed and direction at the $n$th instance is calculated based on the value of speed and direction at the (n-1)th instance and a random variable using the following equations:

$$s_n = a s_{n-1} + (1 - a) \mu + \sqrt{(1 - a^2)} s_{xn-1}$$

$$\alpha_n = a \alpha_{n-1} + (1 - a) \mu + \sqrt{(1 - a^2)} \alpha_{xn-1}$$

where $s_n$ and $\alpha_n$ are the new speed and direction of the MN at time interval $n$, $a$ is a tuning parameter used to vary the randomness, $0 \leq a \leq 1$, $s_{xn-1}$ and $\alpha_{xn-1}$ are random variables drawn from a Gaussian distribution with zero mean and standard deviation equal to 1. The value of $\mu$ is fixed at 1. For $a = 0$, the equation yields totally random values, equivalent to Brownian motion. For $a = 1$, the equation yields fixed values, equivalent to linear motion. The value of $a$ can be adjusted between these two extremities to obtain different levels of random movement. At every time interval the next location of the mobile node is calculated based on the current location, speed, and direction of movement. Specifically, at time interval $n$, an MNs position is given by the equations:

$$x_n = x_{n-1} + s_{n-1} \cos \alpha_{n-1}$$

$$y_n = y_{n-1} + s_{n-1} \sin \alpha_{n-1}$$

where $(x_n, y_n)$ and $(x_{n-1}, y_{n-1})$ are the x- and y-coordinates of the MNs position at the nth and (n-1)th time intervals, respectively. $s_{n-1}$ and $\alpha_{n-1}$ are the speed and direction of the MN at the (n-1)th time interval, respectively.

To ensure that mobile node does not remain near an edge of the grid for a long period of time, the MNs are forced away from an edge when they move within a certain distance of the edge. This is done by modifying the mean direction variable $d$ in the above direction equation as shown in Fig. 1. For example, when the mobile node is near the right edge of the simulation grid, the value $d$ is changed to 180 degrees. Thus, the MNs new direction is away from the right edge of the simulation grid. So in short, for the Gauss-Markov model, the velocity of a mobile node at any time slot is a function of its previous velocity. We could say that the Gauss-Markov Model is a mobility model with chronological dependency. The degree of dependency is determined by the memory level parameter $a$.

2.2. Mobility Prediction Techniques

To maximize connectivity, mobility prediction techniques are used to predict the future location of user nodes to allow proper deployment of agent nodes during the mission time [9]. Fig. 2 illustrates a classification of the mobility prediction methods based on the basic information used in the prediction process.

Wang and Chang [10] propose the use of mobility prediction for a reliable on-demand routing protocol (RORP). GPS information is acquired to estimate the duration of time between two connected nodes. In their model (RORP), mobility prediction is carried out by a simple location and velocity estimation to assist the routing protocol. The prediction solution does not consider the node direction, change in direction or the change in velocity. Tang et al. [11] propose a solution to compute a duration prediction table which contains the guaranteed worst-case duration of the corresponding wireless link between source and destination nodes. In [12], Ashbrook and Starner describe a predictive model of the users future locations that automatically groups GPS data taken over an extended period of time into specific locations at multiple scales. Then, a Markov model is created using these clustered locations to predict the user’s future locations (or movements) in two different scenarios (sineuser and collaborative). Similarly, in this prediction model, the user velocity and direction information are not considered. Moreover, the prediction model is restricted to the geographic
area used during the learning phase. Mitrovic [13] proposes an algorithm for short-term prediction of vehicle mobility using ANNs. The propose ANNs are trained using specic maneuvers on certain road conditions. It is worth noting that these ANNs can be extended to the prediction problem in MANETs as it is shown in this paper. Another mobility prediction method to forecast the future node positions in MANETs is described by Creixell and Sezaki [14][15]. The prediction approach is developed using pedestrian tracked data. Then, the proposed prediction method is integrated with a novel geographical routing protocol where the prediction results are used in the routing decision process.

3. Extreme Learning Machines (ELMs)

Huang proposed extreme learning machines (ELMs) to speed up the learning process of single-hidden layer feedforward networks (SLFNs) [16]. ELMs were then extended to generalized SLFNs where the network structure is not required to be neuron alike. Unlike conventional SLFNs, ELMs do not require the parameter tuning of the hidden layer of SLFNs. Moreover, ELMs apply random computational nodes in the hidden layer independently of the training data. In this way, ELMs do not achieve smaller training error but also the smallest norm of output weights. Using fixed parameters in the hidden layer, ELMs compute the
output weights using a least-square solution. Fig. 3 illustrates a typical representation of SLFNs.

The output function of the SLFNs, shown in Fig. 3, is given by:

\[ f_L(x) = \sum_{i=1}^{L} \beta_i g_i(x) \]  

where \( x \in \mathbb{R}^d \), \( \beta_i \in \mathbb{R}^m \) and the output of the ith hidden node, \( G(a_i, b_i, x) \), is given by \( g_i \). Depending on the node type, the output is given by:

\[ g_i = \begin{cases} 
  g(a_i \cdot x + b_i) & \text{with } a_i \in \mathbb{R}^d, b_i \in \mathbb{R} \\
  g(b_i \|x - a_i\|) & \text{with } a_i \in \mathbb{R}^d, b_i \in \mathbb{R}^+ 
\end{cases} \]  

Using \( N \) arbitrary distinct samples, \( (x_i, t_i) \in \mathbb{R}^d \times \mathbb{R}^m \), the solution of the output weights is given by:

\[
\begin{bmatrix}
G(a_1, b_1, x_1) & \cdots & G(a_L, b_L, x_1) \\
\vdots & \ddots & \vdots \\
G(a_1, b_1, x_N) & \cdots & G(a_L, b_L, x_N)
\end{bmatrix}
\begin{bmatrix}
\beta_1^T \\
\vdots \\
\beta_L^T
\end{bmatrix}
= 
\begin{bmatrix}
t_1^T \\
\vdots \\
t_N^T
\end{bmatrix}
\]  

The hidden layer output matrix of the SLFN is given by:

\[
H = 
\begin{bmatrix}
G(a_1, b_1, x_1) & \cdots & G(a_L, b_L, x_1) \\
\vdots & \ddots & \vdots \\
G(a_1, b_1, x_N) & \cdots & G(a_L, b_L, x_N)
\end{bmatrix}
\]  

The output of the ith hidden node to the input vector, \( (x_1, x_2, \ldots, x_N) \), is given by the ith column of the hidden matrix \( H \). The hidden layer feature mapping is given by \( G(a_1, b_1, x), \ldots, G(a_L, b_L, x) \) and the hidden layer feature mapping with respect to the ith input, \( x_i \), is defined as: \( G(a_1, b_1, x_i), \ldots, G(a_L, b_L, x_i) \). Huang proved that for an infinitely differentiable activation function, the hidden layer parameters can be randomly generated. The smallest norm least-squares solution of the linear system, given in Eq. 5, is:

\[
\hat{\beta} = H^+T
\]
where $H^+$ is the Moore-Penrose generalized inverse of matrix $H$ and $T = [t_1^T, t_2^T, \ldots, t_N^T]^T$.

Given a training set $N = \{(x_i, t_i) | x_i \in \mathbb{R}^d, t_i \in \mathbb{R}^m, i = 1, 2, \ldots, N\}$, a hidden node output function, $G(a_i, b_i, x)$, and the number of hidden nodes, $L$, the algorithm for the computation of Eq. 7 is summarized below:

- Randomly generate hidden node parameters $(a_i, b_i), i = 1, 2, \ldots, L$.
- Calculate the hidden layer output matrix $H$.
- Calculate the output weight vector $\hat{\beta}$ using Eq. 7.

It should be noted that the singular value decomposition (SVD) is used to compute the Moore-Penrose generalized inverse of matrix $H$. It should be noted that unlike other learning algorithms, the ELM learning can handle a wide type of activation functions including threshold networks.

4. Simulation Results

To evaluate the performance of the proposed ELM-based mobility prediction technique, BonnMotion [17] is used. BonnMotion is a Java-based simulation platform to create and analyze node mobility scenarios. Several mobility models are represented in BonnMotion. However, this paper considers only the mobility models described in Section 2.1. It should be noted that for all simulated scenarios, a MANET configuration with 5 nodes moving in a grid of 1000 × 1000 meters. Training and testing of the ELM-based prediction models are carried out using equal number of data points set to 3000. Figs. 4-5 show the prediction performance of the proposed ELM-based technique for Gauss-Markov and Random Walk mobility models, respectively. It is clear that the universal approximation capability of ELMs enables them to track the nodes mobility once adequate training is achieved.

To further assess the prediction capability of the ELM-based technique, a mobility scenario consisting of 3 different mobility models (Gauss-Markov, Random Walk and Manhattan) is considered. The prediction result using training and testing data sets is shown in Fig. 6. Although using mobility data emanating from different models, the ELM-based algorithm achieved an excellent prediction performance which reinforces the generalization capability of ELMs in proper handling of unseen data.

Finally, to highlight the performance of the proposed ELM-based prediction technique, the performance of the node mobility prediction using a model based on the well-known MLP architecture is shown in Fig. 7. By comparing Figs. 6-7, it is clear that the ELM-based prediction outperforms that based on MLP given

2Because MLPs yield lower prediction performance, only 2 mobility models are considered for MLPs (Gauss-Markov and Random Walk)
that the former technique does not require any parameter tuning and the initial weights do not affect the prediction performance [16].
5. Conclusions

In this paper, we have proposed a new scheme to predict the node mobility in a mobile ad hoc network (MANET). The proposed scheme is based on a single feedforward layer architecture known as the extreme learning machine. Unlike MLPs, ELMs do not require any parameter tuning and the initial weights do not affect the prediction performance. In addition, ELMs capture better the existing interaction/correlation between the cartesian coordinates of the arbitrary nodes leading to more realistic and accurate mobility prediction based on several standard mobility models. Simulation results using standard mobility models illustrate how the proposed prediction method can lead to a significant improvement over conventional methods based on MLPs. In a future work, the proposed prediction technique will be extended to predict routing tables which would reduce the data exchange in MANETs and extend further the life of the node battery.

Acknowledgement

L. Ghouti and T. R. Sheltami would like to thank King Fahd University of Petroleum and Minerals (KFUPM) for supporting this work. K. S. Alutaibi is supported by the Ministry of Interior, Saudi Arabia.

References

[1] X. Li, H. Frey, N. Santoro, I. Stojmenovic, Strictly localized sensor self-deployment for optimal focused coverage, Mobile Computing, IEEE Transactions on 10 (11) (2011) 1520–1533. doi:10.1109/TMC.2010.261.
[2] X. Li, N. Mitton, I. Simplot-Ryl, D. Simplot-Ryl, A novel family of geometric planar graphs for wireless ad hoc networks, in: INFOCOM, 2011 Proceedings IEEE, IEEE, 2011, pp. 1934–1942.
[3] H. Frey, I. Stojmenovic, On delivery guarantees and worst-case forwarding bounds of elementary face routing components in ad hoc and sensor networks, Computers, IEEE Transactions on 59 (9) (2010) 1224–1238.
[4] B. Kumar, P. Venkataram, Prediction-based location management using multilayer neural networks, Journal of Indian institute of science 82 (1) (2002) 7–22.
[5] J. Broch, D. Maltz, D. Johnson, Y. Hu, J. Jetcheva, A performance comparison of multi-hop wireless ad hoc network routing protocols, in: Proceedings of the 4th annual ACM/IEEE international conference on Mobile computing and networking, ACM, 1998, pp. 85–97.
[6] W. Stallings, Data and Computer Communications 7th Edition, Prentice Hall, Upper Saddle River, NJ, 2000.
[7] Z. Haas, A new routing protocol for the reconfigurable wireless networks, in: Universal Personal Communications Record, 1997. Conference Record., 1997 IEEE 6th International Conference on, Vol. 2, IEEE, 1997, pp. 562–566.
[8] T. Camp, J. Boleng, V. Davies, A survey of mobility models for ad hoc network research, Wireless communications and mobile computing 2 (5) (2002) 483–502.
[9] O. Dengiz, A. Konak, A. E. Smith, Connectivity management in mobile ad hoc networks using particle swarm optimization, Ad Hoc Networks 9 (7) (2011) 1312 – 1326. doi:10.1016/j.adhoc.2011.01.010.
[10] N.-C. Wang, S.-W. Chang, A reliable on-demand routing protocol for mobile ad hoc networks with mobility prediction, Computer Communications 29 (1) (2005) 123 – 135. doi:10.1016/j.comcom.2005.05.003.
[11] J. Tang, G. Xue, W. Zhang, Reliable routing in mobile ad hoc networks based on mobility prediction, in: Mobile Ad-hoc and Sensor Systems, 2004 IEEE International Conference on, 2004, pp. 466 – 474. doi:10.1109/MAHSS.2004.1392187.
[12] D. Ashbrook, T. Starner, Learning significant locations and predicting user movement with gps, in: Wearable Computers, 2002. (ISWC 2002). Proceedings. Sixth International Symposium on, 2002, pp. 101 – 108. doi:10.1109/ISWC.2002.1167224.
[13] D. Mitrovic, Short term prediction of vehicle movements by neural networks, in: Knowledge-Based Intelligent Information Engineering Systems, 1999. Third International Conference, 1999, pp. 187 –190. doi:10.1109/KES.1999.820151.
[14] W. Creixell, K. Szakaki, Mobility prediction algorithm for mobile ad hoc network using pedestrian trajectory data, in: TENCON 2004. 2004 IEEE Region 10 Conference, Vol. B, 2004, pp. 668 – 671 Vol. 2. doi:10.1109/TENCON.2004.1414684.
[15] W. Creixell, K. Szakaki, Routing protocol for ad hoc mobile networks using mobility prediction, International Journal of Ad Hoc and Ubiquitous Computing 2 (3) (2007) 149–156, cited By (since 1996) 11.
[16] G. Huang, Q. Zhu, C. Siew, Extreme learning machine: theory and applications, Neurocomputing 70 (1) (2006) 489–501.
[17] K. Sadasivam, V. Changrani, T. Yang, Scenario based performance evaluation of secure routing in manets, in: 2nd International Workshop on Mobile Ad Hoc Networks and Interoperability Issues MANETI, Vol. 5.