ESANN 2014 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 23-25 April 2014, i6doc.com publ., ISBN 978-287419095-7.
Available from http://www.i6doc.com/fr/livre/?GCOI=28001100432440.

Mobility Prediction Using Fully-Complex Extreme Learning Machines

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Abstract. Efficient planning and improved quality of service (QoS) in wireless networks call for the use of mobility prediction schemes. Such schemes ensure accurate mobility prediction of wireless users and units which plays a major role in optimized planning and management of the available bandwidth and power resources. In this paper, fully-complex extreme learning machines (CELMs) model and predict the mobility patterns of arbitrary nodes in a mobile ad hoc network (MANET). Unlike their real-valued counterparts, CELMs properly capture the existing interaction/correlation between the nodes' location coordinates leading to more realistic and accurate prediction. Simulation results using standard mobility models and real-world mobility data clearly show that the proposed complex-valued prediction algorithm outperforms many existing real-valued learning machines in terms of prediction accuracy.

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 mobile nodes in a highly dynamic fashion. Since the last decade, MANETs are found in several deployments in both civilian and military environments. All connected nodes in such networks are peer nodes (user and agent) having similar functionalities and capabilities which allow them to operate as mobile routers as well. User nodes, with free mobility and unknown future locations, can forward packets and maintain routes while having limited communication range. However, several issues emerge in MANETs such as self-configuration and adaptive reconfiguration. Also, timing constraints are imposed on data traffic calling for proactive routing and maintenance procedures. The goal of this paper is two-fold: 1) develop a new mobility prediction technique using a CELM-based formulation; and 2) demonstrate the positive effect of the incorporation of the statistical and spacial correlation of the mobility patterns on the prediction performance. Complex (and hypercomplex)-valued formulations not only allow processing and analyzing the amplitude and phase of processed data but provide deeper insights into the underlying statistical correlation/dependence between the data constituents in the time/space, frequency, and phase domains. This paper is organized as

*Research supported by King Fahd University of Petroleum and Minerals.

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follows. Section 2 provides a brief overview of the mobility models adopted in MANETs and machine learning-based prediction techniques. CELMs and their underlying learning scheme are described in Section 3 where the rationale behind the complex-formulation of the spacial coordinates of the mobile nodes in MANETs is given as well. Section 4 gives a summary of the performance analysis carried out to assess the prediction accuracy of the proposed learning scheme. The paper concludes with Section 5 where conclusions and directions for future work are given.

2 Mobility Models and Prediction Techniques

2.1 Mobility Models

Mobility models provide a detailed description of the movement patterns followed by mobile users/nodes in MANETs and other wireless networks. Moreover, such models capture the close interaction between the node location, velocity and acceleration and their variability over time as well. Some of these models are considered in this paper [1]:

1. Random-Walk Model;
2. Random-Way Point Model;
3. Gauss-Markov Model;
4. Manhattan Model;

2.2 Mobility Prediction Techniques

To maximize node connectivity, mobility prediction techniques are used to predict the future location of user MNs to allow proper deployment of agent nodes during the mission time [2]. Wang and Chang [3] propose the use of mobility prediction for a reliable on-demand routing protocol (RORP). In this model, mobility prediction is carried out by a simple location and velocity estimation to assist the routing protocol. Tang et al. [4] 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. Mitrovic [5] proposes an algorithm for short-term prediction of vehicle mobility using artificial neural networks (ANNs). The proposed ANNs are trained using specific maneuvers on certain road conditions. Another mobility prediction method to forecast the future node positions in MANETs is described by Creixell and Sezaki [6]. 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. An adaptive learning automata-based mobility prediction method is proposed by Torkestani assuming a Gauss-Markov random process where the correlation of the mobility parameters over time is astutely exploited [7]. Finaly, mobility prediction using real-valued extreme learning machines (RELMs) is proposed by

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Ghouti et al. [8] where mobility data, produced using mixed models, is used to predict the MN mobility. The prediction performance based on RELMs is contrasted to that using the standard ANN architecture based on the multilayer perceptron.

3 Complex-Valued Extreme Learning Machines (CELMs)

In [9], Li et al. propose an extreme learning machine based on fully-complex activation functions called CELMs. CELMs do not require parameter tuning of the input-to-hidden layer connections. Instead, only random computational nodes are applied independently of the training data. In this way, CELMs do not only achieve a smaller training error but also the smallest norm of the output weights. Using fixed parameters in the hidden layer, CELMs compute the output weights using a least-square solution. Fig. 1 illustrates a typical representation of single layer feedforward networks (SLFNs). The output function of the SLFNs model, shown in Fig. 1, is given by:

$$f_L(\mathbf{x}) = \sum_{i=1}^{L} \beta_i \mathbf{g}_i(\mathbf{x}) \text{ with } \begin{cases} \mathbf{g}_i^{+} = G(\mathbf{a}_i, b_i, \mathbf{x}) = g(\mathbf{a}_i \cdot \mathbf{x} + b_i) \\ \mathbf{g}_i^{rbf} = G(\mathbf{a}_i, b_i, \mathbf{x}) = g(b_i \,||\mathbf{x} - \mathbf{a}_i|\,|) \end{cases} \tag{1}$$

where $\mathbf{x} \in \mathbb{C}^d$, $\beta_i \in \mathbb{C}^m$ and the output of the ith hidden node, $G(\mathbf{a}_i, b_i, \mathbf{x})$, is given by $\mathbf{g}_i^{+}$ and $\mathbf{g}_i^{rbf}$for additive and radial basis function (RBF) types, respectively. Using N arbitrary distinct samples, $(\mathbf{x}_i, \mathbf{t}_i) \in \mathbb{C}^d \times \mathbb{C}^m$, the solution of the output weights is given by:

$$\underbrace{\begin{bmatrix} G(\mathbf{a}_1, b_1, \mathbf{x}_1) & \cdots & G(\mathbf{a}_L, b_L, \mathbf{x}_1) \\ \vdots & \vdots & \vdots \\ G(\mathbf{a}_1, b_1, \mathbf{x}_N) & \cdots & G(\mathbf{a}_L, b_L, \mathbf{x}_N) \end{bmatrix}}_{\mathbf{H}} \cdot \underbrace{\begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_L^T \end{bmatrix}}_{\beta} = \underbrace{\begin{bmatrix} \mathbf{t}_1^T \\ \vdots \\ \mathbf{t}_N^T \end{bmatrix}}_{\mathbf{T}} \tag{2}$$

where $\mathbf{H}$ defines the hidden layer output matrix of the SLFN. The output of the ith hidden node to the input vector, $(\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N)$, is given by the ith column of the hidden matrix $\mathbf{H}$. The hidden layer feature mapping is given by $G(\mathbf{a}_1, b_1, \mathbf{x}), \ldots, G(\mathbf{a}_L, b_L, \mathbf{x})$ and the hidden layer feature mapping with respect to the ith input, $\mathbf{x}_i$, is defined as: $G(\mathbf{a}_1, b_1, \mathbf{x}_i), \ldots, G(\mathbf{a}_L, b_L, \mathbf{x}_i)$. The smallest norm least-squares solution of the linear system, given in Eq. 2, is:

$$\hat{\beta} = \mathbf{H}^{+}\mathbf{T} \tag{3}$$

where $\mathbf{H}^{+}$ is the Moore-Penrose generalized inverse of matrix $\mathbf{H}$.

4 Simulation Results and Discussions

The performance of the proposed prediction technique is assessed using model-based synthetic and real-world mobility data (*BonnMotion* and CRAWDAD

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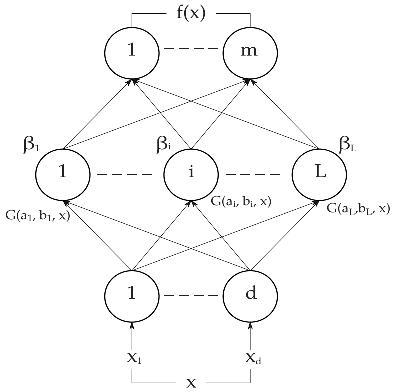

Fig. 1: Typical representation of SLFNs.

data). The *BonnMotion* tool generates mobility data according to the models introduced in Section 2. In this case, a MANET configuration with 5 nodes moving at a normalized speed of 10 m/s in a grid of 1000×1000 meters is considered. Model evaluation (training and testing) is carried out using equal number of data points set to 3000. Fig. 2 shows the performance of mobility prediction using 40 neurons in the hidden layer of the SLFNs model. Using mobility data pertaining to mixed models, the prediction performance of the proposed CELM-based is reported in Fig. 2. It is clear that the universal approximation capability of CELMs enables them to track the nodes mobility once adequate training is performed. For comparison purposes, ELM- and MLP-based prediction schemes are trained and tested using the same procedure adopted for the proposed prediction algorithm. Finally, real-world MANET mobility data (CRAWDAD data) is used to assess the prediction performance of the proposed algorithm. Mobility traces of the master and some ordinary nodes are shown in Fig. 4. It is worth noting that the master node, shown in Fig. 4 (left), has a different mobility pattern than user nodes. Prediction performance using training and testing trace data is shown in Fig. 5. Similar to the case of synthetic mobility data, CELM-based prediction algorithm is capable of accurately predicting node mobility in real-world scenarios.

5 Conclusion

In this paper, a new scheme is proposed to predict the node mobility in a mobile ad hoc network (MANET). The proposed scheme is based on a fully-complex single layer feedforward networks (SLFNs) architecture known as the fully-complex extreme learning machines (CELMs). CELMs capture better the existing interaction/correlation between the Cartesian coordinates of the mobile nodes leading to more realistic and accurate mobility prediction. Simulation results using model-based synthetic and real-world mobility traces illustrate the improved prediction performance achieved by this new scheme. In a future work,

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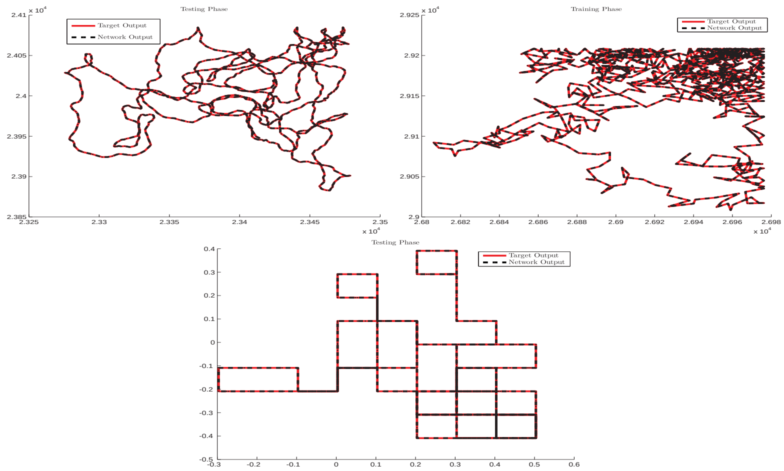

Fig. 2: CELM-based prediction of Gauss-Markov, Random Walk and Manhattan mobility models (testing phase).

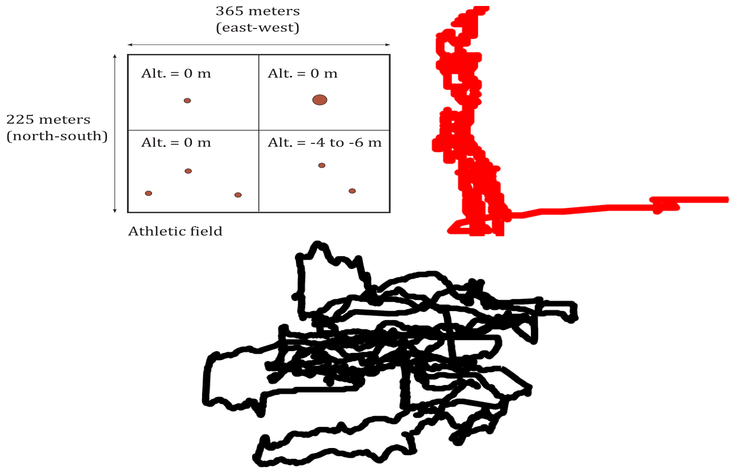

Fig. 3: CRAWDAD mobility model (left). Master node mobility pattern (middle). User node mobility pattern (right).

the proposed prediction technique will consider the node speed and direction (angle) information using hypercomplex-valued learning architectures.

Acknowledgment

The author would like to acknowledge the support provided by King Fahd University of Petroleum & Minerals (KFUPM).

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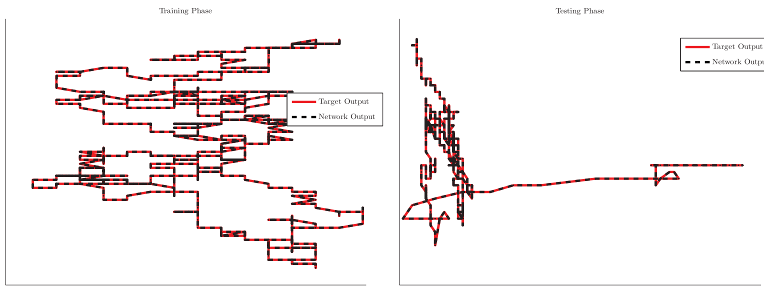

Fig. 4: CELM-based prediction of CRAWDAD mobility traces of the master node (training and testing phases).

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