Research Article

Efficient Mobility Prediction in MANET using Linear Predictive Approach

[1]J.Manimaran, [2]Dr.T.Suresh

[1]Assistant Professor, Department of Information Technology, FEAT, Annamalai University, India.
[2]Associate Professor, Department of computer Science and Engineering, FEAT, Annamalai University, India.

Article History: Received: 10 January 2021; Revised: 12 February 2021; Accepted: 27 March 2021; Published online: 28 April 2021

Abstract: Mobility has recently sparked a lot of interest, as users' demand for more reliable connections and higher service quality has risen. In mobile networks, effective estimation of consumer mobility allows for efficient resource and handover management, preventing undesirable loss of perceived efficiency. As a result, predicting mobility in wireless networks is important, and several studies have been conducted on the subject. The importance of mobility prediction is discussed in this paper, as well as its inherent attributes in terms of predictability of the node movement, outputs of the prediction, and evaluation metrics. Furthermore, the learning perspective of mobility prediction solutions has been explored.This work outlines a similarity estimation based approach to mobility prediction. To obtain a time series of past measurements, each node tracks the Signal to Noise Ratio (SNR) of its wireless connections with the other nodes. When a prediction is requested, the node uses the collected training data to calculate the normalized cross-correlation function of the recent past in order to identify situations similar to the current one in the background of its relations. The matched records are then utilized as the prediction's basis.

Keywords: MANET, Mobility Prediction, RMSE, SNR

1. Introduction

In mobile networks, mobility is an intrinsic function of nodes, and it includes several high priority issues in mobile networks, including handover, regulateddata transmission, dimensioning of signaled network, regular location update, registration, and managing network with multiple layer [1].

Mobility is a significant gain for user convenience, but it can also be a significant drawback if not properly handled. Furthermore, as tiny networks become a common function of the fifth-generation mobile system (5G), the effect of device dynamic movement increases as the cell transmission radius shrinks [2]. As a result, versatility has gotten a lot of attention in academia and business, where there are still a lot of problems to solve.

Implementing mobility prediction [3] is an effective way to handle mobility and preserve connectivity between the nodes. The ability to predict a user's next cell or even the direction they will follow in the future mobile network system [4] is crucial. Mobility prediction systems in mobile networks are grouped into three categories: handover handling, resource management, and location sensitive applications.

The effect of handover poses one of the most common problems for mobile networks. When a node leaves a transmission area but is unable to connect to the neighboring nodes smoothly, inappropriate delays or even call dropping events can occur, necessitating proper handover management [5]. Furthermore, the introduction of a passive resource reservation policy [6] is the primary way to ensure continuous data transmission without having to reserve a significant number of nodes and other communication devices across the entire network.

This strategy will reserve a certain portion of available bandwidth that are likely to be accessed by nodes, eliminating the need to reserve bandwidth across the entire system and thereby saving a large amount of resources. Furthermore, if the network can correctly predict nodes' further movements, certain location sensitive contents that are strongly correlated to nodes are transmitted, and the network would be able to predict traffic conditions and design more effective plans.

Prediction of node location can be described as a tool that predicts where users will be in the future. But, forecasting a network node's future position is challenging, mainly in the view of a network. A general architecture for implementing mobility prediction is presented in this survey and can be divided into four components, as shown in Figure 1. Source of the data, necessary information, algorithms used for prediction, prediction outputs, evaluation metrics, and application categories are the components.

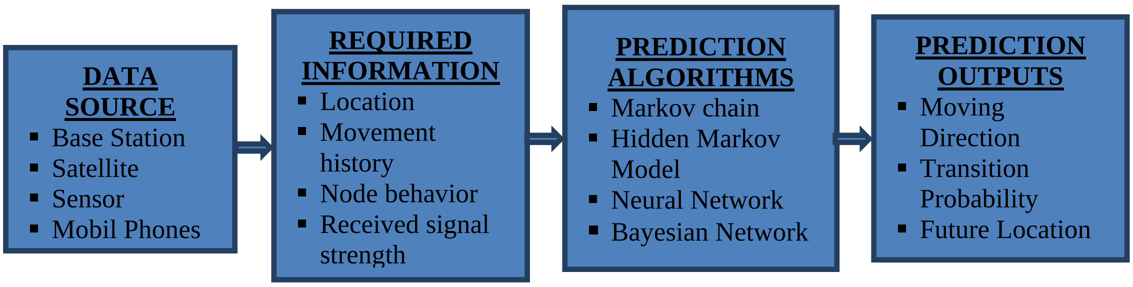

Figure 1. Flow of information in Mobility Prediction

A pattern matching-based prediction algorithm was introduced in this work. Such an approach to for predicting the mobility of the network node is efficient when compared to most of the existing methods use linear predictive models which accepts localization information from hardware components, such as GPS devices. The Signal to Noise Ratio of the links is monitored constantly track the movement of a node while preventing the use of specialized hardware.

2. Related Work

Mobility prediction has been thoroughly researched over the last two decades with the aim of predicting users' potential locations and enhancing their QoS. These studies use a range of techniques to accomplish different aims, such as managing hand-over, managing network resources, and LBSs. Because of the diversity of this area, several surveys focusing on various topics have been created.In mobile networks, users' versatility is an intrinsic feature. It's important to have a better understanding of how users navigate around. It's vital for any investigation in which the relative locations are relevant. The value of accessibility users cannot be overstated. Understanding and utilizing user mobility are two major obstacles in communication systems. Mobility forecasting is important for building successful communication networks.

In [7], emerging geo-location prediction solutions in the view of node mobility were provided. Similarly, in [8, 9] looked at a number of large-scale data mining applications but concentrated on providing a short overview of the field of trajectory data mining. The work proposed in [10] examined and evaluated proposed methods for localization, path tracking, and time-series prediction techniques that can be used to predict a vehicle's future position in vehicular ad hoc networks rather than conventional mobile networks.

Even [11] provides a brief overview of mobility prediction or location estimation which focuses on processingnode trajectory movement data. This paper, like [5] utilizes the idea of node mobility estimation and addresses various traditional and unconventional methods that take into account pre-reservation of resource to ensure nodeconnectivity and boostQoS innetwork. However the proposed methods in [5] looked at current methods for handling the request and failed to exhibit a full image of mobility prediction, such as which outputs are important for prediction and the parameters need to be utilized for accurate prediction.

3. Proposed Mobility Prediction

The problem of mobility prediction's basic structure is represented in Figure 2. The state observation role is to maintain record of the node's mobility state. Through doing so, it guarantees that the first assumption, the observability of the mobility condition, is satisfied. Its input is extracted from the input space, which is defined by a set of parameters. The prediction component uses the Observer's output as an input. If the parameters vary from the input essential for the Predictor, the Observer must perform a mapping of the parameter.

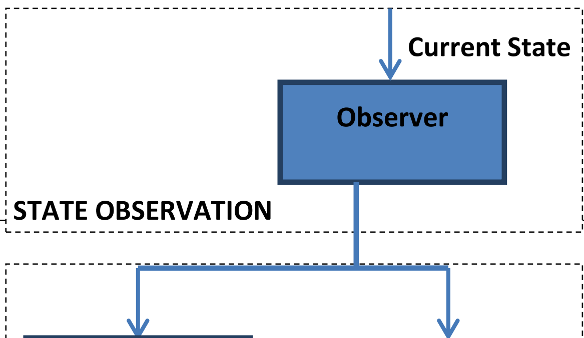

Figure 2. Block Diagram of Mobility Prediction

The input space is created by the difference in the time of arrival determined from the signals sent from three satellite sensors (see [13] for an explanation on how GPS works). The predictor requires a geographic location, so the GPS system must perform a conversion, which is the real phase of GPS geo-location. When the estimated RSS is the input and series of RSS measured values are given as output, the Observer must save the past values and rearrange them to form a time series so it can be sent to the predictor component as areference mapping of the input to the output.

3.1. State Prediction

The Predictor is the first of two main tasks that make up the prediction portion. The Predictor is the model of the system that estimates the location of the nodes. The Observer and the parameter estimator, the second component of the forecast, provide inputs. The location predictor takes the training data from the first part as input and computes a set of device model parameters from it. Assuming a linear model of a node's movement as a basic example where the device model includes the real geo-coordinates as input and the velocity and acceleration as argumentsfor linear prediction of node location. As a consequence, the estimator component takes a series of estimated coordinates, calculates the speed and the node movement direction, and transfers these values to the model as parameters. The linear model will predict the node's future location using these attributes and the real position as data.

Constructing a linear model of the node mobility simply means predicting that the nodes will continue to travel in the same direction and at the same speed as they are now. In mobile ad hoc networks, determining the current speed and location of the nodes typically necessitates the use of specialized hardware, such as a GPS system. This approach has been used in a number of mobility prediction algorithms anddifferent schemes for improving routing protocol performance using mobility prediction are proposed in this method. The expiration time of a link is determined assuming that both ends of the link have GPS location information. The amount of time two mobile hosts can remain connected can be determined using a simple formula assuming a free space radio propagation model, where the received signal intensity solely depends on the distance between sender and receiver:

$$D_t = \frac{-(ab+cd) + \sqrt{(a^2+c^2)r^2 - (ad-bc)^2}}{a^2+c^2}$$

where$a = v_i cos\Theta_i - v_j cos\Theta_j,\ b = x_i - x_j, c = v_i sin\Theta_i - v_j sin\Theta_j,\ d = y_i - y_j$

The physical environment is one of the most significant factors that affect the node's behaviour patterns. Nodes in a network area typically move in and out of a specific zone. Another physical limitation is that they can never travel faster than 2 meters per second.A lazy learner can construct a local model of the relation by looking for similar trends in the background and predicting that the nodes will replicate their actions with a high probability based on the available time series of the parameters including the speed, moving direction and the SNR.

One advantage of using the SNR as a measure of a node's mobility state is that it is easy to calculate. For example, in 802.11 wireless LAN network interfaces [12], the firmware and driver generally provide some measurements of signal intensity and background noise observed on the channel.

The parameters that the Parameter Estimator can pass on to the model portion of the location prediction algorithm are references to previous instances of a similar situation. The training data and the question are the pieces of information it gets from the state observation. The Parameter Estimator's role is to find patterns identical to the question in the training data. To do so, a distance measurement between the question and the previous measurements is needed.

The squared Euclidean distance motivates the use of cross-correlation for pattern recognition [13]. At times$m \dots . (m + o)$, the squared Euclidean distance between the query q and the piece of training data $t_{j,k}$ is expressed mathematically as

$$d^2_{q,t_{j,k}}(m) = \sum_{i=1}^{o} [q(i) - t_{j,k}(m + i)]^2$$

When a node has $k$neighbors, $k$normalized cross-correlation functions are created.

4. Experiments and Results

The algorithm was implemented in the network simulator ns-2 so that a large number of experiments could be performed to assess its accuracy and effect on server (node which executes the prediction) selection.The Random way point mobility model, which is essentially a set of rules for how nodes should behave, was used. The advantage of this approach is that it allows large numbers of node trajectories to be used for simulation without having to conduct detailed measurements in real-world scenarios.

4.1. Performance Metrics

In the current literature, different methods and performance metrics are used to estimate device mobility. This section focuses on the concept of the main performance indicators (KPIs) that are used to measure the efficacy of the proposed strategies and schemes. Metrics are divided into two categories: measurable metrics and application metrics. Application metrics are used to describe the performance of the application of the prediction outcome, for example, handover dropping probability and new call blocking probability. Observable metrics can be derived directly from the prediction result, such as prediction accuracy and deviation error.

4.1.1. Prediction Accuracy

The most widely used performance metric for evaluating whether a forecast is reliable and whether the approach used is correct is prediction accuracy. As shown below, prediction accuracy is commonly defined as the ratio of correct predictions to total predictions.

$$AccuracyinPrediction = \frac{numberof correctpredictions}{totalnumberofpredictions}$$

Since authors may have different meanings of prediction accuracy, the criteria for accurate predictions varies across literature. For example, contrary to common belief, a good prediction is one in which the predicted state (cell, location, and so on) matches the user's actual state. In [56] prediction accuracy was defined as the ratio of a trajectory sequence's hit rate and the length of points in the predicted sequence (the value is set to 1 if the Euclidean distance between a predicted point and corresponding practical point is less than a threshold).

4.1.2. Deviation Error

It can be difficult to tell whether a prediction is right or not at times. As a consequence, the deviation error is used to calculate the average magnitude of errors in a series of predictions without taking into account their direction. For example [16]has given the following concept of deviation:

$$Deviation = \frac{1}{N} \sum_{i=1}^{N} d_i$$

$$d_i = \sqrt{\left(x_{i.\ pre} - x_{i,\ pra}\right)^2 - \left(y_{i.\ pre} - y_{i,\ pra}\right)^2}$$

Where $d_I$represents the Euclidean distance between the predicted and actual location of the node, and N denotes the count of predictions. In the same way using the speed and position of the node Root Mean Square Error (RMSE) can be estimated [17] which can be used to analyze and evaluate the similarity between the predicted and actual trajectory of the node which can be expressed mathematically as

$$RMSE = \sqrt{\frac{1}{k} \sum_{m=1}^{k} (\hat{x}_k - x_k)^2 - (\hat{y}_k - y_k)^2}$$

where$k$ denotes the number of iterations.

Table 1. Performance Evaluation under various node velocity

Node velocity (m/s)	Prediction Accuracy in %	% of Deviation	Avg. RMSE in Parameter Estimation
0.25	96.8	8.2	2.4
0.5	95.2	8.6	3.4
0.75	94.3	8.9	4.2
1	93.8	9.1	5.1
1.25	93.5	9.3	6.2
1.5	93.2	9.4	7.5
1.75	92.8	9.6	8.6
2	92.5	9.8	9.1

Table 2. Performance Evaluation under various nodePause Time

Pause Timein seconds	Prediction Accuracy	% of Deviation	Avg.RMSE in parameter Estimation
1	97.2	7.9	2.6
1.5	96.5	8.2	3.9
2	95.6	8.4	4.4
2.5	94.3	8.9	5.3
3	93.8	9.2	6.4
3.5	93.2	9.6	7.9
4	92.6	9.8	8.8
4.5	91.7	9.9	9.5

5. CONCLUSION

The Signal to Noise Ratio of the links is constantly controlled in order to observe the mobility state of a node while preventing the use of dedicated hardware.The algorithm was implemented in the network simulator ns-2 in order to validate it. It was possible to find optimal choices for certain algorithm design parameters, such as query order and match threshold, using this implementation. The obtained predictions for different node speeds and pause times, as well as the Random Waypoint model, were shown to be rational.If the expectation of being able to localise nodes using localization hardware is dropped, mobile ad hoc networks become a difficult area for mobility prediction.The only thing left is to concentrate on relative distances between nodes since there are no fixed points in the network with known positions. The discussed algorithm is able to cope with this challenge and predict changes in the network topology by using the SNR as a measure of distance, not in geographical space but in 'signal space.

References

1. M. Zonoozi and P. Dassanayake, ''User mobility modeling and characterization of mobility patterns,'' IEEE J. Sel. Areas Commun., vol. 15, no. 7, pp. 1239–1252, Sep. 1997.
2. Ge, J. Ye, Y. Yang, and Q. Li, ''User mobility evaluation for 5G small cell networks based on individual mobility model,'' IEEE J. Sel. Areas Commun., vol. 34, no. 3, pp. 528–541, Mar. 2016.
3. Nadembega, A. Hafid, and T. Taleb, ''Mobility-prediction-aware bandwidth reservation scheme for mobile networks,'' IEEE Trans. Veh. Technol., vol. 64, no. 6, pp. 2561–2576, Jun. 2015.
4. V. Klaine, M. A. Imran, O. Onireti, and R. D. Souza, ''A survey of machine learning techniques applied to self-organizing cellular networks,'' IEEE Commun. Surveys Tuts., vol. 19, no. 4, pp. 2392–2431, 4th Quart., 2017.

5. Fazio, F. D. Rango, and M. Tropea, ‘‘Prediction and QoS enhancement in new generation cellular networks with mobile hosts: A survey on different protocols and conventional/unconventional approaches,’’ IEEE Commun. Surveys Tuts., vol. 19, no. 3, pp. 1822–1841, 3rd Quart. 2017.
6. D. Rango, P. Fazio, and S. Marano, ‘‘Utility-based predictive services for adaptive wireless networks with mobile hosts,’’ IEEE Trans. Veh. Technol., vol. 58, no. 3, pp. 1415–1428, Mar. 2009.
7. Xu, S. Gao, M. Daneshmand, C. Wang, and Y. Liu, ‘‘A survey for mobility big data analytics for geolocation prediction,’’ IEEE Wireless Commun., vol. 24, no. 1, pp. 111–119, Feb. 2017.
8. Feng and Y. Zhu, ‘‘A survey on trajectory data mining: Techniques and applications,’’ IEEE Access, vol. 4, pp. 2056–2067, 2016.
9. Zheng, ‘‘Trajectory data mining: An overview,’’ ACM Trans. Intell. Syst. Technol., vol. 6, no. 3, p. 29, Sep. 2015.
10. N. Balico, A. A. F. Loureiro, E. F. Nakamura, R. S. Barreto, R. W. Pazzi, and H. A. B. F. Oliveira, ‘‘Localization prediction in vehicular Ad Hoc networks,’’ IEEE Commun. Surveys Tuts., vol. 20, no. 4, pp. 2784–2803, 4th Quart., 2018.
11. Wu, G. Luo, J. Shao, L. Tian, and C. Peng, ‘‘Location prediction on trajectory data: A review,’’ Big Data Mining Anal., vol. 1, no. 2, pp. 108–127, Jun. 2018.
12. IEEE-SA Standards Boards. Part11: Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications, June 2003. http://standards.ieee.org/getieee802/802.11.html.
13. Lewis. Fast normalized cross-correlation. in vision interface., 1995.
14. Qiao, N. Han, W. Zhu, and L. A. Gutierrez, ‘‘TraPlan: An effective three-in-one trajectory-prediction model in transportation networks,’’ IEEE Trans. Intell. Transp. Syst., vol. 16, no. 3, pp. 1188–1198, Jun. 2015.
15. Qiao, D. Shen, X. Wang, N. Han, and W. Zhu, ‘‘A self-adaptive parameter selection trajectory prediction approach via hidden Markov models,’’ IEEE Trans. Intell. Transp. Syst., vol. 16, no. 1, pp. 284–296, Feb. 2015.
16. Mihaylova, D. Angelova, S. Honary, D. R. Bull, C. N. Canagarajah, and B. Ristic, ‘‘Mobility tracking in cellular networks using particle filtering,’’ IEEE Trans. Wireless Commun., vol. 6, no. 10, pp. 3589–3599, Oct. 2007.