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Salim M. Zaki
Department of Computer Science, Dijlah University College, Baghdad-Iraq, salimzki@gmail.com

M. A. Ngadi
Faculty of Computing, Universiti Teknologi Malaysia, Johor-Malaysia

Maznah Kamat
Faculty of Computing, Universiti Teknologi Malaysia, Johor-Malaysia

Shukor A. Razak
Faculty of Computing, Universiti Teknologi Malaysia, Johor-Malaysia

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A Review of Location Prediction Techniques in Mobile Ad Hoc Networks

Authors Names

a. Salim M. Zaki
b. M. A. Ngadi,
b. Maznah Kamat,
b. Shukor A. Razak

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ABSTRACT

Predicting future locations of mobile objects has received a lot of attention in research due to its importance in mobile ad hoc networks. The precise location of a mobile node is essential in determining the location of the destination node for communication. High mobility of nodes and delay in sending current location affect the accuracy of mobile nodes' locations. Providing accurate location needs well-designed location prediction technique considers several factors that assist in retrieving up-to-date locations. This paper reviews available models: mathematical models and models with neural network and address the problems in location prediction techniques and provides a deep analysis of the good features for improved prediction techniques.

1. Introduction

Location information is strongly associated with many applications and location service protocols in mobile ad hoc networks, such as smart parking and safety messages dissemination and geographic routing [1] [2] [3] [4] [5]. Retrieving accurate location information of vehicles usually leads to accurate routing of messages to destinations [6]. Where accurate location means the closest value of a retrieved location to a reallocation of a mobile node. Mobile Ad hoc Networks create big challenges to protocol design [7] [8]. In high mobility environments such as VANET, nodes change their locations frequently within a short time, therefore, looking for a destination's new location requires sending control packets to locate it. This creates a high overhead of sending packets. Additionally, high overhead may produce packets congestion that deteriorates the performance of routing protocol in the ad-hoc network [9]. The mobility of nodes changes the location frequently which makes geographical routing protocol keep searching for the new location of the destination node [10]. Furthermore, other related problems such as storage of outdated, and inaccurate locations on location servers are affecting the delivery of packets to their

[a] Department of Computer Science, Dijlah University College, Baghdad-Iraq, E-Mail: salimzki@gmail.com
[b] Faculty of Computing, Universiti Teknologi Malaysia, Johor- Malaysia

destination accurately in geographic routing. This is due to the dependence of forwarders on a destination location inside the packets being forwarded. Figure 1 demonstrates an example of the future position of a mobile node moved farther than usual with a change in its trajectory. However, predicting the locations of the mobile destination node is a solution to avoid sending extra control packets and also to predict an accurate location.

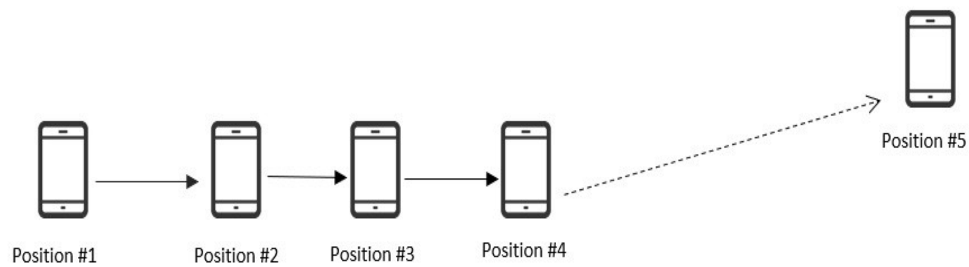

Figure1. Future position of a mobile node moved farther than usual with change in its trajectory

2. *Review of Literature*

2.1 *Location Prediction in Mobile Ad-Hoc Networks*

In [11] authors proposed a Quality of Service (QoS) prediction based protocol. The protocol can predict destination's location, forwarder location, and the propagation delay. The packet forwarder has to predict the location of the destination node specified inside the header and predict intermediate node's location. Additionally, the delay propagation prediction is useful in predicting the future location of a node at a time. All these steps of prediction are to ensure a reliable routing to destination. The protocol that depends on update packets should include direction of the node to produce precise future location of it. However, if no direction information included in the updates, at least two update packets are needed to predict node's location. However, this prediction might not be able to predict an accurate trajectory to a target's location or predict the time needed to reach this target.

Authors in [12] proposed a model that follows the road- level or map-level granularities in predicting a mobile node's location. The proposed Predictive Location Model (PLM) uses a database to store information about both environment (e.g., City places) and mobile user historical locations, and speed. PLM utilizes radius of wireless to detect the number of intersected points on the outer edge of this radius with other points on surrounded roads. These exit-points are used to calculate trajectories; where the trajectory is the path between current mobile node location and each exit-point. The probability of a mobile node on the road to turn on next intersection is high; therefore, PLM uses a probability matrix to overcome this limitation. In PLM paper, it is assumed that the speed is limited to road class that the mobile node moves on, and it is not taking into account the acceleration of nodes on the road which may have significant effects on prediction accuracy. Moreover, it is assumed that a mobile client sends its location information over a fixed time period, which may keep nodes sending locations even though no changes have occurred which causes redundancy in sent information and an increase in control packets overhead.

Mobility of nodes in a mobile environment has a significant impact on locations error. Therefore, authors in [9] studied the effects of mobility model on location accuracy and addressed two main problems caused by nodes mobility. First problem is link lost between neighbor nodes, and the second problem is the loop of packets forwarded to destination moving out of forwarder radius. Consequently, [9] proposed two prediction schemes. Neighbor Location Prediction (NLP) scheme proposed to solve link lost problem between neighbors, where a packet receiver saves beacons received from neighbor which includes position, speed and time of beacon. A basic calculation is used to predict neighbor location before forwarding packets to neighbor based on received information of last sent beacon packet. The up-to-date of information sent in beacons makes the prediction producing accurate location. The second proposed scheme is Destination Location Prediction (DLP) to solve loop problem of packets sent to the destination node. Destination location is predicted similarly as prediction in NLP scheme, and a packet forwarded to destination based on predicted location in case destination is out of forwarder range. Nevertheless, this may not be a suitable solution in large-scale networks with high mobility of nodes, additionally the proposed scheme does not estimate the link between neighbors before prediction [13]. Moreover, in a mobile environment a node sends late beacons and if it is still in the range of forwarder, then no prediction of this neighbor's location is needed.

The high frequency of sending location update packets causes an increase in the control overhead in wireless networks. Authors in [14] addressed this problem and proposed the Prediction Location Update algorithm (PLU) which has two stages in dealing with invoking updates packets sending. The first stage is to send update packets periodically based on a relatively long time period between each sent update and based on the wireless range and speed of node. This may ensure a long period between sent updates. The long period between updates may lead to low overhead with the cost of outdated information of network topology that changes frequently in high-speed networks. Consequently, the second stage solves this problem by invoking update packet sending when a significant change in the mobile node location occurs. The interval of the second stage is shorter than the first. The second stage uses linear equations to predict changes in the previous and current location. The shortcoming in PLU is that the acceleration effects are not considered as the speed is calculated as fixed and this does not reflect the real situation.

Authors in [15] enhanced GPSR protocol [16] by adding a prediction scheme. The RH-GPSR protocol uses two historical locations (x1, y1, t1) and (x2, y2, t2), where (x) and (y) are coordinates with timestamps (t) of neighbors. RH-GPSR calculates the distance between these two locations by assuming that a node takes the shortest path in moving between two positions. Available timestamps and calculated distance make RH-GPSR to calculate speed of a node. The three variables and calculated data which are velocity, time, and route topology, are utilized in RH-GPSR to predict the current location of a mobile node. This prediction usually invokes before any forwarding process of packets is made in order to guarantee successful packets delivery. Limitations in RH-GPSR are that the acceleration effects of a mobile node are not taken into account in this prediction. Additionally, RH-GPSR does not discuss the irregular intervals between stored locations, which may affect the accuracy of prediction.

Authors in [17] used machine learning techniques for location prediction. A spatiotemporal classifier was developed in order to predict the trajectory of a mobile node. A number of historical locations with timestamps are saved and used to predict the location of a mobile node. A threshold issued to check successfulness of prediction. This threshold is calculated by comparing predicted value with real one, if the value is greater than the error rate of threshold, then the prediction fails, otherwise it is successful. The learning part in this prediction scheme is that feedback is returned from the environment to spatiotemporal classifier in order to check successful prediction and its accuracy. However, the limitation with this prediction scheme is that it has slow response to changes which may influence its adaptability. High storage is also required in maintaining patterns of users used by machine learning prediction.

In [18] authors proposed a location prediction protocol that predicts future locations of VANET nodes by utilizing Kalman filter techniques. Prediction Location Management protocol (PLM) exploits the high mobility of VANET nodes to distribute mobile nodes location information among other nodes. PLM uses Kalman filter to predict locations by utilizing historical data locations stored on each node's database. Even though, Kalman filter with extended features can predict precise locations, PLM uses standard Kalman filter to avoid complexity of calculations with extended version. PLM shows lower overhead compared to without prediction protocol. However, the effects of irregular time intervals between sampled locations on PLM performance are not tested.

Authors in [19] proposed the Predictive Hierarchical Location Service protocol (PHLS) which uses a hierarchy of regions to achieve scalability. PHLS predicts the demanded position when the precise position is unidentified by exploiting previous nodes' information (location and velocity). Through joining the hierarchy structure together with the prediction such the one proposed in PHLS, flooding packets is avoided and the performance is improved. Two prediction schemes were presented in [19]. The first scheme is PHLS1 that predicts locations based on velocity, previously stored position of a node, current time, and the time when last position where received. A mathematical formula utilizes mobile node's information to predict its future location. Meanwhile, the second prediction scheme, PHLS2, predicts the average velocity through the most recent velocities update received recently from the mobile node. PHLS2 also calculates the average velocity, and as a result, the future location can be predicted by location server. In testing results, PHLS showed satisfactory performance compared to the original protocol, HLS. However, both presented prediction schemes in PHLS do not take into account the acceleration effects of irregular time intervals between stored locations of mobile nodes.

A Kalman filter is utilized for anticipating the vehicle's future position in [20]. Authors performed tests utilizing real vehicle mobility traces and model-driven traces. A comparison conducted of the position prediction performance of a Kalman filter compared to neural network-based techniques. Authors in [2] used Extended Kalman Filter (EKF) to predict the location of VANET nodes moving in nonlinear way. Whereas the standard Kalman filter not suitable for such situations. Authors show results of better performance in predicting future location on nodes moving in nonlinear routes.

2.2 Location Prediction Using GM (1,1) in Ad-Hoc Networks

One of the mathematical models of grey theory is grey prediction model called Grey Model First Order One Variable GM (1,1), which is a quantitative prediction model. It is based on theoretical treatment of the original data and establishment of grey models. Therefore, it discovers and controls the development rules of the system of interest so that scientific quantitative predictions about the future of the system can be made [21] [22]. One of the smart features of the grey model for prediction is the quasi-smoothness check [21]. It detects whether or not the prediction model will predict correct values. The detection of correct values is through the sequence data input to model, the data generated by AGO, and by checking the results against a given threshold. If the result is equal to, or below the threshold, the prediction is correct. Otherwise, the produced predicted values are noisy.

Authors in [13] proposed On-Demand Multicast Routing Protocol based Grey Prediction (ODMRP GP) in Vehicular Sensor Network (VSN). ODMRP GP utilizes GM (1,1) to predict a mobile node's distance in order to send alert messages in reconstructing a path between a pair of communicating nodes. ODMRP GP treats the received signal power (four values) from nodes as input to the grey model. The predicted value by grey model is compared to distance threshold, and whenever a mobile node's distance meets the threshold it is considered as out of the source node's range. Therefore, the node broadcasts a warning message and generates rerouting packets. Nevertheless, ODMRP GP does not consider the effects of vehicle acceleration and irregular time intervals of collected data on grey model and how these factors may affect predicting distance between mobile nodes. Moreover, ODMRP GP shows positive control packets overhead, and it causes latency in packet transmission.

In [23] authors proposed a prediction model based on grey model. The proposed model manipulates the input sequence of mobile object locations with their timestamps. This sequence is divided into multiple correlative subsequence representing values of x axis and y axis of stored locations. Merging these values creates the location prediction model. In this model, three functions were constructed to predict the location of mobile object at the time t with the first two functions constructed by adopting grey prediction model. The proposed model by [23] showed accurate predictions compared to prediction with linear equations. However, the acceleration effect was not considered in designing the model as the acceleration was assumed to be fixed. Furthermore, the intervals between sampled locations were collected over regular intervals and no test for irregular intervals was shown in order to show the efficiency of the proposed prediction model.

Authors in [24] proposed Grey Model-Based Particle Filter (GP-PF) by utilizing the efficiency of grey prediction model in order to overcome drawbacks of Standard Particle Filter (SPF) [25]. The problem with SPF is sample degeneracy that is caused due to representing true dynamics of mobile objects. Grey model used in GP-PF is for sampling data input for the filter. Then SPF filter employs the accurate particles to produce filtered values. The key factor here is that grey model for prediction is accurate in predicting state transition and has an advantage of no priori dynamic model of destination needed. These features make prediction model suitable in providing SPF with the ability of tracking moving objects. Nevertheless, the acceleration is not considered in GP-PF or sampling data over irregular intervals where these two factors affect the efficiency of prediction.

Authors in [26] has compared grey prediction model GM (1,1) with Kalman filter for efficiency in tracking moving objects. A straight forward algorithm building was used to extract historical data moving object. Grey model retrieves the latest 5 locations saved about the moving object and uses them in predicting the future location. With the use of recent historical data, the grey model showed relatively higher accuracy compared to Kalman filter. Additionally, the actual algorithm assumed that the object moves in a constant speed. However, the assumed speed of nodes does not represent the actual situation on road.

Authors in [27] proposed a prediction protocol based on grey prediction model. The proposed protocol uses a double- queue mechanism to synchronize the prediction data series of both sensor node (source) and the sink node. This to ensure reduction in the cumulative error of continuous predictions. Based on this protocol, three prediction-based data aggregation approaches are proposed: Grey-Model-based Data Aggregation (GMDA), Kalman-Filter based Data Aggregation (KFDA), and Combined Grey model and Kalman Filter Data Aggregation (CoGKDA). By combining the excellence of grey model in fast modelling with the benefit of Kalman Filter in filtering noise in data series, CoGKDA could achieves high prediction accuracy. CoGKDA does not take the acceleration of the mobile node into account that might affect the accuracy of grey model. In CoGKDA design, there is no consideration for the effects of irregular time intervals of sending updates on time-series prediction model.

The prediction models to predict locations of mobile nodes are affected by factors such as noisy input or acceleration; therefore, a filtering for this noise predicted values is needed.

Grey prediction model is used for predicting future locations of mobile nodes in ad-hoc environment. However, the efficiency of this model is affected that leads to corruption in predicted values, which leads to inaccurate locations of the destination node. Inaccuracy in locations of nodes in a mobile network may lead to error in delivery of packets or increase in control packets overhead [9]. Consequently, noise filters can be used to reduce noise in predicted values. The grey model for prediction experiences a limitation in high mobility network; therefore, an efficient hybrid between grey model and a filter might predict accurate locations of moving objects.

2.3 Location Prediction Using Artificial Intelligence

Adopting Artificial Intelligence techniques in location prediction gain attention of researchers. In this section, number of those techniques is summarized.

Authors in [28] proposed a recurrent neural network for long term series of predicting mobile nodes' locations to solve the main problem of location prediction which is time series. Authors designed a three-layer architecture of the proposed neural predictor. The algorithm trained using back propagation. To exam the productivity of the predictor, authors tested the proposed technique on time series representing locations of a mobile nodes in mobile ad hoc environment.

Authors in [29] used neural learning machine-based model to predict node's location in MANET. the proposed technique used extreme learning machine (ELM) that does not need tuning for the parameters and it gives realistic locations of nodes. Results in the study shows better performance of this techniques compared to conventional techniques.

In [1] authors proposed a vehicular position prediction model using an artificial neural network. The location prediction model intended for cooperative active safety systems. Authors claim that the proposed model has consistent and shorter calculation time and additionally higher precision features. The performance of the proposed model was tested with a real-time testbed and compared with Kalman filter.

Authors in [30] proposed a deep learning-based model to integrate contextual features to predict next location. The first step in proposed method, finding the resemblance among location of candidates. Then, the contextual features have been modeled of trajectories, considering periodical forms and dynamic features of trajectories. Third, we adopt both Convolution Neural Network (CNN) and bidirectional long short-term memory (LSTM) networks to predict next location in each trajectory with related information. Extensive test done on tracking cars' locations based on their plate numbers.

Authors in [31], proposed a Spatial-Temporal Long-Short Term Memory (ST-LSTM) model that associates spatial-temporal impact into LSTM to alleviate the problem of data sparsity. The aim is to predict users' location in short time (i.e. minutes or hours).

Additionally, proposed method employs a hierarchical extension to the proposed model which models the contextual historic visit information to achieve better prediction performance. The proposed model is assessed on a real-world trajectory data set and the experimental results demonstrate the efficiency of the proposed model.

3. *DISCUSSION AND ANALYSIS*

Location prediction models used in wireless mobile nodes are affected by a number of factors such as noisy input data and acceleration of mobile nodes. Hence, the filter for the noise is needed. Predicting future locations of mobile nodes possibly will be a good solution in the case of a high mobility environment. Figure 2 depicts the main stages of location prediction models.

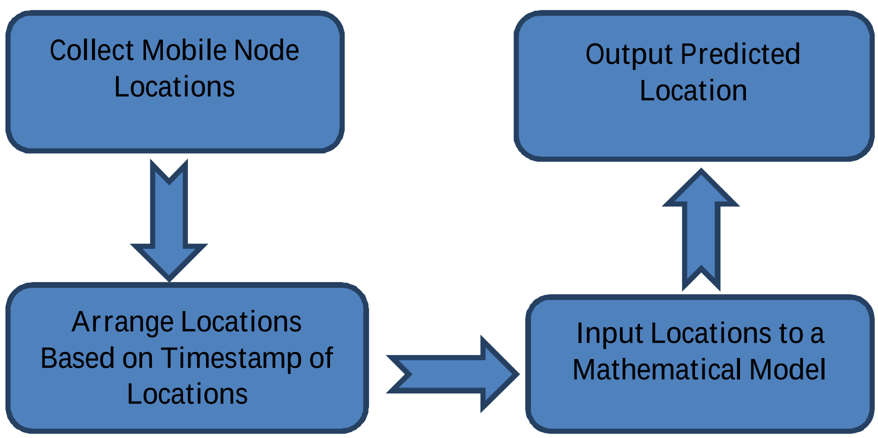

Figure 2: Principles of Location Prediction

Current location service protocols suffer from some limitations and face challenges, specifically when they are applied in a VANET environment. The nature of urban areas, such as intersections and restricted movements of vehicles on roads influences the performance of the protocol. Some protocols propose location service protocols for VANET environment, but they do not tackle important issues faced by the protocols such as stability of the selected location server node. This stability mainly affects the control packets overhead. TABLE I summaries the location prediction techniques.

The high mobility of VANET's nodes causes nodes to move further away from each other in a short time which causes storing of outdated locations on location servers which influences the efficiency of location service. Outdated location information degrades the delivery of the packet to their destinations. Frequent beacon sending helps keeping nodes locations up-to-date, but it interferes with other data transmission and causes packets collisions and retransmissions in addition to network congestion. Nodes moving at very high speed may cause frequent link breakage, which affects the performance of the network. Moreover, the delivery success ratio is affected by link loss. In VANET, the high mobility of nodes influences the effectiveness of the conventional protocols and may degrade the performance of the network. Therefore, a prediction possibly will be a good solution to overcome the problem of outdated locations and reduced control overhead in high mobility environment.

The Grey prediction model is widely used to efficiently predict future locations of mobile nodes in the ad-hoc environment and other applications. However, the accuracy of the model is affected by some factors such as irregular intervals of nodes location updates and variable speed of mobile objects. These factors corrupt the predicted value by the grey prediction model. One of the smart features of the grey model for prediction is the quasi-smoothness check [21]. It detects whether or not the prediction model will predict correct values. The detection of correct values is through the sequence data input to model, the data generated by AGO, and by checking the results against a given threshold. If the result is equal to, or below the threshold, the prediction is correct. Otherwise, the produced predicted values are noisy.

A mobile object which could be a car, mobile robot, or aircraft moves off of sensor range or stop sending its status to the tracker for an interval might cause the tracker to lose the information of that object's current position and status. Thus, tracking of this object is exploited to retrieve information about its possible current position, speed, and direction. Several mathematical models are used in tracking those mobile objects by using previous sampled information about objects. Examples of those models are Alpha-Beta filter proposed by Sklansky and Kalman filter, which are used for mobile objects tracking, and they proved acceptable performance [32]. These filters filter the noise of objects' locations, where noises occur due to inaccurate values returned about objects location [32]. Usually, the noise affects the prediction accuracy that degrades the performance of trackers.

Using artificial intelligence techniques in location prediction gains attention of researchers. However, the learning process of those techniques may take time and need resources to achieve the accepted level of accurate prediction. The results of simulating those techniques show good results which make it a welling area of research in predicting the location of a highly mobile environment.

TABLE I: SUMMARY OF REVIEWED LOCATION PREDICTION TECHNIQUES.

No.	Reference	Using AI	Grey Prediction Model
1	Predictive Location-Based QoS Routing in Mobile Ad Hoc Networks	No	No
2	A Predictive Location Model for Location-based Services	No	No

3	The effect of mobility-induced location errors on geographic routing in mobile ad hoc sensor networks: analysis and Improvement using mobility prediction	No	No
4	A Prediction-Based Location Update Algorithm in Wireless Mobile Ad-Hoc Networks	No	No
5	VGITS:ITS based on intervehicle communication networks and grid technology	No	No
6	An Online Adaptive Model for Location Prediction	Yes	No
7	On Peer-to-peer Location Management in Vehicular Ad Hoc Networks	No	No
8	Predictive Scheme for Location Service in Mobile Ad-Hoc Networks	No	No
9	Location Prediction of Vehicles in VANETs Using a Kalman Filter	No	No
10	Grey Target Tracking and Self-Healing on Vehicular Sensor Networks	No	Yes
11	Location Prediction for Tracking Moving Objects Based on Grey Theory	No	Yes
12	Grey Prediction Based Particle Filter For Maneuvering Target Tracking	No	Yes
13	Object Tracking Algorithm Based on Grey Innovation Model GM(1,1) of Fixed Length	No	Yes
14	Prediction-Based Data Aggregation in Wireless Sensor Networks	No	Yes
15	Mobility Prediction in Wireless Ad Hoc Networks using Neural Networks	Yes	No
16	Mobility prediction in mobile ad hoc networks using neural learning machines	Yes	No
17	Neural Network Based Vehicular Location Prediction Model for Cooperative Active Safety Systems	Yes	No
18	Location prediction algorithm for a nonlinear vehicular movement in VANET using extended Kalman filter	No	No
19	A Deep Learning Approach for Next Location Prediction	Yes	No
20	HST-LSTM: A Hierarchical Spatial-Temporal Long-Short Term MemoryNetwork for Location Prediction	Yes	No

4. CONCLUSIONS

Several location prediction techniques of mobile nodes analyzed in this manuscript. Different ways used by researchers to provide accurate locations of mobile nodes. However, we conclude few points need to be addressed; these points make location prediction better.

- It is good to develop a technique that improves the accuracy destination location prediction by hybrid of location prediction model and noise filter.
- Considering nodes acceleration and irregular time intervals between sampled data make the technique realistic. Taking those points into consideration can increases the location prediction accuracy in a high mobility environment.
- Light weight calculations of prediction model make it faster to predict which helps in consuming low resources of mobile nodes.
- Prediction based on artificial intelligence is a desirable technique in predicting location.

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