Link Duration Estimation using Neural Networks based Mobility Prediction in Vehicular Networks

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***Abstract*—The knowledge of Inter-vehicle link duration is an important parameter in Vehicular Ad hoc Networks (VANETs), as it is useful for vehicles to delay their information transmission if link breakage is anticipated before completing the transmission. In addition, it plays a pivotal role in routing, as it allows proactive construction of long-life paths, and optimizing next-hop selection in position-based routing (PBR). However, due to the high mobility of vehicles and the complicated vehicular mobility patterns in urban areas, the estimation of link duration in urban VANETs is still an open research issue. Different from other complex link duration estimation methods, we introduce a lightweight neural networks (NNs) based mobility prediction scheme which allows vehicles to autonomously predict their future mobility speed for a certain time window. Then, the expected speed is used in an urban area mobility prediction model to estimate link duration between neighbouring vehicles. Extensive simulation results are given to demonstrate the validity of the proposed methods.**

I. Introduction

Enabling vehicular communication is essential for a wide range of technological applications in road safety, traffic management and travellers' comfort. In VANETs, vehicles are equipped with on-board communication units (OBUs) to enable vehicle-to-vehicle (V2V) communication, and a set of roadside units (RSUs) are installed along the roads to support vehicle-to-infrastructure (V2I) communication. The high mobility of vehicles and the short communication range of OBUs and RSUs result in transient connections even with enabled multi-hop routing. Due to vehicles mobility, established links between vehicles fail during packet transmission causing delay in packets delivery and wastage of network's bandwidth. Links failure can also cause intermittent routing paths which can deplete the network's resources via frequent route establishment and maintenance procedures. Efficient estimation of link duration can minimize packets transmission failure due to link breakage, and help in constructing long-life routing paths.

The purpose of this paper is to develop an autonomous link duration estimation method in order to enable vehicles to determine the residual link duration prior to transmission. Based on the available mobility information for one-hop neighbouring vehicles, relative mobility can be predicted, and accordingly, link residual time between two vehicles. Vehicles are required to broadcast safety messages periodically (e.g., every 100 $msec$) to their one-hop neighbours which include information about location, speed, direction, break status etc [1]. The aim of this study is to provide an efficient scheme to utilize this information for mobility prediction and link duration estimation.

Several previous studies consider mobility prediction to estimate link lifetime in the context of VANETs, such as in [2]–[7], and few of them deploy it for route construction, e.g., [2]–[5]. In [3], physical layer information is used for link duration estimation by observing the changes in transmission power level and predicting the residual time until it drops below a certain threshold. In [6], vehicles mobility analysis is used to investigate link duration and connection duration. Vehicles mobility vectors and the impact of traffic lights on inter-vehicle links are considered in [7] for a practical link prediction model in VANETs city scenario. Link duration information is used in [2] and [3] for paths construction, in order to improve VANETs multi-hop routing performance.

In this paper, we propose a new method to utilize the available mobility information, delivered via safety messages, for a short-term mobility prediction in order to estimate link duration between two neighbouring vehicles. First, an NNs model is proposed to enable autonomous vehicles speed prediction for a certain time window. The inputs for the NNs are the mobility information obtained from the safety messages and static maps information while the output is the predicted average speed. Second, the predicted average speed is deployed in a mobility prediction model to estimate the remaining time before the first possible disconnection occurs due to vehicles' mobility.

The remaining of this paper is organized as follows: in section II we describe the system model under consideration. We introduce NNs-based speed prediction model in Section III, followed by the link duration estimation model in Section IV. Simulation-based evaluation and discussion of the proposed scheme are presented in Section V. Section VI concludes this paper.

II. System Model

A typical urban VANETs system is considered. VANETs OBUs are synchronized, have the same communication range R, have access to identical maps with well-defined road segments and intersections, and are able to obtain the vehicle's geographic location $Loc_m = (x_m, y_m)$, mobility speed S_m, direction Dir_m, and turning signal status Sig_m. In addition to mobility vector and turning signal information,

The first author acknowledges the financial support from Al-Baha University, Saudi Arabia, and the Saudi Arabian Culture Bureau, Ottawa, Canada, to carry out this research.

the predicted speed of the vehicle, ES_m, is also included in the periodic safety messages. Vehicles broadcast safety messages every 100 $msec$, however, mobility vector information for the vehicle and its neighbours is updated less frequently in the vehicle's routing table. The urban environment includes road segments with variable lengths, widths, and vehicular traffic densities. Each road segment $e_{i,j}$ is bounded by two controlled intersections I_i and I_j.

Every vehicle v_m frequently updates its ES_m by simply applying some information derived from its routing table to the NNs model, as will be shown in Section III. Periodically, each vehicle v_m receives updated mobility information from its one-hop neighbours. In order to update the estimated link duration between v_m and the broadcasting neighbour, the link duration estimation model is used by applying information from both the received safety message and mobility information of v_m. Links duration information is kept in vehicles' routing tables and updated frequently based on a probabilistic method shown in IV-B

III. Neural Networks based Speed Prediction Model

The objective of this model is to predict the average speed of v_m, ES_m, for the next W seconds, where W is the prediction time window. This problem is more challenging in the city scenarios than highway scenarios, as drivers change their mobility speed and direction more frequently due to their different driving habits and routes, traffic lights, or vehicular traffic densities on the roads. By observing different microscopic and macroscopic traffic forecasting and mobility prediction model-based approaches, such as in [8] and [9], we have selected a number of factors that have direct impact on vehicular mobility patterns and can help in the autonomous average speed prediction. These factors are:

1) Vehicle's speed S_m at the prediction moment
2) Number of leading vehicles
3) Average speed of the leading vehicles
4) The distance to the next intersection
5) Number of lanes in the road segment

where leading vehicles of v_m are the set of v_m's neighbours which are in front of v_m, within the same road segment, have the same signalling status and driving direction.

As the relation between these factors are complicated, we deploy neural networks (NNs) as an efficient data-driven approach to find ES_m. NNs approaches show the capabilities to map non-linear input and output patterns in order to solve the complicated non-linear traffic related prediction problems [9]–[11]. In our NNs design, three networks have been trained based on the turning signal status (idle turn signal, right turn signal, and left turn signal). Each network has been trained using more than 4000 normalized samples with the five aforementioned inputs and single output, the actual average speed of v_m in the following W sec. To avoid the effect of red traffic signal duration, samples with zeros in the first and the third inputs are excluded.

Vehicular traces files are generated using the microscopic vehicular traffic simulator VISSIM [12]. MATLAB Neural Networks tool is used for NNs training, validation, and testing. For each NN, a two-layer feed-forward supervised data fitting network is used with five inputs, twenty sigmoid hidden neurons, and a single output. The network is trained with Levenberg-Marquardt backpropagation algorithm. Input samples are generated by VISSIM considering three vehicular traffic densities in the urban area around the University of Waterloo (UW) campus: light, moderate, and congested traffic. Using VISSIM output trace files, random v_ms are selected, and the associated input factors are extracted and calculated as well as the associated target ES_ms.

IV. Link Duration Estimation

The objective of this module is to predict the time left for two communicating vehicles before the communication becomes no longer possible due to the anticipated increase in the distance between them caused by their mobility. Thus, the relative mobility between them should be first investigated, and then, according to the available mobility and map information, the possible mobility scenarios can be predicted to estimate the residual link lifetime.

A. Underlying Structure of Relative Mobility

Given mobility information of two mobile vehicles v_m and v_n, it is required to find a closed form equation that relates their anticipated mobility vectors for a certain predicted mobility scenario ω, with the link residual time $LRT_{m,n}(\omega)$. Let the locations of v_m and v_n to be $Loc_{m,0}(x_{m,0}, y_{m,0})$ and $Loc_{n,0}(x_{n,0}, y_{n,0})$ respectively to represent the Cartesian coordinates of vehicles locations at the prediction time, t_0. Without loss of generality, we assume constant velocity vectors for v_m and v_n, $u_m = (u_{m,x}, u_{m,y})$ and $u_n = (u_{n,x}, u_{n,y})$ respectively. u_m and u_n will be replaced with the predicted average speed for the associated scenario as will be shown in the next section. It follows that the temporal change in the distance $d(\Delta t)$ between v_m and v_n is given by:

$$d(\Delta t) = \sqrt{(\Delta x_0 + \Delta u_x \Delta t)^2 + (\Delta y_0 + \Delta u_y \Delta t)^2} \tag{1}$$

where $\Delta k_0 = k_{m,0} - k_{n,0}$, $\Delta u_k = u_{m,k} - u_{n,k}$, $k \in \{x, y\}$, and $\Delta t = t - t_0$.

$LRT_{m,n}$ is the value of Δt that increases the distance between the mobile vehicles to reach the effective transmission range $\hat{R}$. By setting $d(\Delta t) = \hat{R}$ in Eq. 1, and solving for Δt:

$$\begin{aligned} LRT_{m,n} = \frac{1}{\Delta u_x^2 + \Delta u_y^2} * (&-\Delta x_0 \Delta u_x - \Delta y_0 \Delta u_y \\ &\pm \sqrt{\hat{R}^2(\Delta u_x^2 + \Delta u_y^2) - (\Delta x_0 \Delta u_y - \Delta y_0 \Delta u_x)^2}) \end{aligned} \tag{2}$$

B. Prediction of Mobility Scenarios in Urban Areas

A mobility scenario is the description of the anticipated mobility trajectories for the communicating vehicles, e.g., stopping at a red traffic signal, changing mobility direction or proceeding with the predicted average speed in the same direction. In this section, we set some rules to generate possible mobility scenarios based on the available mobility and location information. A vehicle v_m that received a safety message from v_n and extracted mobility information in order to estimate $LRT_{m,n}$, generates a set of scenarios according to scenario generating rules. For each scenario ω, the mobility variables, e.g., $u_{m,x}$ and $u_{m,y}$, are extracted according to ω assumptions, and Equation 2 is applied.

With respect to the urban VANETs environment, we define the effective communication range $\hat{R}$ according to ω under consideration as follows. When v_n belongs to the same road segment or a front road segment, $\hat{R}$ takes a value of αR which is the effective communication range that has acceptable channel quality for line-of-sight situations. When v_n belongs to a right or left road segment (or making a turn is considered by ω), βR replaces $\hat{R}$ in Equation 2 representing a non-line-of-sight effective communication range; α and $\beta \in [0,1]$. Road segments can be described to be in front, to the right, or to the left, according to the current road segment of v_m, the common intersection between v_m and v_n, and the map information. The averaged maximum speed S_{max} is another design constant where it represents the average speed for a vehicle that is moving with its maximum acceleration from a stopping position until reaching the maximum speed for a displacement of $\hat{R}$.

In the following, we present the rules to generate the different mobility scenarios in our model:

1) When v_m, one of the communicating vehicles, has an idle turning signal status, ES_m is used in Equation 2 (substituting u) as well as its original reported location and driving direction
2) When a communicating vehicle v_m has an active turning signal, three scenarios are added: a) v_m proceeds in the same driving direction with the speed of ES_m, b) v_m stops at the reported location (i.e., waiting to make a turn) and u is substituted by zero, and c) v_m changes the driving direction according to the turning signal and proceeds with the maximum averaged speed S_{max}
3) When v_m and v_n are not within the same road segment, and v_m is moving toward the common intersection, two scenarios are added: a) v_m stops immediately (i.e., for a red traffic light) and b) v_m proceeds with the speed of S_{max} (i.e., for a traffic signal turning green with no leading vehicles).

Figure 1 shows an example of a case where v_m and v_n belong to different road segments, v_m is heading the common intersection and have an idle turning signal, while v_n has an active right turn signal. According to the aforementioned rules, a set of 9 mobility scenarios are generated. $LRT_{m,n}$ equation is used for the different scenarios with respect to the corresponding variables of each scenario. Finally, the minimum $LRT_{m,n}$ is maintained in the routing tables of v_m and v_n. $LRT_{m,n}$ is upper-bounded by the prediction time window W.

$LRT_{m,n}$ is updated frequently in v_m routing table as long as safety messages are received from v_n. In order to reduce the calculation overhead, v_m updates $LRT_{m,n}$ according to the following probability function:

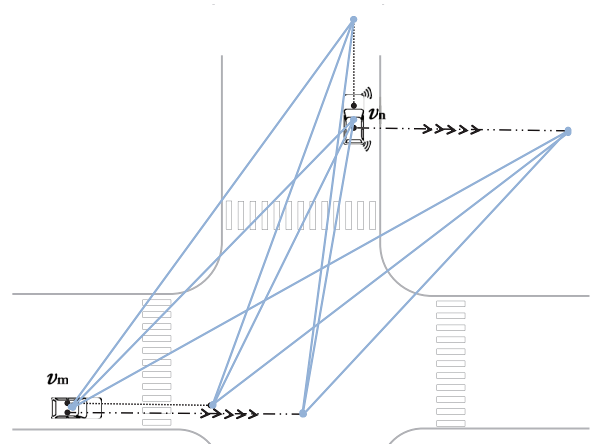

Fig. 1. An example of mobility scenarios

$$P_{upd}(LRT_{m,n}) = \begin{cases} \frac{1}{1+e^{-(LRT_{m,n}+\frac{\hat{R}}{2S_{max}}+\frac{\mu}{2})}}, & t-ts \geq \mu \\ 0 & t-ts < \mu \end{cases} \quad (3)$$

where t is the current system time, ts is the timestamp of the last link information update, and μ is a constant design parameter to prevent frequent updates for a leaving vehicle.

V. Scheme Validation

In this section, we present the evaluation and simulation set-up to validate the proposed NNs model and the link estimation module, as well as results and discussion. The performance of NNs model can be validated using two metrics, the correlation between the networks outputs and the desired average speed target, and the root mean square (RMS) between them. Link estimation model performance is measured by comparing the estimated link duration with the actual disconnection time between vehicles. The introduced computation overhead is also considered.

First, VISSIM simulation setup and parameters are set according to the setup in [13]. In this setup, all intersections are controlled according to the real intersections around University of Waterloo. Each road has a maximum/desired speed. We set turning signal information to be given 30 meters before the intersection. As in [13], the car following model is Wiedemann74 model [14] developed for urban traffic. Trace files have been generated from several simulation runs with different traffic densities. Then, the NNs have been set according to the setup in Section III with different W values. The result network parameters (NNs weight and bias values) have been extracted. Finally, a MATLAB simulation has been developed to evaluate the estimated link durations using VISSIM trace files. We have considered an idle channel condition, $S_{max} = 14m/sec$, $\mu = 2sec$, $R = 250m$, $\alpha = 1$, and $\beta = 1$.

The results show that the proposed NNs model successfully relates the inputs factors with the target average speed. The

TABLE I
CORRELATION AND RMS BETWEEN THE NNS MODEL OUTPUTS AND TARGET ES

W (Seconds)	5	10	15	20	25
Correlation	0.97	0.96	0.93	0.87	0.80
RMS	0.02	0.04	0.08	0.11	0.18

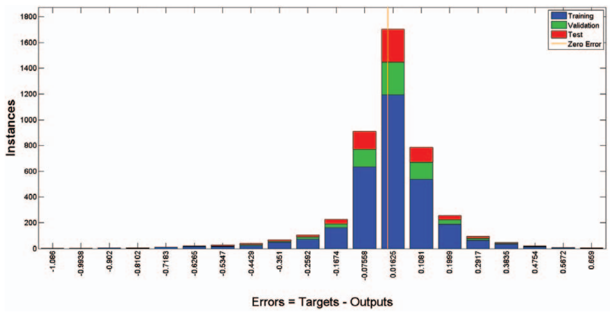

Fig. 2. An Error Histogram for the NNs Model with $W = 10\ sec$

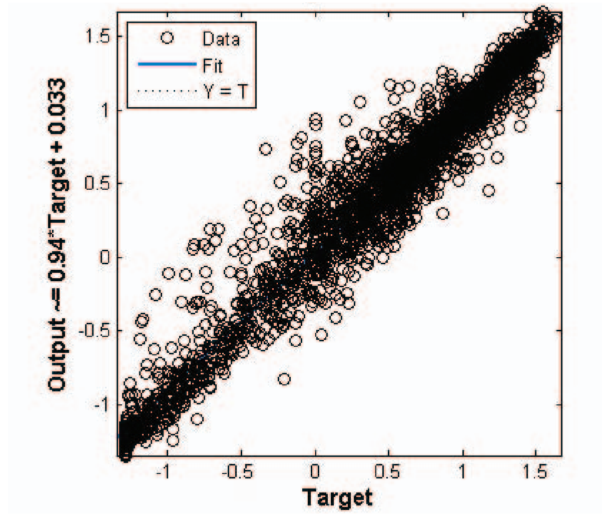

Fig. 3. Correlation between the NNs outputs and the Target ES with $W = 10\ sec$

accuracy of the model is highly dependent on the prediction time window W. Table I summarizes the resulting correlation and RMS values for different prediction time windows. Figure 2 and Figure 3 show error histogram and correlation diagrams, respectively, for the NNs performance.

The evaluation of link estimation model show that our model demonstrate to set a lower bound of link lifetime in more than 98% of the examined cases with $W = 20$. In fact, the average link duration between vehicles, especially vehicles belong to the same road segments, is much higher than the estimated values. This is because vehicles in our model examine the different possible mobility scenarios and select the scenario that gives the minimum LRT. These *worst* case scenarios occur with low probability. Moreover, less than 2% of the cases have link breakage just before the estimated time, due to an inaccuracy the in average speed prediction.

The main communication overhead in the network is the safety messages, which has been standardized [1]. Our scheme requires including the resulting ES_m to be *piggybacked* in these messages. In terms of computational overhead, our scheme introduced a reduced calculation overhead that is controlled by Equation 3. In general, receiving and processing safety messages every 100 $msec$ introduce a huge computational overhead, especially at intersections, and require high performance OBUs with sufficient computational resources. At intersections, vehicles have lower speeds on overage and higher links duration, which introduces less updating overhead by the proposed scheme.

VI. CONCLUSIONS

We have proposed an NNs-based link duration estimation scheme that enables vehicles to determine and maintain minimum connectivity to their one-hop neighbouring vehicles. By providing temporal connectivity information to OBUs, vehicles can optimize their transmission decisions, next-hop forwarders selections, and route construction protocols. For our future work, a connectivity aware position-based routing protocol with a pre-determined path validity duration will be developed.

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