Location Information Verification using Transferable Belief Model for Geographic Routing in VANETs

Dalya Khalid Sheet¹, Omprakash Kaiwartya¹, Abdul Hanan Abdullah¹, Yue Cao^{2,*}, Ahmed Nazar Hassan¹, Sushil Kumar³

 ¹Faculty of Computing, Universiti Teknologi Malaysia (UTM), Johor, 81310, Malaysia
 ²Department of Computer Science and Digital Technologies, Northumbria University, Newcastle upon Tyne, NE1 8ST, UK.
 ³School of Computer & Systems Sciences, Jawaharlal Nehru University, New Delhi-110067, India

*Corresponding Author: yue.cao@northumbria.ac.uk

Abstract: Location verification has witnessed significant attention in vehicular communication due to the growth in number of location based Intelligent Transport System (ITS) applications. The Traditional cryptography based techniques have been suggested to secure and verify location of vehicles. The traditional techniques increase protocol complexity and computational overhead due to the adhoc nature of vehicular network environments. In this context, this paper proposes two layered Location Information Verification cum Security (LIVES) technique based on Transferable Belief Model (TBM). In layer 1, Tiles based Verification (TV) is performed using the concepts of virtual tiles on roads and received signal strength. In layer 2, TBM based verification is performed. Specifically, the belief of the presence of a vehicle on each tiles, and the belief to attest the location claim of a neighbour vehicle. The performance of LIVES is evaluated with road-based and map-based network environments. The single, mixed and multiple adversary vehicles are considered in both the network environments. The comparative performance evaluations attest the benefits of LIVES as compared to the Verification and Inference of Position using Anonymous beaconing (A-VIP) and without using LIVES (W-LIVES).

Keywords: Location verification; Geographic routing; Transferable belief model; Vehicular communication.

1. Introduction

Recently, vehicular communication has witnessed remarkable attention in both academia and industries [1]. In vehicular communication, the major location based Intelligent Transport System (ITS) applications include cooperative traffic monitoring, blind crossing, prevention of collisions, control of traffic flows, nearby information services, and Internet access in vehicles [2]. To realize these location based applications, geographic routing has got foremost attention for information dissemination in vehicular communication as compared to the other routing techniques [3-5]. In geographic routing, location of neighbouring vehicles is obtained by broadcasting location query in neighbourhood [6,7]. The location query creates a security hole for malicious location attacker vehicles. The malicious vehicles disrupt the functionality of geographic routing by either introducing false location claim or modifying the location claim of other vehicles [8-10]. Although, various techniques have been suggested to verify the location claim yet, the dependency of these techniques

on cryptography reduces the applicability in vehicular traffic environments where majority of location based applications require real time response [11-13].

In this context, this paper proposes a Location Information Verification cum Security (LIVES) technique based on Transferable Belief Model (TBM) for geographic routing in Vehicular Adhoc Networks (VANETs). The technique is an extension of our initial work in terms of mathematical modelling, map-based network evaluation, metrics and comparative analysis of results between map-based and road-based networks [14]. The location verification is carried out into two layers. In layer 1, Tiles based Verification (TV) is performed using the concepts of virtual tiles on roads and received signal strength. In layer 2, TBM based verification is performed. Specifically, the belief of presence of a vehicle on each tiles, and the belief of presence of a vehicle as neighbour of other neighbouring vehicles are combined as collective belief to attest the location claim a neighbour vehicle. An algorithm for secured geographic routing (SGR) is developed utilizing the two layered location verification. Simulations are carried out in NS-2 considering single, mixed, and multiple adversary vehicles in road-based and map-based network environments.

The rest of the paper is organized in following sections. Section 2 qualitatively reviews location verification in VANETs. Section 3 presents the detail of LIVES as theoretical and mathematical modelling. The simulation setup and results are discussed in section 4. Section 5 concludes the work presented in this paper.

2. Related Work

In this section, a qualitative review on location verification in VANETs is presented. A-VIP has been suggested as a server based approach for location verification [15]. The verification technique infers the correct location of the vehicles who claim fake locations. It uses a trusted server to verify location claim. Although the technique is claimed to be promising, yet the requirement of server for location verification reduces the applicability of the technique due to the growing importance of distributed approach in VANETs. The Time of Flight (ToF) based location verification technique has been suggested using cooperative neighbour vehicles [16]. The two vehicles, namely, verifier and co-operator verify location claim of a vehicle. Although, ToF based location verification is suitable for static network yet, its accuracy reduces in dynamic vehicular networks. Additionally the impact of vehicle speed on ToF based distance calculation has not considered.

The Non-Line of Sight (NLOS) issue in location verification has been addressed using cooperative neighbour vehicles [17]. The angle based distance measurement with control packet communication has been utilized. Although angle based distance measurement is appropriate for static network yet, the accuracy of the distance measurement could not be guaranteed in dynamic vehicular networks. The major location verification techniques for VANETs have been explored [18]. The techniques are based on autonomous sensors, cooperative sensors, and digital street map. A Neighbour Position Verification (NPV) technique has been suggested for Mobile Adhoc Networks (MANETs) [19]. NPV is a reactive and cooperative technique based on cryptography. Although authors have claimed that NPV verifies both single and multiple adversary vehicles yet, the dependency on cryptography reduces the applicability in vehicular networks. Due to the page limitation, readers are advised to consult the literature [20-22] where location verification has been critically reviewed.

3. LIVES

In this section, two layered location verification technique is proposed.

3.1 Layer 1: Tiles based Verification

In this layer, virtual tiles on the roads are considered. These tiles are utilized to verify location claim of neighbour vehicles. The forwarding vehicle v_{cf} calculates the location of tiles within transmission range using own location and the architecture of tiles (see Fig. 1). Let *T* is the set of tiles and *V* is the set of neighbour vehicles of v_{cf} . The ideal received signal power $PW_{t_i}^r$ from i^{th} tile t_i can be calculated by v_{cf} using shadow fading model as expressed by Eq. (1).

$$PW_{t_i}^r = PW_{t_i}^t \left\{ 10 \log_{10} C - 10 \ \omega \log_{10} \left(\frac{d_{v_{cf}, t_i}}{d_0} \right) - \tau \right\}$$
(1)

where $PW_{t_i}^t$ is the transmitted signal power from tile t_i , C denotes the constant representing antenna characteristics and channel attenuation, ω represents the path loss exponent, d_{v_{cf},t_i} represents the distance between v_{cf} and t_i , d_0 is the reference distance for antenna, and τ represents a Gaussian random variable. The distance d_{v_{cf},t_i} can be calculated using the latitude and longitude location of tile $L_{la,lo}(t_i)$ and vehicle $L_{la,lo}(v_i)$. The received signal power $PW_{v_i}^r$ from i^{th} neighbour vehicle v_i can be calculated by v_{cf} as expressed by Eq. (2).

$$PW_{v_i}^r = PW_{v_i}^t \left\{ 10 \log_{10} C - 10 \ \omega \log_{10} \left(\frac{d_{v_{cf}, v_i}}{d_0} \right) - \tau \right\}$$
(2)

where $PW_{v_i}^t$ is the transmitted signal power from vehicle v_i , d_{v_{cf},v_i} is the distance between v_{cf} and v_i . An approximation method is proposed to verify the location claim $L_{la,lo}(v_i)$ of i^{th} neighbour vehicle. For each neighbour vehicle, an approximation set is constructed based on the number of tiles on which the presence of a particular neighbour vehicle can be approximated. The approximation set AS_{v_i} for vehicle v_i can be constructed as expressed by Eq. (3).

$$AS_{v_i} = \{ t_j, t_j \in T \text{ and } \left| PW_{v_i}^r - PW_{t_j}^r \right| < \gamma \}$$

$$(3)$$

where t_j represents the j^{th} tile and γ represents the threshold value used to determine the equality of two received signals from vehicle v_i and tile t_i . The probability $p_{v_i}^{TV}$ of TV of a neighbour vehicle v_i can be expressed as given by Eq. (4).

$$p_{\nu_i}^{TV} = \frac{1}{\left|AS_{\nu_i}\right|}, \nu_i \in V$$
(4)

A neighbour vehicle passes TV if its probability $p_{v_i}^{TV}$ is greater than a threshold value δ , i.e., $(p_{v_i}^{TV} > \delta)$. A set of steps for TV is provided in Algorithm 1.





Fig. 1. Transmission range of a vehicle with virtual tiles

3.2 Layer 2: TBM based Verification

In this layer, verification of location is carried out using TBM for the neighbouring vehicles who clear TV at layer 1 [23]. TBM is based on two sequential computation phases, namely, credal and pignistic. In credal

phase, belief functions are used for quantifying and updating individual beliefs whereas in pignistic phase, quantified beliefs are transformed into probabilities, and are combined to take a decision. In credal phase of LIVES, firstly, the belief of the presence of each neighbouring vehicle on each tile $t_k \in T$ is calculated by the current forwarder vehicle v_{cf} . The belief of a vehicle v_j about the presence on a tile t_k is represented by b_{t_k,v_j} . Secondly, the belief of the presence of a vehicle v_j as a neighbour is calculated by other neighbouring vehicles $v_k \in SSV^{TV} - \{v_j\}$ of the current forwarder. The belief calculated by vehicle $v_k \in SSV^{TV} - \{v_j\}$ about a neighbouring vehicle v_j is represented by b_{v_k,v_j} . In pignistic phase of LIVES, the collective belief b_j^c of the location information of a neighbour vehicle v_j is computed by the forwarding vehicle v_{cf} by combining the tiles based belief b_{t_k,v_j} and neighbour vehicle based belief b_{v_k,v_j} which are calculated in the credal phase. The calculation of tiles based belief, neighbour vehicle based belief, and collective belief in the context of TBM are described in following sections.

3.2.1 Frame of Discernment: In TBM, a set Ω containing each possible states of a system is called Frame of Discernment (FoD). In the context of location verification system, the set of location of tiles L^t of current forwarder vehicles is considered as FoD, and can be expressed as given by Eq. (5).

$$\Omega = L^t = \{L_{la,lo}(t_i), \forall t_i \in T\}$$
(5)

where $L_{la,lo}(t_i)$ represents the location information of tile t_i in terms of latitude and longitude.

3.2.2 Tiles based Belief: The belief of the presence of a neighbour vehicle v_j on a tile $t_k \in T$ is represented by b_{t_k,v_j} . It can be calculated as expressed by Eq. (6).

$$b_{t_k,v_j} = \frac{\left| PW_{v_j}^r - PW_{t_k}^r \right|}{PW_{t_k}^r} , 0 \le b_{t_k,v_j} \le 1$$
(6)

where $PW_{t_k}^r$ and $PW_{v_j}^r$ can be calculated using Eq. (1) and (2), respectively. The tiles based belief b_{t_k,v_j} is calculated w.r.t. each tile by the current forwarder vehicle. This belief is not used solely to make decision on the correctness of location information. However, it contributes on decision making as a component with another component; i.e., individual belief of neighbouring vehicles, which is calculated in the next section. These two component beliefs collectively contribute on the decision regarding the correctness of location information vehicle.

3.2.3 Neighbour based Belief: The belief of the presence of a vehicle v_i as neighbor of a vehicle $v_k \in$

 $SSV^{TV} - \{v_j\}$ is represented by b_{v_k,v_j} . The number of metrics are used to calculate b_{v_k,v_j} including number of outgoing packets n_{out} routed though vehicle v_j , number of other neighbouring vehicles n_n having an entry of v_j into their neighbour table, difference of speeds s_d between v_k and v_j , number of incoming packets n_{in} though vehicle v_j , and percentage quality $q_{PW_{v_j}}$ of received signal strength as compared to the ideal received signal. It can be calculated as expressed by Eq. (7).

$$b_{v_k,v_j} = w_{out}\left(\frac{n_{out}^{th} - n_{out}}{n_{out}^{th}}\right) + w_n\left(\frac{n_n^{th} - n_n}{n_n^{th}}\right) + w_d\left(\frac{s_d^{th} - s_d}{s_d^{th}}\right) + w_{in}\left(\frac{n_{in}^{th} - n_{in}}{n_{in}^{th}}\right) + w_{pw}\left(\frac{q_{pw}^{th} - q_{PW}v_j}{q_{pw}^{th}}\right)$$
(7)

where w_{out} , w_n , w_d , w_{in} , w_{pw} represent the weights of corresponding parameters which are used to adjust the impact of the parameters, and n_{out}^{th} , n_n^{th} , s_d^{th} , n_{in}^{th} , q_{pw}^{th} represent the threshold values of the corresponding parameters. The values of these weight parameters and thresholds are highly oriented to network environments. The values considered in the implementation are mentioned in Table 1.

3.2.4 Pignistic Transformation for Collective Belief: The collective belief $b_{v_j}^{collect}$ of a vehicle $v_j \in SSV^{TV}$ is calculated by combining the tiles based belief obtained using Eq. (6) and neighbour based belief obtained using Eq. (7) to take the final decision regarding the presence of a vehicle as neighbour. The calculation carried out by current forwarding vehicle v_{cf} is known as pignistic transformation in the context of TBM. The collective belief can be calculated as expressed by Eq. (8).

$$b_{\nu_{j}}^{collect} = \prod_{k=1}^{|T|} b_{t_{k},\nu_{j}} + b_{\nu_{k},\nu_{j}} + \sum_{k=1}^{|T|} \left(1 - b_{t_{k},\nu_{j}}\right) \prod_{\substack{x,y,z,\dots l=1\\x \neq y \neq \dots \neq z \neq i}}^{|T|} \underbrace{\left(b_{t_{k},\nu_{j}}\right)_{x} \left(b_{t_{k},\nu_{j}}\right)_{y} \dots \left(b_{t_{k},\nu_{j}}\right)_{z}}_{1:|T|-1 \ terms}$$
(8)

Where k and x, y, z, l represent the subscript used for referring tiles. The collective belief calculation $b_{v_j}^{collect}$ is the addition of three major components. The first component represents the individual belief attached with each tile regarding the considered vehicle v_j . The second component represents the individual belief attached with the considered vehicle v_j . The third component represents the individual disbelief attached with each tile regarding the considered vehicle v_j . The collective belief $b_{v_j}^{collect}$ is used to verify the location claim of a neighbour vehicle in geographic routing.

3.2.5 *The Verification Framework:* The two layered location verification framework is presented as a Secured Geographic Routing (SGR) algorithm for VANETs (see Algorithm 2). In the 1st layer (steps 1 and 2), tiles

based verification is performed to initially select legitimate vehicles, and thus, avoid malicious vehicles. In the 2^{nd} layer (steps 3, 4 and 5), TBM based verification is performed to attest the location claim of the vehicles selected in the 1^{st} layer. Specifically, the belief of the presence of a vehicle on each tiles is calculated in step 3 using Eq. (6). The belief of the presence of a vehicle as neighbour is calculated in step 4 using Eq. (7). The tiles based belief of step 3 and neighbour based belief of step 4 is combined in step 5 using Eq. (8) to calculate collective belief of a neighbour vehicle to take the final decision regarding the presence of the vehicle as neighbour. The steps 6, 7, and 8 are used to select a vehicle as next forwarder which has maximum collective belief among neighbour vehicles.

Algorithm 2: Secure Geographic Routing (SGR)

Notations

v_{cf}: Current Forwarding Vehicle, SSV^{TV}: Set of Secure Vehicles passing TV test, v_D: Destination Vehicle, v_S: Source Vehicle, v_{NHV}: Next hop Vehicle, SONV: Set of One hop Neighbour Vehicles, T: Set of tiles of v_{cf}
 Input δ, Ω, nth_{out}, nth_n, sth_d, nth_{in}, qth_{pw}, w_{out}, w_n, w_d, w_{in}, w_p ; Output: v_{NHV} (v_j)
 Process
 Initialization

 $SSV^{\text{TV}} = SONV = \phi \text{ and } v_{NHV} = NULL$ 2. find SSV^{TV} by executing TV Algorithm 1
3. for each $(t_k \in \text{T})$ calculate b_{t_k,v_j} using equation (6)
endfor
4. for each $(v_k \in SSV^{\text{TV}})$ calculate b_{v_k,v_j} using equation (7)
endfor
5. for each $(v_j \in SSV^{\text{TV}})$ calculate $b_{v_j}^{collect}$ using equation (8)
endfor
6. find $v_j = \max\{b_{v_j}^{collect}, v_j \in SSV^{\text{TV}}\}$ 7. $v_{NHV} = v_j$ 8. transmit the packet to v_{NHV} and $v_{NHV} = v_{cf}$ 9. exit

4. Simulation and Analysis of Results

Simulations are performed in both road-based and map-based network environments. In road-based network, software defined road network with four junctions is considered. In map-based network, real road map of the Universiti Teknologi Malaysia (UTM) is utilized. Three types of malicious vehicular environments are implemented. Firstly, single adversary vehicle is considered within the transmission range of each vehicles in the network. Secondly, mixed (one or two) adversary vehicles are considered. Some vehicles have single adversary and the remaining have two adversary vehicles within their transmission range. Thirdly, multiple

(three or more) adversary vehicles are considered within the transmission range of each vehicle. Simulation results obtained for LIVES are compared with that of A-VIP. The results are also compared with that of W-LIVES to assess the benefits of LIVES more clearly. W-LIVES is the modified implementation of SGR. W-LIVES selects next hop vehicle according to the location claim of neighbour vehicles without verifying the claims. The benefits of the proposed location verification technique can be clearly understood with the help of this implementation.

4.1 Performance Evaluation Metrics

The performance evaluation metrics are defined below.

• *Location Error*- The selection of adversary vehicles during one-hop transmission in packet forwarding is considered as location error, due the inability in recognizing fake location claims. The statistical formula utilized to calculate location error can be expressed as given by Eq. (9).

Location Error (LE %) =
$$\left\{ \frac{\left(\sum_{i=1}^{10} \frac{N_i^{av}}{T^{av}}\right)}{10} \right\} \times 100$$
(9)

Where N_i^{av} represents the number of adversary vehicles selected in i^{th} simulation, and T^{av} represents the total number of adversary vehicles considered in the simulation.

• *Throughput*- The number of packets successfully delivered from a source to the destination in per second time with the presence of fake location claims is considered as the throughput for a particular simulation run. The statistical formula utilized to calculate the throughput can be expressed as given by Eq. (10).

Throughput (kbps) =
$$\frac{\sum_{l=1}^{10} (N_l^{ps} - N_l^{pl})}{10} \times \frac{512}{1024 \times 600}$$
 (10)

Where N_i^{ps} represents the number of packets sent in i^{th} simulation, and N_i^{pl} represents the number of packets lost in i^{th} simulation.

• *End-to-End Delay-* The time taken by a packet in travelling across the vehicular network with the presence of fake location claims, starting from a source vehicle to the destination vehicle is considered as the end-to-end delay of the packet. The statistical formula utilized to calculate the end-to-end delay can be expressed as given by Eq. (11).

$$End - to - End \ Delay \ (ms) = \frac{\sum_{i=1}^{10} \sum_{j=1}^{N^{pr}} \left(T_{i,j}^{st} - T_{i,j}^{rt}\right)}{N^{pr} \times 10}$$
(11)

Where N^{pr} represents the number of packets received at the destination, $T_{i,j}^{st}$ represents the sending time of

 j^{th} packet in i^{th} simulation and $T_{i,j}^{rt}$ represents the receiving time of j^{th} packet in i^{th} simulation.

4.2 Simulation based on Road Network

The simulations are carried out in network simulator NS-2 considering realistic vehicular network environments generated using Mobility model generator for Vehicular networks (MOVE). The essential scenario of the vehicular environments has been implemented using the two main modules of MOVE, namely, road map editor, and vehicle movement editor. The scenarios are represented by number of roads, number of lanes in each road, number of flows of vehicles in each lane, number of junctions in the area, positioning of traffic lights at junction points, speed of vehicles, and left or right turning probability of vehicles at different junctions. The simulation parameter setup is summarized in Table 1 which is approximately similar to the setup considered in [24]. Simulations are performed after setting the network and traffic environments with the aforementioned set of parameter values. The source vehicle and geographic region are randomly selected near the two pre-determined junctions which are kept same for all the ten simulation runs for recording results. Average of ten simulation runs is taken for each data value used in results.

Parameters	Values	Parameters	Values	Parameters	Values
Total time	600 s	Ifqlen	50 packets	Hello timeout	0.5 <i>s</i>
Simulation area	$1200 \times 1200 \ m^2$	Channel type	Wireless	Query period	2.5 <i>s</i>
Vehicle speed	5–60 Km/h	Antenna model	Omni directional	Frequency	5.9 <i>GHz</i>
Number of vehicles	100- 500 vehicles	Propagation model	Shadowing	Routing protocol	SGR
N ^{av}	10-50 vehicles	MAC data rate	5 Mbps	Traffic type	CBR
Packet senders	20 vehicles	MAC protocol	<i>IEEE</i> 802.11 <i>p</i>	Packet type	UDP
Transmission range	300 m	CBR rate	6 Packets/s	Packet size	512 bytes
$W_{out}, W_n, W_d,$	0.25 0.2 0.1 0.25 0.2	$n_{out}^{th}, n_n^{th}, s_d^{th}, n_{in}^{th}$	400kbps, 250,	Thresholds (δ, v)	0 0 0 0
W _{in} , W _{pw}	0.23, 0.2, 0.1, 0.23, 0.2	, q_{pw}^{th}	60km/h, 350kbps, 1	$1 \text{ mesholds}(0, \gamma)$	0.9, 0.9

 Table 1. Simulation Parameters and their considered values

Fig. 2(a) shows the impact of single adversary vehicle on the location error of LIVES and the state-of-thearts techniques. It can be clearly observed that the location error of LIVES is lower as compared to those of the state-of-the-arts techniques. For example, considering 20 adversary vehicles, location error is approximately 5.5% for LIVES whereas it is 15.4% and 30.1% in case of A-VIP and W-LIVES, respectively. Considering 40 adversary vehicles, it reaches up to 9.9% for LIVES, whereas 39.2% and 60.8% for A-VIP and W-LIVES, respectively. Additionally, the increment in location error with the increase in number of adversary vehicles is also lower in case of LIVES as compared to those of A-VIP and W-LIVES. This is due to the usage of distributed tiles based location verification which effectively identifies false location claim by single adversary vehicle in the network. Although A-VIP also uses tiles based verification yet, the location error is higher as compared to that of LIVES due to the usage of server based verification in A-VIP. Server based verification requires to maintain reliable connectivity with servers which is quite challenging in vehicular environments. The location error of W-LIVES increases rapidly with the increase in number of adversary vehicles due to the absence of location verification technique.



(d) (e) **Fig. 2.** Impact of number of adversary vehicles on location error with (a) single adversary, (b) mixed adversary, (c) multiple adversary vehicles (d) throughput, (e) end-to-end delay considering road-based network

Fig. 2(b) shows the impact of mixed adversary vehicles on the location error of LIVES and the state-ofthe-arts techniques. The results clearly states two things, firstly, the location error of LIVES is lower in comparison with those of the state-of-the-arts techniques. Secondly, location error with mixed adversary vehicles is higher as compared to the error with single adversary vehicle shown in Fig. 2(a). Specifically, considering 25 adversary vehicles, the location errors are approximately 13.2%, 24.9% and 55.2% for LIVES, A-VIP and W-LIVES, respectively whereas the errors reach up to 21.5%, 38.2% and 77.9% with 45 adversary vehicles. The increment in location error with the increase in number of adversary vehicles is lower in case of LIVES as compared to those of A-VIP and W-LIVES. This is because of the collective belief computation in the 2nd layer location verification which effectively verifies the presence of mixed adversary vehicles in the network. A-VIP does not have 2nd layer verification therefore, the rate of increment in location error is higher as compared to that of LIVES. Due to the presence of mixed adversary vehicles, rate of increment of location error is higher for W-LIVES which does not perform any location verification.

Figure 2(c) shows the impact of multiple adversary vehicles on the location error of LIVES and the state-ofthe-arts techniques. It can be clearly observed that the location error with multiple adversary vehicles is higher as compared to the error with single adversary and mixed adversary vehicles shown in Fig. 2(a) and (b), respectively. In particular, considering 30 adversary vehicles, the location errors are approximately 21.3%, 36.2% and 69.8% for LIVES, A-VIP and W-LIVES, respectively, whereas the errors reaches up to 27.2%, 47.9% and 91.3% with 50 adversary vehicles. The increment in location error with the increase in number of adversary vehicles is lower in case of LIVES as compared to those of A-VIP and W-LIVES. The reason is the layer wise location verification which effectively recognizes multiple adversary vehicles in the network. The layer wise verification is not followed in A-VIP resulting in higher location error in comparison with that of LIVES in the presence of multiple adversary vehicles. The impact of multiple adversary vehicles on location error in case of the absence of verification technique can be clearly noted as the higher location error of W-LIVES.

Fig. 2(d) shows the impact of location error caused by mixed adversary vehicles on the throughput of LIVES and the state-of-the-art techniques. The throughput of LIVES is higher as compared to those of the state-of-the-art techniques. The rate of decrement of throughput with the increase of mixed adversary vehicles is lower for LIVES. Specifically, the throughput of LIVES is in the range 99 - 205Kbps whereas the ranges are 74 - 203Kbps and 10 - 109Kbps for A-VIP and W-LIVES, respectively. Fig. 2(e) shows the impact of location error with mixed adversary vehicles on the end-to-end delay of LIVES and the state-of-the-art techniques. The impact of location error on the end-to-end delay is lesser in case of LIVES which can be clearly observed as the lower and stable end-to-end delay in comparison with those of the state-of-the-art

techniques. This is due to the lower location error of LIVES with mixed adversary vehicles as depicted in Fig. 2(b).

4.3 Simulation based on Map Network

In this section, the performance of LIVES is analyzed using real road network of UTM. The Open Street Map is utilized to obtain the satellite image of UTM road network (see Fig 3(a)). ArcGIS 10.2.2 and MOVE is utilized to integrate vehicular network environments with the map (see Fig 3(b)). The other setup of the mapbased simulation is similar to the setup considered in [25].



Fig. 3. The real road network of UTM: (a) Open Street Map view, (b) imported view in MOVE





Fig. 4. Impact of number of adversary vehicles on location error with (a) single adversary, (b) mixed adversary, (c) multiple adversary vehicles (d) throughput, (e) end-to-end delay considering map-based network

The impact of number of single adversary vehicles on the location error of LIVES and the state-of-the-art techniques with map-based network is presented in Fig. 4(a). The location error of LIVES with single adversary vehicles is significantly lower with map-based network as compared to the error with road-based network shown in Fig. 2(a). The location error of LIVES with map-based network is in the range 4 -10.3% whereas the error range is 5-19% with road-based network. This can be attributed to the presence of higher number of junctions in map-based network as compared to the only four junctions in road-based network. The presence of more junctions with map-based network results in better directional location verification which reduces location error. The location errors of A-VIP and W-LIVES are higher with map-based network in comparison with the errors with road-based network. In particular, the location error of A-VIP with map-based network is in the range 11-42.1%, and the range is 25- 81% for W-LIVES. In road-based network, the error ranges are 8 -34%, and 20-73% for A-VIP and W-LIVES, respectively. This is due to the single layer verification of A-VIP, and no location verification in W-LIVES.

The impact of mixed adversary vehicles on the location error of LIVES and the state-of-the-arts techniques with map-based network is presented in Fig. 4(b). It can be observed that the location error of LIVES with map-based network is lower as compared to the error with road-based networks shown in Fig. 2(b). The location error of LIVES with map-based network is in the range 6-15.1% whereas the range is 7-23% with road-based network. This can be attributed to the effective location verification of LIVES at junction points resulting in lower location error with map-based network having more junctions. The location errors of A-VIP and W-LIVES are in the range 17-45.6% and 46-87%, respectively with map-based network whereas

the error ranges are 15-39% and 40-79% with road-based network. The impact of multiple adversary vehicles on the location error of LIVES and the state-of-the-art techniques is presented in Fig. 4(c). In case of LIVES, the lower location error range is observed with map-based networks as compared to the error range with road-based network shown in Fig. 2(c). The error range of LIVES with map-based network is 7.3-20.2% whereas the error range is 9.5-27.2% with road-based network. This is due to the multiple adversary identification ability of 2nd layer verification of LIVES which performs better with more junction. The location errors of A-VIP and W-LIVES with map-based network are higher as compared to the error with road-based network. The location error ranges of A-VIP and W-LIVES are 19-54% and 53-94% with map-based network whereas the error ranges are 16-48% and 50-91% with road-based network. This is because of absence of layer wise verification for handling multiple adversary vehicles. The location verification problem worsens in dense road networks due to the availability of routes in different directions.

The impact of location error caused by mixed adversary vehicles on the throughput of LIVES and the state-of-the-art techniques with map-based network is shown in Fig. 4(d). The throughput of LIVES with map-based network is higher as compared to those of the state-of-the-art techniques. Specifically, the throughput of LIVES with map-based network is in the range 145 - 315Kbps whereas the ranges are 52 - 201Kbps and 8 - 102Kbps in case of A-VIP and W-LIVES, respectively. The impact of location error caused by mixed adversary vehicles on the end-to-end delay of LIVES and the state-of-the-art techniques with map-based network is shown in Fig. 4(e). The impact of location error on the end-to-end delay of LIVES with map-based networks is lower as compared to those of the state-of-the-art techniques. It can be clearly observed as lower and stable end-to-end delay of LIVES in the results. The reason is the better location verification of LIVES with map-based network as shown in Fig. 4(b) for mixed adversary vehicles.

4.4 Comparative Discussion between Road-based and Map-based Results

The simulation results obtained considering the two different types of vehicular network environments are comparatively assessed for magnifying the performance benefits of the proposed location verification technique in realistic map-based environments (see Table 2). It can be clearly observed that the performance of LIVES improves in map-based environments whereas the performance of A-VIP and W-LIVES degrades in map-based environments. In particular, the average location errors of LIVES are 9.2%, 15.7% and 19.3% for single, mixed and multiple adversary vehicles, respectively, with road-based environments whereas these errors are 7.6%, 10.3% and 14.4% with map-based environments. The average throughput and end-to-end delay of SGR (LIVES) are 152Kbps and 10.5ms, respectively, in case of road-based environment whereas the

through and end-to-end delay are 245Kbps and 5.7ms with map-based environment. The lower location error and end-to-end delay, and higher throughput of LIVES with map-based environment in comparison with the road-based environments can be attributed to the higher number of junctions in map-based environments. The more junctions result in better localization of vehicles, and thus, the throughput of LIVES increases and endto-end delay decreases. The average location errors of A-VIP are 21.8%, 26.7% and 34.3% for single, mixed and multiple adversary vehicles, respectively, with road-based environments whereas the locations errors are 27.7%, 30.4% and 39.5% with map-based environment. The average throughput and end-to-end delay of GR (A-VIP) are 114Kbps and 17.3ms, respectively, with road-based environments whereas the throughput and end-to-end delay are 109.4Kbps and 19.4ms with map-based environments. The performance degradation in terms of higher location error and end-to-end delay, and lower throughput with map-based network is because of the absence of second level verification in A-VIP. The mixed and multiple adversary vehicles are not recognizable in case of more junctions with map-based environment. These performance differences are higher in W-LIVES due to the selection of non-verified location of vehicles.

Protoco	ls and Traffic En	vironment	LI	VES	A-1	VIP	W-L	IVES
Metrics			Road	Мар	Road	Мар	Road	Мар
¥	Single	Minimum	5	4	8	11	20	25
	Aaversary	Maximum	19	10.3	34	42.1	73	81
Location Error		Average	9.2	7.6	21.8	27.7	44.8	50.4
	Mixed	Minimum	7	6	15	17	40	46
	Aaversary	Maximum	23	15.1	39	45.6	79	87
		Average	15.7	10.3	26.7	30.4	59.6	66.5
	Multiple	Minimum	9.5	7.3	16	19	50	53
	Auversary	Maximum	27.2	20.2	48	54	91	94
		Average	19.3	14.4	34.3	39.5	71.2	73.7
	Mixed	Minimum	99	145	74	52	10	8
Inrougnput	Aaversary	Maximum	205	315	203	201	109	102
		Average	152	245.5	114	109.4	38.8	36.2
End to End	Mixed	Minimum	7	5	7.5	8.5	15	25
Delay	Aaversary	Maximum	23	10	36	41	92	149

Table 2. Comparative assessment of road-based and map-based simulation results

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5. Conclusion and Future Work

In this paper, a two layered location verification technique is presented for geographic routing in VANETs. The first verification layer is based on the concept of virtual tiles on roads and received signal strength. The second layer verification is based on the belief of neighbor vehicles computed using TBM. From the design, implementation and evaluation of the location verification technique, following conclusions have been made. The single adversary vehicles can be effectively identified using virtual tiles and received signal strength based first layer verification of LIVES. The TBM based second layer verification of LIVES is required for identifying mixed and multiple adversary vehicles. The location verification capability of LIVES significantly improves with map-based realistic network environments due to the higher number of junctions. In future, authors will focus on enhancing the accuracy of GPS-based location of non-adversary vehicles using the concept of cooperative positioning. Addressing GPS outage issue in urban vehicular environment will also be the quest.

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