International Journal of Computer Networks and Applications (IJCNA)
DOI: 10.22247/ijcna/2017/41285 Volume 4, Issue 1, January – February (2017)

RESEARCH ARTICLE

Connectivity Based Positioning System for Underground Vehicular Ad Hoc Networks

Salah Abdel Mageid
Systems and Computers Department, Faculty of Engineering, Al-Azhar University, Cairo, Egypt.
smageid@azhar.edu.eg

Published online: 07 January 2017

Abstract – Underground vehicular ad-hoc networks are indorsing wireless networks because they can realize many goals such as improving the driving safety and monitoring the emergency alerts in underground environments (i.e., road tunnels). It is necessary for vehicular nodes to recognize their positions to achieve these goals. However, Global Positioning System (GPS) devices cannot operate in underground environments; furthermore, the signal propagation faces many effects such as attenuation, multipath and shadow fading. Traditional distance measurement techniques are inadequate to estimate vehicular node locations in underground environments because the expected measurement errors lead to poor positioning. In this paper, the network connectivity is exploited to estimate vehicular node positions instead of radio ranging methods. This work investigates one of the most important techniques that are based on the network connectivity (i.e., Monte Carlo) and proposes new heuristics that achieve an appropriate position estimation accuracy for vehicular nodes. As the underlying method is predictable, it enables these nodes to know their positions all the time inside underground environments. In addition, an efficient deployment strategy is proposed in this work to well organize reference nodes (i.e., fixed nodes that their positions are preconfigured) inside a road tunnel. The proposed scheme performance is verified by NS2 simulator and compared with the current Monte Carlo localization schemes where the simulation results indicate the superiority of the proposed scheme.

Index Terms – Underground VANET, road tunnels, positioning, network connectivity, Monte Carlo localization.

1. INTRODUCTION

An Intelligent Transportation System (ITS) refers to a collection of entities such as people, vehicles, a management information system and wireless communication technologies. ITS is used in road transportation to achieve many objectives, such as collision avoidance and road safety, in a typical environment (i.e., highways and streets), or an underground/underwater environment (i.e., road tunnels). Different wireless communication technologies can work with ITS in typical environments such as GPS, WiMAX and 3G. However, these technologies cannot work in underground/underwater environments. Vehicular ad-hoc networks are recommended to overcome the communication problems in such case. A vehicular ad-hoc network (VANET), a type of mobile ad-hoc networks (MANETs), points to certain vehicles that are self-organized and communicate with each other or communicate with fixed reference nodes (i.e., roadside units) [1, 2, 3, 4]. In addition, vehicles can be organized in sets of clusters to avoid any kind of collisions [5, 6].

In fact, creating underground vehicular ad-hoc networks to operate in road tunnels faces many challenges because the electromagnetic fields cannot continually connect wireless devices together all the time in underground/underwater environments. Signal propagation in road tunnels suffers from higher attenuation compared to air due to unpredictable obstacles in soil (i.e., tree roots or rocks) that cause additional path loss. Moreover, signal propagation also faces signal reflection and refraction from tunnel walls that cause multipath and shadow fading in received power. Vehicular nodes themselves are obstacles for signal propagation resulting in additional reflections and refractions [7]. Recently, research works have been introduced navigation schemes for wireless nodes in underground environments such as [8, 9, 10]. The authors in [8] have introduced a grid based localization solution based on received signal strength indicator (RSSI) for cities and road tunnels while a localization scheme based on both of time of arrival (ToA) and time difference of arrival (TDoA) techniques has been presented in [9]. However, those solutions suffer from large end-to-end latency. The work in [10] merges RSSI and ToA techniques to overcome the underground effects. Nevertheless, a small radio measurement error leads to poor localization accuracy.

In this paper, connectivity based positioning (COPO) system is proposed for underground vehicular networks which depends on the network connectivity instead of radio ranging techniques. The proposed system introduces two contributions. Firstly, a positioning algorithm is proposed which exploits the principles of Monte Carlo localization and vehicular nodes' movement direction. New heuristics are introduced in this algorithm to improve the localization accuracy and increase the number of vehicular nodes that can estimate their positions all the time inside the road tunnel. In this work, the combined path loss and shadowing model is used which is more suitable propagation model for road tunnels. Furthermore, tunnel structure is taken into account whether the tunnel is curved or straight, narrow or wide, short or long, with one or two tubes, with double or more lanes, operates in one direction or both.

RESEARCH ARTICLE

Secondly, COPO system proposes a new deployment strategy for the reference nodes to organize them along the road tunnel in which each vehicular node is covered at least with two reference nodes. Such method considers the road tunnel structure; for example, it is either straight or curved. An analytical model is introduced to derive an expression for the optimal distance between two following reference nodes in terms of the tunnel width and the radius of curvature under certain coverage constraint. Such constraint guarantees that each point in the road tunnel is covered with at least two reference nodes. Afterwards, NS2 simulator is used to verify the performance of COPO system at different circumstances. The proposed scheme is compared to the existing connectivity based schemes in terms of reference node density (number of reference nodes per km), traffic density (number of vehicular nodes per lane per km), percentage of vehicles that know their preceding positions before entering the road tunnel via GPS, path loss, and shadowing deviation.

This paper is organized as follows. Section 2 introduces a literature review for current localization schemes based on radio ranging techniques and the current connectivity based solutions for road tunnels. Combined path loss and shadowing model is presented in Section 3. Section 4 illustrates the proposed framework which two algorithms are discussed; the former is the reference nodes' deployment and the latter is for positioning vehicular nodes. Simulation results and performance comparisons are introduced in Section 5. Section 6 concludes this paper.

2. LITERATURE REVIEW

Many research works have been introduced for node navigation in wireless networks using radio ranging techniques. There are four types of radio ranging techniques: time of arrival (ToA), time difference of arrival (TDoA), angle of arrival (AoA), and received signal strength indicator (RSSI) in free space. A wireless node that estimates its position using one of those types requires additional hardware to measure a specified radio range. In ToA type, a wireless node measures propagation time of electromagnetic signal received from anchor (or reference) nodes and estimate the distance while, in TDoA type, it uses at least two signal generators to measure the difference between two signal propagation times and estimate the distance. In this work, an anchor node refers to a mobile node equipped with GPS to update its position information while a reference node (RN) refers to a static node that has a preconfigured position. The AoA type is also a radio ranging technique that allows a wireless node to estimate the relative directions of neighbors and efficiently estimates node location by adding an antenna array and/or an ultrasonic receiver to node architecture. In RSSI type, a wireless node measures the energy of electromagnetic signal received from at least three anchors/RNs to estimate node location. Such type is low cost compared to other radio ranging techniques.

Earlier, radio ranging techniques have been exploited in wireless sensor networks (WSNs) to estimate a sensor node's location. For example, the authors in [11] have introduced a localization scheme for WSNs based on ToA technique while TDoA technique has been exploited in [12] with a training model generated by neural networks to estimate a sensor node location. On the other hand, antenna arrays have been exploited in wireless sensor nodes to estimate their location based on AoA technique [13], while an autonomous localization scheme based on RSSI has been introduced for WSNs which advises certain rules to correct the localization error in fading environments [14].

Recently, many research works have been introduced for vehicular node localization based on radio ranging techniques. For example, Yan et al. [8] have introduced a grid-based solution that exploits RSSI to estimate a vehicular node position in cities and road tunnels. In case of road tunnels, certain number of vehicular nodes are assumed that they receive GPS signals at a short distance from the tunnel exit. These nodes work as anchors to help other nodes far away the tunnel exit to estimate their positions; afterwards, those nodes broadcast their locations via location messages to neighbors. When the nearest nodes receive location messages, they determine the measured distance to anchors and estimate their locations using a grid-based method; afterwards, they broadcast their locations. Other vehicular nodes incrementally estimate their locations via messages received from the nearest nodes and so on. However, the incremental solution generates an incremental error in location estimation that begins with a small value for the nodes close to the tunnel exit and gradually increases for the farthest nodes. Moreover, signal propagation from vehicle to vehicle faces different environmental effects in the road tunnels. The end-to-end latency also increases when a vehicular node is far from the tunnel exit.

A localization solution has been introduced in [9] to estimate a vehicular node position in road tunnels based on ToA and TDoA techniques. In addition, vehicular nodes are assumed working in vehicular cloud networks in which pictures and video for certain vehicular node are taken by its neighbors and sent via cloud to centralized cloud server. The suggested vehicular cloud network cannot include roadside units because they are not available in road tunnels. However, system messages take more than two hops in this network resulting in an increase in the localization delay. The work in [10] combines two radio ranging techniques for navigation, RSSI and ToA. RSSI is firstly used to find approximated range for node position by three RNs (trilateration method). Afterwards, ToA technique is performed which the signal propagation time between current vehicular node and each anchor node is measured to obtain more accurate location. It is assumed that RNs are vertically distributed along the narrow tunnel, and a vehicular node continually receives from RNs until it discovers three RNs. However, it is possible that a vehicular node cannot

RESEARCH ARTICLE

find three RNs for long time due to different noise effects in underground environment resulting in large localization delay.

As mentioned above, radio ranging based navigation schemes can effectively work when electromagnetic signals propagate in free space environments. However, the localization accuracy rapidly decreases in underground environments due to high path loss, shadowing and so on. For example, a vehicular node in RSSI based localization receives from at least three RNs to estimate its position. Therefore, a vehicular node may move long distance in underground environments until it discovers three RNs which means it estimates its position for short time periods only resulting in significant localization delay. Though three RNs are discovered, a small measurement error due to rapid change in the network topology leads to poor localization accuracy. The work in [15] has studied the effect of vehicular ad-hoc network topology in free space environments on node localization. Connectivity based localization (i.e., Monte Carlo localization) can solve those problems.

Many research works have been exploited Monte Carlo method to introduce range free solutions for WSNs in the past years. When a mobile node in free space environment discovers an anchor node, it can receive the anchor location and forwards it to neighbors. According to Monte Carlo method, a mobile node can generate location samples around preceding estimated samples and filter those samples by one and 2-hop anchors' constraints. For example, the work in [16] has investigated Monte Carlo method in mobile sensor networks (it is called MCL). Assume the number of valid location samples at preceding time slot is k. A mobile node generates new location samples around each sample of previous k-samples at the current time slot with radius $S_m\Delta t$ where S_m represents the maximum node speed and Δt is the time between two successive position estimations. When a new sample satisfies anchors' constraints at current time slot, it is chosen as a candidate sample; otherwise, it is removed from the candidate sample list. Such procedure is repeated until the number of candidate samples reach an adequate number (i.e., 50 location samples [16]).

Such scheme works well with large number of anchor nodes that are randomly distributed in the target field and guaranteed that each node discovers at least two anchor nodes. However, the localization error is unacceptable with limited number of anchors which varies from 0.5R to 1.5R where R represents node transmission range. In addition, MCL, similar to all Monte Carlo localization schemes, depends on 1-hop anchors, that are directly discovered, and 2-hop anchors, that are forwarded from neighbors, to improve the localization accuracy. In fact, many 1-hop anchors cannot be discovered due to noise level and forwarded as 2-hop anchors; accordingly, using 2-hop anchors may be unsafe in noisy environments. During the filtering phase, samples that have a distance to 1-hop anchor less than R are chosen while samples with distance to 2-hop anchor greater than R and less than 2R are chosen. In such case, 2-hop anchor may choose false samples and discard true samples (it will be called here untruthful 2-hop anchor). Therefore, it is expected the localization error in MCL increases in noisy environments.

The authors in [17] has improved the processing time compared to [16] by involving anchor constraints in the processes of generating and filtering location samples. The communication area for each 1-hop anchor is approximated by square with side length (R) where R represents the transmission range while each 2-hop anchor is approximated by square with side length (2R). All new location samples are generated in the intersection area of all squares (it is called bounded box), then they are filtered by anchor constraints and preceding location samples. This work has minimized the processing time; nevertheless, the localization error is slightly improved compared to [16] because it is still affected by untruthful 2-hop anchors; therefore, the same filtered samples are approximately obtained.

The constraints of 1-hop and 2-hop neighbors have been exploited in [18]. To alleviate the effect of untruthful 2-hop nodes, weighted samples are used in estimating node position. However, the communication cost largely increases in this work. The authors in [19] and [20] have minimized the communication cost by exploiting 1-hop neighbors only besides 1-hop and 2-hop anchors. The work in [20] has achieved more reduction in localization error by expecting the movement direction of sensor nodes. The research works in [19] and [20] have reduced the communication cost compared to [18]; however, it is still high compared to [16] and [17]. In addition, improving the localization error in the current node depends on the quality of neighbors' position estimation process. Since such quality is varied because it depends on the number of anchor nodes that are discovered by each neighbor (i.e., minimum quality requires at least two 1-hop anchors). In noisy environments, it is unguaranteed to each node to discover sufficient number of 1-hop anchors; accordingly, an incremental error is expected in node localization.

Recently, the authors in [21] have introduced adapted the work in [17] for vehicular ad-hoc networks in cities (it will be called here, Vehicular Monte Carlo Boxed, VMCB). Similar to Monte Carlo localization principles, generated samples for vehicular nodes are filtered by 1-hop and 2-hop anchors’ constraints. Higher weights are assigned for valid samples; typically, they take a weight equals one. In noisy environments, low number of valid samples realize on anchors' constraints. In such case, VMCB scheme increases the radio range of vehicular nodes and iteratively try to obtain samples that achieve the anchors’ constraints. Lower weights are assigned for those samples from 0.25 to 0.5. However, many iterations are required to obtain location samples in noisy environments. In addition, VMCB cannot achieve higher localization accuracy in noisy

RESEARCH ARTICLE

environments because untruthful 2-hop anchors are still presented.

The proposed scheme (COPO) is based on the network connectivity in which radio ranging techniques are completely avoidable. This work exploits the principles of Monte Carlo localization similar to MCL [16], VMCB [21] which new heuristics are proposed to avoid the problem of untruthful 2-hop reference nodes improving the localization accuracy in underground vehicular ad-hoc networks. The vehicular node movement direction in road tunnels is also exploited. In addition, reference nodes deployment strategy is proposed to efficiently minimize the number of required reference nodes to cover all road tunnel points by at least two reference nodes. For performance comparison purposes, MCL and VMCB are adapted to exploit the movement direction. In what follows, a model for combined path loss and shadowing is discussed.

3. A MODEL FOR COMBINING PATH LOSS AND SHADOWING

Many radio propagation models have been introduced for wireless communications such as free space, two-ray ground, and combined path loss and shadowing models [22]. The free space and two-ray ground reflection models use a deterministic formula of distance to estimate the received power in which the transmission range seems as a circular disk. Therefore, the average received power is obtained at certain distance when those models are used. In particular, the received power randomly changes at certain distance as a result of path loss and shadowing effects in road tunnels. Therefore, the combined path loss and shadowing model is recommended in our study to represent the signal propagation inside road tunnels. Such model is illustrated as follows.

The combined path loss and shadowing model is an extension to Friis Free space model. Signal propagation loss can be perfectly expected for a wide range of environments using the combined path loss and shadowing model. On the other hand, the Friis Free space model works when the transmitter and receiver locate at the same line of sight which no obstacles separate between them. The combined path loss and shadowing model consists of two components. The first part is the path loss component which is described as follows

$$PL(d)\,\alpha\left(\frac{d}{d_0}\right)^n \tag{1}$$

where PL(d) represents the average path loss for an arbitrary T-R separation (d). The exponent n represents the path loss exponent and d_0 represents the close-in reference distance which is close to the transmitter and determined from the measurements. The following formula represents the path loss component at distance (d) in decibels.

$$PL(d)=PL(d_0)+10n\log\left(\frac{d}{d_0}\right) \tag{2}$$

The second component is the shadowing component which represents the deviation in received power due to multipath fading effect expected in road tunnels. Such effect occurs due to the tunnel walls and the curved surface. When the shadowing component is combined with the path loss component described in Eq. (2), the received power by certain receivers varies even though they are located at the same distances from the transmitter. The shadowing component is described by χ_σ where χ_σ is a zero-mean Gaussian distributed random variable (in dB) with standard deviation (σ). This component indicates to the existence of shadowing which there is no shadowing effect (its value is zero). The formulation of combined path loss and shadowing model can be described as follows.

$$PL(d)=PL(d_0)+10n\log\left(\frac{d}{d_0}\right)+\chi_\sigma \tag{3}$$

The received power at distance (d), according to this model, can be determined as follows.

$$P_r(d)=P_t-PL(d) \tag{4}$$

Where all terms are measured in (dB) and the antenna gain included in *PL(d)*. Therefore, the received power at distance (d) can be represented as follows.

$$P_r(d)=P_t-PL(d_0)-10n\log\left(\frac{d}{d_0}\right)-\chi_\sigma \tag{5}$$

Ideally, tunnels act as a form of waveguide in which path loss exponent values are less than or equal 2. Real measurements have been performed in [23] which the path loss is observed in different railway tunnels in western India. According to these measurements, path loss exponent is greater than two and multipath and shadowing deviation (σ) is greater than 7.38 dB. In what follows, the COPO system is introduced in details illustrating system stages, the proposed algorithms, and their remarks.

4. CONNECTIVITY BASED POSITIONING SYSTEM

Connectivity based positioning (COPO) system contains two stages, RNs deployment stage and position estimation stage. In the first stage, the RNs are efficiently deployed in offline along the road tunnel. Many issues are taken into account during the deployment implementation such as tunnel shape (curved or straight), tunnel width (narrow or wide), tunnel length (short or long), number of tubes (one or two), number of lanes (2 or more), and lanes' direction (one or two ways). RNs deployment (RN-Deployment) algorithm is proposed to achieve two goals, minimum number of RNs and high coverage for tunnel area (i.e., each point in the road tunnel is covered by at least two

RNs). The second stage of COPO system is vehicular node position estimation. This work proposes another algorithm for vehicular node position estimation (VN-PE algorithm) which exploits the Monte Carlo methods and introduces new heuristics to improve the localization accuracy for vehicular nodes in road tunnels and increase the number of vehicular nodes that can estimate their locations. In what follows, two stages of COPO system are illustrated in details.

4.1. RN Deployment Stage

Given a digital map of a road tunnel in terms of points defined by their latitude and longitude (i.e., Google map). Assume left and right border points of the road tunnel can be obtained (i.e., using one of Google maps APIs). Such tunnel border points are stored in a list called *Tunnel Border Points* list (TBP list). One of the endpoints of the road tunnel is selected as the origin and all border points are translated. Assume a road tunnel with length (L), width (W), one tube with four lanes (two lanes per direction), and curved with radius of curvature (RC_i). The tunnel width (W) is known while L and RC_i parameters require analytical study to precisely compute their values as shown below. Initially, all left and right border points (TBP list) are scanned along the x-axis to choose the midpoints between left and right border points. These points represent the *Middle Tunnel Curve* (MTC) represented by small circles as shown in Figure 1. Those points are reduced to (n) points, in which the distance between two consecutive points are (ΔS) where ΔS is a small distance with the same curvature, and stored in MTC points list.

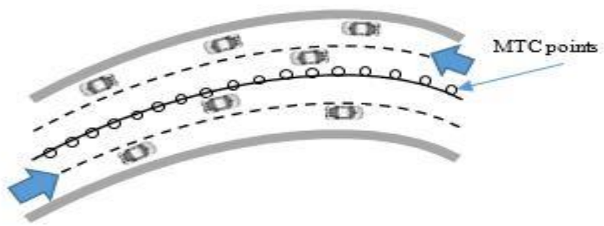

Figure 1 A segment of curved road tunnel

A parabolic fit is performed for each three adjacent points separated by ΔS. Assume three points are located at (x_1, y_1), (x_2, y_2), (x_3, y_3). In general, the parabola form is described as follows.

$$y = ax^2 + bx + c \tag{6}$$

By substituting three points in Eq. (6), three linear equations are obtained. Solving those linear equations provides with the values of a, b and c. The radius of curvature RC_i at middle point (i) can be obtained as follows.

$$RC_i = \frac{\left[1+\left(\frac{dy}{dx}\right)^2\right]^{\frac{3}{2}}}{\left|\frac{d^2y}{dx^2}\right|} \tag{7}$$

In addition, the curve length (ds_i) can be obtained as follows.

$$ds_i = \Delta x\sqrt{1+\left(\frac{dy}{dx}\right)^2} \tag{8}$$

Where Δx represents the x-component of Δs. The tunnel length (L) can be determined as follows.

$$L = \sum_{i=1}^{n} ds_i \tag{9}$$

Where n represents the number of MTC points. Lines (1-9) in the RN-Deployment algorithm show how to compute L and RC_i.

RN-Deployment Algorithm

```
1.  TBP_list = assignTunnelBordersPoints (digitalMap);
2.  Translate(TBP_list);
3.  MTC = computeMiddeCurve(TBP_list);
4.  MTC_points_list = reduceMTC (MTC, ΔS);
5.  FOR i = 1 TO n-1
6.       RC(i) = computeRC(i-1, i, i+1);
7.       ds (i) = compute_ds(i, ΔS);
8.       L =  L + ds (i);
9.  J = 2;
10. REPEAT
11.     S(J) = locateRN(J, RN(J-1));
12.     Lc = Lc + S(J)
13. UNTIL Lc > L
```

Figure 2 shows how RN-Deployment algorithm organizes the RNs in a straight tunnel. The transmission ranges of two non-consecutive RNs such as n_2 and n_4 (dashed circles) must achieve the minimum overlapped area shown in Figure 2. Such situation guarantees that all points in the straight tunnel are covered at least with two RNs with minimum number of RNs.

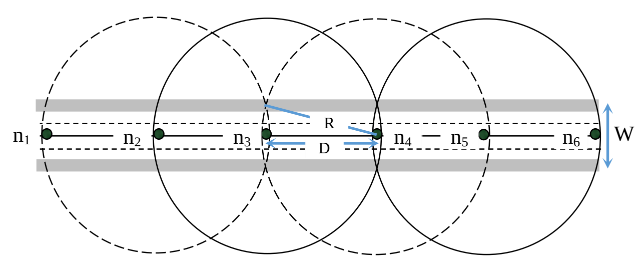

Figure 2 Deploying the RNs along straight tunnel

The designed distance (D) that represents the required space between two consecutive RNs can be determined as follows.

$$D = \frac{1}{2}\sqrt{4R^2 - W^2} \tag{10}$$

Where W represents the road tunnel width. For example, when the tunnel width (W) equals 16 meters and the RN transmission range (R) equals 50 meters, the designed distance (D) is chosen less than or equal 49.36 meters.

For curved tunnels, assume that N_i represents a position of a reference node (i) and the radius of curvature at N_i is RC_i which the circle center is located at (C_i). Assume $\underline{RC_i}$ drawn from N_i to C_i intersects the tunnel border at B_i as shown in Figure 3.

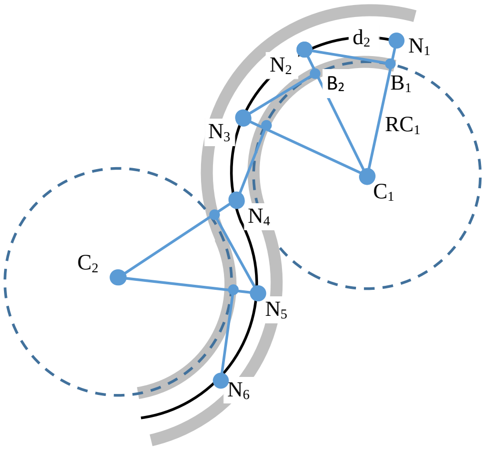

Figure 3 Deploying the RNs along curved tunnel

Initially, the first reference node RN_1 is located at N_1. To determine the location of N_2, a circle is drawn at C_1 with radius (CR_1 – $W/2$). Such radius represents the radius of curvature at a border point (B_1). A tangent for such circle is drawn from B_1 and intersects the middle curve at N_2 which N_2 represents the location of RN_2. Assume the distance from B_1 to N_2 is d_2. By the Pythagorean theorem, d_2 is determined as follows.

$$d_2 = \sqrt{RC_1^2 - \left(RC_1 - \frac{W}{2}\right)^2} \tag{11}$$

Equation (11) can be simplified as follows.

$$d_2 = \frac{1}{2}\sqrt{4RC_1 \cdot W + W^2} \tag{12}$$

As shown in Line (11) in RN-Deployment algorithm, the procedure *locateRN* finds a location for N_2 over MTC curve based on the value of d_2. MTC points are checked to find an optimal point that satisfies the distance from B_1 to N_2 and approximately equals d_2. Afterwards, the procedure *locateRN* returns S(2) that represents the length of curvature from N_1 to N_2 which S(2) is less than or equal the designed distance D from Eq. (10). Otherwise, S(2) is forced to be the designed distance D to keep each node covered with at least two RNs. The distance between two adjacent RNs are directly proportional with the radius of curvature (RC) as shown in Eq. (12). When the radius of curvature (RC) increases, the distance between two adjacent RNs also increases. The maximum RC occurs at d_2 approximately equals $\sqrt{R^2 - (W/2)^2}$ where R is the transmission range and W is the tunnel width. By substituting d_2 in (12), the maximum RC approximately equals (R^2/W). When RC is greater than (R^2/W), the distance between two adjacent RNs remains equal D.

RN-Delpoyment algorithm repeats *locateRN* procedure for all RNs until it reaches the tunnel exit as shown in Lines (10-13). It is easy to verify that each point in the road tunnel is covered with at least two RNs by drawing a line from N_i to N_{i+2}. Such line is tangent to tunnel border at B_{i+1} where (i $\geq$ 1) as shown in Figure 3. Finally, the curved tunnel length is computed in L_c as shown in Line (12). Briefly, RN-Deployment algorithm guarantees that each vehicular node is covered with at least two RNs for straight or curved tunnels with minimum number of RNs as mentioned above.

4.2. Vehicular Node Position Estimation Stage

In this section, the vehicular node position estimation (VN-PE) stage is discussed in details. VN-PE algorithm is proposed to be applied at vehicular nodes to estimate their positions inside the road tunnel. Periodically, reference nodes (RNs) broadcast location message contains RN-ID and RN-location. The transmission time period (Δt) is constrained by the maximum allowed speed in the road tunnel (v_{max}) and RN transmission range (R).

VN-PE Algorithm

At RN RN(i)

```
    RN(i) broadcasts msg(rnID, rnLOC) each Δt
At vehicular node VN(j)
IF VN(j) receives msg(i) THEN
    RN(i) is stored in 1-hop list, L1
    VN(j) forwards RN(i) to neighbors VN(k, j)
IF VN(k , j) receives p(i) THEN
    RN(i) is stored in 2-hop list, L2
applyHeuristics (L1, L2);
IF VN(j) previous LOC and speed is NULL THEN
    IF n(L1) + n(L2) >= 1 THEN
        IR  = computeIntersectionRegion( );
        sampleList = generateSamples(IR);
ELSE                    /* VN(j) has previous location */
        sampleList = generateSamples(preLOC);
sampleList = filterSamples(sampleList);
VN(j).location = estimateLocation(sampleList);
previousLocation = VN(j).location;
prevoiusSpeed = currentSpeed;
```

The transmission time period is chosen less than RN transmission range divided by the maximum allowed speed ($\Delta t < R/v_{max}$). For example, when R equals 50 meters and v_{max} reaches 100 km/h (or 27.78 m/sec), the transmission time period (Δt) is less than 1.8 seconds. Such interval enables *VN-PE algorithm* to generate samples from VN previous location

International Journal of Computer Networks and Applications (IJCNA)
DOI: 10.22247/ijcna/2017/41285 Volume 4, Issue 1, January – February (2017)

RESEARCH ARTICLE

to improve the localization error. On the other hand, when a VN receives a location message from RN, it obtains RN-ID and RN-location, then it stores them in a list structure (it is called nearest RN list, L_1). VN forwards such message to vehicular neighbors. When VN receives a forwarded message from a vehicular neighbor, it obtains RN-ID and RN-location, and stores this information in farthest RNs list (named L_2) as shown in Lines (1-6).

After a VN discovers the nearest and farthest RNs, Monte Carlo principles can be used to estimate VN position such as [16] and [21]. However, underground environmental effects, such as path loss and multipath and shadow fading, have greatly impact on the signal propagation. As shown in Figure 4, an example of underground environmental effects. Assume a vehicular node (VN_1) receives a message from RN_2; therefore, VN_1 stores RN_2 in L_1. Since RN_3 transmission range is greater than the distance between VN_1 and RN_3, RN_3 location is forwarded from VN_2 to VN_1 to be stored in L_2.

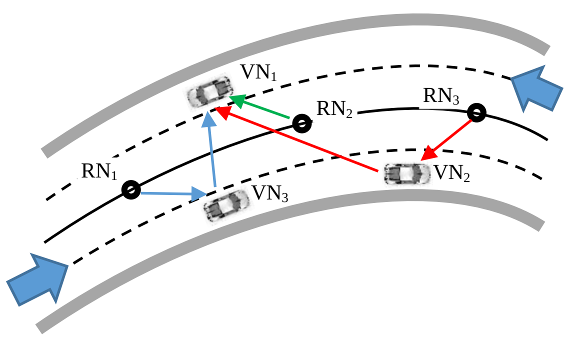

Figure 4 The impact of underground noise on signal propagation

Although RN_1 is a nearest RN for VN_1 because its transmission range is theoretically greater than the distance between VN_1 and RN_1, VN_1 cannot receive its message due to underground environment effects. Since VN_3 is close to RN_1, it receives from RN_1 and forwards its message to VN_1; hence, VN_1 is forced to store RN_1 in L_2. In this work, RN_1 is considered an untruthful two-hop RN to VN_1 and should be discovered as shown below. The existing Monte Carlo localization schemes cannot discover untruthful 2-hop RNs. Therefore, during the filtering phase, false samples are obtained from RNs constraints which increase the localization error as shown in Figure 5.

Assume a vehicular node (VN) estimated its position at time slot (k-1) and wants to estimate its position at time slot (k). Such node generates location samples from its preceding position with distance R. In original MCL, samples are generated in all directions around its previous position (P) while, in the adapted version, we assume it reaches the actual position (A) at time slot (k), then it generates samples in movement direction from (P) to estimate its current position as shown in Figure 5 (a). In ideal state, such node receives two location packets from two reference nodes (RN_1) and (RN_2). When the vehicular node applies the reference nodes' constraints, it can obtain a valid sample area (i.e., case 1) during the filtering phase as shown in Figure 5 (b). The estimation process estimates a VN position at point (E_1) which the distance from A to E_1 represents the localization error in such case.

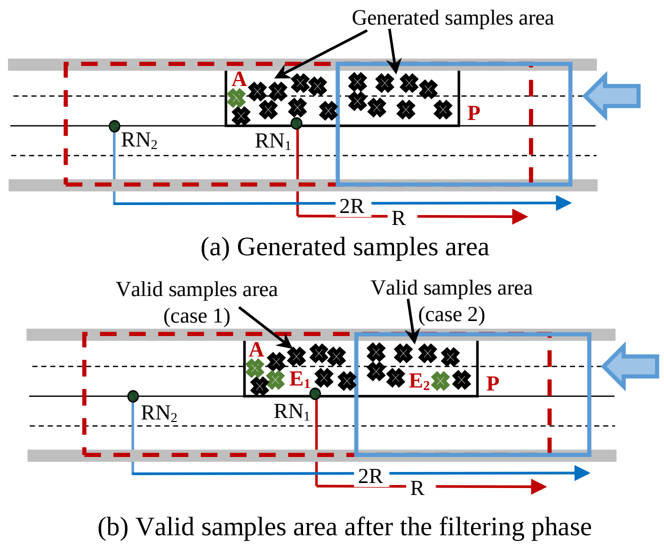

Figure 5 Filtering phase in the existing Monte Carlo localization schemes

In noisy environments, such node may miss a location packet from RN_2 due to signal attenuation or fading reasons. Meanwhile RN_2 may be forwarded to that node as a farthest reference node. The filtering phase generates a valid sample area (case 2), as shown in Figure 5(b), which contains false samples that lead to estimated position at point (E_2). The distance between A and E_2 represents the localization error in such case. Clearly, the localization error in case (2) is greater than case (1) which can reach a value exceeding the transmission range.

In this paper, new heuristics are proposed to solve the problem of untruthful 2-hop reference nodes. As shown in Line (6), L_1 and L_2 are examined to decide that RNs cause positive or negative effect according to the following remarks. Assume a road tunnel pattern (i) in a rectangular form with length (D) where D represents the space between two adjacent RNs and given from Eq. (10), and width (W) where W represents the tunnel width. Such pattern contains one RN (RN_i) at the pattern center as shown in Figure 6.

Corollary 4.1: When a vehicular node (VN) moves inside a pattern (i) and reaches close to (RN_i), its normal to receive from three RNs (RN_{i-1}, RN_i and RN_{i+1}) or from two adjacent RNs only. It receives from (RN_{i-1} and RN_i), when it is located

RESEARCH ARTICLE

between RN_{i-1} and RN_i, and receives from (RN_i and RN_{i+1}), when it is located between RN_i and RN_{i+1}.

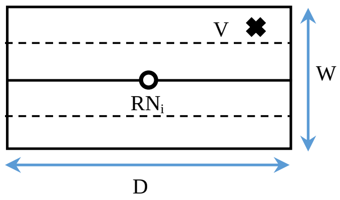

Figure 6 A road tunnel pattern (i)

Remark 4.1: When a vehicular node receives from three nearest RNs, then a VN is so close to the middle RN and any farthest RN discovered gives positive effect.

Explanation of Remark 4.1: Assume five road patterns as shown in Figure 7, when a vehicular node (VN) receives from three RNs (RN_2, RN_3 and RN_4). From Corollary 4.1, node (VN) is so close from node (RN_3) as shown in Figure 7. When other vehicular nodes forward RN_1 and RN_5 as farthest RNs to VN, this is a normal state to the following.

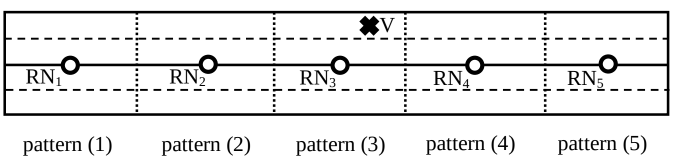

Figure 7 Five road patterns and a vehicular node moves near RN_1

Neglect the distance between (VN) and (RN_3), and assume the distances between (VN) and (RN_1) is d_1 and between (VN) and (RN_5) is d_5. The distances d_1 and d_5 are approximately equal 2D where $D = 0.5\sqrt{4R^2 - W^2}$ as shown in Eq. (10), R represents RN transmission range and W represents the tunnel width. Assume W varies from 10% to 40% of RN transmission range (R), then D will vary between 0.979R and 0.998R. Accordingly, the distances d_1 and d_5 vary between 1.96R and 1.99R. Since the expected distance to a farthest RN varies between R and 2R, RN_1 and RN_5 are truly farthest RNs (truthful 2-hop RNs).

Remark 4.2: When a vehicular node receives from two nearest RNs, then a farthest RN discovered gives positive effect with high probability.

Explanation of Remark 4.2: Assume a vehicular node (VN), as shown in Figure 7, leaves a pattern (3) and moves to pattern (4). VN is located between RN_3 and RN_4. Accordingly, VN can easily receive from RN_3 and RN_4 and consider them as nearest RNs. Assume the distance from VN to RN_3 is d_3 and from VN to RN_4 is d_4. When VN is exactly located between RN_3 and RN_4, d_3 and d_4 approximately equal 0.5D. When other vehicular nodes forward RN_2 and RN_5 to (VN), this is a normal state to the following.

Assume the distance from VN to RN_2 is d_2 and from VN to RN_5 is d_5. The distances d_2 and d_5 approximately equal 1.5D. Accordingly, the distances d_2 and d_5 varies between 1.4R and 1.48R. Since the expected distance to a farthest RN varies between R and 2R. Then, RN_2 and RN_5 are farthest RNs. When VN moves between RN_3 and RN_4 and have a close distance to RN_3 or RN_4; for example, VN is close to RN_4, the distance to RN_5 (d_5) may be little bit less than R (around 0.95R) and RN_5 is discovered as a farthest RN. Since d_5 is out of range (R, 2R) by small amount (0.05R), a small additional error is expected in node localization which happens with very small probability.

Remark 4.3: When a vehicular node receives from one nearest RN, then a farthest RN discovered gives negative effect.

Explanation of Remark 4.3: Assume a vehicular node (VN), as shown in Figure 7, moves inside the pattern (3), VN receives only from RN_3, then RN_3 is a nearest RN for VN. When other vehicular nodes forward the neighbor RNs of RN_3 (RN_2, RN_4 or both) to VN, this is a conflict state to the following.

Assume VN is close to RN_3 and located between RN_3 and RN_4 and the distance to RN_2 and RN_4 are d_2 and d_4, respectively. As shown in explanation of Remark 4.2, d_2 approximately equals 1.5D which means it will vary between 1.4R and 1.48R. Accordingly, RN_2 can be considered a true farthest RN. On the other hand, d_4 can be computed from a triangle with three varices (RN_2, RN_4 and VN). Assume an angle θ at the vertex (RN_2), the projection of VN over the line of reference nodes = W/4, and the distance from RN_2 to VN equals 1.5D; therefore, $\sin(\theta) = 0.25W/1.5D < 0.0667$ at $W < 0.4D$. Accordingly, an angle (θ) is less than 4 degrees. Then, when applying the cosine law, d_4 is less than 0.5D. Accordingly, d_4 will vary between 0.48R to 0.49R which indicates that RN_4 must be a nearest RN when RN_2 is a farthest RN. In similar, when we assume RN_4 is farthest RN, RN_2 must be nearest RN. Therefore, discovering RN_2 and RN_4 as farthest RNs is a conflict state and one of them must be a nearest RN.

The proposed scheme can solve this problem using the preceding location information and preceding speed reading. At time slot $(\Delta t)_i$, the average speed (S_{avg}) is determined which equals $(S_i + S_{i-1})/2$. The expected distance that a vehicular node (VN) is travelled approximately equals than ($S_{avg}\Delta t_i$). Few samples are generated at such distance and a farthest RN that is located near those sample is chosen as the second nearest RN. When the previous location information is absent, we exclude RNs with distance 2D to the nearest RN. For example, RN_3 is a nearest RN to (VN). When RN_1 or RN_5 belongs to L_2 list, then RN_1 or RN_5 is surely a farthest RN because the distance to RN_3 is 2D. On the other hand, when RN_2 and RN_4 belongs to L_2 list, they are untruthful 2-hop RNs because one

RESEARCH ARTICLE

of them is a nearest RN. We change untruthful RN range to (pR, (1+p)R) where p = 1/n which n is greater than or equal 2.

Remark 4.4: When a vehicular node does not receive from any nearest RN, then a farthest RN discovered gives negative effect.

Explanation of Remark 4.4: Assume a vehicular node (VN), as shown in Figure 7, moves inside the pattern (3), VN does not receive from any RN. When other vehicular nodes forward two or more farthest RNs; for example, RN_2, RN_3 and RN_4 are discovered, this is a conflict state, according to Corollary 4.1, because two of those RNs must be nearest RNs.

The proposed scheme can easily solve this problem in case of receiving two farthest RNs by considering both of them are nearest RNs. In case of receiving three farthest RNs, RN in the middle is considered a nearest RN and choose one from other RNs as the second nearest RN as follows. When the preceding location information and the preceding speed reading are available, the second nearest RN is chosen by the same way as shown above. In the absence of previous location information, we change untruthful RN range to (pR, (1+p)R) where p = 1/n and n is greater than or equal 2. The same rule is applied when more than three farthest RNs are received.

As shown above, COPO heuristics are proposed to alleviate the effect of untruthful 2-hop RNs to improve the localization accuracy more than traditional Monte Carlo schemes to be applicable for underground vehicular ad-hoc networks. After applying the proposed heuristics, a vehicular node, VN(j), begins to estimate its position. It examines the preceding location information and preceding speed reading. When they are unavailable, VN(j) examines the sum of L_1 items and L_2 items. VN(j) begins when it discovers at least one nearest or farthest RN. As shown in Line (9), an intersection region (IR) is determined as follows. Each RN transmission range is represented by a square with side (R) for nearest RN, side 2R for farthest RN, or side (1+p)R for untruthful 2-hop RN. All squares are intersected to create the intersection region (IR). Afterwards, as shown in Line (10), samples are generated in IR in grid form and stored in sample list.

In case of the preceding location information and the preceding speed reading are available, VN(j) generate samples from its previous estimated location in lane direction, as shown in Line (12), which the distance from previous position to each sample varies between $S_{min}\Delta t_i$ and $S_{max}\Delta t_i$ where S_{min} is the minimum value of (S_{i-1} and S_i) and S_{max} is the maximum value of (S_{i-1} and S_i). The generated samples are stored in the sample list. The sample list is filtered, as shown in Line (13), by nearest RN constraint which its distance to each sample is less than R. When the distance is greater than R, such sample is removed. In addition, when there is a farthest RN, its constraint is applied which its distance to each sample is greater than R and less than 2R. Otherwise, a sample is removed. When there is untruthful 2-hop RN, its constraint is applied which its distance to each sample is greater than pR and less than (1+p)R.

Finally, VN(j) estimates its position based on the filtered samples. The centroid of filtered samples that represents the estimate position of VN(j) at the current Δt is determined. Two values are stored for the next time slot, the value of estimated location and the current speed reading as shown in Lines (15, 16). In what follows, simulation results are introduced which the performance of COPO system is compared to existing Monte Carlo schemes such as MCL [16] and VMCB [21]. In addition, MCL and VMCB are adapted to generate samples only in the movement direction and compared with COPO scheme.

5. SIMULATION RESULTS AND PERFORMANCE COMPARISON

COPO system is verified by NS2 simulator to examine its effectiveness. Several experiments are performed to measure localization accuracy of underground vehicular ad-hoc networks and compute the average values. In these experiments, RNs are distributed along the road tunnel and vehicular nodes are randomly deployed in a road with two lanes in each direction. The maximum transmission range for vehicular and reference nodes equals 50 meters. The NS2 simulation parameters used in this study are shown in Table 1.

Table 1 Simulation Parameters

Parameter	Value
maximum speed (m/s)	20
maximum transmission range (m)	50
number of reference nodes per km	20 ~ 40
path loss exponent	2.7 ~ 4.7
shadowing deviation (dB)	8 ~ 18
vehicle antenna height (m)	1.5
reference node antenna height (m)	7.0
time slot (sec)	2
road tunnel length (m)	3000
road tunnel width (m)	16
road tunnel height (m)	7.6

In this work, we use a simple car-following and free motion mobility model introduced in [24] which is considered more suitable to model the mobility in road tunnels. Such model assumes each vehicular node moves at the highest velocity compatible with the traffic restrictions in the road tunnels. Assume a vehicular node at distance, *D(t)*, at time (t). It can move to new position, $D(t+\Delta t)$, after a time slot (Δt) which $D(t+\Delta t) = D(t) + S(t+\Delta t)\Delta t$. The term $S(t+\Delta t)$ represents the new vehicular node speed that can be considered the maximum value of zero and $S_d(t)$. The speed $S_d(t)$ is the desired speed at time (t) which is the minimum value of three terms: the maximum speed in road tunnel, the safe speed, and $S(t) + a(t)\Delta t$. S(t) and a(t) represent the node speed and acceleration at time (t). The safe speed depends on the gap distance between the current vehicular node and the lead one. When the gap distance is small, the safe speed is obviously the minimum value. When a gap distance gradually increases, the safe speed also increases; therefore, the desired speed is restricted by the maximum speed [25].

In this section, a performance comparison is presented to compare the performance of proposed system with existing range-free schemes such as MCL [16] and VMCB[21]. We adapt MCL and VMCB to exploit VN movement direction (they are called MCLwMD and VMCBwMD). We study the impact of the number of reference nodes per km, traffic density, number of vehicular nodes with GPS, path loss, and shadowing deviation on the localization accuracy.

5.1. The impact of the number of reference nodes

In this section, the impact of the number of reference nodes per km on the localization accuracy is studied because curved tunnels require RNs per km more than straight tunnels. The combined path loss and shadowing, described above, is used in which the vehicular nodes move according to the simple car following model [25]. The traffic density is 80 vehicles per lane per km and the number of vehicular nodes that know its preceding position via GPS device before entering the tunnel is 50%. Assume the path loss exponent in road tunnels is 3.1 and the shadowing standard deviation (σ) is 8 dB.

Figure 8 shows the impact of the number of reference nodes on the average localization error. Our experiments are performed at different number of reference nodes per km which RNs are deployed along the middle path in the road tunnel. Assume the distance between two adjacent RNs represents a path segment with length L_s. Increasing the number of reference nodes per km for curved tunnels reduces L_s. The experiments begin with L_s = 49.36m that represents the optimal distance designed by COPO scheme to guarantee all points in straight tunnels are covered with at least two RNs when node transmission range (R) equals 50m. At L_s = 49.36m, COPO scheme requires 20 RNs per km. When L_s is reduced to 45m, COPO scheme requires 23 RNs per km while it requires 25 RNs per km at L_s = 40m. When L_s is reduced to 35m, COPO scheme requires 28 RNs per km while it requires 33 RNs per km at L_s = 30m. Finally, at L_s equals half of transmission range (25 meters), COPO scheme requires 40 RNs per km.

When 20 RNs per km are deployed, the localization error in VMCB and MCL increases to reach 0.99R and 1.07R due to the effect of untruthful 2-hop RNs. Such result is satisfied because more false samples are obtained from generating new samples in all directions around the preceding samples. Since VMCBwMD and MCLwMD schemes are adapted to generate samples only in the movement direction, the localization error reaches 0.45R, 0.49R, respectively. As shown in Figure 8, COPO scheme achieves minimum localization error at 20 RNs per km which reaches 0.1832R because it avoids the effect of untruthful 2-hop RNs; moreover, it generates new samples in the movement direction only.

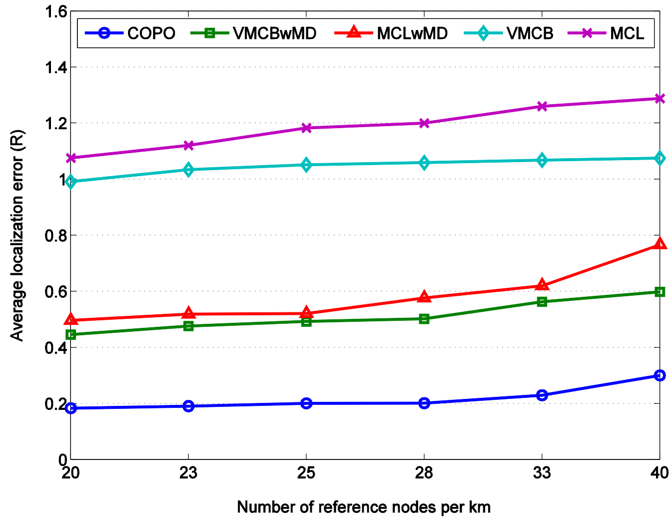

Figure 8 The impact of the number of reference nodes per km

When the number of RNs per km increases, RNs become close to each other. Therefore, a vehicular node can theoretically discover more than two nearest RNs. However, due to the effect of path loss and shadowing in road tunnels, the number of untruthful 2-hop RNs increase which lead to low localization accuracy in the existing schemes. Since COPO scheme alleviates the effect of untruthful 2-hop RNs, it slightly increases with increasing the number of RNs per km. As shown in Figure 8, the average localization error in COPO scheme varies from 0.1832R at 20 RNs per km to 0.29R at 40 RNs per km. The error difference for COPO scheme is 0.11R (i.e., it means 5.5m at R = 50m).

On the other hand, the average localization error in VMCBwMD scheme varies from 0.45R at 20 RNs per km to 0.59R at 40 RNs per km while it varies from 0.49R at 20 RNs per km to 0.76R at 40 RNs per km for MCLwMD scheme. These results show that the error difference is 0.14R and 0.27R for VMCBwMD and MCLwMD schemes, respectively. For traditional schemes that do not exploit the movement direction, the average localization error in VMCB scheme varies from 0.99 at 20 RNs per km to 1.08R at 40 RNs per km while it varies from 1.07R at 20 RNs per km to and 1.29R at 40 RNs per km for MCL scheme. These results show that the error difference is 0.09R and 0.22R for VMCB and MCL schemes,

RESEARCH ARTICLE

respectively. As shown above, the average localization error in COPO scheme achieves minimum localization error compared to all existing schemes in straight tunnels which reaches 0.1832R (9.16m at R = 50 meters). Therefore, it is suitable for VANET in underground environment with taking into consideration that all vehicular nodes can estimate their position at any time in a road tunnel. In addition, COPO scheme achieves minimum localization error in curved tunnels with insignificant increase. For example, when a curved tunnel requires 33 RNs per km, the average localization error reaches 0.201R (10.05m at R = 50 meters).

5.2. The impact of traffic density

The impact of traffic density on the localization accuracy is studied in this section. Both combined path loss and shadowing model and simple car following model are used. Twenty reference nodes per km are deployed and the number of vehicular nodes that know its preceding position via GPS device before entering the tunnel is 50%. Assume the path loss exponent in road tunnels is 3.1 and the shadowing standard deviation (σ) is 8 dB. The traffic density varies from 20 to 80 vehicles per lane per km.

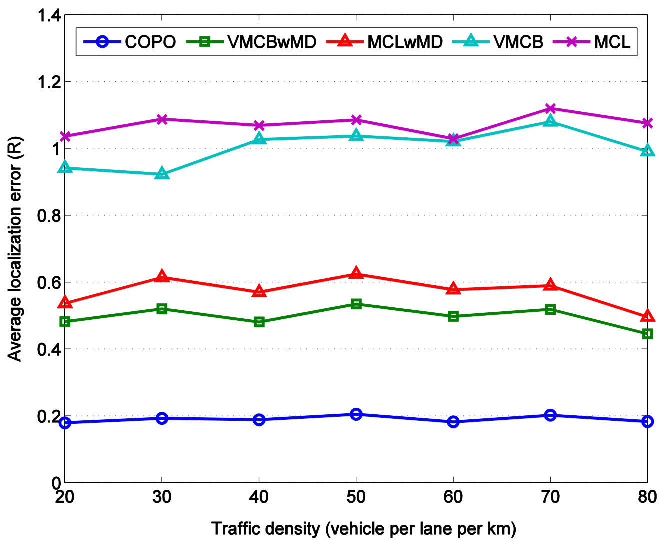

Figure 9 The impact of traffic density.

For ideal environments (i.e., path loss = 1), it is normal to find the average localization accuracy increases with increasing the traffic density (i.e., number of vehicular nodes per lane per km increases). As the number of vehicular nodes (VNs) increases, the neighbor list size of each VN increases. Since each neighbor forwards nearest RNs, each VN has a chance to collect more farthest RNs. More farthest RNs besides nearest RNs reduces valid samples area as much as possible to obtain minimum localization error. However, this fact is different in noisy environments (i.e., underground environments).

As shown in Figure 9 the average localization error for COPO scheme alternates between 0.179R and 0.204R with mean value equals 0.19R and standard deviation 0.009R. While the average localization error for VMCBwMD scheme alternates between 0.445R and 0.534R with mean value equals 0.497R and standard deviation 0.028R, and the average localization error for MCLwMD scheme alternates between 0.496R and 0.624R with mean value equals 0.572R and standard deviation 0.041R. On the other hand, the average localization error for VMCB scheme alternates between 0.922R and 1.079R with mean value equals 1.001R and standard deviation 0.053R, and the average localization error for MCL scheme alternates between 1.029R and 1.119R with mean value equals 1.07R and standard deviation 0.031R.

The results show that, for all schemes except COPO in underground environments, it is unnecessary when the number of vehicular nodes increase, the average localization error decreases because farthest RNs list may contain untruthful 2-hop RNs that increase the localization error. Therefore, the standard deviation for results in all schemes except COPO varies between 0.03R and 0.05R. COPO scheme is better because it achieves minimum localization error at all values of traffic density. In addition, as a result of the proposed heuristics that alleviate the effect of untruthful 2-hop RNs, the standard deviation for COPO results is very small which reaches 0.009R (i.e. at R = 50 meters, σ = 0.45m).

5.3. The impact of the percentage of vehicles with GPS devices

Vehicular nodes that decide to enter a long road tunnels may have GPS devices to know their positions in free space. When those nodes enter a road tunnel, they miss GPS signals, but they keep the last reading. Therefore, a VN with GPS device can begin to estimate its position in the first round by exploiting the preceding GPS position. In this section, we study the effect of percentage of vehicular nodes with GPS devices on the average localization error. Also, both combined path loss and shadowing model and simple car following model are used and twenty reference nodes per km are deployed. Assume the path loss exponent in road tunnels is 3.1 and the shadowing standard deviation (σ) is 8 dB. The traffic is 80 vehicles per lane per km.

As shown in Figure 10, all schemes except COPO are insensitive for changing the percentage of vehicular nodes that know their previous position via GPS devices before entering the tunnel because the random effect of untruthful 2-hop RNs cannot be avoidable. For example, the average localization error for VMCB with movement direction alternates between 0.475R and 0.549R while the average localization for VMCB without movement direction alternates between 1.029R and 1.139R. On the other hand, the average localization error for MCL with movement direction is more stable which begins with 0.712R at zero nodes with GPS while the average

RESEARCH ARTICLE

localization for MCL without movement direction is unstable because it alternates between 1.051R and 1.156R.

COPO scheme is sensitive for changing the percentage of vehicular nodes that know their preceding position via GPS devices before entering the tunnel because the proposed heuristics alleviate the effect of untruthful 2-hop RNs. Therefore, increasing the number of vehicular nodes that know their previous position via GPS devices before entering the tunnel improves the localization accuracy.

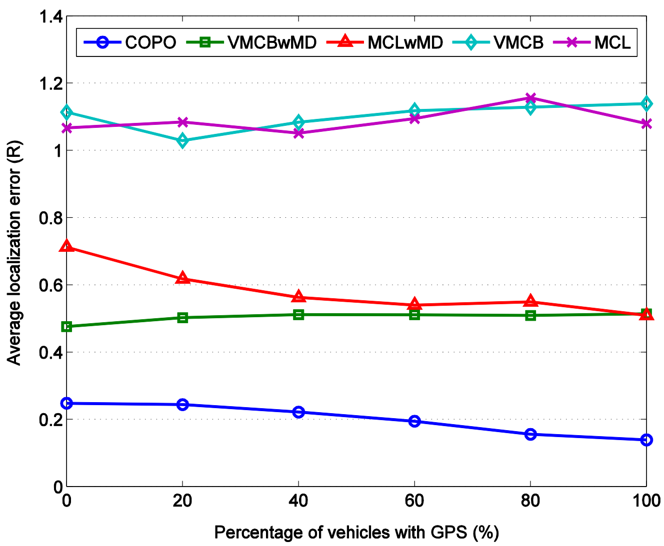

Figure 10 The impact of vehicles with GPS

For example, as shown in Figure 10, when zero nodes with GPS, the average localization error is 0.247R. The best localization accuracy is obtained at 100% of nodes with GPS which the average localization error reaches 0.138R (i.e., at R = 50m, the average localization error equals 6.9m).

5.4. The impact of path loss exponent

Electromagnetic signals in underground environments suffer from higher attenuation due to unpredictable obstacles in soil such as rocks and tree roots; therefore, these signals miss significant amount of their energy before vehicular nodes receive them. This phenomenon is called a signal path loss. In this section, the effect of path loss is studied which the path loss exponent is chosen greater than two (i.e., it varies from 2.7 to 4.7) at constant shadowing effect (i.e., shadowing deviation equals 8 dB). Twenty reference nodes per km are deployed and the number of vehicular nodes that know its preceding position via GPS device before entering the tunnel is 50%. The traffic density is 80 vehicles per lane per km.

When electromagnetic signals are attenuated, a vehicular node receives only from close reference nodes. When a vehicular node lies inside and near the border of RN's perfect transmission range, it cannot receive from a reference node due to signal attenuation. In addition, signal attenuation makes a vehicular node receives forwarded packets only from close neighbors. Therefore, as a signal attenuation increases, both of the list size of 1-hop and 2-hop reference nodes decrease which that may increase the average localization error in classical Monte Carlo based solutions.

Classical Monte Carlo based solutions are not interested to obtain better localization accuracy in initial time slots where the localization accuracy gradually increases after few time slots. When signal attenuation increases, an incremental error is expected for more time slots leading to increase in the average localization error. COPO scheme assumes certain percentage of vehicular nodes know their preceding positions via GPS devices. The other vehicular nodes do not begin estimate their position until they discover nearest RNs or receive farthest RNs. Such rule prevents the incremental localization error; however, the average number of nodes that can estimate their positions slightly decrease because few nodes without GPS device may continue significant number of time slots until they discover nearest or farthest reference nodes. For comparison purposes, we assume all schemes in our comparative study follow up the same rules.

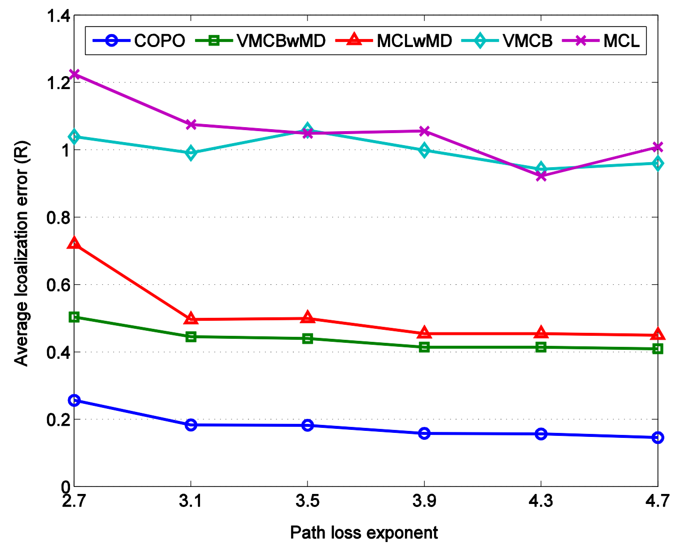

Figure 11 The impact of path loss

Figure 11 shows the impact of path loss (signal attenuation) on the average localization error. As a result of applying the rule mentioned above, when path loss (L) increases, localization error slightly decreases by regular form in COPO, VMCBwMD and MCLwMD schemes and by oscillated form in VMCB and MCL schemes. Such reduction in localization error is achieved on the expense of the average number of location-aware nodes which it relatively decreases with increasing the value of path loss. The results in Figure 11show that COPO scheme achieves minimum average localization error which reaches 0.25R at L = 2.7 and gradually decreases to reach 0.14R at L = 4.7. Similarly, the average localization error in VMCBwMD and MCLwMD schemes gradually decreases. At L = 2.7, the average localization error reaches 0.5R and 0.72R, and decreases to reach 0.41R and 0.44R for VMCBwMD and MCLwMD schemes, respectively.

On the other hand, the average localization error in VMCB and MCL schemes decreases in oscillated form. As shown in Figure 11, at L = 2.7, the average localization error reaches 1.04R and 1.22R, and decreases to reach 0.96R and R for VMCB and MCL schemes, respectively. As mentioned above, the reduction in localization error in all schemes is realized on the expense of the percentage of average number of location-aware nodes. All schemes can estimate all nodes' positions at L = 2.7 while such percentage decreases with increasing the value of path loss. At L = 4.7, the percentage of average number of location-aware nodes reaches 93.75% for all schemes and such result shows why the average localization error slightly decreases when L increases. From mentioned results, COPO scheme achieves minimum stable localization error at all values of path loss.

5.5. The impact of shadowing deviation

As mentioned above, signal propagation faces signal reflection and refraction from tunnel walls which fluctuations of the amplitudes, phases, or multipath delays of a radio signal over a short period or short travel distance are occurred. This phenomenon is called multipath and shadow fading. The impact of shadowing deviation on the localization accuracy is studied in this section. The combined path loss and shadowing, described above, is used in which the vehicular nodes move according to the simple car following model. The traffic density is 80 vehicles per km per lane and twenty RNs per km are deployed. Assume the path loss exponent in road tunnels is 3.1 and the shadowing standard deviation (σ) varies from 8 to 18 dB.

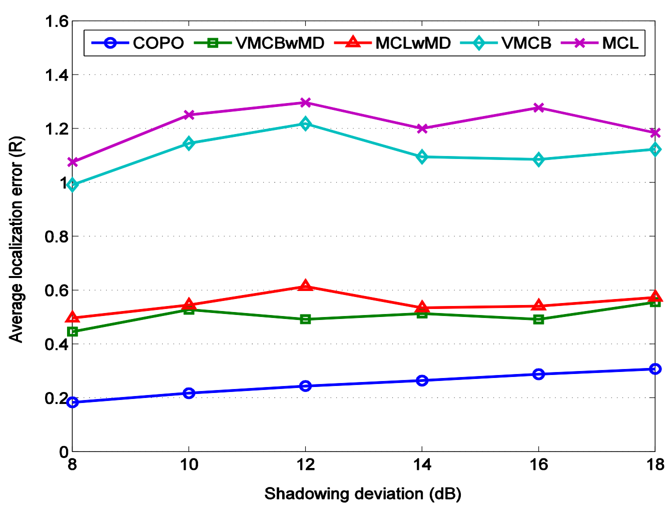

Figure 12 The impact of shadowing deviation

When a multipath and shadow fading increases, signal amplitude rapidly fluctuates. At constant path loss, a vehicular node cannot receive from all nearest reference nodes when it lies inside their transmission range. It randomly receives from certain reference nodes and cannot receive from others. When a vehicular node discovers a nearest reference node, it is unnecessary that a reference node is close to a vehicular node. The nearest RNs list decreases when a shadowing deviation (in dB) increases. On the other hand, farthest RNs list moderately remains constant because a vehicular node can receive a farthest RN from many neighbors. The untruthful two-hop RNs phenomenon strongly affect the average localization error in such case due to farthest RNs are available. Figure 12 shows the impact of shadowing deviation (in dB) on the average localization error at constant attenuation (i.e., L = 3.1).

When a shadowing deviation (σ) increases, the average localization error gradually increases by regular form in COPO scheme and decreases by oscillated form in other schemes. In COPO scheme, the average localization error reaches 0.183R at σ = 8 dB while it gradually increases to reach 0.307R at σ = 18 dB. As shown in Figure 12, the average localization error in COPO scheme varies linearly with error difference equals 0.12R (6 meters) which is acceptable in vehicular node localization. On the other hand, other schemes gradually increase by oscillated form. For example, at σ = 8 dB, the average localization error reaches 0.44R, 0.49R, 0.99R and 1.07R for VMCBwMD, MCLwMD, VMCB and MCL while it reaches 0.55R, 0.57R, 1.12R and 1.18R at σ = 18 dB. These results show that COPO scheme achieves better localization accuracy and remains at the same performance level when a shadowing deviation increases.

Finally the simulation results and comparative study show that COPO scheme achieves better localization accuracy. As shown above, the performance of COPO scheme is studied at different number of reference nodes per km, different traffic densities, different number of nodes that enter the tunnel knowing their preceding locations via GPS devices, different path loss exponent and different shadowing deviation values. In the future work, more improvements in the proposed heuristics introduced in this work will be performed.

6. CONCLUSION

This paper introduces a new navigation system based on network connectivity for vehicular ad-hoc networks in underground environments. Two algorithms are proposed, reference nodes' deployment and position estimation. The first algorithm organizes the reference nodes in all types of road tunnels (straight or curved). The second algorithm estimates a vehicular node's position based on some heuristics that avoid the problem of untruthful 2-hop reference nodes. Simulation results are conducted by NS2 simulator to compare the performance of the proposed scheme with the existing

RESEARCH ARTICLE

schemes. For comparison purposes, we adapt the existing schemes to exploit the movement direction to improve their localization accuracy. The results show that COPO scheme can work well with minimum number of reference nodes per km. Meanwhile a COPO scheme is predictable, its performance remains constant at any traffic density. In addition, the effect of environmental parameters in road tunnels are studied such as path loss, and multipath and shadow fading. As shown in the results, the proposed heuristics alleviate the effect of untruthful 2-hop reference nodes and improve the localization accuracy. In the future, more heuristics will be introduced to completely prevent the effect of untruthful 2-hop reference nodes and achieve optimal localization accuracy based on the network connectivity.

REFERENCES

[1] S. Al-Sultan, M. Al-Doori, A. Al-Bayatti, and H. Zedan, "A Comprehensive Survey on Vehicular Ad Hoc Network, " Journal of Network and Computer Applications, Elsevier, vol 37, pp. 380-392, 2014. *https://doi.org/10.1016/j.jnca.2013.02.036*

[2] Joe, M. Milton, and B. Ramakrishnan, "Review of Vehicular Ad Hoc Network Communication Models including WVANET (Web VANET) Model and WVANET Future Research Directions," Journal of Wireless Netw, Springer, vol. 22, pp. 2369-2386, 2016. *doi:10.1007/s11276-015-1104-z.*

[3] Joe, M. Milton, and B. Ramakrishnan, "WVANET: Modelling a Novel Web Based Communication Architecture for Vehicular Network," Journal of Wireless Pers Commun, Springer, vol. 85, pp. 1987-2001, 2015. *doi:10.1007/s11277-015-2886-0*

[4] H. Hartenstein, and K. Laberteaux, "A Tutorial Survey on Vehicular Ad Hoc Networks, " IEEE Communications Magazine, pp.164 –171, 2008. *doi: 10.1109/MCOM.2008.4539481*

[5] B. Ramakrishnan, M. Selvi, R. Nishanth, and Joe, M. Milton, "An Emergency Message Broadcasting Technique Using Transmission Power Based Clustering Algorithm for Vehicular Ad Hoc Network," Journal of Wireless Pers Commun, Springer, 2016. *doi:10.1007/s11277-016-3772-0*

[6] B. Ramakrishnan, R. Nishanth, Joe, M. Milton, and M. Selvi, "Cluster Based Emergency Message Broadcasting Technique for Vehicular Ad Hoc Network," Journal of Wireless Netw, Springer, 2015. *doi:10.1007/s11276-015-1134-6*

[7] Z. Sun and I. Akyildiz, "Influences of Vehicles on Signal Propagation in Road Tunnels, " IEEE International Conference on Communications (ICC), 2010. *doi: 10.1109/ICC.2010.5502782*

[8] T. Yan, W. Zhang, and G. Wang, "A Grid-Based On-Road Localization System in VANET with Linear Error Propagation", IEEE Trans. on Wireless Communications, vol. 13, no. 2, pp. 861-870, 2014. *doi: 10.1109/TWC.2013.122313.130547*

[9] Y. Agarwal, K. Jain, S. Kumar and G.Bhardwaj, "TLST: Time of Arrival Based Localization and Smart Tunnel concept in VANETs", 3rd International Conference on Signal Processing and Integrated Networks (SPIN), 2016. *doi: 10.1109/SPIN.2016.7566802*

[10] M. Li, "A Novel Ultra-Wideband Hybrid Localization Scheme in Coal Mine, " Journal of Communications Vol. 10, No. 11, Nov. 2015. *doi: 10.12720/jcm.10.11.889-895*

[11] G. Chen, R. Zetik and H. Yan, "Time of Arrival Estimation for Range-based Localization in UWB Sensor Networks," IEEE Int'l Conference on Ultra-Wideband (ICUWB), 2010. *doi: 10.1109/ICUWB.2010.5614041*

[12] P. Singh and S. Agrawal, "TDOA Based Node Localization in WSN Using Neural Networks," IEEE Int'l Conference on Communication Systems and Network Technologies (CSNT), 2013. *doi: 10.1109/CSNT.2013.90*

[13] P. Kułakowskia, J. Vales-Alonsob, E.Egea-Lópezb, W. Ludwina and J. García-Harob, "Angle-of-Arrival Localization based on Antenna Arrays for Wireless Sensor Networks," Computers & Electrical Engineering, Elsevier, vol. 36, no. 6, pp. 1181–1186, Nov. 2010. *http://dx.doi.org/10.1016/j.compeleceng.2010.03.007*

[14] S. Abdel-Mageid, "Autonomous Localization Scheme for Mobile Sensor Networks in Fading Environments", IEEE Int'l Conference on Selected Topics in Mobile & Wireless Networking (MoWNeT), 2016. *doi: 10.1109/MoWNet.2016.7496598*

[15] S. Abdel-Mageid, "Self-Correcting Localization Scheme for Vehicle to Vehicle Communication," International Journal of Computer Networks and Applications (IJCNA), Volume 3, Issue 5, pp. 95-107, September - October 2016. DOI: 10.22247/ijcna/2016/48829

[16] L. Hu and D. Evans, "Localization for Mobile Sensor Networks, " Proc. ACM MobiCom, pp. 45-47, Sept. 2004. *doi: 10.1145/1023720.1023726*

[17] A. Baggio and K. Langendoen, "Monte-Carlo Localization for Mobile Wireless Sensor Networks, " Proc. Second Int'l Conf. Mobile Ad-Hoc and Sensor Networks, pp. 317-328, Dec. 2006. *http://dx.doi.org/10.1016/j.adhoc.2007.06.004*

[18] M. Rudafshani and S. Datta, "Localization in Wireless Sensor Networks, " Proc. Int'l Conf. Information Processing in Sensor Networks (IPSN), pp. 51-60, Apr. 2007.

[19] S. Zhang, J. Cao, L. Chen, and D. Chen, "Locating Nodes in Mobile Sensor Networks More Accurately and Faster, " Proc. Ann. IEEE Conf. Sensor and Ad Hoc Comm. and Networks (SECON), pp. 37-45, June 2008. *doi: 10.1109/SAHCN.2008.15*

[20] J. Sheu, W. Hu, J. Lin, "Distributed Localization Scheme for Mobile Sensor Networks, " IEEE Transaction ON Mobile Computing, vol. 9, no. 4, pp. 516-526, April 2010. *doi: 10.1109/TMC.2009.149*

[21] S. Kumar, K. Kislay, M. Singhy and R. Hegde, "A Range-Free Tracking Algorithm in Vehicular Ad-Hoc Networks," 20th National Conference on Communications (NCC), 2014. *doi: 10.1109/NCC.2014.6811310*

[22] T. Rappaport, "Wireless Communications: Principles and Practice". Prentice Hall, 2nd edition, 2002.

[23] M. Prasad & P. Dalela, "Some Experimental Investigation of the Effect of Railway Tunnels on Mobile Communications in Western India," Ann. Telecommun., springer, vol 64, pp. 247–257, 2009. *doi:10.1007/s12243-008-0052-3*

[24] J. Haerri, F. Filali and C. Bonnet, "Mobility Models for Vehicular Ad Hoc Networks: A Survey and Taxonomy", IEEE Communications Surveys & Tutorials, vol. 11, no. 4, pp 19-41, 2009.

[25] S. Krauss, Microscopic modeling of traffic flow: investigation of collision free vehicle dynamics, PhD Thesis, Mathematisches Institut, Universiät zu Köln, 1998, *http://www.zaik.uni-koeln.de/~paper/index.html?show=zpr98-319.*

Author

Salah M. Abdel Mageid received his M.S. and Ph.D. in Systems and Computers Engineering from Al-Azhar University in 2002 and 2005, respectively. Since 2012, he is an associate professor in Systems and Computers Engineering at Al-Azhar University. He performed his post-doctoral research in 2007 and 2008 in the Computer Science and Engineering Department, School of Engineering, the Southern Methodist University at Dallas, TX, USA. He was a member of TEMPO (Tool for Extensive Management and Performance Optimization) project in Cairo University and Vodafone Egypt as an industrial partner in 2014 and 2015. His research interests include Mobile Computing, Cellular Networks, Sensor Networks, Cognitive Radio Networks, Vehicular Ad-hoc Networks, Big Data and Data Analysis, Internet Services and Applications.