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Self-Correcting Localization Scheme for Vehicle to Vehicle Communication

Salah Abdel Mageid
Systems and Computers Department, Faculty of Engineering, Al-Azhar University, Cairo, Egypt

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Abstract – Vehicle to Vehicle communication (V2V) has taken place in research interest for many purposes such as road safety and traffic management. An accurate estimation for vehicular node position is important for such type of communication. A vehicular node can be equipped with Global Positioning Systems (GPS) to estimate its position. In practice, many vehicular nodes may lose GPS signals in rural regions due to dense foliage, or in urban regions due to compact high buildings. In this paper, the received signal strength indication (RSSI) is exploited to assist vehicular nodes to estimate their locations using inter-vehicle communication. High dynamic network topology in V2V is expected due to high node mobility. As a result, the localization error due to signal strength measurements clearly increases compared to low dynamic network topology. The proposed scheme is self-correcting solution which studies the network topology scenarios that increase localization errors and introduces optimal techniques to minimize such errors. Performance evaluation and simulation results show that this work improves localization accuracy and increases the number of vehicular nodes that estimate their locations compared to existing localization schemes.

Index Terms – Vehicular ad-hoc networks, Vehicle to Vehicle communication, Localization, Radio ranging, Path loss, Shadowing.

1. INTRODUCTION

Vehicular ad-hoc networks (VANETs) are greatly dynamic ad-hoc network topology. VANETs have two types of infrastructure: centralized and distributed. The centralized architecture merges cellular and ad-hoc technologies (V2I) while the distributed architecture is based on ad-hoc technology and known as Vehicle to Vehicle communication (V2V) [1], [2]. Vehicular ad-hoc technology has derived many applications such as road safety, traffic management and entertainment [3], [4]. Such applications depend on an accurate estimation for vehicular node position. Recently, most vehicles come with positioning technology, i.e. Global Positioning System (GPS) devices, to precisely estimate their positions [5].

In practice, vehicular nodes may suffer from GPS unavailability for productive or environmental reasons. The productive reasons include vehicular nodes are not originally equipped with GPS device, or have limitations in the GPS device. On the other hand, the environmental reasons attenuate GPS signals such as dense foliage in rural regions, or compact high buildings in urban regions. Therefore, vehicular nodes particularly in V2V communication can be classified into two types. The first type is that vehicular nodes are denied from GPS service to estimate their locations while the other type is that vehicular nodes predict their locations due to GPS signals (i.e., called vehicular beacon nodes). A vehicular node can internally communicate with surrounding beacon nodes to estimate its location using a radio ranging technique (i.e., RSSI).

Many research works have been introduced in node localization using radio ranging techniques for sensor networks such as [6], [7] and [8] and for vehicular ad hoc networks such as [9], [10] and [11]. The existing solutions for vehicular ad hoc networks estimate node location using basic analytical model for received signal strength indicator (RSSI) by different manners. In fact, basic RSSI model, as shown below, cannot perform well in sparse networks and can be greatly influenced by physical environments such as shadowing and multipath effects. The work in [12] eliminates basic RSSI limitations in sparse networks and improves vehicular node localization where the geometric relationship among multiple nodes are exploited. However, such scheme suffers from the effect of environmental parameters that lead to poor localization accuracy when their values increase.

In this paper, a new node localization scheme, Self-Correcting Localization scheme for V2V Networks (SCL-VNET), is proposed to enhance the localization accuracy by solving the basic RSSI model problems. Firstly, the basic RSSI limitations in sparse networks are eliminated. The proposed scheme introduces a new method (it is called sampling method) to exploit 2-hop beacon nodes as well as previous estimated location in compensating the absence of 1-hop beacons. In addition, SCL-VNET scheme eliminates the effect of environmental parameters by correcting the estimated location. The correction method uses the extended RSSI model, described below, in improving the localization accuracy. Afterwards, the alignment method is proposed to use a preloaded map to estimate the proper lane in case of estimating a location between or outside road lanes. The proposed scheme is evaluated using NS2 simulator, then a comparative study is introduced to compare the proposed scheme with the existing research works at different traffic densities, different values of physical parameters and different beacon nodes densities. The

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Manhattan mobility model is used in our simulation experiments which is more appropriate for urban and suburban regions.

This paper is organized as follows. The existing works of node localization for vehicular ad hoc networks are introduced in Section 2. The analytical model for radio ranging localization is presented in Section 3 explaining the proposed extensions in such model. In Section 4, the proposed scheme is introduced which the proposed algorithm and the corresponding analytical model are illustrated. Simulation results and performance comparison are presented in Section 5. Finally, Section 6 concludes this paper.

2. RELATED WORK

Many research works have been introduced for node localization in vehicular ad-hoc networks to solve the problems of GPS positioning and unavailability. The research works [13] and [14] have introduced localization solutions based the roadside units. In [13], beacon nodes that are located at roadside broadcast messages to vehicular nodes. When a vehicular node receives from such beacon nodes, it estimates its location. Such solution solves the problem of GPS positioning and unavailability in low traffic density. However, the end-to-end latency and deployment of roadside units are open problems in this work. The authors in [14] have introduced another solution which roadside units can disseminate the information of a local map over Wi-Fi. The destination node is prepared by GPS receiver and Wi-Fi device to obtain such map and use matching algorithm to deal with the map achieving better localization. Nevertheless, end-to-end latency is unreasonable besides the problem of roadside units' cost and deployment.

In the future, merging roadside to vehicle communication with 5G networks will solve the problem of end-to-end latency in node localization because higher data rates are expected in 5G networks in which the latency will be less than one millisecond. In addition, 5G networks will provide us with higher capacity, reduced cost, consistent Quality of Experience provisioning and massive device connectivity [15]. The future networks (i.e., 5G networks) will help also in developing autonomous vehicles (i.e., self-driving cars) [16], [17].

Another localization technique in vehicular ad hoc networks uses local relative positioning to estimate the distance between vehicular nodes such as [18] and [19]. Smart phones with GPS are exploited in location-based services, for example finding the nearest gas station [20]. However, such solutions still suffer from the problem of GPS positioning and unavailability. The map matching is considered a way to correct GPS signal errors by alignment method [21]. Since GPS data is inaccurate, map matching aligns vehicular node locations with the road on a digital map. Such work uses a hidden Markov model and an extended Kalman filter to achieve better matching. The work in [22] is more appropriate to estimate positions of nodes moving on freeways. Roadside units are used to collect information and dead reckoning method is exploited to compute the current position of nodes based on the node's initial position.

Since vehicle to vehicle communication achieves minimum localization cost. The works in [9] and [11] have introduced localization schemes based on the basic RSSI model. The basic RSSI model can only operate well with high density of vehicular nodes with GPS; for example, a vehicular node requires at least three nearby nodes with GPS to estimate its location and that is unguaranteed all the time. In addition, when a vehicular node estimates its position based on basic RSSI model in the presence of physical changes such as shadowing and multipath (noise levels), the localization accuracy rapidly decreases. The authors in [12] have introduced a grid based scheme (GOT), to eliminate basic RSSI model and improve vehicular node localization in sparse networks where a vehicular node may not always communicate at least with three 1-hop beacon nodes. GOT solution exploits 2-hop beacon nodes and analyze the geometric relationship among multiple nodes. Afterwards, a grid method is used to decrease the localization error and increase the number of nodes that can estimate their locations. However, GOT scheme suffers from the effect of environmental parameters that lead to poor localization accuracy when their values increase.

In what follows, radio ranging limitations in vehicular node localization is introduced to show how the loss of received signal strength decreases the localization accuracy. Afterwards, the proposed scheme is introduced illustrating how it overcomes the basic RSSI problems and how it solves those problems.

3. RADIO RANGING LIMITATIONS IN VEHICULAR NODE LOCALIZATION

RSSI based localization is radio ranging technique to estimate vehicular node position. This work is based on such localization type; accordingly, a free propagation model is suggested which only one clear line-of-sight path between the transmitter and receiver is assumed. In free space propagation model, we can compute the received signal power at distance d as follows [23].

$$P_r = \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 d^2 L} \tag{1}$$

Where L is system loss including path loss, G_t is transmitter antenna gain, G_r is receiver antenna gain, λ is the wavelength and P_t is transmitted signal power. For hypothetical case, the parameters G_t, G_r, and L equal one. The communication range of vehicular nodes is assumed as a circular disk area around the sending node (i.e., beacon node) with radius R in which a vehicular node entering such area can receive from the sending node.

The free space propagation model can be simplified by assuming a reference point d_0 and a constant (K) as follows.

$$P_r = K\left(\frac{d_0}{d}\right)^2 \tag{2}$$

Particularly, signals in physical environments (i.e. urban and suburban) suffer from more noise due to shadowing and multipath effect resulting in complex path loss. Accordingly, the received power can be described as follows.

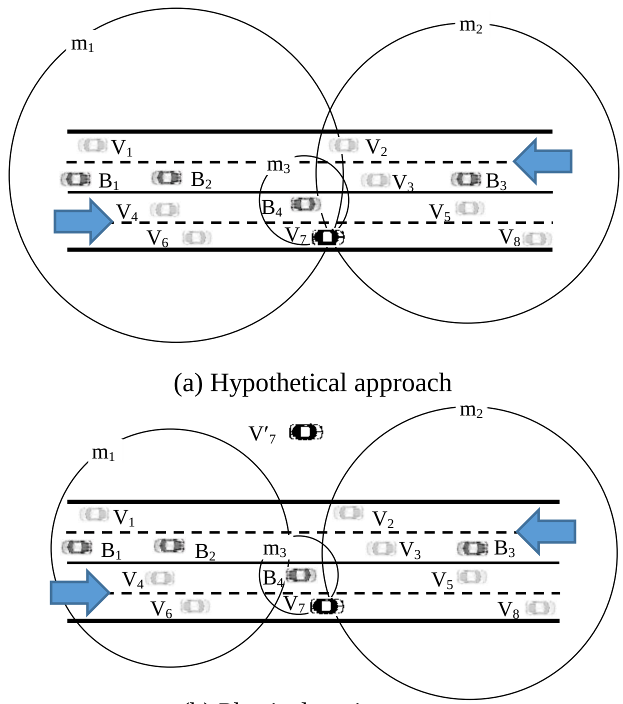
$$P_r = P_0\left(\frac{d_0}{d}\right)^L \tag{3}$$

Where L is the path loss exponent which equals two in free space as shown in Eq. (2). Generally, for physical environments as shown in Eq. (3), path loss exponent increases to reach a value greater than two and less than 6.5 due to many effects such as diffraction, refraction, reflection, propagation medium (dry or humid air), absorption, height of antenna and distance between transmitter and receiver.

In what follows, RSSI limitations for vehicular node localization are explained. Radio ranging localization is mostly related to trilateration analytical model. In such model, when a node begins to estimate its location, it first measures signal strength (P_r) from three nearby beacons. By choosing a proper value for path loss exponent (L) and substituting P_r and L in Eq. (3), the measured distances to beacons can be determined which are analytically used to estimate the vehicular node position. For example, path loss exponent, in urban regions, changes from 2.7 to 3.5; accordingly, the average value (3.1) is chosen as a particular value for L. The localization accuracy decreases due to the expected changes in environmental parameters (i.e., path loss, shadowing and multipath) and network topology. The change in path loss occurs due to the actual shadowing/multipath level (noise level).

Furthermore, the rapid changes in network topology may lead to low localization accuracy. For example, when all beacon nodes have few meters spacing to the current node, trilateration analytical model achieves high localization accuracy where is poorly influenced by environmental parameters. On the other hand, when the distance between a beacon node and the current node is approximately big enough, localization accuracy largely may obviously decrease due to a small change in the noise level because this change leads to an error in measured distances as shown below.

Accordingly, RSSI based localization is reasonable to estimate a vehicular node position when vehicular beacon nodes are near from the current vehicular node by few meters. In practice, vehicular beacon nodes randomly move in lanes; accordingly, RSSI limitations appear when vehicular beacon nodes communicate with the current node and the measured distance nears from the maximum communication range. As shown in Figure 1, there are four vehicular beacon nodes B_1, B_2, B_3 and B_4. Assuming vehicular node V_7 is located at (x, y) and discovers three 1-hop vehicular beacons B_2, B_3 and B_4 at (x_1, y_1), (x_2, y_2) and (x_3, y_3), respectively. Assume the measured distances at V_7 for signals received from those beacons are m_1, m_2 and m_3, respectively.



(a) Hypothetical approach

(b) Physical environment

Figure 1 RSSI trilateration method (two far 1-hop beacons)

According to trilateration analytical model, the estimated location (x_e, y_e) for node V_7 can be determined as follows.

$$x_e = \frac{A(y_3 - y_2) + B(y_1 - y_3) + C(y_2 - y_1)}{2[x_1(y_3 - y_2) + x_2(y_1 - y_3) + x_3(y_2 - y_1)]} \tag{4}$$

$$y_e = \frac{A(x_3 - x_2) + B(x_1 - x_3) + C(x_2 - x_1)}{2[y_1(x_3 - x_2) + y_2(x_1 - x_3) + y_3(x_2 - x_1)]} \tag{5}$$

Where

$A = x_1^2 + y_1^2 - m_1^2$, $B = x_2^2 + y_2^2 - m_2^2$, and $C = x_3^2 + y_3^2 - m_3^2$.

This work extends the trilateration analytical model as follows. The estimated distance between V_7 and beacons B_2, B_3 and B_4 are d_1, d_2 and d_3, respectively.

$$d_i = \sqrt{(x_i - x_e)^2 + (y_i - y_e)^2} \tag{6}$$

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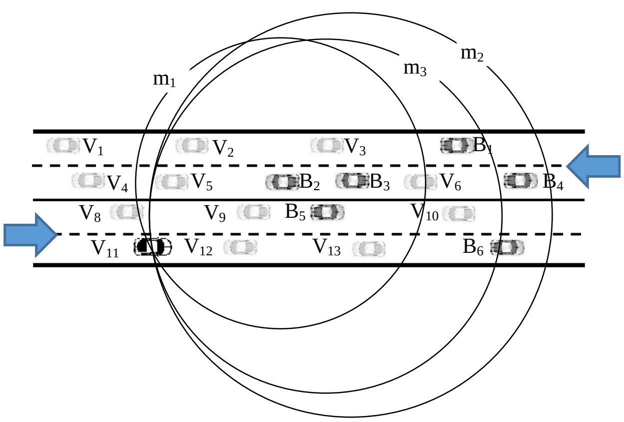
Where i ∈ {1, 2, 3}; the estimated distance difference (ΔS_i) is an absolute value of the difference between V_7 estimated location and measured distance to beacon (i).

$$\Delta S_i = |d_i - m_i| = \left| \sqrt{(x_i - x_e)^2 + (y_i - y_e)^2} - m_i \right| \quad (7)$$

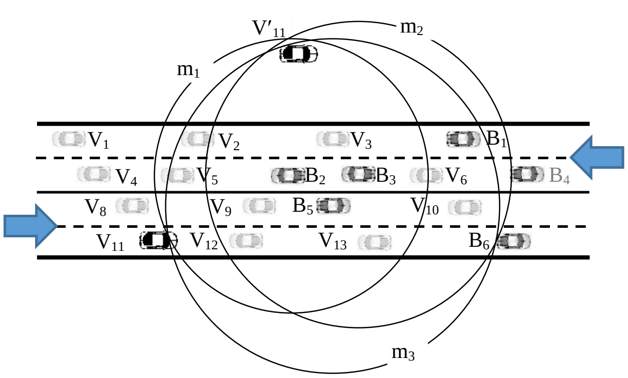
The total value for distance differences (ΔD) is determined as follows.

$$\Delta D = \Delta S_1 + \Delta S_2 + \Delta S_3 \quad (8)$$

Figure 1(a) shows the hypothetical approach (i.e., no noise occurs) which no measurement errors are observed in m_1, m_2 and m_3. As a result, actual and estimated positions for V_7 are matching ($\Delta D = 0$ due to $\Delta S_i = 0$) which means no localization error happens. In practice, for physical environments, received signal strength is influenced by noise added to the path loss. Localization accuracy decreases due to different measurement errors in m_1, m_2 and m_3, respectively.



(a) Hypothetical approach



(b) Physical environment.

Figure 2 RSSI trilateration method (three far 1-hop beacons)

As shown in Figure 1(b), assume urban area where L is chosen (3.1) while the actual path loss due to different noise levels at B_2, B_3 and B_4 equals 2.76, 2.98 and 3.02, respectively. B_2 is more influenced by change in path loss than B_3 and B_4; accordingly, m_1 circle radius decrease more than m_2 and m_3. The estimated location of V_7, computed by Eq. (4) and Eq. (5), is indicated by V'_7 in Figure 1(b). The localization error can be easily detected from ΔD in Eq. (9) where ΔD is greater than zero. Generally, ΔD can be used in this work to indicate to the localization accuracy which the localization accuracy increases as long as ΔD decreases and approaches zero. In this scenario, the localization error exceeds half of the maximum communication range when comparing the actual position V_7 to estimated location V'_7 in Figure 1(b).

The following scenario shows another case, at the same environmental parameters, when beacon nodes are close to each other and have large spacing with the current node. As shown in Figure 2, there are six beacon nodes from B_1 to B_6. Assuming vehicular node V_{11} discovers three nearby vehicular beacons B_2, B_3 and B_5 where are close to each other. For hypothetical approach, estimated location and actual position for V_{11} are congruent as shown in Figure 2(a).

In contrast, when an error occurs in measured distance for one or two beacons as shown in Figure 2(b), the estimated position $V'11$ is imprecise where localization error increases to values greater than R where R represents the maximum communication range for vehicular node. In this paper, radio ranging limitations in physical environments are taken into consideration to improve a vehicular node localization accuracy.

4. THE PROPOSED LOCALIZATION SCHEME

When radio ranging localization is used in vehicle to vehicle communication, the basic RSSI analytical model cannot correctly estimate vehicular nodes' locations due to expected noise in physical environments. For high dynamic network topology, it is unguaranteed that three close beacons are discovered for most vehicular nodes all the time. Furthermore, in lightweight traffic (i.e., rural regions or nightly driving), a vehicular node may originally fail to communicate with three beacons. A vehicular node can exploit farthest beacons (2-hop beacons) besides nearest beacons (1-hop beacons) to estimate its location. The author of this work in [8] has solved RSSI limitations for mobile sensor localization. In this work, many extensions and improvements are introduced to reduce the time complexity and effectively deal with all expected changes in environmental parameters. In what follows, SCL-VNET algorithm is introduced to show those extensions and improvements. A location packet is broadcasted from a beacon node in which each packet contains sender ID and its location at time (t_i). The sender waits for (Δt) and when the time interval (Δt) passed, it broadcasts the next location packet.

SCL-VNET algorithm, for V2V communication, contains three phases: communication, estimation, correction and alignment. Each vehicular node (VN) separately runs such algorithm to estimate its location. The first phase is illustrated in Lines (1-

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6). When a VN receives a location packet from a beacon node, beacon ID and its current location are extracted from the received packet. The measured distance can be determined using the received signal power that can be obtained from PHY/MAC layer. A VN node establishes a new data record containing beacon ID, beacon location and measured distance to save it in a list called (nearest beacon list) as shown in Line (3). A VN changes its mode from receiving mode to sending mode to broadcast new location packet (it is called here forwarded packet) containing nearest beacons information.

SCL-VNET **algorithm**

```
BN (b) at time (t_i)
1.  oneHopBoadcast(ID, LOC);
2.  scheduleNextBroadcast (Δt);

VN (v) at time (t_i)
                 Communication phase:
1.  WHILE t < t_i + ΔT
2.    IF msg_recieved THEN
3.      nearestBeaconList.add (beacon(ID, LOC, mdist));
4.      oneHopBoroadcast(ID, LOC, mdist, ownerID);
5.    IF forwarded_msg_recieved THEN
6.        farthestBeaconList.add (beacon record);
                 Estimation phase:
7.    beaconList = nearestBeaconList;
8.    IF beaconListSize >= 3 THEN
9.       selectBestThreeNearestBeacons ( );
10.   estimateLocationByTrilateration ( );
11. ELSE  /*less than three nearest beacons are discovered*/
12.   IF previous_location_is_available THEN
13.      beaconList.add (previousLocation);
14.   IF beaconListSize < 3 THEN
15.      selectedBeacon = chooseBestFarthestBeacons( );
16.      beaconList.add(selectedBeacons);
17.      IF beaconListSize = 3 THEN
18.         sampleList =
    samplingBeaconMeausredCircle(selected_beacons);
19.         FOREACH sample(i) IN samplesList
20.            estimateLocationByTrilateration ( );
21.   ELSE
22.      estimateLocationByTrilateration ( );
                 Correction and alignment phase:
23. IF beacon (i) is a nearest beacon and m_i > m_th THEN
24.     measuredDistanceList (i) =
    generateNewMeasuredDistance (m_i , Δm);
25. visibleSolutionsList = createVisibleSolution
    (measuredDistanceList (i));
26. FOREACH visibleSolution (j) IN visibleSolutionsList
27.     estimateLocationByTrilateration( );
28. chooseBestSolution( );
29. bestSolutionAlignment( );
```

Finally, a VN returns to receiving mode to receive forwarded packets from VN neighbors. Beacon ID, its current location and its measured distance to its owner (forwarding node) are extracted from forwarded packet. The measured distance to forwarding node can also be determined using received signal power from that can be obtained from PHY/MAC layer. A VN node establishes a new data record containing five attributes, 1) beacon ID, 2) beacon location, 3) measured distance between beacon and forwarding VN, 4) forwarding VN id, and 5) measured distance between forwarding VN and receiving VN. This record is stored in new list called (farthest beacon list) as shown in Line (6).

The second phase is called an estimation phase, illustrated in Lines (7-22), which a new list called (beacon list) is established to contain all existing 1-hop beacons. Such phase is performed whether the number of 1-hop beacons is greater than, equal, or less than three. The first part described in Lines (8-10) shows how SCL-VNET works when the number of beacons is greater than or equal three. When the number of beacons is greater than three, a NV chooses a best three 1-hop beacons. The best three 1-hop beacons have the shortest measured distances to the current vehicular node. Afterwards, VN location is estimated using basic RSSI analytical model, represented by Eq. (4) and Eq. (5) as shown in Line (10), whether there are either exactly three 1-hop beacons, or more and best three 1-hop beacons are chosen.

When the current vehicular node, that already discovered three 1-hop beacons, estimates its location, it moves to the correction and alignment phase. Such phase is based on the extended trilateration analytical model described in equations (6), (7) and (8). When ΔD is examined, a VN decides correcting its estimated position when ΔD is greater than zero which means measured distances to 1-hop beacons suffer from noise in path loss. The correction and alignment phase is described in Lines (23-29). A measured distance list is created for each beacon (i) where $i \in \{1, 2, 3\}$, as shown in Line (24). The measured distance can be corrected by applying a small change in the distance step by step to reach the actual distance (it is called a correction step). A new measured distance for beacon (i) equals ($m_i \pm k\Delta m_i$); $k \in \{0, 1, 2, \ldots, n\}$ where $n\Delta m_i$ represents the expected maximum correction step based on the maximum noise level. Each beacon (i) contains at least one element (at $k = 0$) equals m_i. Meanwhile the time complexity of correction phase is $O(n^3)$, the correction step (CS) parameter (in meters) controls the number of visible solutions in which each visible solution contains one measured distance ($m_i \pm k\Delta m_i$) for each beacon (i).

Figure 3 shows the correction process when SCL-VNET scheme is applied. As shown in Figure 3, new measured distances are generated from ($m_i \pm k\Delta m$). The measured distance list size is 7, 5 and 3 for B_2, B_3 and B_4 constrained by the maximum expected noise level as shown in Figure 3. The

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visible solution space contains 105 solutions. After scanning such solutions, the optimal solution that achieves minimum ΔD is determined and the corrected location for VN is indicated by black dot as shown in Figure 3.

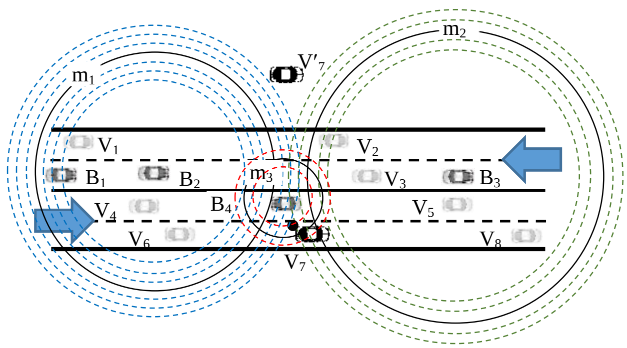

Figure 3 Correction phase

After the correction process finishes, SCL-VNET runs the alignment process, as shown in Line (29), to achieve more localization accuracy. Such process matches the estimated location and the preloaded map. When a vehicular node locates between lanes or outside the road, SCL-VNET aligns a vehicular node and relocates it on the nearest lane.

The second contribution in this work is to estimate a vehicular node position in lightweight traffic density (sparse network). When the number of nearest beacons is less than three, the trilateration analytical model fails to estimate VN location; however, SCL-VNET scheme solves this problem as shown in Lines (11-22) of estimation phase. The estimated location that obtained at (t-Δt) is examined. Supposing VN moves with regular velocity s during Δt, when estimated location obtained at (t-Δt) (it called pervious location) is available, the distance from such location to current location can be considered with value less than or equal sΔt. SCL-VNET generates a virtual beacon node at previous location and add it with its measured distance to beacon list as 1-hop beacon.

When the number of 1-hop beacons is still less than three as shown in Line (14), 2-hop beacon nodes can be exploited. When there are many 2-hop beacon nodes, best three nodes are chosen which they have shortest measured distances to forwarding VNs. Furthermore, the forwarding VNs have also shortest measured distances to current VN. However, there is a problem to use 2-hop beacon nodes in trilateration analytical model because the direct measured distance between VN and 2-hop beacons is unavailable. SCL-VNET solves this problem by firstly estimating a forwarding VN position; afterwards, it estimates the current VN location as follows.

Assuming a vehicular node (V_1) receives from two 1-hop beacon nodes B_1 and B_2 by measured distances m_1 and m_2 in physical environment (i.e. measured distance may be less than actual distances). Assume V_1 receives from a 2-hop beacon (B_3) via a forwarding VN (V_2) as shown in Figure 4. Meanwhile a circle circumference of beacon node (B_3), with a radius represented by m_{23} where m_{23} is a measured distance between a beacon (B_3) and VN (V_2), is the locus of V_2, then SCL-VNET scheme takes samples from the circle circumference. Sampling a circle circumference means considering the integer values that represent the intersection points between the circle circumference and the four lanes.

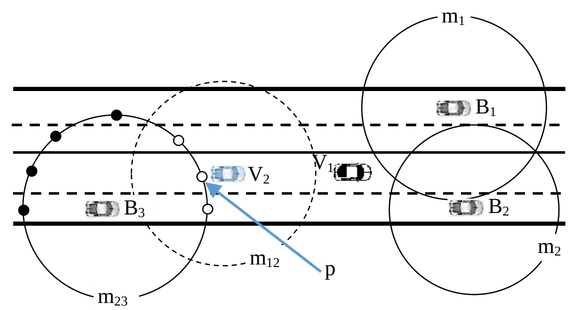

Figure 4 Sampling 2-hop beacon circle circumference

The number of considered samples represented by small circles, as shown in Figure 4, are seven only which reduce the proposed algorithm time complexity. SCL-VNET estimates V_1 position by iterative trilateration process for such samples. Generally, the number of samples (N) taken over a 2-hop beacon circle circumference with measured distance (m) is described in Eq. (9) where W is the lane width and R is the maximum communication range.

$$N = \begin{cases} 2 & m < W \\ 3 & m = W \\ 4 & W < m < 2W \\ 5 & m = 2W \\ 6 & 2W < m < 3W \\ 7 & m = 3W \\ 8 & 3W < m < R \end{cases} \tag{9}$$

When a vehicular node requires two 2-hop beacons to estimate its location, the number of pair samples may reach 8^2 pair samples at the worst case. When three 2-hop beacons are used, the number of triple samples may increase to reach 8^3 triple samples. Therefore, further constraint is used to decrease the number of iterations by picking candidate samples. Such constraint is based on the distance between two 1-hop beacons must be less than 2R where R represents the maximum communication range. As shown in Figure 5, a vehicular node (V_1) discovers two 1-hop beacon nodes B_1 and B_2. The maximum distance between two 1-hop beacons is 2R.

When applying such constraint on the first scenario (two 1-hop beacons and one 2-hop beacon), we assume 1-hop beacons are located at (x_1^b, y_1^b) and (x_2^b, y_2^b), respectively. Also, we assume

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samples (x_j, y_j) are taken from 2-hop beacon circle circumference where j ∈ {1, 2, …., 8}. The proposed constraint can be analytically described as shown in Eq. (10).

$$\forall_i \forall_j \left(\sqrt{\left(x_i^b - x_j\right)^2 + \left(y_i^b - y_j\right)^2} \right) \leq 2R \tag{10}$$

Where i ∈ {1, 2}. The result of applying the constraint is shown in Figure 4; seven samples are filtered to three samples only indicated by whole circles. The iterative process mentioned in correction process can be applied to compute ΔD at each sample. The candidate sample achieves minimum ΔD. Afterwards, the correction process is applied for 1-hop beacon nodes that satisfies the correction conditions to improve the localization accuracy as shown above.

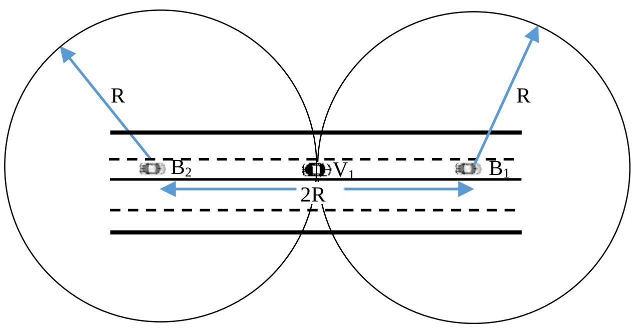

Figure 5 Maximum distance between two 1-hop beacons

Similarly, the second scenario assumes one 1-hop beacon and two 2-hop beacons are available. The sampling process is performed for two 2-hop beacons to obtain $\left(x_j^1, y_j^1\right)$ and $\left(x_j^2, y_j^2\right)$. Assume 1-hop beacon is located at (x, y); accordingly, samples are filtered as shown in Eq. (11).

$$\forall_i \forall_j \left(\sqrt{\left(x - x_j^i\right)^2 + \left(y - y_j^i\right)^2} \right) \leq 2R \tag{11}$$

Where i ∈ {1, 2} and j ∈ {1, 2, ……, 8}. The candidate sample pair achieves minimum ΔD and the correction phase can be also applied for 1-hop beacon, when satisfying the correction conditions, to improve the localization accuracy.

The final scenario assumes three 2-hop beacons are available. The sampling process is performed for three 2-hop beacon nodes to obtain $\left(x_j^1, y_j^1\right)$, $\left(x_j^2, y_j^2\right)$ and $\left(x_j^3, y_j^3\right)$. Samples are filtered as shown in Eq. (12).

$$\forall_i \forall_j \left(\sqrt{\left(x_j^i - x_j^k\right)^2 + \left(y_j^i - y_j^k\right)^2} \right) \leq 2R \quad , \text{i < k} \tag{12}$$

where i ∈ {1, 2, 3}, k ∈ {1, 2, 3} and j ∈ {1, 2, ……, 8}. The candidate sample triple achieves minimum ΔD.

In what follows, the simulation results are introduced to show how SCL-VNET scheme decreases the localization error for V2V communication in physical environments, and how it works in case of lightweight traffic density. In addition, a comparative study is illustrated to show how SCL-VNET scheme overcomes the existing localization schemes.

5. PERFORMANCE EVALUATION AND SIMULATION RESULTS

In this section, the effectiveness of SCL-VNET scheme is examined and verified by NS2 simulator. Several experiments are performed to measure localization accuracy of vehicular ad-hoc networks and compute the average values. Beacons and vehicular nodes are randomly deployed in a road with four lanes for simplicity (two lanes for each direction). The traffic density is assumed 20, 40 and 60 vehicles per km per lane for low, moderate and high traffic density in which beacon node density represents 25% for each. The maximum inter-vehicle communication range equals 50 meters. We assume the average speed is 54 km/hour (15 m/s) and a time slot is 2 sec. The NS2 simulation parameters used in this study are shown in Table 1.

Table 1 Simulation parameters

Parameter	Values
average speed	15 m/s
communication range	50 m
traffic density	20, 40, 60 per km per lane
path loss exponent	3.1, 5.1
noise level	0-30%
correction step (meters)	0.25-2.0
propagation model	two ray ground
MAC type	802.11p
antenna model	omni antenna
time slot	2 sec
field size (km^2)	5x5

In this section, the impact of the correction step (CS) parameter is evaluated for the proposed scheme at different performance metrics such as localization accuracy and processing time. Each metric is studied for urban and suburban regions at low, moderate and high traffic density. Afterwards, a comparative study is conducted to show the impact of noise level and the percentage of vehicular beacon nodes (nodes with GPS) on the performance of SCL-VNET scheme and existing solutions for V2V communication [9, 11], [12] at different performance

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metrics such as localization accuracy, and the number of vehicular nodes that can estimate their locations. Also, each metric is studied at low, moderate and high traffic density for urban regions.

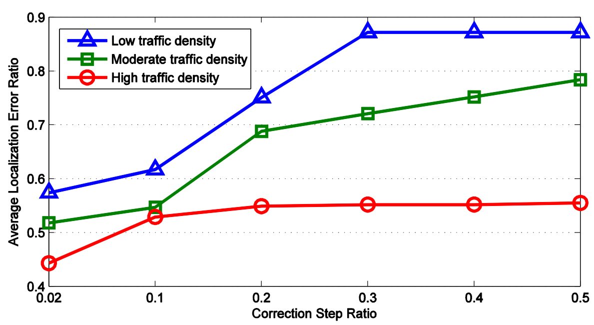
In this work, we use Manhattan mobility model introduced in [24] with some enhancements to increase the number of lanes per road to four instead of one avoiding frequent collinear beacons. Manhattan mobility model is considered more appropriate to model the mobility in urban and suburban regions. More details for Manhattan mobility model have been introduced in [25]. Typically, path loss exponent for urban regions changes from 2.7 to 3.5 while it changes from 3.7 to 6.5 for suburban regions. The noise in path loss is chosen to vary from zero to 30%.

5.1. The impact of correction step parameter

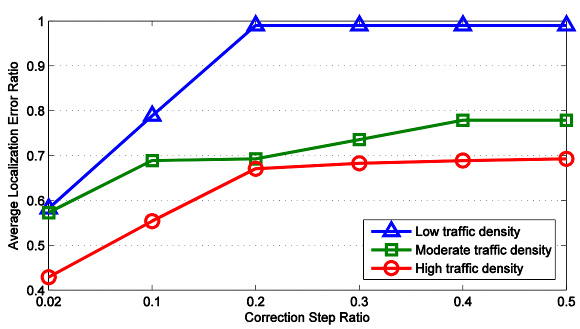
The first set of experiments show the impact of the correction step parameter on SCL-VNET scheme at different performance metrics such as localization accuracy and processing time. Each metric is studied for urban and suburban regions at high, moderate and low traffic density. The path loss exponent is 3.1 and 5.1 for urban and suburban regions with 30% noise level.

traffic densities in urban region, as shown in Figure 6(a), and suburban region, as shown in Figure 6(b), at different CS ratios 0.02, 0.1, 0.2, 0.3, 0.4 and 0.5.

The average localization error ratio is defined as the average localization error for SCL-VNET divided by the average localization error for basic RSSI solution. While CS ratio is defined as the correction step (in meters) divided by the maximum communication range (in meters) of vehicular node. As shown in Figure 6 (a), the minimum average localization error ratio occurs at CS ratio of 0.02 which it equals 0.443, 0.518 and 0.575 for urban region at low, moderate and high density traffic, respectively. Also, as shown in Figure 6 (b), the average localization error ratio equals 0.429, 0.573 and 0.582 for suburban region at low, moderate and high density traffic, respectively. The average localization error ratio slightly increases at low traffic density compared to both moderate and high traffic densities. Similarly, the average localization error ratio slightly increases at moderate traffic density compared to high traffic density. Such increase occurs as long as more virtual beacons are used to compensate the absence of 1-hop beacon nodes because small computational errors are expected in the estimated locations of virtual beacons.

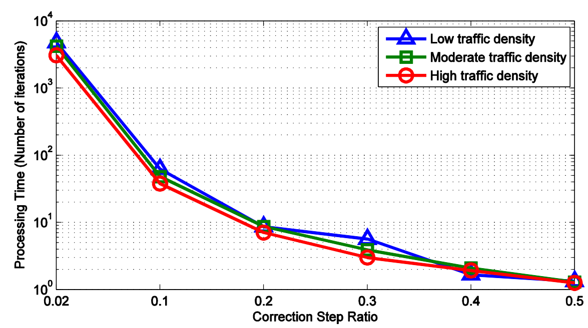


(a) urban area

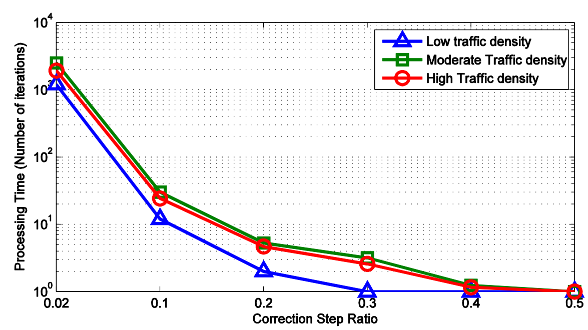


(b) suburban area

Figure 6 The impact of correction step (CS) parameter on localization accuracy



(a) urban area



(b) suburban area

Figure 7 The impact of correction step on processing time

As shown in Figure 6, the average localization error ratio is evaluated for SCL-VNET scheme at low, moderate and high

At low traffic density, more virtual beacon nodes are used resulting in more increase in average localization error compared to other traffic densities. For the same reason, the average localization error ratio at moderate traffic density is greater than it at high traffic density. When CS ratio increases as shown in Figure 6 (a) and (b), the average localization error ratio also increases. When CS parameter increases, the number of feasible solution decreases which means reduction in processing time. However, the precision of location estimation decreases resulting in more increase in average localization error.

Figure (7) shows the impact of CS parameter on the processing time of correction process. The processing time is evaluated for SCL-VNET scheme at low, moderate and high traffic densities in urban region, as shown in Figure 7 (a), and suburban region, as shown in Figure 7 (b), at different CS ratios 0.02, 0.1, 0.2, 0.3, 0.4 and 0.5. The processing time of correction phase is defined by the average number of iterations to evaluate all feasible solutions. As shown in Figure 7 (a), the maximum processing time occurs at CS ratio of 0.02 which the average number of iterations are 4790, 4216.87 and 3077.67 for urban region at low, moderate and high density traffic, respectively.

Also, as shown in Figure 7 (b), the average number of iterations equals 1211, 2512.24 and 1924.58 for suburban region at low, moderate and high density traffic, respectively. Few thousands of iterations are required to correct the estimated location when CS ratio equals 0.02 (i.e., CS parameter equals one meter when the maximum communication range equals 50 meters). When CS ratio increases as shown in Figure 7 (a) and (b), the average number of iterations obviously decays. As mentioned above, SCL-VNET creates the feasible solutions between $0.5m_i$ and $1.5m_i$ where m_i is the original measured distance for beacon (i). When the average number of iterations at CS ratio of 0.1 (or a CS parameter equals 5 meters), the average number of iterations are 62.67, 48.23 and 37.85 for urban region at low, moderate and high density traffic, respectively.

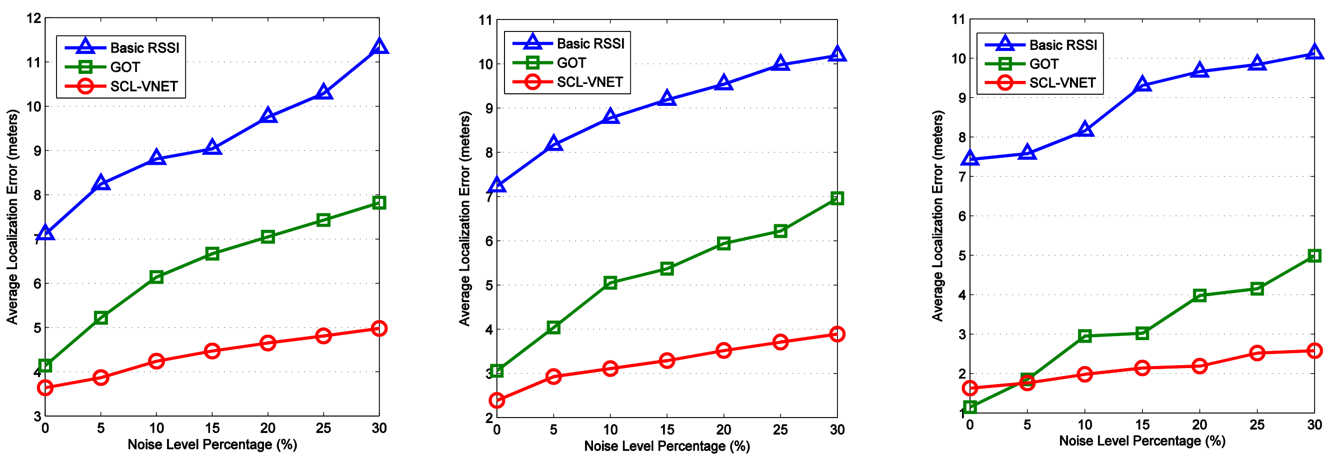
Also, as shown in Figure 7 (b), the average number of iterations equals 12, 30.12 and 24.23 for suburban region at low, moderate and high density traffic, respectively. Few ten iterations are required when the correction step equals 5 meters. When the correction step ratio is greater than 0.1 (or CS parameter is greater than 5 meters), the number of iterations is less than 10 iterations.

Consequently, there is a tradeoff between the average localization error and the processing time. We choose CS ratio equals 0.06 (or the correction step equals 3 meters) in our comparative study because it achieves a proper average localization error and an acceptable processing time which such values are reasonable for real time processing.

5.2. The impact of noise level

The impact of noise level on the performance of SCL-VNET scheme and existing solutions for V2V communication [8, 10], [11] are performed in this section at different performance metrics such as localization accuracy and the number of vehicular nodes that can estimate their locations. Each metric is studied for urban regions at high, moderate and low traffic density in which the path loss exponent is 3.1 and 25% of beacon nodes are available.

As shown in Figure 8, the average localization error (in meters) is evaluated for SCL-VNET scheme, basic RSSI and GOT at low traffic density, as shown in Figure 8 (a), moderate traffic density, as shown in Figure 8 (b), and high traffic density, as shown in Figure 8 (c), at different noise levels from zero to 30%. Clearly, the average localization error increases when the effect of shadowing and multipath (noise level) increases. As shown in Figure 8 (a), at low traffic density, the average localization error increases from 7.11 meters at zero noise to 11.32 meters at 30% of noise in basic RSSI solution.



(a) Low traffic density (b) Moderate traffic density (c) High traffic density

Figure 8 The impact of noise level on localization accuracy

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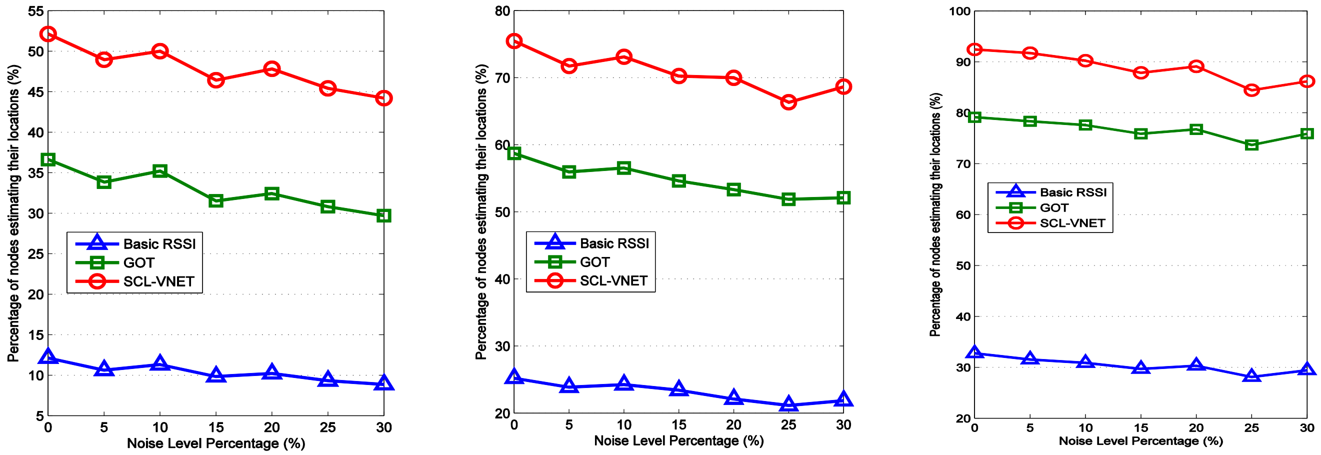

(a) Low traffic density (b) Moderate traffic density (c) High traffic density

Figure 9 The impact of noise level on the number of nodes estimating their locations

While it increases from 4.14 meters at zero noise to 7.82 meters at 30% of noise in GOT scheme. The average localization error in SCL-VNET increases from 3.64 meters at zero noise to 4.98 meters at 30% of noise. Accordingly, the average localization accuracy in SCL-VNET scheme is better than the localization accuracy of basic RSSI and GOT schemes. Such result reflects the role of correction and alignment phase in achieving more reduction in the average localization error. Furthermore, the average localization error in SCL-VNET scheme records a small change (i.e., 1.34 meters) when a noise level changes from zero to 30%. While the change in localization error reaches 4.21 and 3.68 meters in basic RSSI and GOT schemes, respectively.

At moderate traffic density, as shown in Figure 8 (b), the average localization error in all schemes achieves more reduction in localization error because the number of nodes with GPS increases. A VN has a chance to communicate with more than three beacons and chooses three beacon nodes with shortest measured distances. SCL-VNET scheme still achieves higher localization accuracy and a small change in localization error in moderate traffic density.

Figure 8(c) shows GOT scheme achieves lower localization error at zero noise in high traffic density which reaches 1.15 meters while SCL-VNET scheme reaches 1.63 meters. When a noise effect is involved, the proposed scheme outperforms GOT scheme which the average localization error reaches 2.58 meters at 30% noise while it reaches 4.99 meters in GOT scheme.

The impact of noise level on the percentage of nodes that can estimate their locations is evaluated, as shown in Figure 9, for SCL-VNET scheme, basic RSSI and GOT at low traffic density, as shown in Figure 9 (a), moderate traffic density, as shown in Figure 9 (b), and high traffic density, as shown in Figure 9(c), at different noise levels from zero to 30%. The percentage of nodes that can estimate their locations is the number of such nodes divided by all vehicular nodes without GPS. It is obvious that such percentage slightly decreases when the effect of shadowing and multipath increases.

As shown in Figure 9 (a), at low traffic density, 25% of beacon nodes cannot guarantee three beacons for each vehicular node. Consequently, the basic RSS scheme records a poor percentage of nodes estimating their locations which varies from 12.14% at zero noise to 8.87% at 30% of noise. While such percentage varies from 36.63% at zero noise to 29.71 at 30% of noise in GOT scheme because it exploits a special case of 2-hop beacons to enable more vehicular nodes to estimate their locations. The percentage of nodes estimating their locations in SCL-VNET varies from 52.14% at zero noise to 44.22% at 30% of noise. Accordingly, the percentage of nodes estimating their locations in SCL-VNET scheme is better than it in basic RSSI and GOT schemes. Such results also reflect the role of estimation phase in achieving more percentage of nodes estimating their locations for most vehicular nodes because it exploits 2-hop beacon nodes to compensate the absence of 1-hop beacon nodes.

At moderate traffic density, as shown in Figure 9 (b), the percentage of nodes estimating their locations in all schemes increases because the number of nodes with GPS increases (but it is still 25%). SCL-VNET scheme achieves higher percentage of nodes estimating their locations in moderate traffic density which varies from 75.45% to 68.66%. Similarly, at high traffic density, as shown in Figure 9 (c), increasing in traffic density increases the number of nodes with GPS. Therefore, the percentage of nodes estimating their locations in SCL-VNET varies from 92.44% to 86.18% outperforming other schemes.

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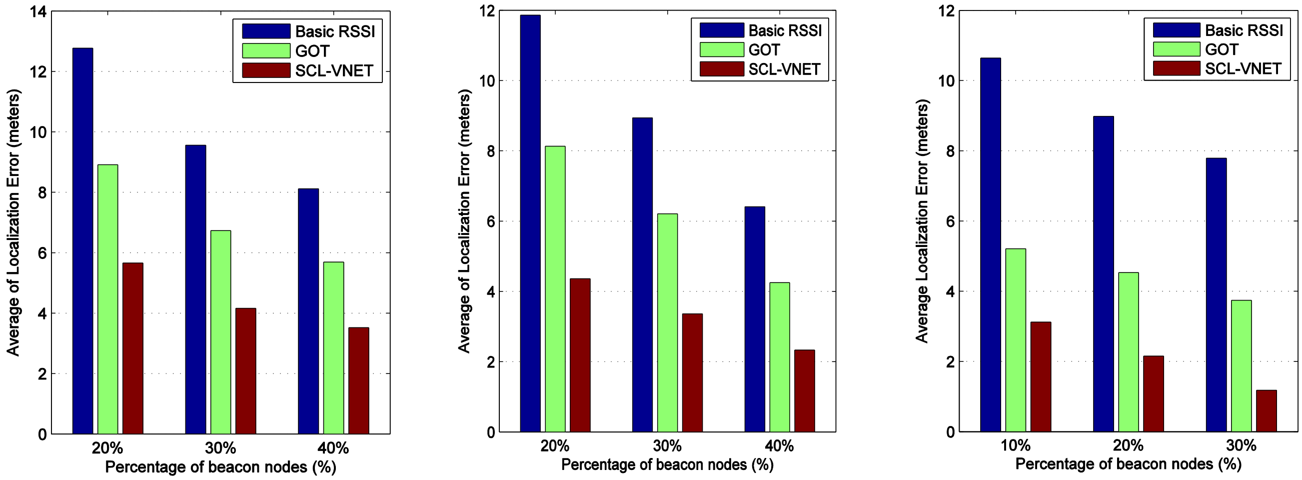

(a) Low traffic density (b) Moderate traffic density (c) High traffic density

Figure 10 The impact of vehicular beacon node density on localization accuracy

5.3. The impact of vehicular beacon node density

In this section, the impact of vehicular beacon node density (nodes with GPS) on the performance of SCL-VNET scheme and existing solutions for V2V communication [8, 10], [11] are performed at different performance metrics such as localization accuracy and the number of vehicular nodes that can estimate their locations. Similar to pervious section, each metric is studied for urban regions at high, moderate and low traffic density in which the path loss exponent is 3.1 with 30% of noise level.

As shown in Figure 10, the average localization error (in meters) is evaluated for SCL-VNET scheme, basic RSSI and GOT at low traffic density, as shown in Figure 10 (a), moderate traffic density, as shown in Figure 10 (b), and high traffic density, as shown in Figure 10 (c), at different percentage of beacon nodes (20%, 30% and 40%). The average localization accuracy evidently increases when the percentage of nodes with GPS increases. The percentage of nodes with GPS represents the number of such nodes divided by the total number of vehicular nodes.

As shown in Figure 10 (a), at low traffic density, the average localization error is 12.77, 8.91 and 5.66 meters at 20% of beacon nodes for basic RSSI, GOT and SCL-VNET schemes, respectively. At 30% of beacon nodes, it decreases to reach 9.56, 6.73 and 4.16, respectively. At 40% of beacon nodes, more chance to decrease the localization error which reaches 8.12, 5.69 and 3.52 meters, respectively. Such results show the localization accuracy of the proposed scheme is better than existing schemes at different percentage of beacon nodes. In addition, SCL-VNET scheme achieves minimum change in localization error (i.e., 2.14 meters) due to the performance of correction process.

At moderate traffic density, as shown in Figure 10 (b), the total number of nodes increase resulting in increase in beacon nodes. Moreover, when the percentage of beacon nodes also increases, the localization accuracy achieves more improvement. The average localization error is 11.86, 8.13 and 4.36 meters at 20% of beacon nodes for basic RSSI, GOT and SCL-VNET schemes, respectively. At 30% of beacon nodes, it decreases to reach 8.94, 6.21 and 3.36, respectively. At 40% of beacon nodes, more chance to decrease the localization error which reaches 6.41, 4.25 and 2.33 meters, respectively.

Similarly, at high traffic density, as shown in Figure 10 (c), the average localization error is 10.64, 5.12 and 3.12 meters at 20% of beacon nodes for basic RSSI, GOT and SCL-VNET schemes, respectively. At 30% of beacon nodes, it decreases to reach 8.98, 4.53 and 2.15, respectively. At 40% of beacon nodes, more chance to decrease the localization error which reaches 7.79, 3.74 and 1.18 meters, respectively.

The impact of percentage of beacon nodes on the percentage of nodes that can estimate their locations is evaluated, as shown in Figure 11, for SCL-VNET scheme, basic RSSI and GOT at low traffic density, as shown in Figure 11 (a), moderate traffic density, as shown in Figure 11 (b), and high traffic density, as shown in Figure 11 (c), at different percentage of beacon nodes and 30% of noise. Clearly, the percentage of nodes that can estimate their locations increases when the percentage of nodes with GPS increases.

As shown in Figure 11 (a), at low traffic density, the percentage of nodes that can estimate their locations is 7.56%, 28.44% and 43.24% at 20% of beacon nodes for basic RSSI, GOT and SCL-VNET schemes, respectively. At 30% of beacon nodes, it decreases to reach 17.65%, 41.51% and 59.78%, respectively.

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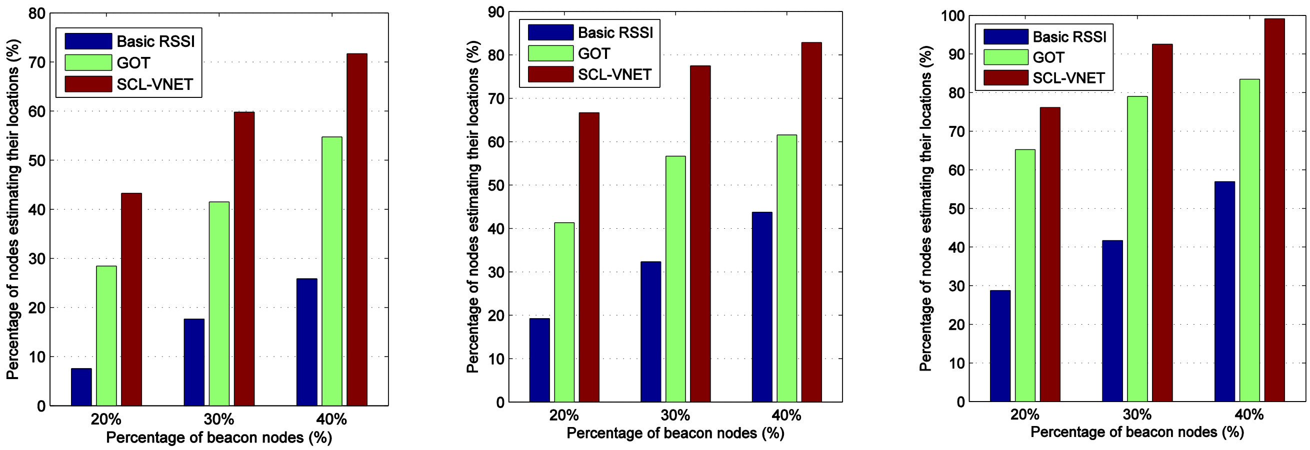

(a) Low traffic density (b) Moderate traffic density (c) High traffic density

Figure 11 The impact of vehicular beacon node density on the number of nodes estimating their locations

At 40% of beacon nodes, more chance to increase the percentage of nodes estimating their locations which reaches 25.86% 54.76% and 71.69%, respectively.

Such results show the percentage of nodes estimating their locations of the proposed scheme is better than the existing schemes at different percentage of beacon nodes. In addition, SCL-VNET scheme achieves higher change in such percentage (i.e., 28.44%) due to the performance of estimation phase in exploiting 2-hop beacon nodes.

At moderate traffic density, as shown in Figure 11 (b), the percentage of nodes estimating their locations increase in all schemes. Such percentage is 19.22%, 41.34% and 66.68% at 20% of beacon nodes for basic RSSI, GOT and SCL-VNET schemes, respectively. At 30% of beacon nodes, it increases to reach 32.34%, 56.67% and 77.47%, respectively. At 40% of beacon nodes, more chance to increase such percentage which reaches 43.76%, 61.56% and 82.83%, respectively. SCL-VNET scheme still achieves higher percentages.

Similarly, at high traffic density, as shown in Figure 11 (c), as long as the percentage of beacon nodes increase, SCL-VNET scheme can reach to approximately estimate the locations of all nodes. The percentage of nodes estimating their locations is 28.76%, 65.22% and 76.15% at 20% of beacon nodes for basic RSSI, GOT and SCL-VNET schemes, respectively. At 30% of beacon nodes, it increases to reach 41.67%, 78.98% and 92.54%, respectively. At 40% of beacon nodes, we reach higher percentages which reach 56.93%, 83.49% and 99.12% meters, respectively.

Finally, simulation results show that SCL-VNET outperforms basic RSSI and GOT schemes which effectively corrects the localization errors in vehicular ad hoc networks. In addition, it can perfectly work at different traffic densities, different noise levels and different percentage of beacon nodes.

6. CONCLUSION

Node localization in vehicular ad hoc networks is important for many purposes such as road safety and traffic management. This paper presents a new node localization scheme to solve the limitations of current existing schemes. As shown above, this work exploits the inter-vehicle communication to enable each vehicular node without GPS to estimate its location. A new method is proposed to correct an error in the estimated location via received signal strength. In addition, 2-hop nodes with GPS are exploited to compensate the absence of 1-hop nodes with GPS due rapid change in the network topology to increase the number of vehicular nodes that can estimate their locations. The proposed scheme performance is evaluated at high dynamic topology with different environmental changes. The simulation results show that three meters for correction step parameter is appropriate to achieve proper localization accuracy and processing time. The performance evaluation conducted in this work shows that for the proposed scheme achieves better localization accuracy compared to basic RSSI and GOT schemes. For instance, at high traffic density, 30% of noise level and 25% of beacon node density, the average localization error reaches 2.58 meters while it reaches 10.12 and 4.99 meters in basic RSSI and GOT schemes respectively. In addition, SCL-VNET achieves more percentage of nodes that can estimate their locations compared to basic RSSI and GOT schemes. The percentage of nodes estimating their locations in SCL-VNET reaches 86.18% while it reaches 29.45% and 75.91% for basic RSSI and GOT schemes at the same conditions in the last example. When percentage of beacon nodes increase more than 25%, SCL-VNET scheme has more chance to enable all vehicular nodes to estimate their

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locations. Further work will study the proposed scheme with many complex mobility models to show its effectiveness in all circumstances.

REFERENCES

[1] M. Joe, and B. Ramakrishnan, "Review of Vehicular Ad hoc Network Communication Models including WVANET (Web VANET) Model and WVANET Future Research Directions," Wireless Networks, Springer, vol. 22, no. 7, pp. 2369-2386, 2015.
[2] M. Joe, and B. Ramakrishnan, "WVANET: Modelling a Novel Web Based Communication Architecture for Vehicular Network," Wireless Personal Communications, Springer, vol. 85, no. 4, pp. 1987-2001, 2015.
[3] S. Biswas, R. Tatchikou, and F. Dion, "Vehicle-to-Vehicle Wireless Communication Protocols for Enhancing Highway Traffic Safety," IEEE Communications Magazine, vol. 44, pp. 74-82, 2006.
[4] H. Zhu, and M. Li, "Studies on Urban Vehicular Ad-hoc Networks". Springer, 2013.
[5] A. Leick, "GPS Satellite Surveying". John Wiley, 1995.
[6] N. Patwari, J. N. Ash, A. O. Hero, R. L. Moses, and N. S. Correal, "Locating the Nodes: Cooperative Localization in Wireless Sensor Networks," IEEE Signal Process. Mag., vol. 22, no. 4, pp. 54–69, Jul. 2005.
[7] A. Boukerche, H. Oliveira, E. Nakamura, and A. Loureiro, "Localization Systems for Wireless Sensor Networks," IEEE Wireless Communications, vol. 14, pp. 6-12, 2007.
[8] 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.
[9] R. Parker, and S. Valaee, "Vehicle Localization in Vehicular Networks," IEEE VTC, 2006.
[10] A. Benslimane, "Localization in Vehicular Ad hoc Networks," Systems. Communications, pp. 19–25, 2005.
[11] R. Parker, and S. Valaee, "Vehicular Node Localization using Received Signal-strength Indicator," IEEE Trans. Veh. Technol., vol. 56, no. 6, Nov. 2007.
[12] 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.
[13] C. Ou, "A Roadside Unit-based Localization Scheme for Vehicular Ad Hoc Networks," International Journal of Communication Systems, vol. 27, pp. 135-150, 2014.
[14] H. Li, X. Chen, L. Huang, and D. Yao, "A GPS/Wi-Fi Integrated System for Positioning in Cooperative Vehicle and Infrastructure System," in Proc. of IEEE International Conference on Vehicular Electronics and Safety (ICVES), pp. 285-289, 2012.
[15] A. Gupta, and R. Jha, "A Survey of 5G Network: Architecture and Emerging Technologies," IEEE Access Journal, Special Section on Recent Advances in Software Defined Networking for 5G Networks, vol. 3, pp. 1206-1232, 2015.
[16] J. Rodriguez, "Fundamentals of 5G Mobile Networks". John Wiley & Sons, Ltd, 1st Edition. 2015.
[17] P. Goyal, and A. Buttar, "A Study on 5G Evolution and Revolution," International Journal of Computer Networks and Applications (IJCNA), vol. 2, no. 2, 2015.
[18] R. Parker, and S. Valaee, "Vehicle Localization in Vehicular Networks," in Proc. of IEEE 64th Vehicular Technology Conference, pp. 1-5, 2006.
[19] V. Kukshya, H. Krishnan, and C. Kellum, "Design of a System Solution for Relative Positioning of Vehicles using Vehicle-to-Vehicle Radio Communications during GPS Outages," in Proc. of IEEE 64th Vehicular Technology Conference, pp.1313-1317, 2005.
[20] M. Ikram, and J. Cazalas, "Efficient Collaborative Technique using Intrusion Detection System for Preserving Privacy in Location-based Services," International Journal of Computer Networks and Applications (IJCNA), vol. 2, no. 5, 2015.
[21] O. Pink, and B. Hummel, "A Statistical Approach to Map Matching using Road Network Geometry, Topology and Vehicular Motion Constraints," in Proc. of the 11th International IEEE Conference on Intelligent Transportation Systems, 2008.
[22] S. Lin, W. Ying, X. Jingdong, and X. Yuwei, "An RSU-assisted Localization Method in non-GPS Highway Traffic with Dead Reckoning and V2R Communications," in Proc. of the 2nd International Conference on Consumer Electronics, Communications and Networks (CECNet), pp. 149-152, 2012.
[23] D. Niculescu and B. Nath, "Ad hoc Positioning System (APS) using AOA," in 22nd IEEE Annual Joint Conference on the Computer and Communications Societies(INFOCOM '03), pp. 1734–1743, April 2003.
[24] http://sys.cs.uos.de/bonnmotion/.
[25] B. Ramakrishnan, R. Nishanth, M. Joe and R. Shaji, "Comprehensive Analysis of Highway, Manhattan and Freeway Mobility Models for Vehicular Ad hoc Network," International Journal of Wireless and Mobile Computing, vol. 9, no. 1, pp. 78-89, 2015.

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.

E-Mail: smageid@azhar.edu.eg