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# Enhanced local density estimation in internet of vehicles 

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#### Abstract

The Internet of vehicles allows connecting vehicles to the Internet to make all data from vehicles available for applications aimed towards improving safety and comfort for passengers. Density is one of the most important sensed data to gather. This information is mainly obtained through periodic messages broadcast by the neighbouring vehicles. However, the availability of this information depends on the Internet. A low penetration rate of Internet of vehicles, or the loss of Internet connection, can significantly affect the accuracy of the sensed density. Moreover, the reception rate of the periodic messages seriously drops at short distances caused by the broadcast storm problem in high-density scenarios. To address this problem, using inter-vehicular communications, we propose a segment-based approach for enhancing the accuracy of the local density estimation. This approach provides a highly accurate estimation with low overhead over the maximum vehicles transmission range to all the vehicles. The proposed approach is extensively evaluated analytically and by simulation. Performance evaluation results show that our approach SLDE allows about $3 \%$ of mean error ratio with low overhead over the maximum transmission range.


## 1 Introduction

The considerable expansion of Internet of things (IoT) technologies made it possible to consider the Internet of vehicles (IoV). This technology allows vehicles to communicate with public networks using V2X (X: vehicle, road, human, and the Internet) communication types and through a variety of communication technologies such as IEEE 802.11p and cellular networks [1]. This technology is mainly developed for supporting intelligent traffic management, intelligent dynamic information service, and intelligent vehicle control. In fact, IoV is a typical application of IoT technology in Intelligent Transportation Systems (ITS) [1]. Indeed, the IoV enables vehicles to collect data regarding roads and their surrounding environment, and share it with the interested users via Internet. However, sharing the collected data cannot always be performed. This is due to the low penetration rate of the Internet-equipped vehicles and the intermittent loss of Internet connection under certain circumstances or areas such as tunnels. The inter-vehicular communications (V2V) is the best alternative that can be used to overcome this issue. Indeed, the dissemination of the collected data to the Internet-equipped vehicles will make these data available to the end users.

The local density is one of the most important sensed data that can be estimated locally and shared by vehicles via exchanging safety messages (beacons). It is the number of neighbours in the communication range, where the communication range is the range where the vehicle packets can be decoded. The local density estimation is useful to drivers for choosing less congested roads, which significantly reduce fuel consumption, travel time, and pollution. Moreover, it enhances the performance of the densitydependent applications and protocols such as dissemination, congestion control, and routing protocols by improving their robustness, delay, and efficiency. Density-dependent IoV applications performance is based on the accuracy of the local density. However, it is difficult to accurately estimate the local density in high traffic density scenarios. Indeed, the communication range is reduced by up to $90 \%$ in such situations [2], which results in a serious lack of neighbourhood awareness and affects the functioning of density-dependent IoV applications.

To address this problem, in this paper, we introduce an original accurate local density estimation strategy, called segment-based local density estimation (SLDE). The existing approaches [3-10] aim to estimate the traffic density of a whole road or section. In contrast, our proposed approach provides an accurate and efficient local density estimation approach within the maximum transmission range, i.e. only the number of vehicles that may affect the communication quality. SLDE is based on: (i) the segmentation of the road into a set of segments that are smaller than the maximum transmission range and (ii) an efficient strategy for the propagation and the exchange of the density calculated in each segment. The performance evaluation results demonstrate the accuracy of the proposed approach and its efficiency regarding the generated overhead.

This paper is organised into six sections. In Section 2, we review the most relevant works. In Section 3, we describe the proposed SLDE strategy. Performance analysis is presented in Section 4. In Section 5, the simulation results are presented and finally in Section 6, this paper concludes with outlooks on future work.

## 2 Related work

There have been few works addressing local density estimation despite its numerous applications in VANETs. In this paper, we review the infrastructure-free solutions where the vehicles estimate the density using movement patterns or collaboration. The considered strategies can be divided into two categories: speedbased strategies $[5,6,11]$ and communication-based strategies [710, 12, 13].

Speed-based mechanisms make use of the speed/density correlation to estimate the road density. In [5], the density estimation is based on vehicles mobility patterns, which are the car-following model and the two-fluid model. Density estimation is used to choose the transmission range dynamically. The authors in [6] propose the velocity aware density estimation (VADE). In VADE, each single vehicle tracks its velocity, acceleration, and traffic density is estimated based on the observed speed and the traffic flow theory [14]. For instance, if the vehicles move with


Fig. 1 Illustration of a sample scenario of the SLDE process
high speed, the density would be estimated as sparse. In [11], fluid dynamics and the car-following model are used to assess vehicle density. Nevertheless, these approaches cannot estimate the density in free-flow traffic due to the absence of interactions between vehicles, nor in a situation where the speed is not related to the density. For example, vehicles can stop at intersections without having a high density. Moreover, these strategies are developed for global density estimation, not local density estimation where the precision is relatively high.

Communication-based strategies make use of communication by exchanging messages between the vehicles to estimate the density.

In [12], the authors propose a framework that allows vehicles to estimate the node density of their surrounding network independent of beacon messages and other infrastructure-based information. Two equations were introduced indicating the relationship between the received signal strength versus transmitting nodes and transmitting nodes versus node density. According to the presented results, the vehicles can estimate their real-time surrounding node density, which corresponds to transmission range.

In [7], the density is calculated based on the number of local neighbours. Then, the global density of the road is concluded based on assuming that the inter-vehicle spacing is exponentially distributed, which might not be the case for all possible traffic scenarios.

In [13], the proposed strategy calculates the density of a particular target area. At each sampling instant, the sampler vehicle broadcasts a message called 'POLL' that contains the position and radius of the target area. When a vehicle in this area receives 'POLL', it will reply after waiting for a random amount time to avoid flooding the receiver. After a period, the sampler will count the received messages to estimate the density. This strategy gives accurate results compared with the actual density. However, this approach requires a relatively long period, and it cannot be used for critical applications such as congestion control where a timely reaction is critical.

In [9], the authors present D-FPAV, a congestion control protocol. In this study, they need the actual number of all neighbours in the transmission range (not only within communication range). For that, they use a multi-hop strategy. Each ' $n$ ' beacon, the vehicles send an extended beacon containing its neighbours. After the reception of these extended beacons, vehicle will be aware of all the vehicles in its transmission range. D-FPAV uses the density information to measure the load on the channel. The major drawback of this approach is the high generated overhead.

In [10], DVDE is proposed to overcome the overhead generated by the extended beacons. DVDE is based on the segmentation of the transmission range into an odd number of segments. Instead of sending neighbours in extended beacons, the vehicles send the density of each segment periodically. When a vehicle receives the extended beacon, it chooses information comes from the nearest vehicle to the centre of the target segment. If the segments are different, the vehicle uses linear interpolation to calculate the density. By assembling this information from the different vehicles, the vehicle enhances the accuracy of its estimation. DVDE decreases the overhead compared with the D-FPAV method. Moreover, it has interesting results regarding the accuracy. However, it still has some shortcomings. Indeed, the DVDE
strategy supposes that each vehicle has its own segments. As result, the procedure of data density sharing between vehicles is complex because of the different segment positions. For this reason, in the DVDE, the authors suggest using linear interpolation to estimate the density of a target segment if the segments are different, which occurrences frequently. However, this process gives less accurate results when the vehicles are not uniformly distributed. In addition, if the vehicles are in the same area sharing the same information, the periodic sending of extended beacons will be ineffective. This periodic redundancy generates an extra overhead. This overhead can be avoided if only selected vehicles share their density.

We can notice that speed-based mechanisms do not require any extra overhead. However, they fail to accurately estimate the density in situations where the speed is not related to the density. For the communication-based strategies, we observed that the shared information could be optimised to have higher accuracy with acceptable generated overhead. Moreover, none of the reviewed strategies deal with the estimation of density over the maximum transmission range $(1000 m)$. We have chosen DVDE [10] strategy to evaluate and compare it with our strategy as they belong to the same family of segment-based strategies. Moreover, both strategies are based on local density estimation that aims to extend the local density awareness for all vehicles on the road.

In the next section, segment-based local density estimation (SLDE) is detailed. It is an accurate local density estimation strategy over the maximum vehicles transmission range. The density information will be available for every vehicle, which improves the performance of many density-dependent applications. In the following, we provide a detailed description of SLDE and present its added value compared with existing approaches. This paper is an extension of our previous work [15].

## 3 Segment-based local density estimation (SLDE)

In this section, we introduce segment-based local density estimation (SLDE) density estimation strategy. Within the maximum transmission range, SLDE allows VANETs applications to collect an accurate estimation of the number of neighbours with minimum overhead. This information enhances the vehicles environment awareness specifically for density-dependent protocols and applications. For example, VANETs applications for traffic assessment. Besides, the density information is used to make VANETs applications adaptive to the ongoing traffic density state.

In the following, we describe first the environment. Afterwards, we present the core elements of the SLDE strategy.

We designed SLDE under the following assumptions:

- All vehicles use 802.11 p technology and omnidirectional antennas with the same receiving sensitivity and transmission power.
- Some vehicles have Internet connections (based on the penetration rate on IoVs).
- Each vehicle knows its velocity and its geographical location through a global positioning system (GPS).
- All vehicles are equipped with preloaded digital maps that provide the identity of each segment (Fig. 1).
802.11p technology works on 5.9 GHz spectrum that is dedicated for road safety and traffic efficiency applications. This


Fig. 2 Simple scenario shows the functioning of SLDE


Fig. 3 The format of the used messages: beacons and extended beacons
spectrum is composed of six service channels ( SCHs ) and one control channel CCH. Safety and traffic efficiency applications use SCHs, while the critical road safety applications and periodic awareness messages use CCH. These periodic messages known as basic safety messages (BSMs) messages in Europe, cooperative awareness messages (CAMs) in the USA, or beacons. Safety applications require a reliable communication to enhance the driver awareness about the surrounding environment.

The problem of packet loss affects beacons in long distances or even short distances when the control channel is congested. Indeed, the communication range could be reduced by up to $90 \%$ in such situation [2]. This situation affects the well-functioning of densitydependent VANETs applications because it causes a severe lack of neighbourhood awareness.

To address the problem of insufficient accuracy of density estimation, we propose our novel accurate local density estimation approach, called segment-based local density estimation (SLDE). SLIDE is mainly based on the cooperation of vehicles by their estimations. Then, the vehicles use the gather data from the neighbours to estimate the density. The goal is to have a more accurate estimate of the density by using data from the nearest vehicle for each area.

The cooperation between the vehicles in SLDE is based on exchanging the density information. Instead of sending the density of the entire range, we choose to send it segmented. In other words, the road is divided into segments, and the vehicle sends the density of each segment in its range. We call the beacon messages that hold the density information extended beacon.

SLDE is based on careful selection of vehicles that will share the density information, while ensuring that all the vehicles will have the same potential to estimate the local density. This is to ensure fair access to the service with low generated overhead. Therefore, the vehicles in SLDE might be in one of the following states: estimator vehicle (EV), when it is estimating the local density; reference vehicle (RV), when it is sharing its local density; normal vehicle, when it is not participating in the density estimation.

To facilitate reading, we describe the essentials of the SLDE strategy through the scenario shown in Fig. 2. $N_{0}$ is the EV. The $N_{-2}, N_{-1}, N_{1}$ and $N_{2}$ are the RVs. Each RV has a specific colour to identify its actions and information. EV uses all received density histograms (DHs). The DH is an array that contains the densities of the segments within the maximum transmission range of a specific vehicle (Fig. 3). For each segment in EV range, EV uses the density of the nearest RV to the centre of that segment; it is important to note that there are two ways of receiving the density
segment information either directly (solid lines) or included in other DH (dashed lines). This is because the received DH are sent through the same estimation process. Therefore, the source of the density information of one segment can be computed using another RV. For example, the density of segment $S_{i+2}$ estimated by $N_{2}$ can be received directly or included in the DH of $N_{1}$.

SLDE strategy is described in Algorithm 1 (see Fig. 4). We divided the strategy into two main modules: data fusion and density propagation module. In the following, we explain in detail, the two modules of SLDE strategy.

The data fusion is done during DH (Fig. 3) building. Normal beacons contain the current speed, position $(x, y)$, and heading direction information. Extended beacon contains additionally to normal beacon information: DH , the three next selected RVs $\left(\mathrm{RV}_{1}\right.$, $R V_{2}$ and $R V_{3}$ ), and the number of used RVs in the construction of $\mathrm{DH}(R V n b)$. The received data is merged based on using the most accurate information. For each segment, the EV uses the valid data of the closest RV. In this segment, the RV has the highest probability of detecting the vehicles there. In the case of no reception of DH with better accuracy, the EV uses the received regular beacons. Finally, the EV will have a DH that contains the densities of the various segments.

The density propagation plays an important role to disseminate the accurate density information in a short time. In the following, we show when the density process starts and how SLDE selects vehicles to be RVs.

When the vehicle passes through the centre of a segment, it is selected as RV if the density information is outdated. The selection of the next RV in SLDE is based on two ways. One way is based on timers. Every vehicle receiving an extended beacon, sets a timer that corresponds to the distance to the centre of the segment (TimeToWait). The other way is based on including in the sending extended beacon the next three RVs: $R V_{1}, R V_{2}$, and $R V_{3}$ in the consequent segment (Fig. 3). Based on the distance to the centre of the target segment, the RVs are sorted to make the delay time as short as possible.

$$
\begin{equation*}
\text { TimeToWait }=\frac{D x, \text { segment }}{\text { SL } / 2} \times \mathrm{LTEB} \tag{1}
\end{equation*}
$$

where: $D x$,segment is the distance between the vehicle and the center of its segment, (m); SL is the segment length (m); LTEB is the lifetime of an extended beacon(s).

Equation (1) guarantees that the closest vehicle to the centre has less TimeToWait. The lowest value is 0 when the vehicle is exactly

```
At the reception of extended beacon of \(R V_{j}\) by \(R V_{i}\)
Data: DH of \(R V_{j}\)
if \(\operatorname{Segment}\left(R V_{i}\right)=\operatorname{Segment}\left(R V_{j}\right)\) then
    \(R V_{i}\) cancel the scheduled sending of the extended beacon;
else
Calculate TimeToWait;
After TimeToWait, \(R V_{i}\) send an extended beacon;
\(R V_{i}\) send extended beacons
if (the vehicle passes through the center of a segment and newest density information of
Segment \(\left(R V_{i}\right)\) is outdated) then
Build DH;
Send (extended beacon);
if (Extended beacon waiting and TimetoWait \(=0\) ) then
if newest density information of Segment \(\left(R V_{i}\right)\) is outdated or Accuracy(extended beacon
waiting) \(>\) Accuracy(sent extended beacon) then
                    Build DH;
                    Send (extended beacon);
```

Fig. 4 Algorithm 1: SLDE strategy

```
At the reception of extended beacon of \(R V_{j}\) by \(R V_{i}\)
if Segment \(\left(R V_{i}\right) \neq \operatorname{NextSegment}\left(R V_{j}\right)\) then
    TimetoWait \(\leftarrow\) TimetoWait \(+\left(\left|\operatorname{Segment}\left(R V_{i}\right)-\operatorname{Segment}\left(R V_{j}\right)\right| * \alpha\right)\);
else
    if \(i=R V_{1}\) then
        TimetoWait \(\leftarrow 0\);
    else
        if \(i=R V_{2}\) then
            TimetoWait \(\leftarrow\) TimetoWait*0.3;
        else
            if \(i=R V_{3}\) then
                    TimetoWait \(\leftarrow\) TimetoWait*0.6;
            end
        end
    end
end
```

Fig. 5 Algorithm 2: SLDE TimetoWait calculation
at the centre of a segment $D x$,segment. The highest value is the extended beacon lifetime when the vehicle is on the border of a particular segment $(D x$, segment $=\mathrm{SL} / 2)$.

The number of the used RVs in the constructed DH has a great impact on its accuracy. This is because as the numbers of RVs increases, the number of the accurate information increases. The previous strategy might jump some RVs because a far RV can start first the propagation if it is nearer to its segment centre comparing with near RVs to their segments centres.

To avoid the previous situation, we choose to increase the probability of sending DHs segment after segment. This is ensured by including in the extended beacon, the next three $R V s\left(R V_{1}, R V_{2}\right.$, $R V_{3}$ ) sorted according to the distance to the centre of the next segment (Fig. 3). The distance is calculated based on the received normal beacons. In each segment, the DH is reassembled; this increases the precision by including the accurate information of the corresponding RVs. The TimeToWait is adapted to make the vehicles outside the target segment wait more, and the chosen RV wait less (Algorithm 2 (see Fig. 5)). We keep both mechanisms to ensure segment after segment propagation and also ensure the functioning of SLDE even if there are empty segments. In addition, if a more accurate extended beacon is received, the propagation strategy starts even if the density information not yet outdated, as shown in Algorithm 1 (Fig. 4). The accuracy is measured based on the number of the used RVs. This information is included in the extended beacon (Fig. 3). This allows propagating the extended
beacons rapidly making their information ready for use before becoming outdated.

Fig. 1 is a simple scenario to show the functioning of SLDE. The density process starts by vehicle A (the first RV) by its passing through the centre of a segment. Based on the valid received extended beacons and regular beacons, RVA estimates the density. Next, it broadcasts the extended beacon by selecting vehicle B as $R V 1$. For the segments where the EV has the best accuracy, the regular beacons are used for the estimation. While for other segments the received DHs are used. In the next segment, as the vehicles receive the DH , they compete to be the next RV. In this scenario, without waiting, vehicle B receives the extended beacons and elects itself as the next RV by broadcasting its extended beacon, hence suppressing other vehicles of the same segment. In the next segments, the other vehicles will wait more time, which gives time for DH to be assembled from one segment to another. Following the same procedure, vehicles C, D, and E will behave.

In the next sections, we evaluate SLDE performances analytically and by simulation. We first evaluate the error ratio analytically to know what the maximum possible detection ratio is. Then, SLDE will be subject for further simulations, and we will compare it with F-SLDE and DVDE [10].

F-SLDE (fundamental SLDE) is a variant of SLDE. In F-SLDE, the propagation of extended beacons is based just on the timers. The RV does not include the next RVs in its extended beacon. As a result, the RVs of the different segments send their DHs directly without waiting for the reception of DHs segment after segment.


Fig. 6 Illustration of the considered scenario for an analytical estimation of the density accuracy over the transmission range of a specific node $n_{0}$

Table 1 Overview of the functions and symbols used in our performance analysis
Function Meaning
$\overline{P_{d}\left(k, C o_{i}, r\right) \text { The density accuracy ratio of segment } k \text { using } C o_{i} \text { after } r}$ hops.
$P_{h}\left(\mathrm{Co}_{i}\right) \quad$ The reception probability of all DHs from RVs marked with 1 in Coj.
$P_{r v}\left(\mathrm{Co}_{i}\right)$ The probability that a specific combination of DHs is received.
$P_{r}(d) \quad$ The reception probability of a packet at distance $d$.
Symbol Meaning
DH Density histogram, a vector that contains the estimated densities in the transmission range.
NBS The number of segments on one side.
$C_{i} \quad$ A sorted set with NBS elements representing the state of reception.
DEA Density Estimation Accuracy, the average density estimation accuracy over the transmission range.
$\mathrm{RV}_{i} \quad$ The reference vehicle of a segment i , which is located at its center.

The following metrics are considered in our performance evaluation:

- Communication overhead: The communication overhead evaluates the generated overhead per second by all vehicles (bytes/s). This metric is used to evaluate the scalability the evaluated strategies. It is the size of extra bytes used for the density information multiplied by the mean number of sent extended beacons per second. The size of extended beacons is based on the number of segments. Each segment requires one byte.
- Error ratio: The error ratio evaluates the percentage of undetected neighbours. This metric is used to evaluate the estimation accuracy (2)

$$
\begin{equation*}
\text { Errorratio }=\frac{\mid \mathrm{EN}-\mathrm{RN\mid}}{\mathrm{RN}} \times 100 \% \tag{2}
\end{equation*}
$$

where, EN is the estimated number of neighbours in the maximum transmission range; RN is the real number of neighbours in the maximum transmission range.

## 4 Analytical analysis

The most important metric of the local density strategy is essentially the error ratio. In the following, we will develop a probabilistic model for estimating the error ratio for SLDE strategy.

For this analysis, we use a basic scenario illustrated in Fig. 6. RVs are located in the centre of each segment. The vehicle $n_{0}$ is the EV that will estimate the density using SLDE based on the received DH . The vehicle $n_{0}$ receives the different density histograms with different probabilities. In each DH , there are the estimated densities of the segments on the maximum transmission range of the sending RV. The density segment information either
directly (solid lines) or included in other DH (dashed lines). Table 1 presents the used functions and symbols.

### 4.1 Density estimation accuracy

The density estimation accuracy (DEA) depends on the reception of DHs and their accuracy.

If an EV has NBS segments on one side, there are $\left(C_{2}^{1}\right)^{\text {NBS }}$ of possible combinations $\left(\mathrm{Co}_{i}\right)$ of the received set of DHs.

The DEA is calculated using the probability of happening $P_{\mathrm{h}}\left(C o_{i}\right)$ and its density accuracy ratio $P_{\mathrm{d}}\left(C o_{i}\right)$. The following equation gives the density estimation accuracy:

$$
\begin{equation*}
D E A=\sum_{i=1}^{\left(C_{2}^{1}\right)^{\mathrm{NBS}}} P_{\mathrm{h}}\left(C o_{i}\right) \times P_{\mathrm{d}}\left(C o_{i}\right) \tag{3}
\end{equation*}
$$

We start first by the calculation of the probability that a specific combination $C o_{i}$ happens. We define $C o_{i}$ as a sorted set that contains NBS elements. Each element can take 0 or 1 as a value. If DH of RV on the segment $j$ is received, then $\left(C o s o_{i}(j)=1\right)$, else $\left(C o_{i}(j)=0\right)$.

$$
\begin{equation*}
C o_{i}=\{1 \text { or } 0,1 \text { or } 0,1 \text { or } 0,1 \text { or } 0, \ldots, 1 \text { or } 0\} \tag{4}
\end{equation*}
$$

The probability $P_{\mathrm{h}}\left(C o_{i}\right)$ of a specific combination $C o_{i}$ happens is calculated as follows:

$$
\begin{gather*}
P_{\mathrm{h}}\left(\operatorname{Cos}_{i}\right)=\prod_{i=1}^{\mathrm{NBS}} P_{r v}\left(\operatorname{Co}_{i}\right)  \tag{5}\\
\begin{cases}C_{i}(j)=1 & \rightarrow P_{r v}\left(\operatorname{Co}_{i}\right)=P_{r}(d(0, j)) \\
\operatorname{Co}_{i}(j)=0 \rightarrow P_{r v}\left(C o_{i}\right)=1-P_{r}(d(0, j))\end{cases} \tag{6}
\end{gather*}
$$

$P_{r}(d)$ is the probability of reception of a packet from distance $d$. This is calculated based on the model proposed in [16], which is an empirical model based on a large number of simulations. By knowing the transmission power $\Psi$ and the communication density $\xi$ [17] and the distance $d$, this model estimates the probability of reception as follows:

$$
\left\{\begin{align*}
P_{r}(d) & =\mathrm{e}^{-3(d / \Psi)^{2}}\left(1+a_{1}\left(\frac{d}{\Psi}\right)+a_{2}\left(\frac{d}{\Psi}\right)^{2}++a_{3}\left(\frac{d}{\Psi}\right)^{3}++a_{4}\left(\frac{d}{\Psi}\right)^{4}\right)  \tag{7}\\
a_{i} & \simeq h_{i}(\xi, \Psi)=\sum h_{i}^{(j, k)} \xi^{j} \Psi^{k}, \quad i=1,2
\end{align*}\right.
$$

where $\xi$ is the communication density ( $\Psi *$ density $*$ beacon frequency); $\Psi$ is the transmission power; $\boldsymbol{d}$ is the distance between the sender and the receiver; $h_{i}$ is the twodimensional polynomial used to provide the corresponding fitting parameter $a_{i}$.

More details can be found in [16] regarding the used equation and coefficients.

For the calculation of density accuracy ratio of one segment, we define $P_{d} . P_{d}$ is based on the $C o_{i}$ which defines the number of the received DHs. The accuracy of the received DHs also depends on


Fig. 7 Error ratio evaluation of SLDE using the proposed model
Table 2 The detection ratio of vehicles inside the segment using the empirical model [16]

| Density, v/l/km | 10 segments (100 m) | 20 segments (50 m) |
| :--- | :---: | :---: |
| 7 | $98.847 \%$ | $99.245 \%$ |
| 11 | $98.299 \%$ | $98.828 \%$ |
| 16 | $97.195 \%$ | $98.234 \%$ |
| 22 | $94.400 \%$ | $97.033 \%$ |
| 25 | $92.049 \%$ | $96.020 \%$ |
| Mean | $96.158 \%$ | $97.872 \%$ |

the number of hops $r$ from RV to RV during its propagation. Now, the equation 3 is redefined as follows:

$$
\begin{align*}
& \mathrm{DEA}=\sum_{i=1}^{\left(C_{2}^{1}\right)^{\mathrm{NBS}}} P_{\mathrm{h}}\left(C o_{i}\right) \times \sum_{k=1}^{\mathrm{NBS}} P_{\mathrm{d}}\left(k, C o_{i}, r\right) / \mathrm{NBS}  \tag{8}\\
& \mathrm{DEA}=\sum_{k=1}^{\mathrm{NBS}} \sum_{i=1}^{\left(C_{2}^{1}\right)^{\mathrm{NBS}}} P_{\mathrm{h}}\left(C o_{i}\right) \times P_{\mathrm{d}}\left(k, C o_{i}, r\right) / \mathrm{NBS} \tag{9}
\end{align*}
$$

The EV use the DH of the nearest RV for the calculation of the density of each segment. From a global view, the construction process of DHs can be seen as a recursive process where each built DH depends on the received DHs. The following equation shows how $P_{d}$ is calculated:

$$
\begin{align*}
P_{d}\left(k, C o_{i}, r\right)= & \sum_{i=1}^{\left(C_{1}\right)^{\text {NBS }}} P_{h}\left(C O_{i}\right)  \tag{10}\\
& \left.\times P_{\mathrm{d}( } \min _{j \in[0, \mathrm{NSS}]}(|k-j|) / C o_{i}(j)=1, r-1\right) \\
P_{d}\left(k, C o_{i}, 0\right)= & 1-\left(1-P_{r}\left(\min _{j \in[0, \mathrm{NBS}]}(|k-j|\right.\right.  \tag{11}\\
& \left.\left.\times \operatorname{SegmentSize}) / C o_{i}(j)=1\right)\right)^{\text {Beaconfrequency }}
\end{align*}
$$

In this modelling, we considered that all vehicles have the same communication conditions, so their probability of detection for the same distances will be the same. The idea is to start by constructing a vector that represents the detection ratio of each segment using the empirical model [16], that is $P_{\mathrm{d}}\left(k, C o_{i}, 0\right)$. then the process continues until $P_{\mathrm{d}}\left(k, C o_{i}, \mathrm{NBS}-1\right)$ to cover the maximum transmission range since the DH in SLDE is sent from one segment to another.

In the following, we will evaluate the performance of the SLDE strategy using this model. For this analysis, we conducted simulation using ns-2 with the empirical simulation model parameters used in [16].

Fig. 7 depicts the error ratio for SLDE as a function of the vehicular density using ten and twenty segments. As observed, SLDE has a lower error ratio using 10 segments compared with 20 segments. It is clear that by increasing the density, the error ratio rises. This is mainly due to packets collisions that increase with the number of the vehicles that use the same wireless medium. However, these errors correspond exactly to the detection error of the main segment (the segment where the vehicle is in its centre). In other words, all the vehicles have a detection ratio over their maximum transmission range ( 1000 m ) that equals a detection ratio over their main segment and the minimum possible error ratio. All the detection ratios within the segment are shown in Table 2.

The reduced error ratio for SLDE is mainly due to the fast propagation strategy, which ensures fresher and accurate density information to the different vehicles.

### 4.2 The effect of the number of used $R V$ s

In the ideal situation, the accuracy converges to its maximum value, which corresponds to the detection ratio in the main segments (Table 2). All the vehicles will have the maximum detection ratio if the extended beacons are constructed and propagated by more RVs. This is confirmed by the simulation results shown in Figs. $8 a$ and $b$.

Fig. 7 shows that using small segments permits a better detection ratio even if the number of RVs that are used in the construction of the DH is lower. This comes at the cost of additional overhead. The overhead consists of the extra bytes used for the density of the additional segments. The analysis of this basic scenario shows that SLDE can give vehicles the capacity to have a very high detection ratio over its maximum transmission range $(1000 \mathrm{~m})$ that corresponds to the detection ratio over the main segment.

In the next section, SLDE will be subject for further simulations, and we will compare it to the F-SLDE and DVDE [10] strategies.

## 5 Simulation

In this section, we carry out a simulation study to evaluate the performances SLDE and compare them with both F-SLDE and DVDE. The simulations are performed using ns- 2.35 network simulator [18] and an overhauled Mac PHY-model is used [19]. This model is adapted to the characteristics of IEEE 802.11p, which the standard used for the inter-vehicle communications. In addition, the probabilistic Nakagami propagation model is used to ensure more realistic simulations. The three simulated strategies are DVDE [10], F-SLDE, and SLDE. To ensure a fair comparison between these strategies, we have simulated them under the simulation configuration (the simulation configuration of DVDE [10]). The parameters of this simulation are listed in Table 3.

The simulation scenario consists in a three-lane bidirectional highway of 2 km in length. The highway is straight without entrances or exists. To generate realistic traffic patterns for both microscopic and macroscopic environments, we have used SUMO traffic mobility engine Table 4. The mobility scenarios represent the different levels of service on highways. Based on the highway capacity manual, we selected the highest possible density for each service level. Table 4 shows the different levels of service on highways and their corresponding maximum values of densities given by vehicle/lane/km.

### 5.1 Simulation results

The different parameters values for DVDE[10], F-SLDE, and SLDE are analysed to select the best configuration to be applied to each strategy. The results are calculated basing on the mean values of the estimation samples of all vehicles and over the different densities. An estimation sample is taken each second. The performances of F-SLDE and SLDE are directly related to the size of a segment and the validity time of the density information $\triangle T$. For this reason, the different segment size values and $\triangle T$ are analysed to select the adequate ones for ensuring a low error ratio with a minimum of overhead. The same task was performed for

Table 3 Simulation configuration

| Parameter | Value |
| :--- | :--- |
| frequency | 5.9 GHz |
| data rate | 3 Mbps |
| carrier sense threshold | -96 dBm |
| SIFS time | $32 \mu \mathrm{~s}$ |
| slot time | $16 \mu \mathrm{~s}$ |
| preamble length | $40 \mu \mathrm{~s}$ |
| PLCP header length | $8 \mu \mathrm{~s}$ |
| noise floor | -99 dBm |
| SINR for preamble capture | 4 dB |
| SINR for frame body capture | 10 dB |
| MAC | 802.11 P |
| packet size | 400 byte |
| beacon generation | $10 \mathrm{beacons} / \mathrm{s}$ |
| maximum vehicle velocity | $30 \mathrm{~m} / \mathrm{s}$ |
| transmission range | 1000 m |
| radio propagation | Nakagami |
| number of vehicles | $84,132,192,256,300$ |
| road length | 2 km |

Table 4 The service levels of highways and their maximum densities according to [20]

| Level of service | Max density $\mathrm{v} / / / \mathrm{km}$ |
| :---: | :---: |
| A | 7 |
| B | 11 |
| C | 16 |
| D | 22 |
| E | 25 |

DVDE. However, the segment size is the only parameter considered in DVDE. The obtained results are illustrated in Table 5.

The results in Table 5 show the error ratio and the overhead of F-SLDE, SLDE, and DVDE. It is clear that SLDE and F-SLDE outperform in both metrics. In addition, SLDE has the lowest mean error among the three strategies for about $2.96 \%$ with an overhead of $10,558.83$ bytes $/ \mathrm{s}$ by using 100 m as segment size and 0.1 for $\triangle T$. The presented results also show that the size of the segment is inversely proportional to the generated overhead values. Indeed, the smaller the size of the segment is, the higher generated overhead is. However, we can see that F-SLDE has the lowest overhead with 137.25 bytes/s by using 200 m as segment size and 0.9 for $\triangle T$ but with a higher error ratio of $12.66 \%$.


Fig. 8 The effect of the number of used RVs for detection accuracy (a) 10 segments, (b) 20 segments

The best parameters of each strategy are selected based on the weight ( $\omega$ ) of the obtained results. The weight $(\omega)$ ) is calculated as follows:

$$
\begin{equation*}
\omega(S, \triangle T)=\frac{\text { errorratio }}{\max (\text { errorratio })}+\frac{\text { overhead }}{\max (\text { overhead })} \tag{12}
\end{equation*}
$$

In (12), we consider that the error ratio and the overhead have the same impact on the calculation of the weight. For this reason, an equally factor is assigned to each of them. Besides of this, the function MAX calculated the maximum obtained value using the same strategy.

The results illustrated in Table 5 are all evaluated using the weight function. The results of this evolution are summarised according to the strategies and their parameters as follows: (i) For DVDE, the best results are obtained using segments of 200 m , (ii) For F-SLDE, the lowest weight was found using segments size of 100 m and 0.1 for $\triangle T$ (iii) For SLDE, the lowest weight was found using segments size of 200 with $\Delta T$ equals 0.1 . These selected best parameters are used in the next section for the rest of the performance evaluation.

### 5.2 Evaluation of overhead

The generated overhead for DVDE, F-SLDE, and SLDE, using the selected parameters, are shown in Fig. 9. The overhead is the number of extra bytes sent per second for the density information. In Fig. $9 a$, the mean overhead of using the different densities is shown using a boxplot with $5 \%, 95 \%$ percentiles. The bottom and top of the boxes are the lower and upper quartiles of results while the line between them is the median. The upper whisker is $95 \%$ percentile, and the lower whisker is $5 \%$ percentile. Fig. $9 a$ shows that DVDE has a lower overhead. The overhead for all strategies is considered as very low compared to the offered bandwidth of 3 $\mathrm{MB} / \mathrm{s}$ in each collision domain. Nevertheless, F-SLDE and SLDE can have less overhead and with a lower error ratio compared to DVDE using other parameters as listed in Table 5. For example, by using 200 m as segment size and 0.9 as $\triangle T$, F-SLDE generated 137.25 bytes/second, and SLDE generated 477 bytes/second.

The generated overhead of the three strategies is illustrated regarding the density for vehicles in $9 b$. We can see that the generated overhead linearly increases with the density of vehicles in all strategies. These results are expected because as the number of vehicles increases as the number of sent extended beacons increased as well.

### 5.3 Evaluation of error ratio

The evaluation of the error ratio as a function of the selected parameters is illustrated in Figs. 10 and 11. The accuracy of estimated number of vehicles compared with the real number of



Fig. 9 Overhead evaluation
vehicles and is shown in the scatter plot presented in Fig. 10. As we can see in this plot both of SLDE and F-SLDE value are concentrated on the black line that represents the real values. However, the values obtained by DVDE are getting away for the line as the number of neighbours increases.

The boxplot ( $5 \%, 95 \%$ percentiles) in Fig. $11 a$ shows the mean error of the different densities. As we can see, the lowest error ratio mean is observed in SLDE compared with the two other strategies.

The error ratio of the strategies as a function of the density of vehicles is illustrated in Fig. $11 b$. We can observe that SLDE generally has the lowest compared with F-SLDE and DVDE strategies. Indeed, thanks to the propagation module used by FSLDE and SLDE that ensures fresh and accurate vehicles, the error ratio is reduced compared to DVDE. In addition, the capacity to use more $R V s$ in SLDE allows it to more reduce the error ratio compared to F-SLDE. The reason is using more RVs permits to increase the accuracy of the information in each hop.

The obtained results can be summarised as follows: In F-SLDE and SLDE, the generated error ratio and overhead were very low even over the maximum range. Indeed, both of two strategies optimistically use the available information and make it more accurate through frequently updating the DH in each RV. Furthermore, the results of obtained by SLDE outperform the ones of F-SLDE in terms both error ratio SLDE (3.16\%) and overhead (SLDE ( 2710.08 bytes/s). This is the result of increasing the number of used RVs by using segment after segment propagation strategy.

## 6 Conclusion

The IoV is one of the most important real-world applications of the IoT. This technology brings new opportunities to intelligent transportation systems applications towards improving safety and comfort on our roads. In many of these applications, the local density of vehicles represents a key element in their functioning. However, getting accurate density estimation in a high traffic density situation is one of the important issues that should be carefully addressed. In this paper, we proposed an efficient local density estimation approach, called segment-based local density estimation (SLDE). This approach provides accurate local density estimation within the maximum transmission range, i.e. the number of vehicles that may affect the communication quality. SLDE is based on: (i) the segmentation of the road into a set of segments that are smaller than the maximum transmission range and (ii) an efficient strategy for the propagation and exchange of the density

Table 5 Simulation results of F-SLDE, SLDE, and DVDE

| Segment <br> size, m | $\triangle T(s)$ | SLDE | Error ratio, \% |  | O-SLDE | DVDE |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |



Fig. 10 Comparison between the real number of neighbours and the estimated number of neighbours (a) DVDE, (b) F-SLDE, (c) SLDE


Fig. 11 Accuracy evaluation
calculated in each segment. The performance evaluation results demonstrated the accuracy of the proposed approach and its efficiency regarding the generated overhead. As a perspective for this work, we intend to use SLDE to enhance the performance of congestion control protocols.

## 7 References

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