V2X-d: a Vehicular Density Estimation System that combines V2V and V2I Communications

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***Abstract*—Intelligent Transportation Systems (ITS) can efficiently manage information on the road, being able to offer drivers a variety of value-added services including safe, efficient, and smart driving. Regarding transportation, road traffic is experiencing a drastic increase, and vehicular traffic congestion is becoming a major problem, especially in metropolitan environments throughout the world. As for communications, the high amount of information that can be generated and processed by vehicles will significantly increase message redundancy, channel contention, and message collisions, thus reducing the efficiency of message dissemination processes. In this work, we present a V2X architecture to estimate traffic density on the road that relies on the advantages of combining V2V and V2I communications. Our proposal uses both the number of beacons received per vehicle (V2V) and per RSU (V2I), as well as the roadmap topology features to estimate the vehicle density. By using our approach, modern Intelligent Transportation Systems will be able to reduce traffic congestion and also to apply more efficient message dissemination protocols.**

***Index Terms*—Vehicular Networks, VANETs, vehicular density estimation, Road Side Unit, V2V, V2I, V2X.**

I. INTRODUCTION

The convergence of wireless telecommunication, computing, and transportation technologies facilitates that our roads and highways can be both our transportation and communication platforms. These changes will completely revolutionize when and how we get access to services, communicate, commute, entertain, and navigate, in the coming future. Intelligent Transportation Systems (ITS) emerge as the technology that can efficiently manage information on the road, being able to offer drivers a variety of added services such as safe, efficient, and smart driving.

Regarding transportation, road traffic is experiencing a drastic increase, and vehicular traffic congestion is becoming a major problem, especially in metropolitan environments throughout the world. In particular, traffic congestion: (i) reduces the efficiency of the transportation infrastructure, (ii) increases travel time, fuel consumption, and air pollution, and (iii) leads to increased user frustration and fatigue [1]. Traditionally, vehicle density has been one of the main metrics used for assessing road traffic conditions. A high vehicle density usually indicates congested traffic; however, the density of vehicles in a city highly varies depending on the area and the time during the day. Thus, knowing the density of a vehicular environment is important since it allows applying traffic congestion countermeasures focused on improving traffic flow, reducing contamination, and increasing drivers' comfort.

Regarding communications, Vehicular Networks (VNs) are wireless communication networks that support cooperative driving among communicating vehicles on the road. VNs involve vehicle-to-vehicle (V2V) [2] and vehicle-to-infrastructure (V2I) [3] communications, and have received a remarkable attention in recent years. The specific characteristics of vehicular networks favor the development of attractive and challenging services and applications. Though traffic safety has been the primary motive for the development of these networks [4], VNs also facilitate applications for managing the traffic flow, monitoring road conditions, environmental protection, and mobile infotainment [5]. Most of these applications could behave more efficiently if the protocols involved become aware of the density of vehicles at any given time, being able to adapt their behavior according to this factor. Hence, knowing the traffic density in vehicular scenarios is of great importance since it promotes using the wireless channel more efficiently, thereby improving ITS wireless-based services.

Currently, most of the vehicle density estimation approaches are designed to use very specific infrastructure-based traffic information systems, which require the deployment of vehicle detection devices such as inductive loop detectors, or traffic surveillance cameras [6], [7]. However, these approaches are limited since they can only be aware of traffic density in *a priori* selected areas (i.e., the streets and junctions in which these devices are already located), making it difficult to estimate the vehicular density along a whole city. In addition, some of these approaches are not able to perform accurate estimations in real time (e.g., using cameras involves hard image processing and analysis). The use of V2I communications can address the aforementioned problems [8].

Other authors, such as Stanica et al. [9] and Sanguesa et al. [10], propose estimating the traffic density by using V2V communications. According to these approaches, each vehicle is able to estimate the number of nearby vehicles by accounting for the beacons received. However, such proposals

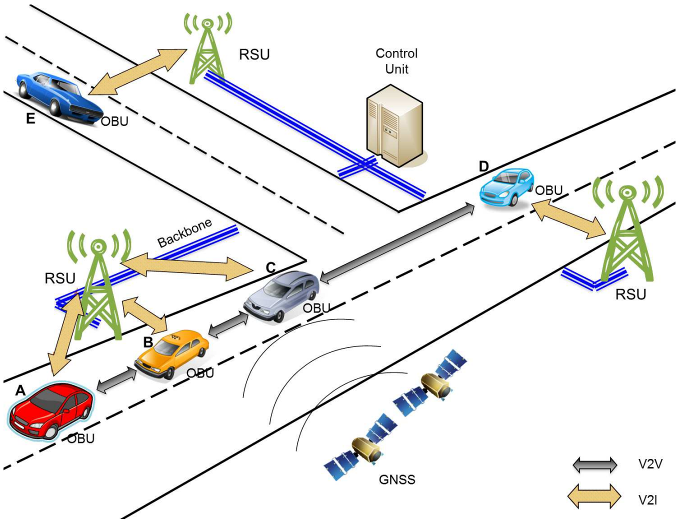

Fig. 1. Architecture of the V2X-based vehicle density estimation.

are only capable of obtaining information about density in their neighborhood, while being unable to infer traffic information for the whole scenario. Hence, vehicles are unable to determine the best route to avoid traffic jams.

Since using V2V or V2I communication approaches separately presents some advantages, but also some drawbacks, in this work we present a V2X architecture to estimate traffic density on the road that combines V2V and V2I communications. Unlike previous proposals, our approach maximizes the advantages of V2V (accuracy, microscopic approach, etc.) with the advantages of V2I (global information, macroscopic approach, etc.). Our proposal uses both the number of beacons received per vehicle (V2V) and per RSU (V2I), as well as the roadmap topology features, to estimate the vehicle density. By using our proposal, modern Intelligent Transportation Systems will be able to reduce traffic congestion and also to apply more efficient message dissemination protocols.

This paper is organized as follows: In Section II we present the V2X-d architecture. Section III presents the simulation environment. Section IV details our V2X real-time density estimation proposal. In Section V we compare our V2X-d proposal with other density estimation approaches. Section VI introduces the most important applications of the V2X-d architecture. Finally, Section VII concludes this paper.

II. V2X-d Architecture for Accurate Density Estimation in Vehicular Environments

Figure 1 presents an overview of our proposed architecture. As shown, each vehicle incorporates an On-Board Unit (OBU) responsible of the wireless communication, hence providing the necessary network interfaces to implement the density estimation mechanism using the data exchanged by the vehicles on the road, i.e., V2V communication. In addition, the OBU must have access to positioning devices corresponding to Global Navigation Satellite Systems (GNSS) such as the Global Positioning System (GPS) [11], or the future Galileo [12] system developed by the European Union. This information may be critical to determine areas of interest for the estimation, or to predict the vehicles' movements to improve future estimations.

The development of the V2I part of the vehicular communication requires the installation of additional infrastructure nodes, called Road Side Units (RSUs), giving support to the vehicles and providing additional services. RSU deployment also allows communication between different areas of the map if necessary, by means of the connection to a common backbone [13].

Using this proposed architecture, the deficiencies of the different systems used, i.e., V2V and V2I, can be addressed by the combination of both technologies. Vehicles can achieve a global awareness of the network around them, whereas the RSUs can improve their information about traffic at microscopic levels through the local information obtained from the vehicles. This opens a wide variety of possibilities to obtain an accurate vehicle density estimation, overcoming blind spots or sparsely connected areas.

In order to achieve an accurate density estimation, we firstly need to develop systems able to determine the density of vehicles by using V2V and V2I communications. Moreover, this system should provide adequate results independently of the scenario in which the communication takes place. That is, the estimation mechanism should adapt to the features of the road topology.

III. Simulation Environment

All the simulations performed in this work were done using the ns-2 simulator [14], where the PHY and MAC layers have been modified to closely follow the IEEE 802.11p standard[1], which defines enhancements to 802.11 required to support ITS applications. We assume that all the nodes are equipped with an IEEE 802.11p interface tuned at the frequency of 5.9 GHz for both V2V and V2I communications.

In terms of the physical layer, the data rate used for packet broadcasting was 6 Mbit/s, as this is the maximum rate for broadcasting in 802.11p. The MAC layer was also extended to include four different priorities for channel access. Therefore, application messages are categorized into four different *Access Categories* (ACs), where AC0 has the lowest and AC3 the highest priority.

Regarding V2I communications, we used the Uniform Mesh deployment policy [13] to deploy RSUs in the maps. This approach consists on distributing RSUs uniformly on the map. The advantage of this deployment policy is that it achieves a more uniform coverage area since the distance between RSUs is the same, preventing RSUs to be deployed too closely, or too sparsely. As for the mobility model, it has been obtained with *CityMob for Roadmaps* (C4R) [15], a mobility generator able to import maps directly from OpenStreetMap [16], and generate ns-2 compatible traces. Table I shows the parameters used for the simulations.

[1] All these improvements and modifications are available at http://www.grc.upv.es/software/

TABLE I
PARAMETERS USED FOR THE SIMULATIONS

Parameter	Value
roadmaps	New York, Minnesota, Madrid, San Francisco, Los Angeles, Amsterdam, Sydney, Liverpool, Valencia, Rio de Janeiro, and Rome
roadmap size	$2000m \times 2000m$
number of vehicles	$[100, 200, 300...1000]$
warning messages priority	$AC3$
beacon priority	$AC1$
interval between messages	1 second
number of RSUs	9
RSU deployment policy	Uniform Mesh [13]
MAC/PHY	802.11p
radio propagation model	RAV [17]
mobility model	Krauss [18]
channel bandwidth	$6Mbps$
max. transmission range	$400m$

TABLE II
MAP FEATURES

Map	Streets	Junctions	Avg. segment size (m.)	Lanes/ street	SJ Ratio
New York	257	500	45.8853	1.5730	0.5140
Minnesota	459	591	102.0652	1.0144	0.7766
Madrid	628	715	83.0820	1.2696	0.8783
San Francisco	725	818	72.7065	1.1749	0.8863
Los Angeles	283	306	408.2493	1.1448	0.9379
Amsterdam	1494	1449	44.8973	1.1145	1.0311
Sydney	872	814	72.1813	1.2014	1.0713
Liverpool	1758	1502	49.9620	1.2295	1.1704
Valencia	2829	2233	33.3653	1.0854	1.2669
Rio de Janeiro	542	401	167.9126	1.1135	1.3516
Rome	1655	1193	45.8853	1.0590	1.3873

Table II shows the main features of each map for the cities under study: the number of streets, the number of junctions, the average segment size, and the number of lanes per street. According to the results obtained in previous work [19], we consider that the parameters that better correlate with the complexity of the roadmap are the number of streets and the number of junctions. Hence, we added a column labeled as *SJ Ratio*, which represents the result of dividing the number of streets between the number of junctions. As shown, the first 5 cities (New York, Minnesota, Madrid, San Francisco, and Los Angeles) present an SJ ratio smaller than 1, which indicates that they have a simple topology, while the rest of the cities (Amsterdam, Sydney, Liverpool, Valencia, Rio de Janeiro, and Rome) present a higher SJ value, which indicates that they have a complex topology. According to this, complex maps like Valencia obtain worse results in terms of communicating vehicles than simple maps as Madrid, where the wireless signal easily reaches more vehicles in less time.

IV. OUR V2X DENSITY ESTIMATION SYSTEM

In this section, we proceed to obtain both V2V and V2I-based functions to estimate traffic density, with the minimum possible error.

We consider necessary to obtain both estimation functions, since the information provided by each one can be applied in different kinds of applications. For instance, applications with the goal of reducing broadcast storm problems and avoiding traffic overhead in vehicular networks only need to know the traffic density of the neighborhood of each vehicle. However, centralized systems with the aim of avoiding traffic jams need information of the whole map to be capable of rerouting vehicles to areas with less traffic density.

TABLE III
V2V EQUATION COEFFICIENTS

Coeff.	Value
a	-1.1138191190298828E+03
b	-1.0800433554686800E+01
c	3.1832185406821718E+03
d	-4.0336415134812398E-01
f	-3.0203454502011946E+03
g	2.8542014049626700E-03
h	9.5199929660347175E+02
i	3.5319225007012626E+01
j	1.6230525995036607E-01
k	-1.6615888771467137E+01

TABLE IV
V2V DENSITY ESTIMATION ERROR

Error	Absolute	Relative
Minimum	-2.61203E+01	-2.28480E-01
Maximum	2.16953E+01	5.71311E-01
Mean	-3.17620E-10	1.02334E-02
Std. Error of Mean	1.36030E+00	1.71408E-02
Median	1.69890E-01	-1.35912E-03

A. V2V-based density estimation

To propose a V2V-based method able to accurately estimate the density of vehicles, we made a total of 4000 experiments. These experiments involved the simulation of controlled scenarios (i.e., scenarios where the actual density is known). According to the results obtained, we propose a density estimation function capable of estimating the vehicular density in every urban environment, at any instant of time.

In order to obtain the best approach, we have tested some different functions (exponential, logarithmic, etc.). To this purpose, we performed a regression analysis by using ZunZun [20] that allowed us to find the polynomial equation offering the best fit to the data obtained through simulation. Equation 1 shows the density estimation function, which is able to estimate the number of vehicles per km^2 in urban scenarios, according to the number of beacons received, and the SJ ratio (i.e., streets/junctions) of the selected roadmap.

$$f(x, y) = a + bx + cy + dx^2 + fy^2 + gx^3 + \\ + hy^3 + ixy + jx^2y + kxy^2 \tag{1}$$

In this equation, x is the number of beacons received by each vehicle, and y is the SJ ratio obtained from the roadmap. The values of the polynomial coefficients $(a, b, c, d, f, g, h, i, j, \ and \ k)$ are listed in Table III.

To determine the accuracy of our proposal, we proceed to measure the estimated error. Table IV shows the different types of errors calculated when comparing our density estimation function with the values actually obtained. Note that the average relative error is of only 1.02%.

TABLE V
V2I EQUATION COEFFICIENTS

Coeff.	Value
a	2.3037584774238823E+02
b	1.9069648769466475E+01
c	-4.2946130569906342E+02
d	3.1880957532509228E+01
f	1.8795302200929001E+02
g	-6.8125878716641097E+01

TABLE VI
V2I DENSITY ESTIMATION ERROR

Error	Absolute	Relative
Minimum	-5.39939E+01	-1.22576E+00
Maximum	4.83735E+01	1.69779E+00
Mean	2.84849E-13	3.04107E-02
Std. Error of Mean	2.42242E+00	3.54373E-02
Median	2.37153E-01	1.58332E-03

B. V2I-based density estimation

Similarly to the V2V-based vehicle density estimation approach, we proceed to obtain a function to estimate vehicle density. To this end, we performed a regression analysis that allowed us to find an equation offering the best fit to the data obtained through simulation. We select Equation 2 as the V2I-based density estimation function, since it obtained the smallest relative error. This proposed function is able to estimate the number of vehicles per km^2 in urban scenarios, according to the number of beacons received per RSU, and the SJ ratio (i.e., streets/junctions) of the selected roadmap.

$$f(x,y) = a + b \cdot ln(x) + \frac{c}{y} + d \cdot ln(x)^2 + \frac{f}{y^2} + \frac{g \cdot ln(x)}{y} \quad (2)$$

In this equation, x is the average number of beacons received by each RSU, and y is the SJ ratio obtained from the roadmap. The values of the coefficients $(a, b, c, d, f, \ and \ g)$ are listed in Table V.

To determine the accuracy of our proposal, we proceed to measure the estimated error. Table VI shows the different errors when comparing our density estimation function with the values actually obtained by simulation. Note that the average relative error is of only 3.04%. As expected, the V2I-based vehicle density estimation approach presents a higher estimation error, but it is almost negligible for the majority of ITS applications. In addition, the use of V2I can enrich and complete the estimation obtained by the V2V approach.

To assess our proposed density estimation function, we simulated a new particular case. Specifically, we chose Mexico D. F., a city with a small SJ Ratio (0.7722), and we simulated a density of 200 vehicles per km^2 during 30 seconds. Figure 2 shows the RSU deployment strategy and the vehicles' location at the end of the simulation for the studied example, and Table VII shows the obtained results. As shown, the average number of beacons received per RSU is 47.56. According to our proposal (i.e., applying the polynomial function as shown in Equation 3), we estimate a density of 196.91 vehicles. In this example, the estimation of vehicular density obtained an error of 3.09 vehicles, which only represents the 1.55% of the total vehicles.

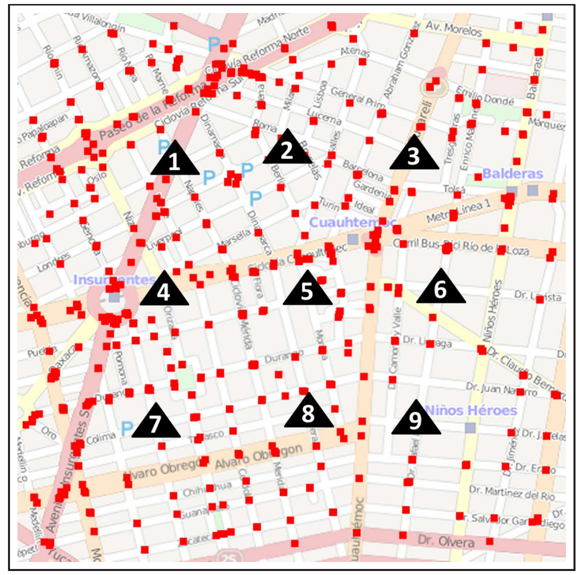

Fig. 2. RSUs deployment and vehicles location at the end of the simulation.

TABLE VII
RECEIVED BEACONS WHEN SIMULATING 200 VEHICLES/km^2 IN MEXICO D.F.

RSU	Received beacons	% of received beacons
1	54	12.62
2	46	10.75
3	43	10.05
4	68	15.89
5	48	11.21
6	38	8.88
7	48	11.21
8	46	10.75
9	37	8.64
Total	**428**	**100**
Average	**47.56**	-

$$f(x,y) = a + b \cdot ln(47.56) + \frac{c}{0.7722} + d \cdot ln(47.56)^2 + \quad (3)$$
$$+ \frac{f}{0.7722^2} + g \cdot \frac{ln(47.56)}{0.7722} = 196.91$$

Moreover, using our system, we are able to estimate the vehicular density in more specific areas. For example, using the data included in Table VII, we can identify areas where the traffic is more congested (i.e., areas where the RSUs receive a higher percentage of beacons). In our experiment, RSUs 4 and 1 received a higher number of beacons compared to RSUs 6 and 9. According to these results, an automatic traffic control system could take advantage from V2I communication capabilities to adapt the vehicles' routes in order to redirect vehicles traveling in more congested areas to those areas where the RSUs receive a lower number of messages (i.e., less congested), thus avoiding traffic jams.

V. COMPARISON WITH OTHER DENSITY ESTIMATION APPROACHES

As mentioned above, other vehicular density estimation proposals rely on the use of infrastructure elements such

TABLE VIII
V2V BEACONS-ONLY FUNCTIONS COEFFICIENTS

Coefficient	Quadratic	Cubic	Quartic	Preece-Baines
a	1.82943E+01	2.27684E+01	3.90472E+01	1.90872E+02
b	4.13673E+00	3.29413E+00	-1.38471E+00	1.63278E+02
c	-2.15091E-02	7.02894E-03	2.97587E-01	2.56730E-02
d	-	-2.55584E-04	-6.47130E-03	4.40558E+01
f	-	-	4.27413E-05	6.86664E-01

TABLE IX
V2I BEACONS-ONLY FUNCTIONS COEFFICIENTS

Coefficient	Quintic Polynomial	Quadratic Logarithmic
a	1.35094E+01	-3.34403E+02
b	2.34872E-02	2.02972E+02
c	8.79406E-01	-1.82578E+01
d	-3.74059E-02	1.49093E+00
f	5.62751E-04	-
g	-2.82498E-06	-

as surveillance cameras, inductive loop detectors, or ambient microphones to estimate the vehicle density (e.g., [1], [6], and [7]). The use of V2I communications has also been studied (e.g., [3], [8]). Those approaches require to deploy RSUs, although they can provide attractive and value-added services when compared to the former. On the contrary, the proposals based on V2V communications do not require the deployment of any infrastructure nodes, but, unlike our proposal, they usually take into account just the number of beacons received (e.g., [9], [21]), while omitting any data related to the map topology where the vehicles are located.

A. Performance comparison of our V2V approach against other V2V-based density estimation approaches

In order to assess the importance of the topology, we compared our proposal with a beacon-based approach, where the vehicular density is estimated by only using the number of beacons received. To make a fair comparison, we followed the same methodology in both approaches.

We tested four different density estimation functions which are solely based on the number of beacons received, trying to obtain the lowest value for the Sum of Squared Errors (SSE). Specifically, we have tested three different polynomial functions (i.e., quadratic, cubic, and quartic), and a non-polynomial function (based on the Preece-Baines Growth function). Equations 4-7 show these functions, and Table VIII shows their coefficients.

$$f(x) = a + bx + cx^2 \tag{4}$$

$$f(x) = a + bx + cx^2 + dx^3 \tag{5}$$

$$f(x) = a + bx + cx^2 + dx^3 + fx^4 \tag{6}$$

$$f(x) = \frac{a - 2 \cdot (a - b)}{(exp(c \cdot (x - d)) + exp(f \cdot (x - d)))} \tag{7}$$

Table X shows the sum of square errors for each of the functions tested. As shown, our V2V-d function yields more accurate results, presenting the lower sum of square absolute error (6.33215E+03, two orders of magnitude lower than the

TABLE X
COMPARISON BETWEEN OUR V2X-D AND THE BEACONS-ONLY DENSITY ESTIMATION APPROACHES

Fitted function	Sum of Square Errors	Avg. vehicles error
Beacons-only Quadratic	1.38234E+05	41.57
Beacons-only Cubic	1.37994E+05	41.53
Beacons-only Quartic	1.36094E+05	41.25
Beacons-only Preece-Baines Growth	1.31231E+05	40.50
V2V-d	6.33215E+03	8.90
Quintic Polynomial	1.89925E+05	45.94
Quadratic Logarithmic	2.01613E+05	47.33
V2I-d	4.70035E+04	22.85

rest), and it has only an average error of 8.90 vehicles, whereas the rest of the functions that only account for the number of beacons show an average error ranging from 40.50 to 41.57 vehicles, depending on the selected function.

B. Performance comparison of our V2I approach against other V2I-based density estimation approaches

Similarly to the V2V-based vehicle density estimation approach, we tested several density estimation functions which are solely based on the number of beacons received, trying to obtain the lowest value of SSE. In particular, we obtained the quintic polynomial function shown in Equation 8, and the quadratic logarithmic function shown in Equation 9.

$$f(x) = a + bx + cx^2 + dx^3 + fx^4 + gx^5 \tag{8}$$

$$f(x) = a + b \cdot ln(dx) + c \cdot ln(dx)^2 \tag{9}$$

The results presented in Table X confirm that our V2I-d function provides more accurate results than the other V2I beacons-only density estimation functions, presenting a low value for the Sum of Squared Errors (i.e., 4.70035E+04), whereas the beacons-based functions present a Sum of Squared Errors value of 1.89925E+05 (for the polynomial) and 2.01613E+05 (for the logarithmic), i.e., one order of magnitude higher than our proposal. Specifically, its average error is of only 22.85 vehicles, whereas the rest of the functions that only account for the number of beacons have an error of 45.94 and 47.33 vehicles, respectively. As shown, the V2V density estimation is more accurate, but, as stated before, this approach also presents some drawbacks since it cannot be used in traffic jam avoidance systems. Hence, we consider that a method that combines both V2V and V2I communications is necessary.

C. Qualitative comparison of our V2X-d approach against other density estimation approaches

To conclude this section, Table XI presents a summary of the different vehicle density estimation methods focusing on their main characteristics. As shown, there is no density estimation approach that can fulfill all the desired capabilities needed by traffic control authorities and modern ITS services, with the exception of our V2X-d.

TABLE XI
QUALITATIVE COMPARISON OF THE DIFFERENT DENSITY ESTIMATION APPROACHES

Feature	**Cameras**	**Loop detectors**	**Microphones**	**V2I**	**V2V**	**V2X-d**
24/7 availability	✖	✔	✔	✔	✔	✔
All-sound conditions	✔	✔	✖	✔	✔	✔
Different light conditions	✖	✔	✔	✔	✔	✔
All-Weather conditions	✖	✔	✖	✔	✔	✔
Wide Coverage	✖	✖	✖	✔	✖	✔
Real-time estimation	✖	✔	✔	✔	✔	✔
Traffic jams avoidance	✔	✔	✔	✔	✖	✔
Broadcast storms mitigation	✖	✖	✖	✖	✔	✔
Fault tolerant	✖	✖	✖	✖	✔	✔

Traditional infrastructure-based methods, such as surveillance cameras or ambient microphones, are highly affected by the environmental conditions (bad light, adverse weather, etc.). Although inductive loop detectors can overcome these problems, similarly to previous approaches, their area of potential density estimation is relatively small (i.e., the streets and junctions where the data acquisition devices are located), they are not fault tolerant, and, obviously, they cannot be used to mitigate broadcast storms since they do not involve wireless communications.

V2I density estimation approaches exhibit good traffic congestion control capabilities, but they are limited in other important functions such as broadcast mitigation features, or fault tolerance (e.g., whenever an RSU stops working or malfunctions, the density estimation inside its target area will become unavailable). As for V2V approaches, they can overcome all these problems, but they cannot be used to provide optimal routes to vehicles, and the vehicle density estimation is always limited, since each vehicle obtains its own neighbor density estimation. Our V2X-d architecture brings together the benefits of both approaches (i.e., V2V and V2I), providing great possibilities to authorities, transport agencies, and drivers, in terms of traffic control, travel time reduction, vehicle emissions control, as well as better and faster wireless communications.

VI. V2X-D APPLICATIONS

Our V2X-d architecture can support a wide variety of useful ITS applications. In this section we present the most remarkable ones.

- Reducing broadcast storm. Broadcasting messages blindly may lead to packet collisions and channel congestion and contention, which drastically reduces the performance of message delivery schemes [22]. Using the density estimated by means of V2V communication, the vehicles can determine when they are competing with a high number of vehicles for the channel, and thus limiting the transmission of non-critical information to avoid channel saturation.
- Avoiding traffic jams, reducing pollution emissions. The global knowledge provided by V2I communication and the information exchanged by the RSUs allow detecting areas with high traffic density prone to traffic jams. Vehicles can be informed about these areas, thus modifying their routes to reach their destination sooner.
- Reducing the emergency services arrival time to the location where an accident has taken place, routing these emergency vehicles through streets with small vehicle density, or rerouting the rest of vehicles to ease the emergency vehicles' movements.
- Collecting historical data about more frequently traveled zones, with the goal of increasing road maintenance in areas with more traffic, or allowing authorities to better plan future actions.
- Adjusting vehicle density estimation when vehicles or RSUs are no able to collect all the needed information separately. During RSU deployment, some areas may become out of reach of any infrastructure unit, creating a blind spot that will not allow achieving an accurate global estimation. Figure 3 shows an example of RSU deployment to cover a specific area with high vehicle density, presenting a blind spot in the center of the scenario out of reach from the RSUs. This could lead to discrepancies between the estimated density and the real density of vehicles located in the area. However, using the data collected by means of V2V communication, the RSUs can complete the missing information and adjust the estimation. This strategy can also be used to overcome failures in the system, such as damaged infrastructure elements, backbone errors, and so on. Having both V2V and V2I communication available helps completing the information, increasing the fault tolerance of the system.

VII. CONCLUSIONS

This paper proposes V2X-d, an architecture that allows estimating vehicle density in urban environments at any given time by combining both V2V and V2I communications. Our proposal allows improving proactive traffic congestion mitigation mechanisms to better redistribute vehicles' routes, while adapting them to the specific traffic conditions. Additionally, it allows implementing more efficient and adaptive information dissemination schemes.

Unlike existing proposals, our V2X-d vehicular density estimation architecture accounts not only for the number of beacons received, but also for the map topology in the region where the vehicles are located. We demonstrate how our

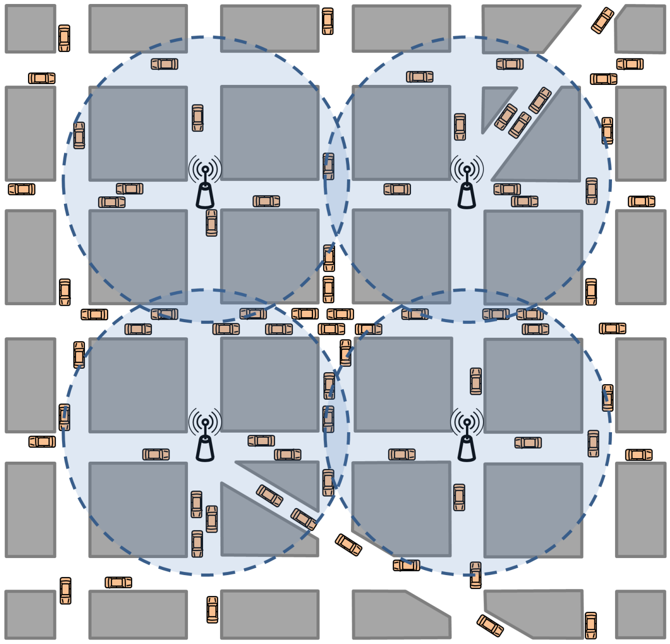

Fig. 3. Example of blind spot due to insufficient RSU deployment.

approach is able to accurately predict the vehicular density. Moreover, our proposal can solve the problems associated to existing approaches, (e.g., those caused by bad light conditions, adverse weather, etc.).

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