I-VDE: An Infrastructure-based Vehicular Density Estimation Approach

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Abstract. Road traffic is experiencing a drastic increase in recent years, thereby increasing the every day traffic congestion problems, especially in cities. Vehicle density is one of the main metrics used for assessing the road traffic conditions. Currently, most of the existing vehicle density estimation approaches, such as inductive loop detectors or traffic surveillance cameras, require infrastructure-based traffic information systems to be installed at various locations. In this paper, we present I-VDE, a solution to estimate the density of vehicles that has been specially designed for Vehicular Networks. Our proposal allows Intelligent Transportation Systems to continuously estimate the vehicular density by accounting for the number of beacons received per Road Side Unit, as well as the roadmap topology. Simulation results indicate that our approach accurately estimates the vehicular density, and therefore automatic traffic controlling systems may use it to predict traffic jams and introduce countermeasures.

Keywords: Vehicular Networks, vehicular density estimation, Road Side Unit, VANETs.

1 Introduction

Enhancing transportation safety and efficiency has emerged as a major objective for the automotive industry in the last decade [12]. However, road traffic is experiencing a drastic increase. Hence, vehicular traffic congestion is becoming a major problem, especially in metropolitan environments throughout the world. 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 [14].

Some of the factors that cause traffic congestion are badly managed roads, poorly designed roads, or bad traffic lights sequencing [13]. These factors provoke that vehicles are not uniformly distributed on the roads, making it possible to find extremely high congested areas where vehicles travel very slow or even get stuck.

In vehicular environments, wireless technologies enable peer-to-peer mobile communication among vehicles (V2V) [9], and communication between vehicles and the infrastructure (V2I) [11]. Vehicles can broadcast warning messages in case of an accident, and also periodically exchange other messages (beacons) that contain information about their position, speed, route, etc. These messages are received by the rest of vehicles and by the *Road Side Units* (RSUs), which are communication nodes installed to create a vehicular infrastructure.

Traditionally, vehicle density has been one of the main metrics used for assessing the road traffic conditions. A high vehicle density usually indicates that the traffic is congested. However, the density of vehicles circulating in a city highly varies depending on the area and the time ~~during the day~~.

Currently, most of the vehicle density estimation approaches are designed for using infrastructure-based traffic information systems, which require the deployment of vehicle detect~~ing~~ devices such as inductive loop detectors or traffic surveillance cameras. However, these approaches are limited since they can only be aware of traffic density in a very specific and reduced area (i.e., the streets and junctions in which these devices are already located), making it difficult to estimate the vehicular density of a neighborhood, or a whole city. In addition, some of these approaches are not able to perform the density estimation process in real time (e.g., using cameras involves hard image treatment and analysis).

We consider that a vehicular communications system able to estimate the traffic density in real-time could mitigate or even solve traffic congestion problems. In this work, we present a solution to estimate the traffic density on the roads that relies on the V2I communication capabilities offered by Vehicular Networks. In particular, we intend to estimate the density, taking into account the number of beacons received by the RSUs and the characteristics of the topology of the selected area. Hence, real-time traffic controlling systems can precisely estimate the vehicular density in a determined area, and then redirect vehicles to lower traffic density areas in order to avoid traffic jams. This could be possible by using the in-vehicle communication capabilities and navigation systems.

The rest of this paper is organized as follows: Section 2 reviews previous approaches related to our work, focusing on infrastructure-based solutions to estimate traffic density. Section 3 details our proposal for real-time RSU-based vehicular density estimation, assessing its goodness. Additionally, we discuss the obtained results and measure the estimated error. In Section 4 we validate our proposal. Finally, Section 5 concludes this paper.

2 Related Work

In this section we review previous works related to our proposal. In particular, we focus on the infrastructure-based solutions to estimate traffic density.

Despite the importance of determining the vehicular density to reduce traffic congestion, so far there have been few studies that explored the density estimation process.

Tyagi et al. [14] considered the problem of vehicular traffic density estimation, using the information cues available in the cumulative acoustic signal acquired from a roadside-installed single microphone. This cumulative signal comprises several noise signals such as tire noise, engine noise, engine-idling noise, occasional honks, and air turbulence noise of multiple vehicles. The occurrence and mixture weightings of these noise signals are determined by the prevalent traffic density conditions on the road segment. Based on these learned distributions, they used a Bayes' classifier to classify the acoustic signal segments spanning a duration of 5-30 s. Using a discriminative classifier, such as a *Support Vector Machine* (SVM), results in further classification accuracy compared to a Bayes' classifier. Tan and Chen [13] proposed a novel approach based on video analysis which combines an unsupervised clustering scheme called AutoClass with *Hidden Markov Models* (HMMs) to determine the traffic density state in a *Region Of Interest* (ROI) of a road. Firstly, low-level features were extracted from the ROI of each frame. Secondly, an unsupervised clustering algorithm called AutoClass was applied to the low-level features to obtain a set of clusters for each pre-defined traffic density state.

These works established the importance of vehicular density awareness for neighboring areas, but none has deepened in the analysis of the accuracy of the method used to estimate this density, or the effect of the topology in the results obtained. Moreover, this estimation does not take place in real time.

Regarding the use of Vehicular Networks, Garelli et all. [6] proposed a fully-distributed approach to the online estimation of vehicle traffic density. Their approach makes communicating vehicles to cooperate in order to collect density measurements through a uniform sampling of the road sections of interest. The proposed scheme does not require the presence of any network infrastructure, central controller or devices triggered by the passage of vehicles, and it is suitable for both highway and urban environments. Results derived through simulations show that their solution is very effective, providing accurate, on-line estimates of the traffic density with minimal protocol overhead. More recently, Akhtar et al. [1], proposed a fully distributed and infrastructure-free mechanism~~s~~ for the density estimation in vehicular ad hoc networks. Unlike previous distributed approaches, that either ~~rely~~ on group formation~~,~~ or on vehicle flow and speed information to calculate density, their proposal is inspired by the mechanisms proposed for system size estimation in peer-to-peer networks. Authors adapted and implemented three fully distributed algorithms, namely Sample & Collide, Hop Sampling, and Gossip-based Aggregation. The simulations of these algorithms at different vehicle traffic densities and area sizes for both highways and urban areas reveal that Hop Sampling provides the highest accuracy in least convergence time and introduces least overhead on the network, but at the cost of higher load on the initiator node.

Although these works studied the use of Vehicular Networks to estimate vehicular density in real time, authors did not account for the effect of obstacles in the wireless signal propagation which can make results very inaccurate, especially

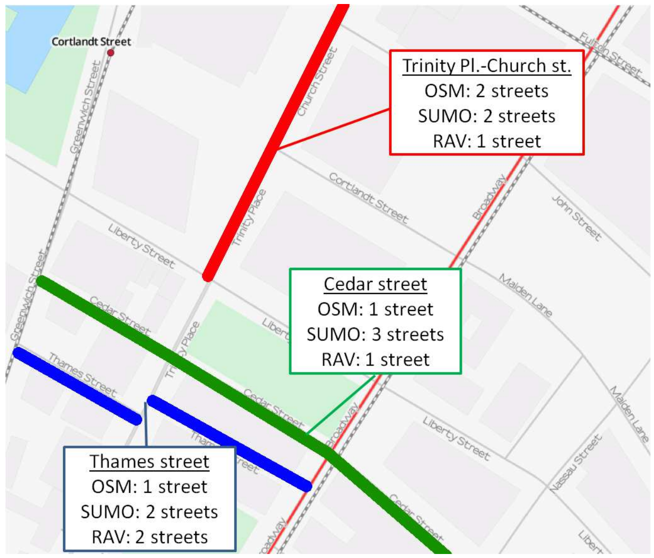

Fig. 1. Different criteria when counting the number of streets.

in urban scenarios. Moreover, they only accounted for the number of beacons received, while omitting the map features where the vehicles are located.

3 Real-Time Vehicular Density Estimation

In this work we propose a method able to accurately estimate the density of vehicles, which is based on the number of beacons received by RSUs and the roadmap topology. We made a total of 900 experiments. These experiments involved the simulation of controlled scenarios (i.e., scenarios where the actual density is known). According to the results obtained, and using a regression analysis, we propose a density estimation function capable of estimating the vehicular density in every urban environment at any instant of time.

In this section we first present a discussion about the most important features of the different city roadmaps. Later, we present the parameters and the methodology used in our simulations. Finally, we detail our proposed density estimation function, and estimate its error.

3.1 Features of the Cities Studied

The roadmaps used during the experiments to achieve the density estimation were selected in order to have different profile scenarios (i.e., with different topology characteristics).

The first step before starting the simulations was to obtain the main features of each roadmap (i.e., the number of streets, the number of junctions, the average

Table 1. Number of Streets obtained depending on the approach used

City	SUMO	OSM	RAV
New York	700	827	257
Minnesota	1592	105	459
Madrid	1387	1029	628
San Francisco	1710	606	725
Amsterdam	3022	796	1494
Sydney	1668	315	872
Liverpool	3141	1042	1758
Valencia	5154	1050	2829
Rome	2780	1484	1655

distance of segments, and the number of lanes per street). As for the streets, we realized that different alternatives could be selected to obtain the number of streets of a given roadmap. Basically, they are: (i) the number of streets obtained in SUMO [7], where each segment between two junctions is considered a street, (ii) the number of streets obtained in *OpenStreetMap* (OSM) [10], where each street has a different "name", and (iii) the number of streets according to our *Real Attenuation and Visibility* (RAV) radio propagation model, where the visibility between vehicles is taken into account when identifying the streets [5].

Figure 1 shows a small portion of New York City to depict the different criteria when counting the number of streets. For example, Thames Street is considered only one street in OSM, whereas the SUMO and RAV models consider that there are two different streets instead. However, if we observe Cedar Street, the RAV visibility model and the OSM approaches consider a single street (as expected), whereas it is represented by three different streets according to SUMO, since it has three different segments. Finally, according to both the OSM and SUMO approaches, Trinity Place and Church Street are represented as two different streets, whereas the RAV model considers that only one street exists.

Table 1 shows the values obtained according to each criterion to count the number of streets for the cities studied. As shown, the differences between these approaches are significant (e.g., New York has 700, 827, or 257 streets when considering SUMO segments, OSM streets, or the RAV visibility approach, respectively, whereas Sydney has 1668, 315, or 872 streets, depending on the selected criterion). Therefore, it is important to decide which one to use in order to obtain accurate results. After some experiments, we realized that the third approach better correlated with the real features of cities, since the other two present some drawbacks: they are not accurate enough, or they present some errors. So, we choose this approach for the analysis that follows.

Table 2 shows the main features of each map of the cities under study (i.e., the number of streets according to the RAV algorithm, the number of junctions, the average distance of segments, and the number of lanes per street). We also 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 city (New York) presents a SJ ratio of 0.5130, which indicates that it has a simple topology, whereas the last cities in the table present a SJ greater value, which indicates a

Table 2. Map Features

Map	Streets	Junctions	avg. segment distance (m.)	lanes/street	SJ Ratio
New York	257	500	45.8853	1.0590	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
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
Rome	1655	1193	45.8853	1.0590	1.3873

more complex topology. This aggregated factor correlates well with the obtained results.

3.2 Simulation Environment

Simulations were done using the ns-2 simulator [3], where the PHY and MAC layers have been modified to follow closely the IEEE 802.11p standard, which defines enhancements to the 802.11 required to support ITS applications. We assume that all the nodes of our network have two different interfaces: (i) an IEEE 802.11n interface tuned at the frequency of 2.4 GHz for V2I communications, and (ii) an IEEE 802.11p interface tuned at the frequency of 5 GHz for V2V communications. In terms of the physical layer, the data rate used for packet broadcasting is 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.

To prove how maps affect the performance of vehicular communications, we selected nine street maps, each one representing a square area of 4 km^2. Figure 2 shows the topology of the maps used in the simulations. In order to deploy RSUs in the maps, we use the Uniform Mesh deployment policy [2], that 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 positioned too closely, or too sparsely.

As for the mobility of the vehicles, it has been performed with *CityMob for Roadmaps* (C4R) [4], a mobility generator able to import maps directly from OpenStreetMap [10], and generate ns-2 compatible traces. Table 3 shows the parameters used for the simulations.

We tested our proposal by evaluating the performance of a Warning Message Dissemination mechanism, where each vehicle periodically broadcasts information about itself or about an abnormal situation (traffic jams, icy roads, etc.). To increase the realism of our results, we include the possibility that vehicles share accident notification messages in our simulations. In fact, we consider that vehicles can operate in two different modes: (a) warning, and (b) normal. Vehicles in

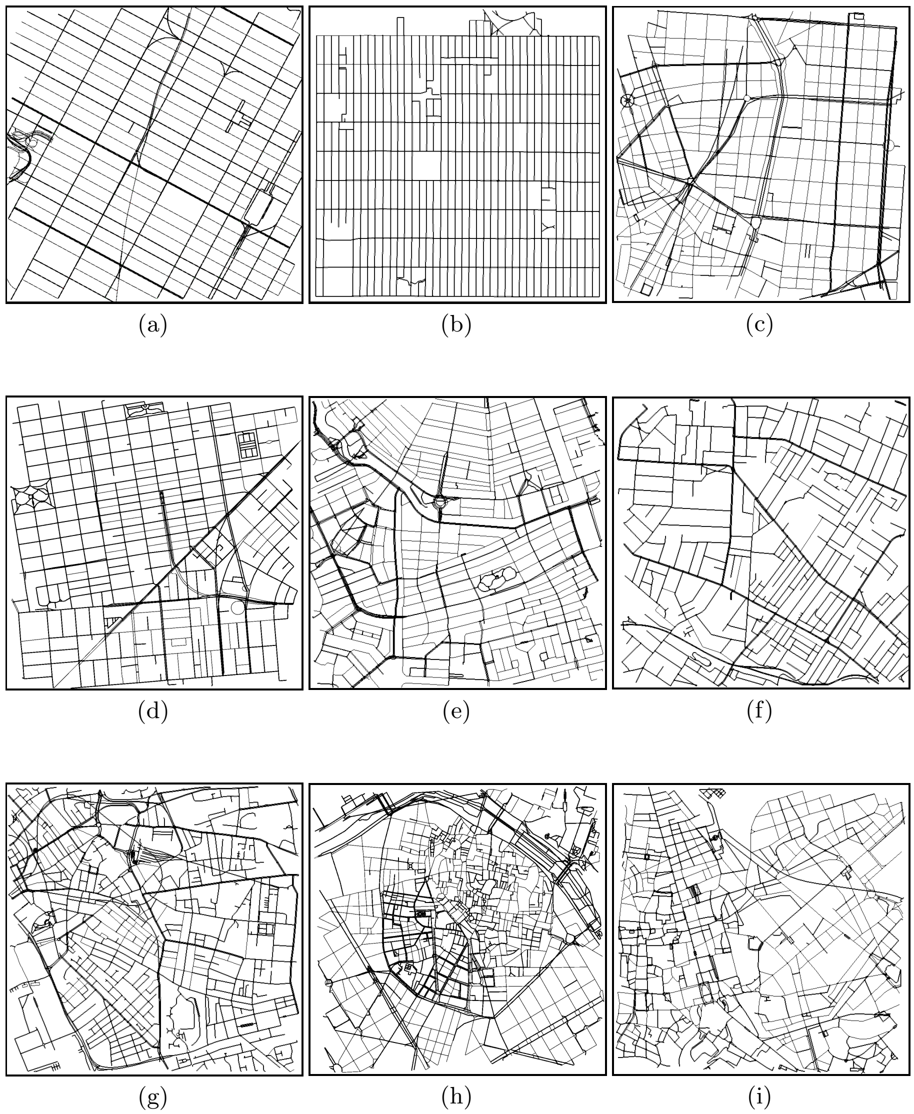

Fig. 2. Scenarios used in our simulations. Fragments of the cities of: (a) New York (USA), (b) Minnesota (USA), (c) Madrid (Spain), (d) San Francisco (USA), (e) Amsterdam (Netherlands), (f) Sydney (Australia), (g) Liverpool (England), (h) Valencia (Spain), and (i) Rome (Italy).

Table 3. Parameters used for the simulations

Parameter	Value
roadmaps	New York, Minnesota, Madrid, San Francisco, Amsterdam, Sydney, Liverpool, Valencia, and Rome
roadmap size	$2000m \times 2000m$
number of vehicles	$[100, 200, 300...1000]$
beacon message size	$512B$
warning messages priority	$AC3$
beacon priority	$AC1$
interval between messages	1 second
number of RSUs	9
RSU deployment policy	Uniform Mesh [2]
MAC/PHY	802.11p
radio propagation model	RAV [5]
mobility model	Krauss [8]
channel bandwidth	$6Mbps$
max. transmission range	$400m$

warning mode inform other vehicles about their status by sending warning messages periodically (every second). Normal mode vehicles enable the diffusion of these warning packets and, every second they also send beacons with information such as their positions, speed, etc. These periodic messages are not propagated by other vehicles.

All the results represent an average of over 10 repetitions with different scenarios, and each simulation run lasted for 30 seconds.

3.3 Density Estimation Function

After performing the topological analysis of the studied maps, we obtained the number of beacons received by each RSU during 30 seconds, taking into account that each vehicle sends one beacon per second, and that these messages, unlike warning messages, are not disseminated by the rest of the vehicles.

Figure 3 shows the results obtained for the different cities studied. As shown, the performance in New York and Minnesota in terms of number of beacons received highly differs from the rest of the cities. This is caused because New York and Minnesota have a low SJ ratio (i.e., they are simple roadmaps). As expected, complex roadmaps (maps which have a higher SJ Ratio) present a number of beacons received lower than simple roadmaps for a similar vehicular density. Figure 3 also shows that the vehicular density not only depends on the number of beacons received, but also on the SJ ratio (according to data shown in Table 2). Therefore, the characteristics of the roadmap will be very useful in order to accurately estimate the vehicular density in a given scenario.

After observing the direct relationship between the topology of the maps, the number of beacons received, and the density of vehicles, we proceed to obtain a function to estimate, with the minimum possible error, each of the curves shown in Figure 3. To this purpose, we performed a regression analysis that allowed us to find a polynomial equation offering the best fit to the data obtained through

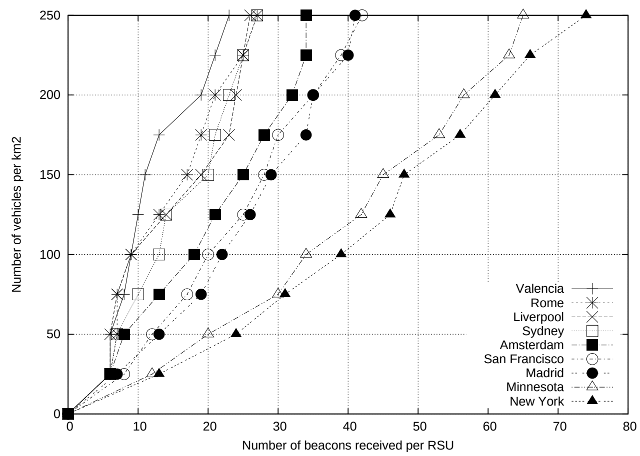

Fig. 3. Number of beacons received when varying the vehicular density.

Table 4. Proposed equation coefficients

Coeff.	Value
a	2.4328753582642619E+02
b	8.8667060945557523E+00
c	-4.2340086242746855E+02
d	3.2563178030488615E+01
f	1.8200236614892370E+02
g	-6.4626326366022894E+01

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 per RSU, and the SJ ratio (i.e., streets/junctions).

$$f(x,y) = a + b \cdot ln(x) + \frac{c}{y} + d \cdot ln(x)^2 + \frac{f}{y^2} + \frac{g \cdot ln(x)}{y} \qquad (1)$$

In this equation, x is the number of beacons received by each RSU, and y is the SJ ratio obtained from the roadmap. The values of the polynomial coefficients $(a, b, c, d, f,\ and\ g)$ are listed in Table 4.

To determine the accuracy of our proposal, it is necessary to measure the estimated error. Table 5 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 3.63%. We consider that this error can be neglected in the majority of traffic congestion mitigation applications, thus validating our proposed function.

Table 5. Density Estimation Error

Error	Absolute	Relative
Minimum	-5.736426E+01	-1.218902E+00
Maximum	5.135632E+01	1.784647E+00
Mean	-1.642143E-14	3.634060E-02
Std. Error of Mean	2.596603E+00	3.592458E-02
Median	-1.914503E+00	-2.313015E-02

Table 6. 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**	-

4 Validation of our Proposal

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. Figure 4 shows the RSU deployment strategy and the vehicles' location at the end of the simulation for the studied example, and Table 6 shows the obtained results. As shown, the average number of beacons received per RSU is 47.56. According to I-VDE (i.e., applying the polynomial function as shown in Equation 2), 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 1.51% of the total vehicles.

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

Moreover, using our system, we are able to estimate the vehicular density in more specific areas. For example, using the data included in Table 6, our I-VDE 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.

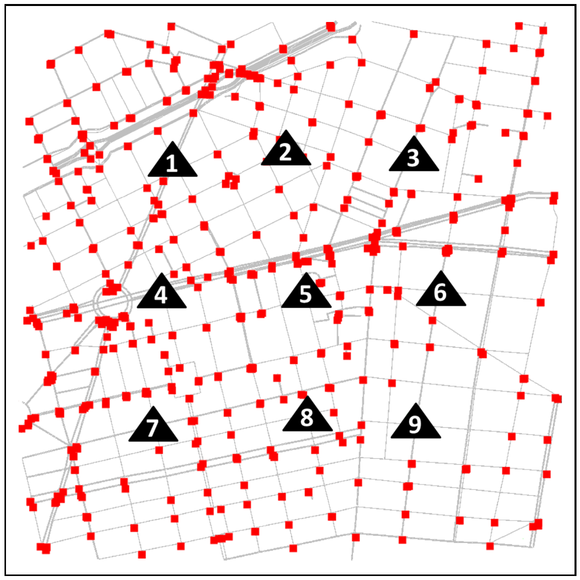

Fig. 4. RSUs deployment and vehicles location at the end of the simulation.

5 Conclusions

This paper proposes I-VDE, a method that allows estimating the vehicular density in urban environments at any given time by using the communication capabilities between vehicles and RSUs. Our proposal allows improving traffic congestion mitigation mechanisms to better redistribute the vehicles routes, adapting them to the specific traffic conditions.

Unlike existing works, our vehicular density estimation algorithm takes into account not only the number of beacons received by the RSUs, but also the topology of the map where the vehicles are located. As a result of a large number of simulations, using maps from different cities, we have obtained an equation that is able to accurately predict the vehicular density. Results show that our proposal allows estimating the vehicular density for any given city with a high accuracy, thereby allowing governments to improve their traffic control mechanisms.

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