

MobSampling: V2V Communications for Traffic Density Estimation

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Abstract—We propose a fully-distributed approach to the on-line estimation of vehicle traffic density. Our approach envisions vehicles communicating within a VANET and cooperating 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 ns-2 simulations in realistic mobility scenarios show that our solution is very effective, providing accurate, on-line estimates of the traffic density with minimal protocol overhead.

I. INTRODUCTION

The estimation and prediction of vehicle traffic over highways and urban areas is deemed to play a major role in the improvement of travel times and reduction of road congestion in future transportation systems. Today's solutions for the measurement of traffic levels mainly involve mechanical techniques, such as piezoelectric sensors or magnetic loop detectors deployed under the road surface, roadside infra-red or radar counters, surveillance cameras, or even manual counts. However, these technologies suffer from limited coverage, low reliability, high likeliness to be damaged (leading to short life expectancy), as well as high deployment and maintenance costs [1].

As more performing vehicular traffic monitoring solutions are sought, the growing availability of user-generated data is seen as an opportunity to improve the existing estimation techniques. Novel approaches are emerging, which exploit Floating Car Data (FCD), i.e., information about GPS localization or cellular handoffs of users aboard vehicles, so as to improve real-time traffic estimates [2]. However, even these top-notch technologies require infrastructure-based communication and centralized data processing, which imply high costs, significant computational complexity, and non-negligible latencies. Moreover, the accuracy of FCD-based traffic estimation is still improvable.

In such a context, vehicle-to-vehicle (V2V) communication has the potential to revolutionize the way information about road traffic volumes is gathered, processed and disseminated [3]. Indeed, direct data transfers among moving vehicles would make it possible to determine traffic densities in a distributed fashion, without the need for sensors, cameras or roadside telecommunication infrastructures. This would significantly reduce both costs and delays while increasing the precision of the estimate.

In this paper, we propose MobSampling, a lightweight, fully-distributed, V2V-based technique for the real time assessment of vehicular densities in localized areas of a road topology, with a good accuracy. Such an information could be used locally by the vehicles to, e.g., take driving decisions at intersections, or by dynamic traffic lights or signs to adapt maximum speed limits, green/red light periodicity and on-ramp metering to the actual level of traffic. If the traffic density information is instead propagated in the vehicular network or conveyed to some central controller, it can be exploited to derive better estimates of the overall road traffic, and thus to inform drivers about the shortest route to destination. Applications of MobSampling beyond transportation are also foreseeable: e.g., the same data, coupled with information on the vehicle type, could be exploited to monitor CO₂ emissions in different areas of a metropolitan region.

The paper is organized as follows. After a discussion of related works in Sec. II, we introduce the system model in Sec. III. Then, in Sec. IV, we present the MobSampling scheme and in Sec. V we show its good accuracy in different road and traffic scenario. Sec. VI summarizes our findings and points out future research directions.

II. RELATED WORK

Most of the existing intelligent transportation systems (ITS) for traffic estimation require the use of dedicated infrastructure indicating the presence or passage of vehicles (e.g., loop detectors, roadside sensors and cameras). The high deployment and maintenance costs involved in the use of such devices has motivated several studies that aim at minimizing the number of devices and optimizing their placement (see e.g., [1]).

Few, recent works exploit V2V and vehicle-to-infrastructure (V2I) communications for vehicular traffic estimation. The majority of them, however, present infrastructure-centric approaches and focus on information-fusion techniques, i.e., how to combine measurements coming from different sources in order to estimate some traffic parameters of interest. As an example, the study in [4] presents a data fusion algorithm that combines measurements from loop detectors and GPS-equipped taxi cabs, and computes the vehicle density or mean speed over a road section. The work in [5], instead, resorts to cellular phones to transfer measurements to roadside infrastructure and compute vehicles speed on a freeway, while in [6] V2I communications are used to collect measurements on speed, as well as speed and lane changes, and detect

anomalies in traffic conditions (e.g., queues or accidents). Unlike the above studies, in our work we do not require, for either data transfer or measurements collection, the availability of any infrastructure node; rather, we fully exploit vehicle cooperation for a distributed collection of the samples.

Cooperation among vehicles is exploited in [7], [8], which are the most relevant works to ours. In particular, [7] proposes a distributed vehicle density estimation scheme: a road segment is divided into multiple fixed-size cells and, within each cell, a probe vehicle, called group leader, computes the number of vehicles. The leader then exchanges such a measurement with other group leaders so as to obtain the average density on the road. The scheme in [8] is still based on a neighbor density estimation, but it does not require a fixed cell size. There, the authors compute the local density as the ratio of the number of vehicles in the range of the probe vehicle to the transmission range. They found that, if inter-vehicle spacing is exponentially distributed, then the local density can be considered to be a good estimate of the global density. Like [8], our approach does not require fixed-sized cells and lets the probe vehicle take samples of the density anywhere within the area of interest. However, while the method in [8] exhibits low accuracy in sparse networks as well in presence of inhomogeneous density conditions, the approach we propose effectively exploits V2V communications to uniformly sample a target area, proving to be extremely accurate in several different conditions.

III. SYSTEM MODEL

We envision a Vehicular Ad hoc NETWORK (VANET) composed of vehicles, each equipped with a IEEE 802.11-like interface with nominal transmission range R_C , identical for all nodes, and a global positioning system device, such as a GPS receiver. For ease of description, in the next section we consider that all vehicles in the target area participate in the VANET¹. We define as target area the geographical region where we are interested in estimating the vehicle traffic density during a period of time called *estimation period*, T . Without loss of generality, we assume that such an area is a circle of radius R_A centered at a target location.

The task of sampling the vehicular density in the target area is started by a (fixed or mobile) source node, possibly far away from the target location. Such a procedure is initiated when the source node generates a “sampling kit”, in the form of a data packet including the target location and the radius R_A , the map of the road topology inside the target area, and the different parameters driving the sampling process. The sampling kit is then transferred to the target area by means of a geocasting routing protocol [9]. The first vehicle in the target area receiving the sampling kit becomes the Sampler.

When the Sampler is about to leave the target area, it hands over the sampling kit (hence the role of the Sampler)

¹In Sec. V, we show through simulation that, given a penetration estimate of the technology (i.e., a percentage of vehicles with communication capabilities and implementing the application), an accurate estimate of the vehicle density is obtained even when such an assumption is dropped.

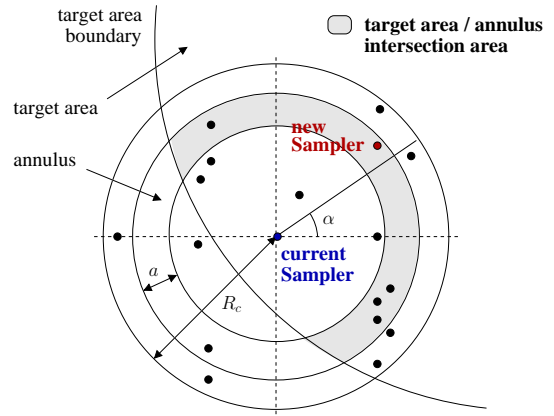


Figure 1. Example of the new Sampler selection when the radio proximity of the old Sampler is not fully contained in the target area. The shaded area represents the intersection of target area and annulus of width a

to another, more suitable vehicle, as detailed below.

IV. MOB SAMPLING

The Sampler is in charge of the following two tasks: *role switching* and *density estimation*. The role switching is the procedure by which the sampling kit is handed over to another vehicle, selected among those which, given their position and movement pattern, are better suited as new Samplers. The density estimation refers to the process of initiating and collecting messages from nearby vehicles, used to estimate the traffic density.

A. The role-switching procedure

Role switching is triggered when the current Sampler is about to exit the target area. Upon such an event, the Sampler broadcasts an ADVERT message that carries the position and range of the target area. Vehicles receiving an ADVERT will reply with a unicast message called BID, if they detect their location as being inside the target area. A BID includes the identity and position of the message sender, and its transmission time is randomized to avoid flooding the receiver.

Based on the received BIDs, the current Sampler selects as the next Sampler the vehicle (i) that is inside an annulus uniformly extracted in the area in its radio proximity and of fixed width $a < R_C$, and (ii) that is as close as possible to a random angle α uniformly extracted in $[0, 2\pi)$. Note that if the Sampler’s radio proximity is not fully contained within the target area, the above random values are extracted within the intersection between the two regions. If no vehicle exists within the annulus, the one closest to it is selected, regardless of its angular position. An example of the the new Sampler selection is depicted in Fig. 1.

We stress that the selection procedure has a significant impact on the performance of the sampling process. Indeed, if a simple approach (such as one based on gossip algorithms) were adopted, the Sampler would end up being selected randomly among all the vehicles that sent a BID. However, this procedure would confine the information in areas with higher

vehicular densities (e.g., around a traffic light), sampling some regions inside the target area with very low probability. To avoid such an effect, in our algorithm we prefer to randomize the distance between the old and the new Sampler rather than their relative angular position.

After selecting a new Sampler, the old one hands it the sampling kit, enriched with records of density estimates computed up to that moment. Note that, in case the Sampler gets too far out with respect to the target area, i.e., its radio range and the target area become disjoint, it gives up the sampling role and resorts to geocasting in order to return the sampling kit inside the area.

B. The density estimation

We now focus on the estimation activity of the current Sampler, which samples the vehicle density at random intervals, whose duration is uniformly distributed with mean equal to τ seconds.

At each sampling instant, the Sampler broadcasts a POLL message, including the center position and the radius of the target area. Any vehicle that receives the POLL and is within the target area will respond to the sender with a REPLY message; the REPLY transmission time is again randomized to avoid flooding the receiver.

For every issued POLL i , the Sampler uses the number r of returned REPLYs and its own position at the POLL broadcast time t_i , to compute the instantaneous vehicle lane density as:

$$\delta(t_i) = \frac{r + 1}{L_s \cdot l}. \quad (1)$$

In (1), L_s denotes the sampled lane length, while l denotes the number of lanes. Indeed, recall that the Sampler knows the map of the road topology inside the target area, thus, based on its own position, it is capable of computing the number and the length of the lanes that are in the intersection between its radio range and the target area, upon the POLL broadcast. Also, the number of REPLYs is incremented by one in order to take into account that, apart from the vehicles that sent a REPLY, the Sampler itself is inside the sampled area.

Given the estimation period $[t, t + T)$ over which one is interested in computing the lane density estimation, the resulting value is obtained as the temporal average of the estimates in (1), i.e.,

$$\bar{\delta} = \frac{\sum_{t_i \in [t, t+T)} \delta(t_i)(t_{i+1} - t_i)}{T}. \quad (2)$$

The value $\bar{\delta}$ can then be returned to the source node via geocasting, or distributed to vehicles in the VANET.

V. PERFORMANCE EVALUATION

We implemented our algorithm as well as the communication protocol in the *ns-2* simulator. We consider that each vehicle is equipped with a 802.11 interface, whose data rate is forced to the basic rate so as to ensure maximum reliability of transmissions. The nominal radio range is set to 100 m, a value that is consistent with recent experimental results on V2V communication [10]. Vehicles are also equipped with a GPS

receiver, allowing their position information to be updated every second.

The vehicular mobility was generated with VanetMobiSim, a well-known, validated, microscopic-level simulator of car traffic [11]. In particular, we employed the IDM-LC car-following model, which accounts for car-to-car interactions, overtakings and road signaling. We study two street layouts, representing a highway environment and a urban crossroad, respectively. The former is a straight 2 km-long road section with two lanes in each direction, where drivers travel at speeds from 70 to 130 km/h, according to their attitude as well as to traffic conditions. The latter is an intersection with four incoming roads and traffic lights regulating the car flows, where drivers' speed ranges between 35 and 50 km/h.

As far as the MobSampling configuration is concerned, we set $\tau = 10$ s, $a = 40$ m, while we chose the transmission jitter for REPLY and BID messages as a value uniformly distributed between 0 and 0.1 s. These settings were identified as the best configuration after extensive sampling of the parameter space through simulation. In each simulation, the sampling kit is generated by a source randomly located over the road topology, and it is given an estimation period T equal to either 3 or 15 minutes. The geocasting technique we use to route the sampling kit toward the target area is the scheme in [9]. Also, we set the target area radius to $R_A = 200$ m.

The combination of mobility environment and position of the target area heralds three evaluation scenarios:

- **highway**: the target area is centered at the middle point of the road segment of the highway environment;
- **urban road**: the target area is centered at one of the incoming roads in the crossroad environment, and does not include the intersection;
- **intersection**: the target area is centered at the intersection in the crossroad environment.

In all these scenarios, results are obtained by averaging over five runs, each simulating 15 minutes of traffic.

We first evaluate the performance of MobSampling over periods of 15 minutes, i.e., by averaging results over the duration of a whole simulation run. We consider the three different evaluation scenarios, in Fig. 2(a), Fig. 2(b), and Fig. 2(c), respectively: in each scenario, we vary the per-road vehicular inflow, i.e., the volume of vehicles entering the area under study from each road. As increasing inflows induce higher vehicular densities, varying such a parameter allows us to control the density of car traffic in the region².

From Fig. 2, we can note that MobSampling provides a very accurate estimate of the actual average value of the vehicular lane density, under all combinations of evaluation scenarios and inflow volumes. As expected, both actual and estimated densities grow along with the vehicular inflow. However, we can notice that such a growth is steeper in the intersection scenario: there, the presence of two crossing roads in the target

²Note that per-road inflows in the urban environment are approximately halved with respect to those in the highway environment: this setting is chosen so as to have comparable densities in the two environments, although the car speed is much higher in the latter than in the former.

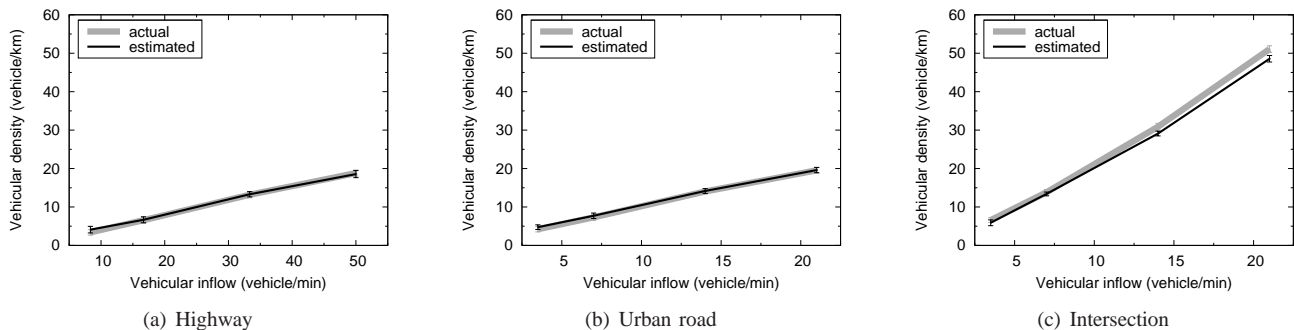


Figure 2. Actual and estimated vehicular density: averages over 15 minutes versus the traffic inflow volume, in presence of different evaluation scenarios

area, jointly with the fact that traffic becomes slower at the bottleneck represented by their junction, results in longer and longer queues as the inflow volume is reinforced.

In a second set of tests, we increase the granularity of observations, by requesting estimation periods of $T = 3$ minutes. In Fig. 3 we observe that MobSampling is still capable of providing estimates that are fairly accurate with respect to the actual vehicular densities measured during the 3-minute long intervals. Again, such a consideration holds throughout the different evaluation scenarios and inflow volumes.

We then further increase the granularity level, bringing it to the maximum allowed, i.e., the sampling interval. In this case, estimates do not represent an average, rather, the outcome of single instances of the protocol. In Fig. 4 we detail the results for different inflows, in presence of the Intersection scenario only, due to space limitations. The choice of this scenario is motivated by the fact that the actual vehicular density tends to vary more rapidly and significantly at crossroads than along roads, making the Intersection scenario the most challenging for the instantaneous tracking of the traffic density.

This notwithstanding, the results in Fig. 4 show that MobSampling generates accurate estimates of the instantaneous vehicular lane density in the target area, even on the basis of a single observation. Indeed, the estimated traffic density nicely follows the actual one in its fast variations over time.

The overhead of the MobSampling communication protocol is presented in Fig. 5(a). The plot refers to the Urban road scenario, but similar results were obtained in the two other scenarios as well. The outcome is that MobSampling induces minimal load in the network: even in presence of high inflows (and thus high traffic densities), the overhead of REPLY and POLL messages is in the order of a few tens of bytes/s.

As far as the impact of the transmission range on the performance of the protocol is concerned, we stress that the default value of the radio range employed in the previous tests, i.e., 100 m, implies that the sampler vehicle receives REPLY messages only from a subset of the vehicles in the target area, whose range is 200 m. More precisely, the POLL messages reach at most one fourth of the surface of the target area, when the Sampler coverage area is completely within the target area. The effect of such a sub-sampling is studied in Fig. 5(b), which portrays the actual estimated lane densities when the

radio range varies from 50 to 200 m. The results refer to the Intersection scenario, which, as already discussed, is the most challenging from the point of view of the estimation precision. From the plot, it is clear that increasing the transmission range yields a better performance, since the set of sampled vehicles grows accordingly. Nonetheless, even with a small radio range of 50 m, which covers at best 1/16 of the target area, estimates are accurate at low inflows and have acceptable errors (15 to 20% of the actual value) at high inflow volumes. The fact that MobSampling only overestimates the actual density is due to a slight bias in the spatial sampling toward more crowded areas.

Finally, we comment on the effect of the market penetration rate of the V2V communication technology and/or of the MobSampling application. Fig. 5(c) shows the actual and estimated vehicular density as 30 to 100% of the vehicles are involved in the estimation process, and assuming that such a penetration rate is known. The considered scenario is the Urban road, but similar results were obtained in the other cases (omitted due to space limitations). It is quite clear that the quality of the estimation is not affected by the percentage of vehicles participating in the network, as long as the penetration ratio of the application among vehicles is accurate.

VI. CONCLUSION

In this paper, we proposed a framework for sampling and estimation of vehicle traffic density in highway and urban environments, called MobSampling. Our approach exploits vehicle mobility and V2V communication to uniformly sample areas of interest. MobSampling is a fully-distributed, lightweight scheme, which does not require the presence of any infrastructure, nor a complete penetration ratio of the technology. Results derived through ns-2 simulation in realistic mobility settings showed the excellent accuracy achieved by our solution as the vehicle density and the time granularity used to compute the estimate vary.

Future work will evaluate the performance of MobSampling in larger, more complex road topologies, as well as with real-life mobility traces. Also, other techniques for computing lane densities and their average values will be investigated.

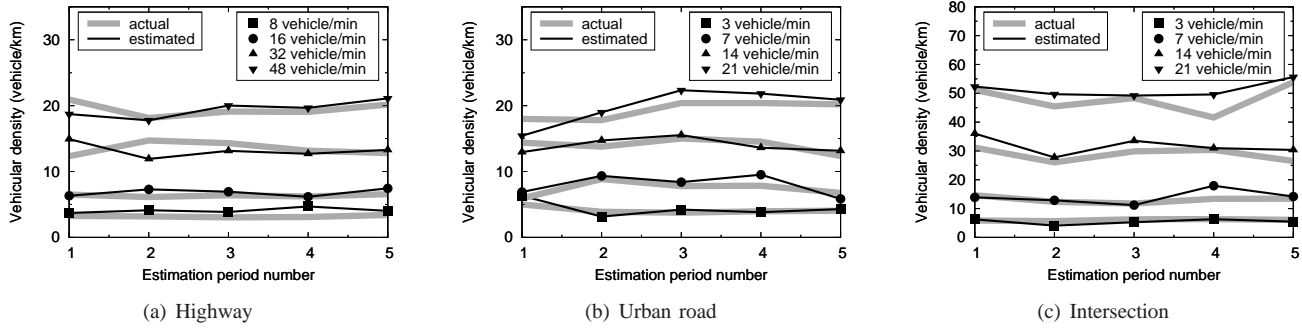


Figure 3. Actual and estimated vehicular lane density: averages over 3 minutes, in presence of different evaluation scenarios and traffic inflow volumes

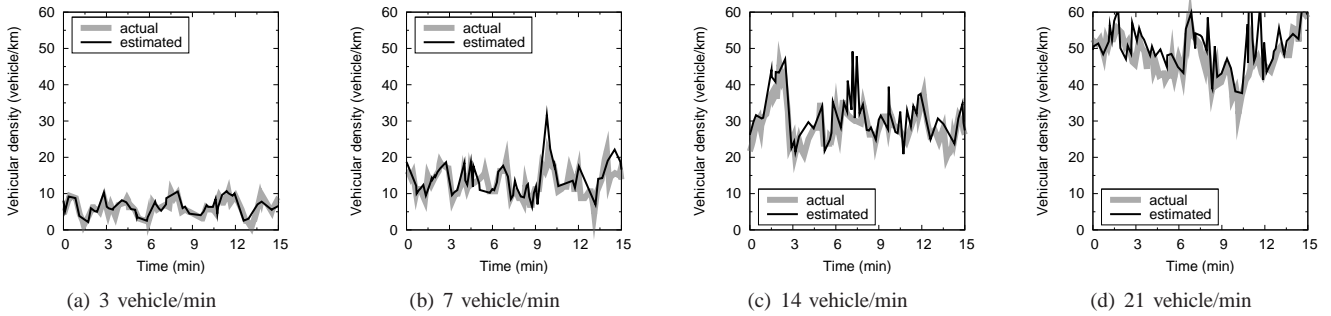


Figure 4. Actual and estimated vehicular lane density: instantaneous (frequency $1/\tau$) result in the Intersection scenario with different traffic inflow volumes

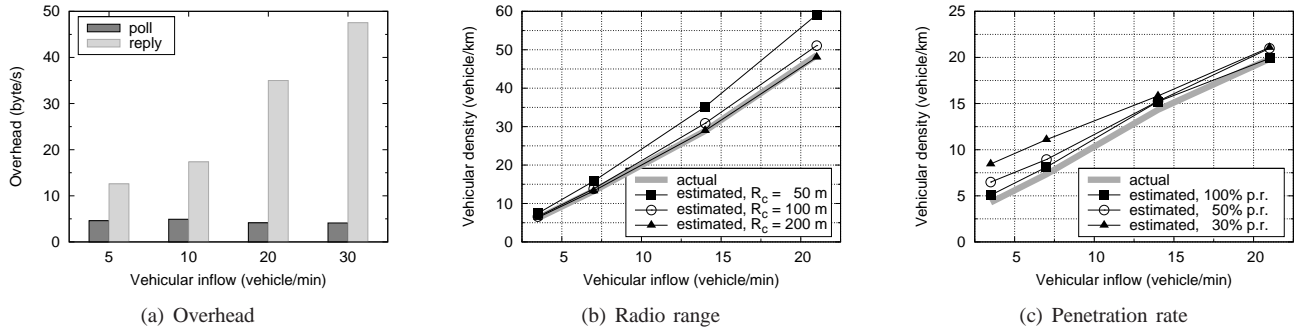


Figure 5. Overhead of the MobSampling communication protocol and impact of transmission rate and market penetration on the estimated vehicular density

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