Real-Time Traffic Monitoring using Wireless Beacons with the Cell Transmission Model

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***Abstract*— One of the exciting emerging uses of DSRC/WAVE technology is the ability to monitor real-time road traffic conditions with high resolution, using beacons transmitted by individual vehicles, and make informed traffic control decisions such as traffic light timing or route advice. However, previous studies have shown that achieving a high level of accuracy in traffic density estimation requires very frequent beacon transmissions as well as a high adoption rate of the technology, which raises a scalability problem in dense urban settings and effectively requires a dedicated radio transceiver, precluding the wireless channel from being used for any other purpose at the same time. In this paper, we propose an approach that allows the wireless channel load due to beacon transmissions to be significantly reduced while retaining very low traffic estimation error levels, by using tools from traditional traffic theory (such as the Cell Transmission Model, CTM) to analyze position and speed signals from infrequent wireless beacons and predict the dynamics of the traffic behavior in between. Our approach is evaluated in a typical urban scenario consisting of a signalized intersection of multiple-lane roads, leading to new insights about how the value of the information in vehicles' beacons depends strongly on their location with respect to the intersection.**

I. Introduction

Recent years have evidenced a growing interest in intelligent traffic information systems (TIS) where current traffic state information is applied towards purposes such as incident detection and travel time prediction [1]. While the traffic information can be fused from a variety of sources, ranging from traditional loop detectors to cameras and probe vehicles [2], increasing attention is devoted to systems where real-time traffic information is communicated from the vehicles themselves. Some studies have considered a macroscopic view of the impact of vehicular communication on road operations generically, abstracting the complexity of any particular communication layer [3], while others focused on detailed protocol design either using cellular communications [4], [5] or, more recently, using the Direct Short-Range Communications (DSRC) technology, based on the IEEE 802.11 physical (PHY) and medium-access (MAC) communication layers and the IEEE 1609 Wireless Access in Vehicular Environments (WAVE) standards for higher layer functionalities [6], [7]. With vehicles using DSRC to transmit regular 'beacons' with their position and speed, very fine-grained traffic information can be collected, analyzed, and used for traffic decisions in real time, either by roadside infrastructure units (RSU) or other vehicles overhearing the beacon messages [8], [9]; more recently, an adaptive beaconing protocol was studied in [10], based on perceived "message utility", or the amount of new information contained in a beacon message.

However, if a high level of accuracy is required for the real-time traffic monitoring then the beacon communication overhead may be quite substantial. For example, our recent study of a typical urban signalized intersection scenario, with an RSU employing a simple beacon-counting algorithm to assess the number of vehicles in its communication range in each 1-sec interval, demonstrated that a rate of 10 beacons per second is required to bring the average vehicle density estimation error below 1% [11]. This significant "over-sampling" is required to combat the high rate of beacon packet losses due to the the adverse outdoor radio environment and the hidden node effect. Clearly, such a high beaconing rate is not scalable in dense urban situations, leading to a high radio channel occupancy which effectively precludes its use for other applications. Moreover, any estimation algorithm based on counting of beacons can only assess the number of cars equipped with DSRC technology, and therefore requires a high rate of adoption in order to be effective.

Motivated by the above, in this paper we explore a low-overhead traffic monitoring approach that uses beacons transmitted with a relatively low frequency, combined with the Cell Transmission Model (CTM) traffic model [12] to fill in the vehicle density estimates in between. Alternatively, our traffic estimation approach can be viewed in control-theoretic terms as a system that plays out the CTM dynamic equations with a partial feedback loop from the occasional beacons. Following up on the scenario of [11], we conduct an in-depth simulation study which compares the estimated traffic density values to the actual traffic traces, and sheds light on the level of estimation accuracy that can be achieved with this approach, as opposed to the basic method of beacon

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counting.

Our contribution consists of two parts. Initially, we evaluate how the accuracy of the traffic estimation is improved when the kinematic information (namely, vehicle speed) contained in each beacon is taken into account, by applying the Drew and the Pipes-Munjal models for the speed-density relationship [13], [14]. We show that, even with just one beacon per vehicle per estimation interval, this technique matches the same low estimation error that is only attained by beacon counting with significant oversampling, while reducing the beacon message load by an order of magnitude. We then consider traffic estimation with even lower beaconing rates (i.e. less than one beacon per estimation interval) and show that the low error rate can be maintained using the dynamic equations of CTM [12] to model the vehicle propagation between the beacon transmissions. In the process, we find that certain locations have a disproportionately higher impact on the estimation accuracy, due to the effect of the initial conditions on the CTM model. This leads us to suggest that an adaptive beaconing strategy with a location-dependent beaconing rate will achieve the most efficient tradeoff between wireless channel load and the resulting accuracy of the traffic monitoring application.

The rest of the paper is structured as follows. Section II describes the simulation framework and explains the scenario used in our evaluation. Section III evaluates the technique based on kinematic (speed) information and the theoretical relationship between speed and density. Section IV presents the results for estimation using a low beaconing rate in conjunction with CTM. Finally, Section V concludes the paper.

II. Simulation framework

We simulate a typical basic block of an urban traffic network, consisting of a signalized intersection with four road segments (Fig. 1), with a 3-lane horizontal (east-west) and 2-lane vertical (north-south) road segments carrying unidirectional traffic flows set to near-saturation levels (determined according to the capacity of the intersection) of 2700 vehicles/hour and 1800 vehicles/hour, respectively. The traffic light is switched periodically with $t_{cycle} = 100$, $t_{red} = 50$ and $t_{green} = 50$ seconds. The speed limit is set to 20m/sec and the average driver reaction time is 1 sec. Using these traffic parameters, we obtain a large number of independent traffic mobility traces (i.e. corresponding to different random seeds) from the Paramics traffic micro-simulator. Each mobility trace is then recreated in a network simulation conducted on the Veins framework [15], which implements the DSRC protocol in the OMNeT++ discrete event simulator and uses MiXiM for the physical layer modelling. For the wireless vehicle-to-infrastructure (V2I) communication parameters such as carrier sensing, channel switching, and MAC-layer queue management, we use the optimal combination of settings as explained in [11]. Each node (vehicle) in the network simulation transmits beacon messages with a certain regular period, and an RSU, positioned at the intersection, receives these messages — subject to limitations of reception range, channel losses and collisions due to the hidden-node effect — and uses them to estimate the traffic density.

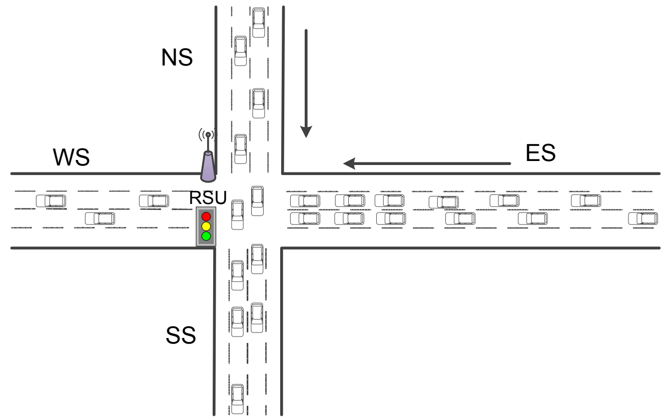

Fig. 1: Traffic scenario

III. Estimation using kinematic information

In our previous work [11], we focused on a simple estimate of the overall occupancy (i.e. number of vehicles) in the communication range of the RSU, obtained via a simple count of the number of unique beacons received within a density estimation interval, which is set to 1 sec. In this context, the estimation error corresponding to a given estimation interval is calculated as $err = \frac{k_{trc} - k_{sim}}{k_{trc}}$, where k_{sim} and k_{trc} are the density estimated by the RSU and the actual density of the traffic traces, respectively. Fig. 2, quoted from [11], demonstrates that the average estimation error can be brought down to under 1%; however, this is only achieved when the beaconing frequency is high, and, moreover, requires certain changes from the default DSRC parameter settings — most notably, introducing a random jitter to the timing of each beacon transmission, so as to overcome the hidden node effect and maximize the probability of at least one beacon from each node to be received.

In this work, we move beyond simple counting of beacons by the RSU, and make a more sophisticated use of the information contained within the beacons, by drawing upon traffic modeling theory and using well-established models for the relationship between traffic density and speed. A good detailed discussion of a wide range of speed-density models in the traffic modeling literature can be found in [16]. Broadly, these can be categorized as *single-regime* models and more sophisticated *multi-regime* models, where the latter use different separate formulas for the speed-density relationship depending on the state of the traffic. For our purposes, we use two well-known single-regime models, namely the Drew and the Pipes-Munjal models [13], [14]. In both of these models, the instantaneous speed v is related to the density k by the following expression:

$$v = v_f \left(1 - \left(\frac{k}{K_j}\right)^n\right) \tag{1}$$

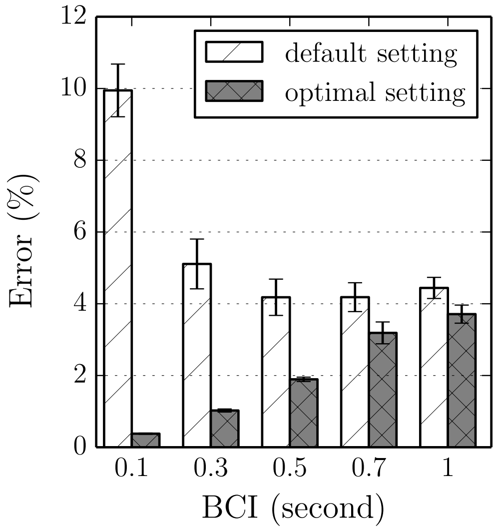

Fig. 2: Density estimation error by beacon counting, as a function of beaconing interval (BCI).

where v_f is the free-flow road speed and K_j is the jam density (measured in vehicles per meter). The exponent n is a model parameter, which is equal to $\frac{1}{2}$ for the Pipes-Munjal model; for the Drew model, it is set according to the calibration experiments reported in [17, p.212], resulting in a value of $n = 0.6$. As we shall see, the choice of the exponent n has a significant consequence on the ultimate accuracy when the models are used in the traffic density estimation context.

To apply the speed-density formula in different road locations, we use the concept of *cells* introduced by the Cell Transmission Model (CTM) [12], and adopt a similar traffic model to that used in the CTM linear programming approach of [18] and the CTM time-expanded network implementation of [19]. Specifically, every lane on each road segment is partitioned into cells, with the length of each cell set to $v_f \cdot CL$, where v_f is the free-flow speed at the corresponding location and CL corresponds to the CTM parameter known as the update interval or clock step. In our scenario, we assume the free-flow speed is equal to the speed limit of 20 m/sec, and we set the update interval to be 1 sec (equal to the estimation interval), resulting in a cell length of 20 meters. The jam density $K_j = \frac{1}{6}$ vehicles/meter is obtained from our experimental configuration, which uses a minimum vehicle length of 4 meters and a minimum inter-vehicle gap of 2 meters. These parameter values are summarized in Table I.

With the above settings in mind, we experiment with traffic density estimation that is based on the above formula, rather than simple counting of beacons. Specifically, the RSU extracts the position and velocity information from every beacon received. It then uses the position information to map the vehicle to a cell, and at the end of each estimation interval, determines the average speed observed in each cell during the interval. This average speed (denoted by $\bar{v}_c$ for a cell c) is then converted to an estimate of the cell density,

TABLE I: Traffic model parameters and configuration values

Parameter	Value
Free-flow speed (v_f)	20 m/s
Jam density (K_j)	$\frac{1}{6}$ veh/m
Pipes-Munjal exponent (n)	0.5
Drew exponent (n)	0.6
CTM update interval (CL)	1 sec

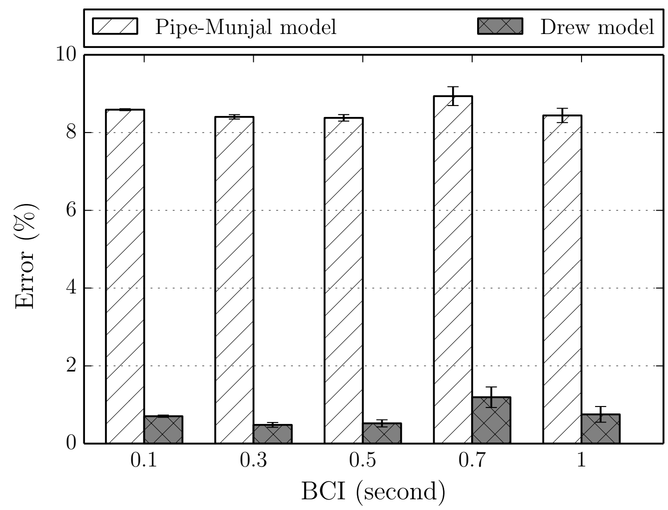

Fig. 3: Comparison of Pipe-Munjal and Drew models for density estimation based on kinematic information

by an inversion of formula (1):

$$k_c = K_j \left(1 - \frac{\bar{v}_c}{v_f}\right)^{\frac{1}{n}}. \tag{2}$$

After obtaining the density of all cells $c \in C$ in the communication range of the RSU, we determine the estimation error in the current interval:

$$err = \frac{\sum_{c \in C} (k_{trc,c} - k_{sim,c})}{\sum_{c \in C} k_{trc,c}} \tag{3}$$

where $k_{sim,c}$ and $k_{trc,c}$ are the density of a cell c estimated by the RSU and the actual density of the cell according to the traffic traces, respectively.

The estimation error performance achieved with the two road traffic models is shown in Fig. 3. We observe that the Drew model outperforms the Pipe-Munjal model by nearly an order of magnitude for all BCI values, which stresses the fact that the traffic model has a significant impact on kinematic-based density estimation.

Fig. 4 compares the density estimation error achieved with the proposed kinematic information-based scheme using the Drew model with that attained using simple beacon counting under optimal settings of the wireless communication parameters, as illustrated in Fig. 2. We note that the kinematic-based estimation generally outperforms beacon counting,

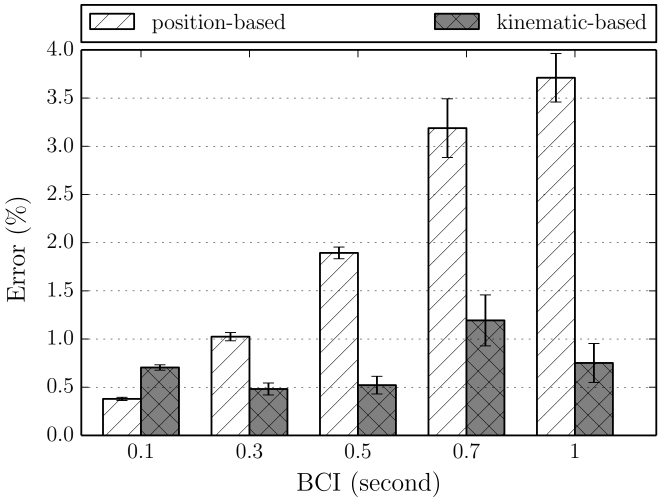

Fig. 4: Comparison of beacon counting and kinematic information-based methods

and most importantly, even with low-frequency beaconing (BCI=1 sec), it is able to attain a level of accuracy of under 1%, roughly equivalent to the best that the beacon counting method can achieve only with significant oversampling (BCI=0.1 sec).

To conclude this section, we emphasize that the above results — which allow the same estimation accuracy to be achieved with a much lower beaconing rate, thereby freeing the wireless channel for other uses — were obtained with a relatively simple, single-regime traffic model; we expect that a more fine-tuned multiple-regime model, explicitly accounting for the red and green phases of the traffic signal (i.e., the build-up and release processes at the stop line of the intersection), would lead to even more accurate density estimation results. This promising extension is left for future work.

IV. Estimation with low-rate beacons and the Cell Transmission Model

So far, in the experiments reported in Section III, the estimation algorithm always operated independently on one estimation interval (of 1 sec duration) at a time. We now turn to consider an estimation approach that takes into account the *history* of recent estimations as well, so as to reduce the required beaconing overhead even further and achieve a high accuracy with beaconing periods greater than the actual estimation interval. To that end, we use the difference equation-based approach of CTM [12], according to which, the occupancy (number of vehicles) in cell i in a given time slot can be predicted from its occupancy, and that of its neighbor cells, in the previous time slot as follows:

$$n_i^{\mathrm{CTM}}(t+1) = n_i(t) + y_i(t) - y_{i+1}(t) \tag{4}$$

where n_i is the occupancy of cell i and $y_i(y_{i+1})$ is the inflow of cell i (resp. $i+1$) from its upstream cell, estimated as follows:

$$y_i(t) = \min\{n_{i-1}(t), Q_i(t), N_i(t) - n_i(t)\} \tag{5}$$

where Q_i is the capacity flow (i.e. the free-flow speed, normalized to the cell length) and N_i is the maximum (jam) density of cell i, respectively. In our scenario, the free-flow speed and jam density values of all cells are set as described in Table I. For simplicity, we consider the four road segments independently; i.e., the last cell before the intersection is considered an exit cell and the first cell after the intersection is an entry cell, which are dealt with by separate boundary conditions as explained below, and we do not attempt to use CTM to predict the behavior of vehicles through the intersection.

We now introduce the estimation approach that blends the use of the CTM difference equations and the real-time beacons. Specifically, the estimated occupancy of a cell is calculated according to the following formula:

$$n_i(t+1) = \beta \cdot n_i^{\mathrm{CTM}}(t+1) + (1-\beta) \cdot n_i^{\mathrm{BC}}(t+1), \tag{6}$$

where n_i^{BC} is an estimated value based on real-time beacons in the same estimation interval, obtained by counting the number of individual beacons and scaling it by the ratio between the beaconing interval and the estimation interval. For example, if a beaconing interval of 2 sec is used (thus, only half of the cars transmit beacons during any given 1-sec estimation interval), then the number of individual beacons counted from a cell during the estimation interval is multiplied by 2 before being used in (6).

An exception to using expression (6) occurs in one of the following two situations:

- In the first cell after the intersection and the cell at the edge of the RSU communication range (upstream from the intersection). For these cells, there is no "prior" (upstream) cell $i-1$ that can be used to compute n_i^{CTM}. Accordingly, only the beacon-based estimation is used to provide an occupancy value for those cells, which effectively serves as an initialization for the CTM process for downstream cells.
- When no beacons at all happen to be received from a cell during an estimation interval, only the CTM-based estimate is used to calculate the cell occupancy (as opposed to using (6) with a value of zero for n_i^{BC}).

Equation (6) brings about a process akin to exponential averaging, where the impact of the occupancy estimate of the furthest upstream cell trickles downstream in the subsequent time slots, being "smoothed" by a factor of β in each slot. Thus, the occupancy estimate of a given cell at a particular time is obtained by taking into account the beacon-induced estimates of that cell as well as the historical estimates of all the upstream cells, with the weight of the impact of other cells decreasing exponentially with the distance from the current cell. The factor β determines the rate at which the history of past estimations is discounted. When $\beta = 0$, the history is not used at all and the estimation is entirely based on the beacons received in the current interval. At the other

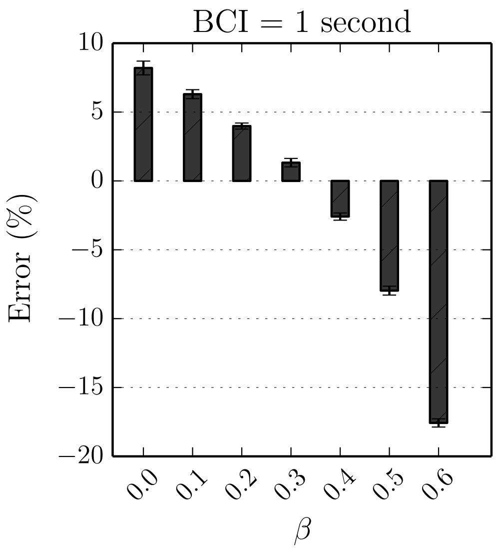

Fig. 5: Estimation error as a function of β, beaconing period of 1 sec.

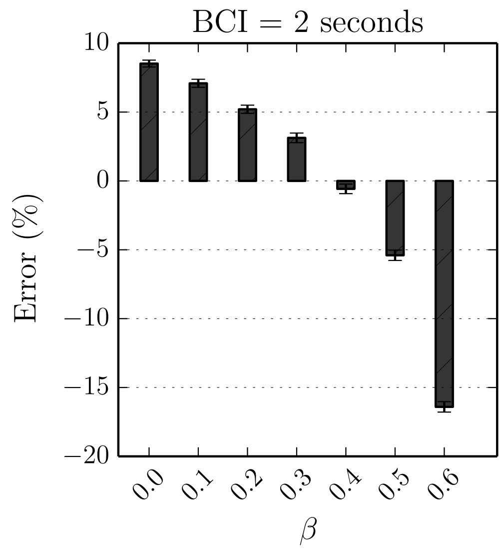

Fig. 6: Estimation error as a function of β, beaconing period of 2 sec.

extreme, in the limit of $\beta \to 1$, the estimation policy reduces to open-ended CTM, using beacons only for initialization of the first cell in each road segment and thereafter applying the CTM model and ignoring all subsequent beacons from intermediate cells.

The results achieved with the above traffic estimation strategy are presented in Fig. 5–7, showing the error rate as a function of the parameter β for beaconing intervals of 1 sec, 2 sec, and 3 sec, respectively.[†] The crosshairs at the tip of each bar show the 95% confidence interval for the corresponding experiment. Note that, as defined by (3), a positive error value indicates that the real occupancy (as determined from the traffic traces) is higher than the one estimated by (6), while a negative value means that the average occupancy is over-estimated.

The first effect that is clearly observed from these figures is that, as β is increased (i.e., as the estimation depends more directly on CTM and less on real-time beacons), the scheme tends to increasingly over-estimate the network density. This is consistent with the observation made in many previous studies of CTM's tendency to overestimate the density of cells further downstream from the traffic entry point, especially when applied to urban scenarios or congested highways [20]–[23]. The magnitude of the error grows as β tends towards 1, since pure CTM-based estimation is highly sensitive to the correctness of the density value of the incoming traffic, i.e. the occupancy values obtained from beacons in the first cell of each road segment. Unfortunately, for the incoming traffic segments, the first cell is in fact the most far away from the RSU, therefore with the lowest quality wireless channel and the highest probability of beacon transmissions to be lost.

[†]Due to space constraints, we omit the figures for other values of the beaconing interval but they display similar patterns to those discussed in the text.

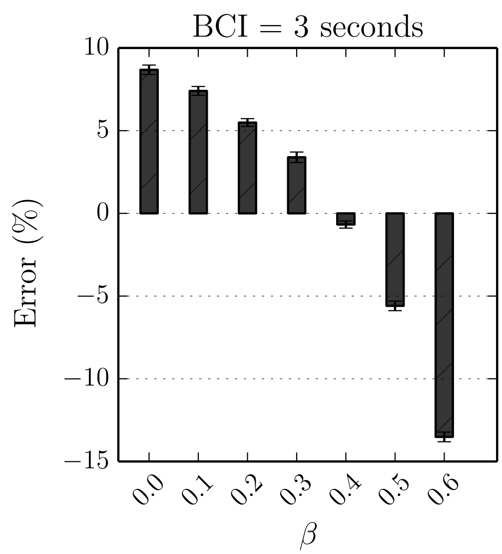

Fig. 7: Estimation error as a function of β, beaconing period of 3 sec.

The above effect is mitigated when the information from wireless beacons from all the upstream cells, even though partial and subject to losses due to wireless channel failures, is used to adjust the estimation from CTM alone; as seen in Fig. 5–7, the "sweet spot" in our scenario, with the best weighting mix between current (beacon-based) and historical (CTM-based) information that achieves the lowest average aggregate error, occurs with β set to between 0.3 and 0.4. It is notable that the optimal β is almost constant regardless of the beaconing interval, increasing only slightly when beacons are less frequent so as to compensate by lowering the rate of discounting of older information. The optimal β may depend on the road topology and may need to be calibrated according to the traffic scenario, and this dependency is currently being explored in ongoing work.

Finally, we point out that, when the density estimation is based in part on the application of the CTM model, the beacons from all cells are not equal in importance: those from the most upstream cells have a greater impact as any inaccuracies propagate and affect all subsequent cells, while the beacons from the most downstream cells (i.e. the closest to the intersection in the incoming traffic segments, and the furthest in outgoing traffic) only have a short-lived impact on the overall estimation accuracy. Consequently, it makes sense to apply a location-dependent beaconing strategy, where a new car just entering the communication range of the RSU starts with a high beaconing rate (to achieve maximum reliability) and gradually reduces it as it approaches the RSU, and similarly when it departs away from the RSU. In practice, the RSU may periodically broadcast a map digest specifying the requested beaconing rates at different locations, which may take into account the recently observed channel quality as well. The design of a detailed beaconing protocol based on these ideas, so as to maximize the accuracy of the traffic estimation application while keeping the overall beaconing overhead low, is left as a subject for future work.

V. Conclusion

In this paper, we investigated the performance of traffic density estimation using wireless beacons, an essential component of any DSRC-based traffic information system. We have demonstrated that a high level of estimation accuracy can be achieved with beaconing rates far lower than recommended in the DSRC standard, by using the kinematic information from the vehicles' beacons and applying a well-known relationship between road speed and density from traffic modeling theory, as well as by applying a dynamic model of traffic propagation and using the feedback from beacons to adjust the model's predictions. Our results show the power of a traffic estimation algorithm that draws on both real-time information (from wireless beacons) and an offline road traffic model, as opposed to an estimation method that uses only one of these sources. From a practical perspective, our results provide a low-overhead alternative to simple beacon-counting approaches, which thereby allows the traffic monitoring application to coexist with other applications on the same wireless channels.

The results in this paper have been based on a traffic scenario involving a single RSU at a signalized intersection. In future work, we plan to explore more complicated road topologies (from two neighboring intersections to entire urban regions), and extend the ideas of this paper on the combined use of real-time information and a priori road traffic model to *distributed* density estimation, involving "blending" of information from multiple RSU with backhaul communications.

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