Bayesian Network based speed estimation in case of C2X data at very low equipment rates

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1   Introduction

The estimation of the traffic state, particularly speed and vehicle counts, is important for modern traffic light control (TLC) algorithms. Recent developments in the field of so called self-organizing TLC focus on using cooperative traffic data transmitted via Car-to-Infrastructure (C2I) or Car-to-X (C2X) communication. In this context, vehicles periodically exchange their GPS position and speed via so called Cooperative Awareness Messages (CAM) in the EU (a.k.a. Basic Safety Messages (BMS) in the US) transmitted on a vehicular-specific extension to the WiFi ad-hoc mode IEEE802.11p[1]. Equipped with such technology, TLC may intercept CAM/BSM and use the contained data to estimate its local traffic state. This technology is yet emerging and car manufacturers are not expecting a sufficient penetration at the time future self-organizing TLC systems will be deployed. In this paper, a novel approach proposes to complement missing C2X technology with Bluetooth technology (BT), which is already widely available in all modern vehicles as well as smartphones. BT data has notably been tested for traffic data acquisition for years, but neither provide the same type nor the same quality of C2X cooperative data. Accordingly, we propose to rely on a stochastic data fusion engine based on Bayesian Networks (BN) to enrich and integrate traffic state data from a low C2X equipment rate (about 1%) and moderate BT equipment rate (30%). One of the challenges addressed is to be able to extrapolate mobility from detection processes, and then extract the estimated BT and C2X speed likelihoods. Using BN, we will propose to link such likelihood to different a-priori knowledge of mobility states. Another challenge is to integrate the BT and

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[1]the IEEE802.11p is known as ITS-G5 in the EU and as DSRC in the US.

C2X speed likelihood, considering both processes have different properties. We show the robustness of our approach assuming a BN being able to reach already 2m/s speed RMSE and complete the traffic state estimation by 35% by fusing 1% C2X with 30% BT.

2 Methical approach

Bayesian Networks (BN) are capable of providing reliable and accurate data, in this case speed estimations within a certain road segment, by inferring the results of the sensor measurements and combining them with a-priori knowledge. C2X protocols were designed to exchange sensor measurements, such as position and speed, between vehicles and road side units (RSU). In contrast, deriving speed data from BT is challenging. Therefore, in the following it is shown how speed estimations can be obtained by BT occupancy detectors (sec. 2.1) and, then the BN for the problem in question is developed (sec. 2.2).

2.1 Bluetooth based speed estimation

In the BT inquiry process solely the IDs of sender and receiver are exchanged. Therefore, the speed of a BT device V_{BT} can only be estimated in an indirect way, e.g. by considering the time interval $[t_{\mathrm{First}}; t_{\mathrm{Last}}]$ between entering and leaving a known detection range r_{BT}:

$$V_{\mathrm{BT}} \approx \frac{r_{\mathrm{BT}}}{t_{\mathrm{Last}} - t_{\mathrm{First}}}, \qquad t_{\mathrm{Last}} - t_{\mathrm{First}} > 0. \tag{1}$$

Obviously, (1) cannot be applied if there is one detection only. The more frequent the same device is detected the more accurate is V_{BT}, which means a slow vehicle is within r_{BT}. In contrast, a quick vehicle will be detected more rarely, and thus, (1) leads to bigger velocity errors. Consequently, speed estimation should involve some additional facts about the underlying traffic process, which can be written as with V (true speed), V' and ΔV (speed of and speed difference to the preceding measured vehicle), Q (traffic volume), Δt (time gap) and TLC (traffic light control):

$$V_{\mathrm{BT}} \propto f\left(V, V', Q, \Delta V, \Delta t, TLC, \ldots\right) = P\left(V, V', Q, \Delta V, \Delta t, TLC, \ldots\right). \tag{2}$$

In (2) $f(.)$ models the measuring process, which may be formulated as a probability density function $P(.)$. Analogous to (2) a similar connection can be found to model V_{C2X}, which is not shown here. Modelling the behaviour of the two sensors in question and further the underlying traffic process will lead us to consider the whole measuring and data fusion processes probabilistically (sec. 2.2).

2.2 Sensor data fusion of C2X and Bluetooth

A BN is a causal, acyclic graph with nodes and arcs. The nodes represent the random (process) variables, i.e. the underlying traffic process with unknown speed data V and the

measurements of the sensors V_{BT} and V_{C2X}. The directed arcs model the causal relationships between process and measurements, i.e. from the process in question (cause) to the measurements (effect). The relationships between the nodes are quantified as conditional probability density functions (CPDFs). First we developed a complex BN consisting of
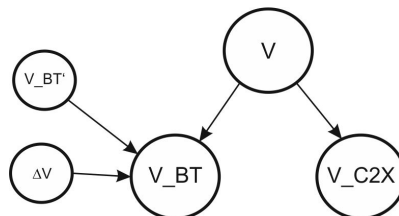

Figure 1: BN for merging C2X with BT data

three nodes mentioned above and additional nodes, which involved the relationships considered in (2). Then we simplified this BN to the one shown in fig. 1, which takes into account the traffic process node V, the two sensor nodes V_{BT} and V_{C2X} as well as the additional nodes modelling the mean speed of the preceding measured BT vehicle V'_{BT} and the speed difference of the current and the preceding measured BT vehicle ΔV. All other nodes were ignored. After modelling, the nodes needed to be quantified by CPDFs, which was realised by parameter learning (see e.g. (Neapolitan, 2004)). The challenge here was to obtain values for ΔV and V'_{BT}, which relate to the preceding measured BT vehicle yielding a time-dependent BN. After building the BN and quantifying the CPDFs the BN is instantiated. Now, each measurement at V_{BT} or V_{C2X} is a diagnostic evidence that is propagated up through the BN. Further, the results concerning the preceding measured vehicles, i.e. V'_{BT} and ΔV, are a-priori knowledge, which propagates down through the BN. Therefore, computing the a-posteriori distribution and applying an adequate estimator yields the most likely result of speed estimation. The fusion equation can be written as follows with the a-priori probabilities $P(V)$, $P(\Delta V)$ and $P(V'_{\mathrm{BT}})$, the sensor likelihoods $P(V_{\mathrm{BT}}|V, V'_{\mathrm{BT}}, \Delta V)$ and $P(V_{\mathrm{C2X}}|V)$ and the normalising constant α:

$$P\left(V|V'_{\mathrm{BT}}, \Delta V, V_{\mathrm{C2X}}\right) = \alpha \cdot P(V)\, P(\Delta V)\, P\left(V'_{\mathrm{BT}}\right) \cdot P\left(V_{\mathrm{BT}}|V, V'_{\mathrm{BT}}, \Delta V\right) P(V_{\mathrm{C2X}}|V) \quad (3)$$

3 Experiments and results

The proposed method was implemented and tested using the microscopic traffic simulation SUMO (Simulation of Urban MObility). A 4-arm intersection scenario called RiLSA 1 was chosen, in which approximately 2000 vehicles approach a signalised intersection. The traffic volumes for each arm are different. The simulation time is about 3600s and the vehicles' target speed is 13.9m/s. The C2X and BT equipped vehicles were randomly set into the simulation. The C2X and BT detector behaviors were integrated in the

simulation model resulting in clean, unbiased and noiseless speed data. We applied the method proposed in sec. 2.2 for speed estimation within a 30m horizon in all four arms of the traffic light, and considering a constant average 30% BT average equipment rate while increasing the average C2X equipment rates within [1,2,5,10,20,50,100]%. The results show (see tab. 1) that our approach favorably compares to other approaches in the field (Härri et al., 2015). The RMSE could be reduced by a factor of two.

	V_{RMS} [m/s] with resulting data completeness q_c [%] (in brackets)			
C2X equipment rate	northern arm	eastern arm	southern arm	western arm
1%	2.3 (34.6)	4.7 (33.6)	1.7 (37.3)	5.3 (38.6)
2%	2.3 (37.2)	4.8 (36.0)	1.8 (43.3)	4.9 (41.9)
5%	2.3 (42.0)	4.2 (40.5)	2.0 (49.8)	4.5 (47.3)
10%	2.4 (51.9)	3.9 (47.4)	2.1 (52.6)	3.9 (56.6)
20%	2.3 (62.3)	3.4 (61.9)	2.2 (67.6)	3.2 (69.5)
50%	2.2 (84.8)	2.6 (85.7)	2.1 (88.7)	2.6 (90.9)
100% (benchmark)	1.8 (99.9)	2.1 (100.0)	1.6 (99.9)	2.1 (100.0)

Table 1: Speed RMSE V_{RMS} and completeness q_c for different C2X equipment rates.

4   Conclusions

An algorithm based on the concept of BN was developed and tested providing speed information in case of very low C2X equipment rates. Specifically, BT occupancy detectors for each arm of an intersection being used as speed estimators, were fused with a C2X-RSU collecting CAMs to obtain estimations of the vehicles approaching an intersection. Applying the proposed algorithm we could show that the RMSE in case of a equipment rate of 1% differed from 1.7m/s (southern arm), 2.3m/s (northern arm), 4.7m/s (eastern arm) to 5.3m/s (western arm). These error levels are suitable for applications in the field of TLC, e.g. extending green phases. The results are quite astonishing, particularly in comparison to other currently developed methods and the fact of using BT as a speed detector. The method applied promises better results if further aspects and connections between the different parameters in the BN are considered, e.g. as expressed by (2). Moreover, aspects of timely queuing, multiple detections, different BT equipment rates, noisy and biased data, etc. are to be taken into account, which will be part of our future work.

References

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