IMPROVED TRAFFIC STATE ESTIMATION BY BAYESIAN NETWORK DATA FUSION OF V2X AND VEHICULAR BLUETOOTH DATA

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Word Count: 6,497 words + 4 tables (1,000 words) = 7,497 words
Submission Date: January 7, 2019

ABSTRACT

A recently published probabilistic method for vehicle based traffic state estimation on the basis of fusing two wireless communication based technologies, i.e. Bluetooth and Vehicle-to-X communication data, is analyzed in three different scenarios ranging from “academic” to “realistic”. On the one hand there is accurate, but extremely rare V2X speed data and on the other, there is frequent, but inaccurate speed data based on a one unit Bluetooth reader approach. Therefore, this analysis takes into account specific traffic related variables, such as traffic flow and traffic density as well as traffic light control (TLC), which affect the Bluetooth based detection results. The findings are used to improve the method. A Bayesian Network (BN) is developed that merges Bluetooth and V2X based speed detection results to provide an improved speed estimation. The novel BN is compared to the previous one for different V2X penetration ratios using the open source microscopic traffic simulation package SUMO (Simulation of Urban MObility). The results show that the novel method can improve the vehicular speed estimation in the academic as well as in the realistic scenarios.

Keywords: V2X communication, Bluetooth, Bayesian Networks, Data Fusion, Traffic Management, Traffic State Estimation, COLOMBO, Digitaler Knoten 4.0

INTRODUCTION

An accurate and reliable estimation and prediction of the traffic state is a key task of Traffic Management Centers (TMC) to make traffic safer, cleaner and more efficient. Cameras, radar systems, loop detectors and other sensor technologies have been in use successfully for decades to obtain information about the number of road users and their microscopic properties like speed, acceleration and origin-destination behavior. Intelligent Traffic Light Control (TLC) algorithms take advantage of these information to achieve a local, a section based or even network wide optimized traffic state adequate TLC algorithm with a minimum of waiting or loss times.

In the European funded project COLOMBO[1] (*1*) the aim was to pay attention to a reliable traffic state estimation by developing and providing "...a set of methods for traffic surveillance and traffic control applications that target at different transport related objectives, such as increasing mobility, resource efficiency, and environmental friendliness" (*2*). One aspect of COLOMBO was to adopt data sources for this purpose, which particularly take into account availability, accuracy, resource efficiency and costs.

Some of the established sensor technologies provide accurate and reliable data, but lack applicability for different reasons. Loop detectors, for instance, are labor-intensive and require costly installation and maintenance. Camera sensors provide wide-area traffic data, but have to cope with occlusion phenomena and weather dependencies, such as snow and sun-glare (*3, 4*). Radar sensors and loops are traffic state dependent, since they provide less accurate data at low vehicular speeds. On the other hand there are low price communication based sensors, such as Bluetooth or even WiFi detectors, which suffer from the equipment ratio of Bluetooth/WiFi devices on board of vehicles. Although only a fraction of road users can be detected (3% to 50% depending on urban/suburban area, penetration ratio, street type, amount of trucks, speed limit, etc. (*5, 6*)), they have great potential for different traffic management purposes.

The fusion of dynamic data of connected vehicles, e.g. on board diagnostic and sensory data, with static road data, e.g. map and road geometry data, is state of the art (*7*). In contrast, fusing vehicular data with dynamical infrastructure based data for automation purposes is currently intensively under research, e.g. estimation of the risk of collision between right turning motorists and straight driving cyclists (*8, 9*). Also, self-organizing TLC algorithms were developed, which make use of sparse traffic data provided by cooperative communication based sensors, such as Vehicle-to-Infrastructure (V2I) or Vehicle-to-Vehicle (V2V) (*10, 11*). The abbreviation V2X (Vehicle-to-X communication) combines them to a single term. Vehicles equipped with V2X technology periodically exchange information via Cooperative Awareness Messages (CAM) with other vehicles or Road Side Units (RSU) on a vehicular-specific extension to the WiFi ad-hoc mode IEEE802.11p (*12*). These information could be used to feed a TLC algorithm to obtain a maximum of traffic safety taking into account a maximum of efficiency in traffic flow. However, car manufacturers expect to take years to achieve sufficient V2X penetration ratios of 1% to 3%, which makes powerful TLC algorithms on the basis of accurate speed data a real challenge (*13*). This motivates the fusion of Bluetooth and V2X data for speed estimation.

In regards of the COLOMBO project Junghans and Leich (*13*) showed that accurate vehicular speed data can be obtained by fusing extremely rare, but rather accurate V2X data, with frequent, but less accurate Bluetooth data. Although these results cannot be used for TLC yet at very low V2X penetration ratios, they proved their usefulness. In regards to the project "Digitaler

[1] Cooperative Self-Organizing System for low Carbon Mobility at low Penetration Rates

Knoten 4.0" (*14*) this method is reviewed in detail and its improvement makes use of the recent findings in (*15*), which may be the basis for traffic adaptive TLC algorithms on the basis of V2X and vehicular Bluetooth data. These investigations are obtained by coupling the microscopic traffic simulator SUMO (Simulation of Urban MObility) with a probabilistic speed estimator on the basis of Bayesian Networks (BNs).

The paper is organized as follows: In the next section the methodical approach of traffic state estimation with Bluetooth and V2X is described and analyzed with regard to specific boundary conditions. Then, the general simulation setup and the experimental results are described. Finally, conclusions and future prospects are given.

PROBLEM ANALYSIS

In this section the methodical approach is described how speed data can be obtained by a one unit Bluetooth reader. Then, BNs are applied to formulate the fusion task of Bluetooth based speed sensor with a V2X based one. Further, this BN is analyzed in detail. Finally, on the basis of novel findings the resulting BN is created. Further simulative analyses follow.

Methodical Approach

As stated in (*13*), RSUs for V2X communication receive the broadcast speed information by CAMs of the vehicles equipped with V2X technology. Due to the expected extremely low penetration ratios of V2X vehicles it is challenging to obtain reliable speed estimations for the remaining road users. On the other hand, they frequently use Bluetooth devices (e.g. Bluetooth speakers, hands-free equipment, navigation systems) and thus, their occupancy can be detected by their device identification number, e.g. MAC address, within a specific detection range. This is due to the Bluetooth inquiry process (*16*), which characterizes the handshaking procedure between Bluetooth sender and receiver. It results in the exchange of the device IDs of the communication partners. Typically, two Bluetooth detectors are applied to obtain accurate and reliable speed information: One detector is mounted at position 1, the other at position 2. Knowing the distance between both positions and the time interval needed for road users to pass positions 1 and 2 enables the determination of the journey time.

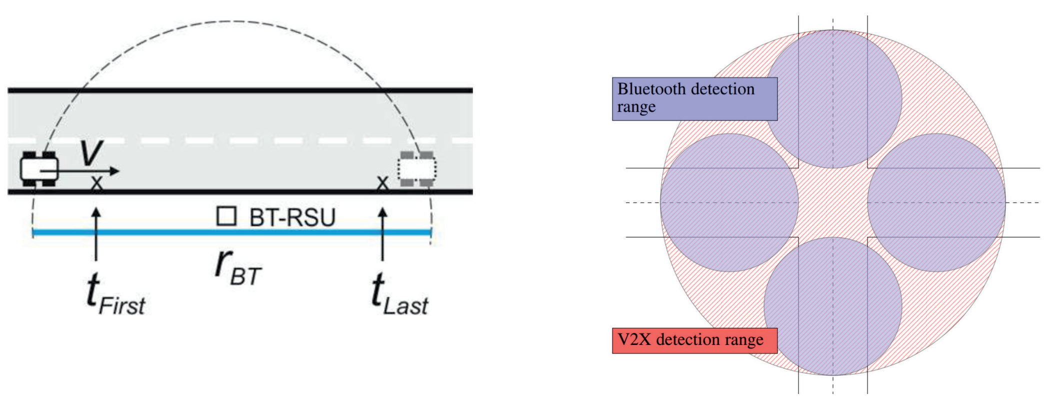

FIGURE 1 Left: Principle of Bluetooth based speed detection with a one unit Bluetooth reader (*13*); right: Schematic diagram of V2X and Bluetooth based detection ranges (*15*)

In (*13*) it was shown that speed information v_{BT} can also be obtained by a single Bluetooth reader unit taking into account the time of first t_{first} and last detection t_{last} of the road user as well as the detection range r_{BT} (see left side of figure 1):

$$v_{\mathrm{BT}} \approx \frac{r_{\mathrm{BT}}}{t_{\mathrm{last}} - t_{\mathrm{first}}}. \tag{1}$$

These assumptions are rather idealistic, since detection ranges of such Bluetooth/WiFi readers strongly depend on their antenna characteristics, environmental and other influencing factors. On the other hand those assumptions serve to find out whether the method is promising and what aspects have to be considered further. Looking again at equation (1), we can state that the slower a road user passes through r_{BT} the more accurate the speed estimation is. Fast moving road users will be detected only once or not at all, which consequently leads to problems in speed estimation. Further, v_{BT} is always over-estimated, since the Bluetooth inquiry process will neither instantaneously detect a Bluetooth device the first time it enters r_{BT} nor the last time before it leaves r_{BT} (*15*). Consequently, the estimation of v_{BT} is rather rough. However, such a rough speed estimation result can be improved by merging Bluetooth based speed observation results with highly accurate V2X speed data. Obviously, analyzing traffic in detail seems to be a reasonable way to improve the quality of the Bluetooth based speed estimation and consequently the fused speed estimation results. In order to understand how V2X and Bluetooth signals could be merged we first want to show the different detection ranges of Bluetooth and V2X—on the right hand side of figure 1 the detection ranges of V2X ($\approx$ 200 meters) and Bluetooth ($\approx$ 30 meters in case of Bluetooth class 2 readers[2]) are depicted taking into account an idealized Bluetooth and V2X road side unit (RSU) placed in the middle of the intersection.

Bayesian Network based Data Fusion

Bayesian Networks (BNs) are well-established to quantify cause-effect relationships by conditional probability density functions and make diagnoses by inferring expert knowledge or observation results of the applied sensors and combining them with stationary or instationary a-priori knowledge. The authors recommend to refer to (*17–19*) for detailed insights in BNs, their structure, computational characteristics and applications.

In figure 2 (left hand side) a naïve BN is depicted. It consists of the node V as unknown speed variable and the two sensor nodes V_{BT} and V_{V2X} observing V, i.e. measuring speed. Clearly, the realizations $v \in V$ where V denotes the set of all n possible discrete speed classes $V = \{v_1, \ldots, v_n\}$ cause the observation results $v_{\mathrm{BT}} \in V_{\mathrm{BT}}$ and $v_{\mathrm{V2X}} \in V_{\mathrm{V2X}}$ with V_{BT} and V_{V2X} defined similarly. The joint probability density function is given by equation (2) taking into account the structural Markov property of BNs (*17*):

$$P(v, v_{\mathrm{BT}}, v_{\mathrm{V2X}}) = P(v) \cdot P(v_{\mathrm{BT}}|v) \cdot P(v_{\mathrm{V2X}}|v). \tag{2}$$

If observation results have occurred at the nodes V_{BT} and V_{V2X} these diagnostic evidences are spread through the BN to affect V, i.e. to diagnose what to expect at V given the values of v_{BT} and v_{V2X}. This can be computed by the a-posteriori probability density function with normalization constant $\alpha^{-1} = P(v_{\mathrm{BT}}, v_{\mathrm{V2X}})$:

[2]Note that there are three classes of Bluetooth readers, which vary in their detection ranges, i.e. class 1: $\approx$ 100 meters, class 2: 10-50 meters, class 3: 1-10 meters.

$$P(v|v_{\mathrm{BT}}, v_{\mathrm{V2X}}) = \alpha \cdot P(v) \cdot P(v_{\mathrm{BT}}|v) \cdot P(v_{\mathrm{V2X}}|v). \tag{3}$$

where

- $P(v|v_{\mathrm{BT}}, v_{\mathrm{V2X}})$ is the a-posteriori probability density function needed to estimate v given the observation results v_{BT} and v_{V2X},
- $P(v)$ is the a-priori probability density function of the underlying speed variable characterizing the stationary expectation on V,
- $P(v_{\mathrm{BT}}|v)$ and $P(v_{\mathrm{V2X}}|v)$ are the corresponding sensor likelihoods for Bluetooth and V2X. These sensor likelihoods are conditional probability density functions that quantify the behavior of the sensors with regard to v.

In the next subsection these equations are used to derive accurate speed estimations by inferring observation results of the Bluetooth and V2X sensors. In general, it can be stated that BNs are capable of probabilistically combining several sensors in order to provide reliable and accurate data of some stochastic variable as shown in (*20–22*).

Analysis of the BN

On the right hand side of figure 2 a BN is shown that was used for first investigations for accurate speed estimations (*13*). It contains variables that have an influence on the traffic state and hence, may affect speed estimation. Node V expresses the unknown mean instantaneous speed of a vehicle passing through the common detection area of Bluetooth and V2X sensors; node V_{V2X} represents the V2X sensor node observing speed and V_{BT} represents the Bluetooth sensor node observing speed as well. The nodes V_{pre} and ΔV represent the mean instantaneous speed of the preceding vehicle equipped with a Bluetooth sensor and the difference of the current speed with the previous one, respectively, thus $\Delta V = V_{\mathrm{pre}} - V_{\mathrm{BT}}$. Therefore, the nodes V_{pre} and ΔV were considered to affect the speed observation results of the Bluetooth sensor, due to the assumption that traffic conditions do not change quickly in case of two vehicles following each other.

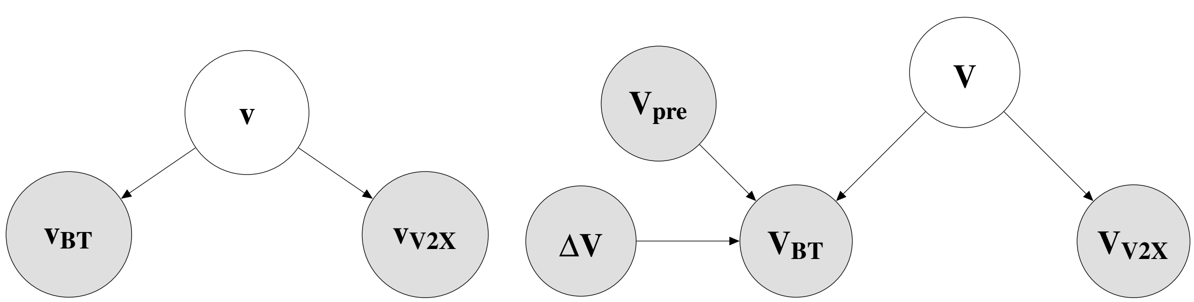

FIGURE 2 Naïve BN (left) and improved BN from (*13*) (right)

In (*13*) the BN on the right of figure 2 was adopted for optimal speed estimation of an academic intersection (figure 4 left) for changing V2X penetration ratios of $[0; 1; 2; 5; 10; 20; 50; 100]\%$ and a constant Bluetooth penetration ratio of 30%. The authors obtained speed estimation accuracies between an RMSE of $[1.7; 5.3]$m/s and completeness values of $[33.6; 38.6]\%$ at a V2X penetration value of only 1% at the four arms of this intersection. Klüber (*15*) analyzed this BN to identify influencing factors, which improve the speed estimation quality. The following traffic process related variables were taken into account to have an influence on the Bluetooth based speed estimation:

- **Traffic flow Q and density** D: Both variables correspond with each other by the fundamental flow relation $Q = v \cdot D$ in case of an ergodic traffic process (*4*). D and Q affect V_{BT}. In the experimental results it appeared that although D and Q have an influence on V_{BT} the effect was marginal; only for heavy traffic it made sense to consider them in the BN. Therefore Q and D were not considered for later analyses.
- **Traffic light control** TLC: In the investigations made a fixed-time TLC program was running. Since vehicles accelerate to their desired speeds and then constantly continue at that speed in case of green light and decelerate to zero for red light, it seems reasonable to model TLC as a separate node in the BN. Further, the Bluetooth based speed estimation is dependent on the vehicles' speeds. The slower a vehicle is the more accurate the Bluetooth based speed detection. Finally, in all investigations it turned out that modeling the BN with an additional TLC node had a significant influence on the quality of V_{BT}. Experiments using a TLC node have shown that results improve when splitting the green phase in an accelerating phase *green1* in the first seconds of the green phase and a free flow phase *green2*. Best results were obtained when splitting the phases after 7.5 s of green light.
- **Preceding Bluetooth speed V_{pre}**: As described above, it is assumed that traffic conditions change over time slowly, thus it seems reasonable to assume that the speeds of leader and follower vehicles should not be too dissimilar. Therefore, it is assumed that V_{pre} affects V_{BT} as well. Our experiments showed that it is indeed reasonable to model this variable in the BN.
- **Speed difference** ΔV: The speed difference of the current Bluetooth vehicle with its preceding is a redundant information, thus this node was deleted from the BN. The experimental results confirmed this.

Final BN and Fusion equation

On the basis of (*15*) the final BN for merging rare but accurate V2X speed data with frequent but rather inaccurate single unit Bluetooth based speed data is depicted in figure 3.

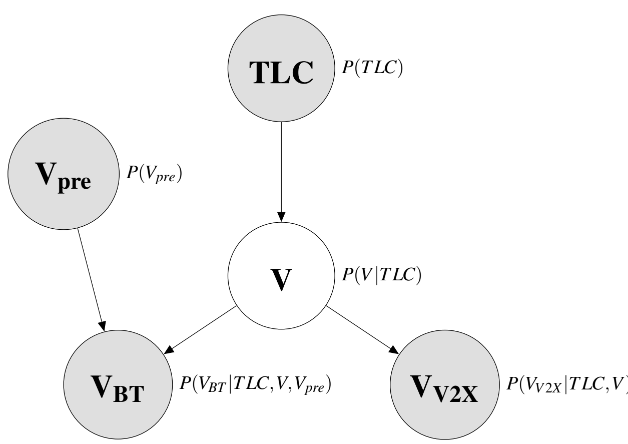

FIGURE 3 Improved BN taking into account the node TLC. Additionally, the probability density functions are shown

This BN consists of the hidden physical speed node V and the two sensor nodes V_{BT} and V_{V2X} for speed estimation of the Bluetooth and V2X based sensors as in the BNs applied before. As shown in figure 3 the speed of the preceding Bluetooth vehicle affects the current Bluetooth based detection. In addition the node TLC with its realizations $tlc \in TLC$ models the traffic light control.

The joint probability distribution of the BN shown in figure 3 can be derived easily:

$$P\left(v, v_{\mathrm{BT}}, v_{\mathrm{V2X}}, v_{\mathrm{pre}}, tlc\right) = P\left(v|tlc\right) \cdot P\left(v_{\mathrm{pre}}\right) \cdot P\left(v_{\mathrm{BT}}|v\right) \cdot P\left(v_{\mathrm{V2X}}|v\right). \tag{4}$$

The resulting fusion equation $P(v|v_{\mathrm{BT}}, v_{\mathrm{V2X}}, v_{\mathrm{pre}}, tlc)$ can be computed with the normalizing constant $\alpha^{-1} = P(v_{\mathrm{BT}}, v_{\mathrm{V2X}}, v_{\mathrm{pre}}, tlc)$ by applying message passing, as described in (*18*):

$$P\left(v|v_{\mathrm{BT}}, v_{\mathrm{V2X}}, v_{\mathrm{pre}}, tlc\right) = \alpha \cdot P\left(v|tlc\right) \cdot P\left(v_{\mathrm{pre}}\right) \cdot P\left(v_{\mathrm{BT}}|v, v_{\mathrm{pre}}\right) \cdot P\left(v_{\mathrm{V2X}}|v\right). \tag{5}$$

In equation (5) $P(v|v_{\mathrm{BT}}, v_{\mathrm{V2X}}, v_{\mathrm{pre}}, tlc)$ is the a-posteriori probability density function of the desired speed taking into account the a-priori knowledge about the unknown physical speed with regard to the state of the traffic light $P(v|tlc)$, the sensor likelihood of V2X $P(v_{\mathrm{V2X}}|v)$ and the sensor likelihood of Bluetooth $P(v_{\mathrm{BT}}|v, v_{\mathrm{pre}})$ considering the influence of the previously detected Bluetooth vehicle on the current measurement.

EXPERIMENTAL RESULTS

In this section experimental setup and road network scenarios are analyzed and the obtained results of speed estimation are presented. The open source microscopic traffic simulator Simulation of Urban MObility (SUMO) was used (*23*). SUMO enables the integration of traffic flows on custom road networks as well as the simulation of Bluetooth and V2X detectors. Various combinations of Bluetooth and V2X penetration ratios are examined.

Experimental setup

The experiments were conducted using the following core parameters and methods in three different scenarios ranging from “simply academic” to “realistic”:

- *Training*: Data from 500 detection runs were used to quantify the sensor likelihoods
- *Simulation time*: 3600 s
- *Detection ranges*: Bluetooth: 30 m, V2X: 200 m
- *Penetration ratios*: Bluetooth: $[0, 30, 50, 100]\%$, V2X: $[0, 1, 5, 10, 20, 50, 100]\%$
- *Maximum speed*: 50 km/h ($\approx$ 13.89 m/s) due to urban scenario analyses
- *Traffic conditions*: Varying traffic flows between 100 and 1500 veh/hour, in scenario 1 up to 2160 veh/hour
- *Sensors*: Vehicles are equipped with Bluetooth and/or V2X at random
- *Data fusion*: Simulation is run 100 times
- *Speed estimator*: Maximum-a-posteriori estimator (MAP) is applied on equation (5) to estimate speed as $\hat{v} = \arg\max P(v|v_{\mathrm{BT}}, v_{\mathrm{V2X}}, v_{\mathrm{pre}}, tlc)$
- *Evaluation measures*: Accuracy determined by root mean square error (RMSE) and mean absolute error (MAE); completeness determined by percentage.

Three scenarios have been chosen such that basic characteristics of the BN could be determined while realistic applications were also tested:

Scenario 1 It contains a straight, one-directional road (not shown here) equipped with V2X and Bluetooth detectors. It serves as a basic example to examine the fusion results according to equation (5) depending on the true speed and traffic flow yet free from influencing factors such as intersection geometry or TLC phase. Since there is no intersection the TLC node in the BN in figure 3 was dropped.

Scenario 2 A simple intersection with TLC is considered. Again, roads that meet at 90 degree angles and constant traffic flows are used for simplicity. The intersection is shown on the left of figure 4. The traffic is controlled by a TLC with a fixed-time control with 72 s cycle time. The green phases on the North-South axis lasts for 12 s, on East-West axis for 40 s. It is followed by a 3 s amber phase and a 7 s red phase. This scenario combines a high traffic volume of approximately 1000 veh/hour (600 vehicles going straight and 200 each turning left/right) East-West and West-East and a lower traffic volume of approximately 300 veh/hour from North-South and South-North heading equally distributed to all three directions. The volumes are chosen such that usually no traffic tailback remains after a green phase.

Scenario 3 This "realistic" scenario is a replication of a real intersection in the town Brunswick, Germany, sharing its geometry and traffic demand from real traffic counts compiled in August 2014. It is more complex than the previous one and enables an evaluation of the BN for speed estimation further away from academics. The right hand side of figure 4 shows the intersection's model in SUMO. In the simulation altogether 364 vehicles are simulated in the Northern arm, 586 in the Eastern, 645 in the Southern and 472 in the Western arm. In contrast to the previous scenario 2 a constant traffic flow cannot be assumed. The vehicles are inserted into the simulation at their actual occurrence. The traffic lights again follow a fixed-time control containing a 33 s green, 9 s of left-turn and 3 s of amber phase.

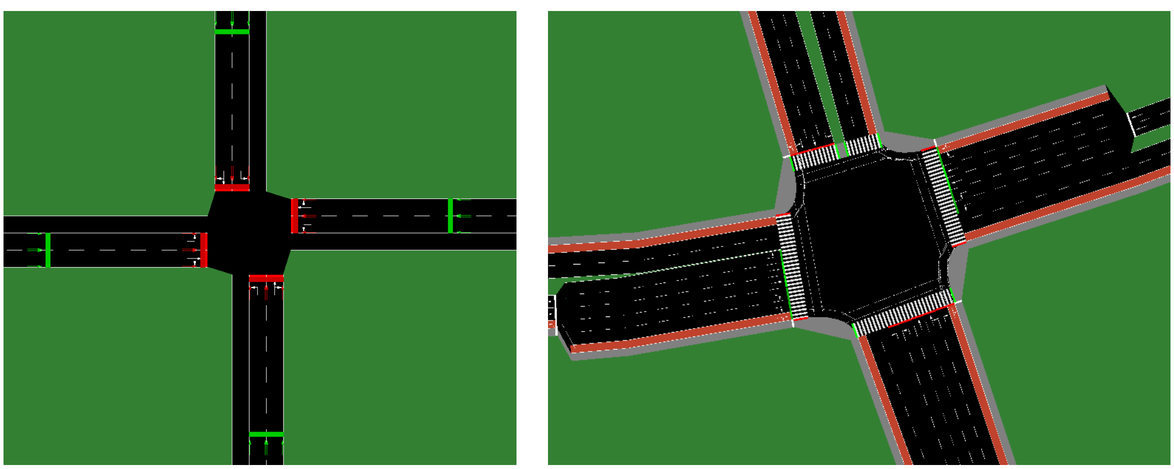

FIGURE 4 SUMO view on academic scenario 2 (left) and realistic scenario 3 (right)

Process chain

The simulation of each scenario contains three steps relevant for speed estimation by fusing data of V2X and Bluetooth. The first prepares the fusion framework, the second realizes data fusion and the the third evaluates the results.

1. Training During the training, the simulation is run 500 times to collect data on the vehicles in the scenarios. The data recorded are then used for BN parameter learning, i.e. for quantification of the sensor likelihoods and the a-priori probability distributions. Here, simple event counting on the basis of Dirichlet density functions can be applied as described by Neapolitan (*17*). The real-time traffic control interface TraCI (*24*) is adopted to enable detector placement and real-time tracking of vehicles and detector data during simulation.

2. Data fusion Similar to the training step the simulation is executed while a speed estimation is computed for each simulation step by computing equation (5) and evaluating it by MAP. To analyze the performance of the BN in question the data fusion step is run 100 times.

3. Evaluation An evaluation framework is available to assess the logged true physical and estimated speed data as well as Bluetooth and V2X speed and TLC state information.

Results

The overall quality of estimation is characterized by accuracy and completeness of the data. The influence of the V2X and Bluetooth detection ratios on the speed estimation are of special interest.

Scenario 1 The first scenario's main purpose was to analyze the estimation for different combinations of speed and traffic volume. The speed decreases stepwise from 14 m/s to 2 m/s while the traffic flow changes between 360, 1440 and 2160 veh/hour. The estimation works better for lower traffic volumes; an example is shown in figure 5. In general an overestimation of speed is obvious. When increasing the V2X penetration ratios from 20% to 50% the estimation results improve. In the first row of table 1 MAE, RMSE and their standard deviations as well as completeness are depicted for V2X penetration ratios of 0, 1, 5, 10, 20, 50 and 100%.

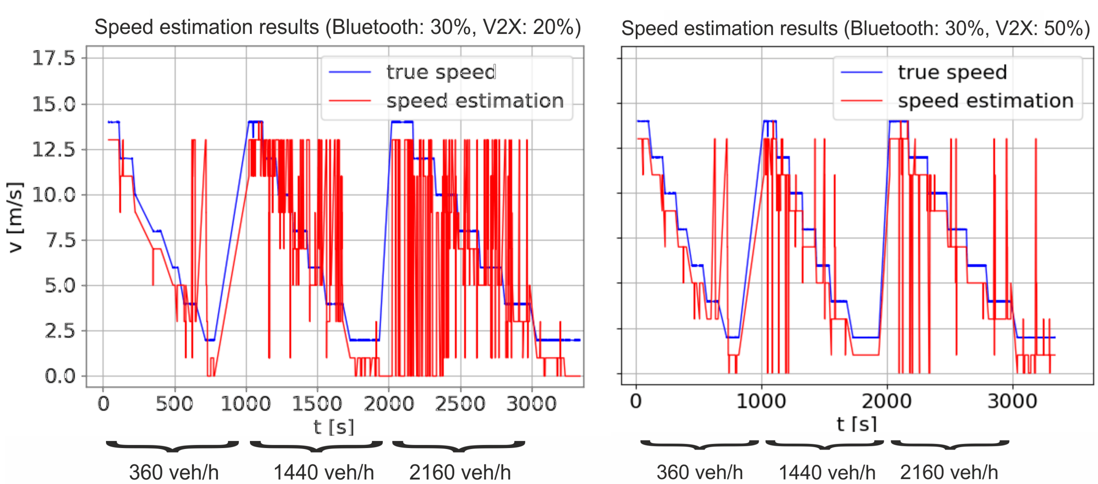

FIGURE 5 Example for the comparison of estimated and real speeds for a Bluetooth penetration ratio of 30% and a V2X penetration ratio of 20% (left) and 50% (right) respectively.

Scenario 2 To elaborate further on the importance of the V2X penetration ratio, experiments with differing penetration ratios were conducted. The results (MAE, RMSE, their standard deviations and completeness) are shown in the middle row of table 1. Both quality measures, accuracy and completeness, increase as the V2X penetration ratio increases. A V2X penetration ratio of only 20% is needed to obtain a completeness value of more than 80%. The accuracy is nearly constant for penetration ratios between 0 and 10% with an MAE of approximately 1.71-1.72 m/s and an RMSE of approximately 2.68-2.72 m/s, but higher than in case of lower or even higher V2X penetration ratios. In case of V2X penetration ratios of more than 20% MAE and RMSE decrease to 1.26 m/s and 2.1 m/s respectively.

Interesting findings regarding the sensor likelihoods of Bluetooth and V2X can be obtained. The Bluetooth sensor likelihood depicted on the left in figure 6 shows the expected behavior at TLC phase *green2* due to the measuring principle: While the likelihoods for lower speeds tend to be close to the actual speed the results get worse as the true speed increases. For this Bluetooth sensor a mean speed greater than 11 m/s cannot be measured.

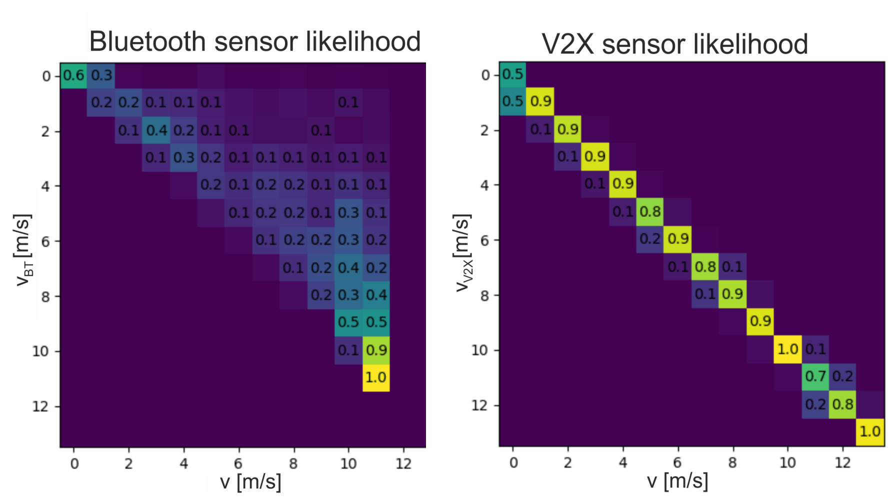

FIGURE 6 Sensor likelihoods for Bluetooth and V2X at traffic light green phase *green2*.

The sensor likelihood for V2X as shown in figure 6 right has its maximum at the true speed class for each speed detection class. Our expectation that V2X provides more accurate speed detections than Bluetooth can be confirmed.

Scenario 3 The speed estimation results are depicted in the third row of table 1. For low V2X penetration ratios the "academic" scenario (scenario 2) performs better than the "realistic" one (scenario 3). But once a 20% V2X penetration ratio is reached, results are even better than in the previous scenario. For instance, a MAE of 1.20 m/s (RMSE: 2.06 m/s) is reached at 50% and 0.98 m/s (RMSE: 1.63 m/s) at 100% V2X penetration ratios.

The influence of the Bluetooth penetration ratio was examined at a constant V2X penetration ratio of 10%. Ratios of 0, 30, 50 and 100% were used for Bluetooth equipment. Results are shown in table 2 where completeness increases quickly when the penetration ratios are raised. Without Bluetooth data only 40.0% completeness can be reached, whereas at 30% Bluetooth penetration already 74.6% completeness can be obtained. In contrast, the accuracy decreases with

	V2X penetration ratio [%]	MAE [m/s]	σ_{MAE}	RMSE [m/s]	σ_{RMSE}	completeness [%]
Scenario 1	0 (Bluetooth only)	5.27	0.51	6.65	0.55	48.8
	1	4.94	0.50	6.38	0.56	50.6
	5	4.10	0.50	5.67	0.64	56.0
	10	3.35	0.42	4.96	0.59	61.5
	20	2.37	0.25	3.87	0.43	72.2
	50	1.28	0.08	2.02	0.24	89.7
	100	0.98	0.00	0.98	0.01	99.7
Scenario 2	0 (Bluetooth only)	1.71	0.64	2.68	0.56	63.1
	1	1.71	0.63	2.68	0.56	64.3
	5	1.72	0.60	2.71	0.56	68.6
	10	1.72	0.57	2.72	0.55	73.5
	20	1.68	0.52	2.68	0.53	81.1
	50	1.50	0.40	2.44	0.45	93.1
	100	1.26	0.26	2.10	0.25	99.6
Scenario 3	0 (Bluetooth only)	2.37	0.23	3.69	0.45	64.3
	1	2.30	0.21	3.62	0.43	65.7
	5	2.07	0.15	3.36	0.33	70.2
	10	1.86	0.16	3.08	0.28	74.6
	20	1.59	0.13	2.71	0.20	81.6
	50	1.20	0.09	2.06	0.12	92.8
	100	0.98	0.06	1.63	0.07	99.8

TABLE 1 Evaluation results of scenario 3 with fixed Bluetooth penetration ratio of 30%

increasing Bluetooth ratio, which is in line with our expectations. The Bluetooth equipment serves the role to improve completeness, but increases the speed estimation error compared to V2X data.

Bluetooth penetration ratio [%]	MAE [m/s]	σ_{MAE}	RMSE [m/s]	σ_{RMSE}	completeness [%]
0 (V2X only)	1.32	0.11	2.22	0.18	40.0
30	1.86	0.16	3.08	0.28	74.6
50	1.94	0.15	3.17	0.24	84.6
100	2.05	0.14	3.29	0.20	94.8

TABLE 2 Evaluation results of scenario 3 with fixed V2X penetration ratio of 10%

It further appeared that similar to the findings in (*13*) the results differ greatly depending on the intersection arms, which is shown in table 3. Very likely we can assume that the different traffic volumes $Q \in [364, 645]$ veh/hour in connection with the driven mean speeds cause this behavior. Thus, for low V2X penetration ratios we can expect MAEs of up to approximately 2.1 m/s, 2.5 m/s, 2.6 m/s and 2.3 m/s for the Eastern, Southern, Western and Northern arms, respectively. In case of the Northern and Eastern arms the MAEs are significantly lower than in the Southern and Western arms. In case of fully V2X equipped vehicles we obtain MAEs between 0.88-1.04 m/s on all intersection arms.

	MAE [m/s]			
V2X penetration ratio [%]	North	East	South	West
0 (Bluetooth only)	2.32	2.05	2.46	2.64
1	2.28	2.01	2.38	2.53
5	2.02	1.89	2.09	2.29
10	1.80	1.73	1.79	2.09
20	1.54	1.55	1.49	1.76
50	1.18	1.24	1.08	1.30
100	0.98	1.02	0.88	1.04

TABLE 3 MAE under consideration of the intersection arms and the V2X penetration ratio. The Bluetooth penetration ratio is 30%

Comparing the obtained results to previous research (*13*) (see table 4) the mean RMSE over all intersection arms can be used. For low V2X penetration the results in scenario 2 show the lowest errors and the RMSE values in scenario 3 are slightly worse than those obtained in (*13*). At a V2X penetration ratio of 20% the RMSEs for all scenarios are similar. For V2X penetration ratios higher than 20% the errors in scenario 3 are the lowest.

V2X penetration ratio [%]	Scenario 2	Scenario 3	Junghans and Leich (*13*)
1	2.68	3.62	3.50
5	2.71	3.36	3.25
10	2.72	3.08	3.08
20	2.68	2.71	2.78
50	2.44	2.06	2.38
100	2.10	1.63	1.90

TABLE 4 RMSE [m/s] of the scenarios 2 and 3 in comparison with results obtained in (*13*). The Bluetooth penetration ratio is 30%

CONCLUSION & FUTURE PROSPECTS

In this paper a recently published method for fusing rare, but accurate V2X data with frequently used, but rather inaccurate one unit Bluetooth reader data of vehicle speeds was analyzed and improved. This analysis included the investigation of (i) specific traffic related variables, such as traffic flow and traffic density and (ii) the consideration of the traffic light control (TLC) influencing the Bluetooth based speed detection. Hence, an improved Bayesian Network (BN) was developed with regard to its applicability for speed estimation in three different traffic scenarios ranging from "academic" trials (i.e. artificial traffic areas and traffic data) to "realistic" (i.e. real intersection model and real traffic demand).

The microscopic traffic simulation SUMO was used. It appeared that the BN had to be modified twofold, to be reduced by some redundant variable and to be extended by an additional variable modeling the TLC behavior. The newly added TLC node was taking into account free flow and stop-and-go characteristics of the vehicles passing the intersections. Further, it turned out that the green phase had to be separated into two different states modeling vehicles that cross the intersection in free flow and vehicles that accelerate due to phase switches.

The results obtained show that the newly developed BN improved the speed estimation results in case of 1-20% V2X penetration ratios in academic example scenario 2 taking into account a fixed Bluetooth penetration of 30%. However, it is not clear, why the accuracy decreases in case of moderate V2X penetration ratios between 5-20% in scenario 2. Additionally, the application of the proposed BN in the realistic example improved the speed estimation results in case of V2X penetration ratios greater than 20%. Particularly, the inclusion of a TLC node greatly improved the estimation results. Even this rather idealistic approach shows that we can expect a cost efficient application for traffic light control in cases of moderate V2X penetration ratios. Further, the application of this method emphasizes the suitability of Bayesian Networks for data fusion purposes, especially in case of communication based sensor technologies in traffic and transportation. However, it is still unclear, whether low price solutions, such as one unit Bluetooth readers in combination with accurate V2X sensors, can substitute current sensor technologies, particularly invasive technologies like inductive loop detectors for adaptive traffic traffic light control. But we are on the way to find out what the limits of these technologies are. Currently, we are quite sure that the V2X penetration ratio has to reach approximately 20% to achieve satisfactory speed estimations, which we expect the car manufacturers to take some years.

Our future work will deal with the problem of decrease in accuracy for moderate V2X penetration ratios. Further, since the investigations were made under idealistic assumptions, we will consider the method under more realistic conditions, e.g. changing detection ranges depending on the weather conditions, different antenna designs and propagation characteristics. Further, this proposed methods can be improved by using two Bluetooth detectors instead of one only. Tests on a real intersection are also part of our future work.

ACKNOWLEDGMENTS

The authors would like to thank the German Federal Ministry of Transport and Digital Infrastructure (BMVI) for supporting this work in the project “Digitaler Knoten 4.0”.

AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: study conception and design: M. Junghans, K. Klüber; data collection: K. Klüber; analysis and interpretation of results: K. Fackeldey, M. Junghans, R. Kaul, K. Klüber; draft manuscript preparation: M. Junghans, K. Klüber.

All authors reviewed the results and approved the final version of the manuscript.

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Improved Traffic State Estimation by Bayesian Network Data Fusion of V2X and Vehicular Bluetooth Data

Kim Klüber, Marek Junghans, Konstantin Fackeldey, Robert Kaul

Motivation

Objectives

- Cleaner, safer and more efficient traffic
- Intelligent V2X based traffic light control (iTLC): Quantify, what is currently possible using V2X!

What traffic data quality level can be obtained in case of V2X based traffic detection?

- Sparsity of the data due to extremely low V2X penetration ratios (1 – 3%) within the next years
- Combine data with other wireless technologies, e.g. vehicular WiFi / Bluetooth (≈3 – 50%)
- Analyze and improve the existing method

Bayesian Networks (BN)

- BN are a graphical representation of cause-effect relationships quantified by conditional probability density functions
- Satisfy the structural Markov property
- Allow to handle and quantify uncertainty
- Allow to take into account hard and soft evidences at each node to infer the true, and usually unknown realization of stochastic variable
- Common usage of BN:
  - Modelling cause-effect relationships
  - Monitoring and diagnosing: drawing conclusions from observations on their causes

Initial BN analysis

- The initial BN and particularly node V_{BT} was analyzed with regard to:
  1. Traffic flow (Q) and density (D)
  2. Traffic light control (TLC)
  3. Preceding Bluetooth speed (V_{pre})
  4. Speed difference (ΔV)

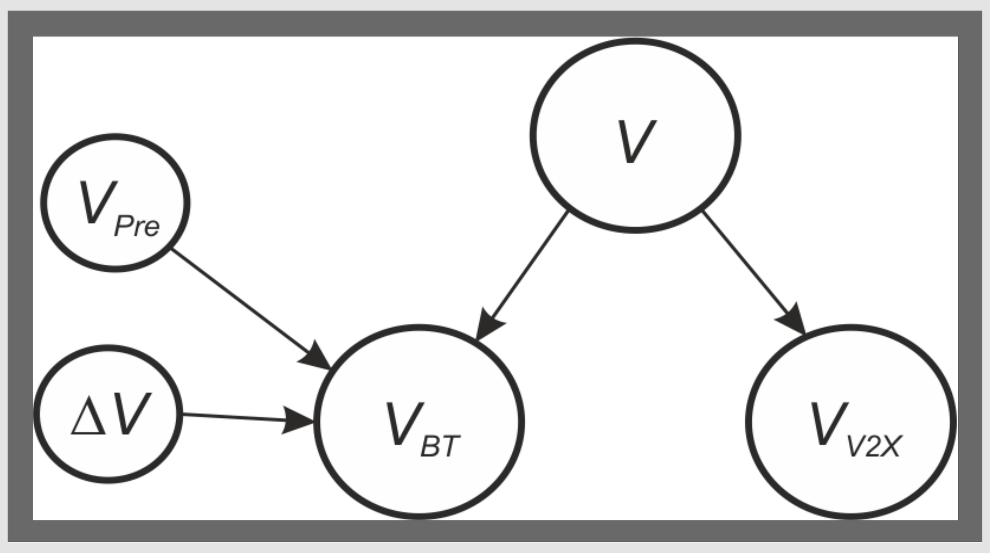


Figure 2: Initial Bayesian Network for fusing V2X and Bluetooth based vehicular speed estimates. (Junghans & Leich)

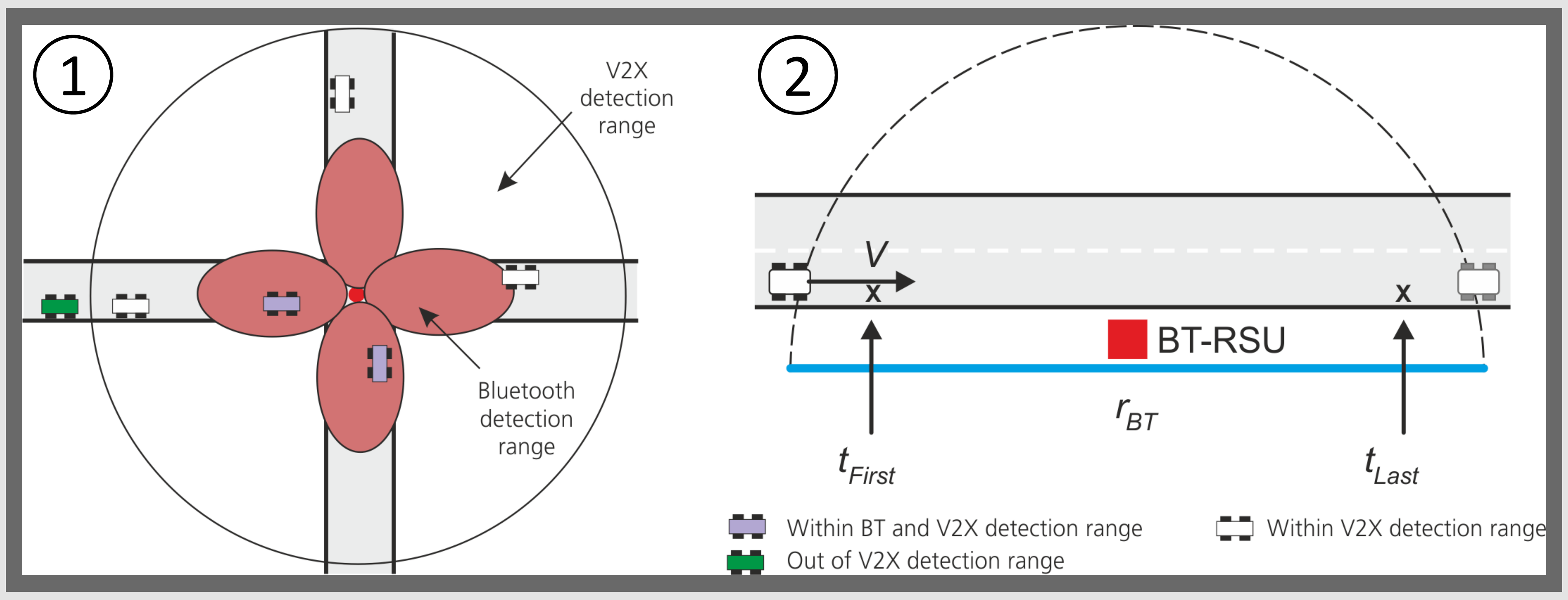


Figure 1: Bluetooth and V2X based detection ranges (1.1) and principle of speed estimation with a single unit Bluetooth reader (1.2).

Simulation of Urban MObility (SUMO)

- sumo.dlr.de
- Open source package
- Microscopic traffic simulation also allowing mesoscopic analyses
- Main applications:
  - traffic and transportation management (intermodal, multimodal)
  - car following
  - vehicle communication (V2X)
  - (analysis of safety-related traffic situations)

Resulting fusion equation

$$P(v|v_{BT}, v_{V2X}, \Delta v, v_{pre}) = \alpha \cdot P(v|tlc) \cdot P(v_{pre}) \cdot P(v_{BT}|v, v_{pre}) \cdot P(v_{V2X}|v)$$

Method

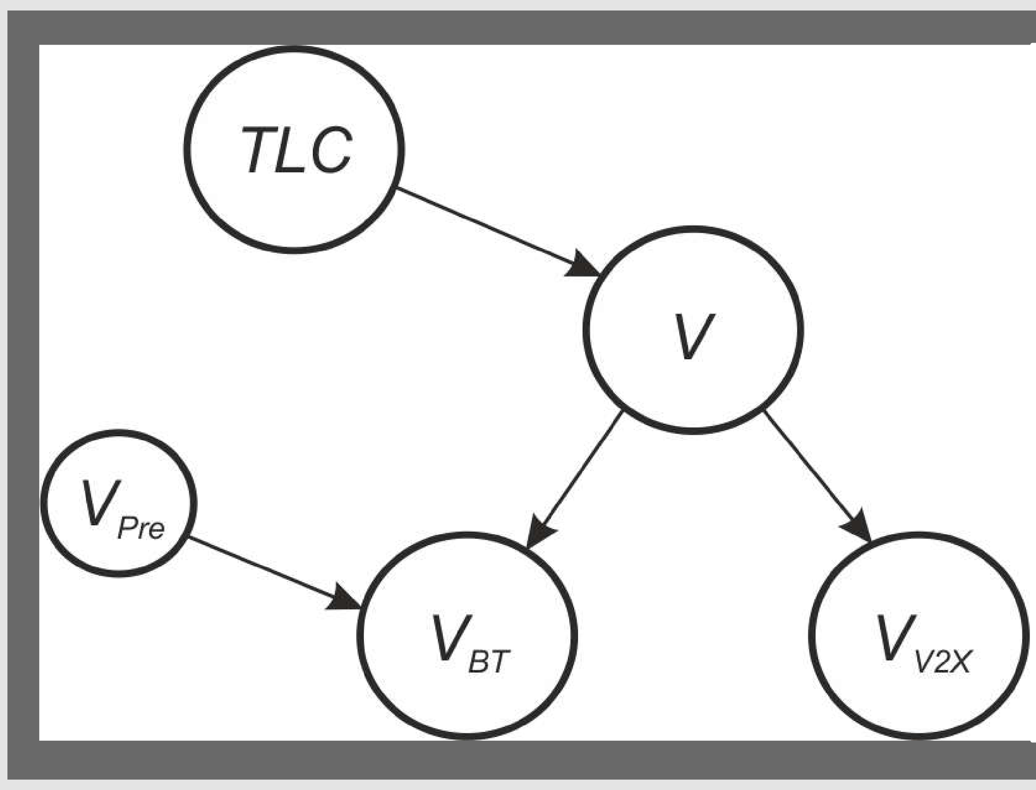
- Single unit Bluetooth speed estimation:
$$V_{BT} \approx \frac{r_{BT}}{t_{Last} - t_{First}}$$
- V2X based speed estimation V_{V2X}
- Fusing the speed estimates by Bayesian Network (BN) taking into account
  - V_{pre}: speed of the preceding Bluetooth equipped vehicle
  - ΔV: speed difference of the currently detected and the preceding Bluetooth equipped vehicle

Conclusions

- V_{BT} is strongly speed-dependent
- Speed dependence should be modeled

Results

- Marginal effect of traffic flow and density on node V_{BT}
- TLC node should be added to model the required speed dependence of the Bluetooth-based speed estimator
- Node ΔV contains information of node V_{pre} and is redundant



- TLC – traffic light control
- V – true physical speed of the vehicle
- V_{BT} – Bluetooth-based speed estimate
- V_{V2X} – V2X based speed estimate
- V_{Pre} – speed estimate of the preceding Bluetooth equipped vehicle

Figure 3: Final Bayesian Network to fuse vehicular single unit Bluetooth-based speed estimates with V2X speed estimates. Note that the node *TLC* complements the initial BN.

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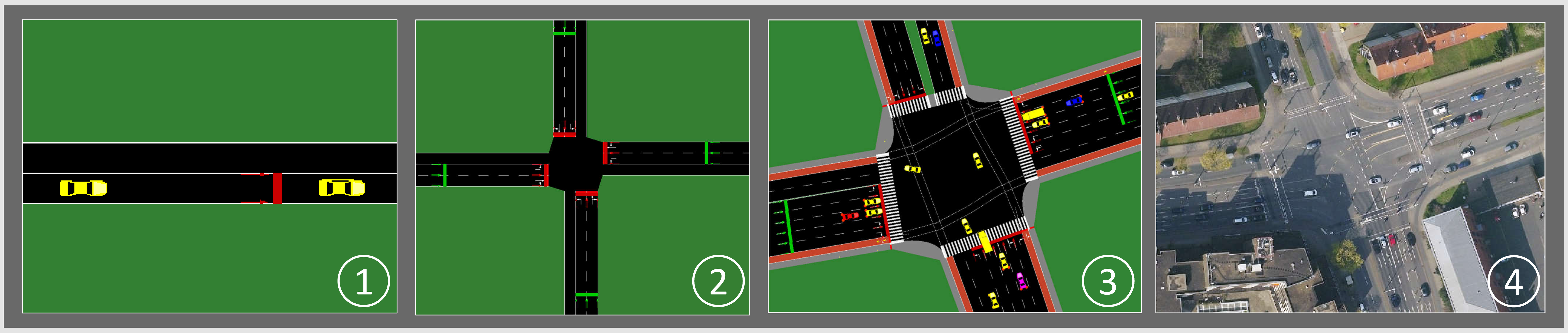

Figure 4: SUMO view on the scenarios 1, 2 and 3: Analysis on (4.1) an intersection free straight road, (4.2) academic intersection with fixed TLC and different traffic volumes, (4.3) real world intersection (Brunswick, Germany) with real traffic demand and fixed TLC and (4.4) aerial photograph of this real intersection.

Experimental results

Setup

- Microscopic traffic simulator SUMO (Simulation of Urban MObility)
- Simulation time: 3600s
- Detection ranges:
  - Bluetooth: 30m
  - V2X: 200m
- Penetration ratios:
  - Bluetooth: [0, 30, 50, 100]%
  - V2X: [0, 1, 5, 10, 20, 50, 100]%
- Traffic conditions: 100 – 1500 (2160) veh/hour
- Training runs: 500
- Simulation runs: 100
- Speed estimator: MAP
- Evaluation metrics:
  - MAE [m/s]
  - RMSE [m/s]
  - completeness [%]

Three Scenarios

1. Straight road (Figure 4.1): Speed decreases from 14 m/s down to 2 m/s while increasing traffic flow from 360 to 2160 veh/hour
2. Academic intersection (Figure 4.2): Identified two "green" traffic light phases for the TLC-node in the BN
3. Real intersection (Figure 4.3): Real traffic demand data used for analysis

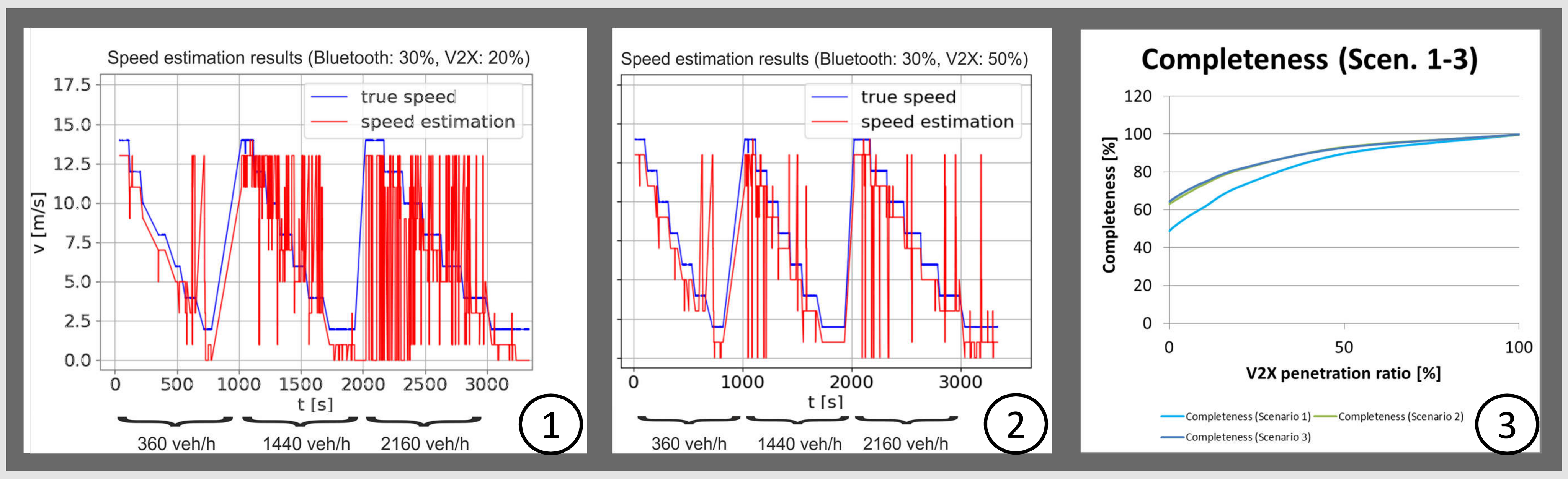

Figure 5: Comparison of estimated with real speeds in case of a Bluetooth penetration ratio of 30% and a V2X penetration ratio of 20% (5.1) and 50% (5.2); completeness value of fusing Bluetooth with V2X (5.3).

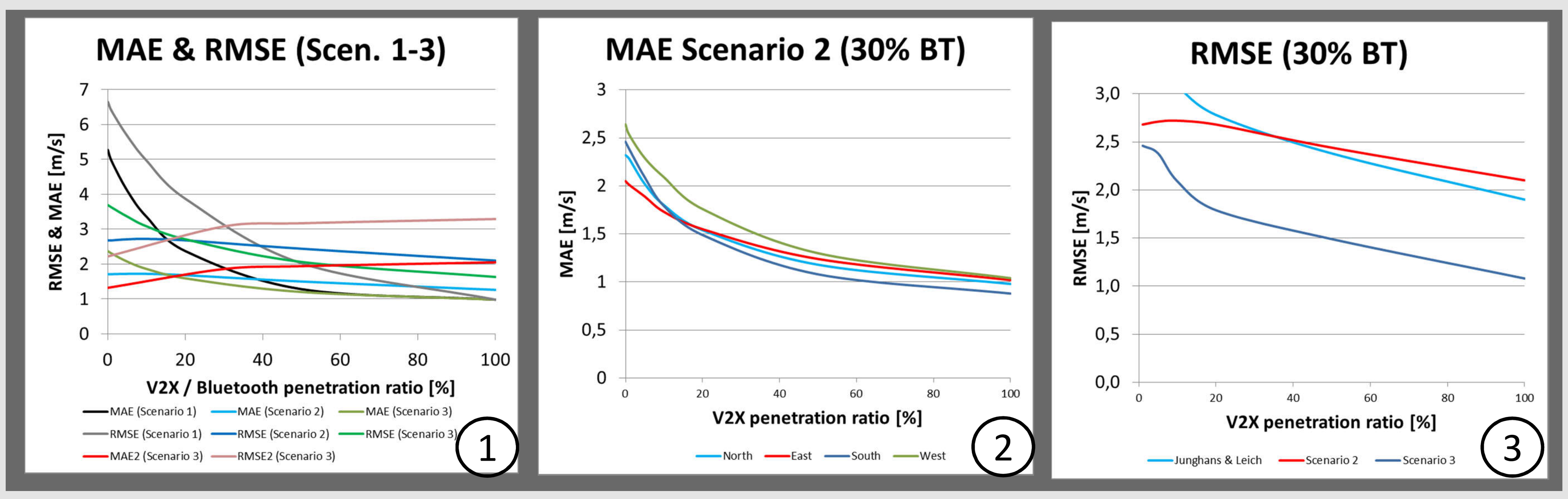

Figure 6: Evaluation results: MAE and RMSE for all scenarios (6.1), MAE for scenario 2 considering the different intersection arms (6.2) and RMSE compared for scenario 2, 3 and Junghans & Leich (6.3).

General results

Scenario 1

- Speed estimation better for lower traffic volumes

Scenario 2

- MAE and RMSE for low V2X (0 – 10%) penetration ratios approximately 1.7 m/s and 2.7 m/s, respectively

Scenario 3

- MAE and RMSE for low V2X (0 – 10%) penetration ratios approximately 2.2 m/s and 3.5 m/s, respectively
- Increasing the Bluetooth penetration ration increases the traffic state estimation error

Conclusions & Future prospects

Conclusions

- Single unit Bluetooth speed estimation overestimates speed
- Due to Bluetooth equipped vehicles the completeness of the speed data increases, but the accuracy of traffic state estimation decreases. In contrast, an increase of V2X equipped vehicles increases the accuracy
- Only about 20% V2X penetration is needed to achieve 80% completeness
- TLC node needed to handle free flow and stop-and-go traffic
- Method gives an idea what can be expected in case of wireless, vehicular speed estimation data
- Possibly estimated 20% V2X penetration needed to realize a good TLC algorithm

Future Prospects

- Find out the cause of the increased speed estimation error in case of moderate V2X penetration ratios
- Analyze more realistic conditions

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