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Abstract

The concept of the Macroscopic Fundamental Diagram (MFD) has been recognized as a powerful tool to develop network-wide control strategies. Recently, it has been extended to the three-dimensional MFD (3D-MFD), used to investigate traffic dynamics of multimodal urban cities where different transport modes compete for, and share road infrastructure. Due to the limited amount of available data used to develop the MFD or 3D-MFD, different estimation methods have been proposed. In most cases, the data comes from either loop detectors or GPS-equipped mobile probe vehicles. Recent research has shown the value of fusing those two data sources for improving the accuracy of an estimated MFD, but requires a priori information about the probe penetration rate (PPR). Considering that this information is not very often available or is very difficult to infer, implementation of such a fusion method has been constrained so far only to simulation data. In this study, however, we propose a methodology to estimate the 3D-MFD that does not require the PPR as an input. To that end, we have developed a fusion algorithm that combines information from probe vehicles and automatic vehicle location devices of public transport to estimate the average speed of cars and further a 3D-MFD in a mixed bi-modal urban network. The findings show that the proposed algorithm can significantly reduce the estimation error when compared to an estimation method that uses only one data source.

Keywords

Three-dimensional MFD, MFD, Traffic state estimation

1 Introduction and background

In traffic flow theory, the concept of the Macroscopic Fundamental Diagram (MFD), which provides a well-defined relationship between the spatially-averaged flow and density, has been recognized as a powerful tool to develop network-wide control strategies. Only recently did researchers proved its existence, using empirical data from the city of Yokohama (Geroliminis and Daganzo, 2008) and derived an analytical approximation method based on variational theory (Daganzo and Geroliminis, 2008).

Despite the large amount of research efforts that have been placed on investigating different aspects of single-mode networks, only few studies have looked at the features of multi-modal operations, focusing on designing an optimal transit service (Wirasinghe and Hurdle, 1977), special bus lanes (Daganzo and Cassidy, 2008), pre-signals for bus priority (Guler and Menendez, 2014a,b, He *et al.,* 2016, 2017) or providing traffic signal priority for public transport (Eichler and Daganzo, 2006). Aiming to fill this gap in the current state of the art, Geroliminis *et al.* (2014) extended the concept of the MFD to the three-dimensional MFD (3D-MFD), with the purpose to investigate traffic dynamics of multi-modal urban cities where different transport modes compete for, and share road infrastructure. The authors derived both vehicular and passenger 3D-MFD, relating the accumulation of cars and buses and the total circulating flow of vehicles (passengers) in a mixed bi-modal network. The discussion on passenger MFD can also be found in (Chiabaut, 2015). Previous studies also used bi-modal MFD as a quantitative approach connecting the impact of dedicated space to the global traffic performance (Zheng and Geroliminis, 2013, Ortigosa *et al.,* 2017).

Due to the limited amount of available data used to develop an MFD, different estimation methods have been proposed (Courbon and Leclercq, 2011, Leclercq *et al.,* 2014). In most cases, the information comes from either loop detector data (LDD) or floating car data (FCD). If none of these sources is available, traffic information might also come from some other sources, such as adaptive traffic control systems that report a density-like performance measures, which can potentially be used for constructing the fundamental relationships (Dakic and Stevanovic, 2017). Recent research (Ambühl and Menendez, 2016) has shown the value of fusing LDD and FCD to improve the accuracy of an estimated MFD, but requires a priori knowledge about the probe penetration rate (PPR). Given that this information is not very often (if ever) available or is very difficult to infer (Du *et al.,* 2016), implementation of such a fusion method has been constrained so far only to simulation data. This study tries to close this gap by proposing a methodology for estimating the space-mean speed of cars and further a 3D-MFD in a mixed bi-modal urban network, combining information from FCD, automatic vehicle location devices (AVL) of public transport, and LDD. As such, it does not require the PPR as an input.

2 Limitations of the existing estimation methods

Assuming that GPS equipped mobile probe vehicles are homogeneously distributed across the network, Nagle and Gayah (2014) proposed an MFD estimation method using the FCD. This assumption, however, cannot be considered to be realistic, as, in most cases, the market penetration level of mobile probes is not uniform across the entire set of origin-destination (OD) pairs. Aiming to address such problems, Du *et al.* (2016) derived an MFD from FCD, using a new probe penetration estimation method based on the *k*-means clustering analysis. Although the findings are encouraging, the following constrains are imposed on the implementation of the proposed method: (i) the detector location can have a great impact on the estimated number of probes for a given OD pair, which has not been addressed in the study; (ii) the optimal number of clusters, shown to have a significant impact on the accuracy of the results, can be network-specific, making the generalization of the procedure very difficult; (iii) LDD and FCD might come in different time formats (e.g. detectors counts are given in a 5-min resolution, whereas the GPS data are only available in a 15-min resolution), preventing one to utilize the proposed methodology to estimate the FCD penetration rate.

On the other hand, the accuracy of an estimated MFD can be improved by fusing LDD and FCD (Ambühl and Menendez, 2016). However, the main assumptions on which such a fusion algorithm is based, is to have a priori knowledge about the PPR and that loop detectors can properly measure flow and density. Considering that the PPR is not often available or is very difficult to infer, as we previously explained, and that, in most cases, loop detectors are not capable of reporting the exact measurements, practical implementation of such a fusion procedure remains challenging.

To overcome the aforementioned problems, Leclercq *et al.* (2014) suggested a method that combines the speed from probes and counts from loops, showing an estimated MFD can be significantly improved compared to a single, LDD data source. Even though the information regarding the PPR is not explicitly required, the accuracy of the proposed method highly depends on: (i) the number of trajectories used to determine the space-mean speed of cars for the entire network; and (ii) the level of homogeneity in terms of the spatial distribution of probe vehicles. Given such dependencies, one can pose the following research questions: What happens if the FCD is very limited or non-existent, especially for some time intervals? Can we still use the combined method in such case and/or have a lack of data for time intervals when the FCD is not available? Is there any other data source that can provide us with additional information about the state of traffic (e.g. speed) when no FCD exists?

In this study we seek to find the answers to these questions, by proposing a novel method for estimating the space-mean speed of cars in a mixed bi-modal system of cars and buses. The proposed method fuses different data sources including FCD and AVL data. Moreover, a lack of the trajectory data is compensated with the information coming from public transport vehicles.

3 Methodology

3.1 Estimation of the space-mean speed of cars from the trajectory data

Let $\{i \mid i \in \mathcal{L}\}$ be an index of the one-directional link, where $|\mathcal{L}|$ is the total number of one-directional links in the network. For any given time interval τ, denote a dynamic set of one-directional links with FCD as $\mathcal{F}(\tau) = \{i \mid i \in \mathcal{L} \wedge \exists j \in \mathcal{P}_i(\tau)\}$, where $\mathcal{P}_i(\tau)$ is the set of probe vehicles traveling on link i at time τ. Then, the space-mean speed of cars from FCD can be derived using generalized definitions of Edie (1961):

$$\hat{v}_c^{FCD}(\tau) = \frac{\sum_{i \in \mathcal{F}(\tau)} \sum_{j \in \mathcal{P}_i(\tau)} d_{i,j}(\tau)}{\sum_{i \in \mathcal{F}(\tau)} \sum_{j \in \mathcal{P}_i(\tau)} t_{i,j}(\tau)} \tag{1}$$

where $d_{i,j}(\tau)$ and $t_{i,j}(\tau)$ stand for the distance and time traveled by probe vehicle j during time τ, on the subnetwork where the FCD is available.

In multi-modal systems, data can be acquired from different modes, which can be used to draw some conclusions regarding the mode for which the data is not available. For instance, in (Zheng and Geroliminis, 2013), the speed of buses is estimated based on the known speed of cars, following the concept of the two-fluid theory (Herman and Prigogine, 1979). Building on such ideas, in the following we will present a novel AVL-based estimation model for the space-mean speed of cars.

Let us first define a dynamic set of shared mixed-lane one-directional links containing the AVL data, $\mathcal{A}(\tau) = \{i \mid i \in \mathcal{L} \wedge \exists z \in \mathcal{B}_i(\tau)\} \subseteq \mathcal{L}$, where z is a bus index and $\mathcal{B}_i(\tau)$ is a dynamic set of buses operating on link i in time τ. If we assume that cars and buses drive with the same free-flow speed in a shared mixed-lane (excluding the dwell time), we can approximate the space-mean speed of cars, $\hat{v}_c^{AVL}(\tau)$, based on the ground truth space-mean speed of buses, $v_b(\tau)$, and the fraction of cruising time in the total time traveled by buses, $\omega_b^{AVL}(\tau)$:

$$v_b(\tau) = \frac{d_{b,tot}(\tau)}{t_{b,tot}(\tau)} \tag{2a}$$

$$\omega_b^{AVL}(\tau) = \frac{t_{b,tot}(\tau) - t^w_{b,tot}(\tau)}{t_{b,tot}(\tau)} \tag{2b}$$

$$\hat{v}_c^{AVL}(\tau) = v_b(\tau)\frac{\bar{n_l}(\tau) + \max\{0, 2 - \bar{n_l}(\tau)\}\bar{\delta}(\tau)\omega_b^{AVL}(\tau)}{\max\{\bar{n_l}(\tau), 2\bar{\delta}(\tau) + \bar{n_l}(\tau)\left(1 - \bar{\delta}(\tau)\right)\}\omega_b^{AVL}(\tau)} \tag{2c}$$

with $\bar{n_l}(\tau) = \dfrac{\sum_{i\in\mathcal{S}(\tau)} n_{l,i}}{|\mathcal{S}(\tau)|}$ $\bar{\delta}(\tau) = \dfrac{\sum_{i\in\mathcal{S}(\tau)} \delta_i}{|\mathcal{S}(\tau)|}$ $\forall i \in \mathcal{S}(\tau)$ $\delta_i = \begin{cases} 1, & \text{if link } i \text{ has a curbside bus stop} \\ 0, & \text{if link } i \text{ has a bus bay} \end{cases}$

where $d_{b,tot}(\tau)$, $t_{b,tot}(\tau)$ and $t^w_{b,tot}(\tau)$ stand for the total distance traveled, total time traveled, and the total dwell time of public transport vehicles; $n_{l,i}$ represents the number of lanes on link i; and $\mathcal{S}(\tau) \subseteq \mathcal{A}(\tau)$ stands for the dynamic subset of shared mixed-lane one-directional links containing a bus stop (curbside or bus bay).

Eq. 2 for the AVL-based estimation model suggests that, to account for the possibility to overtake a bus while boarding passengers at the location of a bus stop if the number of lanes on that particular link is $n_{l,i} \geqslant 2$ or if the link contains a bus bay ($\delta_i = 0$), we weighted the ground truth speed of buses (including the dwell time), $v_b(\tau)$, and the estimated cruising speed (excluding the dwell time), $v_b(\tau)/\omega_b^{AVL}(\tau)$, using the average number of lanes and the percentage of curbside bus stops within the subset $\mathcal{S}(\tau)$. In other words, the AVL-based estimation model accounts for the impact of the dwelling time of buses on the speed of cars in a mixed-lane link, by incorporating parameters for the network topology and configuration of the public transport system.

3.2 Data fusion method for estimating the space-mean speed of cars

In this section we propose the following fusion algorithm for estimating the space-mean speed of cars, shown in a form of pseudo code below. Essentially, the algorithm dynamically divides the entire network into two subnetworks, where each of two data sources is available. To incorporate link i at time slice τ in the set of links that have FCD, $\mathcal{F}(\tau)$, at least one probe vehicle traveling at that time on link i has to exist. If there are no probe vehicles on that particular link, the link can be included in the set of AVL links, $\mathcal{A}(\tau)$, if there is a public transport line operating on that link at time τ. In other words, rather than using $\mathcal{A}(\tau)$ and $\mathcal{S}(\tau)$ sets for the AVL subnetwork that can overlap with $\mathcal{F}(\tau)$, we are interested only in the subset of shared mixed-lane one-directional links, $\{\mathcal{X}(\tau) \mid \mathcal{X}(\tau) = \mathcal{A}(\tau) \setminus \mathcal{F}(\tau)\}$, and the subset of bus stops, $\{\mathcal{Y}(\tau) \mid \mathcal{Y}(\tau) = \mathcal{S}(\tau) \setminus \mathcal{F}(\tau)\}$, with no FCD. The main idea behind dividing the entire network into subnetworks, is to isolate the set of links containing FCD, as the information obtained from at least one probe vehicle traveling along a certain link is more accurate, and therefore valued more for estimating the traffic conditions (e.g. speed) than the AVL information obtained for the same link.

Algorithm: Data fusion

for $\tau \in [1, m_t]$ **do**

Calculate the network coverage of FCD and AVL:

$$\phi^{FCD}(\tau) = \frac{|\mathcal{F}(\tau)|}{|\mathcal{L}|} = \frac{\sum_{i \in \mathcal{L}} \xi_i^{FCD}(\tau)}{|\mathcal{L}|} \;\; \forall i \in \mathcal{L} \;\; \xi_i^{FCD}(\tau) = \begin{cases} 1, \text{ if } \exists j \in \mathcal{P}_i(\tau) \\ 0, \text{ otherwise} \end{cases} \tag{3a}$$

$$\phi^{AVL}(\tau) = \frac{|\mathcal{X}(\tau)|}{|\mathcal{L}|} = \frac{\sum_{i \in \mathcal{L}} \xi_i^{AVL}(\tau)}{|\mathcal{L}|} \;\; \forall i \in \mathcal{L} \;\; \xi_i^{AVL}(\tau) = \begin{cases} 1, \text{ if } \exists z \in \mathcal{B}_i(\tau) \wedge \mathcal{P}_i(\tau) = \emptyset \\ 0, \text{ otherwise} \end{cases} \tag{3b}$$

Calculate the estimated speed of cars using Eq. 1-2

Calculate the fused, average space-mean speed of cars for the entire network:

$$\tilde{v}_c^{FUS}(\tau) = \begin{cases} \hat{v}_c^{AVL}(\tau), \text{ if } \phi^{FCD}(\tau) = 0 \wedge \phi^{AVL}(\tau) \neq 0 \\ \dfrac{(1 - \phi^{AVL}(\tau))(\phi^{FCD}(\tau))^{\lambda(\tau)^{-1}} \hat{v}_c^{FCD}(\tau) + \phi^{AVL}(\tau)(1 - \phi^{FCD}(\tau))^{\lambda(\tau)} \hat{v}_c^{AVL}(\tau)}{(1 - \phi^{AVL}(\tau))(\phi^{FCD}(\tau))^{\lambda(\tau)^{-1}} + \phi^{AVL}(\tau)(1 - \phi^{FCD}(\tau))^{\lambda(\tau)}} \\ \hat{v}_c^{FCD}(\tau), \text{ if } \phi^{FCD}(\tau) = 1 \vee (\phi^{AVL}(\tau) = 0 \wedge \phi^{FCD}(\tau) \neq 0) \end{cases} \tag{4}$$

where $\lambda(\tau) = \frac{1}{2} \phi^{FCD}(\tau)^{\left(1 - \phi^{FCD}(\tau)\right)} \times 100$ [%]

Then, the algorithm computes the network coverages of FCD, $\phi^{FCD}(\tau)$, and AVL, $\phi^{AVL}(\tau)$ (Eq. 3). The following explains the weighting procedure (Eq. 4):

- The estimated speed of cars for each subnetwork is weighted by the network coverage of the corresponding data source: $\phi^{FCD}(\tau)$ in case of FCD, and $\phi^{AVL}(\tau)$ in case of AVL.
- To account for the fact that the network might not be entirely covered by both data sources at a given time τ, each weight is complemented by the fraction of the network not covered with the information coming from the complementary mode of transport: $1 - \phi^{AVL}(\tau)$ in case of FCD, and $1 - \phi^{FCD}(\tau)$ for the AVL.
- The magnitude of the weights depending on the FCD network coverage, $\phi^{FCD}(\tau)$ and $1 - \phi^{FCD}(\tau)$, is increased by the power of $\lambda(\tau)^{-1}$ and $\lambda(\tau)$, respectively. The reason for

defining $\lambda(\tau) = f(\phi^{FCD}(\tau))$, and for taking the inverse value of $\lambda(\tau)$ as the exponent for $\phi^{FCD}(\tau)$, but not for $1 - \phi^{FCD}(\tau)$, is based on: (i) the knowledge that the FCD, if available, is considered to be more accurate than the AVL and therefore valued more for the fusion process, as we stated before; (ii) the nature of numbers that can be obtained for $\phi^{FCD}(\tau)$ and $1 - \phi^{FCD}(\tau)$, ranging between 0 and 1, and the way how such numbers can be increased (using the positive exponent < 1) or decreased (using the positive exponent > 1), depending on the FCD network coverage; (iii) the fact that the proposed fusion algorithm should be generalized (should perform equally well for different settings in terms of the network configuration and operational characteristics of public transport); and (iv) the large number of empirical trials.

3.3 Accuracy of the estimated space-mean speed of cars

Let $v_c(\tau)$ and $\tilde{v}_c(\tau)$ stand for the full network coverage (the ground truth) space-mean speed of cars and the estimated average speed of cars (calculated when the network has incomplete coverage), respectively. Following the approach by Nagle and Gayah (2014), we can formulate the measurements error for a given time slice τ using Eq. 5. The average relative error for the entire period of time can then be computed as $\overline{\Delta R}_V = \sum_{\tau=1}^{m_t} \Delta R_V(\tau)/m_t$.

$$\Delta R_V(\tau) = \left| \frac{v_c(\tau) - \tilde{v}_c(\tau)}{v_c(\tau)} \right| \tag{5}$$

3.4 Performance of the proposed fusion method

To determine how accurately the proposed fusion algorithm estimates the space-mean speed of cars, we will compare its performance with the performance of a reference method, considered to be the best possible estimation given the available, incomplete measurements. The solution is obtained using Nelder and Mead heuristic search approach:

$$\tilde{v}_c^{REF}(\tau) = \alpha \hat{v}_c^{FCD}(\tau) + \beta \hat{v}_c^{AVL}(\tau) \tag{6}$$

where α and β are model parameters. In the first step, the starting value are set to be (0.5,0.5). In the next iteration, values are changed depending on the obtained objective function, $\overline{\Delta R}_V$, according to Nelder and Mead procedure. The procedure is repeated until convergence (a difference of less than 10^{-8}) is reached at an iteration step. In addition to the reference method, we will also compare the fusion algorithm with the method by Leclercq (Eq. 1).

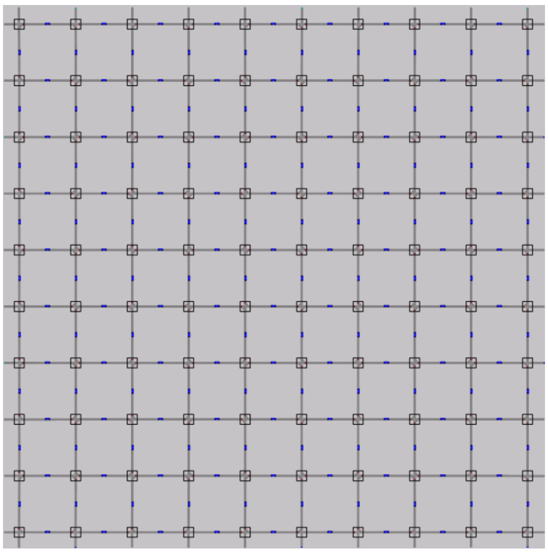
4 Case study

4.1 General simulation setting

The abstract network (Fig. 1) was developed using VISSIM microsimulation platform, as 10×10 grid, with 180 one-lane one-directional links, which are 120 m long. Each signalized intersection was modeled with a cycle length of 60 sec, and 27 sec of green (plus 3 sec of lost time) for all conflicting signal phases.

Tested traffic scenarios ranged from 5% of both FCD network coverage and the probe penetration rate (PPR) to 100%, using an increment of 5%. To account for the randomness, 500 combinations for each of the 400 scenarios were tested. PPR was obtained by randomly selecting corresponding portion of vehicles for a given scenario, either uniformly, across the entire network (homogeneous distribution) or from only one quadrant of the network (inhomogeneous distribution), similarly to Du *et al.* (2016). For each traffic scenario we also varied the network coverage of public transport (25% and 50%) and the bus frequency (2.5 and 7.5 min).

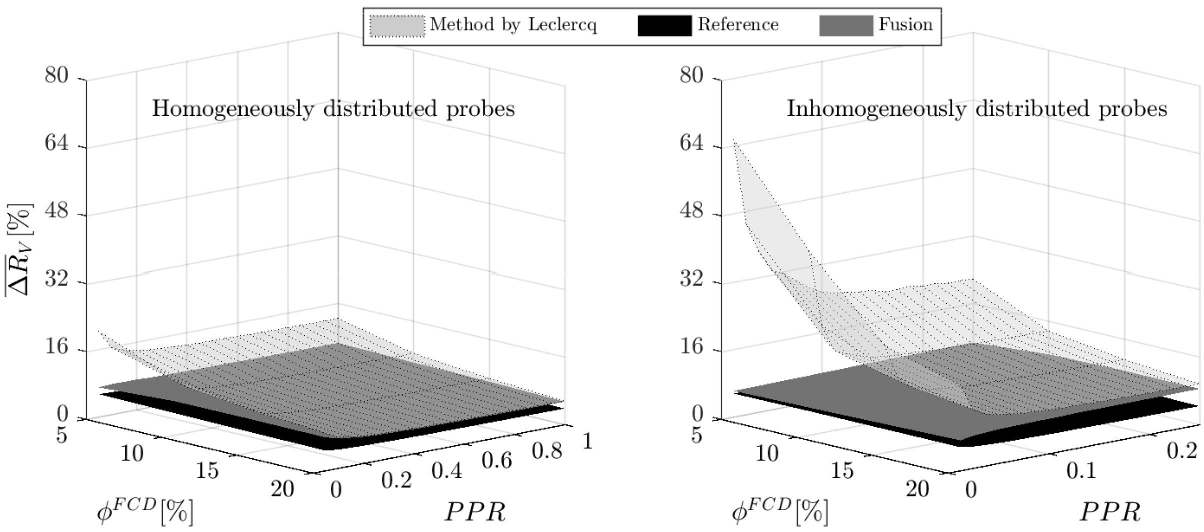
Figure 1: Snapshot of the simulated network layout.



4.2 Results of the data fusion algorithm

In Fig. 2 we show the error plot for the scenario with 50% of lanes being mixed and the bus frequency of 2.5 min, under varying FCD coverages and PPR. It can be seen that for the very low coverages of FCD, the proposed fusion algorithm can substantially reduce the error on the space-mean speed of cars, when compared to the method by Leclercq. This holds true even when the probe vehicles are homogeneously distributed across the network.

Figure 2: Average error on the space-mean speed of cars when 50% of lanes are mixed-lanes and the bus frequency is 2.5 min.



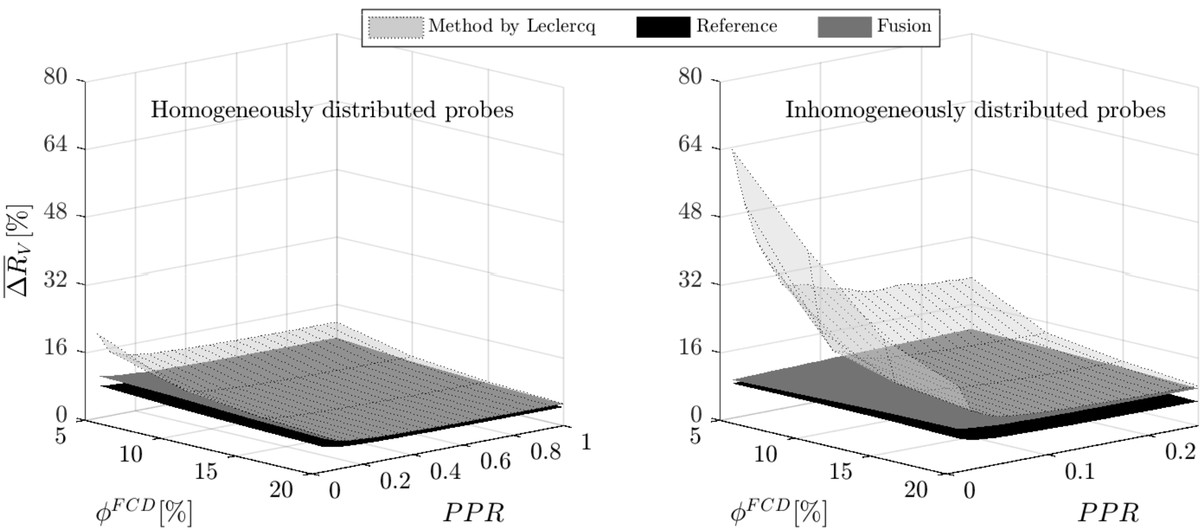
For the same FCD network coverage, the fusion method does not benefit from the increase in the PPR, making the errors relatively constant. Similarly, for the same PPR, the errors in the fusion algorithm are almost invariant to the FCD coverage, whereas the errors in Leclercq's method highly depend on the FCD network coverage. Thus, the difference between these methods decreases with an increase in the FCD coverage, until all the errors converge to the same value, when the network is completely covered by the FCD and no fusion takes place. For the visualization purposes we only show the FCD network coverage up to 20%; other FCD coverages reveal the same trend.

When compared to the reference method, we observe that the reference method is only slightly better than the fusion algorithm. This means that the results of the relatively simple fusion algorithm can supersede a much more complex and computationally demanding optimization procedure, for which the ground truth MFD for cars has to be known priori.

In terms of the comparison of the methods under inhomogeneous distribution of probe vehicles, the errors in the method by Leclercq are significantly higher. This is because public transport system does not cover the entire network, meaning that the traffic conditions and interactions between the private and public mode of transport may be different for different regions. In addition, selection of probe vehicles from only one quadrant (ca. one-quarter of all OD pairs) cannot lead to the equal availability of the FCD across the entire network, especially for low FCD network coverages. These problems do not appear in case of the fusion algorithm, which complements the lack of data (low FCD coverage) with the information coming from public transport. In other words, the fusion algorithm only depends on the percentage of links covered by the FCD. For the rest of the network where no FCD is available, the speed of buses in a mixed-lane is used to estimate the speed of cars, according to the network configuration layout (i.e. number of lanes in mixed-lane links) and configuration of public transport system (i.e. location of the bus stop in a mixed-lane link) (Eq. 2). As the result, the proposed fusion algorithm becomes independent of the distribution of probe vehicles, substantially reducing the error on the estimated space-mean speed of cars and outperforming the commonly used method by Leclercq (Fig. 2).

To address a potential question, how does the fusion algorithm perform when the granularity of the AVL data is rather low, we have performed another set of experiments, using the same percentage of mixed-lanes as in the previous scenario (50%) and the bus frequency of 7.5 min. Results of these experiments are shown in Fig. 3 and reveal the lower error obtained by Leclercq's method compared to the previous case, due to the reduced interactions between different modes of transport.

Figure 3: Average error on the space-mean speed of cars when 50% of lanes are mixed-lanes and the bus frequency is 7.5 min.



Nevertheless, the proposed fusion algorithm once again outperformed the method by Leclercq. This is because the overall percentage of mixed-lanes is relatively high (50%), suggesting that the AVL data can still provide a good approximation of the speed of cars, especially in case of the sparse FCD. In addition, due to the reduced coverage of the AVL data, more weight is given to the FCD-based estimated speed of cars (Eq. 5), which by itself has a lower error compared to the previous scenario. Finally, we have executed additional experiments for assessing the impact of the low AVL network coverage on the performance of the proposed fusion algorithm.

Additional experiments include 25% of mixed-lanes and the bus frequency of 2.5 min (Fig. 4) and 7.5 min (Fig. 5).

Figure 4: Average error on the space-mean speed of cars when 25% of lanes are mixed-lanes and the bus frequency is 2.5 min.

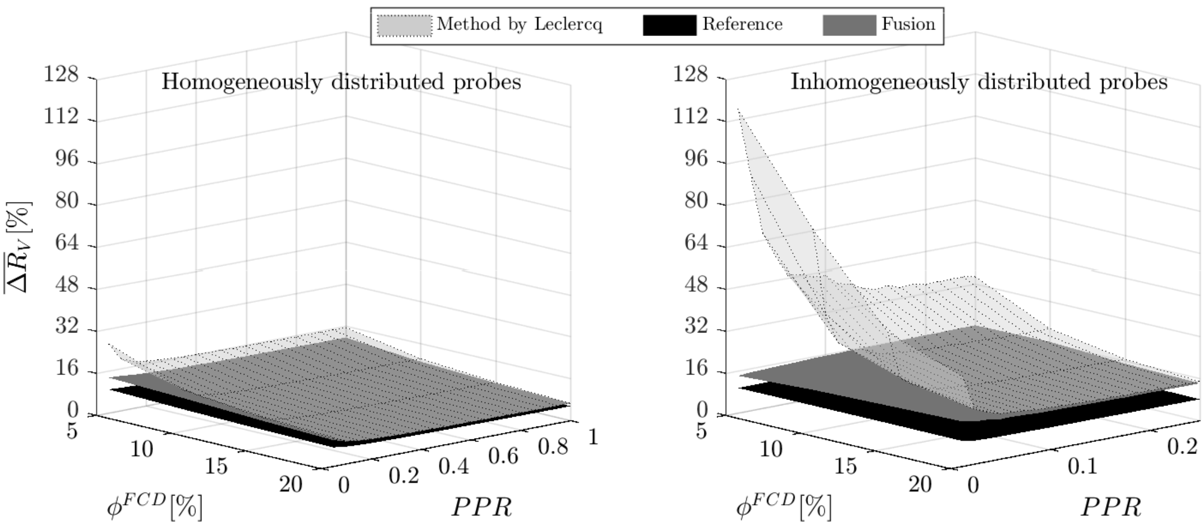
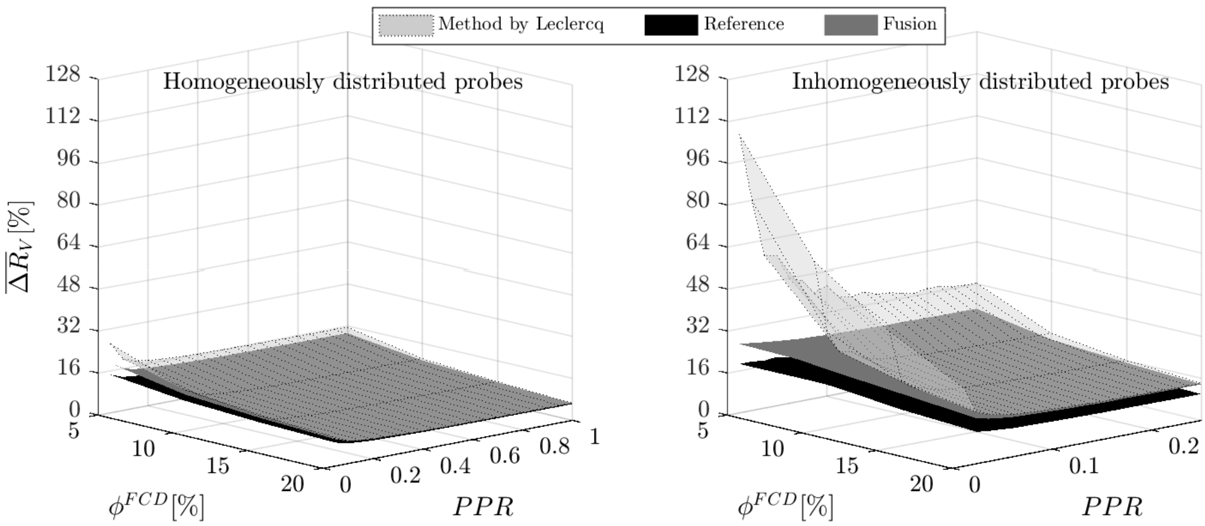


Figure 5: Average error on the space-mean speed of cars when 25% of lanes are mixed-lanes and the bus frequency is 7.5 min.



Results shown in Fig. 4 and 5 imply the following findings. First, the error of the method by Leclercq in case of inhomogeneous distribution of probe vehicles is increased in contrast to the previous scenario. The reason for such an outcome lies in the fact that only a small portion of the network is covered by public transport lines, thus the probes generated from only one quadrant may not travel along the mixed-lane links at all. This in turn results in the estimated speed of cars higher than the ground truth space-mean speed, thus the error is higher. Second, due to the less space allocated to the mixed traffic and reduced interactions between cars and buses when the bus frequency is reduced, the error in the FCD-based method is also reduced. Third, the fusion algorithm once again significantly outperformed Leclercq's method, especially for inhomogeneous FCD distribution Last, the difference between the methods is reduced for the lower bus frequency, due to the limited amount of AVL data and the higher weight given to the FCD.

5 Concluding remarks

This paper presents a novel fusion algorithm for estimating the space-mean speed of cars in bi-model urban networks that fuses different sources of information including the FCD and AVL data. To that end, we have derived a new estimation model for estimating the speed of cars in mixed-lane network based on the AVL data, which accounts for the network topology and configuration of public transport system (number of lanes and the location of bus stop in mixed-lane links).

The preliminary simulation results revealed that it substantially reduces the error on the space-mean speed of cars, especially for low FCD network coverages. In all tested scenarios, it outperformed the commonly used method by Leclercq *et al.* (2014). The results are relatively consistent under different public transport settings and network configuration, and are independent of the spatial distribution and the penetration rate of probe vehicles. This makes the proposed fusion algorithm a very robust and promising framework for assessing the performance of multi-modal traffic.

Future research should test the impact of other network configurations on the performance of the fusion algorithm and confirm the robustness of the proposed method. In addition, future efforts should try to incorporate other public transport modes to estimate the speed of cars. Finally, empirical data should be included to demonstrate the applicability of the proposed methodology.

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