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► **To cite this version:**

Aurélien Clairais, Aurélien Duret, Nour-Eddin El Faouzi. Sequential data assimilation for a Lagrangian Space LWR model with error propagations. The 7th International Workshop on Agent-based Mobility, Traffic and Transportation Models, Methodologies and Applications (ABMTrans 2018), May 2018, Porto, Portugal. pp810-815, 10.1016/j.procs.2018.04.140 . hal-01850468v2

HAL Id: hal-01850468

<https://hal.science/hal-01850468v2>

Submitted on 13 Apr 2021

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The 7th International Workshop on Agent-based Mobility, Traffic and Transportation Models, Methodologies and Applications (ABMTrans 2018)

Sequential data assimilation for a Lagrangian Space LWR model with error propagations

Aurélien Clairais^a, Aurélien Duret^a, Nour-Eddin El Faouzi^a

^aUniv Lyon, ENTPE, IFSTTAR, UMR-T9401, 25 Avenue François Mitterrand, Case 24, F-69675 Lyon, France

Abstract

Decision support systems are of paramount importance to propose traffic control strategies and reliable information to road users. They usually take benefits from data-driven methods which represent a reliable way to gather real time traffic information and make predictions for recurring situations. Data Assimilation (DA) consists in considering both observed data and a traffic flow model to monitor and forecast traffic state. Traditionally, Kalman filtering methods with macroscopic traffic models have been widely used. More recently, mesoscopic approaches proved to be relevant for large scale network applications. However, errors on traffic state is a key information for DA methods. The paper proposes a DA framework that accounts for two types of error: (i) errors from the data collection system and (ii) errors that are propagated and amplified in time and space by the dynamic traffic flow model. When applied on a basic network, the proposed framework demonstrates its ability to track errors and the traffic state information is enriched with a level of uncertainty. It paves the way for new traffic indicators and new solutions for traffic forecast applications. © 2018 The Authors. Published by Elsevier B.V.

Peer-review under responsibility of the Conference Program Chairs.

Keywords: traffic modeling ; data assimilation ; LWR; data fusion

1. Introduction

Decision support systems are the keystone of traffic management to propose appropriate control strategies and provide reliable information to road users. They benefit from the knowledge of traffic conditions in real time and short term predictions. To reach these goals, practices can be classified into two categories. On one hand the data-driven methods rely on traffic data for traffic monitoring and predictions. Based on statistical methods^{1,2}, they are especially relevant for recurring situations such as morning or evening commute. On the other hand, model-driven methods rely on simulations using models to describe the evolution of the traffic conditions in a controlled environment. They are generally used off-line to evaluate existing or new infrastructures. The calibration process, based on historical data, is important with such methods but not sufficient to avoid the shifts induced by stochasticity and heterogeneity of the

* Corresponding author. Tel.: +33-472-142-572
E-mail address: aurelien.clairais@ifsttar.fr

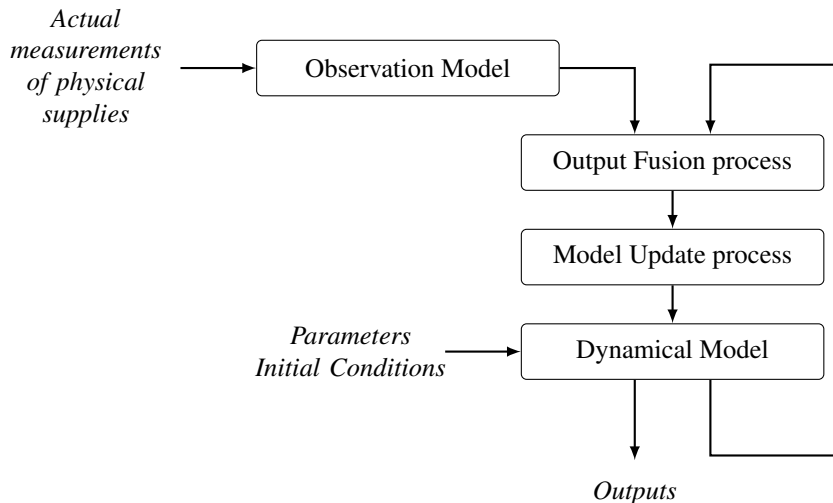


Fig. 1: Conceptual scheme of the data assimilation framework with the 3 main blocks. Adapted from^{13,14}

traffic. Methods that use both model outputs and observed data are known as Data Assimilation (DA) methods. When new traffic data become available, traffic states are estimated based on the model states and the observed states, and the traffic model is updated accordingly.

In traffic, according to³, the DA problems have been addressed with Kalman filters extensions following the seminal work of Kalman⁴. They have been addressed with analytic extensions of the Kalman filter such as the Extended Kalman Filter (EKF)⁵, the Unscented Kalman Filter (UKF)⁶ or the Mixture Kalman Filter (MKF)⁷. Other works lay on replications such as the Ensemble Kalman Filter (EnKF)⁸ or the Particle Filter (PF)⁹. KF-based DA methods assume that the traffic model is linear, or at least differentiable. Several works aimed to use a KF method associated with a Eulerian LWR model: the Cell Transmission Model¹⁰. More recently, DA was explored within a Lagrangian-Space traffic model with both loop data¹¹ and probe data¹². These methods do not take into account model or observation errors. The aim of this work is to develop a DA method based on a Lagrangian-Space model that takes into account errors. The conceptual scheme of the development is based on^{13,14} and is illustrated in Figure 1.

The paper is organized as follows. Section 2 introduces the dynamical traffic model used in the DA scheme. Section 3 introduces the output fusion analytic formulations and model update. Finally, Section 4 presents the results of the method on a straightforward application.

2. The LS-LWR model with error propagation

The Lighthill-Whitham-Richards (LWR) model was introduced in¹⁵ and¹⁶ to describe the dynamic of traffic stream. It consists in a conservative relation and a fundamental diagram. Originally, the LWR model were used considering Eulerian variables like the density k , the flow q and the speed v . The Lagrangian-Time representation was proposed in the 90s, where the traffic variables provide time-position of individual vehicles, with a given time frequency.(see¹⁷). More recently, Lagrangian-Space (LS) representation has been proposed, (see^{18,19}), where traffic variables provide passing time of vehicles at fixed locations on the network. The LS representation has proved to be well suited for assimilating data from inductive loop detectors¹¹.

For the LS representation, the traffic model is solved in the (n, x) coordinates, where n denotes the index of the vehicles and x the space. The LS-LWR model follows the Hamilton-Jacobi theory, where the Hamilton-Jacobi partial derivative equation is derived from the conservation law:

$$\partial_x T = \frac{1}{V(\partial_n T)} \quad (1)$$

Here, V is the flow speed, and the headway h is denoted by its partial derivative formulation : $\partial_n T$. The pace (inverse of speed) and the headway are related following an empirical convex relation: the fundamental diagram, considered as triangular in the remainder of the paper. The solution of the model provides the passing time of vehicle n at location x :

$$T(n, x) = \max \left(T^{(d)}(n, x), T^{(s)}(n, x) \right) \tag{2}$$

, where $T^{(d)}(n, x)$ and $T^{(s)}(n, x)$ are the demand and supply terms, respectively.

For further details on the calculations see¹⁸ and¹¹. In the error-free formulation, all the passing times are computed with purely deterministic variables. Model errors come from errors on the parameters and the initial and boundary conditions. Model parameters are supposed to be distributed following Gaussian distributions. Besides, those considerations were legitimated by empirical studies on traffic stochasticity²⁰. The outputs errors are not Gaussian. A previous work²¹ enabled to propagate the errors to the outputs errors with Gaussian mixtures. A Gaussian mixture is defined as a convex combination of J Gaussian components. The notation of a passing time in the model with error propagation is the following:

$$T(n, x) = \left[\left\{ \pi_{T(n,x)}^{(j)}, \mu_{T(n,x)}^{(j)}, \sigma_{T(n,x)}^{(j)} \right\} \right]_{1 \leq j \leq J} \tag{3}$$

where $\pi_{T(n,x)}^{(j)}$, $\mu_{T(n,x)}^{(j)}$ and $\sigma_{T(n,x)}^{(j)}$ are respectively the weight, the mean and the standard deviation of the j th component of the Gaussian Mixture.

3. Output Fusion and Model Update

The observation model consists in observed passing times of vehicles detected by the inductive loop detectors. Observation errors are supposedly Gaussian, which gives:

$$T^o(n, x) = \left\{ \mu_{T^o(n,x)}, \sigma_{T^o(n,x)} \right\} \tag{4}$$

where $\mu_{T^o(n,x)}$ denotes the mean and $\sigma_{T^o(n,x)}$ the standard deviation of the observed passing time distribution. According to²², the assimilated states $T^a(n, x)$ follow a Gaussian Mixture distribution with the same number of components J . The aim of the method is to estimate the weight $\pi_{T^a(n,x)}^{(j)}$, the mean $\mu_{T^a(n,x)}^{(j)}$ and the standard deviation $\sigma_{T^a(n,x)}^{(j)}$ of the j th component of the assimilated state. The multi-component Kalman gain is introduced in order to reduce the mathematical formulation.

$$K_j = \left(\sigma_{T^f(n,x)}^{(j)} \right)^2 \left(\left(\sigma_{T^f(n,x)}^{(j)} \right)^2 + \left(\sigma_{T^o(n,x)} \right)^2 \right)^{-1} \tag{5}$$

The following equations correspond respectively to the weight, the mean and the standard deviation of the j th component of the distribution of the assimilated state.

$$\pi_{T^a(n,x)}^{(j)} = \frac{\pi_{T^f(n,x)}^{(j)} \times \mathcal{N}(\mu_{T^o(n,x)}, \mu_{T^f(n,x)}^{(j)}, (\sigma_{T^f(n,x)}^{(j)})^2 + (\sigma_{T^o(n,x)})^2)}{\sum_{m=1}^M \pi_{T^f(n,x)}^{(m)} \times \mathcal{N}(\mu_{T^o(n,x)}, \mu_{T^f(n,x)}^{(m)}, (\sigma_{T^f(n,x)}^{(m)})^2 + (\sigma_{T^o(n,x)})^2)} \tag{6}$$

$$\mu_{T^a(n,x)}^{(j)} = \mu_{T^f(n,x)}^{(j)} + K^{(j)} \left(\mu_{T^o(n,x)} - \mu_{T^f(n,x)}^{(j)} \right) \tag{7}$$

$$\left(\sigma_{T^a(n,x)}^{(j)} \right)^2 = \left(1 - K^{(j)} \right) \left(\sigma_{T^f(n,x)}^{(j)} \right)^2 \tag{8}$$

Note that \mathcal{N} denotes the Gaussian density function such as:

$$\mathcal{N}(X, M, (\Sigma)^2) = \frac{1}{\sqrt{2\pi\Sigma}} \exp \left(-\frac{1}{2} \frac{(X - M)^2}{(\Sigma)^2} \right) \tag{9}$$

The model state is then updated according to the assimilated state. Indeed, the sequential data assimilation is activated as new observed data are available. The model update ensures that the vehicles count and the traffic regime both remain consistent with the assimilated traffic states. During the update process, vehicles can either be added, deleted, delayed or advanced¹¹.

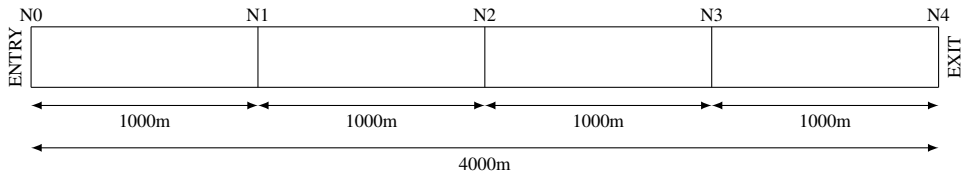


Fig. 2: Experimental Scenario

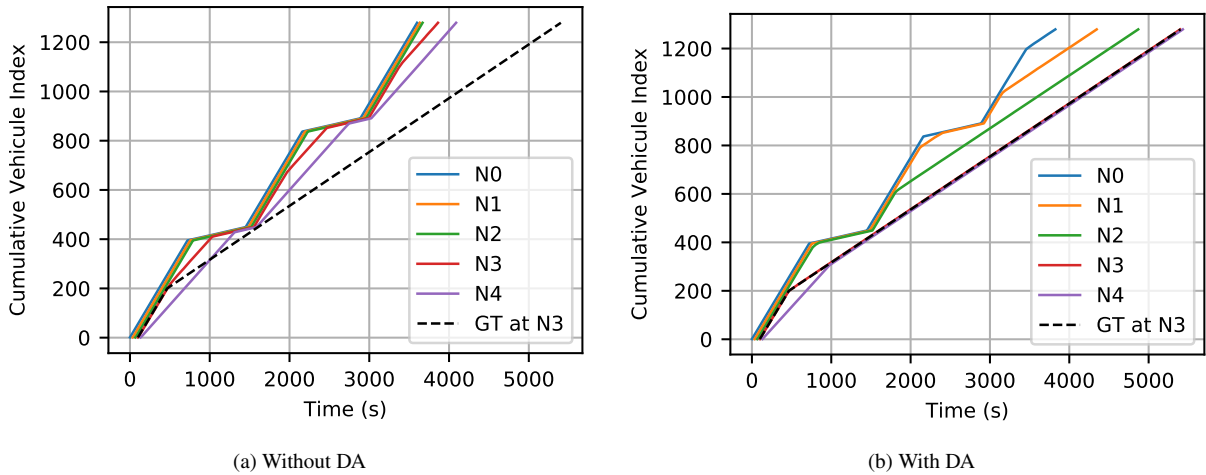


Fig. 3: Comparison in terms of Cumulative Vehicle Index through simulation

4. Illustration

The proposed data assimilation framework is tested on an experimental network composed of 4 consecutive cells where boundaries are numbered from $N0$ to $N4$ (see Figure 2). The ground truth consists in the results of a mesoscopic LWR model²³, designed so that a congestion starts and propagates from $N4$ to $N0$ during the scenario. A loop detector is supposedly deployed at $N3$, which collects noised passing times (standard deviation of 0.5s), which constitute the observations.

Then boundary conditions of the experiment scenario differs from the ground truth (GT) scenario: the outflow capacity of the network has been voluntarily increased. Two simulations will be examined, without DA and with DA, based on two indicators: *Cumulative Count Curves* (CCC), also known as *N-curves* for flow analysis and the shockwave analysis; *Travel Times* to complete with the analysis the propagation of errors/uncertainties through the network.

(i) *Cumulative Count Curves*. A cumulative count curve represents the cumulative vehicle index with respect to the time at a given position on the network. CCC are plotted for successive positions (without source or sink in between). CCC is the raw output of the LS-LWR model. The performance of the proposed DA framework is illustrated, without DA on Figure 3a, and with DA on Figure 3b. In Figure 3a, three shockwaves can be observed: starting from $N4$, they respectively reach $N3$ at around 500s, 1950s and 3300s. However, no shockwave is observed at boundaries $N2 - 0$, unlike the ground truth scenario. In Figure 3b, a shockwave can be observed, which propagates backward from $N3$ (450s) to $N0$ (3500s) through nodes $N3$. This scenario matches the observations at boundary $N3$, and traffic states are properly propagated upstream. We conclude that the proposed DA framework enables to properly update the passing

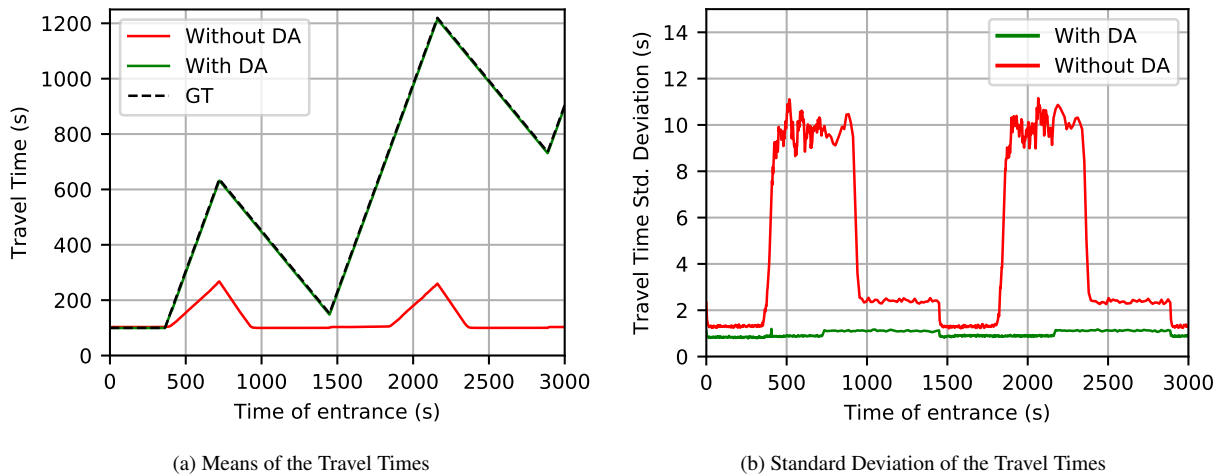


Fig. 4: Comparison in terms of Travel Times through simulation

times at loop sensor locations, and shockwaves are properly propagated through the area of the network where no sensor is located.

(ii) *Travel Times*. In Figure 4a, travel times between $N0$ and $N3$ are illustrated with respect to the time.

Without DA, two congestion patterns are observed, between 400s and 800s; and then between 1300s and 2300s, but delays are significantly lower than delays from the ground truth. As expected, the congestion pattern is modified with DA. The travel times are consistent with travel times from the ground truth scenario. It should be noted that DA allow for the tracking errors on traffic state, which is illustrated in Figure 4b. Standard deviations of the travel time are plotted with respect to time. Errors remain low when the traffic is free-flowing, and they are greatly amplified during congestion (by a factor of nine times in this scenario) which is consistent with previous observation²¹.

5. Conclusion

The paper proposes a new DA framework based on a Lagrangian-Space LWR model with errors propagation. It consists in several steps. First, the model propagates traffic states and errors in time and space and provides passing times of vehicles at fixed location. The errors are considered distributed following Mixture of Gaussian distributions. In parallel, an observation model provides noised passing times of vehicles at a fixed locations of the network. Then an output fusion method has been proposed, to mix traffic states from the model with observed traffic states. Finally, the model is updated to ensure that the number of vehicles assimilated agree with the observations.

The proposed framework enables to propagate traffic states to locations with no observations. When boundary conditions are unknown or flawed, DA enables to update and propagate reliable traffic state through the network. Uncertainties are lower with DA than without, which paves the way for more reliable operational indicators.

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