A UAV-Based Real-Time Traffic State Estimation System for Urban Road Networks

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1 INTRODUCTION

Recently, Unmanned Aerial Vehicles (UAVs) have become an alternative to both stationary and fixed location sensors for traffic monitoring purposes as they can efficiently and quickly obtain high quality vehicle trajectory data over any area of a traffic network with no installation costs. A recent research trend has been to monitor a traffic network using a fleet of UAVs (Butilă & Boboc, 2022, Gohari *et al.*, 2022). Recently, Barmpounakis & Geroliminis (2020) conducted an experiment where a fleet of UAVs was deployed over a real urban traffic network, demonstrating the use of UAV video feed in obtaining vehicle trajectories from virtual loop detectors (and hence transfer flows), average speed of links, congestion propagation, lane-changing behaviour and extraction of Fundamental Diagrams.

Recent studies indicate that for large urban areas, an infeasibly large fleet of UAVs would be needed to monitor the relevant components of a traffic network (Garcia-Aunon *et al.*, 2019, Kyrkou *et al.*, 2018). To circumvent this problem, we propose a UAV-based, real-time traffic estimation system, which obtains real-time measurements of traffic and estimates traffic densities for both the observed and unobserved areas of the traffic network using *a priori* knowledge of traffic dynamics. The proposed estimation method comprises of two parts. Firstly, we use a Gaussian Process model to obtain virtual density estimates and their corresponding uncertainties given sparse and noisy density measurements from UAVs (Englezou *et al.*, 2022). Secondly, we incorporate the non-linear traffic dynamics of congested traffic flow into a moving horizon estimation (MHE) optimization problem via successive convexificaton, which guarantees a convex

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and global solution (Jiang *et al.*, 2007, Mao *et al.*, 2018). Our results show that accurate density estimates can be obtained even when density and flow measurements obtained from UAVs are noisy and sparse.

2 METHODOLOGY

2.1 Traffic Dynamics

We conduct a macroscopic simulation, assuming that the urban traffic environment being tested is partitioned into homogeneous regions. In each region, traffic dynamics are described by a triangular Macroscopic Fundamental Diagram (MFD). These dynamics entail slow changes in traffic demand over time, and traffic congestion is evenly distributed, meeting the criteria outlined by Daganzo (2007). We represent the dynamics of each region $r \in \mathcal{R}$, where $\mathcal{R}$ is the set of homogeneous regions, with the following dynamic equation:

$$\rho_{rd}(k+1) = \rho_{rd}(k) + \frac{T_s}{l_r} \sum_{j \in \mathcal{J}_r} [c_{jrd}(k) - c_{rjd}(k)] + \frac{1}{l_r} D_{rd}(k) + w_{rd}(k). \tag{1}$$

Above, $\rho_{rd}(k)$ is the density of region r with trips ending in region $d \in \mathcal{D}$, where $\mathcal{D}$ is the set of destination regions. Moreover, the discrete time-step of the simulation is denoted as $k \in \mathcal{K}$, where $\mathcal{K}$ is the set of discrete time-steps of the simulation. The term $c_{rjd}(k)$ is the transfer flow from region r destined to region d which passes through neighbouring region $j \in \mathcal{J}_r$, where $\mathcal{J}_r$ is the set of neighbouring regions around region r. Note that $c_{rjd}(k)$ is computed by taking into account the capacity of neighbouring region j. Furthermore, $D_{rd}(k)$ is the origin-destination matrix denoting the number of vehicles entering region r destined to region d at time-step k and $w_{rd}(k) \sim \mathcal{N}(0, \sigma_w)$ is white Gaussian noise that is added to the model. The constants T_s and l_r are the duration of each discrete time-step and the average length of trips within region r.

2.2 UAV measurements

Each UAV is assigned a pre-defined path, calculated based on the number of regions in the urban traffic network and number of UAVs available. The paths are cyclical and each region belongs to at least one path, ensuring that each region is monitored by at least one UAV at some point during the cycle. While hovering over region r, a UAV obtains noisy measurements of traffic density $\tilde{\rho}_r(k)$ and transfer flow from region r to neighbouring region j, $\tilde{c}_{rj}(k)$ at time-step k:

$$\tilde{\rho}_r(k) = \rho_r(k) + \nu_r^{\rho}(k), \tag{2}$$

$$\tilde{c}_{rj}(k) = c_{rj}(k) + \nu_{rj}^{c}(k). \tag{3}$$

The terms $\nu_r^{\rho}(k) \sim \mathcal{N}(0, \sigma_{\rho}^2,)$ and $\nu_{rj}^{c}(k) \sim \mathcal{N}(0, \sigma_c^2)$ are Gaussian white noise, added to the true density and transfer flows $\rho_r(k)$ and $c_{rj}(k)$, respectively. Each region is small enough (no more than 300m across) such that all transfer flows in and out of the region can be observed by a UAV hovering at a suitable altitude h. After monitoring region r, the UAV transitions to the next region in the path. This transition typically takes about 30 seconds, during which no traffic measurements are collected.

2.3 Gaussian Process model

Gaussian Process models are a non-parametric Bayesian technique frequently utilized for interpolating sparse datasets by assuming a Gaussian distribution over functions. For a given region $r \in \mathcal{R}$, the GP model is trained on $\tilde{\rho}_r(k)$ which are available $\forall r \in \mathcal{R}$ for time-steps $k \in \{1, 2, ..., k'\}$, where k' is the current simulation time-step. The output is a distribution of $\hat{\boldsymbol{\rho}}_r(k)$ $\forall k$ up until and including k', given as

$$\hat{\boldsymbol{\rho}}_r(k) \,|\, \tilde{\boldsymbol{\rho}}_r(k), \sigma^2, \varphi, \nu^2 \sim \mathcal{N}(\hat{\mu}_r(k), \hat{\sigma}_r^2(k)), \tag{4}$$

where φ is the unknown correlation parameter, σ^2 is the unknown variance of the parameter and ν^2 is the noise-to-signal ratio (Rasmussen, 2004).

2.4 Successive Convexification

A MHE optimization algorithm is developed which minimizes the weighted least squares of the measurement and process errors over a moving horizon window (MHW), with objective function:

$$\underset{\mathbf{e}_k}{\text{minimize}} \sum_{k \in \mathcal{W}_{k-W+1}^{k}} \mathbf{e}_k^T \boldsymbol{\Sigma}_k^{-1} \mathbf{e}_k.$$

Matrix $\boldsymbol{\Sigma}_k^{-1}$ is the inverse of the error variances $\sigma_w, \sigma_\rho, \sigma_c$, where σ_ρ is updated according to the uncertainty of each virtual measurement from the GP model. The set $\mathcal{W}_{k'-W+1}^{k'}$ comprises measurements from time step $k' - W + 1$ to the current time-step k', where W represents the length of the MHW. The vector $\mathbf{e}_k$ is a column vector of variables which model the process noise $w_{rd}(k)$ from Eq. (1) and measurement noises $\nu_r^\rho(k)$, $\nu_{rj}^c(k)$ from Eq. (2) and (3):

$$\mathbf{e}_k = [e_{rd}^\rho(k), e_r^\rho(k), e_{rj}^c(k)]^T \in \mathbb{R}^{N \times 1}. \tag{5}$$

For a given MHW, $\mathcal{W}_{k-W+1}^{k}$, the transfer flows measurements $\tilde{c}_{rj}(k)$ observed during the window are included, as well as a full set of virtual density measurements $\tilde{\rho}_r(k)$, obtained from the GP model. The non-linear traffic constraints are transformed to linear constraints by taking their convex hull. Once the initial optimization problem is solved an iterative procedure follows where the same problem is solved with tightening bounds imposed on the density estimates $\hat{\rho}_r(k) \forall k \in \mathcal{W}_{k-W+1}^{k}$. This process is repeated until the bounds are suitably small.

3 SIMULATIONS AND RESULTS

3.1 Simulations

We simulate an urban environment with a Macroscopic Traffic model in `MATLAB`, where the number of homogeneous regions is $|\mathcal{R}| = 7$. We test the robustness of the proposed estimator by altering the measurement and process noise between high, medium and low. We also alter the number of UAVs observing the urban network, with a minimum of one UAV surveying the network to a maximum of seven. For each measurement and process noise pairing, we run the simulation 20 times and average the results.

3.2 Results

We compute the Mean Average Percentage Error (MAPE) for both $\hat{\rho}_r$ and $\hat{\rho}_{rd}$ for varying measurement noise, process noise and number of UAVs. We run these tests using the virtual measurements of $\tilde{\rho}_r$ provided by the GP model and sparse measurements of $\tilde{c}_{rj}$. For brevity, we only show the MAPE results for varying measurement error and number of UAVs, shown in Fig. 1.

As shown in Fig. 1 we observed a decrease in MAPE for both $\hat{\rho}_r$ and $\hat{\rho}_{rd}$ as the number of UAVs increases, which is expected as the set of $\tilde{\rho}_r$ and $\tilde{c}_{rj}$ is more complete. Moreover, we observe a decrease in MAPE for $\hat{\rho}_r$ as the standard deviation of measurement error decreases. This is also partially observed for $\hat{\rho}_{rd}$, however it is not as pronounced as measurement noise mainly impacts $\hat{\rho}_r$, according to Eq. (2).

Assuming the worst case scenario of one UAV and high measurement noise, the MAPE of $\hat{\rho}_r$ is around 32 %. Considering that this includes estimates of all unobserved regions and is in real-time, we consider this an encouraging result. Moreover, the MAPE of $\hat{\rho}_{rd}$ given the same scenario is around 40 %.

4 DISCUSSION

In this work, we propose a real-time urban traffic state estimator with measurements provided by UAVs, where the urban traffic network is partitioned into homogeneous regions. As the

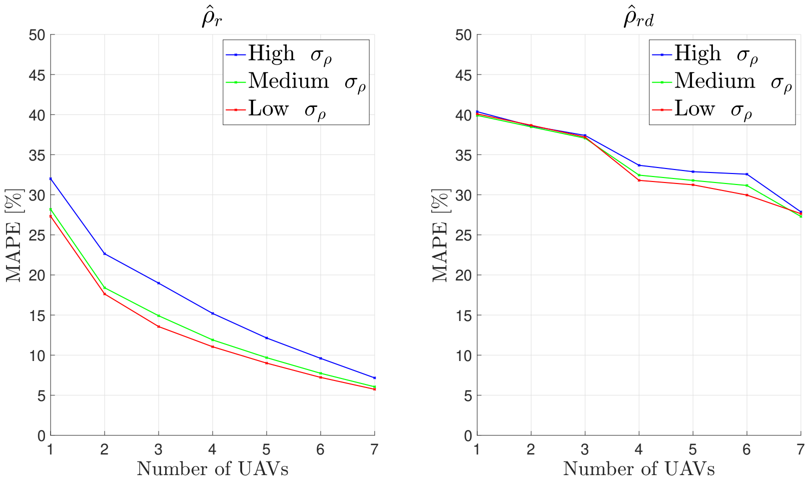

Figure 1 – *Varying measurement noise results for $\hat{\rho}_r$ and $\hat{\rho}_{rd}$.*

measurements are sparse, we firstly produce virtual measurements of the traffic density which are computed by a Gaussian Process model. We include *a priori* knowledge of traffic dynamics by forming a moving horizon weighted least squares optimization problem which minimizes the measurement and process errors. Since the traffic dynamics are non-linear we propose a successive convexification method, where at each iteration, the bounds on state variables are tightened, resulting in a global solution. Our results indicate that even when high noise is present and measurements are sparse due to a limited number of UAVs monitoring the traffic network, the proposed estimator provides accurate estimates of traffic density $\hat{\rho}_r$ and traffic density with known destinations $\hat{\rho}_{rd}$.

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