A State-Space Model for Assimilating Passenger and Vehicle Flow Data with User Feedback in a Transit Network

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ABSTRACT
This note explores the idea of utilising a state-space model, congruent with the underlying equations of the Kalman filter with control input, for reconstructing the state of crowdedness in a transit network. The envisaged role of the proposed scheme is twofold: first, to provide an estimate of the state of crowdedness given input data on vehicle movement, on passenger inflow/outflow at stations and on measured crowdedness; second, to trigger localised requests for feedback based on the estimated system state as well as on the data assimilation performance indices. The latter is applicable to a scenario where the crowdedness is measured through passenger feedback. The feedback loop is conceptualised to be realised with a participatory crowd-sensing smartphone-based system in which reported perceived levels of crowdedness are assimilated in near-real-time with the aim of improving the estimation of the model state. Presented model is also applicable for assimilating other relevant measurements, for instance, vehicle weighing, automatic passenger counting, aggregated smartcard data or passive wireless device monitoring data.

KEYWORDS
state-space model; transit network; data assimilation; crowd-sensing; user feedback; crowdedness

1. Introduction

Despite ubiquitous and ever-growing availability of datasets on the operation and schedules of public transportation, crowdedness levels – to the authors’ knowledge – are currently not among the variables disseminated through public channels. Crowdedness is intuitively one of the key factors affecting perceived level of service what has been corroborated in numerous research reports (see e.g., Haywood, Koning, and Monchambert 2017, and references therein). The level of crowding determines the ability for a passenger to seat, the ability to spend time productively on board, and – in the extreme case – the ability to board. Moreover, high passenger density causes stress due to safety, security, hygiene or thermal comfort concerns, and all of these have the potential to influence route and mode choices of passengers (see e.g., Kim et al. 2015). From the operators’ perspective, overcrowding translates to increased accident risk, decreased customer satisfaction, and suboptimal infrastructure utilisation due to lengthening of dwell times and unbalanced passenger loading potentially leading to

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unused seating capacity (see Regirer and Shapovalov 2003; Ball 2016; Haywood, Konning, and Monchambert 2017, for examples of modelling and data-analysis studies, and a review, respectively).

The stimuli for the presented work have been the realisations that: (i) given even a simple macroscopic model of passenger loading dynamics, the levels of crowdedness are retrievable from existing datasets (as demonstrated e.g., in Reyes and Cipriano 2014) and (ii) crowdedness is one of the variables that is “measurable” through passenger feedback (e.g., Farkas et al. 2015) realised with a participatory crowd-sensing smartphone-based system (Guo et al. 2016). Achieving both of the above would create the potential for enrichment of existing public transportation datasets with assimilated levels of crowdedness. This, in turn, creates the potential for incorporation of information on crowdedness in route planning (e.g., Handte et al. 2016) as well as in real-time provision of data to passengers (e.g., Nuzzolo et al. 2016; Drabicki et al. 2017), all with the aim of optimising network usage and passenger comfort.

The focus of this work is placed on formulation and demonstration of a simple data fusion methodology capable of assimilation of the following data into a macroscopic simulation of passenger distribution in a transit network: (i) data on passenger inflows/outflows to/from stations (differential macroscopic data), (ii) measurements of passenger density (integral macroscopic data), (iii) vehicle location information (microscopic data).

The concept of a feedback loop between the system and its users is conceptualised similarly as in Farkas et al. (2015) with a simple yet real-time-processed smartphone interface for reporting perceived crowdedness around a user. Noteworthy, interpreting user perceptions of crowdedness is a complex problem that has been researched over the years from psychological/behavioural angles (Stokols 1972; Kalb and Keating 1981; Mohd Mahudin, Cox, and Griffiths 2012; Li and Hensher 2013). In a wider context, human perception of numerosity is a factor here with suggested geometric or logarithmic (Weber-Fechner-like) principles (Toyosawa and Kawai 2005; Cicchini, Anobile, and Burr 2016). In the present study, from the point of view of the data assimilation approach, such “measurements” are treated as any other noisy data on crowdedness and the methodology is, in principle, applicable for assimilation of data from vehicle weighing (Frumin 2010; Nielsen et al. 2014; Ball 2016), data obtained by counting distinct personal electronic devices (e.g., Schauer, Werner, and Marcus 2014), data available in smartcard-based ticketing systems (e.g., Zhang, Jenelius, and Kottenhoff 2017) or data from automatic passenger counters (APCs, e.g., Pinna, Dalla Chiara, and Defiorio 2010).

In the following section, the model formulation is given in a generalisable form, yet the nomenclature is shifted towards urban train network, for the example implementation presented in subsequent section focuses on the Boston subway system.

2. Model formulation

The model represents macroscopic dynamics of passenger loading in a transit network conceptualised as an arbitrary connected graph with \( n_s \) station nodes and \( n_e \) edges. For every edge in the graph, there is a pair of state-variable triplets defined - one triplet for northbound and another for southbound directions, each consisting of “boarding”, “on-board” and “alighting” passenger counts (nomenclature consistent e.g., with Nuzzolo et al. 2016). The system state vector \( x \) consists, thus, of \( n_x = 6 \times n_e \) state variables hereinafter referred to as grid boxes.
The system dynamics covering passenger flow (due to vehicle movement), response to control input (inflow and outflow of passenger to/from stations) and observation process (crowdedness perception feedback) are linear and represented in line with the stochastic formulation underlying the Kalman filter with control input:

\[
    x_k = F_k x_{k-1} + B_k u_k + w_k \\
    z_k = H x_k + v_k
\]

where \( k \) denotes timestep index, \( z \) is the vector of passenger count measurements, and the right-hand side terms are defined with:

- \( F_k \): state transition matrix for vehicle movements and transfer probabilities,
- \( B_k \): control transition matrix representing north-/southbound probabilities,
- \( u_k \): control input vector with entry/exit counts (turnstiles, smart cards, APCs),
- \( H \): observation matrix expressing spatial granularity of measurements,
- \( w_k, v_k \): Gaussian noise terms expressing model and observation uncertainties.

In the case of a single line, \( F_k \) can be thought of as a representation of a Marey diagram using a Boolean bidirectional time-dependent matrix with values of one set either on the diagonal (e.g., passengers waiting on boarding platforms) or on the subdiagonal (passengers moving to adjacent grid boxes). Flow of passengers between adjacent grid boxes is associated with vehicle departure or arrival at a station, which must occur in different time steps to account for movement of passengers between “alighting” and “boarding” grid boxes of a station (allowing also for representation of actual dwell times). The rationale of introducing “alighting” and “boarding” grid boxes is to allow for representation of probabilities of transfers in multi-line networks (in which case the \( F_k \) matrix is no longer bidirectional or Boolean).

The control vector \( u_k \) is meant to contain estimates of passenger inflow and outflow at station entry and exit gates expressed in passenger count per timestep. The role of \( B_u \) is to represent the probabilities of passengers travelling north- or southbound (both in the case of arrival or departure). The matrix could, thus, be derived from an origin-destination (OD) matrix or more simply by defining a gravity-like model in which \( B \) is constant in time and conveys the assumption that in the centre of gravity (centre of the city) the probability of north- or south-bound travel is 50%/50%, at termini it is 100%/0% and remaining matrix coefficients are linearly interpolated. In a broader context, the \( Bu \) term allows to feed the model with differential macroscopic data, i.e. the numbers of passenger added or subtracted at a given time, at a given location in the network.

The interplay between the two additive terms \( F_k x_{k-1} \) and \( B_k u_k \) makes the model capable of representing, e.g., accumulation of waiting passengers on platforms. At the same time, it has to be noted that the interplay between these two terms may lead to appearance of negative passenger loading. In the case of an alighting grid box, it can be interpreted as an expression of station’s “potential” as a destination. In the case of a vehicle carrying fewer passengers than expected to alight at a station, the negative signal will propagate to adjacent stations. Negative values in “on-board” grid boxes are proposed to trigger feedback requests aimed at correcting the bogus datum after assimilating the feedback response.

The role of the observation process is to enable assimilation of integral macroscopic data, i.e. the numbers of passengers present at a given time at a given location in the network. The \( H \) matrix allows to express the spatial extent of the measurement, e.g. that a platform-reported crowdedness is to be interpreted as the sum of both north-
bound and southbound passenger counts. Similarly, a summation over consecutive “on-board” grid boxes encoded in $H$ can express positioning uncertainty in correlating feedback from on-the-move passengers with a particular grid box. Noteworthy, $H$ and $z$ can embody data and assumptions pertinent to multiple measurement methods.

Presence of the noise terms that embody model and feedback data uncertainties allows to apply the standard Kalman optimal filtering scheme widely used in transportation applications (see e.g., Pagani et al. 2016, section III and references therein). It is noteworthy, that given the Markovian character of the model and the central role of nearest-neighbour interactions (adjacent grid boxes), the model bares some resemblance with a scalar conservation problem – with $B_k u_k$ resembling a source term and the ones on the subdiagonal of $F_k$ corresponding to Courant numbers of unity, using the PDE numerics nomenclature. The predict step of the Kalman filter is bound to a conservation constraint $\Sigma u_k + \Sigma x_{k-1} = \Sigma x_k$ (summations over all elements of $u$ and $x$) expressing conservation of total passenger count in the network and constituting a validity condition for $F_k$ and $B_k$.

3. Prototype implementation and sample results

The above-defined representation of the network and its dynamics has been prototypically implemented in Python using Jupyter, networkX, FilterPy (Labbe Jr 2018) and visJS2jupyter (Rosenthal et al. 2017). The prototype has been applied to simulate passenger loading in the Boston subway network using an open dataset released with the MBTAViz project of Barry and Card (http://mbtaviz.github.io/). The dataset consists of four-week-long timeseries of turnstile inflow and outflow passenger counts with 1-minute time resolution, of the train departure and arrival times and of a record of alerts on service disruptions. The dataset covers three lines: red, orange and blue (as compared to red-line-limited datasets used in Heimburger, Herzenberg, and Wilson 1999; Koutsopoulos and Wang 2007). As a side note, interestingly, the Boston subway has been used as an example in studies of the so-called small-world networks (Marchiori and Latora 2000; Latora and Marchiori 2002).
Since the original dataset has a mixed microscopic/macroscopic character with the train arrival/departure times associated with particular vehicles, these data were aggregated using the resolution of the turnstile dataset and recast in a macroscopic form of counts of trains departing and arriving at a given station (effectively carrying the same information content as the vehicle events defined in Reyes and Cipriano 2014).

Figure 1 depicts selected components of the interface of the developed prototype implementation named MoveWise. The top left section of the figure depicts simulation controls not discussed herein. The bottom left section of the figure depicts the interactive animated representation of the subway network and simulation grid with passenger loading indicated with a colour scale. The “boarding” and “alighting” grid boxes are represented with small circles, “on-board” ones with squares. The right section of the figure depicts the feedback emulation panel with a smartphone mock-up and an application interface consisting of six cartoons corresponding to different crowdedness levels (images adapted from Haywood, Koning, and Monchambert 2017).

Two panels of Figure 2 depict input and output data of a sample simulation. The plot in the left panel reveals documented deficiency of the dataset, namely missing (or largely underestimated) data on the numbers of passengers exiting from some of the stations. Since the depicted data correspond to a terminus (Ashmont station), the missing data on the amounts of passengers exiting the station ought to be retrievable from simulation output, for all passengers arriving at the terminus are assumed to exit the station. The plot in the right panel confirms plausibility of this hypothesis: the depicted breakdown of passengers travelling from the penultimate station to the terminus has an arguably realistic time profile. The magnitude of the outgoing passenger flux (orange filled histogram) is likely overestimated, for any errors in the turnstile data (in particular, uncounted exiting passengers) accumulate along a line and cause overestimation of simulated passenger counts at the terminus. Presented simulation was performed without any feedback data and with the simple gravity-like assumption resulting in constant-in-time matrix $B$ and with an arbitrary transfer probabilities at the fork of the red line (50%-50% probabilities of transferring towards Ashmont or Braintree for passengers going out of town, 95% probability to go towards the centre of town for passengers arriving at the JFK fork from the south). Presented output data exemplifies that, despite these simplifications, the methodology is capable of enriching (or gap-filling) existing datasets, even without leveraging the potential for assimilation of crowdedness measurements.
4. Summary and discussion

This note covered discussion of an approach to modelling passenger number dynamics (and conservation) within a transit network using the system of equations congruent with the underlying equations of the Kalman filter with control input. Presented approach allows to assimilate both integral (passenger counts) and differential (passenger fluxes) data on passenger density, along with vehicle movement data. Sample results from a simulation driven by vehicle-location and passenger-flow data for the Boston subway exemplify how the methodology can be used to enrich an existing dataset.

The potential of the methodology lies in leveraging the applicable filtering techniques (Kalman filter and beyond) for setting up data fusion workflows feeding from diverse sources of data on passenger density and assimilating them taking into account the relevant information on spatial and temporal uncertainty of the data. One of the advantages of the methodology is the potential for rapid implementation thanks to employment of a standard model for which software libraries are readily available.

This note outlined an idea of a participatory crowdsensing platform focused on real-time provision of information on the levels of crowding. In such scenario, the role of the presented state-space model and the data assimilation methodology is twofold: (i) to assimilate passenger-reported feedback into simulations driven by operator-provided data and (ii) to provide basis for defining feedback-request triggers using the estimated system state as well as using the filter performance indices.

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