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Freeway Loop Detector Data Reconciliation Based on Vehicle Conservation

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Abstract

Loop detector is the most common source of traffic flow measurements on freeways. Though being a mature technology, loop detector is prone to miscounts even when it is properly deployed and adjusted. If a loop detectors systematically over- or under-counts, the estimation based on vehicle conservation leads to results that are not physically plausible such as negative density or density higher than the jam-density. Here we propose an optimization-based method in which plausible values of accumulation is guaranteed through explicit constraints. Compared to similar methods, the proposed method distinct in the following: (i) the optimization problem is convex therefore leads to shorter computational time; (ii) occupancy is also taken into account in order to estimate upper and lower bounds in the accumulation between stations; (iii) no modifications are required when data from one or multiple lanes are missing. The method is first validated using micro-simulation by disturbing the loop-detector from micro-simulation, applying the method and then comparing the results with the ground truth data. The results show the method is able to capture the average counts almost exactly while providing estimate of density with satisfactory accuracy. The method is also successfully applied in a scenario in which field-data is available.

Keywords: Loop-detector, data reconciliation, optimization;

1. Introduction

Loop detector is the most common source of traffic flow data in freeways [13]. Loop detectors provide all basic traffic measurements - flow, occupancy and vehicle presence - and it is considered a mature technology [5]. Nevertheless, loop detectors require frequent maintenance which is costly and inconvenient because it requires traffic lanes to be closed. As evidence, the California Performance and Measurement System (PeMS) [2], as of January 2nd, 2019, reports 70% of the detector as healthy with the other 30% presenting consistently some error or lack of communication. Aside failures, loop detectors are prone to miscounts even when working properly in the order of 3% [3].

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Though small, the accumulation of these errors over time can lead to physically unfeasible state when inflow and outflow balance is used to estimate traffic density or accumulation - the number of vehicles between two loop detector stations. For example, in [7] they used California PeMS data to study the capacity drop phenomenon at various freeway bottlenecks. For that type of study, (shifted) cumulative counts are used to measure flows and its variation as function of density and accumulation as computed based on the difference between the cumulative counts. In all cases, the accumulation was unfeasible with some cases presenting negative values and others with density that far exceeds the jam density. This fact had also been reported in longer stretches and small networks [13, 12].

There are various ways for mitigating errors from inconsistent data from loop detectors. Most of them focus in identifying a subset of samples with clear failures and replace them with an appropriate method. Moving average, historical values and current information from neighbor detectors are the most common methods to replace bad samples. Some examples include [6, 1, 17]. More recently, Principal Component Analysis and tensor methods have been also applied using similar input data such as [8, 11]. Though these methods can effectively replace missing and erroneous samples, it cannot deal with the aforementioned inconsistent vehicle accumulation.

Other methods consider explicitly the vehicle conservation and therefore are suitable for these cases. In [13] the counts observed at different stations are corrected through a non-linear optimization procedure that ensures the number of vehicles between stations remains physically plausible. In [4] five methods (a sixth was a manual method) that ensures flow conservation in a general network were tested ranging from least-squares to Fuzzy-Optimization technique and all of them reached reasonable results. In [10], the network health problem is defined and later a method to pick a minimal set of detectors in order to define flows through a network is proposed [16]. Kalman Filter (KF) is another technique that deals with vehicle conservation, though indirectly. KF requires a dynamic traffic flow model and can provide density estimation by mixing information about the model and the sensor data. Relevant work using KF includes [15, 14].

This paper is organized as follows. In Section 2 the data reconciliation method is presented in details. In Section 3 the method is validated first using micro-simulation and later based on field-data. Finally, concluding remarks and future work are presented in Section 4.

2. Method

We consider a freeway stretch with J stations labeled as $1, 2, ..., j, .., J$ increasing in the direction of the traffic stream as depicted in Figure 1. Each station may have up to three types of loop detectors: mainline, on-ramp and off-ramp.

The mainline loop detector provides counts and occupancy at every step i referred to as $c_j(i)$ and $o_j(i)$, respectively. The on-ramp count is denoted as $f_j(i)$ and the off-ramp count as $g_j(i)$, both are them is set to zero if they are nonexistent. Measurements are provided at discrete steps $i = 0, 1, ...T - 1$ such that time $t = i\Delta t$. Also, $\mathbf{c}_j$ is the vector with the input counts on all time steps at station j; similarly definition for $\hat{\mathbf{c}}_j$.

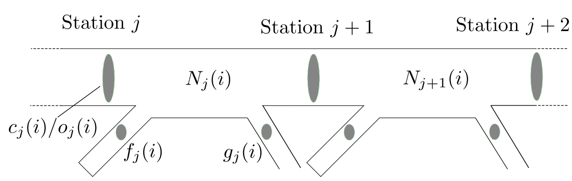

Fig. 1: Schematic of stations and its associated variables.

The accumulation between stations j and $j + 1$ at time step i is $N_j(i)$. From vehicle conservation, the accumulation is updated as:

$$N_j(i + 1) = N_j(i) + \hat{c}_j(i) - \hat{c}_{j+1}(i) + f_j(i) - g_j(i), \quad j = 1, ..., J - 1, i = 1, ..., T. \tag{1}$$

where $\hat{c}_j(i)$ is the corrected count at station j at step i. Note that $\hat{c}_j(i)$ is the output of the optimization problem while $c_j(i)$ is the input data. In general, computing $\mathbf{N}_j$ based on $\mathbf{c}_j$ leads to physically unfeasible results such as negative or too large $N_j(i)$. The goal here is to find $\hat{\mathbf{c}}_j$ as close as possible of the original data while yielding $\mathbf{N}_j$, and $\hat{\mathbf{c}}_j$ physically feasible through explicit constraints.

We use occupancy information to provide bounds on the accumulation. The basic relationship is the conversion from occupancy, o, to density,k, assuming an effective vehicle length: $k = o/G$. The accumulation bounds is obtained assuming homogeneous condition between stations j and $j+1$ along with the section length, L_j, and average number of lanes (n_j):

$$
\begin{aligned}
\tilde{N}_j^L(i) &= \min\{\frac{o_j L_j n_j}{G}, \frac{o_{j+1} L_j n_j}{G}\} \\
\tilde{N}_j^U(i) &= \max\{\frac{o_j L_j n_j}{G}, \frac{o_{j+1} L_j n_j}{G}\} \\
\alpha^L \tilde{N}_j^L(i) \leq N_j(i) &\leq \alpha^U \tilde{N}_j^U(i), \quad \forall i, j = 1, ..., J-1,
\end{aligned}
\tag{2}
$$

where $0 \leq \alpha^L < 1$ and $\alpha^U > 1$ are parameters to be defined. The farther both values are 1 the larger the feasible set becomes. Even though Equations (2) assumes homogeneous conditions, it is only to provide rather conservative bounds: the lower (upper) bound is the minimum (maximum) between the two occupancies. Therefore the most permissive value is used. This allows a broad interval of acceptable values. For instance, if the occupancy downstream (o_{j+1}) is small and the occupancy upstream (o_j) is high, any value from totally congested to totally uncongested is feasible for N_j. The bounds on $N_j(i)$ are the critical part of the complete optimization problem:

The bias factor, β_j, accounts for systematic under-count ($\beta_j < 1$) or over-count ($\beta_j > 1$). Here we assume that there is one reference detector, labeled as p, in which the true bias factor is known to be β_p^{fix}:

Though different assumptions can be used such as assuming an average value across different loop detectors. The complete optimization problem becomes:

$$
\begin{aligned}
&\min_{\hat{c},\beta} J = \sum_{\forall j} \left[||\hat{\mathbf{c}}_j - \beta_j \mathbf{c}_j||_1 + \rho ||\hat{\mathbf{c}}_j - \beta_j \mathbf{c}_j||_\infty \right] \\
&N_j(i+1) = N_j(i) + \hat{c}_j(i) - \hat{c}_{j+1}(i) + f_j(i) - g_j(i), \quad j = 1, ..., J-1, \forall i. \\
&O \leq \hat{c}_j(i) \leq \hat{c}_j^{max}, \quad \forall (i, j) \\
&\alpha^L \tilde{N}_j^L(i) \leq N_j(i) \leq \alpha^U \tilde{N}_j^U(i), \quad \forall i, j = 1, ..., J-1, \\
&\beta_p = \beta_p^{\text{fix}},
\end{aligned}
\tag{3}
$$

where $\hat{c}_j^{max}$ is the highest flow that can be observed at station j, β_j is a bias factor for modeling systematic under and over-counts across detectors. We set a specific detector as the baseline detector with fixed β_p, commonly $\beta_p = 1$. In the objective, $|\mathbf{x}|_1$ refers tot he norm 1 (L_1) and $|\mathbf{x}|_\infty$ to norm L_∞. A quadratic cost was avoided for two reasons. First, L_1 suits better when data has outliers or is missing which is the case for loop detector data. Second, as β_j is also decision variable, the cost would be quadratic but not necessarily convex. All constraints and the cost is linear therefore the optimization problem can be solved through traditional linear programming methods.

3. Results

Our study site is a freeway stretch at US-101, CA, with four stations where PeMS data is available. The mainline detector in the PeMS systems, here labeled as station 1 to 4, are 413786, 401578, 401586, and 41009. Station 1 contains the on-ramp detector 409885 and station 2 the detector 409883. We first model the scenario in microsimulation in which we can mimic the loop detector miscounts. With that we can quantitatively evaluate the proposed method with the ground truth data from the simulation. Later, we use the observed data at the study site as input. In that case we do not have data regarding the accumulation, but we show the results are nonetheless valid.

In all the following experiments, $\rho = 1$, $\alpha^L = 0.7$, $\alpha^U = 1.3$ in all links but link 2 in which $\alpha^U = 3$. Also, in all the reference station is 3 with $\beta_3 = 1$.

3.1. Microsimulation Results

The microsimulation replicates the geometric parameters as the study site. Gipps car-following model is used and a Gipps-like lane-changing model is used for discretionary and mandatory lane changing. Further implementation details can be found in [9]. There are two demand sources for the two hours simulation period, the upstream and on-ramp demand:

$$d_1(t) = 900 \quad vphpl \quad d_2(t) = \begin{cases} 1260 + 600t \quad vphpl & t < 1h \\ 1860 - 925(t-1) \quad vphpl & 1h \leq t \leq 2h, \end{cases} \tag{4}$$

where d_1 is the demand in the station 1 which is all introduced in the mainline (i.e., no on-ramp flow). The second demand, d_2, is the demand originated on the second on-ramp, labeled in 409883. The total demand starts below capacity, which is approximately 2200 vphpl, then it steadily increases and congestion ensues. Thereafter demand ceases and congestion is relieved. Similar to PeMS, data is collected from the four loop detectors simulation in steps of 30 seconds so in the formulation $J = 4$, and i varies from 0 to 240 to cover the two hours period. The effective length, G, is set to 6.5m matching with the microsimulation settings.

The ground truth data is disturbed in order to evaluate the reconciliation method. For all mainline detectors under-count probability, γ_j^U, and over-count probability, γ_j^O are assumed. For every sample with $c_j(i)$ counts, the number of under- and over-counts are sampled from binomial distribution with $c_j(i)$ trials and probability success γ_j^U for under-count and γ_j^O for over-count and the net-effect is added into $c_j(i)$. The assumption is that miscounts are all independent with same probability of occurrence at every count.

The following values are assumed for under- and over-count probabilities: $(\gamma_1^U, \gamma_1^O) = (0.03, 0.01)$, $(\gamma_2^U, \gamma_2^O) = (0.06, 0.02)$, $(\gamma_3^U, \gamma_3^O) = (0.02, 0.02)$, and $(\gamma_4^U, \gamma_4^O) = (0.01, 0.07)$. They were used to generate 20 different disturbed inputs. We denote $c_j^{\mathrm{gt}}(i)$ a sample of the ground truth data. The loop detector data, which was disturbed, is $c_j(i)$ and the corrected value as $\hat{c}_j(i)$ with similar notation for the other variables. For every disturbed input, the relative total flow error (RTFE), the average flow error (AFE), and the average accumulation error (AAE):

$$RTFE_j = 1 - \frac{\sum_{\forall i} \hat{c}_j(i)}{\sum_{\forall i} c_j^{\mathrm{gt}}(i)}, \quad AFE_j^2 = \frac{1}{T} \sum_{\forall i} (1 - \frac{\hat{c}_j(i)}{c_j^{\mathrm{gt}}(i)})^2 \quad AAE_j^2 = \frac{1}{T} \sum_{\forall i} (1 - \frac{\hat{N}_j(i)}{N_j^{\mathrm{gt}}(i)})^2 \tag{5}$$

The average value, standard deviation, minimum and maximum for each of metric at station 2 are reported in Table 1. The station 2 is chosen as the bottleneck is located between stations 2 and 3. Observe that the total relative flow error is very close to zero which suggests that the total flow is recovered correctly in average. The relative flow error is 3% which is in the same order of magnitude of γ_2^U and γ_2^O.

One representative replication result is shown in Figure 2. In the top graphs, the flows at stations 1 (left), 2 (middle), and 3 (right) are depicted. The black lines represents the ground truth, the red lines the corrected values and the blue line the input data with miscounts. Observe the flows at station 2 in which the input data under-counts by roughly 4%, but the corrected counts almost overlaps with the ground truth data. The density (accumulation divided by the length) at station is depicted at the bottom left and middle graphs. In the bottom left one can see that qualitatively

Table 1: Error Metrics Summary.

Metric	Average (%)	St. Dev (%)	Min (%)	Max (%)
$RTFE_2$	0.04	0.11	-0.13	0.21
AFE_2	3.39	0.21	3.04	3.65
AAE_2	9.83	3.19	4.17	14.28

the corrected counts follow the ground truth. From the input data, as station 2 consistently under-counts, it leads to negative accumulation and density as depicted in the middle graph. For reference, the occupancies at all detectors are depicted at the bottom right graph.

Though detailed results are not presented, all the optimization problems were modeled and solved using the package CVXPY using the solver GLPK with processor Intel(R) Core(TM) i7-4510U on a Lenovo Yoga 2 laptop. The optimization problem has 960 variables and 3178 constraints and the largest computational time throughout all replications was 12 seconds.

3.2. Field data

We use as input raw data from PeMS system. Unlike the micro-simulation results in the previous sub-section, for this case we do not have ground truth data and a quantitative analysis is not possible. Nevertheless, we can show that at least qualitatively the method can be used with field data providing physically representative results.

The lane drop between station 2 and 3 is an active bottleneck during the morning peaks with congestion hitting the station 2 and station 1 which is located almost 1km far from station 2. Throughout 2018, on most of the days the total counts on stations 2, accounting the on-ramp, exceeded the counts on the detectors downstream of the bottleneck by about 5%. The two detectors downstream (3 and 4) presents consistently very similar counts. For this reason we set $\beta_3 = 1$. An important observation is that data from one lane at station 1 is missing.

Figure 3 depicts the original data and the pre-processing output. The top graphs show, from left to right, the reported (orange) and corrected (blue) flows at station 1, 2 an 3. In the bottom left graph is shown the densities at stations 1, 2, and 3 based on the corrected output while the density based on the raw data is depicted in the bottom middle graph. Notice that the raw data leads to clearly inconsistent results at all stations. Finally, the occupancies are depicted in the bottom right graph. The counts on station 2 was slightly reduced which is expected as the counts at that stations are consistently higher than the downstream stations. Interestingly, the outputs in the first station, which has one lane data missing, follows the shape of the input counts while leading to feasible values of accumulation and density.

4. Conclusion

A method for data-reconciliation of loop detector was proposed and validated through micro-simulation results and field-data from loop detectors from a similar location. The main contribution of the method is providing an estimation of accumulation (number of vehicles) between stations based on inconsistent loop detector data. The corrected data is obtained as a result of a an optimization problem that ensures vehicle conservation between stations. The method is computationally efficient as the formulation is convex. For a case with 1000 data points the computational time was few seconds.

For future work, we want to apply this method to calibrate various traffic flow models based on loop detectors. Also, the method can be further refined by using per-lane data instead the aggregated over all lanes.

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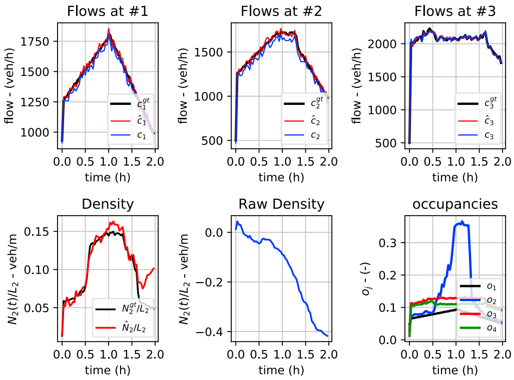

Fig. 2: Results for simulated data. In top graphs the input count (blue), corrected count (red), and ground truth counts (black) at station 1 (left), 2 (middle), and 3 (right). The bottom left show the ground truth and the density based on the estimated accumulation. The bottom middle graph shows the density based on the raw data. The bottom right graph depicts the observed occupancies.

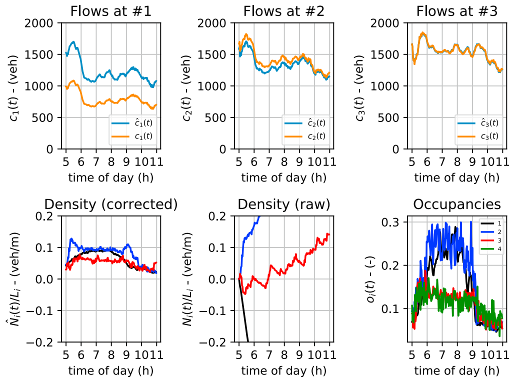

Fig. 3: Results for field-data. The top graphs show the input (orange) and corrected (red) counts at station 1 (left), 2 (middle), and 3 (right). The bottom left show the the density in all stations based on the estimated accumulation. The bottom middle graph shows the density based on the raw data. The bottom right graph depicts the observed occupancies.

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