Assessing Traffic Performance using Position Density of Sparse FCD

Anita Graser, Wolfgang Ponweiser, Melitta Dragaschnig, Norbert Brändle and Peter Widhalm

Abstract—We present an approach for evaluating traffic performance along corridors and its variation based on floating car data (FCD). In contrast to existing work, our approach can cope with long and irregular FCD reporting intervals. Resampling of sparse FCD in time and interpolation increases spatial resolution of FCD positions along the corridors. FCD position density is computed with a uniform kernel, which leads to traffic performance expressed as average travel time per meter and average speed. Experimental results based on real-world FCD for a freeway section and arterial roads in Vienna illustrate the plausibility of the approach, and an example illustrating our approach before and after a traffic influencing measure shows its advantage over using dedicated probe vehicle runs, temporary sensor installations or human observers. A sensitivity analysis provides guidelines for the important parameters.

I. INTRODUCTION

PERFORMANCE of traffic flow along corridors is of interest to road users, general public and specialists alike. Quantitative measures for traffic flow performance include the number of stops, travel speed, bandwidth (maximum amount of green time for a designated movement) or derived values such as level of service (LOS) or delay [1]. Traffic flow performance is typically measured with dedicated infrastructure such as loop detectors capturing traffic flow and speed at cross sections, dedicated probe vehicle runs or manual recordings by human observers [2]. Such approaches are costly either due to necessary investments in the dedicated infrastructures and their maintenance or due to expensive human resources.

Increased availability of navigation satellite systems and communication technology have made it possible to use specially equipped vehicles as moving “floating” sensors: Floating car data (FCD) are composed of 1) vehicle on-board units (OBU) performing positioning and communication tasks, 2) a communication network and 3) a central server for data collection. FCD are frequently used to estimate traffic states based on travel times or speeds [3][4][5][6]. FCD have also been used in [7] for a queue length estimation system at signalized intersection, based on two-dimensional profiles of local traffic density. An FCD-based approach for corridor performance assessment is presented in [8], which uses travel time, number of stops, and stopped delay based on 1189 controlled probe vehicle runs with a sampling frequency of one second. A spatiotemporal data mining method based on taxi FCD for discovering urban network spatiotemporal traffic bottlenecks is presented in [9]. They determine the traffic status on a network link by dividing the average speed obtained from all FCD messages on a road link by the link’s speed limit. The traffic state identification for urban streets described in [10] extracts traffic patterns on individual road segments and identifies unusual traffic states on a segment-by-segment basis. This method depends on the ability to determine red light duration from FCD, and can thus only be applied for high sampling frequency systems. The traffic speed estimation method described in [11] uses FCD messages at regular reporting intervals up to 120 seconds to iteratively reconstruct time-space speed contours and corresponding travel times. The approach is based upon the assumption that each cell of the time-space speed plot has homogeneous traffic conditions. This assumption seems not very realistic, especially for their large cell sizes. Another restrictive assumption is that given FCD are strictly consistent with ground-truth speeds.

The above-mentioned methods require high or regular sampling frequency or additional speed measurement and can thus not be applied to systems with sparse FCD. Many real world FCD systems, however, are based on existing fleets and communication infrastructure which has been built with an intention other than transmitting location data (e.g. radio taxis). The central server of such real world systems often polls the vehicle OBUs in irregular intervals mainly depending on available communication bandwidth and vehicle status, usually between 30 and 120 seconds. A method for deriving velocity fields on road links from such sparse FCD is presented in [12]. We propose a novel method leveraging...
FCD from systems with long and irregular reporting intervals between 30 and 120 seconds that works on the sub-link level. Using only sparse FCD, this method captures traffic performance independent of the arbitrary length of road links in the network and is therefore suitable for both urban and highway conditions where links can be very long.

Figure 1a shows a sample result of our traffic performance assessment for two urban corridors: the colors encode the differences in position density before and after a traffic influencing measure. Fig. 1b shows the temporal evolution of speed difference using FCD before and after a traffic influencing action in the section between the two black lines orthogonal to the road in Figure 1a, showing improved corridor performance. The results of our approach confirm these findings. An additional advantage of our approach is that the higher spatial resolution enables the identification of sections with decreased traffic performance in front of two intersections. Our spatial approach provides flexibility for displaying multiple corridors at the same time. The spatial dimension makes it easier to compare different corridors and assess overall performance. Using interactive geographic information systems, a virtually unlimited number of corridors can be provided for the analyst to improve decision-making.

This rest of this paper is organized as follows: Section II describes the algorithm constituting the FCD position density approach. Section III presents experimental results based on real-world data for a freeway section and urban corridors in Vienna as well as a sensitivity analysis. The paper closes with conclusions and recommendations for further research.

II. OVERVIEW OF PROPOSED METHOD

FCD position density is derived from the number of location messages from probe vehicles on a road section of unit length. Let $M$ be a set of sparse FCD location messages $m = (\text{vehicle id}, \text{time stamp}, \text{position}, \text{vehicle status})$, where messages with the same vehicle id constitute one trip $\tau_i \in T$. Let $c$ be a corridor of interest in a street network graph.

Figure 2 shows positions of FCD location messages marked as a cross in a diagram with time $t$ as the first dimension and location $s$ along corridor $c$ as the second dimension. Obviously, lower speeds cause more densely spaced location messages.

The objective is to estimate from $M$ traffic performance based on FCD position densities $d$ along corridor $c$. The algorithm is divided into preprocessing, FCD position density computation and computation of traffic performance.

A. Preprocessing

Preprocessing of raw FCD location messages comprises the following steps:

1) Select from the set of trips $T$ the trips $\tau_1, \tau_2, ..., \tau_n$ which cover the entire corridor of interest $c$. This is to ensure that all trips within the sample are collected under similar conditions and are not influenced by effects caused by different turning directions at the intersections.

2) Project the 2D GPS positions of the relevant trips $\tau_1, \tau_2, ..., \tau_n$ to the nearest point on the 1D corridor $c$ (in terms of Euclidean distance). This map-matching step is sensitive to “corridor outlier” vehicles temporarily leaving the corridor. Fig. 3 shows example outlier locations and the resulting projected positions. “x” marks the 2D GPS Positions, and “.” marks the projection of the GPS position on the 1D corridor. This would produce high density values at sections where the vehicle leaves/rejoins the corridor, which would lead to the wrong conclusion that traffic performance at these locations is worse than at the rest of the corridor. It is therefore vital to to ensure that all instances of such behavior be removed from the sample.

3) Resample the sparse FCD location messages at regular intervals $\Delta t$ in time to account for irregular reporting intervals of the underlying sparse FCD system. This results in a set $X$ of interpolated vehicle positions $x$ at regular time intervals (Fig. 4). We use linear interpolation to determine a position $x_{\tau_i}$ along $c$ for every time stamp $t_i$. Interpolation of higher degree would only feign a higher accuracy since only positions and no additional information like current speed are contained

\[ FCD \text{ position density is therefore different from traffic density, which is defined as the number of vehicles on a road section of unit length.} \]
within the sparse FCD location messages.

Fig. 4. Interpolated vehicle positions at regular time intervals

B. FCD Position Density

FCD position density is calculated using a kernel density function

\[
d_u(x) = \frac{1}{|X|} \sum_{i=1}^{|X|} K_u(x_i, x),
\]  

(1)

where \(|X|\) is the cardinality of the set of interpolated FCD positions \(X\) and \(K_u\) is the kernel function with kernel size \(u > 0\). In contrast to [13], where optimal kernel weights are estimated from FCD samples, we use the uniform kernel function \(K\) in order to represent the actual number of FCD positions within the kernel. Position density is expressed in FCD positions per meter and is therefore calculated as

\[
d_u(x) = \frac{1}{n} \frac{|X_u|}{u},
\]  

(2)

where \(|X_u|\) is the cardinality of the subset of \(X\) that falls within the kernel \(K_u\), and \(n\) is the number of trips. Normalizing by \(n\) makes it possible to compare different density rasters.

C. Traffic Performance

Based on FCD position density \(d\), the following traffic performance measures for a corridor are calculated: average travel time per meter

\[
tt = d \Delta t,
\]  

(3)

and average speed

\[
v = \frac{1}{tt} = \frac{1}{d \Delta t}.
\]  

(4)

For a comparison of traffic performance between different time periods, e.g. before and after a traffic influencing action, a density difference map is calculated as

\[
\Delta d = d_1 - d_2,
\]  

(5)

where \(d_1\) is the density raster of the “before” period \(p_1\) and \(d_2\) is the density raster of the “after” period \(p_2\). Positive values of \(\Delta d\) are the result of decreased position density during \(p_2\) period, indicating improved performance at the respective section. Negative values indicate a drop in performance and higher position density after the traffic influencing action. A density difference value is mapped to a corresponding change in travel time as

\[
\Delta tt = (d_1 - d_2) \Delta t.
\]  

(6)

The magnitude of performance changes \(\alpha\) is evaluated by calculating the relative change in travel times

\[
\alpha = \frac{\Delta tt}{tt_1},
\]  

(7)

where \(tt_1\) is the average travel time during \(p_1\).

III. EXPERIMENTAL RESULTS

We demonstrate results for two areas covered by the FCD system “FLEET” operated by AIT and ITS Vienna Region which collects sparse FCD from fleets of more than 3000 taxis. The first area represents a section of a freeway connecting the city of Vienna with Vienna International Airport. The second area encompasses an intersection of two urban arteries in the city of Vienna. We show results for a resampling interval \(\Delta t\) of one second and a kernel size of 15 meters – based on an sensitivity analysis of different kernel sizes in Section III-D.

A. Freeway Section

The freeway section was chosen to test the algorithm on a road with constant speed limit and without traffic influencing actions or features during the analysis time period (e.g. traffic lights or construction works). The data sample for the freeway example is composed of 4237 trips collected during eleven days (Tuesdays, Wednesdays, and Thursdays, 24 hours a day) in November and December 2010. Figure 5 shows the resulting position density. As expected, for this type of corridor position density \(d\) computed according to (2) along the corridor remains at a constant level, in this case in average 0.034 positions per meter from which a theoretical average speed \(v\) of 106 km/h is inferred according to (4).
B. Arterial Road

The arterial road region comprises two urban arteries cross paths which are shown in red in Fig. 6. The traffic patterns at this group of signalized intersections are rather complex. This set of intersections is of particular interest to traffic planners due to its importance and influence for the overall traffic flow in Vienna. This analysis focuses on the B221 running north and distinguishes between vehicles that are northbound and those westbound that turn to B1. The analysis period comprises eleven days with similar traffic counts as measured by loop detectors in this area. Only data during the morning peak (between 07:30 and 10:00 am) have been used for this analysis. In the northbound direction the sample size is 286 trips and in the westbound direction 36 trips.

The density map (Fig. 7) shows sections of high density with maxima of $d = 0.23$ positions per meter (average speed $v$ of 15.7 km/h) in front of the last signalized crossing in the northbound direction, and $d = 0.19$ positions per meter (or 18.9 km/h) at the last signalized crossing in the westbound direction. Also, position density along the rest of the corridor is higher than the values of the freeway example reflecting the generally lower average speed along this urban corridor.

C. Traffic Performance Comparison

In May 2011, a modified traffic signal control system aimed at improving traffic flow has been deployed in the region presented in section III-B. Our approach has been used for a before-after study. Only days with similar traffic counts (as measured by loop detectors in this area) are taken into account, limiting the data set to eleven days in the “before” period $p_1$ and eight days in the “test” period $p_2$. For the morning peak between 07:30 and 10:00, this leads to a total number of unique trips of $n_{p_1n} = 286$ and $n_{p_2n} = 244$ for the northbound direction and $n_{p_1w} = 36$ and $n_{p_2w} = 41$ on the westbound direction, respectively.

Fig. 1a shows the resulting density difference map. Positive values of $\Delta d$ (depicted in orange) are the result of decreased position density during the test period, indicating that the changes that were applied to the traffic control system improved traffic performance at the respective section. Black areas depicting negative values indicate a drop in performance and higher position density during the test period.

The results suggest that considerable performance improvements were achieved along the southern part of the corridor with a performance increase of $\alpha = 0.33$ ($d_1 = 0.184$, $\Delta d = 0.060$) at the southernmost traffic light. This performance increase equals a reduction in travel time by 33 % or an increase in average local speed by 48 %. Short sections before the northern and western crossings on the other hand experienced a decrease in performance by $\alpha = -0.18$ at the northern and $\alpha = -0.28$ at the western crossing, probably due to longer average waiting times at these intersections.

D. Sensitivity Analysis

We have performed a sensitivity analysis for the following parameters kernel size $u$, resampling interval $\Delta t$, and sample size $n$ on the resulting FCD position density. This analysis has been carried out using data presented in section III-B (B221 northbound). Figure 8 presents changes in FCD position density with varying values of $u$ between 5 and 200 meters and a resampling interval $\Delta t$ of one second. Low values of $u$ result in high noise, whereas high values of $u$ produce smoother profiles while losing detail – for example, local disturbances in front of traffic lights disappear. It can therefore concluded from Fig. 8 that kernel sizes $u$ smaller than 15 meters should be avoided.

Fig. 9 depicts changes in FCD position density with resampling interval length $\Delta t$ increasing from 0.1 to 30 seconds and a constant kernel size of 15 meters. At increasing values of $\Delta t$, details of the profile – which are visible at resampling intervals $\Delta t \leq 1$ second – are lost in the noise.

Fig. 10 shows an example of FCD position density profiles for sample sizes $n$ increasing from 10 to 286 unique trips, constant kernel size of 15 meters and a resampling interval of one second. Smaller samples are always a random subset of bigger ones as in
and FCD systems even if only sparse FCD are available. Our approach presents a viable alternative to more expensive evaluations using dedicated probe vehicle runs, temporary sensor installations, or human observers.

Areas for further investigation include research into detection of incidents based on FCD position density as well as detection of stop locations and stop probability particularly with regard to identifying routes for energy efficient routing applications.

REFERENCES


