ESTIMATION OF DENSITY AND GAPS IN CONGESTED TRAFFIC

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Abstract
In common practice, traffic measurements are carried out using presence-type detectors, such as magnetic induction loops. When aggregated, a loop detector returns flow, occupancy and average speed, for a given period of time. Sometimes microscopic quantities can also be collected, such as time gaps between vehicles and individual speeds. Spatial quantities, such as density and inter-vehicle gaps, are usually only estimated from temporal data, under the assumption of constant speed. However, in congested conditions, such estimates are likely to significantly differ from the actual values, since the speed varies greatly as a result of stop-and-go waves. Spatial quantities are useful whenever it is important to accurately know the number of vehicles on a stretch of road and their distribution. For instance, they are essential for calculating traffic loading on long span bridges. The aim of this paper is to study both macroscopic and microscopic spatial quantities and evaluate the accuracy of their estimation from one presence detector. A micro-simulation software tool is used. The software implements a car-following model which has been found to successfully replicate many different kinds of single-lane congestion. It can output both temporal quantities from virtual point detectors and spatial quantities from snapshots taken from a virtual camera. Then spatial quantity estimates are compared to their actual values for different kinds of single-lane congestion. It is found that density and gap estimates can greatly differ from the actual values, especially in their maximum values.

INTRODUCTION
A knowledge of the number of vehicles on a stretch of road (density) is crucial for studying the traffic load effect on long-span bridges. In fact, the design of such bridges is often governed by congested conditions and critical loading situations occur when density is at a peak. Density, $k$, is related to flow (or flux), $q$, and space mean speed, $v_s$, through the fundamental equation of traffic:

$$q = k \cdot v_s$$

These are all macroscopic quantities. Flow is a temporal quantity, density is a spatial one, while the mean speed can be either, depending on whether it is averaged over a time interval at a certain location (time mean speed) or over a stretch of road at a certain point in time (space mean speed). However, only space mean speed, $v_s$, complies with (1).
Traditionally, the flow-density diagram (also called fundamental diagram) has been used to describe traffic behaviour. Observations showed that the fundamental equation of traffic works properly for free traffic (i.e. low density), while it may not be reliable during congestion (i.e. high density) [1]. This is apparent when plotting the empirical flow-density diagram (Fig. 1a). The points are aligned at low density, while a wide scattering can be noticed at higher densities. It can be seen that flow itself is not a good indicator of congestion, as for a fixed flow value there may be either free traffic or congestion.

The reason for the wide scattering at high density is the underlying assumption of each vehicle keeping its speed in (1), which allows the link between temporal and spatial quantities. In fact, during congestion, a vehicle’s speed is likely not to be constant, as a result of stop-and-go waves (Fig. 1b).

Nowadays, the most common means of collecting traffic data is induction loops. Such devices are sensors embedded in the road and are able to detect the presence of a metallic object. Flow, occupancy and speed are collected and usually aggregated on a time interval. Occupancy is defined as the fraction of time in which vehicles are over the detector. It is important to note that the arithmetic mean of the speed of the vehicles passing over a loop detector is the time mean speed and therefore does not comply with the fundamental equation of traffic. The space mean speed can be calculated with the generalised fundamental equation of traffic as harmonic mean of the individual speed of the vehicles passing over the detector [3]. The space mean speed is less than or equal to the time mean speed. However, this relationship holds again under the assumption of each vehicle keeping its speed within the section.

Notably, some networks are programmed to output only the time mean speed. The incorrect use of the time mean speed in (1) would lead to under-estimation of density. However, recently a method to work out the space mean speed from time mean speed measurements has been found [4, 5].

Sometimes it is possible to collect the individual speed of vehicles and time gaps between them. This allows a microscopic approach.

On these grounds, density can be only estimated when using data from a loop detector placed on a single location. If the flow is uniform, then density calculated through (1) is reliable. This happens in free traffic, and sometimes in congestion, but only when the speed is low but approximately constant. In all other cases, the accuracy of density estimation should be checked. This includes the frequent case of stop-and-go waves.
Density may also be related to occupancy. However, the relationship holds under the same assumptions of (1) and requires the additional knowledge (or assumptions) about the vehicle lengths. Therefore this option will not be further investigated in this paper.

The accuracy of density (and other spatial quantities) estimates has been relatively little studied, even though it is crucial whenever the exact number of vehicles on a stretch of road is important, for instance in the case of traffic load effect on bridges. A further step is the knowledge of the space gaps between vehicles.

Density on a single-lane can be accurately computed using two point detectors at the beginning and end of the road section of interest [6]. It can also be collected by cameras looking over a stretch of road, with the advantage of collecting space gaps as well. In this latter case, pictures should be then post-processed, in order to recognise vehicles. This is rarely done in common practice, mainly because of the huge amount of data and intensive image post-processing [7]. The main research project in this field is the NGSIM project, promoted by the Federal Highway Administration, which made available video recordings of congested traffic at various sites in California [8].

Thiemann et al. [9] made a comparison between gaps taken from two NGSIM trajectory datasets and their estimation from virtual loop detectors. They found that values differ only in jammed traffic, with the estimates being higher than the actual values.

Traffic micro-simulation models allow the generation of traffic streams with different congestion strengths. They are used in this paper in order to compare density and gap estimation from virtual presence detectors to the actual values collected with virtual cameras.

**MICRO-SIMULATION MODEL**

Many micro-simulation models are available in literature [1]. Among those, the Intelligent Driver Model is a car-following model, which has a modest number of physically-meaningful parameters, is collision-free, and has proven good match with real congested traffic [2, 10, 11]. It has also been calibrated with trajectory data [12, 13].

In order to carry out the traffic micro-simulation, a program called *EvolveTraffic* is used here. *EvolveTraffic* implements the Intelligent Driver Model. The IDM simulates driver behaviour in time through an acceleration function:

\[
a(t) = a \left[ 1 - \left( \frac{v(t)}{v_0} \right)^4 - \left( \frac{s^*(t)}{s(t)} \right)^2 \right]
\]

where \(a\) is the maximum possible acceleration; \(v_0\) the desired speed; \(v(t)\) the current speed; \(s(t)\) the current gap to the vehicle in front, and; \(s^*(t)\) the minimum desired gap, given by:

\[
s^*(t) = s_0 + Tv(t) + \frac{v(t)\Delta v(t)}{2\sqrt{ab}}
\]

in which, \(s_0\) is the minimum bumper-to-bumper distance; \(T\) the safe time headway; \(\Delta v(t)\) the velocity difference between the current vehicle and the vehicle in front, and; \(b\) the comfortable deceleration.

There are five parameters in this model to capture driver behaviour, which are relatively easy to measure. For simulation purposes, the length of the vehicle must also be known.
CONGESTED TRAFFIC STATES

Treiber et al. [10, 11] have shown that congestion can be effectively generated by either decreasing locally the desired speed, $v_0$, or increasing the safe time headway, $T$. It has been also shown that such local parameter variations act as an equivalent on-ramp bottleneck, which instead would require an injecting flow and a lane-changing model. In this paper, inhomogeneity is generated by increasing the safe time headway, $T$, downstream to, say, $T'$, which Treiber et al. [11] state to be more effective than decreasing $v_0$.

A bottleneck strength, $\delta Q$, can be defined as the difference between the inflow, $Q_{in}$, and the outflow, $Q_{out}$:

$$\delta Q(T') = Q_{in} - Q_{out}(T')$$

(4)

Depending on the inflow and the bottleneck strength, the downstream traffic can take up any of the identifiable traffic states listed in Table 1. A combination of these congested states may also occur and these are highly dependent on the previous traffic history.

Figure 2 gives an illustration of typical stop-go waves in congested traffic. Congested zones are present at a discrete number of locations with less congested zones in between them. The congested zones move backwards in the direction opposite to the traffic.

Table 1 – Traffic States Definitions

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Explanation of traffic state</th>
</tr>
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<tbody>
<tr>
<td>FT</td>
<td>Free traffic</td>
</tr>
<tr>
<td>MLC</td>
<td>Moving localized cluster, which moves upstream</td>
</tr>
<tr>
<td>PLC</td>
<td>Pinned localized cluster, which remains near the inhomogeneity</td>
</tr>
<tr>
<td>SGW</td>
<td>Stop and go waves</td>
</tr>
<tr>
<td>OCT</td>
<td>Oscillatory congested traffic</td>
</tr>
<tr>
<td>HCT</td>
<td>Homogeneous congested traffic</td>
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</tbody>
</table>

Figure 2 – Typical traffic behaviour: the black lines indicate vehicles (not to scale).

MODEL AND SIMULATION PARAMETERS

For this study, the vehicle stream is taken as being homogenous (i.e. all cars). Each vehicle is given the same set of parameters, shown in Table 2. These parameters are based on those used in [11].

A single-lane 5000 m long road is used in this work. The safe time headway is $T = 1.6$ s from 0 to 2700 m (see Table 2), then increases linearly to 3300 m where it reaches the value $T'$.

Seven different values of $T'$ (2.2, 2.8, 3.4, 4.6, 6.4, 11.2 and 40 s) with inflow $Q_{in}$ of 1590 veh/h are considered for the simulations, each of which is 30 minutes long. These values are chosen in order to generate a wide range of congestion types. All the vehicles have an initial velocity of 30 km/h.

A virtual point detector is placed at 2000 m. The virtual detector returns flow, time and space mean speed, as well as time headways and individual speeds. No occupancy data is computed. A virtual camera takes snapshots over 100 m centred on the virtual detector. It returns density and space mean speed, as well as gaps between vehicles.
Table 2 - Model parameters of the IDM model

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Desired velocity, $v_0$</td>
<td>120 km/h</td>
</tr>
<tr>
<td>Safe time headway, $T$</td>
<td>1.6 s</td>
</tr>
<tr>
<td>Maximum acceleration, $a$</td>
<td>0.73 m/s²</td>
</tr>
<tr>
<td>Comfortable deceleration, $b$</td>
<td>1.67 m/s²</td>
</tr>
<tr>
<td>Minimum jam distance, $s_0$</td>
<td>3 m</td>
</tr>
<tr>
<td>Vehicle length, $l$</td>
<td>4 m</td>
</tr>
</tbody>
</table>

RESULTS

For the values of $T'$ considered, the bottleneck strengths (found from Equation (4)) are plotted in Figure 3. As it can be seen, three different kinds of congestion are found: stop-and-go waves (SGW), oscillating congested traffic (OCT), and a complex state with stationary congested traffic near the inhomogeneity and oscillatory congestion further upstream (HCT/OCT). Such a state has also been found by Treiber et al. [11].

For each bottleneck strength, the actual density is calculated by taking a virtual photograph every three seconds and counting all the vehicles entirely in the road section. Actual density is plotted as well as two ways of density estimation from the virtual detector:

1) directly, from the flow and space mean speed through equation (1);
2) indirectly, after estimating the space headways from time headways.

The first method is clearly macroscopic, as only aggregated quantities are involved. Data is aggregated over 60 sec, which is a typical value in real applications and represents a trade-off between the loss of traffic dynamics with higher intervals and the risk of not collecting vehicle information during smaller interval. The second one is microscopic, since it estimates space from time headways in order to build up a spatial distribution of vehicles on the road section [14]. As a result of this approach, for each vehicle passing over the detector, we find the space headways between the current vehicle and as many vehicles as occur on the section, thus finding the density.

Data from vehicles with speed less than 3 km/h are filtered out. This is done because in very slow moving traffic the space mean speed estimation is very much sensitive to individual vehicle speed (as the harmonic mean involves the inverse of individual speed), thus resulting in unrealistic density peaks in the macroscopic estimation. It also simulates the real...
behaviour of traditional induction loops which cannot generally collect data when a vehicle stops on it.

Fig. 4 shows the difference between the estimation for an HCT/OCT state. The state at the detector area is OCT. It can be seen that the two estimates have roughly the same value range, although the two initial peaks are missed by both methods. The reason is aggregation in the first method and lack of information in the second one (when traffic is at a standstill and vehicles are at the minimum gap, the point detector does not collect any data).

![Figure 4 - Comparison of density estimation calculated on a basis of a 100 m length (δQ = 903 veh/h)](image)

Fig. 5 shows the difference between the estimations for an SGW state. Now estimates are more accurate, but the peak values are missed again. In the first peak, this is also due to the data filtering.

![Figure 5 - Comparison of density estimation on a basis of a 100 m length (δQ = 297 veh/h, SGW)](image)

Fig. 6a shows the maximum density during congestion, both for filtered and unfiltered data. Congestion is considered after the first time an individual speed drops under 60 km/h. The unfiltered macro-estimates lead to unrealistic density peaks (well over the maximum physical density) for the reason stated earlier. Apart from that, the other approaches under-estimate the actual density peaks, which are actually the same regardless of the congestion type. As expected, data filtering often decreases peak values, especially at heavier bottleneck strengths.

On the other hand, the average density estimation performs better (Fig. 6b). For the lighter bottleneck strengths the average relative error is about 15% (macro) and 25% (micro) and data filtering does not significantly affect the results. For the heavier bottleneck strengths, the macro-estimates still perform better than the micro-estimates, which actually remain constant, differing more and more from the actual values. It can also be seen that data filtering significantly affects the values. For the heaviest congestion (δQ = 1486 veh/h), 50% of the vehicles are filtered out. On the whole, average density is under-estimated.
Estimation of density and gaps during congestion

Fig. 6 shows the average space gaps during congestions. Since gaps can be collected only with a microscopic approach, only the microscopic estimates are shown. In this case, it can be seen that gaps are over-estimated. This comes as no surprise if compared with Fig. 6 and confirms the findings in [9]. The estimates are about 10% greater, as long as the congestion is not too strong. Then they tend to be constant for the three last bottleneck strengths, with increasing difference from the actual values. Again, data filtering affects the values at the heaviest bottleneck strengths.

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CONCLUSIONS

On average, density estimates from one point detector under-estimate actual density during congestion. Density estimates from macroscopic data (i.e. from flow and space mean speed) perform better than that from microscopic data (i.e. from individual speed and time headways). However, for the heaviest bottleneck strengths, the difference from the actual values increases significantly.

Density estimates are not able to catch density peaks, which represent the incidences of heaviest congestion and are critical for bridge loading.

Accordingly, calculations of space gaps from time gaps and individual speeds are over-estimated. Again, the error is roughly constant for lighter congestion then increases for heavier states.

In conclusion, the traditional macroscopic equation of traffic can be used for estimating density, as long as only an average value is necessary and accuracy is not a primary requirement. When this is not the case, the use of multiple loop detectors or cameras is preferable, especially for heavy congestion.
REFERENCES


