Freeway Traffic Shockwave Analysis: Exploring the NGSIM Trajectory Data

by

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Abstract

The paper presents the development and application of a numerical algorithm to estimate the propagation speed of shockwaves on freeways based on vehicle trajectory data. The essence of the algorithm is that the shockwave propagation speed is the traveling speed of local minima of consecutive vehicle speed trajectories. The application of the algorithm on the NGSIM datasets from the I-80 and US101 freeways under congested conditions shows that all the shockwaves have similar propagation speed of about 11.4 mph (18.34 kph), which is independent of the traffic flow speed prior to congestion. The algorithm developed here is generic and can be used for shockwave analysis based on any vehicle-by-vehicle trajectories estimated from any range sensors. The findings have been applied to estimate the upper bound for time delay error in link travel time estimation from point sensor data.

Keywords: traffic flow, shockwaves, NGSIM, vehicle trajectories
1. Introduction

Shockwaves can be defined as boundary conditions between states of traffic flow on highway facilities (e.g., from free-flow to congestion). Understanding the formation and characteristics of shockwaves is important in studying congestion patterns and impacts, developing improved analysis tools and designing traffic management strategies. The study of shockwaves in turn requires data on vehicle movements and interactions over time and space. Such data are very limited; existing databases include vehicle trajectories produced at Ohio State University in the 70’s [1], a FHWA study on vehicle interactions in the early 80’s [2], and more recently sample vehicle trajectories and shockwaves on a short section of I-680 freeway [3].

Recently, data on individual vehicle trajectories were collected and made available under the Next Generation Simulation (NGSIM) project [4], a national effort aiming to develop improved algorithms and datasets for calibration and validation of traffic simulation models. The NGSIM data provide a unique opportunity to investigate driver behavior, better understand traffic dynamics and formulate improved models.

The NGSIM freeway database consists of vehicle trajectories on two test sites [5]. The I-80 (BHL) test section is a 0.40 mile (0.64 Km) 6-lane freeway weaving section with an HOV lane. Processed data include 45 minutes of vehicle trajectories in transition (4:00-4:15 pm) and congestion (5:00-5:30 pm). The US101 site is a 0.3 mile (0.5 km) weaving section with five lanes. Processed data include 45 minutes of vehicle trajectories in transition (7:50-8:05 am) and congestion (8:05-8:35 am). The data have been extracted from video recordings using machine vision algorithms [6].

The paper presents an exploratory analysis of shockwaves on freeways, and the development and application of a numerical algorithm to estimate the shockwave propagation speed based on the NGSIM vehicle trajectory data. The work is part of an ongoing study on empirical understanding of traffic dynamics and formulation of improved models. The algorithm developed here is generic and can be used for shockwave analysis based on any vehicle trajectories estimated from any range sensors as long as the speed trajectories are reasonably smooth.

Section 2 of the paper discusses qualitatively some observations from the inspection of vehicle speed-time and distance-time plots and the characteristics of shockwaves. Section 3 describes the formulation of an algorithm to estimate the shockwave propagation speed. The numerical implementation of the algorithm and the results from its application to the NGSIM data are presented in Section 4. Section 5 presents an application of the findings. The last section summarizes the study findings and outlines future research directions.

2. Data Observations

The NGSIM data format is vehicle ID, lane and position at 0.1 sec intervals. We processed the data to produce time-distance and time-speed plots for each freeway lane, and also speed-distance contour plots. A total of 11,779 vehicles were processed. Detailed description of the data processing and all the plots are included elsewhere [7].

Figures 1 and 2 show sample speed-time and distance-time plots from the two test sites. Figure 1 also illustrates different flow regimes and transitions; from free flow to congestion on-set and...
build up (region a), congested static state (region b), and recovery (region c). The duration of congestion (or shockwave propagation) is also shown as time d over distance e in this Figure. Also, we can observe the correspondence between the speed drops in the multi-vehicle speed envelop and the shockwave in the distance-time plot. The speed envelop drop is approximately proportional to the shockwave propagation distance.

Further observations of these plots show that each wave leads to a valley for the speed curves. The relative depth of the valley represents speed reduction or the effects of shockwave. Thus, such depth could be used to classify the shockwave: long term congestion or short term fluctuation. Each valley corresponds to at least one local minimum. There could be several local minimum if the speed remains constant in the valley (e.g., stopped vehicles), but there is a unique minimum which corresponds to the earliest time. The propagation of those unique minimum values determines the shockwave propagation speed.

Figure 3 shows vehicle trajectories for lanes 1 and 2 of the US101 test site under congested conditions. Shockwaves are shown as straight lines propagating backwards in time and space. The speed of the shockwave is the slope of the line, estimated at about 11 mph. Figure 4 shows the vehicle trajectories and shockwaves for lanes 2 and 3 of the I-80 test site under congestion (lane 1 is the HOV lane, operating under free-flow conditions). These Figures show that the shockwave characteristics and speeds are very similar on both sites.

Figure 5 shows the speed and distance trajectories of selected vehicles related to single shockwave. It is clear that the speed-time curve is of 2nd order parabolic type, and the distance-time curve is a 3rd order curve. Vehicle trajectories related to multiple waves are shown in Figure 6. The speed-time and space-time trajectories for multi waves correspond to combinations of 2nd order and 3rd order curves respectively.

Based on the above qualitative observations, we developed a numerical algorithm to estimate the shockwave speed from the vehicle trajectory data. The algorithm searches for those unique local minimum values for each speed-time trajectories. It then determines how those local minima for each trajectory propagate in space and time, which provides the shockwave propagation speed.

3. Proposed Algorithm for Estimating the Shockwave Propagation Speed

The following notation is used in this section:

- \( j \) – vehicle or trajectory index (each vehicle corresponds to a trajectory) in a consecutive order; two vehicles are consecutive when (a) they are in the same lane, and (b) vehicle \( j + 1 \) is behind vehicle \( j \);
- \( i \) – the index of shockwave: There may be more than one shockwave appeared in one data set; and each vehicle may be involved in more than one shock wave;
- \( t_k \) - discrete time points for \( k = 0,1,2,\ldots, K \); synchronized for all the vehicles;
- \( \Delta t = t_{k+1} - t_k \) is a constant of 0.1 sec – data sample period;
- \( k \) – the index of time step;
\( t_{k_i}^{(j)} \) - time points corresponding to the local minimum of the speed-time trajectory for vehicle j;
\( y_j(t_k) \) - distance of vehicle j at time point \( t_k \); all the vehicle trajectories starting from the same point;
\( v_j(t_k) \) - speed of vehicle j at time point \( t_k \);

For each vehicle j, suppose a time and distance coordinate (in a global inertia coordinate system) for the unique local minimum point corresponding to a speed drop is \( (t_{k_i}^{(j)}, y_j(t_{k_i}^{(j)})) \). The time points for minima of different consecutive trajectories corresponding to the same shockwave are not necessarily equally distributed, i.e., \( t_{k_i}^{(j+1)} - t_{k_i}^{(j)} \) is not necessarily constant for all the vehicles involved in the same shockwave. However, there should hold the following relationship for any two consecutive vehicles \( j \) and \( j+1 \):

\[
\begin{align*}
    t_{k_i}^{(j+1)} &> t_{k_i}^{(j)} \\
y_{j+1}(t_{k_i}^{(j+1)}) &< y_j(t_{k_i}^{(j)})
\end{align*}
\]

which is a necessary condition for a shockwave appearing at the onset of congestion. This is because the vehicle behind begins to decelerate at shorter distance relative a common starting point, and it is impossible that

\[
\begin{align*}
    t_{k_i}^{(j+1)} > t_{k_i}^{(j)} \\
y_{j+1}(t_{k_i}^{(j+1)}) &\leq y_j(t_{k_i}^{(j)})
\end{align*}
\]

The shockwave propagation speed \( V_j^{(i)} \) for consecutive vehicles is estimated as:

\[
V_j^{(i)} = \frac{y_{j+1}(t_{k_i}^{(j+1)}) - y_j(t_{k_i}^{(j)})}{t_{k_i}^{(j+1)} - t_{k_i}^{(j)}} < 0
\]

The negative sign of \( V_j^{(i)} \) indicates that the shockwave is back-propagating. The implementation of the algorithm requires not only the vehicle moving distance but also the start tracking point to get the position of the vehicle with respect to the inertial coordinate system at any time.

Suppose there are \( J \) vehicles involved in the \( i-th \) shockwave. Then the \textit{average shockwave propagation speed} is defined as:

\[
V^{(i)} = \frac{1}{J-1} \sum_{j=1}^{J-1} V_j^{(i)}
\]
4. Numerical Implementation of Shockwave Speed Estimation Algorithm

The implementation of the above described shockwave speed estimation algorithm consists of the following steps: (a) filtering to smooth the speed-time trajectories, (b) searching local minimum of the smoothed trajectories, (c) clustering the time and distance points corresponding to those local minima, and (d) calculating the average shockwave propagation speed from the distance-time points corresponding to the clustered local minima.

Vehicle trajectory filtering

The algorithm requires finding the minimum values of the speed trajectories and their corresponding time and distance points. The trajectories from the NGSIM data used in the study have disturbances due to measurement noise and estimation error, which may cause problems in the search for the true minimum values of speed trajectories. We apply a low pass filter and a rate limit filter to smooth the trajectory data to eliminate those irrelevant local minima due to noise. The following low pass (Butterworth) linear filter is used for filtering purpose:

\[
\begin{align*}
    x_1(k) &= 0.4320x_1(k-1) - 0.3474x_2(k-1) + 0.1210v_{in}(k) \\
    x_2(k) &= 0.3474x_1(k-1) + 0.9157x_2(k-1) + 0.0294v_{in}(k) \\
    v_{out}(k) &= 0.4984x_1(k) + 2.7482x_2(k) + 0.0421v_{in}(k) \\
    k &= 1, 2, \ldots
\end{align*}
\]

Where \( x_1(k) \) and \( x_2(k) \) are the filter state variables, \( v_{in} \) is the input speed signal and \( v_{out} \) is the output filtered speed. The initial condition is chosen as \((x_1(0), x_2(0)) = (0, 0)\). Figures 5 and 6 show smoothed speed-time and distance-time trajectories using the above methods.

Search for local minima of speed trajectories

Several methods exist for search local minimum such as Newton gradient method, steepest decent method for continuous functions and genetic algorithm for discontinuous functions [8,9]. However, these methods are not suitable for the purpose of this analysis, because we need to account for the following:

(a) Although linear filter has been used to smooth the speed-time trajectories, the speed obtained from distance measurement by numerical differentiation still may still have estimation noise, which may cause traps in the local minimum search. Thus the algorithm should be able to move out of the traps due to noise in speed trajectory.

(b) It is sufficient to locate only the appropriate minima, i.e., speed drops exceeding some threshold. Small speed drops that are not due to a shockwave should be filtered out.

(c) The algorithm should simple to facilitate implementation on large data sets

The proposed algorithm is called moving window minimum searching. A time window of width \( L \) is specified (the number of time points to be searched), and the algorithm searches progressively (after each progressive search, moves one step forward). The algorithm searches the local minimum of the speed trajectory for any vehicle \( j \) which may be related to some shockwave \( i \). If the speed is constant for a time interval (e.g., the speed is zero for stopped
vehicles) there are uncountable number of minimum values. In this case, the first minimum is
registered, which is the unique minimum $v_{k_i}^{(j)}$ for each speed valley, and corresponds to a unique
time distance point $\left( t_{k_i}^{(j)}, y_j \left( t_{k_i}^{(j)} \right) \right)$.

The algorithm can be described in generic semantics:

For $j = 1: J$

While $t_k < T$

$k=1$

If $k < L$

$v_{j_i} = \min \{ v_j \left( t_1 \right), v_j \left( t_2 \right), ..., v_j \left( t_k \right) \}$

If $t_s$ is the first time point among $\{t_k, ..., t_k\} \ (s \leq k)$ such that $v_{j_i} = v_j \left( t_s \right)$,

Then

register $t_s$ as $t_{k_1}^{(j)}$ and also $y \left( t_{k_1}^{(j)} \right)$

$i=i+1$

Else

$v_{j_i} = \min \{ v_j \left( t_k \right), v_j \left( t_{k+1} \right), ..., v_j \left( t_{k+L} \right) \}$

If $t_{k+s}$ is the first time point among $\{t_k, ..., t_{k+L}\} \ (s \leq L)$ such that

$v_{j_i} = v_j \left( t_{k+s} \right)$, then

register $t_{k+s}$ as $t_{k_1}^{(j)}$ and also $y \left( t_{k_1}^{(j)} \right)$

$i=i+1$

If Loop End

$k=k+1$

While Loop End

$j=j+1$

For Loop End

Note that for short time window $L$, more local minimum other than the shockwave related
minimum could be registered. Also if $L$ is specified too long, some true local minimum values
related to shockwaves may be missed. In this application, $L$ was set as 20 seconds, or 200 time
steps, i.e., shockwaves lasting less than 20 seconds are ignored.

Clustering of local minimum values

The local minima obtained from the algorithm described in the previous section belong to each
trajectory. It is necessary to cluster consecutive local minima to form a chain of minima for a
shockwave. The minima should satisfy the following criteria to be included in a cluster:

- Two consecutive minima and their time points should have the same sequential order, or:
  $t_{k_i}^{(j+1)} - t_{k_i}^{(j)} > \delta$
Two consecutive minima should come from different but also consecutive speed trajectories;
Corresponding distance point should satisfy the condition (1), i.e. \( y_{j+1}(t^{(i+1)}_k) < y_j(t^{(j)}_k) \)
The following conditions are satisfied:

\[
-V_{\text{max}} \leq \frac{y_{j+1}(t^{(i+1)}_k) - y_j(t^{(j)}_k)}{t^{(i+1)}_k(t^{(j)}_k)} \leq -V_{\text{min}}
\]  

(0.1)

where \( \delta > 0 \) is pre-specified time threshold; \( V_{\text{min}}, V_{\text{max}} \) are possible minimum and maximum shockwave propagation speed respectively. In the algorithm implementation, we used the following values:

\[
\begin{align*}
\delta &= 0.1 \text{ sec} \\
V_{\text{min}} &= 3 \text{ ft/sec (1 m/sec)} \\
V_{\text{max}} &= 30 \text{ ft/sec (10 m/sec)}
\end{align*}
\]

The algorithm for building the clusters can be described as follows:

Step 0: Set \( j = 1 \), \( i=1 \) and Initialize cluster 1 with \( \left( t^{(j)}_k, y_j(t^{(j)}_k) \right) \)

Step 1: Set \( j = j+1 \)

Step 2: Take a tentative point \( \left( t^{(j)}_k, y_j(t^{(j)}_k) \right) \) from trajectory \( j \) and check if \( \left( t^{(j)}_k, y_j(t^{(j)}_k) \right) \) and \( \left( t^{(j-1)}_k, y_{j-1}(t^{(j-1)}_k) \right) \) satisfy the condition in (1.5) for all the previous clusters set up so far;

- If YES: register \( \left( t^{(j)}_k, y_j(t^{(j)}_k) \right) \) as the follower of \( \left( t^{(j-1)}_k, y_{j-1}(t^{(j-1)}_k) \right) \) in the same cluster;
- If NO: Initialize a new cluster with the first minimum point of the second trajectory: Set \( i=i+1; \)
  \( \left( t^{(j)}_k, y_j(t^{(j)}_k) \right) \); Notice that the subscript of \( k \) has been increased by 1;

Step 3: Remove the tentative point \( \left( t^{(j)}_k, y_j(t^{(j)}_k) \right) \) from the set of minima for trajectory \( j \)

Step 4: Repeat Step 2

This process will stop after all the minima for all the trajectories have been put in some cluster.

**Estimation of the shockwave speed**

Once the clustering has been achieved, the average shockwave propagation speed can be calculated from the clustered minima using Equations (3.3) and (3.4). The algorithm was applied to all NGSIM data sets. The estimated shockwave speed was found to be 11.4 mph (18.3 kph).
5. Applications

The findings on shockwave characteristics and propagation speeds can be used to identify the spatial and temporal impacts of congestion, and to develop and calibrate traffic flow models. In this section, we illustrate how the results can be used to estimate the upper bound for time delay error in the link travel time estimation from point sensors, such as loop detectors.

Suppose the detection method needs information from both upstream and downstream loop detectors. In this worst case, let $\tau_c$ denote the upper bound for the shockwave to reach the upstream detector and $V_{shock}$ is the shockwave propagation speed. The following relationship holds:

$$L = V_{shock} \tau_c$$  \hspace{1cm} (5.1)

where $L$ is the detector spacing. Or equivalently

$$\tau_c = \frac{L}{V_{shock}}$$ \hspace{1cm} (5.2)

The upper bound for time delay error estimation can be expressed as:

$$\tau_{max} = \tau_c + \tau_0 = \frac{L}{V_{shock}} + \tau_0$$ \hspace{1cm} (5.3)

Where the time delay $\tau_0$ is caused by data processing delays such as aggregation over time, and/or by persistence checking to reduce false alarm in congestion onset detection. For example, if the data update rate is 0.1s, the data processing delay is 0.5s and persistence checking is 10 steps, then $\tau_0 = 1.5s$. The estimated shockwave speed $V_{shock}$ is 5.1 m/sec (16.72 ft/sec). Equation (5.3) becomes

$$\tau_{max} = \frac{L}{5.1} + \tau_0$$ \hspace{1cm} (5.4)

which provides the upper bound for time delay from the distance between the two detector stations and the instant point speed at the downstream station. Equation (5.4) can be used by traffic engineers to determine how dense the loop stations should be installed on highways to achieve the acceptable estimation error threshold $\tau_{max}$.

Discussion

The estimated shockwave propagation speed of 11.4 mph (18.3 kph) is the same for both the test sites for the time periods studied. The estimated speed from the algorithm is the same with the direct measurement from the Figures 3 & 4. Also, this estimate is also in agreement with the estimated shockwave speed of 12.5 mph reported using the I-680 data [3]. It is also demonstrated how the results can be used for the estimation of upper bound for time delay error in the link travel time estimation based on the detection at two terminal stations such as loops,
which immediately leads to a relationship between sensor density and time delay error threshold.

The time periods analyzed were all in congestion and transition. We will investigate subject to the availability of data, the shockwave speed and characteristics under different traffic flow conditions. Also, we will investigate the effects of the congestion causes on shockwave characteristics.

The algorithm is being implemented as part of a software tool to automate the data processing and analysis of large data sets involving vehicle trajectories and other microscopic data. The findings on shockwave characteristics and propagation speeds are used in the development and calibration of traffic analysis models for oversaturated freeway flow. The results are also used in assessing the effectiveness of alternative methods and surveillance technologies to identify the congestion onset[7].
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