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AVERAGE VELOCITY OF WAVES PROPAGATING THROUGH CONGESTED FREEWAY TRAFFIC

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ABSTRACT

Large portions of traffic flow theory are built upon the bivariate relationship between flow and density. While the chosen shape of the curve implicitly impacts the models predicated upon it, little can be said for certain about the congested regime beyond the fact that in aggregate, flow drops with increasing density. Several researchers have proposed a linear relationship for the congested regime and recent empirical studies of wave velocities propagating upstream during congestion have been consistent with the linear relationship. But all of the empirical studies used small samples, often aggregated across several lanes, to find the wave velocities. To provide a more comprehensive analysis this paper builds off of a cross correlation idea presented previously in the literature and seeks to extract the average wave velocity automatically, and to do so independently in each lane. Replicating earlier efforts based on cumulative arrivals measured at successive detector stations yields mixed results, many of the observations are consistent with the earlier research, but many other measurements are unreasonably fast or slow. It is shown that this outcome should not be surprising, since cumulative arrivals are simply a function of flow, which in turn is a function both of the local traffic speed and vehicle lengths. The latter travels downstream with the vehicles and confounds attempts to extract the velocity of upstream moving waves. Repeating the analysis using traffic speed measured at the detector stations yields much better results. As shown herein, during congestion waves consistently propagate upstream with velocity in the

15-25 km/h range, with little or no discernable dependence on prevailing traffic speed, lane, or location.

INTRODUCTION

Large portions of traffic flow theory are built upon the bivariate relationship between flow and density or the related relationship between headway and spacing. This scope begins with the first-order, macroscopic model of Lighthill, Whitham and Richards (LWR) to predict the propagation of signals or waves through the traffic stream (Lighthill and Whitham, 1955; Richards, 1956) and continues into higher-order macroscopic models and microscopic models that attempt to model the behavior of individual drivers. But because it is difficult to measure density and uncommon to find stationary conditions during congested periods, debate continues about the shape of the bivariate curve and thus, implicitly impacts the models predicated upon it.

It is widely agreed among traffic flow theorists that during free flow conditions flow increases monotonically with density, with a slight drop in slope as conditions approach capacity. But little can be said for certain about the congested regime beyond the fact that in aggregate, flow drops with increasing density. Empirical studies by Hall *et al*. (1986, 1988) propose an inverted V shape for the flow-occupancy curve, while noting that the findings were consistent with earlier studies. A few years later, out of convenience, Newell (1993) also chose to simplify the relationships by using a triangular flow-density curve for illustrative purposes in the course of theoretical development. Given a triangular curve, LWR predicts that during congested periods, waves should propagate upstream with a constant velocity, independent of the given flow, density, or local traffic speed.[1] Subsequent empirical analysis suggests that indeed, during congestion, waves do appear propagate upstream with roughly constant velocity. Windover and Cassidy (2001) showed that the upstream moving waves could be found by comparing the cumulative arrival curves across all lanes between two neighboring loop detector stations. They used data from a 2 km segment of northbound Interstate-880, just south of Oakland, California, and found that the wave velocities during congested periods were nearly constant (17-20 km/h) over the homogeneous freeway segment, independent of flow. Mauch and Cassidy (2002) observed traffic data over multiple days along a 10 km stretch of the Queen Elizabeth Way (Ontario, Canada). They measured wave velocities by plotting the cumulative arrival curve across all the lanes from many successive detector stations with vertical displacements in proportion to the physical distance separating the successive detector stations and found that the waves propagating upstream in congestion had nearly constant velocities in the range of 22-24 km/h, independent of the location and the flow. Smilowitz and Daganzo (2002) employed the LWR model to derive the wave velocity

[1] Throughout this paper, speed refers to motion of the traffic as it travels downstream and velocity refers to the motion of waves through the traffic stream. Furthermore, a positive velocity is used to denote when these waves travel upstream.

from the slope of the line passing through the two states in accumulation-flow relationship, where the accumulation is proportional to the density between two observers. They found wave velocities on a single lane, homogeneous highway segment were 17.2 km/h on one day and 18.8 km/h on another. Deviating from the earlier techniques of manually extracting wave velocities, Munoz and Daganzo (2001) applied cross correlation to cumulative arrival curves summed across selected lanes for a single sample period and found a wave velocity of 19.4 km/h.

These earlier efforts suggest that the flow-density curve is indeed triangular, e.g., Windover and Cassidy (2001) note, "traffic on homogeneous freeway segments might better be modelled using linear (triangular-shaped) relations." But all of the earlier studies used small samples, often aggregated across several lanes, to find the velocity of waves during congestion. If the wave velocities are roughly constant, independent of traffic conditions, they can be used as inputs to estimate link travel times (Coifman, 2002), which is part of the motivation behind this paper. To provide a more comprehensive analysis of wave velocity during congested periods, this research builds off of the cross correlation idea presented by Munoz and Daganzo (2001) and seeks to extract the average wave velocity automatically for each sample. Our methodology can accommodate additional data with little human intervention, thereby allowing the study of much larger data sets to better model the phenomena.

The following section of this paper uses cross correlation of cumulative arrivals measured at successive detector stations. Then the paper discusses the limitations arising from flow-based measures, such as cumulative arrivals, when attempting to measure waves propagating against the flow of traffic. The next section uses traffic speed measurements to address the limitations and then examines the influence of prevailing traffic speed, lane, and location on the results. This paper then closes with a brief discussion and conclusions.

AVERAGE WAVE VELOCITY FROM CROSS CORRELATION OF CUMULATIVE ARRIVALS BETWEEN TWO STATIONS

Our first attempt to extract wave velocities automatically is to simply replicate Munoz and Daganzo's cross correlation method on one month (August, 2003) of cumulative arrival curves sampled every 2-seconds from seven successive detector stations in the westbound direction of the Berkeley Highway Laboratory (BHL) along Interstate-80, north of Oakland, CA (Coifman et. al., 2000). The method seeks to find the time lag at which the cross correlation of the two time series recorded at two successive detector stations reaches a maximum and that time lag corresponds to the dominant travel time of waves in the sample. The details for the cross correlation method are as follows. Assuming that waves propagate between the two stations, the upstream time series, $y(t)$, could be regarded as a scaled and delayed version of downstream time series, $x(t)$, with zero mean additive noise, $n(t)$, i.e.,

$$y(t) = \alpha x(t - \tau_0) + n(t) \tag{1}$$

where α is the scale factor and τ_0 is time delay corresponding to the travel time of waves from downstream location to upstream location. Let $R_{xy}(\tau)$ represent the cross correlation of $x(t)$ and $y(t)$, and $R_{xx}(\tau)$ be the auto-correlation of $x(t)$. From equation (1) and the definitions of $R_{xy}(\tau)$ and $R_{xx}(\tau)$, we have:

$$\begin{aligned} R_{xy}(\tau) &= E[x(t)y(t+\tau)] \\ &= E[x(t)\{\alpha x(t+\tau-\tau_0)+n(t+\tau)\}] \\ &= \alpha E[x(t)x(t+\tau-\tau_0)] \\ &= \alpha R_{xx}(\tau-\tau_0) \end{aligned} \tag{2}$$

where $R_{xx}(\tau) \le R_{xx}(0)$. Thus, $R_{xy}(\tau)$ reaches its maximum when $\tau = \tau_0$. For this study the search window for feasible time lags spanned -4096 sec to 4096 sec and in the rare cases that two maxima were found, the given sample is excluded.

There are 5 lanes in each direction on the freeway segment used in this study (fig. 1). The innermost lane is reserved for high occupancy vehicles (HOVs), because the HOV lane generally exhibits little congestion compared to the general flow lanes it was excluded from the analysis of upstream moving waves. The seven dual-loop detector stations in the segment are denoted st1 through st7, respectively. The stations are spaced about 1/2 km apart from each other and each detector station has a dual-loop detector in each lane, which allows for direct measurement of local traffic speeds.

The event data from each detector are recorded at 60 Hz and then aggregated to 2-second average traffic speed and flow measurements. This 2-second aggregation was chosen because it is roughly on the order of typical headways and is consistent with Munoz and Daganzo (2001), facilitating comparison. Unlike Munoz and Daganzo, who paired lanes together, we applied the cross correlation technique on individual lanes. Because this study is limited to the waves that arise in congested traffic, the following pre-processing step is used to exclude all non-congested periods. The lane is considered congested if the 5-minute average traffic speed remains below a pre-specified threshold for at least one-hour at both the upstream and

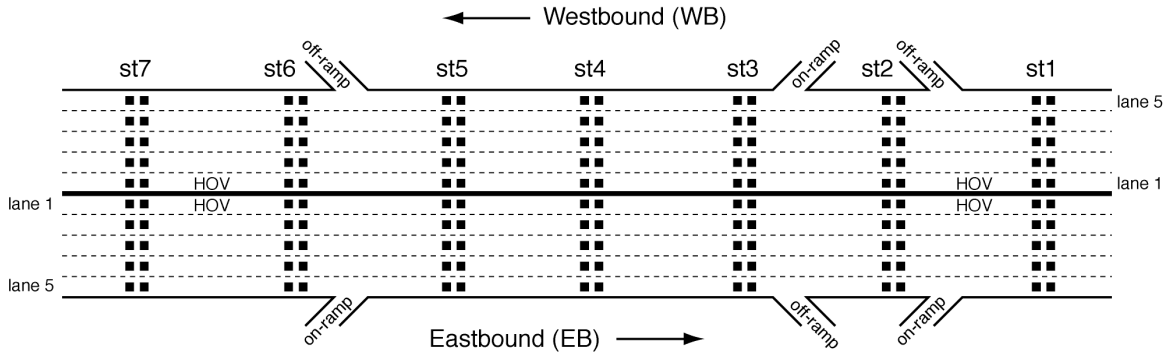

Figure 1, Schematic of the Berkeley Highway Laboratory on Interstate-80, north of Oakland, California.

downstream stations on a link. Each contiguous "congested period" in each lane for each station pair is divided into non-overlapping, one-hour long samples that are used in the cross correlation analysis. The exact threshold was chosen somewhat arbitrarily, with the specific intent to ensure that conditions were indeed congested throughout the entire link for an extended period. A traffic speed threshold of 48 km/h (30 mph) was used in most of the analysis presented in this paper, though a higher threshold at 72 km/h (45 mph) was used as well throughout the research to verify the results did not depend on the choice of the threshold. Other sample durations were studied, such as 45-min and 30-min long, with results similar to those presented herein, but they became noisier as the period decreased.

Fig. 2 shows the cumulative distribution (CDF) of the average wave velocity from each sample, estimated via cross correlation on an individual lane basis applied to the 2-second cumulative arrival curves after subtracting a background flow equal to each lane's average flow during the given period. So each datum in this distribution represents the wave velocity corresponding to the maximum correlation from a one hour long sample for the given lane. Rather than reporting mean or median, the entire distribution is shown to allow detailed evaluation, e.g., the standard deviation could be evaluated from the CDF. Over all links and in all lanes, one sees mixed results. Many of the observations are consistent with the earlier research, with wave velocities between 15 km/h and 25 km/h, but many more of the measurements fall outside this range. For reference, table 1 shows the total number of samples in each of the curves from fig. 2. The research also considered several related variations. In the first case, before employing cross correlation, rather than subtracting a background flow the cumulative arrival curves were filtered to remove the least-squares fit of a straight line from the data. Next, the time series of 2-second "raw" flow and of "filtered" flow (using the same filtering processing as used in cumulative arrival curves) were investigated for estimating the average wave velocity, applied to the same congested periods used in fig. 2. Fig. 3 shows the resulting CDFs of each sample's average wave velocity from the three additional methods for a typical station pair (st4 and st5 westbound, the other station pairs exhibited similar trends), compare to fig. 2D. The filtered cumulative arrivals found almost half of the measurements with zero time lag because in many cases the background flow was the dominant component. As a result, fig. 3A shows the CDF with the zero time lag included as dashed lines and excluding all samples with zero time lag with solid lines for the same lanes. In any event, all four methods had more measurements between 15 km/h and 25 km/h than any other 10 km/h window, with the filtered flow having many more measurements in this range compared to the other three methods. Although encouraging, the results remain mixed for all four methods since several lanes had fewer than 40 percent of the observations falling in the window.

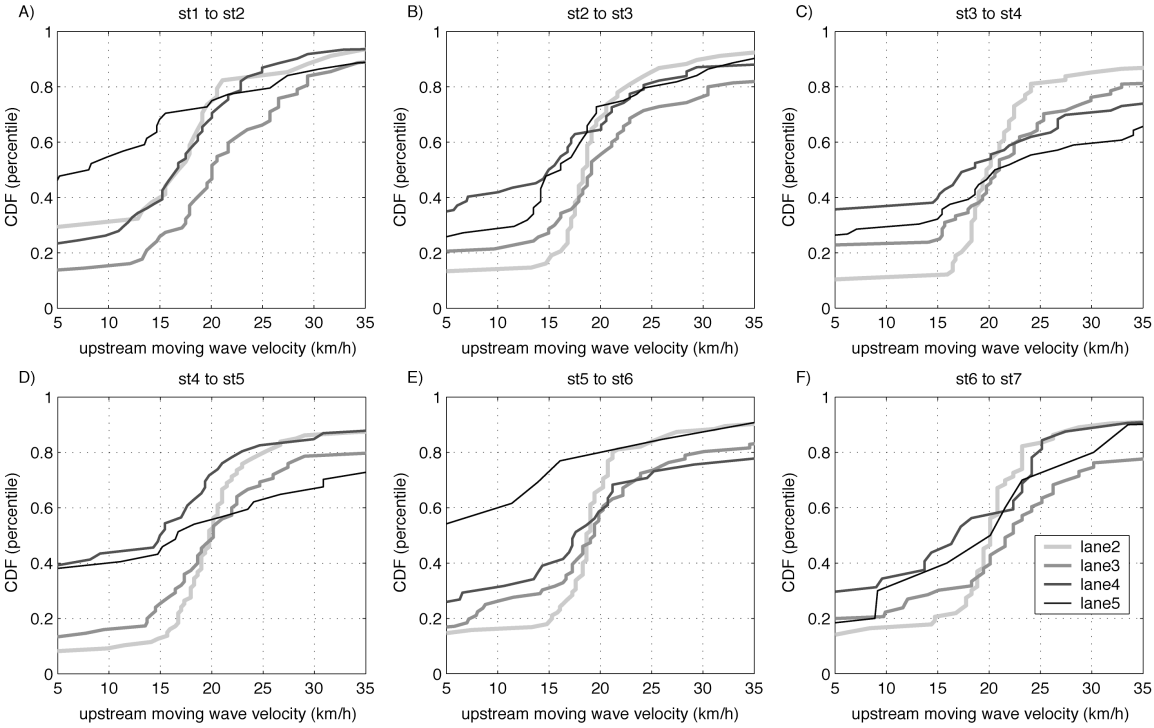

Figure 2, Distribution of the average wave velocity from each sample using cross correlation applied to cumulative arrival curves with background flow subtraction, August 2003, WB, BHL.

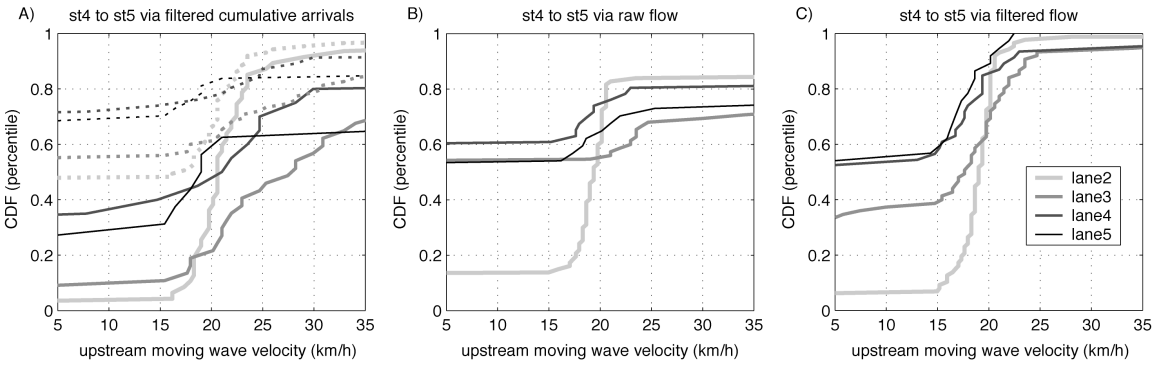

Figure 3, Distribution of the average wave velocity from each sample using cross correlation applied to (A) filtered cumulative arrival curves (B) raw flow (C) filtered flow, st4 to st 5, August 2003, WB, BHL.

Table 1, Number of Samples in each CDF for fig. 2 and fig. 5

	Number of samples by lane					
	st1 to st2	st2 to st3	st3 to st4	st4 to st5	st5 to st6	st6 to st7
lane2	34	68	74	87	95	73
lane3	62	70	84	75	76	63
lane4	61	62	63	46	41	32
lane5	44	44	56	37	13	10

PROBLEMS USING FLOW, OCCUPANCY AND CUMULATIVE ARRIVALS TO EXTRACT AVERAGE WAVE VELOCITY

Given homogeneous vehicles and drivers, LWR predicts that for a convex flow-density relationship all waves should propagate upstream during congestion. Yet there are numerous examples in the literature demonstrating that some information actually travels downstream during congested periods, as observed in flow or occupancy measurements, e.g., Dailey (1993), Petty et al. (1997) and Cassidy and Windover (1998). Cassidy and Windover referred to this phenomenon as "driver memory" with drivers resuming similar headways after passing through disturbances while the other researchers simply used the phenomenon to measure travel time. None of these papers note the seemingly apparent conflict with LWR. To rectify this problem, one can derive an explanation based on the fact that real vehicles simply are not homogeneous.

Consider fig. 4, showing a hypothetical example of several vehicles traveling in a freeway lane. The figure shows four vehicles moving from right to left. The i-th vehicle has a fixed effective length[2], L_i, and a variable spatial gap between itself and the preceding vehicle, g_i, that is likely to be a function of the driver, vehicles, and traffic conditions. The total spatial headway for this vehicle at any instant is simply,

$$s_i = L_i + g_i \tag{3}$$

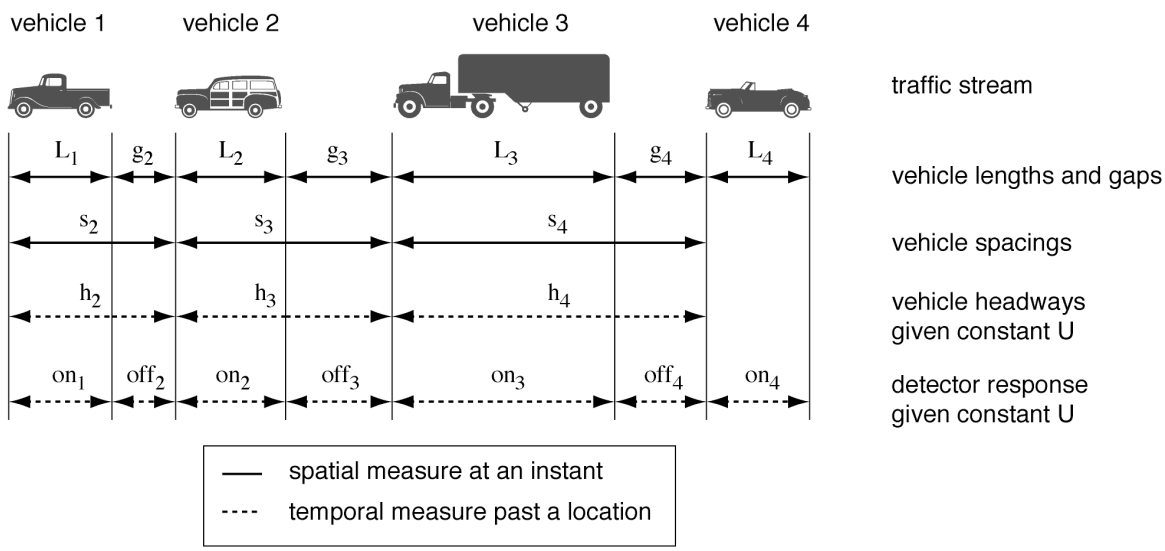

Figure 4, A hypothetical example of the traffic stream showing the corresponding spacings, headways and detector status.

[2] The effective length includes the physical length of the vehicle and the length of the detection zone.

If two successive vehicles, i-1 and i, were traveling at the same constant speed, U, then the i-th vehicle's headway passing a point in space is given by,

$$h_i = \frac{s_i}{U} \tag{4}$$

or relaxing the assumption of constant speed to reflect the varying speeds experienced in congested traffic (as is done throughout the remainder of this paper), the relationship becomes,

$$h_i \approx \frac{s_i}{u_i} \tag{5}$$

where u_i is the i-th vehicle's speed passing the specified point in space, e.g., a detector station. Similarly, as the vehicle passes a detector, it turns on for the following duration,

$$on_i = \frac{L_i}{u_i} \tag{6}$$

where an equal sign is used assuming the vehicle is traveling fast enough so that acceleration is negligible in the on-time measurement. Given these facts, if one measures flow, q_j, and occupancy, occ_j, over a fixed number of vehicles, n, it should be clear that,

$$q_j = \frac{n}{\sum_{i=1}^{n} h_i}, \qquad occ_j = \frac{\sum_{i=1}^{n} on_i}{\sum_{i=1}^{n} h_i} \tag{7}$$

Most operating agencies use fixed sample periods, T, rather than fixed n, in which case the equalities in Equation 7 become "approximately equal" due to edge effects from partial headways observed at the start and end of a given sample.[3] It should be clear from this derivation that both flow and occupancy are functions of u_i and L_i. Obviously, L_i travels downstream with the vehicles even during congested periods, e.g., Coifman and Cassidy (2002) explicitly used measured vehicle lengths to match the observation of a given platoon of vehicles at one station with the earlier observation of the same platoon from an upstream station on the same freeway during congested periods. This information traveling downstream will confound any attempt to extract information propagating upstream against the flow of traffic, e.g., although cut off by the horizontal axis of the plots, many velocities corresponding to downstream moving waves were found in the CDFs of fig. 2. The velocity of many of these

[3] In this case n changes from one sample to the next while T is the summation of the headways during a given sample. Provided the sample includes many vehicles, the contributions from the partial headways at the start and the end of the sample are usually negligible.

downstream moving waves were on the order of the prevailing traffic speed, but they were not the dominant trend in the distribution, as evidenced by the majority of the velocities in fig. 2 indicating upstream moving waves. The relatively low frequency of downstream moving waves in the CDFs is due in part to the large sample period (1 hr), during which time the link travel speed experienced by drivers typically changes significantly and this range usually prevents the downstream moving waves from becoming the dominant feature in the cross-correlation. The existence of downstream moving waves during congestion is consistent with the theoretical development of the mixed flow first-order macroscopic models of Zhang and Jin (2002) and Chanut and Buisson (2003), which extend LWR to heterogeneous flows of two or more vehicle types. Namely, in their models, trucks and cars had different lengths but travel with the same speed during congestion. These models predict that in congestion there are two kinds of waves, waves that move downstream with the vehicles as an artefact of the inhomogeneous vehicle (and driver) fleet and waves that move upstream according to LWR.

If u_i is independent of the inhomogeneities of the vehicle fleet, then one would expect that during congested periods LWR would better predict the evolution of traffic speed over time and space than LWR does for flow during the same periods (or cumulative arrivals, which is simply a function of flow).

AVERAGE WAVE VELOCITY FROM CROSS CORRELATION OF LOCAL TRAFFIC SPEED BETWEEN TWO STATIONS

In an attempt to improve the performance of the automated data extraction, and thus to analyze the characteristics of waves, the analysis now shifts to using local traffic speed from the detector stations to measure the average wave velocity in each hour long sample. As with the cumulative arrival data, the time series of local traffic speed measurements were filtered to remove the least-squares fit of a straight line from the data. Fig. 5 shows the CDFs of average wave velocity from each sample, estimated using the time series of 2-second traffic speed measurements corresponding to the same congestion samples used in fig. 2. The CDFs from local traffic speed exhibit a much tighter distribution compared to those from the cumulative arrival curves or flow measurements. Now all lanes in all links have over 90 percent of the measured wave velocities between 15 km/h and 25 km/h. Grouping all of the lanes and station pairs together, the median wave velocity is 18 km/h.

Note that fig. 2 and fig. 5 only show the results for westbound traffic in August 2003 (WB-03). The analysis was repeated for eastbound traffic (EB-03), as well as data from August 2002 (WB-02 and EB-02). In all four cases the results exhibited the same pattern moving from cumulative arrivals to local traffic speed when measuring the average wave velocity during congestion and all four cases exhibited the dominant wave velocity response in the range of 15-25 km/h, which is consistent with the previous research.

Characteristics of waves

To investigate whether the upstream moving wave velocity is independent of local traffic conditions, this research examined the relationship between average wave velocity and the prevailing traffic speed in each sample. For each one-hour long congestion sample we measured the minimum, median, and maximum of the 2-second traffic speed measurements from the downstream detector station. The results were similar for all three parameters, so this paper only presents the results for the median. The points in fig. 6 show each sample's average wave velocity versus the median of the downstream station's traffic speed from the same data set presented in fig. 5. For brevity, all lane and station pairs are shown in a single plot. Of the 1370 data points in the figure only 8 percent are below 15 km/h. To extract the general trend, these data were binned by 5 km/h increments of the local traffic speed and the total number in each bin is noted in the first column of table 2. The median of each bin is shown in fig. 6 as a solid line, with the median being chosen over the mean to reduce the sensitivity to the small number of points that are far from the center of the distribution. Note that the slowest bin had only 5 samples and the fastest bin had only 1 sample. Ignoring the larger deviations arising from these two bins on the ends, the fitted line is relatively flat, ranging between 17 km/h and 19 km/h. Fig. 7 presents all four of the fitted lines resulting from each direction in each year. As with fig. 6, table 2 tallies the number in each bin, and again, both the first and last bin for each curve has few samples, they are included only for completeness. For each curve in fig. 7, one can see the wave velocities may exhibit a small correlation with the prevailing traffic

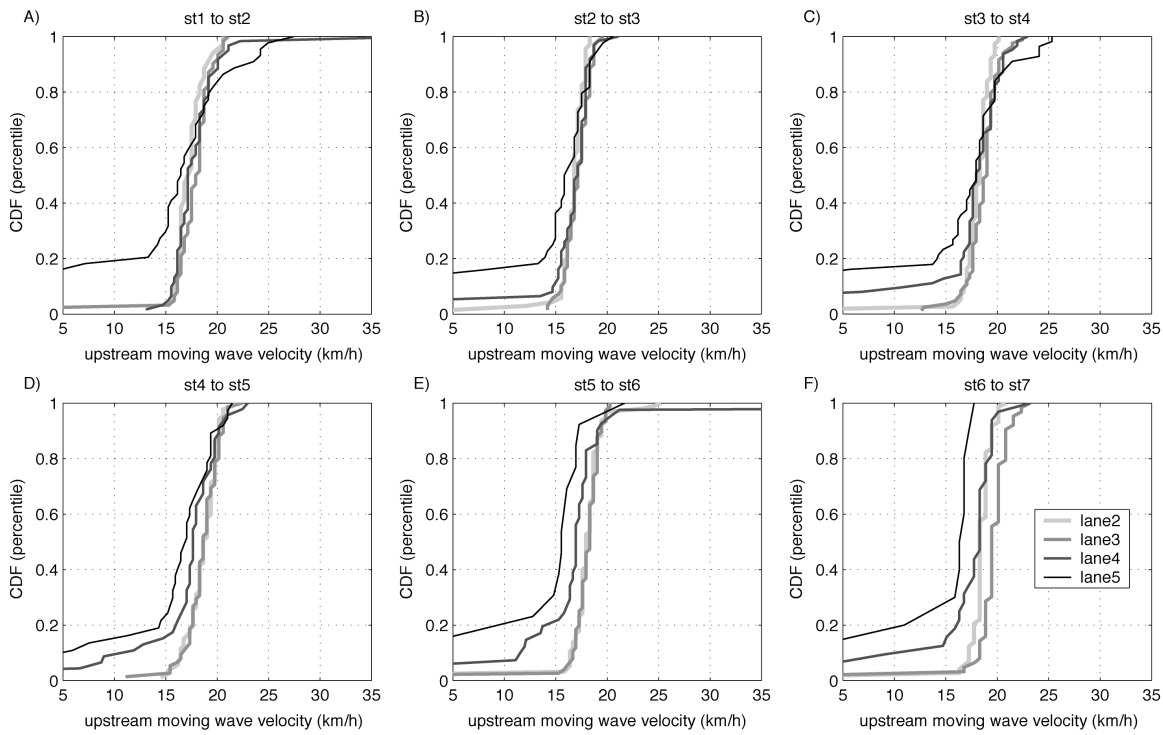

Figure 5, Distribution of the average wave velocity from each sample using cross correlation applied to filtered traffic speed measurements, August 2003, WB, BHI

Table 2, Number of samples in fig. 6 - 9

prevailing traffic speed range	WB-03	EB-03	WB-02	EB-02	Subsampling WB-03					
					on-ramps	off-ramps	lane 2	lane 3	lane 4	lane 5
0-5 km/h	0	0	0	0	0	0	0	0	0	0
5-10 km/h	5	0	0	0	0	2	0	1	2	2
10-15 km/h	71	2	34	0	3	18	8	27	21	15
15-20 km/h	184	3	71	3	12	31	49	63	42	30
20-25 km/h	271	15	104	21	18	30	113	85	49	24
25-30 km/h	310	48	132	55	43	33	107	96	58	49
30-35 km/h	286	61	111	82	28	18	91	101	64	30
35-40 km/h	197	92	66	84	2	24	55	52	51	39
40-45 km/h	45	26	13	20	0	3	8	5	17	15
45-50 km/h	1	4	0	0	0	0	0	0	1	0
Total	1370	251	531	265	106	159	431	430	305	204

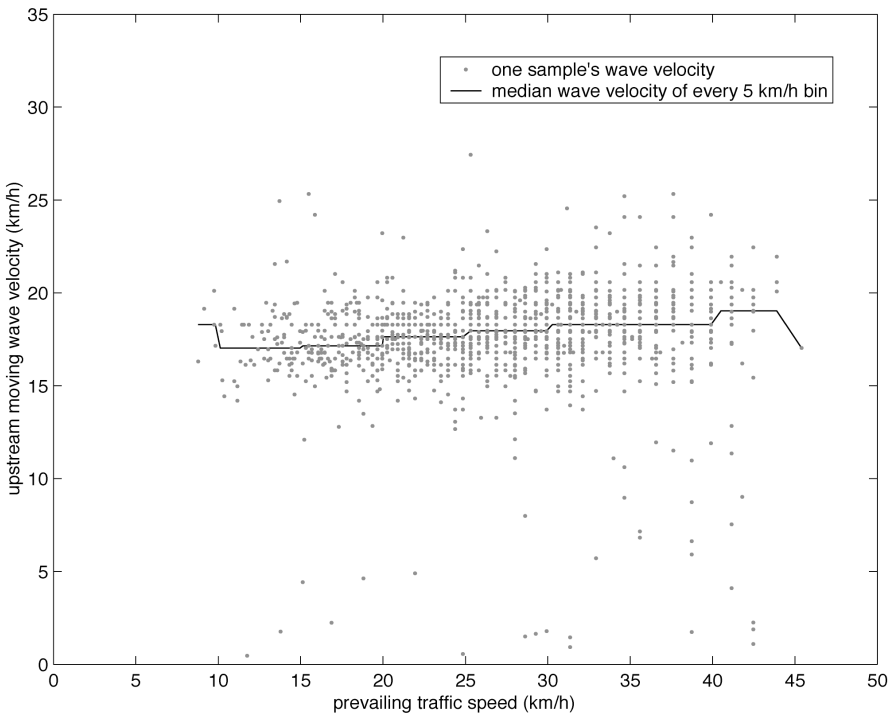

Figure 6, Average wave velocity versus prevailing traffic speed for each sample, August 2003, WB, BHL.

speed, but given the fact that three of the curves increase slightly and one decreases, it would be premature to draw any conclusions about the details of any relationship. Investigating these finer points of the relationship will be the subject of future research. In any event, the range is less than 4 km/h of wave velocity over a span of 35 km/h of local traffic speed for all four of the curves. So if local traffic speed impacts the wave velocity during congested periods this impact is small and there are other unmeasured factors that impact the wave velocity with a similar magnitude. The congestion threshold was set to 48 km/h in fig. 7, but as noted previously, the analysis was repeated with a threshold of 72 km/h. The results from the higher

threshold generally exhibit the same pattern but become slightly noisier at higher traffic speeds because many of the one-hour samples tend to include a mixture of free flow and congested conditions.

After examining each lane and station pair individually, no evidence of a dependence on either of these two parameters was found. For example, the impact on wave velocity from vehicles entering or leaving at ramps is of particular interest. Fig. 8 shows the average wave velocity versus prevailing traffic speed for each sample from station pairs with on-ramps and then with off-ramps. Assuming that traffic entering or leaving a ramp would have the largest impact on the outermost lanes, this figure only shows data from lanes 4 and 5. Comparing to the reference line at 18 km/h, except for the smaller first and last bins in each curve, the wave velocities do not appear to have a dependence on the local traffic speed for these ramp segments. Moreover, the same conclusion can be made when it comes to the impact of different lanes. Fig. 9 shows the average wave velocity versus prevailing traffic speed for each sample from each lane across all six of the westbound station pairs.

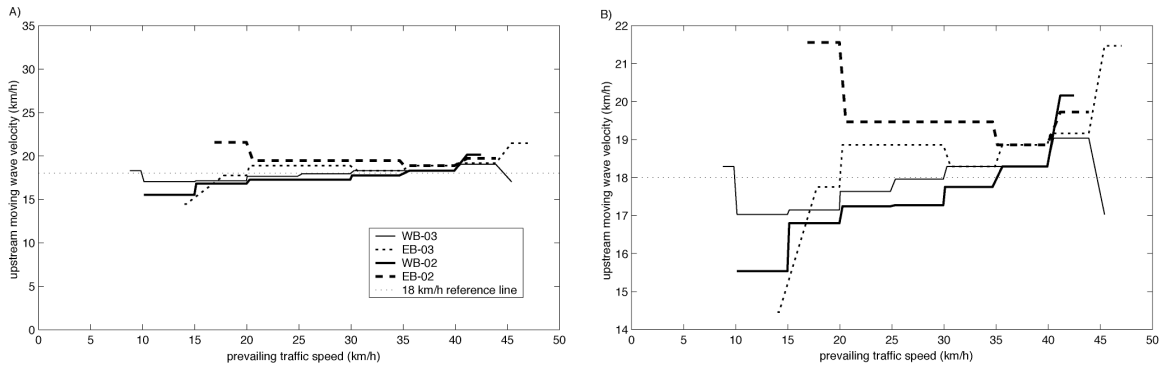

Figure 7, (A) Median average wave velocity versus prevailing traffic speed for each sample from the four data sets. (B) Detail of A.

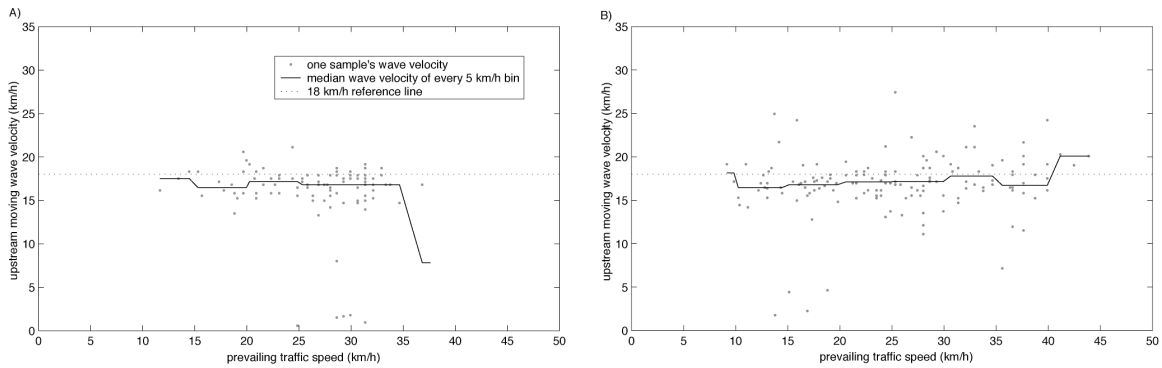

Figure 8, Wave velocity versus prevailing traffic speed, using data from lanes 4 and 5 across station pairs with (A) on-ramps, (B) off-ramps, August 2003, WB, BHL data.

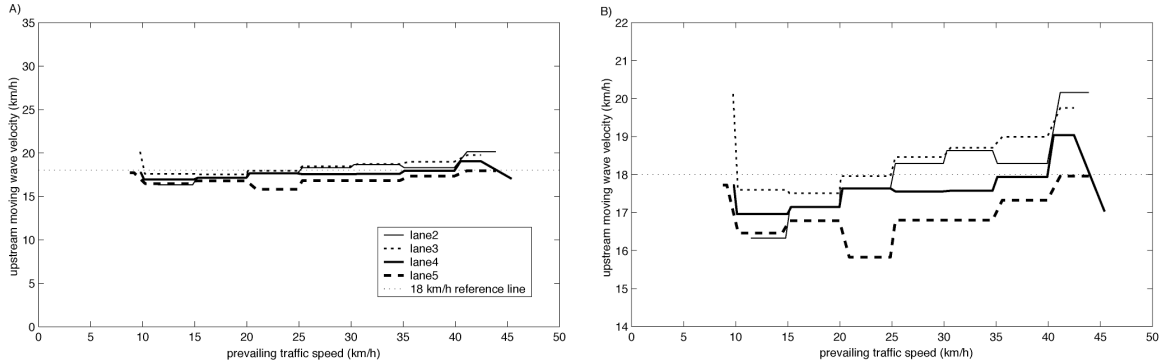

Figure 9, (A) Median wave velocity versus prevailing traffic speed by lane, August 2003, WB, BHL. (B) Detail of A

Finally, we explicitly investigate if there is a strong relationship between lane change maneuvers and wave velocity. Because it is difficult to measure lane change maneuvers directly, inflow is used as a proxy for the net number of lane change maneuvers during a given sample, where the inflow is defined as the cumulative downstream arrivals less the cumulative upstream arrivals in the lane over the hour. Inflow will underestimate the total number of lane change maneuvers since exiting vehicles cancel out entering vehicles during the sample. Noise also arises in the measurement due to the fact that the number of vehicles stored in the lane may change between the start and the end of the sample, though this noise should be unbiased. Fig. 10 shows inflow versus wave velocity. Lane 5 regularly exhibits an outflow (negative inflow) of 500 vph between st 1 and 2, and then an inflow of 400 vph between st 2 and 3 due to the ramps. A few of the other lanes have an inflow on the order of 200 vph for these links, with the magnitude of the inflow being much smaller elsewhere. Yet as shown in Fig. 5 for these same data, all four lanes exhibit similar trends in wave velocity over all of the links. Thereby suggesting that aggregate wave velocity is independent of inflow. Of course it is possible that a relationship to lane change maneuvers may have been obscured by the long sampling period, the use of a proxy measurement, or simply the noise in the data.

CONCLUSIONS

This paper employed cross correlation to estimate wave velocities between several successive detector stations during congested periods and over a large data set. Given homogeneous vehicles and drivers, LWR predicts that for a convex flow-density relationship all waves should propagate upstream during congested periods. The analysis first employed cumulative arrivals -- a function of flow -- and then the local traffic speed at the detector stations. It was shown that the flow-based analysis yield mixed results, with many measurements being consistent with earlier research, but many more measurements falling outside the typical range of measured wave velocities from the literature. But vehicles are not homogeneous and it was also shown that flow and occupancy depend on effective vehicle length as well as the local traffic speed. Because the vehicle lengths travel downstream with the vehicles, this

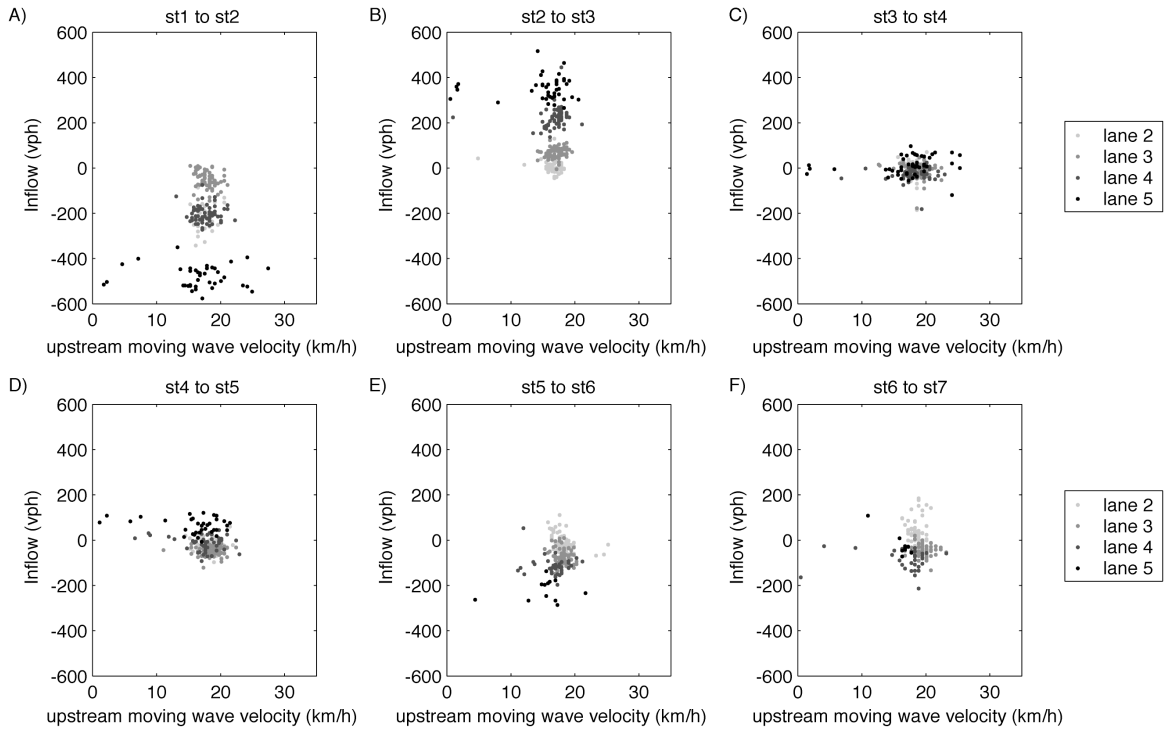

Figure 10, Inflow versus wave velocity from each sample using cross correlation applied to filtered traffic speed measurements, August 2003, WB, BHL.

information will hinder attempts to extract wave velocities propagating against the flow of traffic when using flow-based measures. This fact is evident in fig. 2 and 3. Trucks are restricted from lane 2, thus the standard deviation of vehicle lengths is smaller and less information travels with the vehicles. As a result, comparing across lanes for all of the plots in these figures, lane 2 had the highest percentage of observations that fell within the 15 km/h to 25 km/h window.

To reduce the influence of the confounding vehicle lengths, the analysis was repeated over the exact same samples using local traffic speed measurements. Because drivers are constrained by downstream vehicles in congestion, the traffic speed trends are much less dependent on specific vehicle or driver characteristics. It was confirmed that LWR does a better job predicting the evolution of average traffic speed over time and space, with over 90 percent of the samples having an average wave velocity propagating upstream in the range of 15 km/h to 25 km/h. Of course these results represent the aggregate performance over one-hour samples and individual waves could differ significantly from this range, e.g., it is likely that other sources of noise remain in the data, such as lane change maneuvers disrupting the propagation of waves.

Unlike earlier studies, the method presented in this paper is not labor intensive, thereby allowing for the study of a large amount of data and extracting the general trends in the wave velocity during congestion. Our results over two months of data from both westbound and eastbound lanes of the BHL show that wave velocities are nearly constant over a large range

of local traffic conditions, which is consistent with earlier work and further supports the use of a triangular flow-density relationship at least for a first-order approximation. There was some evidence that the wave velocity may change with local traffic speed but the change is very small, less than 1 km/h of wave velocity for every 10 km/h of local traffic speed. Given the fact that the direction of this trend changed across the four data sets, this small trend may simply be an artifact of the sample size or it is indicative of other factors that have a similar impact on the wave velocity but are yet to be identified. In any event, these outstanding questions are the subject of ongoing research. Unlike most of the earlier efforts to measure wave velocity during congested periods, the analysis was applied on a lane-by-lane basis, allowing for comparisons between lanes and for the analysis to quantify the impact on the wave velocity from vehicles entering or leaving at ramps. To this end, wave velocity does not appear to have a dependence on ramps or the particular lane. However, future research will seek to verify this finding. For example, this analysis was limited to the BHL, which has five lanes in each direction, results may be different for a two or three lane freeway.

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