A Hybrid Model for Reliable Travel Time Estimation on a Freeway with Sparsely Distributed Detectors

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ABSTRACT

This study develops a hybrid model that can reliably estimate travel times on freeways with sparsely distributed detectors having the spacing of more than one mile. The developed model, which includes a clustered linear regression model as the main component and a supplemental enhanced trajectory-based model, can effectively capture impacts of various geometric features, such as ramps and merging lanes, and different traffic patterns on the variability of travel times. The experimental results based on a field demonstration on a 25-mile stretch of I-70 eastbound with 10 detectors have demonstrated the promising properties of the developed model under various congestion levels.

INTRODUTION

As is well recognized, travel times are essential information for traffic controls, operations, transportation planning, and advanced traveler information systems (ATIS). Several measurement methods have been used in practice to estimate travel times, including probe vehicles, vehicle identification with in-vehicle devices (i.e., electronic toll tags), and vehicle identification without in-vehicle devices (i.e., video-based vehicle identification and license plate recognition). However, due to the limited sample sizes the probe vehicle method can provide and the high costs associated with both types of vehicle identification methods, it is not cost-effective for any responsible agency to sustain ATIS operations with those methods.

With recent advances in vehicle detection technologies, more and more studies emerge to provide better estimates of travel times using new traffic detectors, which can provide reliable measurements of cumulative traffic flows and occupancy for any pre-specified time interval. As reported in the literature, most existing models for travel time estimation are developed and tested for short links (i.e., detectors placed less than 0.5 miles apart). These models may not work properly on long links due to the fact that their embedded assumptions may not be valid when detector spacing is longer than 0.5 miles, as in most existing highway systems.

This paper presents a hybrid model that provides reliable travel time estimation with sparsely placed detectors (i.e., more than one mile apart). The performance of the model has been tested with the dataset obtained from 10 road-side detectors installed on a 25-mile stretch of I-70 eastbound and found to be reliable to serve as the basis for a real-time travel time prediction system.

This paper will first summarize previous works on travel time estimation, followed by the introduction of the model structure. A case study on I-70 eastbound will then be presented to demonstrate the potential of the developed model. Conclusion and future research works will be mentioned in the last section.

LITERITURE REVIEW

In review of the literature, many efforts have been made to estimate travel times from the traffic data collected during the time in which the trip has been completed. As reported in the literature, most studies of travel time estimation fall into one of the following categories: flow-based models, vehicle identification approaches, and trajectory-based models.

FLOW-BASED MODELS

Flow-based models have been applied to freeway mainline segments without ramps and having uniform travel speeds across all lanes. This type of model estimates travel times by comparing upstream and downstream flow counts, based on the assumption of first depart, first arrive. Example works can be found from Dailey (1), Nam and Drew (2), Petty et al. (3) and Liu et al. (4) However, existing flow-based models require uniform travel speeds across all lanes and therefore cannot be reliably applied to segments with ramps or complex traffic patterns, i.e., spillback from a downstream off-ramp. Another issue that makes this type of model unsuitable for real-world applications is detector errors. Detector errors are most likely nonsystematic in nature, and the error patterns remain difficult to model well. Unpredictable measurement errors for traffic count may dramatically reduce the model accuracy.

VEHICLE IDENTIFICAIOTN APPROACHES

Vehicle identification approaches estimate travel time by matching the sequence of vehicles in a single lane. The key concept of this type of method is to find vehicles' signatures from the upstream and the downstream detectors in order to calculate their travel times.

Previous studies in this category include matching vehicles with classification information obtained from new detector hardware (5-7),with video-based signatures (8), and with the sequence of vehicles from loop detectors (9-12).

In general, vehicle identification models performed well in one single lane with a low lane-changing rate. They cannot provide reliable travel time estimations for freeway segments near ramps. Using vehicles' visual signatures may potentially improve the model's ability to deal with ramp traffic. However, all VRI models require either improved detection technology or a high bandwidth to transfer the raw data needed to extract vehicle signatures, which will result in high system costs and long system processing times.

TRAJECTORY-BASED MODELS

The common features of trajectory-based models are estimating temporal and spatial traffic conditions within a link from upstream and downstream detector data and drawing a target vehicle's trajectory so as to provide the estimated travel time.

One of the typical studies in this category is by Coifman (13), who estimated the vehicle in-segment speed based on the speed data from a detector placed at one end of a 1/3-mile segment and the traffic propagation relations. With the assumption that the traffic state at one detector location changes discretely and equal to vehicles' headways. Some researchers have made efforts to use both the upstream and downstream detector information for estimating travel times with piecewise constant-speed-based (PCSB) methods (14-16), which assume a constant travel speed within the link. Van Lint and van der Zijpp (17) estimated travel times with a piecewise linear-speed-based (PLSB) model, which is reported to outperform PCSB models in simulated cases.

Note that existing piecewise models do not consider traffic propagation relations, which use the detected speeds at the upstream and downstream detectors at the same time to estimate travel times in short segments (i.e., 0.5 miles).In summary, many studies use the trajectory-based models to estimate vehicles' in-segment speeds, and thereby compute their travel times. This type of method is relatively applicable to long links and can better tolerate detector errors than the flow-based models. With proper modifications, this type of model has the potential for use on segments with non-uniform travel speeds.

Among the three types of travel time estimation models, the flow-based models, which need high accuracy of detector data and uniform geometric features, are the least applicable for use in a real-world system. Vehicle identification models need new detection hardware or take raw detector signals as input and therefore may incur high system costs and the need for a large data transmission bandwidth. In contrast, the trajectory-based model for travel time estimation is relatively promising, since it has the potential to fit with long segments and more complex geometric features.

MODEL DEVELOPMENT

In review of the literature, it is clear that providing a reliable estimate of travel times remains a challenging task, especially for highway segments with long detector spacing (e.g., > 0.5 miles).

Despite the tremendous efforts made by traffic flow researchers over the past decades in modeling the evolution of congestion patterns, it remains quite difficult for any existing method to reliably estimate or predict the propagation of traffic patterns under both recurrent and nonrecurrent congestion patterns. A failure to capture the temporal and spatial distributions of traffic patterns will actively degrade the quality of any model for travel time estimation or prediction.

Changes in geometric features often result in different roadway capacity and traffic patterns, including: Lane drop, Lane addition, On-ramp/off-ramp and Other Factors. Figure 1 illustrates an example of congestion caused by this phenomenon in two through lanes on I-70 near Exit 87A to US29 southbound (Figure 2). Due to their local knowledge of possible delays and congestions caused by weaving traffic near a ramp, drivers may avoid using the through lane next to the ramp. One needs to carefully analyze the discrepancy of traffic flow speeds between lanes to estimate the average speed within one segment.

Aside from the aforementioned factors, the traffic flow patterns and the resulting travel times may also vary with the low visibility caused by weather or sun glare or with poor road surface conditions caused by rain, snow or debris. Quantifying the impacts of those factors, however, has not yet been reported in the literature and is beyond the scope of this study, too.

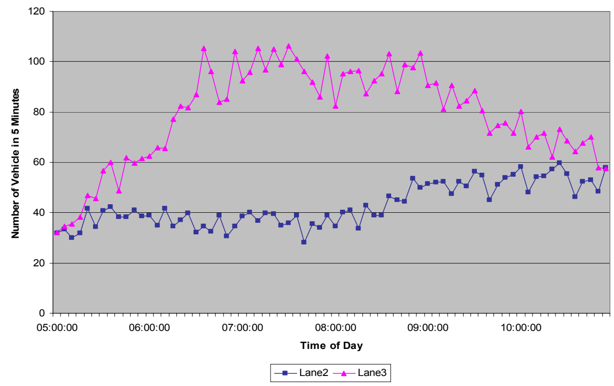


Figure1 Average vehicle counts in 5-minute intervals on four Thursdays in July, 2006 at Exit 87A on I-70

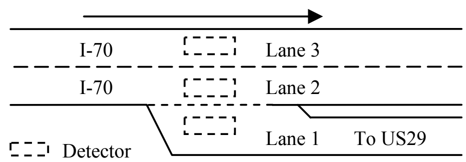


Figure 2 Geometry of I-70 at Exit 87A

FLOWCHART OF THE HYBRID MODEL

Figure 3 shows the flowchart of the proposed hybrid model, which consists of two main components: a clustered linear regression model and an enhanced trajectory-based model. When applying the hybrid model, the system will first cluster traffic scenarios into predefined categories based on the traffic data. The system will employ the linear regression model if the detected traffic scenario belongs to a category in which a linear regression model has been trained with a sufficiently large sample of historical travel times. Otherwise, it will employ the enhanced trajectory-based model, which does not require pre-training with a large amount of historical data, to produce the travel time estimation.

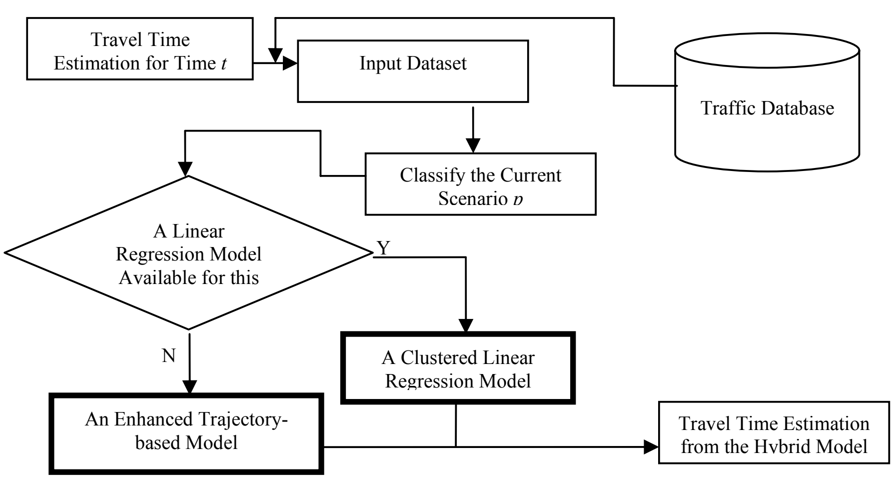


Figure 3 Flowchart of the hybrid travel time estimation model

CLUSTERED LINEAR REGRESSION MODELS

When a vehicle is traveling in a link, the range of possible travel times is usually constrained by the traffic pattern. For example, a vehicle can never reach free-flow travel time when there is heavy congestion in the link. Hence, this study first develops a set of clustered linear regression models to categorize traffic conditions into predefined traffic scenarios and then estimates a travel time for each scenario.

Model Formulations

By dividing a link into two equal-length sub-links, one can express a vehicle's travel time as follows:

$$\tau_d(t) = \frac{L_d}{2\bar{u}_d^1(t)} + \frac{L_d}{2\bar{u}_d^2(t)} \tag{1}$$

where $\bar{u}_d^j(t)$ is the average travel speed in the *j*th half

Coifman (13) estimated a vehicle's in-segment speeds from the upstream detector data after the departure time, or from the downstream detector data before the vehicle's arrival time, to obtain a travel time estimation. To improve the model's robustness for long segments (e.g., > 0.5 miles), this study assumes a linear relation between a vehicle's average in-segment speed and the average speed of the upstream or downstream through traffic during the same time interval, as follows:

$$\tau_d(t) = \frac{L_d}{2(a_{11}\hat{u}_d^{Thru}(t, \tau_d^1(t)) + a_{12})} + \frac{L_d}{2(a_{21}\hat{u}_{d+1}^{Thru}(t+\tau_d^1(t), \tau_d^2(t)) + a_{22})} \tag{2}$$

where a_{ij} are coefficients.

On the right side of Eq. 2, the first term is the travel time for a vehicle to traverse the first half of the link (*d*, *d*+1); the second term is for the second half of the link. Similar to the model developed by Liu et al. (4), Eq. 2 has unknown variables on both sides. The performance of the iteration-based solution algorithm by Liu et al. (4) is conditioned on the quality of detector data, which is often undesirably poor in real world systems. Hence, this study uses a preliminary estimate of the travel time to replace the actual travel time information in the independent variables to achieve better robustness. More specifically, assuming that traffic conditions in a link (*d*, *d*+1) can be divided into *P* scenarios with a relatively small range of travel times in each scenario, one can then replace the actual travel time information in independent variables in Eq. 2 with a preliminary estimate of travel time for this scenario to obtain Eq. 3:

$$\tau_d(t) = \frac{L_d}{2(a_{11}^1\hat{u}_d^{Thru}(t, \gamma_p^d\tau_d^E(p)) + a_{12}^1)} + \frac{L_d}{2(a_{21}^1\hat{u}_{d+1}^{Thru}(t+\gamma_p^d\tau_d^E(p), (1-\gamma_p^d)\tau_d^E(p)) + a_{22}^1)} \tag{3}$$

where p is the index of predefined traffic scenarios in link (*d*, *d*+1);
$\tau_d^E(p)$ is the preliminarily estimated travel time in link (*d*, *d*+1) under the *p*th predefined traffic scenario;
γ_p^d is the estimated proportion of time taken for the vehicle to traverse the first half of the link (*d*, *d*+1) under the *p*th scenario; and
a_{ij}^1 are coefficients.

Note that one can obtain the preliminary estimate of the travel time in various ways. For example, using the average of collected travel times from a sufficient number of samples may be one of the simplest methods. However, for rarely observed traffic scenarios, it is difficult to produce a reliable estimation of the travel time at this preliminary stage. Therefore, it requires at least one supplemental model to deal with scenarios lacking a reliable preliminary estimate.

Because detector data is usually collected on a lane-by-lane basis, the average speed of through traffic is not directly available from the detector information. Most existing studies either take data from one lane (e.g., the far left lane) as the average condition of the through traffic, or simply compute the average over all through lanes. However, as analyzed in the previous section, traffic conditions in some lanes may not affect the through-flow speed. Therefore, one needs to carefully select critical lanes to obtain the average speed of through traffic flow. This study assumes that the average speed of through traffic flow has a linear relation with those in all critical lanes, which may include both the through lanes (first item on the right side of Eq. 4) and the ramp lanes (second item on the right side of Eq. 4):

$$\frac{1}{\hat{u}_d^{Thru}(t,\Delta t)} = \sum_{la \in \mathbf{CLT}_{d,d+1}^{\mathbf{d}}(p)} \frac{a_{la}^5}{u_{d,la}(t,\Delta t)} + \sum_{la \in \mathbf{CLR}_{d,d+1}^{\mathbf{d}}(p)} \frac{a_{la}^6}{u_{d,la}(t,\Delta t)} + a_{11}^7 \qquad (4)$$

where a_{ij}^k are coefficients.

Note that reliable speed data may not be directly available from one detector and thus needs to be estimated from the available data. A commonly used method to estimate speed is to rely on the relation between traffic flow, occupancy and the average vehicle length.

$$u_{d,la}(t,\Delta t) = g\frac{v_{d,la}(t,\Delta t)}{o_{d,la}(t,\Delta t)} \qquad (5)$$

where g is the average vehicle length.

As reported in the literature, Eq. 5 may not be valid when the time interval is short, because average vehicle lengths may vary significantly during short intervals. However, the impact of this error decreases with an increase in the length of the selected time interval and/or the traffic volumes. Assuming that, under scenario *p*, a factor g_p can satisfy Eq. 5, one can then obtain Eq. 6 from Eq. 4 and Eq. 5 as follows:

$$\begin{aligned}\tau_d(t) = &\sum_{la \in \mathbf{CLT}_{d,d+1}^{\mathbf{d}}(p)} b_{d,la}^{T,p} \frac{o_{d,la}(t,\gamma_p^d \tau_d^E(p))}{v_{d,la}(t,\gamma_p^d \tau_d^E(p))} + \sum_{la \in \mathbf{CLR}_{d,d+1}^{\mathbf{d}}(p)} b_{d,la}^{R,p} \frac{o_{d,la}(t,\gamma_p^d \tau_d^E(p))}{v_{d,la}(t,\gamma_p^d \tau_d^E(p))} \\ &+ \sum_{la \in \mathbf{CLT}_{d,d+1}^{\mathbf{d+1}}(p)} b_{d+1,la}^{T,p} \frac{o_{d,la}(t+\gamma_p^d \tau_d^E(p),(1-\gamma_p^d)\tau_d^E(p))}{v_{d,la}(t+\gamma_p^d \tau_d^E(p),(1-\gamma_p^d)\tau_d^E(p))} \\ &+ \sum_{la \in \mathbf{CLR}_{d,d+1}^{\mathbf{d+1}}(p)} b_{d+1,la}^{R,p} \frac{o_{d,la}(t+\gamma_p^d \tau_d^E(p),(1-\gamma_p^d)\tau_d^E(p))}{v_{d,la}(t+\gamma_p^d \tau_d^E(p),(1-\gamma_p^d)\tau_d^E(p))} + b_d^{0,p}\end{aligned} \qquad (6)$$

where $b_{d,la}^{T,p}$ is the coefficient of the lath lane in $\mathbf{CLT}_{d,d+1}^d(p)$ at detector d under the *p*th traffic scenario for link (*d*, *d*+1);

$b_{d+1,la}^{T,p}$ is the coefficient of the lath lane in $\mathbf{CLT}_{d,d+1}^d(p)$ at detector *d*+1 under the *p*th traffic scenario for link (*d*, *d*+1);

$b_{d,la}^{R,p}$ is the coefficient of the lane *la* in $\mathbf{CLR}_{d,d+1}^{d+1}(p)$ at detector *d* under the *p*th traffic scenario for link (*d*, *d*+1);

$b_{d+1,la}^{R,p}$ is the coefficient of the lane *la* in $\mathbf{CLR}_{d,d+1}^{d+1}(p)$ at detector *d*+1 under the *p*th traffic scenario for link (*d*, *d*+1); and

$b_d^{0,p}$ is the intercept for the pth scenario for link (d, d+1).

In order to estimate travel times with Eq. 6, one needs to estimate γ_p^d, which is the portion of time it takes one vehicle to traverse the first half of link (d, d+1).

Defining Traffic Scenarios

Defining the clustering function for a clustered linear regression model for travel time estimation is a challenging task which shall have the following features:

- Travel times in each clustered traffic scenario should always have a relatively small variation;
- The variables used for clustering should be obtainable from detectors;
- The input variables from both the upstream and downstream detectors should be obtained only from critical lanes so as to reflect actual through traffic conditions.
- The following guidelines can help define the traffic scenarios under recurrent congestions:

Predefine the preliminary types of patterns, based on the congestion level detected by the upstream and the downstream detectors as shown in Table 1.

Table 1 Four types of basic traffic scenarios in each link

Traffic Condition at Upstream Detector	Traffic Condition at Downstream Detector	Congestion Level in the Link
No congestion	No congestion	Free-flow condition
Congested	No congestion	Moderate congestion or transition period
No congestion	Congested	Moderate congestion or transition period
Congested	Congested	Heavy congestion

AN ENHANCED TRAJECTORY-BASED MODEL

As it is often difficult to have sufficiently large samples for all possible traffic scenarios from field observations, this research has also developed an enhanced trajectory-based model to serve as a supplemental component for those scenarios with inadequate samples of historical data.

Using the trajectory-based model for travel time estimation, one needs to estimate the speed from known traffic data. Because speed data used in most trajectory-based models are for short intervals, Eq. 5 cannot provide reliable estimates. Instead, this study proposes the following equations for speed estimation:

$$u(x,t) = \begin{cases} u_{free} & , o(x,t) <= o_{free} \\ u_{cong} + (u_{free} - u_{cong})(1 - \dfrac{o(x,t) - o_{free}}{o_{cong} - o_{free}})^m & , o_{free} < o(x,t) <= o_{cong} \\ u_{min} + (u_{cong} - u_{min})(1 - \dfrac{o(x,t) - o_{cong}}{o_{max} - o_{cong}})^n & , o_{cong} < o(x,t) <= o_{\max} \\ u_{min} & , \text{otherwise} \end{cases} \quad (7)$$

where $u(x,t)$ is the speed to be computed at location x at time t;

$o(x,t)$ is the occupancy in the small section near location x at time t;

o_{free} is the upper bound of occupancy under free-flow traffic conditions;

o_{cong} is the boundary of occupancy between moderately and heavily congested conditions;

o_{max} is the maximum occupancy under recurrent congestion;

u_{free} is the free-flow speed;

u_{cong} is the boundary of the speed between moderately and heavily congested traffic conditions;

$u_{\min}$ is the minimum speed under heavily congested conditions; and

m and n are parameters to be calibrated with field data.

One can calibrate the boundaries of occupancy and speed data with collected travel times and detector data. The method reported by Zou and Wang (18)is applicable for estimating m and n in Eq. 7 with collected field travel time information.

Unlike the models in the literature for short links (13, 17), this study develops two types of in-segment speed estimation methods, depending on the vehicle's current position in a link. When the vehicle is within a short distance of the upstream detector or the downstream detector, this study considers a possible range of traffic propagation speeds to estimate the in-segment traffic situations from nearby traffic detectors. Otherwise, this study uses a model combining both traffic propagation relations with the piecewise linear speed-based (PLSB) model to achieve better robustness.

As shown in Figure 4, the model will first estimate occupancy using the enhanced trajectory-based model at the vehicle's position with Eq. 8 and will then apply Eq. 7 to compute the vehicle's speed at location x at time t. The vehicle is assumed to travel at this speed over a short interval, t_{step}, and then its new location at time (t+t_{step}) will be updated. The procedure repeats the same steps until the vehicle arrives at the downstream detector.

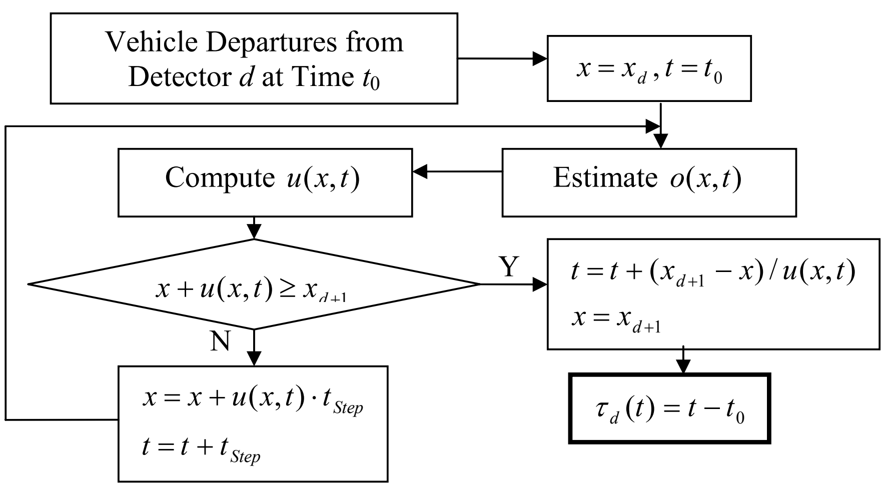


Figure 4 Flowchart of the enhanced trajectory-based travel time estimation model

$$
o(x,t)=\begin{cases}
o_d\left(t+\dfrac{x-x_d}{u_c^{\max}},\, t+\dfrac{x-x_d}{u_c^{\min}}\right) & \text{, if } x-x_d<\hat{x}\\[2ex]
o_{d+1}\left(t-\dfrac{x_{d+1}-x}{u_c^{\min}},\, t-\dfrac{x_{d+1}-x}{u_c^{\max}}\right) & \text{, if } x_{d+1}-x<\hat{x}\\[2ex]
o_d\left(t+\dfrac{\hat{x}-x_d}{u_c^{\max}},\, t+\dfrac{\hat{x}-x_d}{u_c^{\min}}\right) & \\
+\dfrac{(x-x_d-\hat{x})}{\hat{x}} & \\
\times\left(o_{d+1}\left(t-\dfrac{x-(x_{d+1}-\hat{x})}{u_c^{\min}},\, t-\dfrac{x-(x_{d+1}-\hat{x})}{u_c^{\max}}\right)\right. & \text{, otherwise}\\
\left.-\,o_d\left(t+\dfrac{\hat{x}}{u_c^{\max}},\, t+\dfrac{\hat{x}}{u_c^{\min}}\right)\right) &
\end{cases}
\tag{8}
$$

where $\hat{x}=\begin{cases}\min\left(\dfrac{l_d}{3},\dfrac{1}{3}\text{mi}\right) & \text{, when } l_d\ge 1 \text{ mile}\\[1ex] \dfrac{l_d}{3} & \text{, otherwise}\end{cases}$

$x_d \le x \le x_{d+1}$; and

$u_c^{\min}$ and $u_c^{\max}$ are the minimum and the maximum traffic propagation speeds.

PERFORMANCE EVALUATION

The aforementioned hybrid model for travel time estimation has been successfully calibrated and validated with actual travel time data collected from the field site on a 25-mile stretch of I-70 Eastbound from MD27 to I-695 with 10 detectors. (Figure 5)

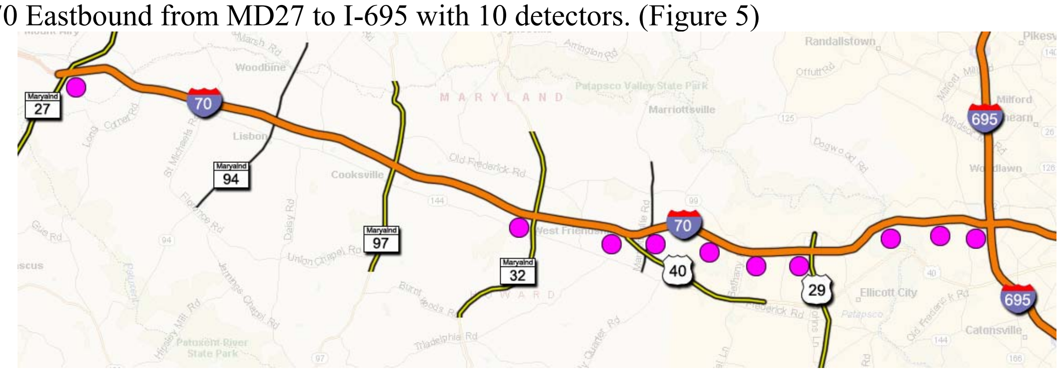


Figure 5. Locations of ten detectors on I-70 Eastbound

After calibrating the developed model for travel time estimation, the research team conducted two travel time surveys in the morning peak hours on April 6th, 2006 and April 20th, 2006 for the sub-segment from Detector 3 to Detector 10. This segment often incurs heavy congestion in the morning peak hours on Tuesdays and Thursdays. The actual travel times were obtained by matching vehicles from two videos taken at the beginning and end of the sub-segment. There were a total of 71 data points collected on April 6th, 2006 and 114 data points collected on April 20th, 2006. The surveys covered both transition periods between congestion and free-flow state, as well as heavily congested periods.

Subsegment from Detector 3 to 7 is about 4-mile in distance that consists of two interchanges and two ramps. Complex geometric features and high variation in traffic volumes have made this subsegment difficult for developing travel time estimation model.

Tables 2(a) and (b) summarize the performance of the developed model on the subsegment against the actual data collected on two different days. Figures 6(a) and (b) show the distribution of estimated and actual travel times vs. departure time for two days, where the estimated travel times showed a similar trend to the actual travel times. The results from the travel time estimation model showed satisfactory results in all travel time categories during those two days with an average of less than 8.8% relative absolute error. Even in the transition periods, the developed model was still able to estimate travel times with an error of less than 70 seconds. In heavily congested cases, in which travel times are mostly greater than twice of the free-flow travel time (520 seconds), the developed model can still provide estimates with average absolute error of less than 90 seconds.

Table 2(c) shows the overall evaluation results for the transition periods (travel times between 520 seconds and 800 seconds), moderate congestion (travel times between 800 and 1000 seconds) and heavy congestion (travel times greater than 1,000 seconds). For all the 184 collected actual cases, the developed model successfully yielded the estimated travel times with the acceptable accuracy.

Table2 Performance evaluation of hybrid model for travel time estimation

(a) Performance evaluation of travel time estimation model on the subsegment from Detector 3 to Detector 10 on April 6th, 2006

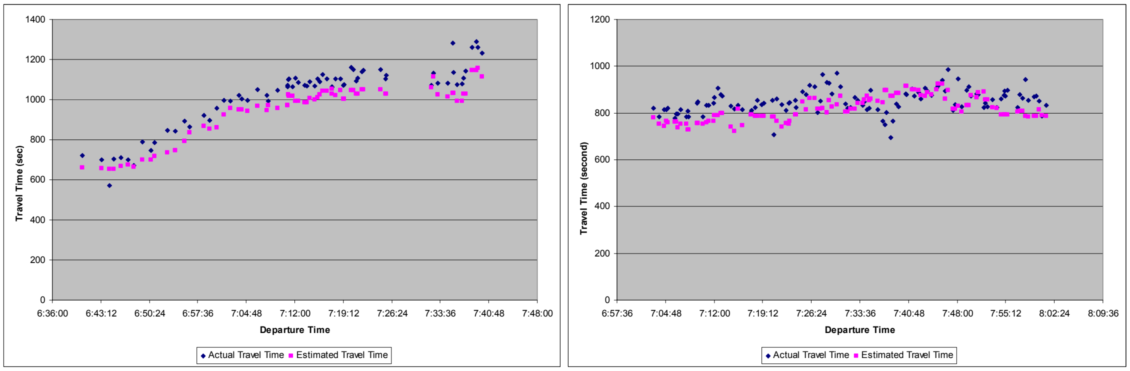
	Travel Time Range (sec)		
	520 to 800	800 to 1000	>1,000
Sample Size	10	12	49
Maximum Travel Time (sec)	791	998	1,290
Average Travel Time (sec)	710	928	1,109
Average Absolute Error (sec)	51.9	60.3	83.6
Average Relative Error (%)	7.3%	6.6%	7.4%

(b) Performance evaluation of travel time estimation model on the subsegment from Detector 3 to Detector 10 on April 20th, 2006

	Travel Time Range (sec)		
	520 to 800	800 to 900	900 to 1000
Sample Size	13	84	17
Maximum Travel Time (sec)	796	898	985
Average Travel Time (sec)	767	847	929
Average Absolute Error (sec)	65.2	49.4	73.0
Average Relative Error (%)	8.7%	5.8%	7.8%

(c) Overall Performance evaluation of travel time estimation model on the subsegment from Detector 3 to Detector 10 on April 6th and April 20th, 2006

	Travel Time Range (sec)		
	520 to 800	800 to 1000	> 1000
Sample Size	23	112	49
Maximum Travel Time (sec)	796	998	1290
Average Travel Time (sec)	742.3	847.2	1109.1
Average Absolute Error (sec)	58.5	54.5	83.6
Average Relative Error (%)	8.1%	6.3%	7.4%



(a) (b)

Figure 6. Comparisons between actual and estimated travel times in the subsegment from Detector 3 to Detector 10 on (a) April 6th, 2006 and (b) April 20th, 2006

CONCLUSIONS

This paper presents a hybrid travel time estimation model that uses a clustered linear regression model as the main model, and an enhanced trajectory-based model as its supplemental component. The clustered linear regression model functions to categorize traffic conditions in a link into several scenarios, based on the exhibited congestion patterns. One can then construct the input dataset with selected critical lanes. The primary reason for using an enhanced trajectory-based model as a supplemental component is to contend with the lack of sufficient samples for some relatively uncommon traffic scenarios. The proposed supplemental model can take advantage of the traditional trajectory-based methods grounded on traffic propagation relations and piecewise linear-speed-based models to provide reliable travel time estimations on long links.

An extensive comparison between the collected and estimated travel times clearly indicate that the developed model is able to provide reliable estimates under transition periods, moderate congestion, and heavy congestion with an average relative absolute error less than 8.8%. During transition periods in the subsegment from Detector 3 to Detector 10, the developed model may yield a relatively large error, but it remains within the range of one minute. Overall, the developed hybrid model is capable of providing reliable travel times estimates from on-line detector data, and serving as a tool for constructing the historical travel time database.

REFERENCE

1. Dailey, D., (1993) "Travel-Time Estimation using Cross-correlation Techniques," Transportation Research: Part B, Vol. 27(2), pp 97-107
2. Nam, D., and Drew, D., (1996) "Traffic Dynamics: Method for Estimating Freeway Travel Times in Real Time from Flow Measurements," *Journal of Transportation Engineering*, Vol. 122(3), pp. 185-191.
3. Petty, K., Bickel, P., Jiang, J., Ostland, M., Rice, J., Ritov Y., and Schoenberg, F., (1993) "Accurate Estimation of Travel Times from Single-Loop Detectors," *Transportation Research: Part A*, Vol. 32(1), pp. 1–17.

4. Liu, Y., Lai, X., and Chang, G., (2006) "Estimation of Freeway Travel Time Based on Sparsely Distributed Detectors," *9th International Conference on Applications of Advanced Technology*, Chicago, USA.
5. Pfannerstill, E., (1984) "A Pattern Recognition System for the Re-identification of Motor Vehicles," *Proc. 7th International Conference on Pattern Recognition*, Montreal, pp. 553–555.
6. Kühne, R., and Immes, S., (1993) "Freeway Control Systems for Using Section-Related Traffic Variable Detection," *Proc. Pacific Rim TransTech Conference*, Vol, 1993, pp. 56–62.
7. Kühne, R., Palen, J., Gardner, C., and Ritchie, S., (1997) "Section-Related Measures of Traffic System Performance," *Presented at the 76th Annual Meeting of the Transportation Research Board*, Washington, D.C.
8. MacCarley, C., (1998) "Video-Based Vehicle Signature Analysis and Tracking Phase 1: Verification of Concept Preliminary Testing," *California Partners for Advanced Transit and Highways* (PATH). Working Papers: Paper UCB-ITS-PWP-98-10.
9. Coifman, B., (1998) "Vehicle Re-Identification and Travel Time Measurement in Real-Time on Freeways Using Existing Loop Detector Infrastructure," *Transportation Research Record* 1643, pp 181–191
10. Coifman, B., and Cassidy, M., (2002) "Vehicle Re-identification and Travel Time Measurement on Congested Freeways," *Transportation Research: Part A*, Vol. 36(10), pp 899–917.
11. Coifman, B., (2003) "Identifying the Onset of Congestion Rapidly with Existing Traffic Detectors", *Transportation Research: Part A*, Vol. 37(3), pp. 277-291.
12. Coifman, B., and Ergueta, E., (2003) "Improved Vehicle Re-identification and Travel Time Measurement on Congested Freeways," *Journal of Transportation Engineering*, Vol. 129(5), pp 475-483.
13. Coifman, B., (2002) "Estimating Travel Times and Vehicle Trajectories on Freeways Using Dual Loop Detectors," *Transportation Research: Part A*, Vol. 36(4), pp. 351-364
14. van Grol, N., Manfredi, S., and Danech-Pajouh, M., (1997) "On-Line Network State Estimation and Short Term Prediction Deliverable D05.2.," *Telematics Application Programme Project TR1017*, INRETS, Brussels.
15. Lindveld, C., Thijs, R., Bovy, P., and van ZIJPP, N., (2000), "Evaluation of Online Travel Time Estimators and Predictors," *Transportation Research Record* 1719, pp 45-53.
16. Cortés, C., Lavanya, R., Oh, J., and Jayakrishnan, R., (2002) "A General Purpose Methodology for Link Travel Time Estimation Using Multiple Point Detection of Traffic," *Transportation Research Record* 1802, pp. 181-189.
17. van Lint, J., and van der Zijpp, N., (2003) "Improving a Travel-Time Estimation Algorithem by Using Dual Loop Detectors," *Transportation Research Record*, No. 1855, pp. 41-48
18. Zou, N. and Wang, J. (2006) "A Video-based Method for Evaluating Traffic Data from Detectors" *9th International Conference on Applications of Advanced Technology*, Chicago, USA.