Estimation of Freeway Travel Time Based on Sparsely Distributed Detectors

Ying Liu and Gang-Len Chang

Department of Civil and Environmental Engineering, University of Maryland at College Park, College Park, MD, 20742; Tel: (301) 405-6959; Email: lyng@wam.umd.edu

Abstract

This study presents a new approach for estimating travel time information along freeway corridors, which experience recurrent congestions but have only a limited number of available detectors due to budget constraints. The proposed iterative estimation procedure, based on a set of empirically calibrated regression models, intends to rebuild the relations between travel times and accumulated flows within each segment of the target freeway corridor. To evaluate the effectiveness of the proposed methodology, this study has conducted extensive numerical experiments with simulated data from a CORSIM simulator. Experimental results under various traffic volume levels have revealed that the proposed method offers a promising property for use in travel time estimation based on sparsely distributed sensors.

Research Background

As a direct indicator of network congestion level, travel time information plays an important role in travelers' route and departure time choices. This research project aims to build an online travel time prediction system for I-70, one of the major commuting corridors in the Baltimore region. In reviewing travel time prediction methodologies (Rilett and Park, 1999; Chien and Chen, 2001; Chien and Kuchipudi, 2003), it is clear that most of those in the literature need extensive and reliable historical travel time data. The limited number of travel time samples available in this project can hardly meet such requirements, which has necessitated an effective travel time estimation approach.

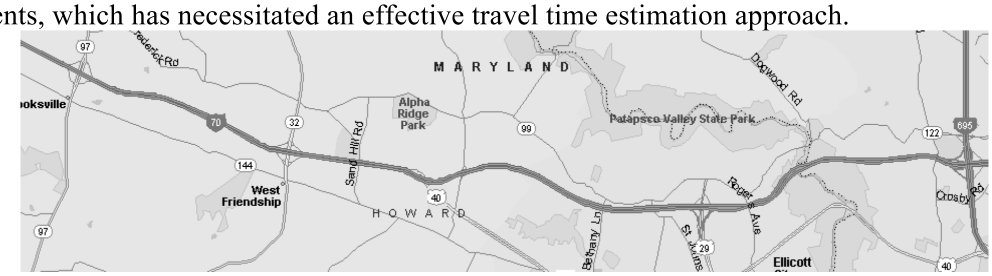

Figure 1. Illustration of the Study Area

Most existing travel time estimation methods in the literature can be classified into three categories. The first category provides the estimated travel time by comparing traffic measurements from up/downstream detectors, such as recognizing platoons, employing the flow conservation law, checking flow correlations, or building the regression relations between up/downstream flows (Kuhne and Immes, 1993; Nam and Drew, 1996; Dailey, 1993; Petty, etc., 1998). The second category uses point speed, either measured or estimated from detector data, to generate a section wide speed for computing the travel time (Smith, etc., 2004; coifman, 2002; Lindveld, etc., 2000; Van Lint and Van der Zijpp, 2002). The last category tries to reconstruct the relations between travel time and detected flow, speed, occupancy data with macroscopic flow equations or other models (Oh, etc., 2003; Sisiopiku, etc., 1994).

The I-70 segment under study experiences heavy congestions during morning/evening peak hours, which has excluded the first category of estimation approaches for this project. Due to budget constraints, the study area of more than 20 miles is only covered with 10 roadside detectors. Speed-based approaches cannot provide reliable travel time estimates under such long detector spacing (usually half-mile or 500m in literature) (Liu, etc. 2005). Thus, this study will follow the direction of the third category and try to rebuild the relations between travel times and detector measurements with a set of regression models and an iterative estimation algorithm.

The rest of the paper is organized as follows. Next section analyzes Type I freeway segments with permanent downstream bottlenecks and tests two different regression models. Similarly, Section 3 discusses Type II freeway segments with temporary downstream bottlenecks such as queue spillbacks, and proposes the regression model as well as the iterative estimation procedures. Some operational issues such as effects of the sample size are discussed in Section 4. Concluding comments constitute the core of the last section.

Type I Segments with permanent downstream bottlenecks

Since travel time of a vehicle between two points is a segment-based parameter, the authors intend to select segment-related parameters as explanatory variables for rebuilding the relationship between travel time and detector measurements. Unfortunately, the flow/speed/occupancy data directly from detectors are only for a single point. Thus, an alternative is to use the number of vehicles within the segment as the regressor, since it is the simplest segment-related parameter obtainable from detector measurements.

On Type I segment whose congestion is due to a permanent downstream bottleneck (Figure 2), the relationship between travel time and the number of vehicles within the segment can be shown with Equation (1) if vehicles are assumed to follow the First-In-First-Out rule.

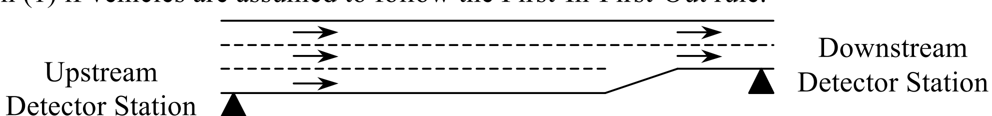

Figure 2. Type I Segment

$$tt(k) = \max\{ft, [n + af(k)]/C\} \tag{1}$$

Here, $tt(k)$ is the travel time of vehicles departed at time k; ft is the free flow travel time; n is the number of vehicles on the segment at time zero; C is the capacity of the downstream bottleneck; $af(k)$ is the accumulated number of vehicles at time k. Assuming that the flow measurements at upstream and downstream detectors at time k are $f_u(k)$ and $f_d(k)$, one has

$$af(k) = \sum_{i=1}^{k-1}[f_u(i) - f_d(i)] \tag{2}$$

Equation (1) can be rewritten as a two-segment expression as in Equation (3). Thus one has to fit a segmented curve and estimate the join point $C \times ft - n$.

$$tt(k) = \begin{cases} ft & : af(k) \le C \times ft - n \\ n/C + af(k)/C & : af(k) > C \times ft - n \end{cases} \tag{3}$$

Based on several related studies in the literature (Quandt, 1958; Hudson, 1966; Kim, etc., 2000), this paper employs Hudson's approach to find the Least Squares (LS) solution. For two submodels $f_1(x;\beta_1)$ and $f_2(x;\beta_2)$ joined together at $x = a$, the LS solution includes vectors $\beta_1 = \hat{\beta}_1$, $\beta_2 = \hat{\beta}_2$ and real values $a = \hat{a}$, $I = \hat{I}$, which minimize the Residual Sum of Squares (RSS):

$$R(\beta_1, \beta_2, a, I) = \sum_{i=1}^{I}[y_i - f_1(x_i, \beta_1)]^2 + \sum_{i=I+1}^{n}[y_i - f_2(x_i, \beta_2)]^2 \tag{4}$$

$$s.t. \quad f_1(\hat{a}, \hat{\beta}_1) = f_2(\hat{a}, \hat{\beta}_2), \qquad x_{\hat{I}} \le \hat{a} \le x_{\hat{I}+1}$$

The fitting procedures are stated below:

- Step 0: Reorganize the data points by the value of x
- Step 1: Assume $x_i < \hat{a} < x_{i+1}$ for some i. For all $I, 3 \le I \le n-3$ and $x_I \ne x_{I+1}$

- Perform regression on data points $\{x_1,\ldots,x_I\}$ and $\{x_{I+1},\ldots,x_n\}$ respectively
- Solve the join point by $f_1(a,\hat{\beta}_1) = f_2(a,\hat{\beta}_2)$
- If $x_{\hat{I}} < \hat{a} < x_{\hat{I}+1}$, compute $T_I = R(\beta_1,\beta_2,a,I)$. Otherwise $T_I = \infty$

- Step 2: Assume $\hat{a} = x_i$ for some i. For all $I, 3 \le I \le n-3$, $x_I \ne x_{I+1}$ and $\{x_I, x_{I+1}\}$ does not contain a valid $\hat{a}$ in Step 1 estimation
  - Perform regression on data points $\{x_1,\ldots,x_I\}$ and $\{x_{I+1},\ldots,x_n\}$ subject to $f_1(x_I,\beta_1) = f_2(x_I,\beta_2)$. (Plackett, 1960)
  - Compute $S_I = R(\beta_1,\beta_2,a,I)$.
- Step 3: The overall solution is the one that yields the minimal RSS T or S

To test the reliability of the proposed segmented curve in relating travel time to the accumulated number of vehicles, the authors have constructed a highway segment of 9000ft with CORSIM, a microscopic simulation package. The three-lane segment is reduced to two lanes at the downstream end. During a simulation period of 6.5 hours, the output for analysis includes the upstream/downstream detector measurements and average travel time for every thirty seconds. The data from the first three hours are used to fit the model. Excluding the initialization period, there are a total of 352 data points. A program is written in Visual Basic 5.0 to perform the iterative fitting procedure. The minimal RSS from Step 1 is 293,001.4, whereas the minimal RSS from step 2 is 293,105.1. The best fitting parameters is as follows

$$\{\hat{\beta}_1, \hat{\beta}_2, \hat{a}, \hat{I}\} = \{98.111, \begin{pmatrix} 54.670 \\ 0.899 \end{pmatrix}, 48.315, 63\}$$

Note that among all numerical experiments with modest congestions, the join point $x = a$ is always much smaller than the maximal accumulated number of vehicles. This implies that the first segment of the curve is short, which justifies the simplified one-segment model $tt(k) = a_1 + a_2 * af(k)$ under congestions. Using the same data set, the estimation result is shown in the following table.

Table 1. Fitting of the One-Segment Model: Type I Segment

	Coefficients	SE	t Stat	P-value		
	Coefficients	SE	t Stat	P-value	R Square	0.987
Intercept	73.021	3.085	23.667	0.000	Adjusted R Square	0.987
X	0.872	0.005	162.083	0.000	RSS	311,049.7

Data from the entire simulation period are used to test both calibrated models. The comparison of actual and estimated travel times is shown in Figure 3. The figure indicates that both models can well capture the change in travel time during the transition and congested periods.

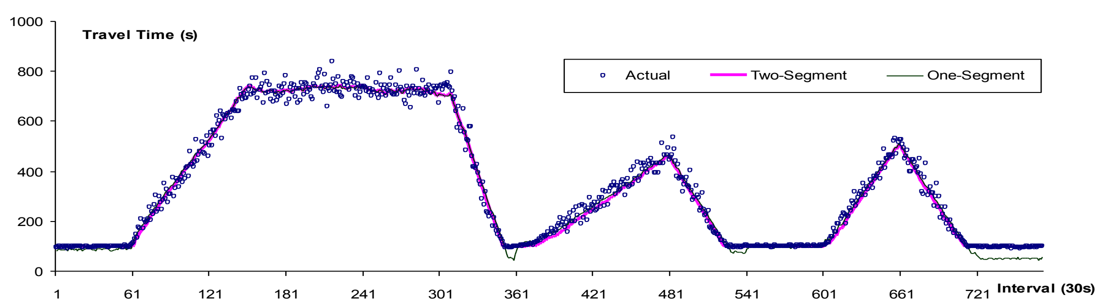

Figure 3. Comparison of Actual and Estimated Travel Time: Type I Segment

Type II Segments with temporary downstream bottlenecks

Type I segment with a permanent downstream bottleneck is mainly controlled by the fixed downstream capacity. This implies a monotonic relationship between travel time and the accumulated number of vehicles within the segment. However, for Type II segment with a temporary downstream bottleneck such as queue spillbacks, the available downstream capacity will vary with time. Thus, a vehicle's travel time depends not only on the accumulated number of vehicles at its departure time, but also on the downstream capacity while it traverses the segment. For example, a vehicle entering the segment during free flow period may experience longer travel time if the downstream queue starts forming during its travel.

The authors propose to use the measurements of either speed or occupancy from the downstream detector as the indicator of downstream congestions. This paper selects speed measurements for convenience of calibration. The formulation of the proposed model is as follows:

$$tt(k) = a_1 + a_2 \times af(k) / av(k) \tag{5}$$

Here $a_i, i = 1,2$ are the model coefficients to be fitted. $av(k)$ is the average downstream speed during the travel of those vehicles departed at time interval k. Assuming the speed measurement at downstream detector at time k is $v_d(k)$, one has $av(k) = ave\{v_d(t) : t = k, \ldots, k + tt(k)\}$

To test the proposed model, the authors select a 3829ft segment from the I-70 simulator, which is built and empirically calibrated in the microscopic simulation environment CORSIM. The traffic pattern indicates that the queue forms and dissipates both from the downstream. During the simulation period of four hours, the upstream/downstream detector measurements are obtained from simulation output. The average travel time for every thirty seconds is computed by tracing sample vehicles. The first two hours' data, excluding those periods without travel time information, are used to fit the model. The estimation result is shown in the following table.

Table 2. Model Fitting Result: Type II Segment

	Coefficients	SE	t Stat	P-value		
Intercept	43.941	2.329	18.868	0.000	R Square	0.973
X	14.086	0.170	82.858	0.000	Adjusted R Square	0.973
					Observations	195

Data from the entire simulation period are used to test the calibrated model. Note that since the computation of $av(k)$ involves vehicles' travel time, it is not known until the travel time is determined. Thus, the following iterative estimation procedures are specially designed for such a need.

- Step 0: For departure time k, set $tt_0(k) = tt(k-1)$, if $tt(k-1)$ is available. Otherwise, set $tt_0(k)$ to the estimated free flow travel time.
- Step 1: Compute $av(k) = ave\{v_d(t) : t = k, \ldots, k + tt_0(k)\}$ and $tt(k) = \hat{a}_1 + \hat{a}_2 \times af(k) / av(k)$
- Step 2: If $tt(k)$ and $tt_0(k)$ fall in the same interval or the number of iterations has reached its upper bound, Stop. Otherwise, set $tt_0(k) = tt(k)$ and go to Step 1.

The comparison of actual and estimated travel times is shown in Figure 4. The data points falling on the x-axis imply that there are no sample vehicles departed during the corresponding interval and there is no actual travel time information available. The figure indicates that the proposed model can capture the change in travel time during the transition and congested periods.

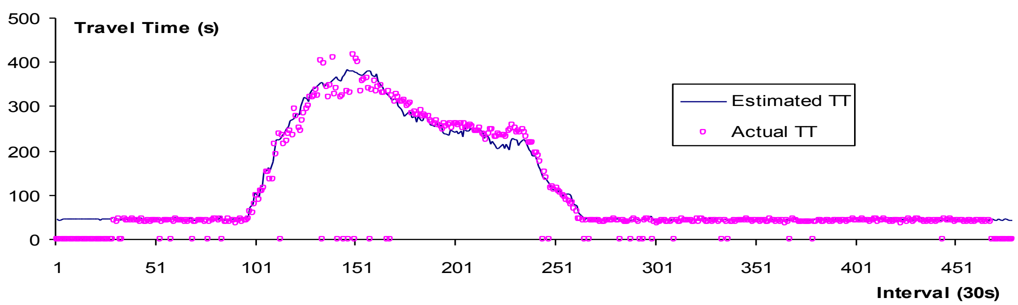

Figure 4. Comparison of Actual and Estimated Travel Time: Type II Segment

Some Operational Issues

Sample size for model calibration

Due to the limited budget, this research project will not have extensive travel time samples for model calibration. Thus, the authors have tested the robustness of the proposed model. With the same simulation experiment for Type II segment Table 3 presents the model calibration results with data points from intervals of 30 seconds, 300 seconds and 900 seconds. As shown in Figure 5, the fitting results are fairly stable even with a very small sample size.

Table 3. Model Fitting Results with Different Sample Sizes

30s	Coefficients	SE	t Stat	P-value	R Square	0.984
Intercept	41.596	0.852	48.799	0.000	Adjusted R Square	0.984
X	14.234	0.089	159.375	0.000	Observations	408
300s	Coefficients	SE	t Stat	P-value	R Square	0.988
Intercept	41.693	2.269	18.373	0.000	Adjusted R Square	0.988
X	14.246	0.245	58.176	0.000	Observations	42
900s	Coefficients	SE	t Stat	P-value	R Square	0.999
Intercept	38.699	1.075	35.999	0.000	Adjusted R Square	0.999
X	15.412	0.140	110.190	0.000	Observations	14

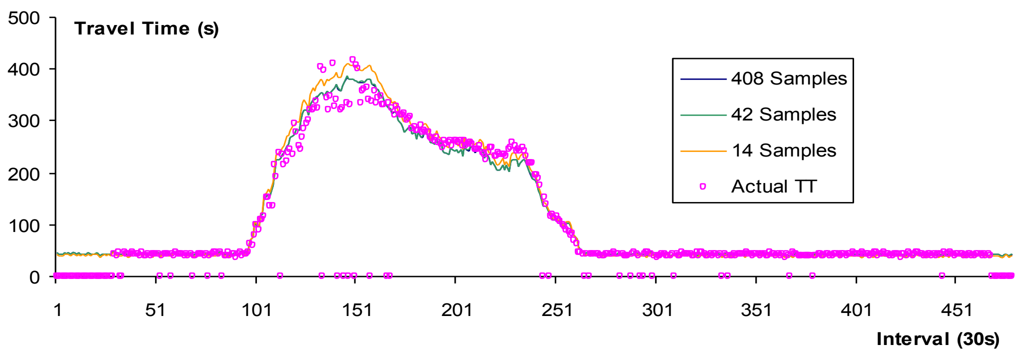

Figure 5. Comparison of Actual and Estimated Travel Time with Different Sample Sizes

Detector Location and Measurement Error

The proposed regression models are site specific. The regression coefficients will depend on various geometric features and traffic characteristics, such as the section length, road gradient, lane width and vehicle composition. For a given freeway segment, the proposed models use the accumulated number of vehicles within the road segment as one major regressor. This number is computed based on the flow measurements of the two end detectors. Thus, there should be no on/off ramps between these detectors.

To deal with the potential measurement errors, the accumulated number of vehicles can be recorded for several days. For an early morning time interval when the traffic is very low, the accumulated number of vehicles should be around a certain value over different days. If an apparent increasing/decreasing trend is observed, one can compute the average increase/decrease rate per interval and thus to adjust the accumulated number of vehicles.

Conclusions

This study has proposed two regression-based approaches to estimate travel time information, respectively, for freeway segments containing congestions due to permanent or temporary downstream bottlenecks. The regression models are designed to rebuild the relations between travel times and accumulated flows within each segment. The numerical experiments with simulated data from a CORSIM simulator have demonstrated the potential of the proposed methodology, especially with respect to its following features:

- Reliable estimation results under various traffic volume levels (i.e., free flow and congestion and even the transition periods).
- Robustness in taking full advantages of available travel time samples for calibration.
- Reliable travel time estimates even under long detector spacing (e.g., 9000ft and 3829ft in the numerical study), which can reduce the required number of detectors for travel time estimation.

References

Chien, S., and Chen, M., "Dynamic freeway travel time prediction using probe vehicle data: Link-based vs. path-based." *Transportation Research Record 1768*, pp.157–161, 2001

Chien, S., Kuchipudi, C.M., "Dynamic Travel Time Prediction with Real-Time and Historic Data," *Journal of Transportation Engineering*, Vol. 129, No. 6, pp. 608-616, 2003

Coifman, B., "Estimating travel times and vehicle trajectories on freeways using dual loop detectors," *Transportation research A*, vol. 36, pp. 351-364, 2002

Dailey, D.J., "Travel time estimation using cross-correlation techniques," *Transportation research B*, vol. 27, pp. 97-107, 1993

Hudson, D.J., "Fitting Segmented Curves Whose Join Points Have To Be Estimated," *Journal of the American Statistical Association*, v.61, pp.1097-1129, 1966

Kim, H.J., Fay, M.P., Feuer, E.J., and Midthune, D.N., "Permutation tests for joinpoint regression with applications to cancer rates," *Statistics in Medicine*, v.19, pp.335-351, 2000

Kuhne, R.D., and Immes, S., "Freeway control systems for using section-related traffic variable detection," *Proceeding of the ASCE third AATT conference*, pp. 57-62, 1993

Lindveld, Ch.D.R., Thijs, R., Bovy, P.H.L., and Van der Zijpp, N.J., "Evaluation of on-line travel time estimators and predictors," *Transportation Research Record 1719*, pp. 45-53, 2000

Liu, Y., Lai, X., and Chang, G.L., "Detector Placement Strategies for Freeway Travel Time Estimation," working paper, University of Maryland, 2005

Nam, D.H., and Drew, D.R., "Traffic dynamics: method fro estimating freeway travel times in real time from flow measurement," *Journal of Transportation Engineering*, v.122, pp.185-191, 1996

Oh J.S., Jayakrishnan, R., and Recker, W. "Section travel time estimation from point detection data," *accepted at the 82nd Annual Meeting of the TRB*, 2003

Petty, L.F., Bickel, P., Ostland, M., Rice, J., Schoenberg, F., Jiang, J., and Ritov, Y., "Accurate estimation of travel times from single loop detectors," *Transportation research A*, vol. 32, pp. 1-17, 1998

Plackett, R.L., *Principles Of Regression Analysis*. Oxford: at the Clarendon Press, 1960

Quandt, R.E., "the estimation of the parameters of a linear regression system obeying two separate regimes," *Journal of the American Statistical Association*, v.53, pp.873-880, 1958

Rilett, L., and Park, D., "Direct forecasting of freeway corridor travel times using spectral basis neural networks." *Transportation Research Record 1617*, pp. 163–170, 1999

Sisiopiku, V.P., Rouphail, N.M., and Santiago, A. "Analysis of the Correlation between Arterial Travel Time and Detector Data from Simulation and Field Studies", *Transportation Research Record 1457*, Washington, D.C., pp. 166-173, 1994

Smith, B.L., Holt, R.B., and Park, B.B., "Travel time estimation for urban freeway performance measurement: understanding and improving upon the extrapolation method," *accepted at the 83rd Annual Meeting of the Transportation Research Board*, 2004

Van Lint, J.W.C., and Van der Zijpp, N.J., "An improved travel-time estimation algorithm using dual loop detectors," *accepted at the 81st Annual Meeting of the TRB*, 2002