REAL-TIME ESTIMATION OF O-D MATRICES WITH PARTIAL TRAJECTORIES
FROM ETC TAG DATA

Jaimyoung Kwon
Institute of Transportation Studies
University of California, Berkeley
367 Evans Hall, Berkeley, CA 94720-3860
Tel: (510)642-2781; Fax: (510)642-7892
kwon@stat.berkeley.edu

Pravin Varaiya
Department of Electrical Engineering and Computer Science
University of California, Berkeley, 94720-1770
Tel:(510)642-5270; Fax:(510)643-7815
varaiya@eecs.berkeley.edu

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1Corresponding author
ABSTRACT

The origin-destination (O-D) matrix of a traffic network is usually estimated from link traffic counts combined with a sample survey. Partially observed vehicle trajectories obtained with vehicle re-identification techniques such as electronic tags provide a new data source for real-time O-D matrix estimation. However, due to incomplete sampling, accurate estimation of O-D matrices from these data is not trivial. We develop a statistically sound, unbiased estimator for O-D estimation, based on the method of moments. The algorithm performs very well under simulation, compared with simpler estimators. Applied to data from vehicles with electronic toll collection tags in the San Francisco Bay Area, the algorithm produces realistic time series of the hourly O-D matrix.

Keywords: real-time O-D matrix estimation; vehicle reidentification; electronic toll collection tags; method of moment estimation
1 INTRODUCTION

Knowledge of the origin-destination (O-D) matrix of a traffic network is useful for various planning and operations tasks. The matrix gives the number of vehicles traveling between different zones in a region. Traditionally, the O-D matrix is estimated from link traffic counts combined with a sample survey. Approaches to O-D matrix estimation using these data include network equilibrium, gravity, and distribution-assignment models (1).

Vehicle locations observed using vehicle re-identification techniques provide a new data source for real-time O-D matrix estimation. Techniques based on video imagery, inductance loop signatures, and laser-based systems report when and where a certain vehicle is observed (2). Similar data may be obtained from vehicles with Electronic Toll Collection (ETC) tags and tag ‘readers’ installed at various locations in the region. ETC tag systems in use include the E-Z pass in the East Coast and FasTrak in the San Francisco Bay Area (3).

Because vehicle re-identification systems do not detect all vehicles, vehicle trajectories are only partially observed. Due to this incomplete sampling accurate estimation of O-D estimation from such data is not easy, as will be made clear in Section 2. This paper proposes a statistically sound, unbiased O-D matrix estimator, based on the moment estimator from such data.

The rest of the paper is organized as follows. Section 2 briefly describes the ETC tag reader system deployed in the Bay Area and points out the sampling problems it creates. Section 3 describes the statistical method in detail. Section 4 investigates the performance of the proposed algorithm using simulated data and a real data set from San Francisco Bay Area. Section 5 concludes the paper.

2 BAY AREA ETC TAG READER SYSTEM

The FasTrak system operates according to the Caltrans Title 21 standard (4). The system has two elements, a reader and a transponder. The reader is mounted on a pole, the transponder is mounted on the vehicle windshield.

The reader transmits a RF trigger pulse to turn the transponder on. After a short time delay, the reader transmits an encoded, polling signal, which, upon detection and decoding by the transponder, provides initial information to the transponder including the type of transaction the reader wishes to conduct.

The reader then transmits an unmodulated CW (continuous wave) RF signal for the transponder to modulate with a reply data message, including the transponder ID, while backscattering to the reader. The reader then transmits an encoded acknowledge message and requests that the transponder not respond to the same polling message again for 10 seconds (4).

A reader system serves four transponder-reading locations, each with its own antenna (5). In the Bay Area deployment, all four antennas are mounted on the same sign structure, located in the freeway divider. Three of the four antennas point in one freeway direction—the major direction, and one antenna points in the opposite direction—the minor direction. The area covered in the minor direction, and the number of detected vehicles, is consequently smaller.

The antennas are mounted at a height of between 16 and 24 ft, unlike at the toll booth where the antenna is close to the vehicle. As a result, only a fraction of tagged vehicles are detected.

The passage of a tagged vehicle generates a record, comprising a scrambled version of the tag (to protect privacy) and a sequence of reader locations where the vehicle is detected and the corresponding time stamp. The resulting data set is incomplete for two reasons. First, the penetration rate, the fraction of vehicles that carry tags, is between 15 and 40 percent, depending on the time of day. Second, the detection
rate, the fraction of tagged vehicles that are detected by a reader is about 80% in the major direction and 40% in the minor direction. Consequently, if a tagged vehicle passes under several readers, only some of these may detect it. A proper statistical analysis must take into account the incompleteness of the data.

3 METHOD

Consider a region comprising several zones, indexed \( j = 1, \ldots, J \). For two zones or ‘nodes’ \( j \) and \( k \), write \( j \rightarrow k \) if \( j \) is immediately upstream of \( k \). This relation defines an ‘edge’ in the freeway network viewed as a directed graph (6). An ‘O-D pair’ is any pair \([j, k]\), sometimes written \([jk]\). Note that \( j = k \) is allowed, in which case we simply write \( j \). A path is a sequence of nodes \((j_1, \ldots, j_A)\) connected by edges. An O-D pair \([j, k]\) is traversable if a path exists starting from \( j \) and ending at \( k \). It is uniquely traversable if such path is unique. A path contains another path if the latter is included in the former. An O-D pair contains another O-D pair if any path that contains the latter is contained by a path for the former. We assume the freeway network satisfies the following requirements:

1. The graph is connected, i.e., there is a path connecting every pair of nodes;
2. An O-D pair is uniquely traversable if it is traversable;
3. The graph has no cycle, i.e., a path which starts and ends at the same node.

We discuss how to relax these requirements in Section 4.

Index time periods, say hours of the day by \( t = 1, \ldots, T \). Denote by \( N(t) \) the total number of vehicles that make a trip during \( t \). Index vehicles by \( i = 1, \ldots, N(t) \). These vehicles are grouped into disjoint sets of vehicles corresponding to different O-D pairs. The O-D volume between zones \( j \) and \( k \) during period \( t \) is denoted by \( N_{jk}(t) \). At \( t \) the O-D matrix is simply \( \{N_{jk}(t), j, k = 1, \ldots, J\} \).

Let \( \psi \) be the penetration probability, i.e., the probability that an individual vehicle is equipped with a tag. Let \( \pi_j \) be the probability that a car with a tag traveling the link \( j \) is detected by the tag reader. We assume that for every vehicle, regardless of its O-D, the event that it is equipped with a tag and the event that it is detected are independent. Although our narration is in terms of electronic tags, a similar formulation applies with other vehicle reidentification techniques.

For an O-D pair \([j, k]\), we define

\[
M[j,k] = \text{Number of cars detected at } j \text{ and } k \text{ but not before } j \text{ nor after } k.
\]  \(\text{(1)}\)

Note that terms like ‘before (after) a zone’ are well defined thanks to requirements above on the freeway network. We can rewrite \( M[j,k] \) as the sum

\[
M[j,k] = \sum_{[l,m]} \sum_i 1(\text{vehicle } i \text{ has O-D path } [l,m] \text{ and vehicle } i \text{ is equipped with a tag and vehicle } i \text{ is detected at } j \text{ and } k \text{ but not before } j \text{ nor after } k) \text{ over all vehicles } i \text{ over all O-D pairs } [lm] \text{ that contain } [jk].
\]  \(\text{(2)}\)

The notation ‘\(1(\cdot)\)’ is the indicator function. Although the accounting identity (2) appears complicated, it allows the computation of various moments in explicit form. The expectation is given by

\[
EM[j, k] = \sum \{N_{lm}P_{l(jk)m} : \text{over all O-D pairs } [l, m] \text{ that contain } [j, k]\}.
\]  \(\text{(3)}\)
Here
\[ p_{t(jk)m} = (1 - \pi_l) \cdots (1 - \pi_{j-1}) \pi_j \pi_k (1 - \pi_{k+1}) \cdots (1 - \pi_m) \]  
(4)
is the probability that a vehicle with path \([l, m]\) is detected at \(j\) and \(k\) but not before \(j\) nor after \(k\). Similarly, the elements of the variance-covariance matrix of the elements of \(M\) are
\[ \text{Cov}(M[j, k], M[j', k']) = \sum \{ N_{lm} \psi^2 [1(jk) = [j'k']] p_{t(jk)m} - p_{t(jk)m} p_{t(j'k')m} \} \]  
(5)
: over all O-D pairs \([l, m]\) that contain both \([j, k]\) and \([j', k']\)

Define the vectors
\[ M = (M[jk] : \text{for all O-D pairs } [jk]), \]  
(6)
\[ N = (N[jk] : \text{for all O-D pairs } [jk]). \]  
(7)

For large number of vehicles \(N_{jk}\), by the Central Limit Theorem, \(M\) approximately has a multivariate normal distribution,
\[ M \sim N(AN, \Sigma(N)), \]  
(8)
in which the matrix \(A\) and the function \(\Sigma(\cdot)\) are specified by (3) and (5) respectively. Since
\[ E(M) = AN \]  
(9)
holds, the method of moment estimator (7) of the unknown \(N\) is given by
\[ \eta = A^{-1}M. \]  
(10)

The approximate error distribution of the estimator \(\eta\) can be obtained from (8)-(10) as
\[ \eta \sim N(N, A^{-1} \Sigma(N)(A^{-1})^T). \]  

Computing \(\Sigma(N)\) is complicated, and so we use the bootstrap procedure (7) to estimate the error of the estimator. Given an estimate \(\eta\), one simulates bootstrap samples \(M^{*(b)}, b = 1, \cdots, B\), for large \(B\), assuming \(\eta\) to be the true parameter. For each of these bootstrap samples, one estimate \(\eta^{*(b)}\) again and uses the bias and standard error of the bootstrap sample as an estimate of the bias and standard error of the estimator itself.

3 ANALYSIS

We apply the algorithm to a simulated data set as well as the real ETC tag data from San Francisco Bay Area.

Simulation

Consider a region with three zones \(j = 1, 2, 3\). The freeway network is defined by edges \(1 \rightarrow 2\) and \(2 \rightarrow 3\). The six O-D pairs are listed in Table 1, together with the paths containing them. Even for this simple network, all O-D pairs except \([1, 3]\) are contained in multiple paths.

Assume the detection probability is 0.5 for all three readers, i.e. \(\pi_1 = \pi_2 = \pi_3 = 0.5\) and \(N_{jk} = 1,000\) for all O-D \([j, k]\). Also assume all vehicles are equipped with a tag, so the penetration rate \(\psi = 1\). We simulate \(M_{jk}\) as the sum of binomial random variables with distribution \(\text{bin}(N_{lm}, \psi p_{lm})\), summed over all O-D pair \([l, m]\) containing path \([j, k]\).
For comparison, we also compute the naive estimator

\[ \eta'_{jk} = \frac{\text{Number of vehicles that are observed at both } j \text{ and } k}{\pi_j \pi_k}. \]  

(11)

The naive estimator gives a rough idea about the number of vehicles that travel between two locations, but it is obviously incorrect for estimation of \( N \).

Figure 1 and Table 2 show the distribution of the estimates from the two methods estimated with 200 simulation runs. Moment estimators are very accurate, exhibiting less than 1% bias for all O-D pairs. The relative errors are less than 10%. As expected, the naive estimator performs very poorly by comparison. Except for O-D pair \([1,3]\), it has huge biases. On the other hand, their standard errors are of similar magnitude as those of the moment estimators. To summarize, a naive approach cannot be used for analysis of O-D patterns, while the moment estimator provides very accurate estimates for all O-D pairs.

**Bay Area ETC Data**

Figure 2 shows the topology of the freeway network and antenna locations, which can be viewed as zone labels. The data were collected over 24-hours of Thursday, 24 July, 2003. The current reader coverage is incomplete. It only includes the northern part of East Bay and a small part of San Francisco. Thus, for example, ‘zone 2’ includes not only the area between zones 3 and 9 but also the huge area that lies beyond 580 West. The reader coverage is being extended.

The graph representation shows all the nodes and edges. If we allow trips between nodes 7 (east and west) and 5 (north and south), denoted by arrows in dashed lines, there are cycles (7E→5N→3E and 7W→3W→5S), so we do not allow these trips. For illustration, we consider only eastbound/southbound traffic involving nodes 1E, 3E, 2E, 9E, 5S, and 7E (gray nodes). The graph is then completely described by five edges: 1 → 5, 1 → 3, 3 → 7, 3 → 2, and 2 → 9. There are \( J = 6 \) nodes and 15 traversable O-Ds. For each O-D (path), the set of containing O-Ds (paths) is shown in Table 3. Note that the path-containing relationship is much more complicated than the network considered for simulation.

The penetration rate \( \psi \) is taken to be 15% and we use this value in the application. The detection rate parameters \( \pi_j \) are estimated using the total volume data obtained from the loop detectors installed at the location close to each antennas. We use the PeMS system (8) to obtain the loop data. From these data, we find \( \pi_j = 0.8 \) for all locations.

We first apply the algorithm to estimate the O-D matrix for the whole 24-hour period. Table 4 shows the estimates and the bootstrap estimates of its bias and variance. Most biases are controlled under 1% of the estimates and the relative errors under 5%, except for O-Ds \([1,1]\) and \([3,2]\). Figure 3 shows the bootstrap distribution of the estimates.

We then estimate hourly O-D matrices by splitting samples into hours according to the vehicle’s last observed timestamp and applying the algorithm for each hourly samples. Figure 4 shows the result.

The trend clearly reveals the changing pattern of vehicle travel demand for each O-D pair over the day. For example, the O-D \([1,3]\) (San Francisco to East Bay) \([5]\) (East Bay to San Jose) has higher demand in the morning while the O-D \([2]\) (East Bay to Richmond) and \([9]\) (Northeast Bay to The Carquinas bridge) has higher demand in the evening.

**5 DISCUSSION AND CONCLUSION**

We developed a method of moments algorithm for estimating time-varying OD matrices from partially observed vehicle trajectories data, together with a bootstrap procedure to estimate the standard error of the estimator.
We restricted our attention to freeways with relatively simple topology, in which the corresponding graph is connected, all traversable O-Ds are uniquely traversable, and there is no cycle. These requirements are too strict for many real world freeway networks and can be relaxed with varying difficulty. For a disconnected graph, one only needs to decompose it into connected components and apply the algorithm to each component. For non-uniquely traversable O-Ds, the accounting equation (2) needs to be appropriately modified. If the route choice probabilities are known, such modification is relatively straightforward, but if they are unknown, they become extra parameters in the model and the extension is not trivial anymore. When there are cycles, one promising approach would be to remove non-likely paths from consideration to reduce the dimension of \( M \) and \( N \) and simplify \( A \). Overall, these are all interesting challenges and we are currently working on extending the current algorithm to cope with such complex networks.

The proposed algorithm performed well. The simulation study shows that the proposed moment estimator and bootstrap standard errors are accurate under ideal settings. The application to data from vehicles equipped with ETC transponders and ‘readers’ installed at various locations in San Francisco Bay Area, leads to credible hourly OD matrices. Combined with the wider deployment of tag readers and greater penetration of tags in the vehicle population, the proposed methods would enable district-wide O-D real-time reporting in timely and accurate manner.

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TABLE 1 O-D path and paths containing the O-D path for the simulated linear freeway

<table>
<thead>
<tr>
<th>O-D path</th>
<th>Paths containing the O-D path</th>
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<td>(2,3)</td>
<td>(1,2,3), (2,3)</td>
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<td>(3)</td>
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TABLE 2 Bias and standard error of the Moment and Naive Estimators from simulation with 200 runs when true $N = 1,000$

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<th>Bias O-D</th>
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<th>SE Naive Estimator</th>
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### TABLE 3 O-D path and paths that containing the O-D path for the Bay Area network

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### TABLE 4 Estimate of 24-hour O-D matrix and standard errors from Bay Area ETC data for 24 July, 2003

<table>
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<tr>
<th>O-D path</th>
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<th>Bootstrap S.E</th>
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