MARKOV CHAIN PROCEDURE FOR ARTERIAL ROUTE TRAVEL TIME DISTRIBUTION ESTIMATION

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ABSTRACT

Recent advances in the GPS technology and the probe vehicles deployment offer an innovative prospect for arterial travel time research. Specifically, we focus on estimation of arterial route travel time distribution which contains more information in regard to traffic network performance measurement. In the proposed technique, probe vehicles provide travel time of the traversing links. For each two consecutive links, a two-dimensional (2D) diagram is established so that data points represent travel times of a probe vehicle crossing both two aforementioned links. States in the 2D diagrams (defined as rectangular clusters) consist of data with homogenous travel times. The state boundaries are set by simple travel time rules such as free flow travel time and oversaturated conditions. In addition, a heuristic biclustering optimization method is done to determine boundaries in order to have more analogous states. Applying markov chain procedure, we relate states of 2D diagrams to the following ones; compute the transition probabilities, and partial travel time distributions to obtain the arterial route travel time distribution. The procedure is tested on a five links arterial Lincoln Blvd., Los Angeles, CA, during morning peak, which has been simulated in a microscopic simulation environment. The simulated results are very close to the markov chain procedure and more accurate once compared to the convolution of links travel time distributions. The promising results capture the fundamental characteristic of field measurements.

Keywords: Arterial performance, Markov chain, Probe vehicle, Travel time distribution

INTRODUCTION

The introduction of Intelligent Transportation Systems (ITS) technologies and new sensing hardware promise significant progress in reducing the congestion level in cities. Nowadays, congestion is a widespread time consuming phenomenon in urban areas and the first step to ease is network traffic data collection. Hence, traffic monitoring is a key component in transportation system management for control and traffic guidance. The integration of Global Positioning System (GPS) technology within the ITS framework introduces a new paradigm for traffic surveillance: probe vehicles. Despite to old-fashioned traffic sensors, loop detectors, probe vehicles offer further information such as vehicles’ trajectories in more convenient manner. In addition, low maintenance cost, inherent distributed characteristics, and incremental public deployment rate justify tackling probe vehicle challenges in traffic monitoring research such as travel time estimation. Travel time is a crucial index in assessing the operating efficiency of traffic network and numerous literatures address different travel time estimation approaches state to different applications and terms.

Recently an analytical model was developed to estimate the travel times on arterial streets based on data commonly provided by loop detectors system and the signal settings at each traffic signal [1]. The model considers the spatial and temporal queuing at the traffic signals and the signal coordination in arterial to estimate travel times. The model implementation is straightforward and unlike other approaches does not depend on site specific parameters or short term traffic flow predictions that make transferability to other locations very difficult. Several extensions and enhancements were developed and implemented to the analytical model explicitly address the issues of long queues and spillovers that frequently occur on arterials in urban areas [2]. The model has also been integrated into a pilot arterial performance measurement system in California.

The aforementioned studies, focused on average travel time estimation of travelling vehicles in one cycle. Nevertheless, statistical scalar index (e.g. mean, variance, and skewness) is not fully informative about travel time variability compare to travel time distribution (TTD). So, there is a need for new travel time research trend. For instance, a multistate model is employed to fit normal mixture distributions into travel time observations of an expressway corridor [3]. Uno et al. analysed routes travel time variability using bus probe data [4]. After a data correction stage for elimination of stopping time at bus stops, they decomposed a route to sections with lognormal TTD and finally calculate the route TTD. In [5] a statistical probe data evaluation is investigated without any validation with field or simulation data. And in [6], an analytical method for estimation of urban link delay distribution is discussed.

Speed of vehicles at a given time in the network is not a deterministic quantity over space because of drivers’ behaviours (conservative vs. aggressive drivers), the spatial effect of signals (near the signal line vs. further upstream) and temporal-spatial pockets, where average speed is temporarily different than the widespread average (e.g. point bottleneck in a freeway system). In this work, we will analyse the distribution of arterial travel time for sub-routes (expressed as series of links) for a period comparable to a signal cycle. In that way first, second, we smooth the variations of traffic for a specific link because of the time-dependent capacity of a signal and the variability in driver’s behaviour as many vehicles pass over a link in that period.

The straightforward method for route TTD estimation while having individual link TTD is to aggregate those
independently [7]. Assume a K links route which we are interested in to find the TTD, the route TTD is computed like (1), where the star operator is convolution:

\[ TTD_K = TTD_1 \ast TTD_2 \ast \ldots \ast TTD_K \] (1)

Evidently, the above method considers no correlation between single TTDs consequently lots of information is lost. In the following section, Markov chain is introduced to overcome this shortcoming.

MARKOV CHAIN PROCEDURE

Markov chain is a technique for statistical modeling of a random process that the system’s state changes through progression. A markov chain is entirely demonstrated with the set of state definition and transition probabilities. The transition probability is probabilities associated with the state transitions. It is worth to mention that the system should have the markov property, which states that the conditional probability of the system at the next state given the current state depends only on the current state and not on the previous states of the system. Mathematically put:

\[ Pr(s_{t+1} = s'|s_t, s_{t-1}, ..., s_1) = Pr(s_{t+1} = s'|s_1) \] (2)

The markov property empowers markov chain to capture both probabilistic nature of travel time and the consecutive links travel time fundamental correlated feature.

Markov chain is utilized in vast fields of transportation research. Discrete time markov chain for estimation of expected freeway travel time is investigated in [8] where the states correspond to congestion level of links. In [9] a markov chain is developed to address the effect of freeway flow breakdown and recovery in travel time reliability. Geroliminis et al. also proposed an analytical model for platoon arrival profiles and queue length prediction considering platoon dispersion in arterial using markov process and loop detectors data [10]. In the following section we discuss about the proposed framework.

METHODOLOGY

In our proposed methodology, the raw measurements are vehicles trajectories and links travel times collected from probe vehicles. Afterward, travel times of all probe vehicles crossing two successive links during data collection period are used to construct a two-dimensional (2D) diagram corresponding to the two aforementioned links. 2D diagrams are graphical representation of vehicles consecutive travel time joint distribution. Given K links route, K-1 2D diagrams are established in order to identify the markov chain structure i.e. states definition and transition probabilities. Figure 1 illustrates such a diagram for link 1 and 2 consisting of 8177 samples.

Since such a diagram is constructed, states are regarded as rectangular regions and number of data within each region indicates the corresponding transition probability.

Let \( X_i = \{x_{i1}, ..., x_{i(m_i-1)}\} \) and \( Y_i = \{y_{i1}, ..., y_{i(n_i-1)}\} \) denote sets of boundaries in 2D diagram i for link i and \( i+1 \) travel times, respectively. Consequently, there are \( m_i \) and \( n_i \) states for link i and \( i+1 \) travel time, respectively. The first state of link i indicates travel times in \([\min(tt_i), x_{i1})\) and the last state represents travel times inside \([x_{im_i}, \max(tt_i)]\) interval. Note that all links except the first and last one have two different sets of states. Thus, there are \( m_1, n_1, ..., m_{k-1}, n_{k-1} \) state combinations and each one of them is named as markov path. For a given markov path, all of the transition probabilities are multiplied to compute path occurrence probability. Then we obtain path TTD using convolution of partial TTD of each state in the path. Finally, the route TTD is equal to weighted sum of markov paths TTD with path transition probabilities weights.

The chief challenge in this methodology is to appropriately identify rectangular clusters (i.e. \( X_i \) and \( Y_i \)) so states exhibit homogenous travel times’ characteristics. Intuitive thumb rules like travel time values in free flow, near capacity, and oversaturated conditions may be utilized to address the state identification problem. Furthermore, heuristic biclustering optimization methods can be applied to determine boundaries in order to have more analogous states. The preliminary results of proposed algorithm are shown in the following section.

PRELIMINARY RESULTS

The proposed procedure is tested on a five links arterial Lincoln Blvd., Los Angeles, CA, during 4 hours morning peak, which has been simulated in the microscopic AIMSUN simulator. Field TTD, convolved estimation of TTD and results of markov chain with 2 and 5 states for 2D diagrams are depicted in fig. 2. It is apparent that the simulated TTD are very close to the markov chain outcomes and more accurate compared to the convolution estimation.
Fig. 2: Various methods' result of link 1 to link 5 travel time distribution

For more comprehensive comparison, the mean absolute errors of methods with regard to real data are summarized in Table 1. It can be inferred that the more states in markov chain, the better results are achieved. Utterly, the markov chain promising results can capture the fundamental characteristic of field TTD measurements.

<table>
<thead>
<tr>
<th>Method</th>
<th>Convolution</th>
<th>2 States Markov Chain</th>
<th>5 States Markov Chain</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Absolute Error (*10^-4)</td>
<td>3.9780</td>
<td>3.1582</td>
<td>2.8271</td>
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</tbody>
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REFERENCES


