A Reliable Travel Time Prediction System with Sparsely Distributed Detectors
Ph.D. Dissertation Proposal

Nan Zou
12/12/2006
Outline

- Introduction
- Research Objectives
- Framework of the Travel Time Prediction System
- Travel Time Estimation Module
  - Existing models
  - The proposed hybrid model
- Travel Time Prediction
  - Existing models
  - The proposed hybrid model
- Summary
- On-going Works
Introduction

- Travel times (completed and en-route trips) are crucial information for an Advanced Traveler Information System (ATIS).
- Travel time prediction is a challenging task due to the impacts of:
  - Geometric features
  - Traffic patterns
  - Availability of detection system, and
  - Nonrecurrent congestion (for example, incidents), etc.
Issues Associated with Existing Models and Systems:

- High system costs
  - Densely distributed detectors (i.e., 0.5-mile apart)
  - Accurate speed detection
  - Recurrent measurement on travel times
    Coifman et al. (2002, 2003), van Lint et al. (2003), Liu et al. (2006)

- Reliability
  - Missing or delayed data
  - Nonrecurrent congestions (for example, incidents)
Features of A Cost-efficient and Reliable Travel Time Prediction System

- Required input variables should be obtainable from sparsely distributed traffic detectors.
- Take advantage of some actual travel times from the field, but not rely on a large number of such data.
- Be capable of operating under non-recurrent congestion or data-missing conditions and effectively dealing with related issues during real-time operations.
Research Objectives

- Develop a travel time estimation module
  - Reliable estimates of completed trips
  - Under all types of recurrent traffic patterns
  - With sparsely distributed traffic detectors

- Construct a travel time prediction module
  - For freeway segments
  - Large detector spacing
  - Historical travel times and traffic patterns
Integrate a missing data estimation module
- To deal with various missing data and delay patterns
Calibrate an incident detection module
- Switch the travel time prediction system to a different mode (i.e., display delay warnings instead of predicted travel times) when an incident has been detected.
T.T. Estimation vs. Prediction

Space

\(d_D\)

\(d_2\)

\(d_1\)

Time

\(t\)

\(t+TT\)
T.T. Estimation

Space

$d_D$

$t$

$t+TT$

Time

$d_1$

$d_2$
T.T. Prediction

Space

$\text{d}_1$

$\text{d}_2$

$\text{d}_D$

Time

$t$

$t + \text{TT}$
Existing Travel Time Prediction Systems

- Example systems
  - Houston, TX; Atlanta, GA; Chicago, IL; and Seattle, WA, etc.

- Almost all real-world systems use current detected traffic conditions as the prediction of the future
  - Completed trips instead of en-route trips
  - Big difference
Completed Trips vs. En-route Trips
Travel Time Estimation Module

Database of Historical Travel Times

Real-Time Detector Data at Time $t$

Database of Traffic Data

Incident Detection Module

Links with Detected Incident

Links with No Detected Incident

Data Missing?

N

System Flowchart

Stop Predicting for Impacted Segments

$\text{Predicted Travel Time for Time } t$

Y

Missing Data Estimation Module

Links with Unreliable Missing Data

Links with Reliable Missing Data Estimation Only

Travel Time Prediction Module

$t=t+1$
Literature Review

- Travel Time Estimation
  - Flow-based models
  - Vehicle identification approaches
  - Trajectory-based models
Limitations of Flow-based Models

- Reliability of detector data
  - Detection errors (volume drifting) vary over time and space
- Traffic patterns
  - Require uniformly distributed traffic across all lanes
- Geometric features
  - Cannot model ramp impact
Limitations of Vehicle Identification Approach

- Traffic patterns
  - Lane-based approach, therefore requires low lane changing rate
  - Requires uniform traffic conditions across lanes

- Geometric features
  - May not fit geometric changes, such as lane drop and lane addition

- System cost
  - High. Require new hardware or high bandwidth

- Reliability
  - Low detection resolution under high speed
  - Reduced accuracy under low light (video-based)
Limitations of Existing Trajectory-based Models

- Assumes constant traffic-propagation speed
- May not perform well on long links
  - currently all studies are based on detectors less than 0.5-mile apart
- Requires reliable speed measurement
  - Not available from most traffic detectors
A Hybrid Travel Time Estimation Model with Sparsely Distributed Detectors

- A Clustered Linear Regression Model as the main model
  - For traffic scenarios that have sufficient field observations
- An Enhanced Trajectory-based Model as the supplemental model
  - For other scenarios
Clustered Linear Regression Model

- Travel times may be constrained in a range under one identified traffic scenario
  - For example, the travel time cannot be free-flow travel time when congestion is being observed at one detector
- Assume a linear relation between the travel time under one traffic scenario with traffic variables from pre-determined critical lanes
Critical Lanes

- Those lanes that directly contribute to estimate the average travel speed of through traffic
- May include both mainline lanes and ramp lanes
- From both upstream and downstream detector locations
Model Formulation of the Clustered Linear Regression Model

\[
\tau_d(t) = \sum_{la \in \text{CLT}_{d,d+1}(p)} b_{d,la}^{T,p} \frac{o_{d,la}(t, \gamma_p^d \tau_d^E(p))}{v_{d,la}(t, \gamma_p^d \tau_d^E(p))} + \sum_{la \in \text{CLR}_{d,d+1}(p)} b_{d,la}^{R,p} \frac{o_{d,la}(t, \gamma_p^d \tau_d^E(p))}{v_{d,la}(t, \gamma_p^d \tau_d^E(p))} + \sum_{la \in \text{CLT}_{d,d+1}(p)} b_{d,la}^{R,p} \frac{o_{d,la}(t, \gamma_p^d \tau_d^E(p))}{v_{d,la}(t, \gamma_p^d \tau_d^E(p))} + b_{d}^0,p
\]
An Enhanced Trajectory-based Model

- Combines and enhances two types of trajectory estimation:
  - Traffic propagation relations when the vehicle is close to one detector
  - An enhanced piecewise linear-speed-based model when the vehicle is far from both detectors
- Does not require speed in input variables
  - Estimate the occupancy first, then use occupancy-speed relation to estimate the vehicle’s speed
Trajectory-based Method

Space

Time

d_1

d_2

t

t + TT_1

Estimated

Actual
Trajectory-based Method

Space

\[ d_2 \]

\[ d_1 \]

Time

\[ t \]

\[ t + TT_1 \]

Estimated

Actual
Trajectory-based Method

- Estimated
- Actual

Space

$\text{d}_1 \rightarrow \text{t} \rightarrow \text{t+TT}_1$

Time
An Enhanced Trajectory-based Method
An Enhanced Trajectory-based Method
Model Formulation

\[
O(x, t) = \begin{cases} 
  o_d \left( t + \frac{x - x_d}{u_c^{\text{max}}}, t + \frac{x - x_d}{u_c^{\text{min}}} \right) & \text{if } x - x_d < \hat{x} \\
  o_{d+1} \left( t - \frac{x_{d+1} - x}{u_c^{\text{min}}}, t - \frac{x_{d+1} - x}{u_c^{\text{max}}} \right) & \text{if } x_{d+1} - x < \hat{x} \\
  o_d \left( t + \frac{\hat{x} - x_d}{u_c^{\text{max}}}, t + \frac{\hat{x} - x_d}{u_c^{\text{min}}} \right) & \text{otherwise} \\
  + \frac{(x - x_d - \hat{x})}{\hat{x}} \\
  \times o_{d+1} \left( t - \frac{x - (x_{d+1} - \hat{x})}{u_c^{\text{min}}}, t - \frac{x - (x_{d+1} - \hat{x})}{u_c^{\text{max}}} \right) \\
  - o_d \left( t + \frac{\hat{x}}{u_c^{\text{max}}}, t + \frac{\hat{x}}{u_c^{\text{min}}} \right) \end{cases}
\]

\[
\hat{x} = \begin{cases} 
  \min \left( \frac{l_d}{3}, \frac{1}{3} \text{ mi} \right) & \text{when } l_d \geq 1 \text{ mile} \\
  \frac{l_d}{3} & \text{otherwise}
\end{cases}
\]

\[x_{d} \leq x \leq x_{d+1}\]

\[u_c^{\text{min}} \text{ and } u_c^{\text{max}} \text{ are the minimum and the maximum traffic propagation speeds.}\]
Model Formation (cont’d)

\[
  u(x, t) = \begin{cases} 
    u_{\text{free}} & , o(x, t) \leq o_{\text{free}} \\
    u_{\text{cong}} + (u_{\text{free}} - u_{\text{cong}})(1 - \frac{o(x, t) - o_{\text{free}}}{o_{\text{cong}} - o_{\text{free}}})^m & , o_{\text{free}} < o(x, t) \leq o_{\text{cong}} \\
    u_{\text{min}} + (u_{\text{cong}} - u_{\text{min}})(1 - \frac{o(x, t) - o_{\text{cong}}}{o_{\text{max}} - o_{\text{cong}}})^n & , o_{\text{cong}} < o(x, t) \leq o_{\text{max}} \\
    u_{\text{min}} & , \text{otherwise}
  \end{cases}
\]
Travel Time Prediction

- Parametric Models
  - Time series model
  - Linear regression model
  - Kalman Filter model

- Nonparametric models
  - Neural Network model
  - Nearest Neighbor model
  - Kernel model and local regression model
Autoregressive Integrated Moving Average (ARIMA)

Advantages:
- Ability to predict a time series data set
- Good for predicting traffic data (volume, speed, or occupancy) at one detector

Disadvantages:
- Focus on the mean value, therefore cannot well predict scenarios that less frequently occur
- It is hard to model multiple sets of time series data together (for example, multiple series of data from detectors)
Linear Regression Models

- One single linear regression model cannot predict well for all traffic scenarios, therefore multi-model structure is often used:
  - Layered/clumped linear regression model
  - Varying coefficient linear regression model
Kalman Filter Model

- Ability to auto-update parameters based on the evaluation of the prediction accuracy of the previous time interval
- Good performance when the true value can be obtained with a short delay (Chien et al., 2002 and 2003)
- May not work well for a prediction system with long travel times (long travel times = long delay for the update process)
Neural Network Models

- Widely used to predict travel times
- Accurate and robust because of its good ability to recognize patterns
- Multi-layer Perceptron (MLP) and Time Delay Neural Network (TDNN) are mostly seen in the literature
- A large amount of training data
\[ x(n) \rightarrow W_1(i,j) \rightarrow \text{MLP} \rightarrow W_2(i,j) \rightarrow \text{TDNN} \]

\[ x(n-1) \rightarrow W_1(i,j) \rightarrow \text{MLP} \rightarrow W_2(i,j) \rightarrow \text{TDNN} \]

\[ x(n-2) \rightarrow W_1(i,j) \rightarrow \text{MLP} \rightarrow W_2(i,j) \rightarrow \text{TDNN} \]

\[ x(n-k) \rightarrow W_1(i,j) \rightarrow \text{MLP} \rightarrow W_2(i,j) \rightarrow \text{TDNN} \]
**k-Nearest Neighbor Model**

- Looks for \( k \) most similar cases as the current condition from the historical database to come out a prediction.
- Requires a fairly large historical database.

\[
dist_{EUC}(p, q) = \sqrt{\sum_{i=1}^{K} (p_i - q_i)^2}
\]

\[
dist_{NUW}(p, q) = \sqrt{\sum_{i=1}^{K} w_i (p_i - q_i)^2}
\]
Other Nonparametric Models

- Share a common structure
  - A clustering function
  - A kernel function (linear, nonlinear and/or other form) for each cluster

- For example
  - Kernel regression
  - Layered linear regression
  - Time-varying coefficient linear regression
A Hybrid Travel Time Prediction Model

- A \( k \)-Nearest Neighbor Model as the main model
  - For cases with sufficient good matches in the historical data
- An enhanced time-varying coefficient model as the supplemental model
  - For other cases
$k$-Nearest Neighbor Model for Travel Time Prediction

- An updated distance function
  - Based on three types of traffic state
- Geometric features
  - Take traffic data from critical lanes only
  - The time range of input data increases with the distance to the origin
- Daily and weekly traffic patterns
  - Varying search window based on historical traffic patterns
Modified Definition of the Distance

\[ mdis = \sqrt{\sum_{i=1}^{k} w_i (p_i^* - q_i^*)^2} \]

\[ p_i^* = \begin{cases} 
  p_i & \text{, when } TC_{\text{d}}^{1a} (t, t + \Delta t) = 0 \\
  OC_{\text{d}}^{1a} & \text{, when } TC_{\text{d}}^{1a} (t, t + \Delta t) = 1 \\
  OF_{\text{d}}^{1a} & \text{, when } TC_{\text{d}}^{1a} (t, t + \Delta t) = -1 
\end{cases} \]

\[ q_i^* = \begin{cases} 
  q_i & \text{, when } TC_{\text{d}}^{1a} (t_h, t_h + \Delta t) = 0 \\
  OC_{\text{d}}^{1a} & \text{, when } TC_{\text{d}}^{1a} (t_h, t_h + \Delta t) = 1 \\
  OF_{\text{d}}^{1a} & \text{, when } TC_{\text{d}}^{1a} (t_h, t_h + \Delta t) = -1 
\end{cases} \]
Consideration of Traffic Patterns

\[ mdis = \sqrt{\sum_{i=1}^{k} w_i (\hat{p}_i - q^*_i)^2} \]

Where

\[ \hat{p}_i = \begin{cases} M, & \text{if } |t - t_h| > T_{th}(d, t) \\ p^*_i \times \hat{w}, & \text{otherwise} \end{cases} \]

\[ \hat{w} = \begin{cases} 1, & \text{if } \exists s, wk_h \in W_s \text{ and } wk_c \in W_s \ (1 \leq s \leq S) \\ M, & \text{otherwise} \end{cases} \]

\[ \bigcup_{s=1}^{S} W_s = \{\text{all weekdays}\} \]

\( M \) is a very large number.
\( wk_c \) and \( wk_h \) are weekdays of the current case and the historical case respectively.
An Enhanced Time-varying Coefficient Model

- Same global linear model structure
- Varying coefficients at each time interval
- A linear relation with time-varying coefficients between the predicted travel time and a status travel time (a preliminary prediction)
Status Travel Time

- Original form

\[ T^*(t, \Delta) = \sum_{d=1}^{D-1} \frac{x_{d+1} - x_d}{v_d (t - \Delta)} \]
Enhanced Status Travel Time for Long Links

- **Real-time data up to time** $t$ in weekday $k$
- **Database of historical detector data**
  - **Historical average after time** $t$ in weekday $k$
  - **Input dataset for travel time estimation**
  - **A hybrid travel time estimation model**
- **A preliminary estimate of travel time**
- **Time-varying coefficients for time** $t$ and weekday $k$
- **Database of historical detector data**
- **Predicted travel time for time** $t$
Model Formulation

- Consider both daily and weekly traffic patterns

\[ T(t) = a_{t_i}^k \hat{T}(t) + b_{t_i}^k \]

Where \( T(t) \) is the travel time to predict.

\( a_{t_i}^k \) and \( b_{t_i}^k \) are the weekly time varying coefficients for the \( t_i^{th} \) interval of the current weekday, \( k \).
Summary

- Completed tasks
  - Perform an *in-depth* review of literature associated with travel time prediction
  - Develop a *modeling framework* for a travel time prediction system with sparsely distributed detectors on the freeway
  - Propose a hybrid model for *estimating travel times* for freeways with sparsely distributed detectors
  - Develop a hybrid model for *travel time prediction* for freeways with sparsely distributed detectors
On-going Works

- Incorporating a **Missing Data Estimation Module** to the Travel Time Prediction System
- Developing an Alternative Model Structure for Travel Time Prediction with **Neural Network Models**
- Developing an **Incident Detection Module** to Avoid Potential Large Errors under Non-recurrent Congestion
- Numerical Analysis with the Off-line Data for System Demonstration
Thank you!

Any questions?