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**Real-time Travel Time Prediction on Urban Arterial
Network**

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Executive Summary

Travel time is one of the most desired operational variables serving as a key measure of effectiveness (MOE) for evaluating the system performance of freeways and urban arterials. However, travel time cannot be easily retrieved from most existing traffic detectors. Even though up-to-date intelligent transportation system (ITS) technology, such as automatic license plate readers (ALPR), can effectively and efficiently collect travel time information, the deployment cost of ALPR over an urban network is tremendously high. This makes it an attractive cost-effective alternative to acquire arterial travel time using the existing sensor measurements. Hence, this study focuses on arterial travel time estimation and prediction using data from existing loop detectors, the most commonly used traffic sensor type for arterial traffic signal control.

The City of Bellevue is selected as the primary study site because its arterial traffic detection system is representative in the US. There are more than 600 advance loops installed to collect fundamental traffic variables, i.e. volume and lane occupancy. The cycle-by-cycle traffic measurements at each signalized intersection are sent to the transportation management center in real-time. In addition, the research team also developed an event data collection system that can collect second-by-second event data onsite to facilitate control delay calculations and potentially other relevant research issues at intersections. The event data collection unit has been installed at an intersection (SR 99 and 196th Street) in the City of Lynnwood, WA to collect and archive signal and detector status (event) data since June 2009.

Travel speed ties directly to travel time and hence is an important measure for quantifying arterial performance. However, accurately estimating link travel speed for urban arterials is difficult due to traffic fluctuations and traffic flow interruptions caused by signal control. In terms of travel time estimation, this study proposes a two-step empirical approach to effectively estimate the link journey speeds merely using advance loop detector outputs. The first step is to estimate the spot speed based on advance loop measurements using Athol's algorithm developed in 1965. A robust regression technique can be used to calibrate the speed estimation parameter (also known as the g-factor) in

Athol's algorithm. The second step is to use the proposed simplified speed estimation model to estimate the link speed only using the calculated loop spot speed without any knowledge of signal timing plans. Traffic operations in the central business district of the City of Bellevue, WA are simulated in the VISSIM traffic simulation model. The test results show that only 50 cycles worth of data are need to calibrate g-factor in loop speed estimation and the same data sets can be used to calibrate the proposed link speed model. Using this model, the mean absolute error over the study links is reduced from 4.24 mph to 1.51 mph. With proper calibration, this average error can be further reduced to 0.91 mph. The results are encouraging and satisfactory. The results also showed that the accuracy of speed estimation may be further increased when more data are applied for calibration.

With good speed estimates and known link lengths, travel time can be easily calculated. Travel time information is critical to success of both Advance Traveler Information Systems (ATIS) and Advanced Traffic Management Systems (ATMS). In practice, these systems face many challenges that may reduce the availability of accurate travel speed data. Challenges lie in issues regarding inconsistent data connections, data errors, query performance, traffic prediction, and computational limitations. These challenges are properly addressed when implementing the proposed algorithms in a web-based system named as Real-time Analysis and Decision-making for ARterial Network (RADAR Net). This system adopts a relational database that consists of link, intersection and detector entities. The relational data demonstrates its query performance and scalability. The system contains four layers: offline server, online server (middleware), online server (Java Servlet) and online client. This four-layer design is capable of properly distributing the computational burden over the entire system to avoid service flow bottleneck.

In order to monitor the arterial performance, link speeds are calculated directly from Bellevue's loop detector data using the developed speed estimation algorithm. The system can dynamically predict and smooth real-time loop spot speeds using an α - β filter, a simplified version of Kalman filter while maintaining high system performance. The link speeds over the entire network are calculated and updated in real-time. Based on the system architecture, many application modules, e.g. capacity analysis and dynamic

routing, are implemented and these modules demonstrated that RADAR Net is capable of supporting real-time arterial network performance monitoring, analysis, and decision making.

In summary, the study proposed travel time estimation and prediction, and shortest travel time path algorithms. These algorithms take real-time performance into account and are successfully implemented into the web-based RADAR Net system. This online system design aims at optimizing real-time arterial traffic operations and facilitating online analysis and decision-making processes. The RADAR Net system is implemented as a sub-system of the Digital Roadway Interactive Visualization and Evaluation Network (DRIVE Net), an online interdisciplinary data integration and analysis platform developed and operated by the TransNow Smart Transportation and Application Research Laboratory (STAR Lab) of the University of Washington. DRIVE Net is accessible online at www.uwdrive.net.

Chapter 1 Introduction

1.1 General Background

From 1980 to 2003, yearly vehicle miles traveled increased by 89% from 1,527,295 million to 2,890,450 million, while road mileage increased only about 3% from 3,859,837 miles to 3,974,107 miles (BTS, 2005). According to the 2005 Urban Mobility Report (Schrank and Lomax, 2005), the annual average delay per person in the 85 surveyed-urban areas was 47 hours in 2003, a 194% increase compared to that in 1982. Improving quality and efficiency of travel on urban networks using Intelligent Transportation Systems (ITS) technologies is crucial for sustainable socio-economic development.

Advanced Traveler Information Systems (ATIS) play an indispensable role in connecting road users with up-to-date traveler information. Well-designed ATIS not only help improve traveler mobility and transportation system efficiency but also provide valuable inputs to traffic operators and researchers. Travel time is one of the most desired variables serving as a key system Measure of Effectiveness (MOE) for evaluating the performance of freeways and urban arterials (Martin et al., 2003). Travel time can be obtained by using several techniques including license plate matching, probe vehicles, traffic detector data based travel time estimation, etc. (Turner et al., 1998). Among these techniques, estimating travel time from traffic detector measurements is considered one of the most feasible and cost-effective solutions to collecting travel time data. Inductive loop detectors are by far the most widely deployed traffic sensors in the existing infrastructure system and serve as the standard form of traffic detection in many transportation agencies (Kell and Fullerton, 1991; Wang and Nihan, 2003). However, loop detectors cannot directly measure travel time. Algorithms are needed to estimate travel time using loop detector data.

Over the years, several such algorithms have been developed (see for example Geroliminis and Skabardonis, 2006; Zhang and Kwon, 1997; Park and Lee, 2004). Most of these algorithms, however, were specifically designed to address freeway travel time estimates. Travel time estimation and prediction for urban arterials remains an open area

that deserves further research efforts, although researchers start to show an increasing level of interest in developing arterial ATIS. Nevertheless, little research has been done in arterial network travel time estimation based on traffic detector measurements. Insufficient deployment of traffic detectors has been one major constraint for arterial ATIS. With the increasing level of sensor coverage on urban arterials, this constraint may be eliminated soon.

Since 1997, U.C. Berkeley has been focusing on developing the Freeway Performance Measurement System (PeMS). PeMS is capable of analyzing freeway traffic sensor data and providing real-time performance measures, including travel times (Chen, 2003; Varaiya, 2007). Following the success of PeMS, the Arterial Performance Measurement System (APeMS) was developed to estimate the travel time on an arterial route using mid-block (system) loop detectors (Petty *et al.*, 2006). However, no online system has demonstrated a network-level travel time estimation or prediction function. This implies that a functional travel time estimation algorithm is yet to be developed for urban arterials.

1.2 Problem Statement

Although the Global Positioning Systems (GPS) technology has been well developed and commonly serves as the direct data source of travel time, there are not a sufficient number of vehicles currently equipped with GPS devices for travel time data collection. Also, commercial fleets whose vehicles are GPS-installed may not be willing to share their data with the public. Therefore, at the current state of the practice, one of the most feasible and cost effective solutions to this practical need is to estimate arterial travel time based on roadway geometry (e.g. link length), signal settings (e.g. timing plan), and traffic sensor measurements (e.g. volume and occupancy).

With the growing deployment of Advanced Traffic Management Systems (ATMS), real-time traffic signal control data and traffic flow data have become increasingly available for research in the Puget Sound region. However, conventional applications of the Highway Capacity Manual (HCM) approach (TRB, 2000) have resulted in inconsistent results when compared to the travel time estimates of other

methods (Zhang, 1999 and Tsekeris and Skabardonis, 2004). This implies that further research efforts are needed in methodology development for improved estimates of arterial travel time. Similar to travel time estimation, travel time prediction is also challenging due to the fact that arterial traffic usually fluctuates tremendously compared with non-interrupted traffic flow. A new arterial online system is desirable to provide users with real-time information. A user-friendly online tool capable of interacting with users for Origin – Destination (OD) input and departure time input for automatically identifying the shortest travel-time route is highly desired. Due to some practical challenges, most current network-level travel time estimation and prediction algorithms have not been implemented online.

However, an ideal real-time online arterial network system has several requirements, including responsiveness to queries, system flexibility, scalability, and real-time computing. Several challenges for such systems are discussed below.

1. Traffic prediction

Traffic status changes dynamically with some randomness. In addition to the reliability and accuracy of short-term traffic prediction, most prediction algorithms require high computational power and are not suitable to implement in a real-time system. Most decision making processes, e.g. shortest path routing estimation, require smoothing and prediction processes for the detector measurements, e.g. volume or speeds.

2. Inconsistent data connections

There are several ways to transmit real-time data between the data providers and clients. For example, the Washington State Department of Transportation (WSDOT) adopts Simple Object Access Protocol (SOAP) to disseminate real time incident Extensible Markup Language (XML) data. The City of Bellevue, WA, archives traffic data as flat files in the data server and the public can fetch the data via File Transfer Protocol (FTP). Regardless of data transmission methods, the data could be missing while being transmitted from the on-site sensors to the Traffic Management Center (TMC). It is often observed in practice that communication fails periodically.

3. Data quality control

A data quality control procedure is a key to provide accurate results. Some erroneous data should be removed. For example, loop detectors generally have sensitivity errors (Cheevarunothai, 2006), resulting in incorrect detection readings. Moreover, speed estimation should be corrected in the situations where occupancy or volume is zero. These erroneous data could be discarded; meanwhile, more data would be lost.

4. Query performance

Arterial networks usually contain hundreds of roadway links and intersections. With the improvement of ITS data collection infrastructure, huge amounts of data are transmitted to the data warehouse. The key to improving query performance is an efficient database design

5. Computational limitation

Calculating statistics and algorithm implementation require computational power. If the computation burden is only on the server side, server performance will be impacted. Arterial networks usually have many links and nodes (intersections) with a large amount of data to process. Distributed computing can mitigate resource problems and should be considered in the system design.

1.4 Research Objectives

This research aims to develop the algorithms for arterial travel-time estimation and prediction based on the loop detector data. A time dependent shortest path algorithm is developed based on the A* algorithm by Hart et al. (1968). To effectively analyze and disseminate the arterial network information to decision makers, traffic engineers and researchers, this study aims to overcome the aforementioned critical issues and develop a web-based Real-time Analysis and Decision-making for ARterial Network (RADAR Net) system based on the previous online Google-Map-Based Arterial Information (GATI) system developed by Wu *et al.*, (2007) and Wu and Wang (2009) at the Smart Transportation Applications and Research Laboratory (STAR Lab) of the University of Washington (UW).

Specifically, this study has the following objectives:

- Design an algorithm for arterial travel time estimation using existing loop detector data;
- Develop a travel time prediction approach to improving robustness and accuracy of travel time estimates;
- Revise the A* shortest path algorithm developed by Hart et al. (1968) for shortest travel-time path identification; and
- Implement travel time calculations and travel routing in a web-based Real-time Analysis and Decision-making for ARterial Network (RADAR Net) system.

Chapter 2 Literature Review

This study mainly aims to develop an approach to predicting travel time. Due to the difficulties in retrieving network-level travel time data, travel time estimations using existing sensors in the network needs to be conducted before network-level travel time prediction. Travel time prediction and estimation are two major fields with different attentions from traffic experts and are reviewed separately in this section.

2.1 Travel Time Estimation

Most previous studies on roadway travel time estimation are for facilities with uninterrupted flows. Examples of these studies are Coifman (2002, 2007), Nanthwwichit (2003), and Wei (2007). However, results of these studies may not be directly applicable to arterials with at grade intersections where traffic movements are interrupted. For urban arterials, travel time estimation is much more challenging than that for freeways because of the uncertainties associated with signalized intersections. As summarized by Park and Lee (2004), existing approaches for estimating arterial link travel time include regression analysis, moving average and time series analysis, data fusion, fuzzy control theory, cellular automata theory, and microscopic traffic simulations. However, most of the approaches require costly GPS data.

The delay-based travel time estimation model developed by Geroliminis and Skabardonis (2006) is able to estimate the travel time on a signalized arterial in real-time based on data (flow volume and occupancy) provided by system loop detectors and signal settings (cycle length, green times and offsets). Their algorithm was implemented in the Arterial Performance Measurement System (APeMS), an ongoing research project at the University of California (Berkeley) that aims to build an online arterial performance measurement system for signalized arterials.

Link journey speed (or link speed) is a more comprehensive and useful MOE which allows engineers to intuitively compare the performance on the same or different links whereas the link travel time is suitable for only comparing the performance on the same route or link. Provided the length of each link on an arterial, the arterial link travel time can be easily estimated using the average link speed.

Average link speed or travel time can be modeled using the volume and/or occupancy data retrieved from the loop detectors. Such speed/travel time modeling approaches include linear (Turner et al., 1996), non-linear (Zhang, 1999), Bayesian (Frechette and Khan, 1998, and Park and Lee, 2004) and K-Nearest Neighbor (KNN) (Robinson and Polak, 2005). Some studies (e.g. Geroliminis and Skabardonis, 2008) have derived delay models in which the travel time is equivalent to free-flow travel time plus the delay caused by external factors, such as traffic control or interaction between vehicles. Some researchers specifically focused on the control delay estimation because control delays are the major contributors to arterial delays. (e.g. Engelbrecht, 1997; Fambro and Roupail, 1997 ; Sharma et al 2007; Zheng et al. 2009; Ban et al. 2009).

Overall, arterial travel time and speed estimation research can be categorized into three levels: microscopic, mesoscopic and macroscopic. The microscopic models estimate/predict travel times based on high-resolution second-by-second data or cycle-by-cycle data (Liu and Ma, 2009; Li, 2009; Zheng et al., 2009; Skabardonis and Geroliminis, 2008). Even though these techniques can effectively capture the fluctuations of traffic, they may not be suitable for practical implementation and require higher data capacity from the supporting infrastructure, resulting in higher costs. As for the macroscopic models, the well-known Bureau of Public Roads (BPR) model (BPR, 1964) has been utilized by many planning agencies for decades. Recently, Tarko et al. (2006) proposed a simple macroscopic model for predicting link speeds on urban streets. This model is derived from the HCM-based delay model and does not require information of traffic signal timing. However, it does require volume information from side streets crossing the main road. Due to coarse data output, macroscopic models may not be suitable for the advanced transportation management systems (ATMS) and advanced traveler information systems (ATIS) applications which require timely updates.

In order to combine the benefits of microscopic and macroscopic models, mesoscopic models, a level between microscopic and macroscopic, have been gaining researchers' attention (Gault and Taylor, 1977) (Sisiopiku and Roupail, 1994) (Zhang, 1999) (Xie et al, 2001). This type of model is commonly used for short-term performance measurement in arterial networks at a level suitable for ATIS and ATMS usage. In the past decades, several regression-based travel speed models have been

developed, such as British model (Gault and Taylor, 1977), Illinois model (Sisiopiku and Roupail, 1994) and Iowa model (Zhang, 1999). After reviewing these link speed models, Xie et al (2001) proposed a calibration-free, HCM-based Singapore model that only requires the detector and signal outputs. These authors showed that the Iowa model has the best performance among these models but the Singapore model provides satisfactory results without calibration efforts. Nevertheless, the Singapore model requires data from both system and advance detectors while the Iowa model only requires data from advance detectors. Most existing infrastructure only has advance detectors, usually located about 100 feet (30.48 m) from the stop bar. Hence, it is more desirable to develop a more generalized approach that only uses the advance detector outputs to estimate link speed.

Therefore, most existing arterial travel time models require knowledge of the traffic signal timing plans implemented on the network (Ban et al., 2009). It would be cumbersome to retrieve either current or historical signal timing data, especially for actuated or adaptive signal control. It is desirable to develop a simple yet effective approach to estimating link speed using the advance loop detector data without the knowledge of signal timing.

2.2 Travel Time Prediction

Travel time is a time-dependent variable. Simply estimating travel time based on the current conditions may not be sufficiently accurate because temporal fluctuation related factors are not taken into account. Yang (2007) predicted arterial travel time using a discrete Kalman filter based on GPS data. As mentioned earlier, GPS data are expensive to collect and are not available from most current roadway users. Liu et. al., (2006) proposed an State-Space Neural Networks (SSNN) and an Extended Kalman Filter (EKF) hybrid model for travel time prediction. Singh (2007) further revised this model and take more variables, such as signal control parameters and geometrics of the arterial, into account. Nevertheless, these studies have not been widely tested nor have the models been implemented in any online traveler information system.

As mentioned in the “travel time estimation” section (Section 2.1), the arterial link travel time can be easily estimated using the average link speed given the length of

each link on an arterial. Hence, speed prediction is an alternative way of travel time prediction. Many speed prediction models are developed and implemented online, such as the probability-based model by Lin et al (2004) and the knowledge-based model by Lee et al (2009). However, these models require many inputs, such as signal timing plans. Moreover, a real-time system requires quick response and low computational cost. A dynamic traffic parameter prediction is suitable for our real-time application. Dynamic filtering techniques can not only smooth the real-time data suffering from the random errors but also predict the data in the next state. Among dynamic filtering techniques, the Kalman filter (Kalman, 1960) has gained attention from system designers because this filter provides high accuracy in prediction and many research projects have demonstrated robustness and reliability for short-term traffic prediction in freeway speeds (Guo et al, 2009, Yang et al., 2004), freeway travel time (Zhang and Rice, 2003), arterial travel time (Liu, et al, 2006) applications. Recently, Guo et al. (2009) proposed a Kalman filter-based method to predict freeway speed using single loop detector data. The results showed the effectiveness of Kalman filter in speed prediction. Therefore, our research will adopt the similar idea and provide a suitable prediction algorithm for a real-time urban network travel time system.

Chapter 3 Data Collection Site Description

This study uses two data sources from two cities: the City of Bellevue and the City of Lynnwood. The traffic data retrieved from the City of Bellevue is mainly used for network travel time estimation and prediction because the minute-by-minute aggregated data can be collected in real-time from loop detectors from the entire city network. In the City of Lynnwood, the data collection unit designed by the research team is capable of capturing real-time second-by-second event traffic data for the entire intersection to facilitate the control delay calculation process. This unit has been instrumented on the experimental site (the SR 99 and 196th Street intersection) for data collection and archival since June 2009.

3.1 City of Bellevue

As of June 2010, there are 603 advance detectors in use to collect cycle-by-cycle volume and occupancy data and push the data back to the traffic management center (TMC) in real-time. In terms of travel time estimation algorithm development, the central business district (CBD) of the City of Bellevue is selected as the test bed for simulation model development. After the algorithm is verified, the travel time estimation and prediction algorithms will be implemented for the entire city network.

The test bed represents a typical city roadway network where each roadway link is equipped with loop detectors in a standard configuration, including one set of advance detectors and presence detectors. Each advance detector is approximately located 100 (30.48 m) ~120 ft (36.58m) from the stop bar. All the data are stored in a File Transfer Protocol (FTP) data server and are downloaded automatically into the DRIVE Net arterial database every minute. More details of the data retrieval process can be founded in (Wu and Wang 2009; Wu et al, 2007). The intersections with real-time data are displayed in the traffic light icons in Figure 3-1. As of July 15th 2010, real-time traffic data from 706 loop detectors are sent data back to Bellevue's TMC.

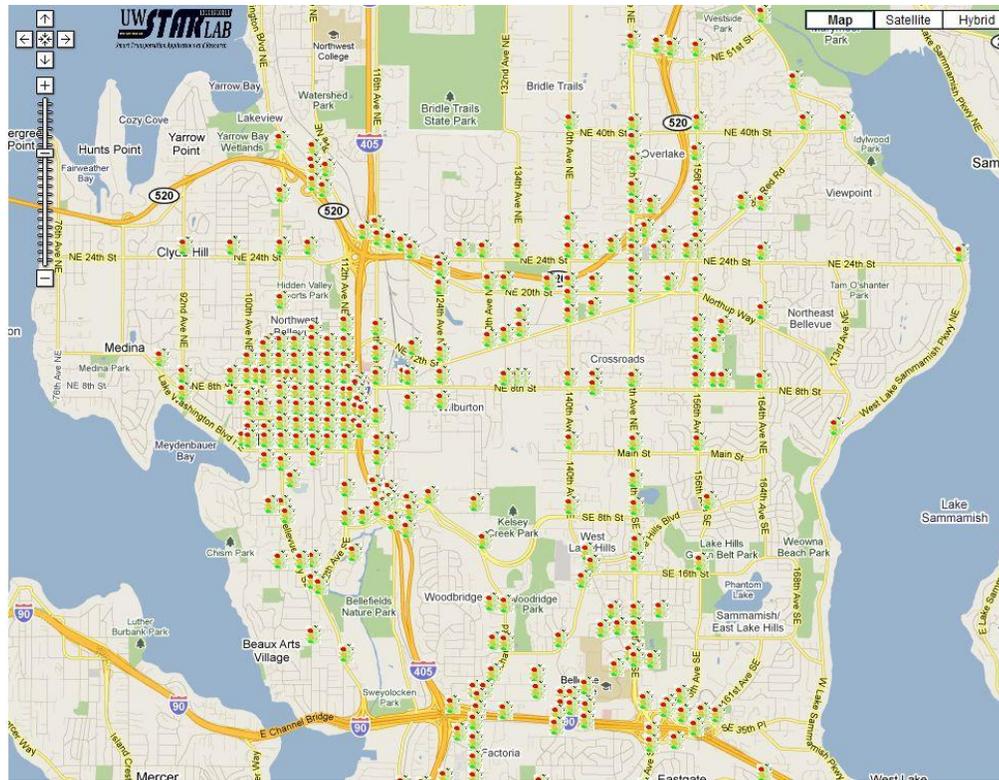


Figure 3-1: Study arterial network in the City of Bellevue, WA

3.2 City of Lynnwood

The study also explored the possibility of using an input/output (I/O) device to tap the cabinet signal to retrieve the real-time second-by-second event data. The original idea was from the Advanced Loop Event Data Analyzer (ALEDA) system (Cheevarunothai et al. 2007; Cheevarunothai et al. 2005) developed in the STAR Lab. The ALEDA was originally developed for freeway loop event data collection. The research team further improved the ALEDA system to fit the need for data collection at signalized intersections.

3.2.1 Data Collection System

The intersection data collection system developed in this study is able to collect real-time high-resolution detector-event data from traffic control cabinets. As shown in Figure 3-2, the system mainly relies on an Ethernet I/O device that collects high-resolution event data from the back panel of the cabinet and transmits the data to the TMC through fiber optics in real time. The event data includes voltages changes in traffic signal lights and traffic

sensors. They are stored in binary format in a Microsoft SQL Server database hosted at the STAR Lab. The system architecture is depicted in Figure 3-2.

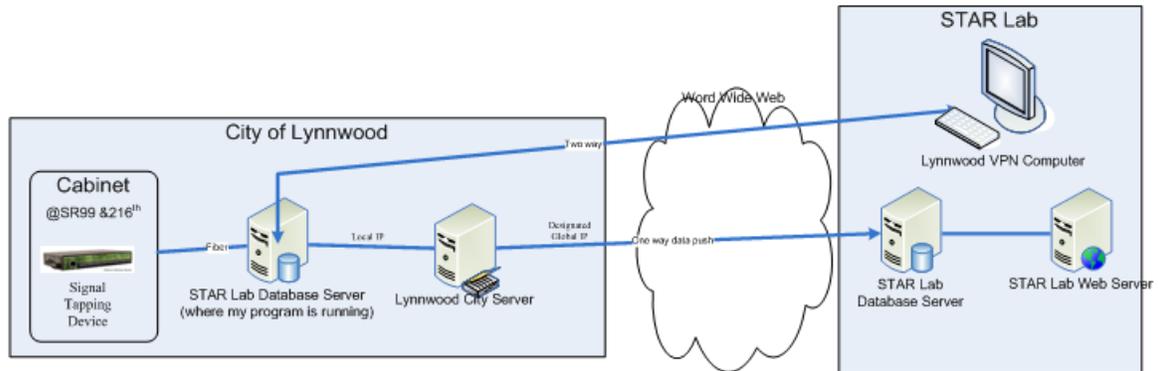
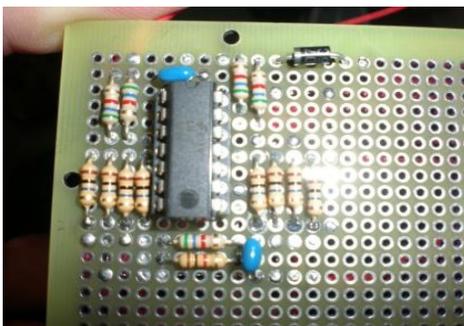


Figure 3-2: Data collection system architecture

One challenging issue encountered during the development stage was the voltage changes caused by the commercial I/O device that led to abnormal traffic light operations. The research team successfully solved the problem by adding a comparator circuit board that effectively separated the cabinet's electronics from the I/O device. As shown in Figure 3-3(a), each comparator can handle six channels of signals. The data collection unit consists of an I/O device, a protection circuit board and an enclosure as shown in Figure 3-3(b).



(a)



(b)

Figure 3-3: The data collection equipment: (a) Protection circuit, and (b) data collection unit (one set)

3.2.2 Field Installation

The data collection unit has been installed and safely operating at the intersection of SR 99 and 196th Street in Lynnwood since June 2009. Prior to field installation, the data collection unit had been tested in the Lynnwood signal workshop for a month to ensure that it is reliable and safe to put in the cabinet.

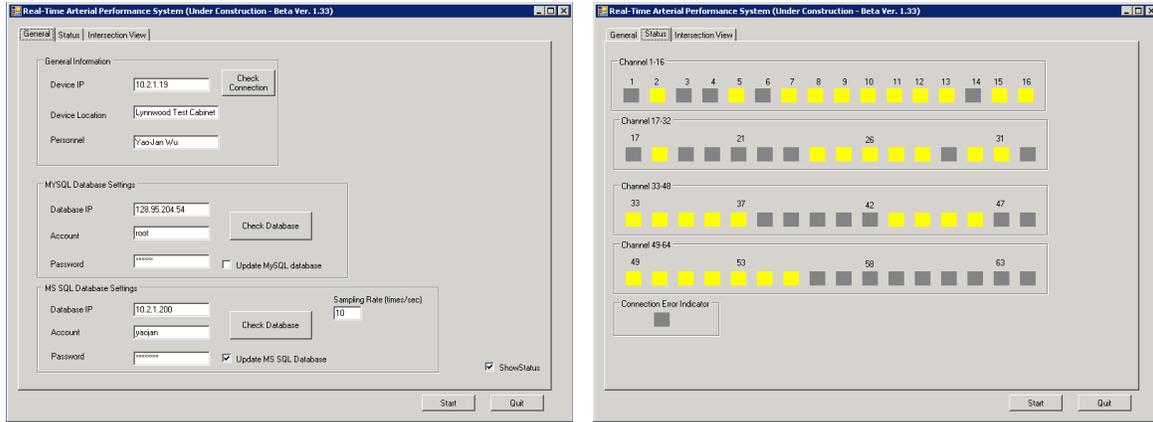


Figure 3-4: Field installation. (a) Discussion with traffic professionals, (b) Before the equipment was installed, (c) All channels being tapped are connected, and (d) the equipment is successfully installed.

3.2.3 Software Development

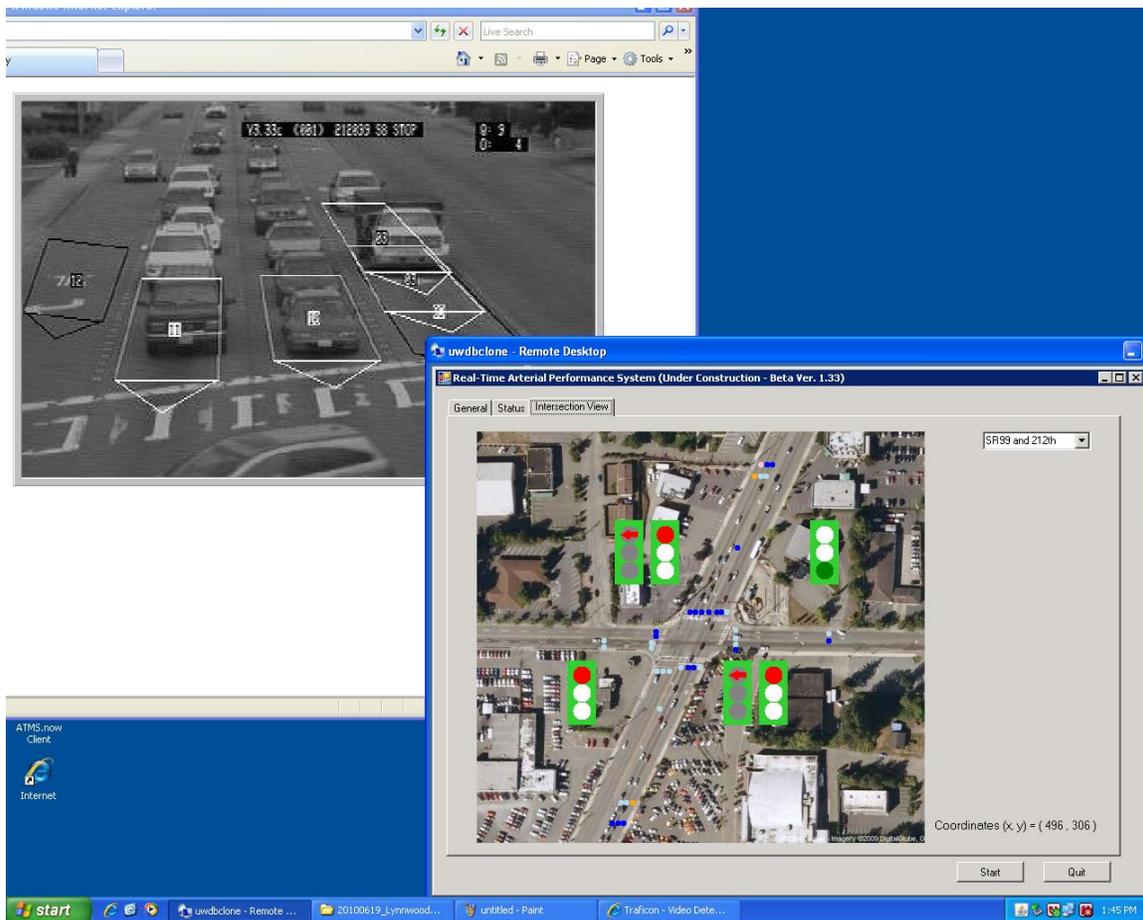
Our intersection data collection system also includes an intersection performance measurement module that visually illustrates real-time status of traffic signal lights and detectors at the intersection. Figure 3-5(a) shows the configuration interface. Figure 3-5(b) shows the status of each signal. Figure 3-5(c) shows the verification process with the detector and traffic signal statuses visualized by a computer program for comparison with real-time traffic video.

The proposed system has proven its capability to stably collect high-resolution data from a traditional cabinet and has a great potential to be used for real-time intersection performance measurement. The offline version the performance measurement system can be found in (Zheng et al, 2009).



(a)

(b)



(c)

Figure 3-5: Software development: (a) Main interface, (b) signal status, and (c) visualization and verification

Chapter 4 Link Travel Speed Estimation

Link travel time estimation requires a large amount of ground truth travel time data. However, collecting ground truth travel time is costly and time consuming. Hence, simulation-based investigation provides a cost-effective, risk-free, and prospective means for exploring the feasibility and applicability of various system design, deployment, and operational strategies. In this study, a VISSIM-based simulation model will be built to simulate traffic operations for an arterial network. With the developed simulation platform, the travel time estimation algorithm can be developed and its effectiveness can be verified.

4.1 Simulation Modeling

4.1.1 Test Bed

The central business district (CBD) area in the City of Bellevue, WA is selected as our test bed for simulation model development. As shown in Figure 4-1, both directions of two major corridors of the network, 112th AVE and 8th Street, are selected as our test corridors. 8th Street is a major east-west corridor connecting Interstate 405 and Bellevue Way. 112th AVE is a north-south arterial that serves as the alternative route for I-405 and Bellevue Way. It usually carries less traffic than 8th Street. Compared with 112th AVE, 8th Street has complicated traffic characteristics and also serves a major corridor for most transit services. Moreover, the intersection approaches on 8th Street have a variety of lane layouts, e.g. dedicated right/left turn lanes and links on 8th Street have more side streets along the corridor. Hence, these factors may cause more weaving traffic and more likely to result in erroneous detection, such as missing counts, from the detectors located in the through lanes. Another challenging part is that both corridors run semi-actuated coordinated control with a cycle length of 140 seconds but variable green time allocations. Additionally, different signal timing plans are used during different times of day in response to traffic demand changes.

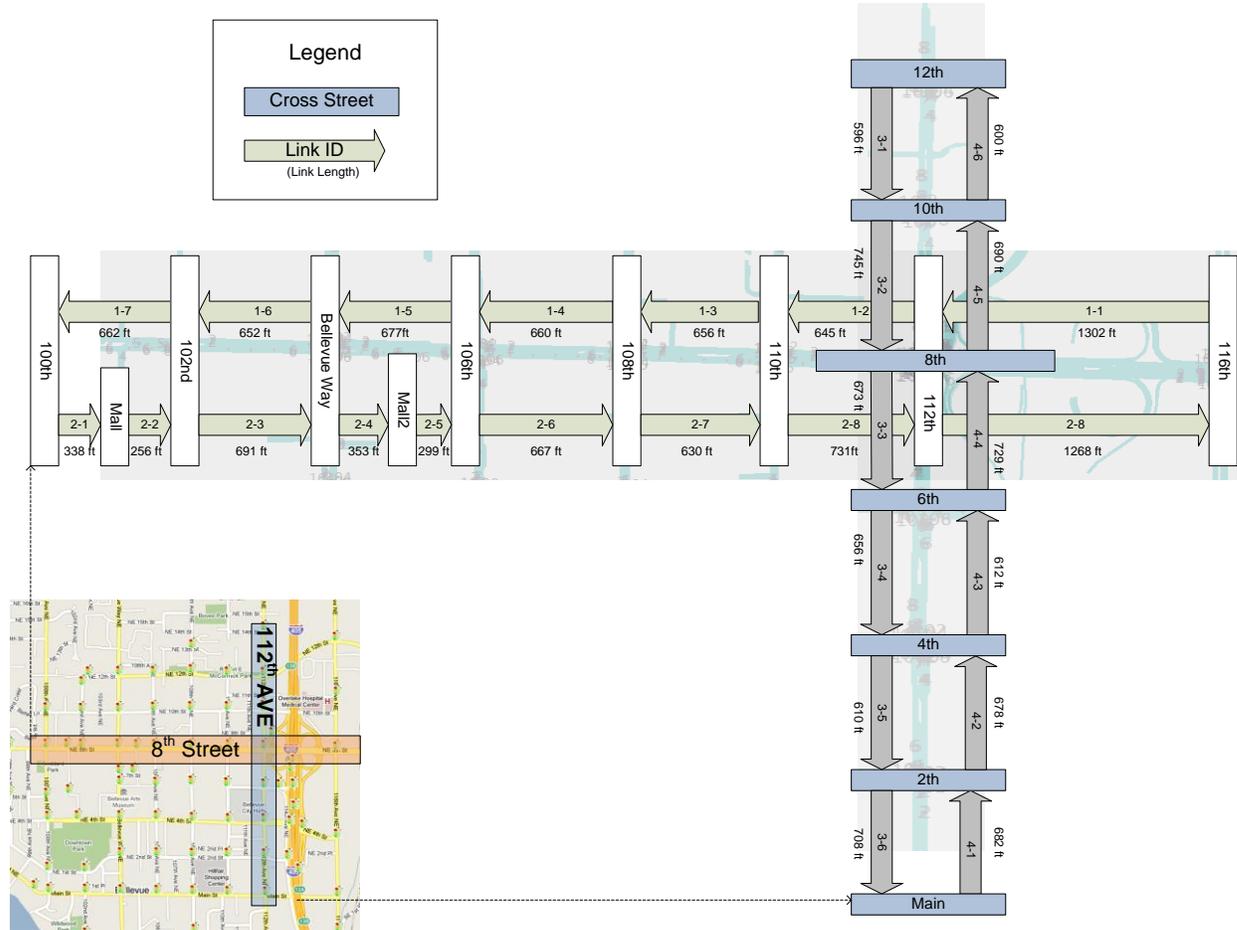


Figure 4-1: Two study corridors, 112th AVE and 8th Street, in the CBD area of Bellevue, WA.

4.1.2 Simulation Model

Many traffic simulation software packages have been developed for intelligent transportation systems (ITS) application evaluation and verification. In this study, VISSIM 5.2 is used to model the entire test bed. VISSIM is one of the microscopic behavior-based traffic simulation software packages that can simulate and analyze traffic operations under a board range of scenarios. Moreover, it is also useful for collecting the MOEs to evaluate various alternatives under consideration. In VISSIM, driver behaviors are modeled following the work published by Wiedemann (1974 and 1991). Individual vehicle behaviors can be simulated independently. Many simulation studies have been conducted using VISSIM. Gomes et al. (2004) developed and calibrated a VISSIM model

for simulating a congested freeway. Moen et al. (2000), Bloomberg and Dale (2000), and Tian et al. (2002) investigated the performance of VISSIM by comparing it to CORSIM, a traffic simulator developed by Federal Highway Administration (FHWA). They concluded that VISSIM performed favorably. Park and Schneeberger (2003) also showed the effectiveness of VISSIM to simulate the coordinated actuated signal system.

The simulation model of the CBD area is provided and calibrated by the City of Bellevue. The model is designed for afternoon peak hours and calibrated using the ground truth volume count data collected during 2009~2010. The model was calibrated following the calibration procedure developed by Dowling *et al.* (2004). Below is the summary of the calibration process applied to this simulation model.

- The simulation mode was calibrated with field travel time data. Probe vehicles ran 10 times on seven major corridors during afternoon peak hours. The hourly travel time errors are less than one minute.
- The turning movement count error is within 5% for critical intersections.
- Hourly volume was converted to the GEH statistics indicated by the FHWA standard. 95% of the links has GEH statistic <1 , showing that the model meets the requirement.

4.1.3 Datasets

The final goal of travel time estimation is to use the data from the advance detector and estimate link speed. To capture the speed data while the vehicles are crossing over the advance detectors, the data detection points (in VISSIM) are placed on those advance detectors in all through lanes at each intersection approach for each link. As for link travel time collection, the definition of link by Zhang (1999) is adopted. The definition of link is “a section of road spanning from the exit corner of one intersection to the exit corner to the immediate downstream intersection.” The ground truth link speed is calculated as

$$S_J(t) = \frac{L_k}{TT(t)} \quad (4-1)$$

where L_k is the link length for Link k and $TT(t)$ is the ground truth link travel time for time interval, t . The link travel time should be composed of cruise time and signal delay (Xie et al, 2001).

Both loop data calculated speed and travel time data are collected every cycle. It was found that cycle-based data can adequately capture the average impact of each link for each cycle and can be easily aggregated based on a specified period. Three data sets, Dataset 1, Dataset 2, and Dataset 3, were generated using different simulation random seeds. Dataset 1 is generated by only one simulation run (50 cycles after 30 minute warm-up period). The second and third datasets were generated by 10 simulation runs (500 cycles). Datasets 1 and 2 are used for model calibration process whereas Dataset 3 is used for model verification process in the Evaluation section.

4.2 Link Speed Estimation

In order to estimate the link speed using single loop detector outputs, we propose a two-step empirical approach. The first step is to calculate the spot speed based on a traditional estimation model with an aid of a speed conversion procedure. The second step is to develop a simplified link speed estimation model only based on the input of spot speed measured at advance loop detectors.

4.2.1 Loop-data-based Spot Speed Estimation

The Athol's speed estimation formula (Athol, 1965), also called the g -factor approach, is used to calculate the spot speed at the advance detector locations. This approach has been widely used in the freeway (Wang and Nihan, 2000, 2003) and arterial speed estimation (Zhang, 1999). The loop spot speed for time interval t is defined as

$$S_L(t) = \frac{N(t)}{T \cdot o(t) \cdot g(t)} \quad (4-2)$$

where, t is time interval index, N is interval traffic volume, o is occupancy (percentage of time a loop is occupied by vehicles per interval), T is the time length per interval; L is the mean effective vehicle length; and g is the speed estimation parameter (often called g -factor) determined by the effective vehicle length. L and g are related by $g(t) = 1/L(t)$. In practice, however, g is considered constant assuming the traffic composition does not change temporally and spatially. For example, the WSDOT uses $g=2.4$ for their freeway applications (Ishimaru and Hallenbeck, 1999). For arterial applications, Zhang (1999) used a constant effective length of 20 ft to determine $g=2.63$ assuming traffic is only composed of passenger cars. On our study corridors, g is mostly affected by the buses and rarely by trucks. It is assumed that g is only site dependent to simplify the estimation process. After removing the time dimension of g , Equation (4-2) is re-defined as

$$S_L(t) = \frac{q(t)}{o(t) \cdot g} \quad (4-3)$$

where $q(t)$ is the flow rate (veh/h) in time interval t . In this case, g is regarded as a site dependent constant that requires calibration. According to Equation (4-3), ground truth loop speed or the effective vehicle length is needed to accurately calibrate g . According to the empirical evidence found by Guo et al. (2009), the ground truth $S_L(t)$ measured from dual loop detectors follows a linear relationship with q/o ratio with an error term $\varepsilon(t)$ as follows

$$\frac{q(t)}{o(t)} = gS_L(t) + \varepsilon(t) \quad (4-4)$$

In Equation (4-4), the slope of the linear regression line is the g value and this line should pass through the origin. The linear model in Equation (4-4) can be easily solved if the ground truth $S_L(t)$ is known. For freeway loop detectors, the ground truth spot speed can be retrieved from dual-loop detectors and used for model calibration (Guo, 2009). For arterial applications, dual loop detectors are rarely seen in practice. Alternatively, “instantaneous spot speed” data can be collected using speed guns while a vehicle is crossing over the loop detector (Dowling, 1996).

The average “instantaneous” spot speed, $S_I(t)$ for each time interval t is defined as:

$$S_I(t) = \frac{\sum_{n=1}^N u_n}{N(t)} \quad (4-5)$$

where u_n is the instantaneous spot speed of the n^{th} vehicle measured by a speed gun when the advance detector is initially occupied by the vehicle in time interval t , and $N(t)$ is the interval traffic volume.

Although speed estimated from single loop measurements is often regarded as “spot” or “point speed” in many previous studies (e.g, Han et al 2010; Zhang 1999), it is different from the spot speed in a strict academic perspective. The reason is that a loop detector has a physical length and its occupancy measurements correspond to a travel distance of the effective vehicle length. Speed measured by radar sensors can be regarded as spot speed (Dowling and Cheng, 1996). Essentially, average instantaneous speed, $S_I(t)$ and single loop data calculated speed $S_L(t)$ are not equal.

In order to explain the discrepancy between $S_I(t)$ and $S_L(t)$, an example is presented here. Assuming a vehicle is regarded as a particle traveling from the beginning of the loop detector toward the end of the detector. $S_I(t)$ can be regarded as the average speed when the particle is measured at the moment of entering the detector whereas the

$S_L(t)$ is the average mean speed while the particle is crossing over the entire link during time interval t . In other words, $S_L(t)$ is regarded as a special case of time mean speed (TMS) and $S_L(t)$ is regarded as a special case of space mean speed (SMS) when vehicles are traveling on a link with a length equivalent to the effective vehicle length, L . Based on the theoretical relationship between TMS and space mean speed (SMS) (Han et al 2010; Dowling and Cheng, 1996), TMS is always no lower than SMS as proposed by Wardrop [please see May, 1990] :

$$TMS = SMS + \frac{\sigma_{SMS}^2}{SMS} \quad (4-6)$$

where σ_{SMS}^2 is the variance of SMS. Time mean speed and space mean speed are identical when all vehicle speeds are equal. Their discrepancy increases with the increase of vehicle speed variance. Due to traffic signal impact, vehicle speeds observed by advance loops during a time period shall not be identical. This implies that the measured $S_I(t)$ should be always higher than $S_L(t)$. The discrepancy between $S_L(t)$ and $S_I(t)$ would be enlarged at the advance detectors where vehicles suffer from control delay. A speed conversion procedure is required to convert $S_I(t)$ to $S_L(t)$ for the calibration process in Equation (4-4).

4.2.2 Speed Conversion

Take Link 1-1 as an example, the relationship between q/o and instantaneous spot speed, $S_I(t)$, is illustrated in Figure 4-2(a) using Dataset 2. One can easily observe that the data points are located in two groups. The first group, as circled by a red dash-dot line, shows $S_I(t)$ has a linear relationship with q/o ratios. The second group, as circled by an orange dot line, does not show any relationship between $S_I(t)$ and q/o but it is found that these data points are with high occupancy. The cause of the second data group is that during a high congestion period, vehicles tend to occupy the loop detector for a long time and few

vehicles can pass the detector, resulting in low $S_L(t)$ while the average “instantaneous” speed, $S_I(t)$ for these passing vehicles could still remain higher than 10 mph, as indicated by data points at the bottom of Figure 4-2(a). Once the high-occupancy data points are removed, the linear relationship can be easily determined. Note that this linear relationship is consistent with the relationship between q/o and $S_L(t)$ except that the regression line does not pass the origin.

Locating g-factor Line

In the preliminary analysis, the threshold of occupancy =10% is used. Figure 4-2(b) shows the data points with occupancy lower than this 10% threshold. An ordinary least square technique (Faraway, 2005) is applied to retrieve this linear relationship between $S_I(t)$ and q/o . As expected, the linear regression line does not pass the origin. It is reasonable that $S_I(t)$, theoretically, should be higher than zero because the speed gun measures a vehicle speed sample at the moment when it is crossing over the advance detector.

In order to re-construct the linear relationship as identified by Equation (4-4), it is assumed that the radar gun reading should be identical to the loop measurement as vehicles are crossing a short distance at a very high speed. In other words, vehicles tend to keep constant speeds as they are passing over a loop detector with a fast speed. Thus, it is assumed that $S_I(t)$ and $S_L(t)$ are equal when the average vehicle speeds reach a speed limit (30 mph used on our study routes). Figure 4-2(b) shows the regression line intersect with the vertical black arrow line when speed limit = 30mph. The solid black line passing through the origin and the intersection is the g -factor line. The slope of the g -factor line is the g being calibrated in Equation (4) for this specific location.

Remedies for Incorrect Occupancy Thresholding.

Least squares regression performs favorably if the errors are normally distributed (Faraway, 2005). Unfortunately, the occupancy threshold is not always constant. A fixed occupancy threshold may not exclude all high occupancy data points. As observed in our datasets, the occupancy threshold values are site dependent. Setting inadequate

occupancy thresholds may result in more “noise” or outliers. Figure 4-2(c) demonstrates the data points when occupancy threshold =30% is applied. In this case, traditional ordinary linear regression suffers from the outliers, resulting in a biased g -factor line. Hence, the robust linear regression technique is adopted. In this research, the linear regression technique adopts iteratively reweighted least squares with a bi-square weighting function (Holland et al, 1977). Figure 4-2(c) shows the result of robust regression in a green dashed g -factor line, which is robust to the outliers (high occupancy data points).

Another remedy for outliers is to determine the threshold based on the percentile of the q/o ratios. In this study, the 30th percentile is used to capture enough high q/o ratio samples for regression analysis. Table 5-1 shows the g -factor calibration results. All the g -factors are smaller than 2.63, meaning the average vehicle length is longer than 20 ft. Columns (1) and (2) show the calibrated g -factors using Datasets 1 and 2, respectively. Based on the paired two sample t -test (Hines, 2003), the g -factors calibrated by using different datasets are not significantly different at $p=5\%$ significance level (p -value = 0.40). Therefore, g -factors calibrated by Dataset 1 (50 cycles) are suitable for the following speed estimation process.

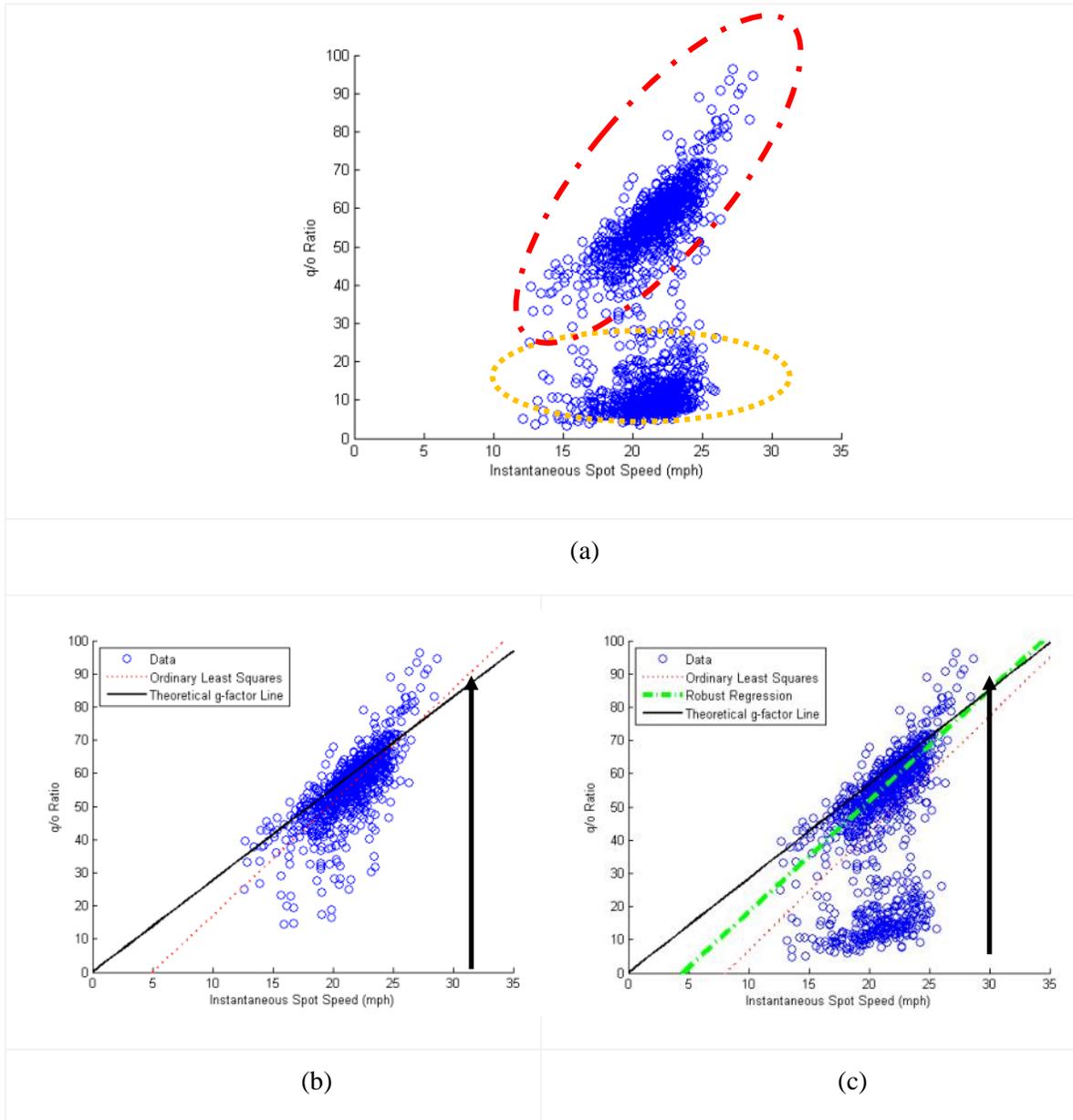


Figure 4-2: Example of Speed Conversion at Link 1-1 : (a) raw data comparisons between $S_l(t)$ and q/o , (b) filtered data when occupancy < 10%, and (c) the effect of robust regression when occupancy < 30%

4.2.3 Simplified Link Journey Speed Estimation Model

According to the Iowa Model proposed by Zhang (1999), the link journey speed is based on two types of speeds. The model is defined as

$$\hat{S}_J(t) = \gamma \hat{S}_{v/c}(t) + (1 - \gamma) \hat{S}'_L(t) \quad (4-7)$$

where $\hat{S}_J(t)$ is the estimated link journey speed for time interval t ; $\hat{S}'_L(t)$ estimates link journey speed based on the loop detector outputs and $\hat{S}_{v/c}(t)$ estimates link journey speed based on v/c ratio; and $0 \leq \gamma \leq 1$ = weigh factor depending on traffic congestion levels ($\gamma = 1$ for heavy traffic and $\gamma = 0$ for light traffic). $\hat{S}_{v/c}$ is defined as

$$\hat{S}_{v/c}(t) = S_F(t) - \alpha \exp(\beta \frac{v}{c}) \quad (4-8)$$

where S_F (free-flow speed), α and β are model parameters that require calibration, and \hat{S}'_L is given by

$$\hat{S}'_L(t) = 0.379 \frac{q(t)}{o(t)} \quad (4-9)$$

where the constant 0.379 is the reciprocal of its $g = 2.63$ assuming the effective vehicle length = 20 ft.

In order to verify the results, the g -factors calibrated by Dataset 2 are applied to itself to show the best result as possible. For all links on Route 4, \hat{S}_L is estimated using Equation (4-3) with calibrated g -factors. Figure 4-3(a) shows the relationship between the ground truth link speed S_j and estimated loop speed \hat{S}_L for 112 AVE (SB). To better visualize the data, the data are aggregated every 10 cycles. One can easily observe that \hat{S}_L tend to be overestimated when the ground truth link speed is high for each individual link. Compared with the speed estimation result in Zhang (1999) as shown in Figure 3(b), each link shows a trend of “overestimation.” This shows that our speed conversion procedure results in the similar outcome. Note that all the links in our research are non-homogenous because the signal timing and street layout are more complicated than previous research mentioned in literature review. Additionally, the links in our research are relatively shorter.

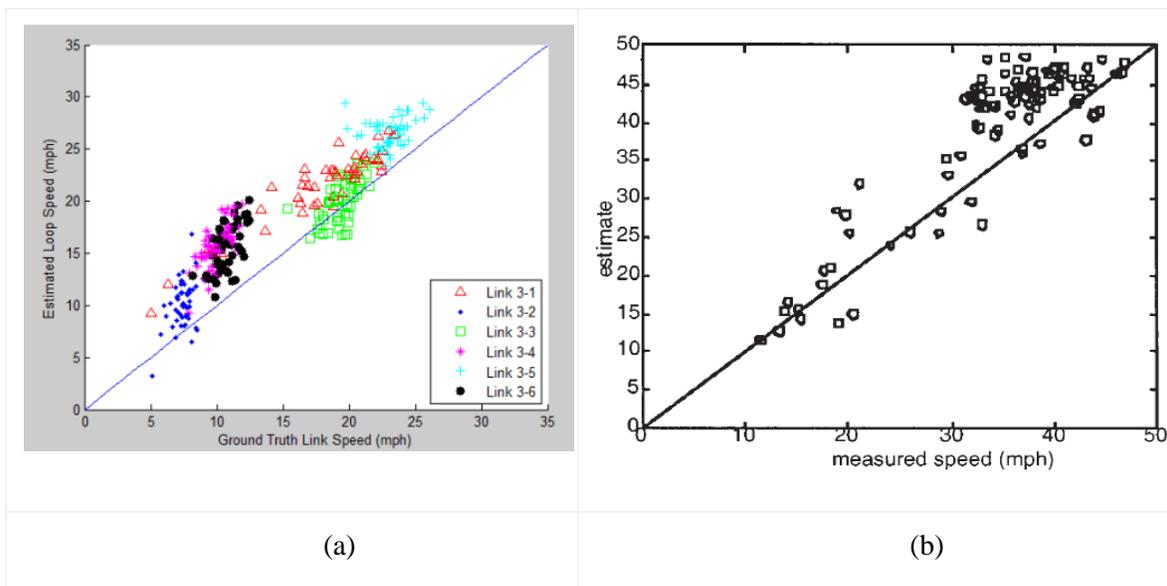


Figure 4-3: The relationship between estimated loop speed (\hat{S}_L) and measured speed (Ground truth link speed S_j) (1) Speed conversion results for 112 SB using Dataset 2 (Aggregated every 10 cycles) (2) Zhang’s results (1999)

To deal with the overestimation errors along with other associated errors, we propose a simplified speed estimation model using a nonlinear modeling approach (Ritz and Streibig, 2008) without the signal timing plan information. As observed in Figure 4-3(a), the loop speeds estimated by accurately calibrated g -factors are not able to be

representative of the entire link speed. The speed need to be “corrected” based on the characteristics of each link.

The proposed simplified link speed estimation model is based on Zhang’s approach. Equations (4-8) and (4-9) can be substitute into Equation (4-7). The estimated link journey speed $\hat{S}_j(t)$ model can be rearranged as

$$\hat{S}_j(t) = \underbrace{\gamma(S_F) + (1-\gamma)\hat{S}_L(t)}_{a\hat{S}_L(t)} - \underbrace{\gamma\alpha \exp(\beta \frac{v}{c})}_{\kappa \exp(b\hat{S}_L(t))} \quad (4-10)$$

The first two terms, free-flow speed and estimated loop speed in Equation (4-10) can be simplified as $\hat{S}_L(t)$ multiplied by the coefficient. The second term can be simplified as $\kappa \exp(b\hat{S}_L)$ assuming the effect of v/c ratio can be captured by \hat{S}_L . It is reasonable based on observations in the situations where traffic volume is high and ground truth link speed S_j is also high, most speed reduction may originate from resistances along the entire link instead of the delays caused by signal control. In this case, the speed measured from the advance loop is less likely to capture such delay.

In our experiments, it was found that including κ in Equation (4-10) does not always improve the modeling results. Hence, the speed estimation model is further simplified and formulated as:

$$\hat{S}_j(t) = a\hat{S}_L(t) - \exp(b\hat{S}_L(t)) + 1 \quad (4-11)$$

where a and b are coefficients that require calibration. The constant value, 1, allows the calibrated model to pass through the origin (0,0). In brief, the first term is to capture the effect of cruise speed and congestion, and the second term is used to reduce the effect of “overestimation“. The overestimation effect mainly results from the fact that the advance

detector can only capture the speed changes when the vehicles are approaching the intersection. When the measured speed is higher, it indicates that vehicles may suffer more from the intersection signal delay than the resistances between vehicles and link infrastructure. In this case, the volume on each link is usually relatively lower. This is why we can replace the v/c ratio with \hat{S}_L . In fact, $\hat{S}_L(t)$ cannot capture all the effects caused by different v/c ratios because the proposed model is designed to potentially estimate link journey speed for most signal control scenarios, especially for the coordinated semi-actuated control cases in our research. The introduced errors will be discussed in the 4.4 Model Evaluation section.

4.4 Evaluation

4.4.1 Measure of Accuracy

In this section, the robustness and transferability of the proposed approach will be evaluated. Three measures of accuracy, mean error (ME), mean absolute error (MAE) and root square mean error (RSME) are used in this study and defined as follows (Washington et al., 2003).

$$ME = \frac{\sum_{t=1}^n (F(t) - G(t))}{n} \quad (4-12)$$

$$MAE = \frac{\sum_{t=1}^n |F(t) - G(t)|}{n} \quad (4-13)$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^n (F(t) - G(t))^2}{n}} \quad (4-14)$$

where $G(t)$ is the ground truth link speed at time interval t ; $F(t)$ is the estimated (corrected) link speed at time interval t ; n is the total number of samples for verification. Estimation error is defined by the difference between $G(t)$ and $F(t)$.

ME shows the effectiveness of mitigating system errors. This measure shows how accurately the model can estimate despite its precision or lack of it. In terms of arterial performance, the link speed estimation is usually averaged over a specific route or link over a time period. In this case, random errors tend to be canceled out. Moreover, ME can show the “directions” of errors, including underestimation and overestimation. Unlike ME, MAE considers both random and system errors and shows how close the estimated link speeds are to the ground truth. RMSE is an appropriate measure of precision. RMSE measures the average magnitude of the error but penalizes large errors. The MAE and RMSE can be used jointly to determine the variation of the errors. The improvement percentage of the before and after study is calculated as

$$Improvement = \frac{B - A}{B} \times 100\% \quad (4-15)$$

where B is the before-statistic and A is the after-statistic.

4.4.2 Experimental Design

Two scenarios are designed for model verification. The first scenario is more ideal than the second one. In this case, the potential model users can decide how much effort is required to calibrate the model to the satisfactory level.

Scenario 1:

- Dataset 1 was used for g-factor calibration (Column (1) in Table 4-1). $\hat{S}_L(t)$ is calculated based on the calibrated g-factor for each individual link.

- The link speed estimation model was calibrated using Dataset 2 (500 cycles).

Scenario 2:

- A universal g -factor ($g=2.2$) calculated by randomly choosing one link from each route (Link 1-5, 2-5, 3-6, 4.4) is used for calculating \hat{S}_L .
- The link speed estimation model is calibrated using Dataset 1 (50 cycles). Note that cycle-by-cycle data are used to increase the sample size.

All the calibrated models are applied to Dataset 3. To better visualize the results, the data are aggregated every 10 cycles. The evaluation results are shown in Table 4-1. Figures 4-4 and 4-5 illustrate the visualization results of Scenarios 1 and 2, respectively. Left and right columns of Figures 4 and 5 are the results before and after link speed estimation, respectively. Visually, the proposed approach provides satisfactory results of estimating the link journey speed. The quantitative analysis is elaborated in the next section.

4.4.3 Discussion

Effect of g -factor

As expected, a universal g -factor ($g=2.2$) results in relatively high MAE, ME and RSME for every study route. As shown in Table 4-1, switching from using a specific g -factor for each link (Scenario 1) to using a universal g -factor (Scenario 2) increases MAE, ME and RSME by 21.14% (from 3.5mph to 4.24mph), 34.83%(from 2.64mph to 3.55mph) and 18.17%(from 4.10mph to 4.58mph), respectively. This is not surprising since a better calibration can be achieved if site specific data is used for the calibration at each location. The differences can be identified by visually comparing Figures 4-4(a), 4-4(c), 4-4(e) and 4-4(f) with Figures 4-5(a), 4-5 (c), 4-5 (e) and 4-5 (f), respectively.

Effectiveness of Speed Correction

The proposed link speed estimation model can be alternatively regarded as a link speed “correction” model because the model only considers one parameter, $\hat{S}_L(t)$ and improves the results of $\hat{S}_L(t)$. After applying the proposed link speed estimation model in Scenario 1, the MAE, ME and RSME of all study route average decrease by 73.97% (from 3.5mph to 0.91mph) , 99.38%(from 2.64mph to -0.02mph) and 70.01%(from 3.87mph to 1.16mph), respectively. For all the links, MEs are reduced to the range of [-0.47, 0.57].

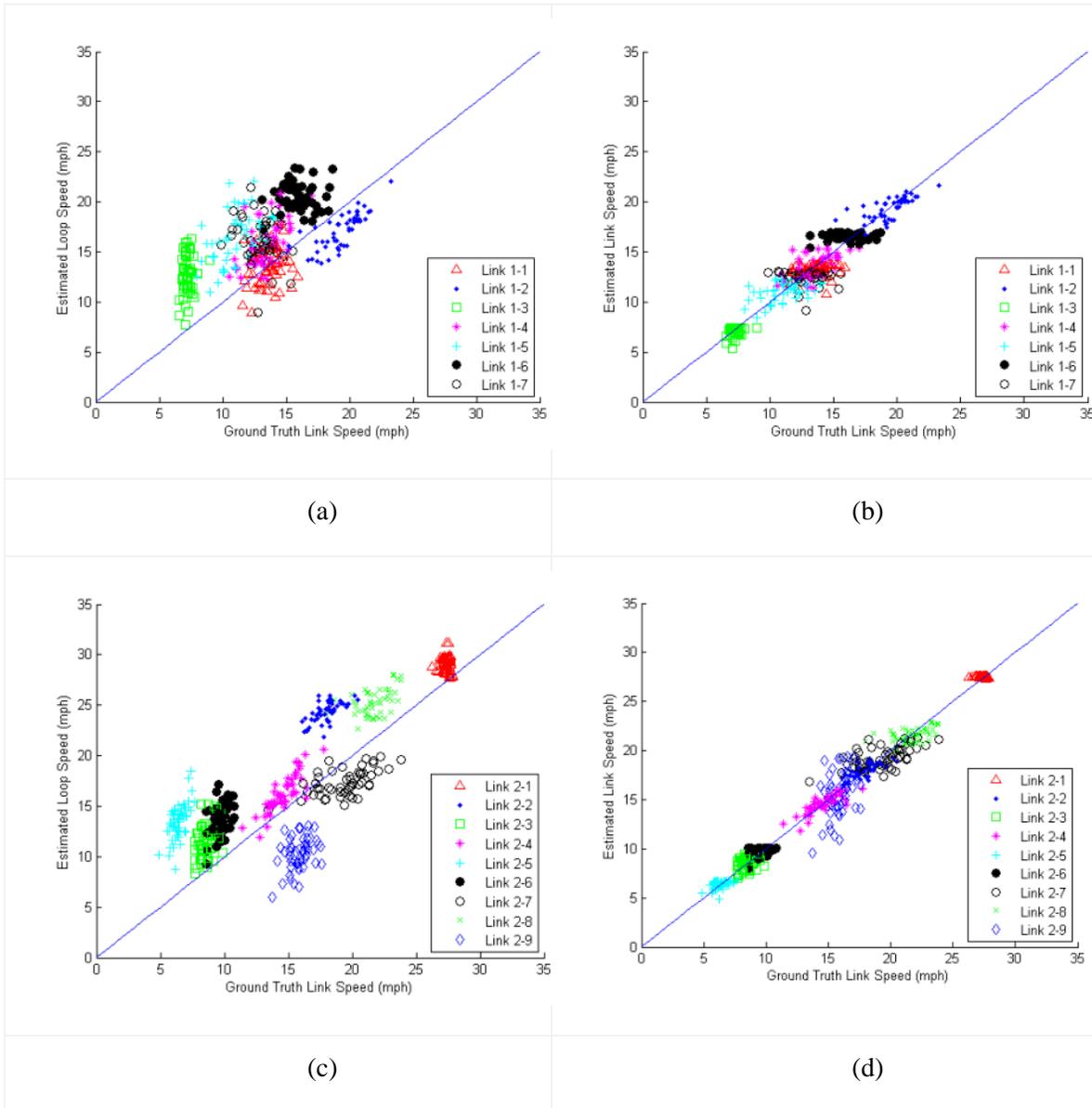
The results are very encouraging. In Scenario 2, even though $\hat{S}_L(t)$ estimation is slightly worse because of a universal g-factor and the link speed estimation model is calibrated using Dataset 1, a smaller dataset, the MAE, ME and RSME of all route average improve by 64.31% (from 4.24 to 1.51mph) , 65.47% (from 3.55mph to 1.23mph) and 59.99% (from 4.58mph to 1.83mph), respectively. This result indicates that the accuracy of link speed estimation can be significantly improved with relatively minor calibration efforts.

In both scenarios, the effectiveness of link speed estimation can be observed in every link. For example, Link 4-2 has a dramatic improvement in the MAE (from 9.20mph to 0.65mph in Scenario 1 and from 10.40mph to 1.19mph in Scenario 2), ME (from 9.20mph to 0mph in Scenario 1 and from 10.40mph to 1.07mph in Scenario 2) and RSME (from 9.45mph to 0.80mph in Scenario 1 and from 10.66mph to 1.38mph in Scenario 2), respectively. This result shows the proposed model can effectively reduce the variation of the errors. The same effectiveness can be observed in Links 2-2 and 2-5. The higher the error is, the more effective the correction will be.

Model Limitation

The model assumes the link journey speed would be overestimated and the effect will increase as the measured loop speed increases. This assumption constrains the correction effectiveness for those underestimated link journey speeds. The drawback brought by this constraint can be clearly found in Link 2-9. This link is a fairly challenging section since

this section begins with two through lanes and ends with three through lanes and two left turn lanes at the intersection approach. Additionally, this section also includes two on-ramps and one off-ramp. All these spatial factors are likely to result in inaccurate loop speed estimation. Nevertheless, the speed estimation model still can capture the underestimation effect by adopting a higher coefficient ($a=1.42$). However, coefficient ($b=-316.81$) in the speed reduction term fails to capture the exponential speed reduction effect. Even though Link 2-9 still has the highest RSME (2.15mph) among all links after link speed estimation, this result is still satisfactory for most applications. However, Link 2-9 performs less effectively in Scenario 2 with only minor improvement in MAE (from 5.94mph to 3.79mph), ME (-5.94 mph to 3.66mph) and RSME (from 6.12mph to 4.24mph). One can observe that the coefficient ($a=2.46$) for link speed estimation model is obviously overestimated and over-corrects the speeds. The same situation can be observed in Link 1-7. This might be because that Link 1-7 begins with two through lanes and ends with a two left-turn lanes, two through lanes and one right-turn lane. Hence, only minor speed correction is made in Scenario 2 according to MAE (from 3.71mph to 2.74mph), ME (3.37 mph to 2.48mph) and RSME (from 4.32mph to 3.07mph). Both examples show the drawback of using a small sample size while calibrating the speed estimation model for a roadway section with a complex geometric design. The corresponding results for Links 2-9 and 1-7 in Scenario 1 demonstrates the “correction” effect can be improved by increasing the sample size.



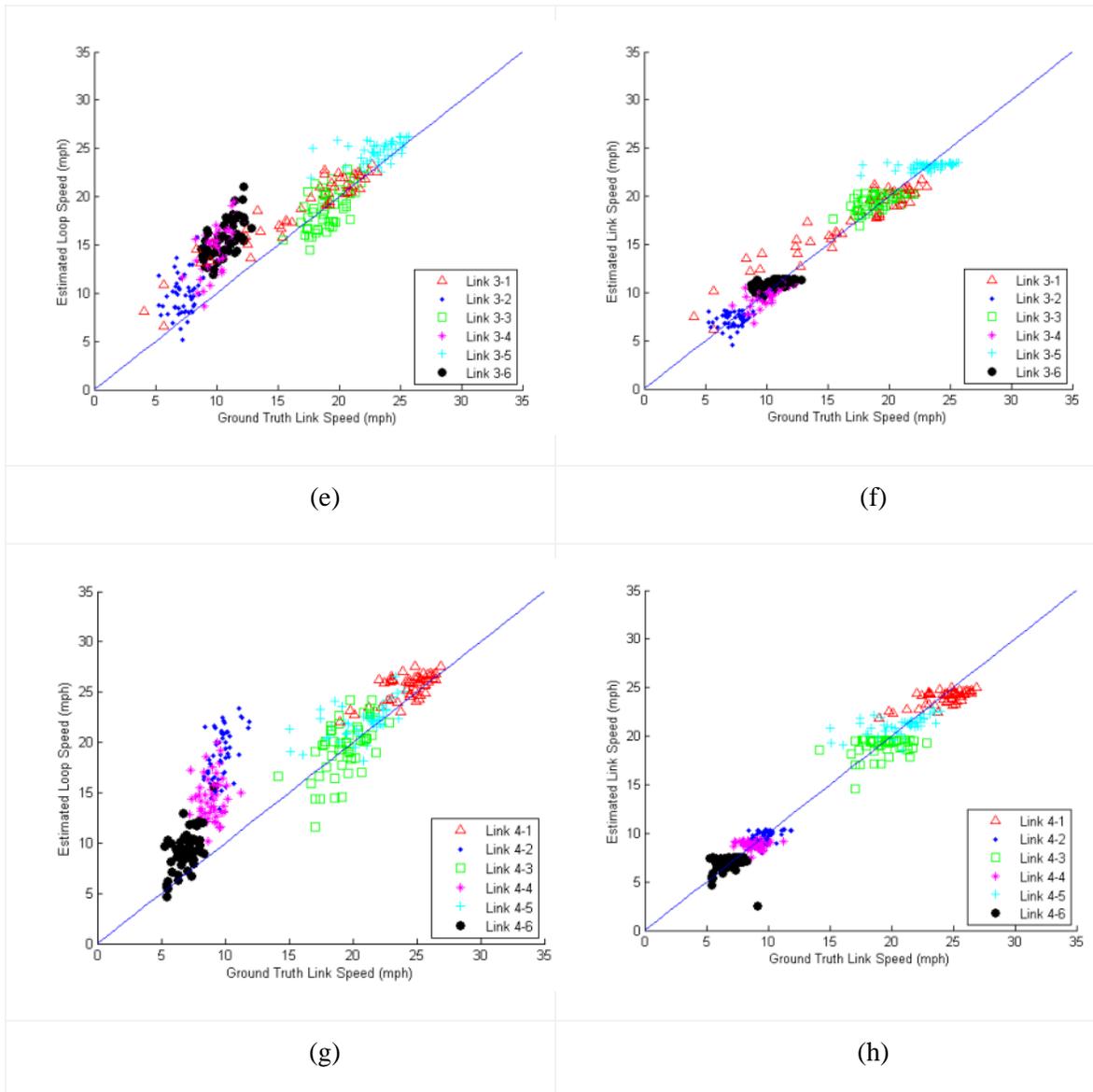
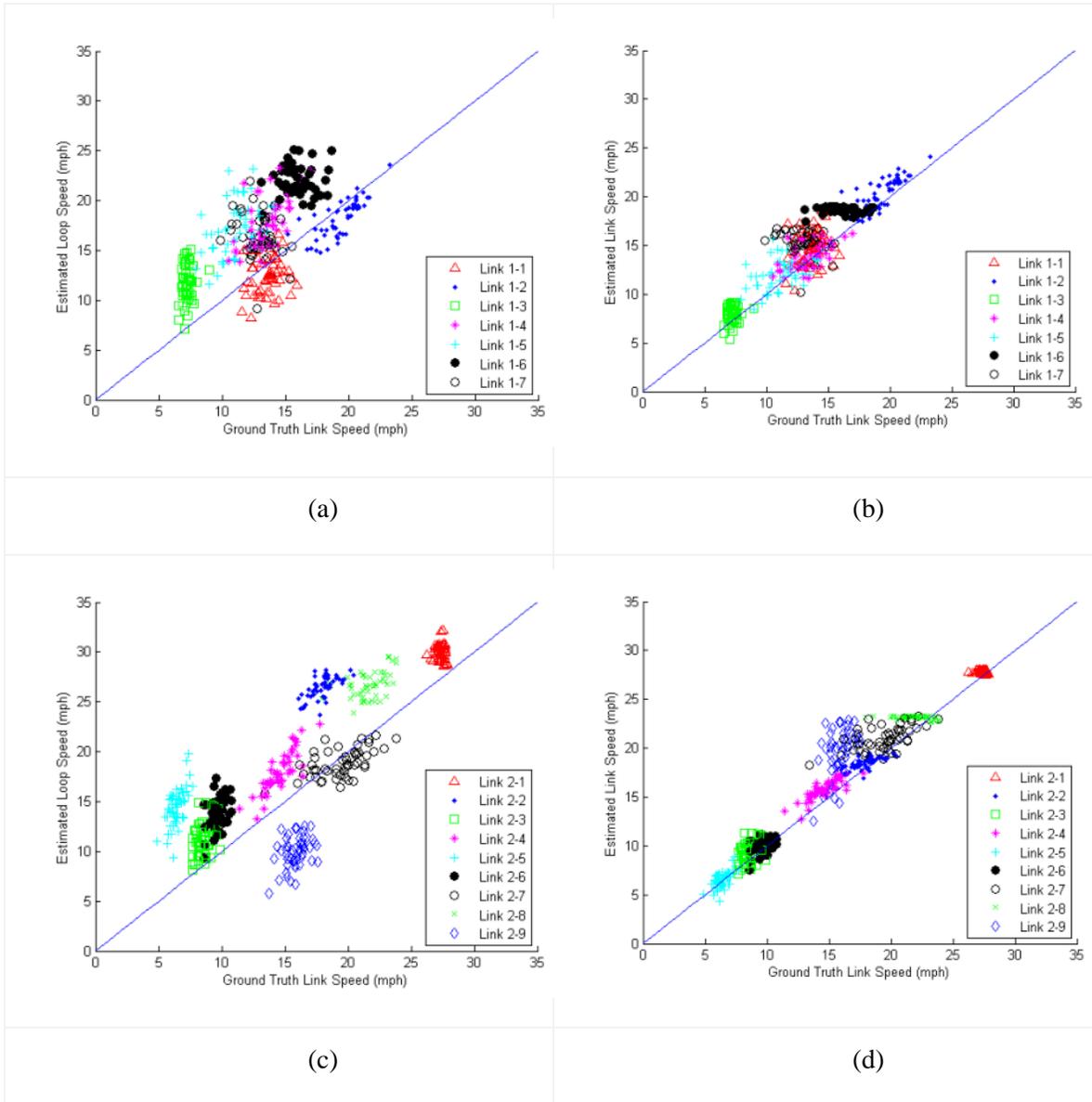


Figure 4-4: Scenario 1: Comparisons between estimated link speed \hat{S}_L , estimated link speed \hat{S}_j and ground truth link speed S_j : (a) 8th Street WB (before), (b) 8th Street WB (after), (c) 8th Street EB (before), (d) 8th Street EB (after), (e) 112th AVE SB (before), (f) 112th AVE SB (after), (g) 112th AVE NB (before), and (h) 112th AVE NB (after)



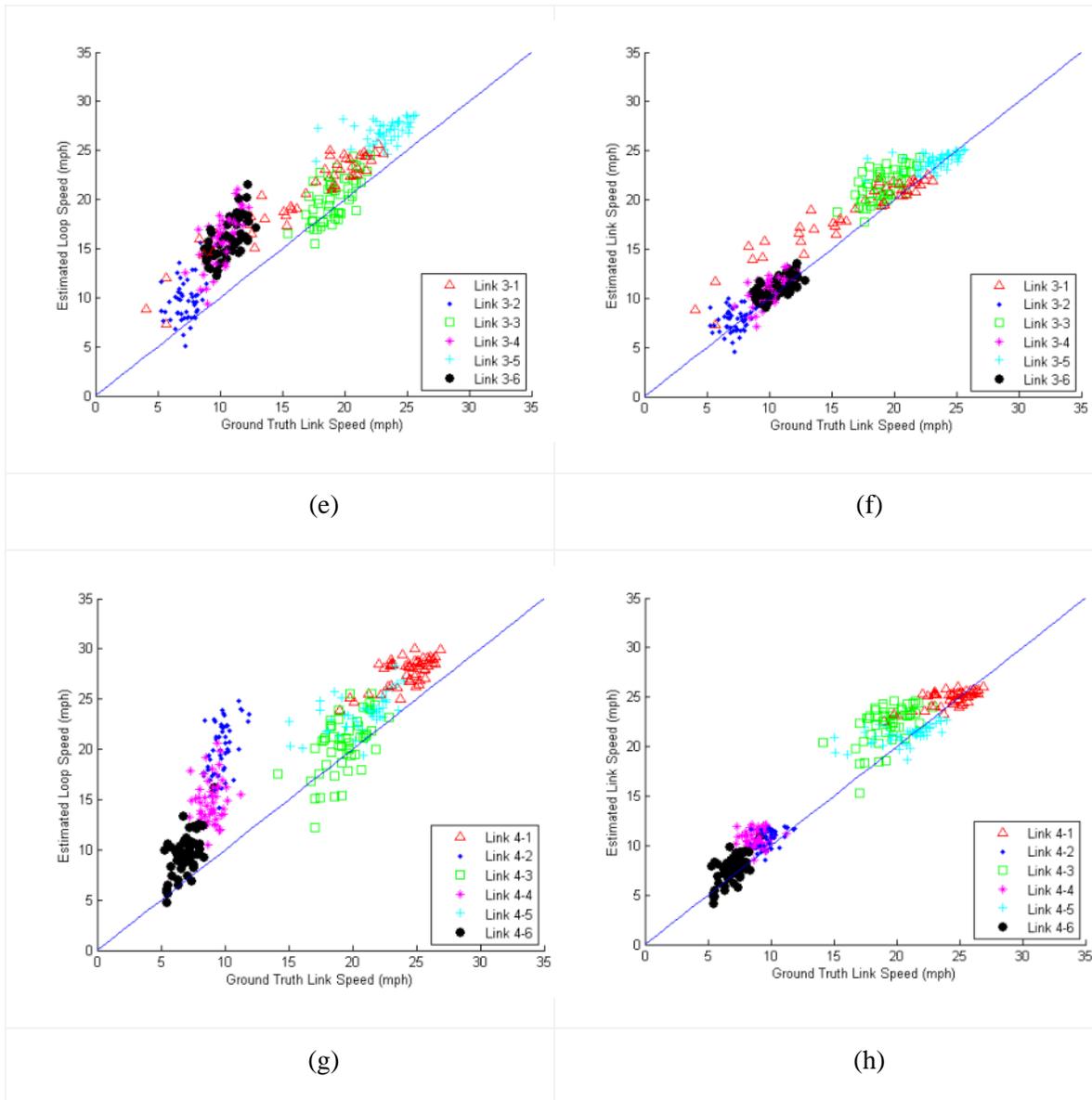


Figure 4-5: Scenario 2: Comparisons between estimated link speed \hat{S}_L , estimated link speed \hat{S}_j and ground truth link speed S_j , (a) 8th Street WB (before), (b) 8th Street WB (after), (c) 8th Street EB (before), (d) 8th Street EB (after), (e) 112th AVE SB (before), (f) 112th AVE SB (after), (g) 112th AVE NB (before), and (h) 112th AVE NB (after)

Table 4-1: Calibration and Evaluation Results for Link Travel Time Estimation

Route	Link ID	g-factor* using Dataset 1	g-factor* using Dataset 2	Individual g-factor for each link									Universal g-factor (g=2.2)								
				Model Coefficients			Before Correction			After Correction			Model Coefficients			Before Correction			After Correction		
				a	b	MAE	ME	RSME	MAE	ME	RSME	a	b	MAE	ME	RSME	MAE	ME	RSME		
Route 1 (8 Street WB)	1-1	2.02	2.01	1.62	0.16	1.56	-0.24	1.96	0.88	-0.41	1.18	1.45	0.11	1.88	-1.31	2.24	1.68	1.12	2.11		
	1-2	2.35	2.29	1.46	0.11	2.34	-2.28	2.57	0.81	-0.17	1.08	1.39	0.10	1.43	-1.13	1.69	1.26	1.11	1.58		
	1-3	2.03	1.95	0.94	0.14	5.43	5.43	5.76	0.38	-0.16	0.53	0.94	0.12	4.46	4.46	4.81	0.91	0.65	1.08		
	1-4	2.45	2.35	1.16	0.11	2.48	2.40	3.03	0.89	0.06	1.14	1.04	0.09	4.22	4.22	4.70	0.96	0.45	1.28		
	1-5	2.31	2.32	0.95	0.10	5.32	5.32	5.79	1.08	-0.07	1.32	0.81	0.06	6.16	6.16	6.60	1.57	1.07	1.99		
	1-6	2.37	2.30	1.20	0.11	4.49	4.49	4.83	1.12	0.57	1.35	1.26	0.10	6.06	6.06	6.33	2.66	2.66	2.93		
	1-7	2.25	2.32	1.29	0.14	3.41	3.01	4.02	1.06	-0.36	1.42	1.32	0.12	3.71	3.37	4.32	2.74	2.48	3.07		
	Average	2.25	2.22			3.58	2.59	3.99	0.89	-0.08	1.14			3.99	3.12	4.38	1.68	1.36	2.00		
Route 2 (8th Street EB)	2-1	2.27	2.38	1.41	0.09	1.73	1.73	1.92	0.29	0.18	0.39	1.34	0.09	2.65	2.65	2.79	0.52	0.49	0.61		
	2-2	2.39	2.37	0.74	0.00	6.34	6.34	6.40	0.65	-0.02	0.78	0.84	0.06	8.44	8.44	8.48	0.76	0.50	0.92		
	2-3	2.16	2.23	1.11	0.14	2.85	2.85	3.28	0.59	0.02	0.70	1.06	0.12	2.63	2.63	3.07	0.95	0.64	1.19		
	2-4	2.43	2.32	1.23	0.11	1.73	1.66	1.96	0.47	-0.03	0.64	1.19	0.10	3.36	3.36	3.57	1.21	1.16	1.32		
	2-5	2.36	2.30	0.76	0.12	7.05	7.05	7.21	0.41	-0.05	0.50	0.51	0.04	8.04	8.04	8.20	0.53	0.13	0.66		
	2-6	2.22	2.24	1.16	0.14	4.04	4.04	4.31	0.39	0.02	0.50	1.02	0.12	4.18	4.18	4.44	0.64	0.33	0.78		
	2-7	2.39	2.36	1.37	0.10	2.26	-2.06	2.60	1.29	-0.07	1.57	1.35	0.09	1.43	-0.57	1.69	1.77	1.58	2.23		
	2-8	2.32	2.35	1.10	0.08	3.57	3.57	3.79	0.89	-0.15	1.12	1.35	0.10	4.94	5.11	5.11	1.59	1.41	1.93		
	2-9	2.12	2.14	1.42	-316.81	5.58	-5.58	5.78	1.75	-0.32	2.15	2.46	0.18	5.94	-5.94	6.12	3.79	3.66	4.24		
	Average	2.29	2.30			3.91	2.18	4.14	0.75	-0.05	0.93			4.62	3.08	4.83	1.31	1.10	1.54		
Route 3 (112th SB)	3-1	2.42	2.39	0.93	0.00	1.84	1.74	2.46	1.48	0.45	1.94	1.10	0.07	3.58	3.58	3.93	2.04	1.87	2.76		
	3-2	2.17	2.17	1.12	0.15	2.73	2.59	3.32	0.93	-0.07	1.10	1.06	0.12	2.61	2.46	3.21	1.19	0.58	1.49		
	3-3	2.35	2.38	1.47	0.12	1.40	-0.32	1.66	0.99	0.32	1.20	1.36	0.09	1.59	0.93	1.96	2.42	2.42	2.76		
	3-4	2.37	2.35	0.98	0.11	4.56	4.55	4.90	0.74	-0.18	0.89	0.90	0.09	5.71	5.71	6.05	1.09	0.85	1.34		
	3-5	2.39	2.37	1.35	0.10	1.52	1.43	2.10	1.19	-0.07	1.58	1.09	0.07	3.62	3.62	3.94	1.11	0.72	1.67		
	3-6	2.25	2.23	1.06	0.12	4.93	4.93	5.16	0.81	0.21	0.99	0.90	0.09	5.33	5.33	5.55	0.89	0.48	1.06		
	Average	2.33	2.31			2.83	2.48	3.26	1.02	0.11	1.28			3.74	3.61	4.11	1.46	1.15	1.85		
Route 4 (112th NB)	4-1	2.39	2.37	1.23	0.08	1.45	1.29	1.84	1.20	-0.29	1.39	1.15	0.07	3.49	3.49	3.73	1.12	0.62	1.47		
	4-2	2.34	2.35	0.78	0.09	9.20	9.20	9.45	0.65	0.00	0.80	0.76	0.08	10.40	10.40	10.66	1.19	1.07	1.38		
	4-3	2.32	2.35	1.53	0.12	1.84	0.06	2.24	1.33	-0.36	1.67	1.45	0.10	2.13	1.10	2.61	3.08	2.98	3.45		
	4-4	2.27	2.32	0.99	0.13	5.54	5.54	5.95	0.71	-0.07	0.89	1.03	0.11	6.00	6.00	6.41	1.90	1.88	2.18		
	4-5	2.35	2.34	1.26	0.09	1.71	1.38	2.28	1.31	0.42	1.82	1.20	0.09	2.92	2.85	3.40	1.30	0.54	1.85		
	4-6	2.28	2.19	1.30	0.19	2.36	2.30	2.84	0.72	-0.01	1.21	1.02	0.12	2.67	2.62	3.14	1.03	0.66	1.27		
	Average	2.32	2.32			3.68	3.29	4.10	0.99	-0.05	1.29			4.60	4.41	4.99	1.60	1.29	1.94		
All-route Average	2.30	2.29			3.50	2.64	3.87	0.91	-0.02	1.16			4.24	3.55	4.58	1.51	1.23	1.83			
Before-after Improvement									73.97%	99.38%	70.01%						64.31%	65.47%	59.99%		

*Note that the data collection point in VISSIM is regarded as a point detector without any loop length. All the g factors have been adjusted by assuming the detector length is 6ft.

Chapter 5 Travel Time Prediction

In order to provide an overview of the network travel time using the proposed travel time estimation algorithm, the traffic parameters on every link of the arterial network are required to be updated and predicted in a timely manner. This timely information can facilitate a real-time decision making and analysis system that relies on an instant, historical and projected overview of the entire arterial network. In this chapter, Kalman filter, a traditional prediction algorithm is first reviewed. Next, the proposed prediction algorithm based on alpha-beta (α - β) filter will be addressed in detail followed by an evaluation process to determine the effectiveness of the proposed method. Lastly, a time-dependent shortest path algorithm will be developed based on the characteristics of the predicated data.

5.1 Review of Kalman Filter

The Kalman Filter (Kalman, 1960) has been used extensively in many traffic prediction studies (Yang, 2007). It provides estimates of the current state of a system which also serve as the input variable to predict the next state. In this study, Kalman filter was first considered to be used to predict and update the state variables (link travel time, intersection travel time, occupancy, and volume) for each link. There are two major reasons for doing this. First, the data feed obtained from loops does not always provide data consistently because of the system errors or unstable internet connection. Second, data itself may contain some random and systematic errors that would lead to data fluctuations. Herein, the procedure of using Kalman filter in the proposed study is briefly described as follows.

Assume that the variable prediction process can be modeled as the following linear stochastic difference equation (Welch and Bishop, 2004):

$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1} \quad (5-1)$$

With a measurement $z \in \mathfrak{R}^m$

$$z_k = Hx_k + v_k \quad (5-2)$$

where the state variable x_{k-1} ($x \in \mathfrak{R}^n$) is the occupancy and volume to be predicted at time k ; A is the $n \times n$ transition parameter relating x_{k-1} to x_k . The $n \times l$ matrix B relates the optional control input $u \in \mathfrak{R}^l$ to the state x . Variable z_k represents the observation, i.e. the link travel time, intersection travel time, occupancy, and volume at time k . The parameter H provides the functional connection between z_k and x_k . The random variable w_k and v_k represent the process and measurement noise respectively. They are assumed to be independent, white and with normal probability distributions.

Let us define $\hat{x}_k^- \in \mathfrak{R}^n$ to be the *a priori* state estimate at step k given the knowledge of the process prior to step k , and $\hat{x}_k \in \mathfrak{R}^n$ to be the *a posteriori* state estimate at step k given measurement z_k . The following is the equation that computes an *a posteriori* state estimate \hat{x}_k as a linear combination of an *a priori* estimate \hat{x}_k^- and a measurement prediction $H\hat{x}_k^-$ as shown below.

$$\hat{x}_k = \hat{x}_k^- + K(z_k - H\hat{x}_k^-) \quad (5-3)$$

where the $n \times m$ matrix K is chosen to be the gain or blending factor that minimizes the *a posteriori* error covariance. K is formulated as follows.

$$K_k = P_k^- H^T (H P_k^- H^T + R)^{-1} \quad (5-4)$$

Then we can update estimate with measurement z_k using Equation (5-2). Last step in measurement update is to update the *a posteriori* error covariance P_k for the next step.

$$P_k = (I - K_k H) P_k^- \quad (5-5)$$

After each time and measurement update pair, the process is repeated with the previous *a posteriori* estimates being used to predict the new *a priori* estimates. This recursive nature is one of the attractive features of the Kalman filter. Figure 5-1 shows a complete picture of the operation steps for the Kalman filter.

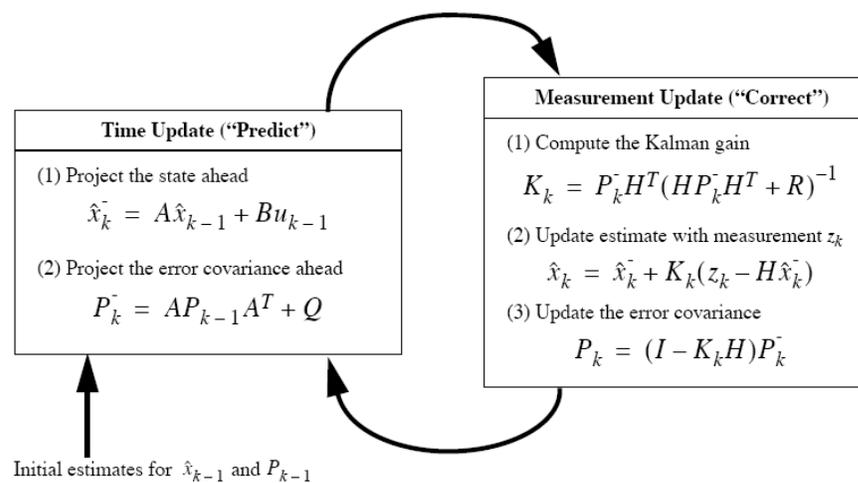


Figure 5-1: A complete picture of the operation of the Kalman filter (Source: Welch and Bishop, 2004)

5.2 Loop Spot Speed Prediction

As discussed in the Literature Review section, the Kalman filter (Kalman, 1960) has been widely applied to short-term traffic prediction in freeway speeds (Guo et al, 2009, Yang et al., 2004), freeway travel time (Zhang and Rice, 2003), arterial travel time (Liu, et al, 2006) applications. Recently, Guo et al. (2009) proposed a Kalman filter-based method to predict freeway speed using single loop detector data. These authors assumed the speed is the state of a discrete time controlled process governed by the linear stochastic difference equation as follows.

$$S_L(t) = S_L(t-1) + e(t) \quad (5-6)$$

where $e(t)$ = state process error with mean 0 and variance Q . Next, based on the empirical findings of Guo et al. (2009), $q(t)/o(t)$, the ratio of flow rate over occupancy (or called q/o ratio), has a linear relationship with $S_L(t)$. This linear relationship justifies the application of the Kaman filter. Thus, the measurement equation can be formulated as

$$\frac{q(t)}{o(t)} = gS_L(t) + \varepsilon(t) \quad (5-7)$$

where $q(t)/o(t)$ = ratio of flow rate over occupancy for time interval t ; g = observation parameter (identical to the g -factor in Equation (4-3)); $\varepsilon(t)$ = observation process error with mean 0 and variance R .

Next, the linear model (Equations (5-6) and (5-7)) can be solved by standard Kalman recursion equations and the Kalman gain needs to be calculated recursively based on calibrated g , Q and R (Kalman, 1960). The method by Guo et al (2009) adopted the smoothing function of Kalman filter, neglecting the prediction capability for the state variable because of the purpose of their research. When the data are missing, $S_L(t)$ is supposed to be updated with a predicated value. However, the system state in Equation (5-6) cannot be updated because this equation lacks a term $u(t-1)$ with a coefficient B to update the speed, $S_L(t)$. Moreover, variances, R and Q usually need to be calibrated based on real-data and the calibration process will be tedious and cumbersome.

In order to take advantage of the prediction capabilities of Kalman filter and minimize the effort of parameter calibration. The alpha-beta (α - β) filter, a simplified version of Kalman filter is used in this study (Blackman, 1986) for the following reasons:

- The α - β filter has been widely applied to object tracking in image processing and can effectively predict the location of the missing objects (Malinovskiy, 2008; Wu et al., 2007; Wu et al., 2006),

- Instead of using the positions in the image, the α - β filter, is able to mathematically predict speeds mainly based on the measurement of q/o (volume/occupancy) ratio. The measurement q/o ratio can be regarded as a moving object moving in a one-dimensional line depending on time, t,
- The α - β filter requires calibration for only one parameter, alpha, and the filter is simplified without computing Kalman gain repetitively.
- Predicting loop spot speeds for the entire arterial network is computationally expensive. The recursive feature of the α - β filter can perform in real-time without much burden to the entire system.

In our implementation, every single measurement $x(t) = \frac{q(t)}{o(t)}$ is smoothed and predicted.

The α - β filter is defined in the following equations (Blackman, 1986):

$$x_s(t) = \hat{x}(t|t) = x_p(t) + \alpha [x_o(t) - x_p(t)] \quad (5-8)$$

$$v_s(t) = \hat{\dot{x}}(t|t) = v_s(t-1) + \frac{\beta}{qT} [x_o(t) - x_p(t)] \quad (5-9)$$

$$x_p(t+1) = \hat{x}(t+1|t) = x_s(t) + T \cdot v_s(t) \quad (5-10)$$

where $x_o(t)$ = the observed measurement (q/o) at the timestamp t ; $x_p(t)$ = the predicted measurement at timestamp t ; $x_s(t)$ = the smoothed measurement at the timestamp t ; $v_s(t)$ = the smoothed measurement changing rate (It can be regarded as the velocity of the measurement) at the timestamp t ; T = the sampling interval ($T=1$ is used since the data is updated every minute); q = the number of discrete timestamps since the last measurement; and α, β = fixed-coefficient filter parameters.

The filter starts with an initialization process defined by:

$$x_s(1) = x_p(1) = x_o(1) \text{ and } v_s(1) = 0 \quad (5-11)$$

$$v_s(2) = \frac{x_o(2) - x_o(1)}{T} \quad (5-12)$$

In order to reduce the calibration effort, the optimal relationship between α and β is known to be (Kalata, 1984).

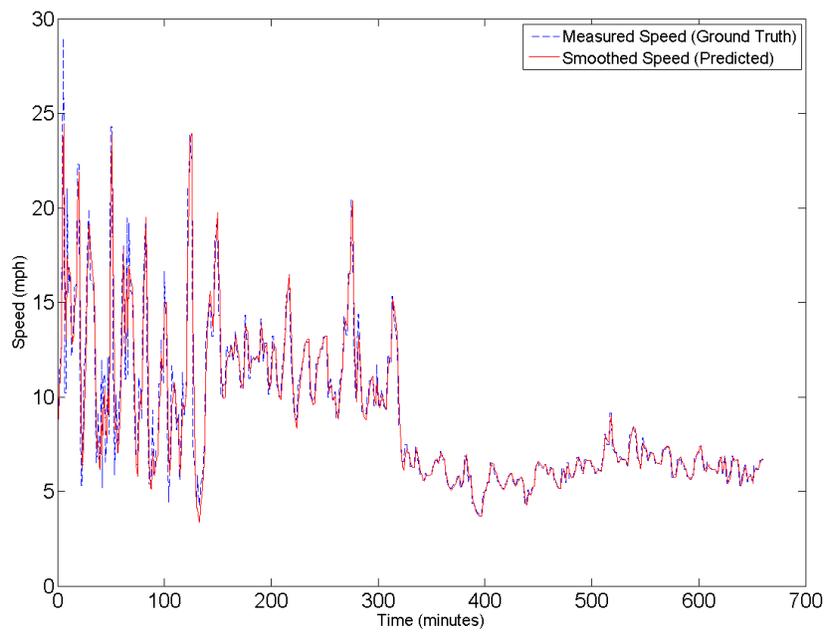
$$\beta = 2 \cdot (2 - \alpha) - 4\sqrt{1 - \alpha} \quad (5-13)$$

Note that Equations (5-8)~(5-12) are used when the measurement can be consistently input into the system. As mentioned in the Introduction section, the data input could be missing due to communication errors or measured speed = 0 (when occupancy or volume=0). In this case, the values of x and v can be predicted as follows:

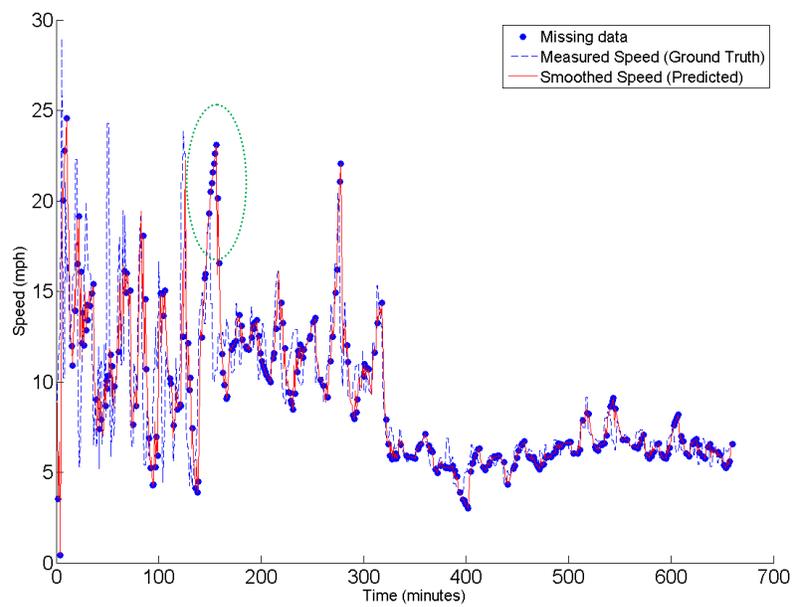
$$x_o(t) = x_s(t) = x_p(t) \text{ and } v_s(t) = v_s(t-1) \quad (5-14)$$

5.2.1 Effectiveness of Prediction

Figure 5-2 shows the application of the α - β filter on the data collected at the advance loop east of intersection 16 (NE 8th AVE and 106th AVE NE), westbound on NE 8th AVE from 6am to 7pm on July 15th, 2010. Figure 5-2(a) shows the effectiveness of filter smoothing. Figure 5-2(b) shows the effectiveness of prediction when 50% of data are missing (randomly removed). The filter still smoothes the predicted measurement while data is missing. However, the area circled in a dotted line shows that the missing multiple data continuously would cause the filter to become increasingly inaccurate. This is also a common prediction constraint for most dynamic filters. In other words, dynamic filters can predict the trend in real-time. If the object is abruptly turning or moving toward other directions, the object tends to be lost. However, the trend can be easily resumed by the filter once the true measurement enters the filter, as illustrated in the prediction results after the circled area.



(a)



(b)

Figure 5-2: Application of α - β filter on loop spot speed prediction ($\alpha=0.6$) (a) No data missing, (b) 50% data missing

5.2.2 Calibration

To improve prediction performance, the parameter, α , needs to be selected carefully. According to Equation (5-8), the higher α is, the more the filter will trust the “correction” from the new measurement. On the other hand, the system will be more sensitive to errors. To demonstrate the feasibility of the α selection process, the calibration process and a sensitivity test for α are conducted in this research. Note that α can be determined based on the characteristics of each link or one single α minimizing the system error can be adopted for the entire network. Either way can be easily implemented offline. This implementation aims to select one single α that can minimize the errors of prediction for the entire network.

5.2.3 Measure of Accuracy

In order to quantify the prediction performance, three measures of accuracy, Mean Absolute Error (MAE), Root Square Mean Error (RSME) and Mean Absolute Percentage Error (MAPE) are used in this study and defined as follows (Washington et al., 2003).

$$MAE = \frac{\sum_{t=1}^n |F(t) - G(t)|}{n} \quad (5-15)$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^n (F(t) - G(t))^2}{n}} \quad (5-16)$$

$$MAPE = \frac{1}{n} \sum_{t=1}^n \left| \frac{F(t) - G(t)}{G(t)} \right| \quad (5-17)$$

where $G(t)$ is the ground truth loop spot speed at time interval t ; $F(t)$ is the predicted link travel at time interval t ; n is the total number of samples. In the application, $F(t) = x_s(t)$. If data is missing, $x_o(t) = x_p(t|t-1)$ will be smoothed in Equation (5-8). Even though the prediction error is defined by the difference between $G(t)$ and $F(t)$, the measures of accuracy shows the relative improvement of the smoothing and effectiveness of prediction concurrently since $G(t)$ itself is likely to contain random errors.

MAE provides an overview of all errors and shows how close the predicted loop speeds are to the ground truth. RMSE shows the average magnitude of the error but penalizes large errors. RMSE indicates the precision of prediction. The MAE and RMSE can be evaluated jointly to determine the variation of the errors. Compared to RMSE, MAPE expresses the error as a percentage without “exaggerating” the error.

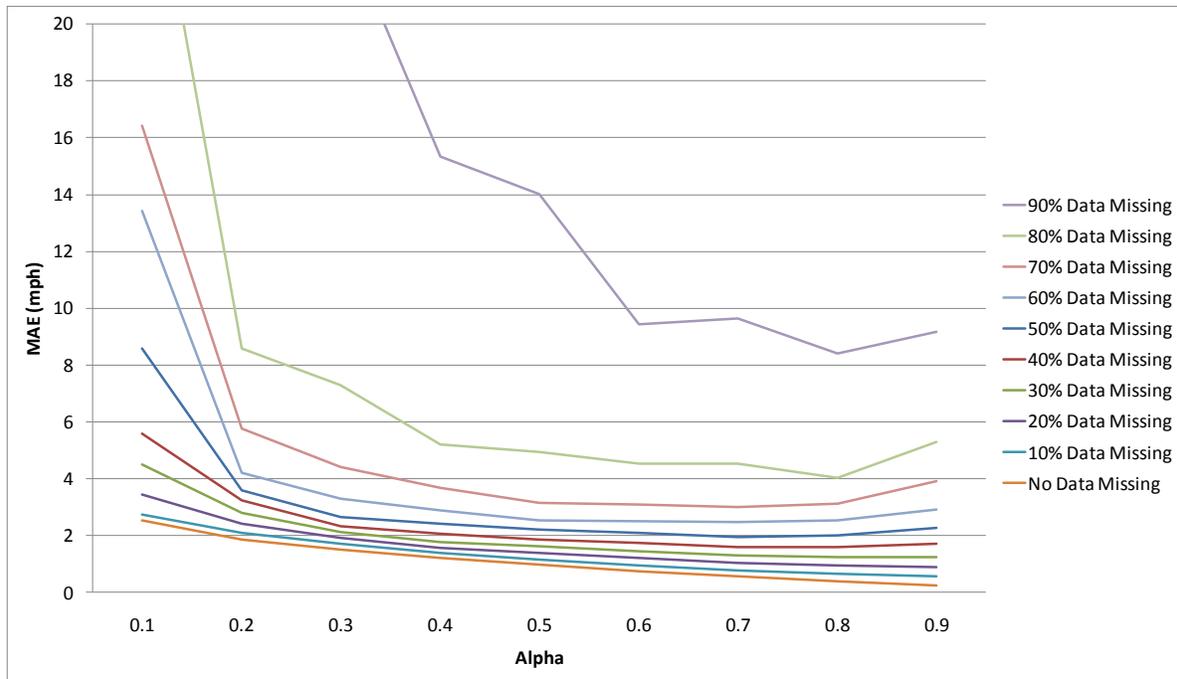
5.2.4 Calibration

One day’s worth of data collected on July 15 (Thursday), 2010 was extracted from the database. Among 708 links, 472 links with advance detectors on the through movement lanes are adopted in the RADAR Net system. Advance loop data on 23 major arterials links (average volume > 400 veh/h and average occupancy >20%) were selected for the calibration and evaluation process. Data before 6am and after 7pm were excluded in the dataset because few traffic fluctuations are observed during this period and may result in underestimating average prediction errors. In order to determine the most suitable α and effectiveness of prediction, for each data set, different portions of data are randomly removed, ranging from 10% to 90% at 10% increments. The results are sequentially illustrated in Figure 5-3, from the bottom to the top. As shown in Figure 5-3(a), if there is no data missing, $\alpha = 0.9$ can result in the “best” results. This is not surprising because the filter “trusts” the new measurement more. It should be worth mentioning that the ground truth measurements may contain random errors. Hence, the ground truth is not “real” ground truth. In this case, the low MAE, RMSE, and MAPE may not absolutely imply that the filter performs better. Therefore, the $\alpha = 0.9$ case in Figures 5-3(a), 5-3(b) and 5-3(c) may imply that the filter is affected by the noise. In contrast, the $\alpha = 0.1$ case shows the “worst” results. It is also reasonable because the filter does not “trust” the new measurement. Figure 5-3(c) shows a

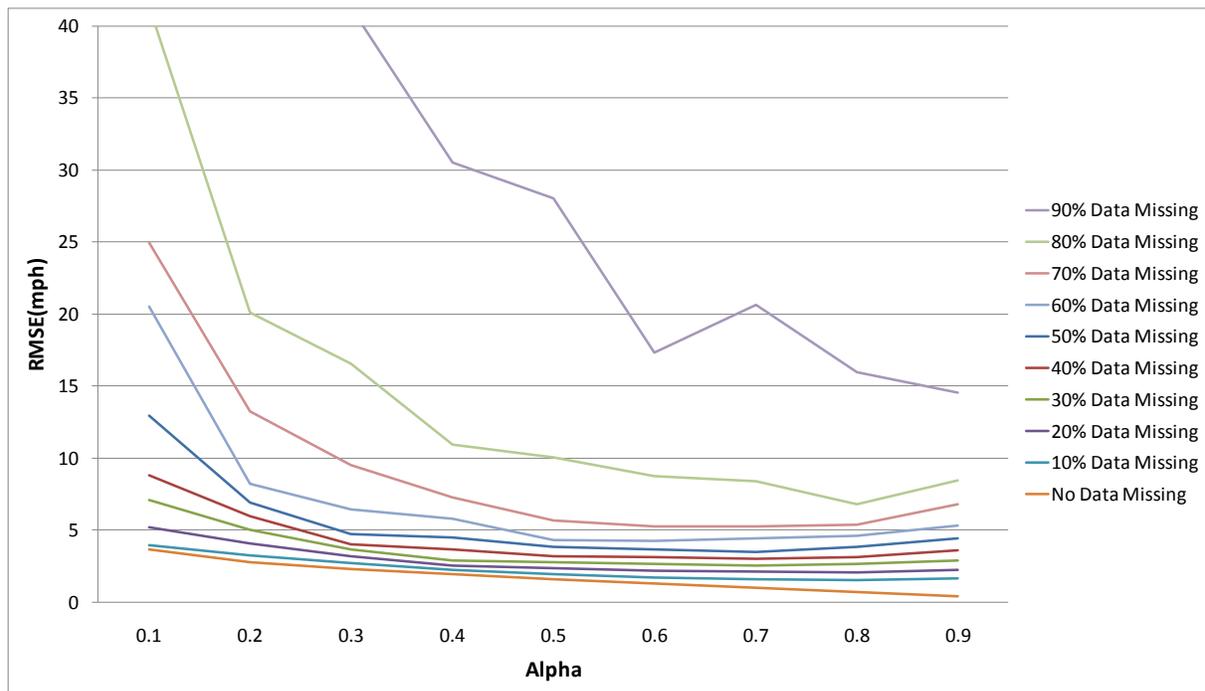
decreasing trend in MAPE, showing the percentage error is reduced when the filter trusts the measurements more. This figure shows there are two drops at $\alpha = 0.2$ and $\alpha = 0.4$, showing these two values could be used if the data quality is poor. Overall, the $\alpha = 0.6$ case shows a drop both in MAE and RSME when the data are 90% missing. This implies $\alpha = 0.6$ is able to reduce the noise and smoothly predict the results concurrently. When 80% of the data is missing, the drop also appears in MAE and RMSE. However, as α increases, the filter becomes more sensitive to noise. Hence, $\alpha = 0.8$ may be used for the links with higher quality of data with low data missing rate. In our application, $\alpha = 0.6$ is selected because this value shows its robustness to long-term data missing and could minimize the random errors when the measurements are available.

5.2.5 Practical Constraint and Remedy

It is worth noting that the loop-based methods, e.g. (Zhang 1999) and (Guo et al 2009), can perform accurately under congested conditions. Overnight the loop-based method would result in incorrect results due to low volume and occupancy. Therefore, 10% occupancy proposed by Guo et al (2009) and Coifman (2001) as a threshold to separate congested and non-congested conditions.

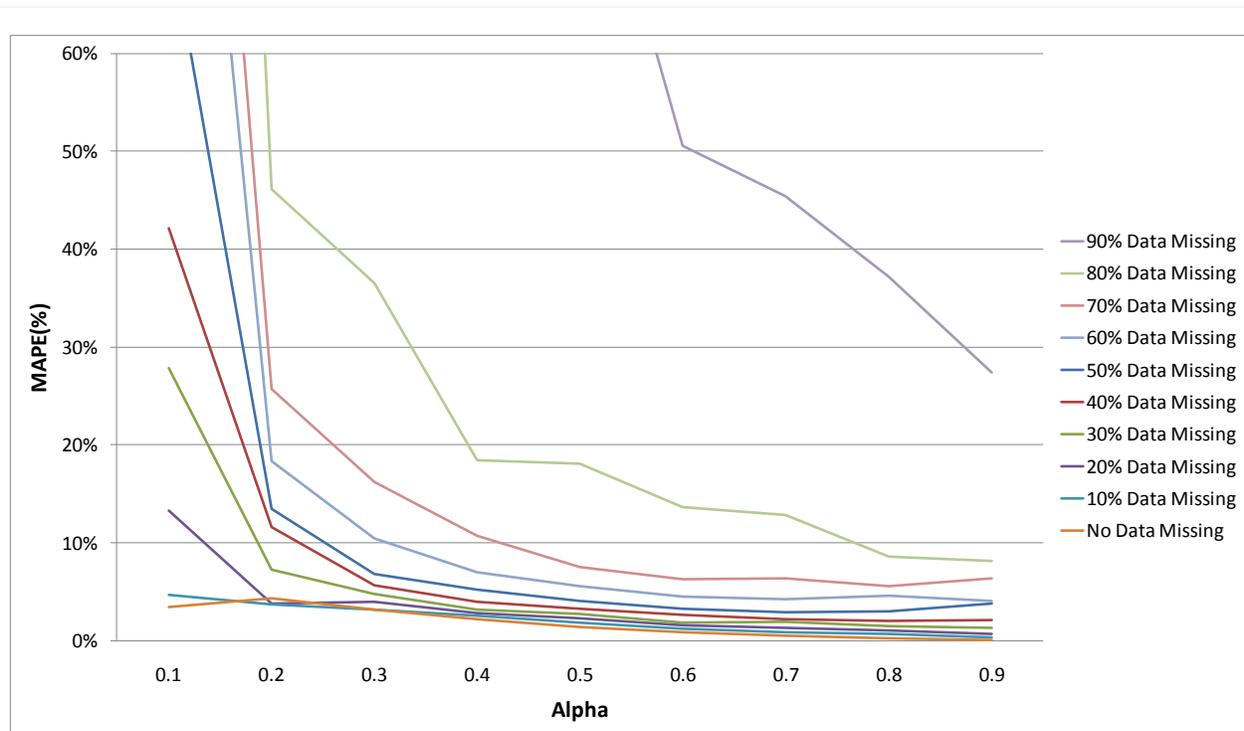


(a)



(b)

Figure 5-3: Optimal Alpha value selection based on different data missing percentage conditions: (a)The relationship between Alpha and MAE, (b) The relationship between Alpha and RMSE



(c)

Continued, Figure 5-3: Optimal Alpha value selection based on different data missing percentage conditions: (c) The relationship between Alpha and MAPE under different data missing percentage conditions

5.3 Shortest Travel Time Path Algorithm

Unlike freeway network, arterial network is much more complicated and routing assistance is desirable because most road users are not able to decide the best route immediately by looking at the network travel times. Therefore, after link travel time is calculated for the entire network, the shortest travel time path can be determined by a shortest path algorithm. The shortest path algorithm should consider the challenges for real-time applicability.

Most of existing shortest path algorithms are based on a static environment because they assume travel time for each link and node keep constant during the entire trip. Dijkstra's algorithm (Dijkstra 1959) and the A* algorithm (Hart et al. 1968) are two most well-known shortest (travel time) path searching algorithms. However, in reality, traffic condition varies frequently with time. For example, a traveler may conduct a trip plan based the current traffic

condition before departure. However, pre-planned routes might not be the optimal way because unexpected event, e.g. incidents might happen and route changes are unavoidable. In this case, a dynamic shortest path searching algorithm based on real-time traffic condition is desirable to provide road users with more accurate traffic information.

Therefore, an iterative A* based time-dependent searching algorithm is proposed. This algorithm not only considers the current traffic condition, but also adjusts the future route based on the travel time for the next time window. Assuming a traveler travels from node A to node B. After the first iteration of the A* algorithm, a static routing is computed. The starting point now is moved to node A', which is the adjacent node to node A in the first iteration route. Then, A* algorithm will be conducted again calculating the shortest path from node A' to node B using the updated network condition. This procedure is performed iteratively until the final route converts to the targeted node B. This route is regarded as the optimal route with the shortest travel time based on varying traffic conditions. To simplify the procedure, Euclidean distance was applied in our algorithm. The proposed path search algorithm is summarized as follows:

- Step 1: Perform the static A* algorithm between origin and destination.
- Step 2: Record the adjacent node, and calculate the travel time between the origin and the adjacent node.
- Step 3: Update travel time for each link in the entire network after time t.
- Step 4: Use the adjacent node as the new origin, and perform the static A* between the new origin and destination.
- Step 5: Return to Step 2
- End until origin=destination, and trace back until the origin is reached. The route is dynamic shortest travel time path, and the summation of each link travel time is the total route travel time.

Chapter 6 System Implementation

The travel time estimation and prediction algorithms developed in this study are implemented in a web-based system based on the Google-Map-based Arterial Traveler Information (GATI) system developed by the STAR Lab. This new system mainly aims to assist in real-time decision making and, thus, named Real-time Analysis and Decision-making for ARterial Network (RADAR Net). This chapter is a brief review of the GATI system. Next, the details of the design flow will be elaborated. In the end, the implementation of each functional module will be introduced and the system performance will be discussed.

6.1 Review of the GATI System

The Google-Map-based Arterial Traveler Information (GATI) system has been running since 2007 (Wu et al, 2007 and Wu and Wang, 2009). The GATI system provides real-time traffic information, historical data query and two visualization functions, scatter and time-domain plots for volume and occupancy. The analytical statistics can be calculated online based on the users' inputs. However, this system suffers from several drawbacks.

- The GATI system is programmed in JavaScript and PHP. Few integrated development environment (IDE) software packages are designed for JavaScript and PHP. The debugging process tends to be slow and tedious.
- Fewer codes and libraries can be found and reused even though JavaScript and PHP are objected oriented. It is probably because of the low programmability (e.g. difficult to debug), few developers are willing to develop and share code.
- The visual component of GATI was hard coded in Cascading Style Sheets (CSS). The interface is difficult to adjust and fit to all types of browser settings.
- The visualization module was completed with third-party packages. The visualization flexibility is limited.
- The database has dependency issue. This issue increases the database size.

These issues are also commonly observed in practical applications. To deal with these issues mentioned above, the RADAR Net system aims to renovate the GATI system design using improved system and database designs.

6.2 Database Design

Real-time decision making relies on prompt query response from databases. For a typical On-Line Transaction Processing (OLTP) system, database design is a key to retrieve timely data through query. The relational database (Codd, 1970), commonly used for OLTP systems, is used in RADAR Net. The relational database can provide many advantages. For example, the data are organized in different relations (tables) and use Structured Query Language (SQL) to query the specific results as desired (Garcia-Molina et al, 2000). Moreover, new relations and attributes can be easily added to the design and increase the design flexibility and database scalability.

The database design proposed in the previous research (Wu et al 2007) was found to contain data dependency and anomalies. The redundant data occupied more than 40% storage space. Therefore, the Entity-Relationship (E/R) diagram was further improved, as shown in Figure 6-1.

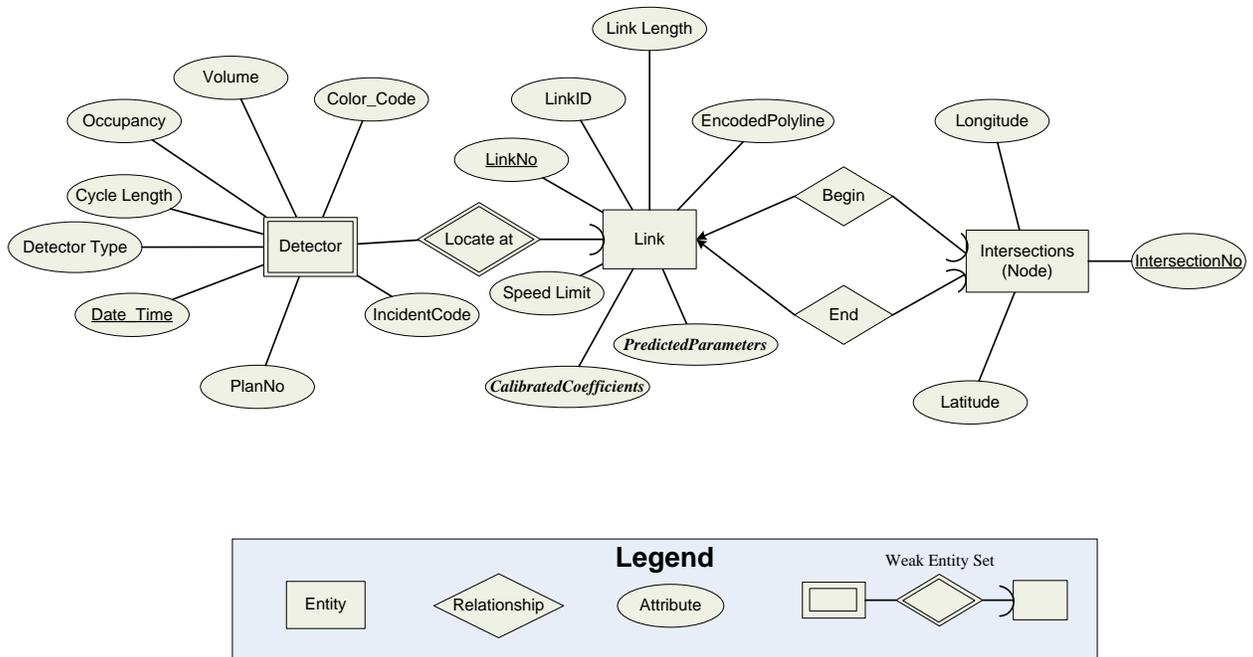


Figure 6-1: E/R diagram design for the arterial network database

Schemas

The E/R diagram in Figure 6-1 is converted to the schema based on (Garcia-Molina et al., 2009). These schemas represent three tables in the SQL database. The Detector table stores the real-time detector data. The link and Intersection tables store the time-independent attributes. Thus, users can add/update links or intersections without affecting the Detector table. The attributes are briefly explained as below.

1. Detector(Date_Time, LinkNo, Volume, Occupancy, PlanNo, Cycle Length, ColorCode, Incident code,)
 - Date_Time: The timestamp for each record.
 - LinkNo: Link number.
 - Volume: vehicles/hour (flow rate)
 - Occupancy: the percentage of time the detector is occupied by vehicles.
 - PlanNo: Real-time timing plan number. In the database, this is linked to a lookup table. PlanNo could be an entity if more attributes, such as phase times, are required to define a timing plan.
 - Color code: the congestion levels determined by the system in Bellevue's TMC.
 - Both attributes, Date_Time and LinkNo and are indexed since these two are most often queried.

2. Link(LinkNo, LinkID, LinkLength, SpeedLimit, BeginNode, EndNode, *CalibratedCoefficients*, *Predicted Parameters*)
 - LinkNo: Link Number,
 - Link ID: stores the info about number of lanes covered by the detector, direction and detector types (system and advance).

- BeginNode and EndNode are the starting and ending intersections, respectively. Each link must be defined by two intersections. These two attributes are foreign keys in the Link table referencing Intersection.IntersectionNo.
- **CalibratedCoefficients**: This is a set of multiple attributes that stores all the pre-calibrated parameters for roadway link estimation and prediction.
- **PredictedParameters**: This is a set of multiple attributes that stores all predicted travel times and speeds in different columns.

The details of **CalibratedCoefficients** and **PredictedParameters** will be explained in the System Design subsection

3. Intersection (IntersectionNo. Longitude, Latitude)

- Intersection No: Intersection number.
- Longitude and Latitude identify the location of each intersection.

According to the new design, the database dependency is mitigated by separating the data into different relations (tables).

6.3 System Design

In order to support real-time decision making, the RADAR Net system needs to consider many aspects of an optimized system. The system follows multi-tier architecture design. The technical details of the client-server architecture can be found in (Ma et al, 2010). As shown in Figure 6-2, the conceptual system design consists of four layers, offline server, online server (middleware), online server (Java Servlet) and online client (Browsers). The tasks are processed in different layers to distribute the computation burden, especially in the server. The function of each layer is explained as follows.

Offline server: the system is designed to estimate and predict traffic parameters. Most algorithms required parameter calibration. The process is mostly done offline using simulations or field observations.

Online server (middleware): This layer is in charge of processing the real-time information commonly used by the online analysis modules. Once the data is downloaded onto

the RADAR Net server, loop spot speed estimation and prediction, link speed estimation and link travel time calculations are executed. The calculated data are automatically imported into the database following the designed schemas. In addition to speed data, other traffic parameters, such as predicted volume, can be stored in the database in the same manner. This layer can reduce the computational burden in Java Servlet.

Online server (Java Servlet): The shortest travel-time path algorithm is one of the real-time analysis modules implemented in RADAR Net to support real-time decision. Other RADAR Net statistical analysis modules are also executed here.

Online client layer: This layer handles the requests from all the web browsers visiting the RADAR Net server through World Wide Web (WWW) and visualizes the query results. The code can be executed in the users' browsers using the computing power from each client computer.

Based on this system design, the computational workload can be distributed and lower the server's computational burden. Details of the proposed computational components will be elaborated in the next section.

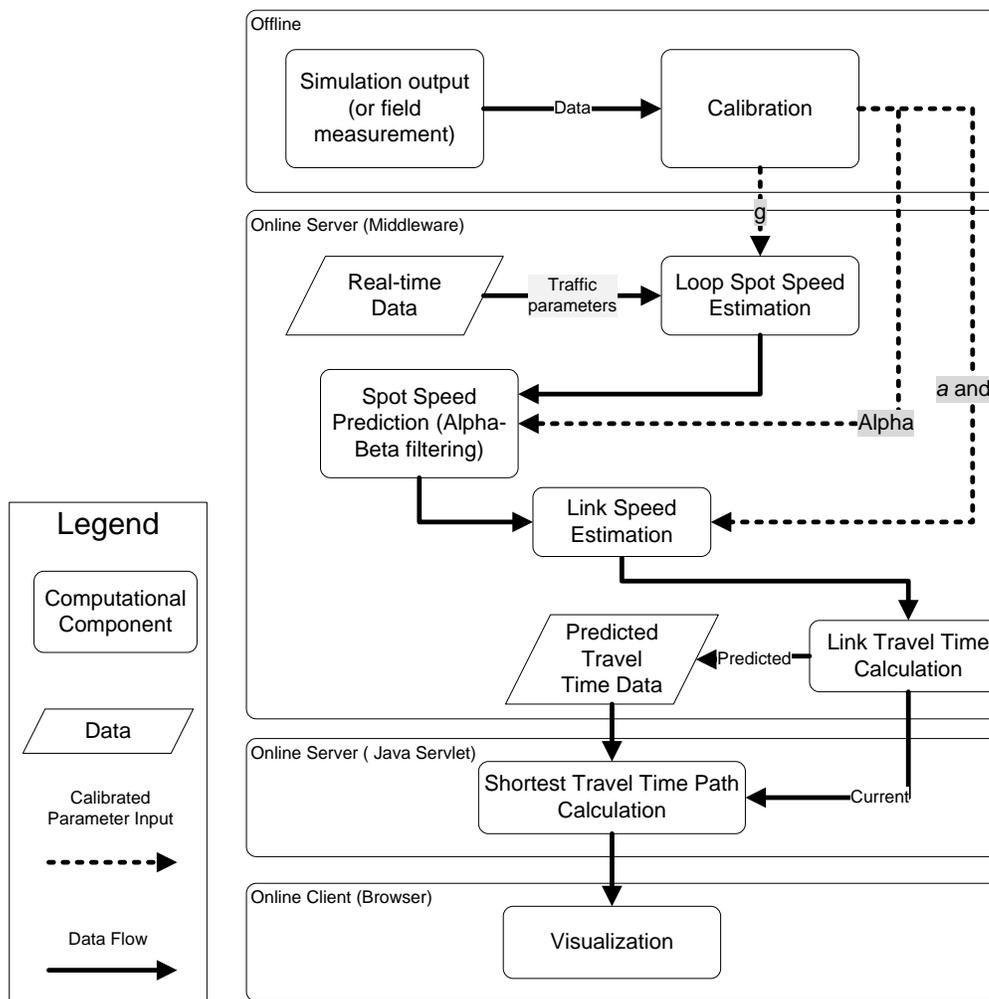


Figure 6-2: System design

6.4 System Implementation

6.4.1 Implementation

Based on the system design shown in Figure 6-2, the online client and online server (Java Servlet) layers of the RADAR Net system is programmed using Google Web-Toolkit (GWT) (Google, 2010) combined with Eclipse (2010), an open-source Java IDE. Compared with the previous GATI system development environment, the development efficiency has been greatly improved. The code is optimized and converted to the JavaScript code by GWT. The online server layer is implemented in C#. The server runs on Windows Server 2008 operating system (OS) with MS SQL Server 2008.

6.4.2 Application Modules

Five application modules have been implemented in the RADAR Net system: 1) Arterial real-time map, 2) Arterial data analysis, 3) Historical arterial map query, 4) Dynamic shortest travel time routing, and 5) Arterial data sharing. Modules (1)~(3) were the re-implementation based on the GATI system (Wu et al, 2009) with improved database design and performance. Figure 6-3(a) shows the volume-occupancy scatter plot during June, 20th ~ June 26th, 2010. The statistical analysis are calculated online once the “statistical analysis button is clicked. Figure 6-3(b) shows the time domain plot of the volume and occupancy data during the same period. The scalable visualization bar can easily zoom into June, 23th and slide the window to investigate traffic variation. Figure 6-3(c) shows the real-time traffic map. One can notice that the links between Intersection A and B are not all experiencing free-flow conditions. Figure 6-3(d) shows the shortest path between Intersections A and B. The shortest (travel time) path is calculated by the A* algorithm (Hart et al. 1968) based on real-time link speeds updated by the α - β filter. Since the speed data are stored in the database, the algorithm can be executed in real-time once two nodes are selected. The path successfully skips the congested links indicated in Figure 6-3(c).

6.4.3 Performance

The database design effectively reduces the query time for loop spot speed estimation and simultaneously increases the online algorithm performance. The query for retrieving all the attributes of the entire network by joining all tables takes less than 500ms. Downloading the raw data, calculating the link speeds, and updating the travel time data for all links in the network takes less than an average of two seconds in the middleware. Moreover, the shortest path algorithm executed within the CBD area can be calculated in an average of one second.

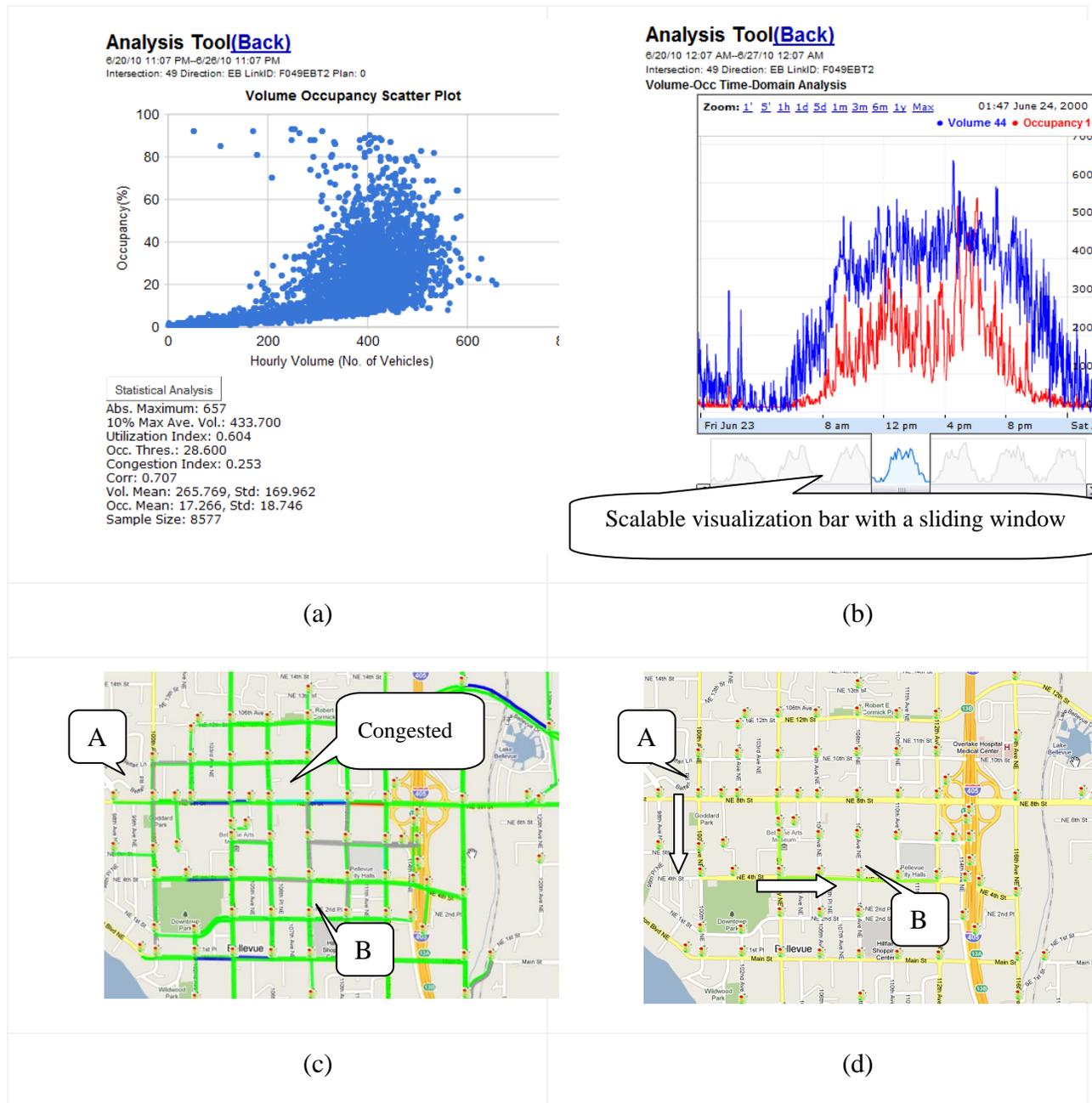


Figure 6-3: RADAR Net modules (a) Volume and occupancy scatter plot and analysis (June, 20th ~ June 26th, 2010), (b) Scalable time-domain plot ((June, 20th ~ June 26th, 2010), (c)Real-time traffic flow map at 5:45pm, July 29th 2010 (Thursday), and (d) real-time dynamic shortest travel time routing

Chapter 7 Conclusions and Recommendations

Travel time estimation and prediction play important roles in traffic operations and travel decisions. This study presented not only a practical method to estimate travel times using loop detector data but also an online system that can predict travel time for a real-life urban network. The conclusions and recommendations for both travel time estimation and predictions are summarized as follows.

7.1 Conclusions

7.1.1 Travel Time Estimation

Travel speed ties directly to travel time and hence is an important measure for quantifying arterial performance. However, accurately estimating the urban link travel speed is difficult due to traffic fluctuations and movement interruptions caused by traffic controls. This research proposed a two-step approach to effectively estimating the link journey speeds merely using advance loop detector outputs. The first step is to estimate the spot speed for the advance loop detector using the g-factor approach (i.e. Athol's algorithm). A robust regression technique can then be used to calibrate the g-factor for loop speed estimation. The second step is to estimate the link speed using the simplified speed estimation model proposed in this research without any knowledge of signal timing plans. Traffic operations in the central business district (CBD) of the City of Bellevue are simulated using the VISSIM microscopic traffic simulation tool. The results show that only 50 cycles worth of loop data are need to calibrate g-factor in speed estimation and the same data sets can be used to calibrate the proposed link speed estimation model. The results are encouraging and satisfactory. The results also show that the accuracy of speed estimation may be further increased when more data are applied for calibration.

7.1.2 Travel Time Prediction

System performance and simple implementation are the keys to the success of a real-time decision making system for large urban arterial network. This paper presents a web-based Real-time Analysis and Decision-making for ARterial Network) RADAR Net system that optimizes the computational capability between server and clients. A practical and scalable arterial database design is also proposed. The schemas can be used as a template for storing arterial data for other agencies. Since the database design is based on the relational model, this design can

incorporate more other arterial data and increase the system scalability. The RADAR Net system contains four layers: offline server, online server (middleware) and online server (Java Servlet) and online client. This four-layer system design successfully distributes the computational burden of the system. Traffic parameters are calculated or retrieved directly from the loop detector. The RADAR system can dynamically predict and smooth real-time loop spot speeds by using α - β filter, a simplified version of Kalman filter while maintaining high system performance. Many application modules are implemented based on the current system architecture and prove feasible to perform real-time analysis and assist decision making.

7.2 Recommendations

7.2.1 Travel Time Estimation

The proposed travel time estimation approach demonstrated its capability of handling system errors but it still has difficulties in minimizing some random errors. Hence, the approach is suitable to assist the arterial performance measurement over a relatively long time period, e.g. hourly. A thorough investigation is needed to reduce random errors when apply this approach to real-time cycle-by-cycle application. Even though the model is designed to accommodate most scenarios, only congestion conditions were considered and tested in this research. More extensive studies are needed to be conducted to test and improve the proposed approach for various scenarios, such as different signal control schemes and congestion levels.

7.2.2 Travel Time Prediction

Even though the RADAR Net system demonstrates its capability of real-time data processing, the system still has some limitations. For example, the prediction function cannot deal with long term missing data and malfunction in loop detectors. Moreover, the performance may be reduced if thousands of queries are executed simultaneously. One possible solution is to use concurrency control. In terms of future work, the RADAR Net system has many potential real-time applications, e.g. emergency evacuation and emergency vehicle routing. In addition, the database design can be further improved by incorporating multi-dimensional databases into the system to handle aggregated data in real-time. To increase the computing power of RADAR Net, cloud computing could be a potential solution.

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