Link Travel Speed Estimation Using Transit GPS Data

by

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A thesis submitted in partial fulfillment of the requirements for the degree of

Master of Science

in
Transportation Engineering

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University of Alberta

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ABSTRACT

This thesis studies the travel speed estimation at road link level using sparse transit GPS data. A link travel speed estimation method is first proposed, which estimates link travel speeds by inferring the timestamp when probe vehicles are passing specific locations along roadways. A field test is conducted on an urban freeway to evaluate the performance of transit bus-based link travel speed estimation using this method, and the impact of probe vehicle type and GPS update interval upon the estimation accuracy are analyzed. The test results suggest that the proposed method can provide reliable link travel speed estimates, with a mean absolute speed difference of 7.0 km/h compared to loop detectors. This approach assumes that the travel speed between two consecutive GPS points of a probe is similar, which is not reasonable when applying to urban arterials, as the existence of intersections and bus stops makes the travel time between two neighbor GPS points not as homogeneous as on freeways. Therefore, a link travel time allocation method for individual probes is developed to overcome this difficulty. The proposed travel time allocation method decomposes travel time into several parts and uses probability functions to estimate travel times of traversed links. A field test is conducted on an urban road corridor to evaluate the performance of the link travel time allocation method using transit bus probe data, which is compared with the previously mentioned link travel speed estimation method. The results show that the proposed link travel time allocation method can improve the estimation accuracy of individual link travel times, especially under congestion condition. It can also provide a good estimation of the travel delay caused by vehicles stopping at intersections or bus stops, which can be used to analyze the dwell time of transit probes at bus stops in the future.

DEDICATION

To my parents, my supervisor Tony Z. Qiu, and my brother-like friend Jiangchen Li.

ACKNOWLEDGEMENTS

I would like to especially thank my supervisor, Dr. Tony Qiu, for his encouragement and guidance, and also Dr. Karim El-Basyouny and Dr. Tae Kwon for serving on my committee.

I want to give my great thanks to Jiangchen Li, who gave me many good suggestions for my thesis. Thanks also to my colleagues in Dr. Qiu's group, for the helpful discussion and collaboration in researches.

I acknowledge the support from City of Edmonton, who provides the data to support my researches.

Thanks to my parents finally, for encouraging me when I am upset and suffering from insomnia. It is you that gives me the chance to see a wider world.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS

n_a	Node *a*
$n(x_a, y_a)$	Node with two-dimension coordinates of x_a and y_a
x_a	Horizontal coordinate of node *a*
y_a	Vertical coordinate of node *a*
l_b	Link *b*
$l(n_{start}, n_{end})$	Link connecting node n_{start} and n_{end}
n_{start}	Start node of a link
n_{end}	End node of a link
$leng(l_b)$	Length of link *b*
k	Index of probe vehicle
$t_{k,i}$	Timestamp of the *i*th GPS point of probe *k*
$g_{k,i}$	The *i*th GPS point of probe *k*
$VehicleID_k$	ID of probe *k*
$x_{k,i}$	Horizontal coordinate of GPS point $g_{k,i}$
$y_{k,i}$	Vertical coordinate of GPS point $g_{k,i}$
$\tilde{g}_{k,i}$	Map matched probe position from GPS point $g_{k,i}$
$l_{k,i}$	Link that $\tilde{g}_{k,i}$ is on
$d(l_{k,i})$	On-road distance from $\tilde{g}_{k,i}$ to the beginning of link $l_{k,i}$
$p_{k,i}$	Path between position $\tilde{g}_{k,i-1}$ and $\tilde{g}_{k,i}$
$l_{k,i,j}$	The *j*th traveled link on path $p_{k,i}$
J	number of links included in a path
α	Location where probe *k* first appears on a link
β	Location where probe *k* last appears on a link
$leng(k_{k,i,j})$	Length of link $l_{k,i,j}$
$d(l_{k,i,j})$	traveled distance on link $l_{k,i,j}$ of path $p_{k,i}$

$t(k, n_m)$	Timestamp when probe k passes node n_m
$d(n_m, \tilde{g}_{k,i})$	Traveled distance between node n_m and position $\tilde{g}_{k,i}$
$leng(p_{k,i})$	Length of path $p_{k,i}$
$l(n_m, n_o)$	Link that connects node n_m and node n_o
$t(k, l(n_m, n_o))$	Travel time of probe k on link $l(n_m, n_o)$
$v(k, l(n_m, n_o))$	Travel speed of probe k on link $l(n_m, n_o)$
S_u	The uth time interval for speed estimation
$V(S_u, l(n_m, n_o))$	Travel speed on link $l(n_m, n_o)$ during time slot S_u
K	Number of probes that travel through a link
$MASD$	Mean absolute speed difference
$MAPSD$	Mean absolute percentage speed difference
v_{bus}	Estimated link travel speed from Transit GPS data
v_{loop}	Travel speed from loop detector data
$T(p_{k,i})$	Travel time on path $p_{k,i}$
$T_f(p_{k,i})$	Free-flow travel time on path $p_{k,i}$
$T_s(p_{k,i})$	Stop time on path $p_{k,i}$
$T_c(p_{k,i})$	Congestion time on path $p_{k,i}$
$t(l_{k,i,j})$	Travel time on link $l_{k,i,j}$
$t_f(l_{k,i,j})$	Free-flow travel time on link $l_{k,i,j}$
$t_s(l_{k,i,j})$	Stop time on link $l_{k,i,j}$
$t_c(l_{k,i,j})$	Congestion time on link $l_{k,i,j}$
$v_f(l_{k,i,j})$	Free-flow travel speed of link $l_{k,i,j}$
w	Congestion degree
$w_{max}(p_{k,i})$	Maximum value of congestion degree w on path $p_{k,i}$
$f(w, p_{k,i})$	Likelihood of probe k experiencing a certain congestion degree w on path $p_{k,i}$
$P_w(w, p_{k,i})$	Congestion probability on path $p_{k,i}$ given congestion degree w

λ	location on a link
$h_s(l_{k,i,j}, \lambda, w)$	Likelihood of probe k stopping at location λ on link $l_{k,i,j}$ given congestion degree w
$g(l_{k,i,j}, \lambda)$	Likelihood of probe k stopping at location λ on link $l_{k,i,j}$ under free-flow condition ($w = 0$)
$\mathrm{H_s}(l_{k,i,j}, w)$	Likelihood of probe k stopping on link $l_{k,i,j}$ given congestion degree w
$\mathrm{P_s}(l_{k,i,j}, w)$	Link stopping probability on link $l_{k,i,j}$ given congestion degree w
$s_{k,i,j,x}$	The xth segment on link $l_{k,i,j}$
$n(s_{k,i,j,x})$	Number of GPS points located on segment $s_{k,i,j,x}$
T_{update}	Average GPS update interval
N	Number of probes that travel through a link in the historical data
$\tau(s_{k,i,j,x})$	Travel time on segment $s_{k,i,j,x}$
$\tau_f(s_{k,i,j,x})$	Free-flow travel time on segment $s_{k,i,j,x}$
$\tau_s(s_{k,i,j,x})$	Stop time on segment $s_{k,i,j,x}$
$\tau_c(s_{k,i,j,x})$	Congestion time on segment $s_{k,i,j,x}$
$leng(s_{k,i,j,x})$	Length of segment $s_{k,i,j,x}$
T_{update}	Average GPS update interval
$t'_c(l_{k,i,j})$	Congestion time on link $l_{k,i,j}$ estimated from historical data
$SEG_A(l_{k,i,j})$	Set of Type A segments on link $l_{k,i,j}$
$t'_s(s_{k,i,j,x})$	Stop time on segment $s_{k,i,j,x}$ estimated from historical data
$\mu(p_{k,i})$	Mean of congestion degree on path $p_{k,i}$
$\mu(l_{k,i,j})$	Mean of congestion degree on link $l_{k,i,j}$
$h'_s\left(l_{k,i,j}, \lambda, \mu(l_{k,i,j})\right)$	Point stopping likelihood on location λ estimated from historical data
$S_{k,i,j,x}$	Segment with the maximum value of segment stop time on link $l_{k,i,j}$

GLOSSARY OF TERMS

ATMS	Advanced Traffic Management Systems
ATIS	Advanced Traveler Information Systems
ANN	Artificial Neural Network
AVI	Automatic Vehicle Identification
AVL	Automatic Vehicle Location
DBN	Dynamic Bayesian Network
ETS	Edmonton Transit Service
ETC	Electronic Toll Collection
GTFS	General Transit Feed Specification
GPS	Global Positioning System
ITS	Intelligent Transportation Systems
K-S Test	Kolmogorov-Smirnov Test
LPR	License Plate Recognition
MAPSD	Mean Absolute Percentage Speed Difference
MASD	Mean Absolute Speed Difference
OCTA	Orange County Transportation Authority
Tri-Met	Tri-County Metropolitan Transit District

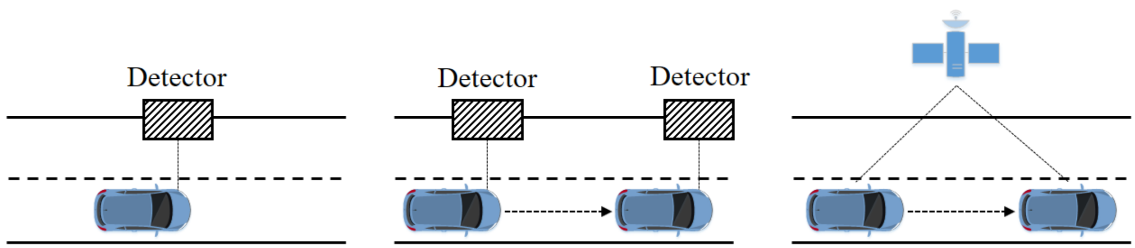
1 INTRODUCTION

Travel speed is one of the most commonly applied measures of performance for traffic facilities and networks. It has been used in transportation operation analysis, traffic simulation models, incident detection and analysis, economic studies, and many other areas of transportation engineering and planning. Moreover, some important decision-making variables such as travel time can be further calculated based on the speed information. Speed information is also relevant for real-time transportation applications. These applications include Advanced Traffic Management Systems (ATMS) and Advanced Traveler Information Systems (ATIS), which are part of the Intelligent Transportation Systems (ITS). Therefore, providing timely and accurate speed information is essential for improving traffic management and control.

Speed data can be collected via manual or automatic ways, while the manual method is less practical and efficient than the automatic method when a large amount of speed data is required for a network. Besides, manual speed measurement apparently cannot meet the need of extensive and continuous real-time data for transportation operation and management. A variety of traffic detecting systems have been applied to automatically collect real-time traffic data, among which probe detecting technology has captured more and more attentions in these years. This technology uses vehicles equipped with positioning devices as probes, and the speed data can be easily obtained by tracking vehicles' trajectories. Comparing to the traditional point-fixed detectors, whose applications are limited by the expensive cost of installation and maintenance, the probe technology has more flexible detection range and is more cost-effective.

1.1 Travel Speed Detectors

Recent progress in advanced technologies for intelligent transportation systems has enabled the extraction of traffic information from many different sources and in multiple formats. Except manual works, traffic data sources can be classified in several ways, while in this thesis the classification presented by Mori *et al.* (2015) has been applied. The traffic data sources are split into two main groups: point detectors and interval detectors.



(a) Point detector (b) AVI detector (c) AVL probe

FIGURE 1.1 Traffic Data Sources

Point detectors (Figure 1.1(a)) are set in fixed points of the road and capture traffic variables in these specific points. Conventional point detectors include single-loop detectors (Coifman, 1996; Hellinga, 2002; Coifman and Kim, 2009b), dual-loop detectors (Lucas, Mirchandani and Verma, 2004; Coifman and Krishnamurthy, 2007; Sun, Yang and Mahmassani, 2008; Yeon, Elefteriadou and Lawphongpanich, 2008; Li *et al.*, 2013), radars, video cameras (Dailey, Cathey and Pumrin, 2000; Schoepflin and Dailey, 2003) and so on. In general, point detectors can provide vehicle speed data with high accuracy, and the sample penetration rate of these detectors are usually very high. Besides, point detectors have already been deployed on most roadways, especially on freeways, and previous literature regarding using point detector data for travel speed estimation is rich. However, point detectors can only collect time-mean-speed of traffic flows on fixed locations, which can hardly reflect traffic conditions of road links. Another disadvantage is that, due to the expensive costs of installation and maintenance, point detectors are difficult to be widely applied, thus the detection range of them is relatively limited, especially on arterials.

Interval detectors capture traffic data between two points on the road. The interval detectors can be further divided into two groups: automatic vehicle identification (AVI) techniques and automatic vehicle location (AVL) techniques. AVI detectors (Figure 1.1(b)) collect traffic data of road segments by identifying individual vehicles that pass specific points on the road. Typical AVI detectors include license plate recognition (LPR) technology (Dion and Rakha, 2006; Ma and Koutsopoulos, 2008; Tam and Lam, 2008), Bluetooth sensors (Barceló *et al.*, 2010; Haghani *et al.*, 2010) and electronic toll collection (ETC) system (Soriguera, Rosas and Robusté, 2010), and some researches use multiple point detectors to imitate AVL detectors as well. Compared to point detectors, AVL detectors can directly measure space-mean-speed for roadway segments, and the data accuracy and quality are relatively high. However, speed data from AVI detectors may suffer from sample bias. For example, the ETC system can only collect data from vehicles equipped with certain devices, and Bluetooth detectors can only collect data from vehicles turning on in-car Bluetooth, so the representativeness of the detected vehicles could be questioned. Another issue is that, similar to point detectors, AVI detectors are usually location-fixed, which limits their detection range. Furthermore, the cost of AVI detectors is relatively high, resulting in limited deployment and researches.

AVL technology (Figure 1.1(c)), on the other hand, utilize mobile probes that can continuously report their location information to obtain moving trajectories, and the vehicle link travel time and travel speed can be directly extracted from the trajectory data. Typical AVL detectors include GPS-enabled smartphones (Herrera *et al.*, 2010), GPS-equipped vehicles (Deng *et al.*, 2015; Zhan, Ukkusuri and Yang, 2016), cellular phone probes (Qiu, Cheng and Ran, 2007; Gao and Liu, 2013), etc. AVL probes have been considered as the most promising detection technology in recent years for several reasons. First, the costs of AVL probes are relatively low. Global Positioning System (GPS) is the most commonly applied AVL devices, and its price has been sharply dropped in the past decades, and many vehicles, such as taxis, transit buses, and trucks, have already equipped GPS devices for safety or operation reasons. Second, AVL probes can provide large and flexible spatial-temporal detection range. For instance, taxis move around urban areas, and truck probes can cover major intercity highways. Third, as a subtype of interval detector, AVL probes provides direct space-mean-speed measurement. However, there also exist practical limitations of AVL probes. First of all, most studies cannot provide sufficient probe sample size for traffic estimation, which harms the accuracy and reliability of estimation results. Besides, like AVI detectors, AVL probes also have to overcome the sample bias issue, e.g. commercial vehicles or transit vehicles. Thirdly, in practice, the update interval of probes' location reports is pretty long, i.e. longer than 30 seconds, due to limited data processing capability, which brings the challenge of inferring the correct traveled path between two consecutive location reports of an individual probe. Last but not the least, for some special types of probes, such as GPS-enabled smartphones, it is necessary first to filter AVL reports that may not be recorded when the users are in on-road vehicles, yet such process, namely probe filtering, is difficult to develop as it relates to complicated map-matching and inference of motion status.

1.2 Transit Buses as Probes

An alternate source of the travel speed data is using transit buses as probe vehicles. Comparing to the other types of AVL probes, such as GPS-equipped taxis and GPS-enabled smart phones, using transit buses has the following advantages. First, practically most vehicle location data is provided with relatively long update interval, which makes it difficult to know the traveled path between two consecutive reports of a probe. However, transit buses operate along scheduled routes. Hence the process of path identification can be simplified if the route number of the bus probe is known. Second, for some types of probes, e.g. GPS-enabled smartphones, it is necessary to first determine what kind of traffic mode a user is using, otherwise, the result may suffer from sample bias. For transit buses, as the positioning devices are installed on the vehicles, it is unnecessary to do such filtering for them. Third, since the departure time of bus routes is easy to access, the number of samples on a certain road link is relatively constant, which can be used as a reference to infer the available scope for its use. Finally, transit buses usually run on major urban roads so that it can provide good detection coverage for the urban road network.

However, using transit buses as probes also has limitations. As a special type of vehicles, the driving behavior and speed characteristics of transit buses are usually different from general vehicles. First, the acceleration and deceleration of transit buses are different from passenger vehicles. Second, when moving on arterials, transit buses have to stop at bus stops for passenger boarding or alighting, causing additional delays known as bus dwell times. Third, buses operate according to schedules and drivers may adjust their driving when running ahead or behind schedule. The above three main travel characteristics of transit buses cause changes in their travel speeds (or travel times) that are irrelevant to the general traffic conditions, and they are hard to be identified from the AVL data alone. This means that the interrelation between bus and car traffic is inevitable and needs to be adjusted. Another challenge of using transit buses as probes is that the limited amount of buses and usually cannot provide sufficient sample size for reliable traffic estimation. Therefore, it is necessary to investigate the concept of using transit buses as probes for travel speed estimation at the link level.

1.3 Objectives

This thesis has two main objectives as follows:

1. To estimate link travel speeds from transit probe AVL data, and investigate factors that may influence the estimation accuracy;
2. To propose a link travel time estimation method for individual probe vehicles on urban arterials based on low-frequency AVL data.

For the first objective, a length-based link travel speed estimation method is proposed. A link represents a road segment connecting two geographical features (namely nodes, such as intersections, road ends, ramps, etc.). This method is first to estimate the timestamp when a transit probe passes a node; then the link travel time can be calculated as the time interval between the estimated timestamps when a vehicle passes the link's upstream and downstream nodes. A field test is then conducted on a typical urban freeway for performance evaluation, and it should be noted that in the past literature there is little research focusing on transit bus-based freeway link travel speed estimation. This thesis can help fill such gap. From the field test results, the impacts of probe vehicle type (as transit bus) and data update interval upon the speed estimation accuracy are studied as well.

For the second objective, a probabilistic travel time estimation method is proposed. Due to the existence of traffic control devices (e.g. signals and stop signs) and bus stops, estimating individual probes' travel states on arterials is more challenging than on freeways. The proposed method aims to allocate the travel time between two consecutive AVL reports of a probe vehicle into each traversed link so that the link travel time estimation can be improved. Another advantage of this method is that it can capture the time interval when a vehicle stops on the road, so it has the potential for estimating bus dwell times at bus stops for transit buses.

1.4 Outlines

The remainder of this thesis is organized as follows. Chapter 2 reviews the prior studies on (1) traffic estimation using transit bus probe data, and (2) link travel time/speed estimation using low-frequency probe data. Chapter 3 describes the transit bus AVL data applied for field tests, and the road network used in this research. Chapter 4 introduces the methodology and field test results of estimating transit bus-based link travel speeds; this chapter also includes the analyses of the impact of probe vehicle type and data update interval on the estimation results. Chapter 5 proposes a link travel time estimation method for individual probes on urban arterials, and its evaluation results through a field test using transit bus data. Finally, chapter 6 gives the summary and conclusions of the work in this thesis.

2 LITERATURE REVIEW

The following literature review has two main parts. Section 2.1 summarizes primary case studies of using transit buses for travel time/speed estimation, and section 2.2 reviews researches on link travel time/speed estimation using low-frequency probe data.

2.1 Traffic State Estimation Using Transit Buses as Probes

Compared with the rich body of literature in travel speed estimation or travel time estimation based on loop detectors, AVI technologies and other types of probes, the literature of bus probes is relatively limited, and eight major case studies are introduced in this thesis.

To the best of the author's knowledge, the first attempt of investigating the potential of using transit buses as probes was provided by Bae in his thesis dissertation, and a field test was conducted in Virginia (Bae, 1995). Later a bus probe project was launched by the Orange County Transportation Authority (OCTA) in California (Hall *et al.*, 1999; Hall and Vyas, 2000). In the late 1990s, Dailey *et al.* used AVL-enabled buses as speed sensors for real-time traffic condition estimation for both freeway and arterial in King County, WA (Elango and Dailey, 2000; Cathey and Dailey, 2001, 2003; Dailey and Cathey, 2002). In the early 2000s, two other case studies were conducted, one was the Tri-County Metropolitan Transit District (Tri-Met) in Portland, Oregon (Tantiyanugulchai and Bertini, 2003; Tantiyanugulchai and Bertini, 2003; Bertini and Tantiyanugulchai, 2004; Berkow *et al.*, 2007, 2008; Glick *et al.*, 2015), and the other one was supported by the Delaware Department of Transportation (Chakroborty and Kikuchi, 2004). Soon after, Coifman and his colleagues started a bus probe study on freeways in Central Ohio (Coifman and Kim, 2006, 2009a; Redmill *et al.*, 2011). In 2008, Pu and Lin introduced a case study in Chicago for bus-probe-based route travel time estimation (Pu and Lin, 2008; Pu, Lin and Long, 2009), and almost at the same time there was another one conducted in the city of Cambridge, UK, which is the most recent study (Bejan *et al.*, 2010; Bacon, Bejan and Beresford, 2011; Bejan and Gibbens, 2011).

TABLE 2.1 Summary of Bus Probe Studies

Study	Road Type	Data Updating	Methodology
Virginia	Arterial	Space-sampled	Linear regression; ANN
Orange County	Arterial	Time-sampled	Linear regression
King County	Freeway; Arterial	Irregularly-sampled*	Maximum likelihood; Kalman Filter
Delaware DOT	Arterial	Space-sampled	Linear regression
Portland	Arterial	Space-sampled	Linear regression
Central Ohio	Freeway	Time-sampled*	Directly measured
Chicago	Arterial	Time-sampled*	State-space model; Bayesian updating
Cambridge	Arterial	Time-sampled*	Analytical model

**the resolution of time-sampled probe data is low, e.g. longer than 30 seconds.*

Table 2.1 summarizes the key information about these case studies, including study objectives, roadway types, data collection methods, data sampling features and methodologies. In general, most case studies were conducted on urban arterials, and only two cases investigated the use of bus probes on freeways. This is reasonable because most transit buses operate on urban road networks. Regarding the mechanism of updating bus AVL data, there are two major types: space-sampled and time-sampled. Space-sampled AVL data sends out location reports when a probe passes a predefined location, e.g. bus stops in most cases, or a probe has traveled through a certain distance since the last update. On the other hand, Time-sampled means the AVL reports update for every predetermined time interval. One thing should be noticed is that for both types of AVL data updating mechanisms, the update interval could variate due to several causes, such as locating device accuracy or weather conditions. The methodology applied in each case study is discussed in detail next.

Bae (1995) first used a simple linear regression model to build the bus-car speed and travel time relationship as follows:

$$CTS = a + bBTS \quad \text{..(2.1)}$$

$$CTT = c + dBTT \quad \text{..(2.2)}$$

where *CTS* and *CTT* refer to car travel speed and car travel time respectively, and *BTS* and *BTT* refer to bus travel speed and bus travel time respectively. Then a three-layer Artificial Neural Network (ANN) model was applied for link travel time estimation. In the ANN model, the static input included spatial features (e.g. link length, number of lanes, speed limit, number of passed intersections and bus stops, etc.) and temporal features (e.g. peak hour factor), and the dynamic input included bus travel time, number of stops, number of boarding and alighting passengers, weather conditions and so on. The result suggested that ANN can provide reasonable speed estimates, however it is difficult to interpret the impact of each input variable upon the estimation result due to the black box process.

In the Orange County study (Hall *et al.*, 1999; Hall and Vyas, 2000), the car link travel speed was estimated by the following equation:

$$CTS = (N_1 * link\ length)/(BTT - BST - N_2) \quad \text{............................ (2.3)}$$

where BST denotes the total stopping time of a transit probe at bus stops on a certain road link, and N_1 and N_2 are empirical adjustment factors accounting for the bus-car speed relationship. Unlike the other literature, the researchers concluded that transit bus is an imperfect kind of probe vehicle, the main reason is that transit buses operate following predetermined schedules, and bus drivers adjust driving speeds when running ahead or behind schedule. Such speed change is irrelevant to actual traffic conditions yet hard to be identified. Another important issue relates to data quality, as the number of missing observations or false location reports in this study is nonignorable. Furthermore, the large bus headway (e.g. 30 minutes) limited the sample rate.

In the King County study, the researchers first adopted a maximum likelihood method to fit the bus-car speed relationship (Elango and Dailey, 2000), then a Kalman Filter model was proposed for speed estimation. Later, a virtual speed sensor system was built for the mass-transit vehicle tracking system, and a complete transit AVL database was defined (Cathey and Dailey, 2001, 2003; Dailey and Cathey, 2002). The virtual sensor system consists of three components, a tracker, a probe speed estimator, and a display application. The database is described in terms defined by the ITS Transit Communications Interface Profile, relevant terms including time point, time point interval, pattern, trip and block. In the tracker component, a Kalman filter was used to transform a sequence of AVL measurements into smooth estimates of vehicle dynamical state, including vehicle speed (Cathey and Dailey, 2001). The probe estimator component contains two subcomponents: a covering arcs builder, which provides an index with which to map the road segments into the spatial schedule information, and a virtual sensor builder. The transit probe-based speed estimation was compared with inductive loop detectors, and the result from the King County study revealed that bus speeds were on average 12.8 km/h lower than car speeds on freeways and 1.6 km/h lower on major arterials.

In the Delaware study (Chakroborty and Kikuchi, 2004), a simple linear regression was developed for modeling the bus-car speed relationship and estimating link travel times. One thing should be noted is that in this study the researchers suggested that for meaningful and reliable travel time estimation or prediction, the length of a link should be not less than the travel distance of a vehicle driving at average speed for 5 minutes. For example, if the assumed average speed is 55 km/h, then the minimum link length should be 4.6 km. For the linear regression model, the authors first considered the number of times bus stops at bus stops as a variable, which can reflect the travel time loss due to acceleration and deceleration, yet the initial analysis showed that its coefficient is not significant, hence the conclusions were given by

$$CTT = \begin{cases} \frac{link\ length}{free-flow\ speed} + 0.14(BTT - BST), & less\ frequently\ congested \\ \frac{link\ length}{free-flow\ speed} + 0.18(BTT - BST), & more\ frequently\ congested \end{cases} \quad (2.4)$$

Equation (2.4) suggests that, first, although there are other factors that may differentiate bus speed from car speed, the dwell time at bus stops has the most significant impact; second, the bus-car speed relationship is sensitive to the dynamics of traffic condition.

In the Portland study (Tantiyanugulchai and Bertini, 2003; Bertini and Tantiyanugulchai, 2004; Berkow *et al.*, 2007; Ou *et al.*, 2011), the bus probes were further processed as hypothetical buses, pseudo buses and modified pseudo buses. The hypothetical bus concept considers a potential non-stop bus trajectory by subtracting the dwell times. A pseudo bus trajectory was created by stringing together segments of a trip where the pseudo bus traveled at its maximum speed between each pair of stops (the bus AVL data was recorded for every stop at bus stops). A modified pseudo bus was created by taking into consideration the dwell times of the actual bus. After analysis, the final bus-car speed relationship developed in this study is given by

$$CTS = 0.72 * (pseudo\ speed) + \varepsilon \qquad (2.5)$$

where ε denotes the random error. Equation (2.5) is applied for the whole test corridor, and the coefficient changes from 0.72 to 0.94 when it is applied to a bridge within the corridor (on the bridge there is no intersection or bus stop). This is similar to the scenarios in the Delaware study, while the roads are classified into less and more frequently congested. Later in 2015, a new 5-second resolution bus AVL data was introduced (Glick *et al.*, 2015), and by comparing the vehicle trajectories, trip speeds and trip times, the authors concluded that the new high-resolution can provide richer information for improving bus travel speed detection, identifying speed drops, and estimating intersection signal and queuing delays.

In the Central Ohio study (Coifman and Kim, 2006, 2009a; Redmill *et al.*, 2011), the field test was conducted only on freeways for travel time and travel speed estimation. Note that the concept of link in the study refers to the traveled roadway segment between two consecutive AVL reports of a bus probe, so the links are not predefined by roadway facilities. In this way, the link travel time can be directly measured and the link travel speed is the quotient of the travel distance and time. The estimates were compared with the travel speed and travel time collected from loop detectors (Coifman and Kim, 2006, 2009a) and test vehicles (Redmill *et al.*, 2011), and the result suggested that on freeways the bus probes can provide reliable traffic estimates, since the impact of intersections or bus stops upon estimation accuracy is not an issue for freeways.

In the Chicago study (Pu and Lin, 2008), Pu and his colleagues studied urban corridor travel time estimation using transit buses as probes. A state space model was used for travel time estimation. The authors found that, first, the model calibration result suggested that the state space models were space-specific and time-specific, for example the model parameters for four different scenarios (eastbound morning, eastbound evening, westbound morning, westbound evening) are significantly different. Second, when traffic is heavier, bus and car speeds are more significantly interrelated and the experienced travel delays are more similar. Furthermore, the small standard deviations of speed estimates suggest good performance of the proposed state space model. Later in 2009, Pu's team used a simple linear regression model to describe the bus-car speed relationship and proposed a Bayesian updating method to improve speed estimation, and the results showed the promise of using bus probes to catch recurrent traffic congestions (Pu, Lin and Long, 2009).

The Cambridge is the most recent bus probe study (Bejan *et al.*, 2010; Bacon, Bejan and Beresford, 2011). In this study, to eliminate the travel delay caused by bus dwell times from the route travel time, a bus stop gate technique was proposed. A bus stop gate is a roadway section where a bus stop is at. While a bus probe has two consecutive AVL reports between which a bus stop gate exists, the estimated travel time between the two reports can be drawn as

$$BTT' = BTT\frac{P_1M}{P_1P_2} \quad \text{..(2.6)}$$

where P_1 and P_2 denote the on-road positions of the two AVL reports and M denotes the position of the bus stop gate. Then the researchers developed a so-called local time profile (described detailly in (Bejan *et al.*, 2010)) for gaining time-space diagrams of bus probe trajectories and analyzing sources of traffic delays. The result from this study confirms the promising use of transit buses as probes.

2.2 Link Travel Time/Speed Estimation on Arterials Using Low-Frequency Probe Data

Hellinga *et al.* (2008) summarized five steps for inferring traffic conditions from low-frequency probe AVL data:

1. Map-matching: to project raw AVL locations into the road network map;
2. Path identification: to infer the traveled paths between adjacent reported locations;
3. Probe filtering: to identify if the probes represent a vehicle;
4. Travel time allocation: to estimate link travel times for individual filtered probes;
5. Travel time aggregation: to estimate travel times of road links from combined probe travel times.

Most literature reviews of probe-based link travel time/speed estimation focus on one or two of the above five process, especially the map-matching, path identification and travel time allocation.

Sananmongkhonchai, Tangamchit and Pongpaibool (2008) proposed an incremental weighted update algorithm to improve road segment speed estimation from historical speed profile and real-time probe vehicle point speeds. The field test was conducted on a frequently congested bridge segment, and the speed estimates from the algorithm were compared with the position-based probe speeds (i.e. the average speed between two consecutive probe location reports on the segment). Results show that the algorithm yields more accurate speed estimation on a road segment than the statistical average speed method. However, the selected road segment is on a bridge that the probe vehicles are little likely to stop, which is impractical for signalized urban network.

Hellinga *et al.* (2008) developed an analytical model for probe-based link travel time estimation on arterials using low-frequency data. The travel times are decomposed into three parts, namely free-flow travel time, stop time and congestion time, then a probabilistic model was built to capture the likelihood of a vehicle experiencing certain level of congestion and the likelihood of a vehicle stopping on a certain road link. This method can significantly improve the accuracy of link travel time estimation for individual probes, especially when the location update interval is between 30 to 60 seconds. However, the estimation error is generally larger for links not controlled by a traffic signal.

Liu, Yamamoto and Morikawa (2006) investigates the cost efficiency of probe vehicle data at different update intervals, ranging from 5 seconds to 60 seconds. By assuming uniform motion, i.e. the travel speed between two consecutive location reports is constant, the link travel time can be simply calculated by estimating the timestamp when a probe vehicle enters and leaves road links. They suggested that, in terms of cost efficiency, 30-second update interval may be the best choice as it can provide reliable travel time estimation for all trips with different travel speeds and different link lengths with 95% accuracy. However, as location update interval increases, the accuracy of map-matching drops, which may influence the final result.

Fabritiis, Ragona and Valenti (2008) used large-scale floating car data from privately own vehicles for traffic estimation and prediction. The AVL data was updated every 100 km or every 12 minutes, and a case study was conducted on a motorway with 33 entry/exit junctions. As the main focus of their research was on traffic prediction, they did not give many details about the method they applied for individual link travel speed, while they mentioned that the aggregated link travel speeds are exponentially weighted. After investigating the relationship between travel speeds of adjacent links, they confirmed that the correlation between neighboring links decreases as the physical distances increase and the number of time lags grows.

In 2010, Shi and Liu (2010) calculated estimated link space mean speeds and road traffic condition indexes using taxi probes. The main focuses of their research are map-matching process for low-frequency AVL data and space mean speed estimation method. They first proposed a point-to-curve map-matching method based on fuzzy logics, which used point projection distance and vehicle traveling angle as the input. Then, for link space mean speed estimation, they suggested that the speed profile of an individual probe vehicle travelling through a road segment can be classified into four types: (1) constant speed, (2) accelerate at the segment entry and then leave at constant speed, (3) enter the segment at constant speed and then decelerate near the exit, and (4) accelerate at the segment entry and decelerate near the exit. Hence, the individual speed profiles can be described by quadratic curves with trajectory-specific parameters a_0, a_1 and a_2,

$$v(l) = a_2 l^2 + a_1 l + a_0 \qquad (2.6)$$

where l is the travel route measured from road segment entry. Further, to reduce the estimation error caused by vehicle slowing down or stopping due to traffic control, the link average travel speeds are calculated only based on the flat parts of individual speed profiles. Results show that in urban signalized network, link speed estimates from their proposed method are reliable, with a 10% difference compared with speeds detected from traffic surveillance video checking. However, to calibrate the parameters in Equation (2.6), it requires at least three AVL location reports that are on the road segment, and the only way to solve this issue, quoting the word from the researchers, is to boost the AVL update frequency.

Hofleitner *et al.* (2012) presented a Dynamic Bayesian Network (DBN) model for urban link travel time estimation. A graphical model was first presented representing the dependence between the travel-time observations and the congestion state of each link at each time interval and their spatiotemporal evolution. Next, they developed an arterial traffic flow model, in which the traffic conditions are divided into two types, namely the undersaturated regime and the congested regime, and the probability distribution functions of vehicle locations are set for each regime. Finally, for calibrating the parameters of the DBN model, an expectation-maximization algorithm was introduced. The field experiment was conducted in San Francisco, and the AVL data update interval is 60 seconds. Compared with a simple baseline approach, the DBN model provides an increase in estimation accuracy of 35%.

Zheng and Van Zuylen (2013) proposed an ANN model for urban link travel time estimation. The ANN model contains one hidden layer with 20 neurons, and the input information in the model includes vehicle positions, timestamps, speeds and link IDs (which represent link-specific geographical features). The performance of the ANN model was compared with the aforementioned Hellinga's model, and the results from both simulation scenarios and field tests prove that the ANN model outperforms the Hellinga's model, especially when the traffic is becoming heavier. A possible reason is that the input information for the ANN model is richer than the Hellinga's model (e.g. speeds and link IDs). The researchers also did a sensitivity test to evaluate the impacts of input parameters on the accuracy of the ANN model, and they suggested that the position information is the most important factor. One thing worths mentioning is that although the ANN model can give relatively good link travel time estimates, such data-based models are hard to explain as the calculation process is a black box. Another limitation is that such models require large-scale data and ground truth for training and model validation.

Jenelius and Koutsopoulos (2013) proposed a complex statistical regression model. This model contains two layers; a network model that specifies the joint distribution of link travel times, and a observation model that specifies the information included in sequences of probe vehicle location reports. Various parameters that may influence link travel times are investigated, including geographical features (e.g. speed limit, functional class, link length and traffic control type), trip conditions (e.g. time-of-day, weekday, holiday, etc.) and weather conditions (e.g. temperature and precipitation), and the correlations were estimated using a maximum likelihood algorithm. Based on the estimation results, they summarized several attributes that have significant impact on the estimation accuracy, and the most important contribution is the use of correlations between traversed links for generalizing the low-frequency probe data.

Zhan *et al.* (2013) tried to use limited information trip-based data for urban link travel time estimation. Unlike the other probe data collected from taxis as mentioned above, the dataset applied in their research only provides locations and timestamps of trip origin and destination and trip fares. At first, they estimated link travel times by minimizing the square difference between the expected path travel times and the actual path travel times, yet historical data were not considered in the model (Zhan *et al.*, 2013). Later, they developed a Bayesian mixture model that can incorporate temporal correlation from historical estimation results and the spatial dependencies among neighboring links (Zhan, Ukkusuri and Yang, 2016). However, the performance of the model was evaluated by comparing the estimation results with the predicted results, which makes the model validation not very solid due to the lack of ground truth.

Recently, Li, Ahmed and Smola (2015) used anonymous low-frequency vehicle GPS data for estimating and predicting link travel speeds, and the focus of their research is to infer trajectories of individual probe vehicles as accurate as possible. Due to the privacy issue, the applied GPS data did not include user IDs. To overcome this difficulty, they developed a model that consists of two parts. The observation model is to infer true locations by using a quadratic log-likelihood function, and the motion model is a likelihood model for a sequence of observations and on-road locations. In their model, a first-order Markov assumption was made, that is the current state is only correlative to the last state, hence the correlation between adjacent probe GPS reports can be taken into consideration. Although the qualitative results suggest good estimation accuracy of the model, their test also lack ground truth data for quantitative comparison.

2.3 Summary

This chapter reviews two main aspects of research. For traffic estimation using transit buses as probes, eight major case studies are introduced. It is found that, first, as a special type of vehicle, the travel characteristics of transit buses is significantly different from general vehicles, reasons of which include the dwelling times at bus stops, different acceleration and deceleration, the requirement of following scheduled departure headways, etc. However, few researches took a deep look into the features of such travel speed differences, e.g. the variance or the distribution of the speed differences. Second, most case studies were conducted on urban arterials instead of the King County study and the Central Ohio study, yet the King County study suggests a fail of using buses as probes, and the links defined in the Central Ohio study is actually the traveled paths between two consecutive location reports. For arterial link travel time estimation based on low-frequency AVL data, most studies focus on map-matching or path identification, and for travel time allocation, regression models and maximum-likelihood models are widely applied, while only few can propose analytical models.

3 DATA PREPARATION

This chapter describes the data used in this study. Section 3.1 introduces the applied transit bus data in the following case studies, and section 3.2 describes the road network built for the proposed link travel speed estimation method and the link travel time estimation method.

3.1 Transit Bus AVL Data

In this thesis, the transit bus AVL data is provided by Edmonton Transit Service (ETS). In Edmonton, Alberta, Canada, most transit buses have been equipped with GPS devices that can send real-time bus location reports to the transit center and help operators monitor and evaluate the performance of transit network. ETS offers free real-time bus AVL data feeds on Edmonton Open Data Portal for developers and researchers to promote the use of transit and information related to transit. The bus AVL data follows the Realtime General Transit Feed Specification (GTFS) data format defined by Google, and the data feed consists of two parts, namely Trip-Update and Vehicle-Position.

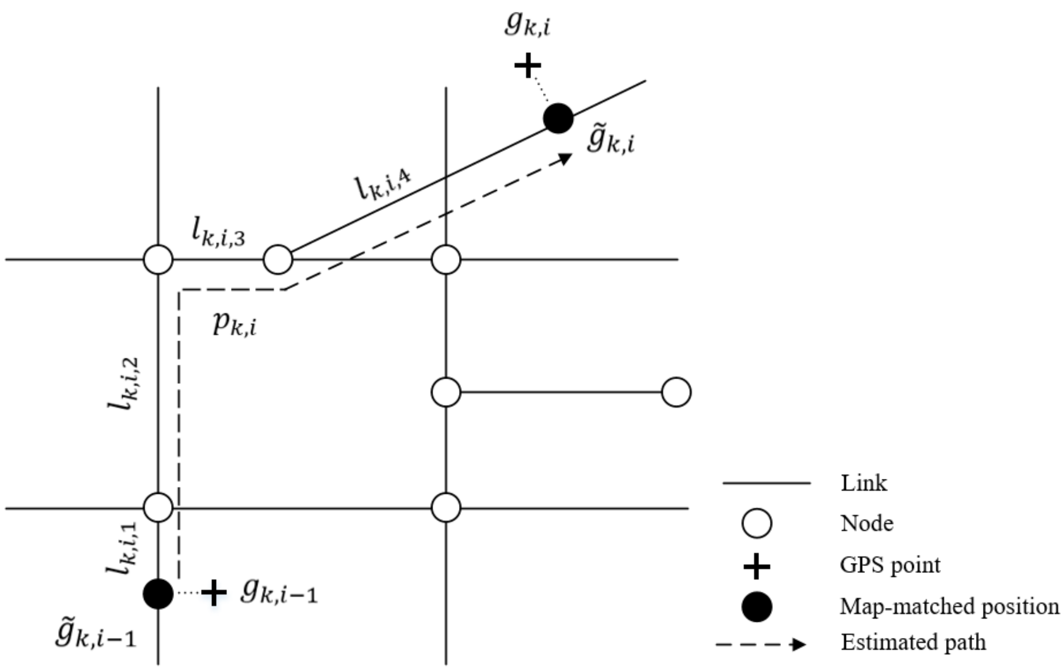
Trip-Update provides trip information. Defined by GTFS, a trip is a sequence of two or more stops that occurs at specific time, and there should be at most one trip update for each scheduled trip at one time. A trip is described by trip ID, bus route number, ID of assigned bus, scheduled trip start time, bus stop sequence number, bus stop ID, scheduled bus stop departure time, real-time predicted bus stop departure time, and actual bus stop departure time. Vehicle-Position provides automatically generated information on the location of a vehicle, including bus ID, trip ID, AVL timestamp and two-dimension geographical coordinates (longitude and latitude).

Trip-Update and Vehicle-Position are synchronously updated every 30 seconds. It should be noted that the timestamps of updated bus AVL reports are not the same as the data feed update timestamp. For example, if the last update of bus AVL data feed happens at 2:00:30 PM, and the most recent AVL update of a bus happens at 2:00:18 PM, then the data feed update timestamp is 2:00:30 PM and the bus AVL timestamp reported in the data feed is 2:00:18 PM. A software was developed to collect and archive the real-time bus AVL data. Trip-Update and Vehicle-Position are first downloaded and archived separately, then based on the data feed update timestamp, trip ID and bus ID, the two datasets are combined in one table, which includes bus ID, trip ID, bus route number, AVL timestamp and geographical coordinates. It should be noted that the provided predicted and actual bus stop departure time information is measured in minutes, which is not sufficiently accurate for link-level traffic estimation and hence they are not taken into consideration in this thesis.

Besides the bus AVL data, there are two additional transit-related data that can be easily obtained and support this research. The bus route schedule brochures can be found on the ETS website, and it provides bus routes' headway and travel routes, which can be used for inferring sample size on road links. The bus stop locations can be downloaded from the Edmonton Open Data Portal website, including bus stop ID, landmark and geographical coordinates.

3.2 Road Network

In this research, the detailed information of road construction, such as road width or number of lanes, is assumed to be unknown. Therefore, the road network can be abstracted into a network consisting of a set of nodes and a set of links (see Figure 3.1).



$$\boxed{p_{k,i} = \{l_{k,i,1}(0.8,1), l_{k,i,2}(0,1), l_{k,i,3}(0,1), l_{k,i,4}(0,0.7)\}}$$

FIGURE 3.1 Road Network

A node n_a is a network feature representing a specific geographical location, including road junctions, signalized or un-signalized intersections, crosswalks, bus stops, dead ends of a road, and so on. Sometimes nodes are set to break a long link into shorter sub-links for the convenience of map-matching or path identification. A node n_a can also be defined by $n(x_a, y_a)$, where x_a and y_a are the two-dimension coordinates.

A link l_b is a network feature representing a specific roadway segment. A link can also be represented by $l(n_{start}, n_{end})$, where n_{start} and n_{end} are the nodes that are at the start and end of the link respectively. It should be noted that (1) l_b does not have to be a straight line, as the link length $leng(l_b)$ is assumed to be known; and (2) n_{start} and n_{end} determines the direction of a link, hence a two-way road link should be represented by two links.

The transit probes report their locations periodically. The *i*th GPS report (termed as GPS points in the following discussion) sent from transit bus k at time $t_{k,i}$ is defined by $g_{k,i} = (VehicleID_{k,i}, t_{k,i}, x_{k,i}, y_{k,i})$, where $VehicleID_{k,i}$ is the unique identity of the transit probe, $t_{k,i}$ is the timestamp of the report, $x_{k,i}$ and $y_{k,i}$ are the two-dimension coordinate indicating the vehicle's position. Before applied to the proposed method, the GPS points should be first map matched with the road network and the two-dimension coordinates need to be transferred into one-dimension coordinates. As the focus of this paper is on link travel speed estimation, it is assumed that the reported locations are error-free and the map matched results are perfect. The map matched probe location is represented by $\tilde{g}_{k,i} = \left(VehicleID_{k,i}, t_{k,i}, l_{k,i}, d(l_{k,i})\right)$, where $l_{k,i}$ is the link that the probe is on, and $d(l_{k,i})$ is the distance from the location of the probe to the beginning of $l_{k,i}$.

The traveled route between two consecutive map matched GPS points of a transit probe is termed as a path, $p_{k,i} = (\tilde{g}_{k,i-1}, \tilde{g}_{k,i})$. A path can also be described by its included links,

$$p_{k,i} = (\tilde{g}_{k,i-1}, \tilde{g}_{k,i}) = \{l_{k,i,j}(\alpha,\beta) \mid j \epsilon J\},\ 0 \le \alpha \le \beta \le 1 \quad \text{..................(3.1)}$$

$$\alpha = \begin{cases} 0 & , \quad j \neq 1 \\ \dfrac{d(l_{k,i,j})}{leng(l_{k,i,j})} & , \quad j = 1 \end{cases}, \quad \beta = \begin{cases} \dfrac{d(l_{k,i,j})}{leng(l_{k,i,j})}, & j = J \\ 1 \quad , & j \neq J \end{cases} \quad \text{......................(3.2)}$$

where

$p_{k,i}$	Path between position $\tilde{g}_{k,i-1}$ and $\tilde{g}_{k,i}$
$l_{k,i,j}$	The *j*th traveled link on path $p_{k,i}$
J	number of links included in a path
α	Location where probe *k* first appears on a link
β	Location where probe *k* last appears on a link
$leng(k_{k,i,j})$	Length of link $l_{k,i,j}$
$d(l_{k,i,j})$	traveled distance on link $l_{k,i,j}$ of path $p_{k,i}$

and an example is given on the bottom of Figure 3.1.

4 LINK TRAVEL SPEED ESTIMATION USING TRANSIT BUSES AS PROBES

In this section, a transit bus-based link travel speed estimation method is introduced. This method is to estimate link travel speed from low-frequency AVL data. A field test conducted on a typical urban freeway is then introduced to evaluate the performance of the proposed method. As transit bus is a special type of vehicle, the impact of the probe vehicle type on the estimated link travel speed is investigated. Besides, considering that the GPS update interval, which is the time interval between two consecutive GPS points, has been proved to have significant influence on probe-based traffic estimation, the impact of GPS update interval on the proposed method is studied as well.

4.1 Link Travel Speed Estimation Method

The time interval between two consecutive GPS points of one transit probe, namely the GPS update interval, is one of the key factors that influence the accuracy of link travel time estimation. When the GPS update interval is very short, e.g. less than 5 seconds, it is reasonable to assume that the probe is moving at relatively constant speed, and the average speed can be obtained by dividing the traveled distance by the time interval. Besides, with such very short update interval, even if there is more than one link included in the path, assigning travel time to each link does not require complicated methods as the error of estimated link travel time would be within this short time interval and does not create a problem.

However, in practice, due to limited data technology, the update interval of most real-time vehicle tracking data is relatively long, i.e. longer than 30 seconds. With the GPS update interval increasing, the number of links traveled by a probe during one interval increases, and the errors of estimated link travel times from simple methods may become significant. Therefore, to estimate link travel speed, the path travel time should be first allocated to each included link, then by dividing the traveled distance on links by the link travel time, the probe link travel speed can be obtained.

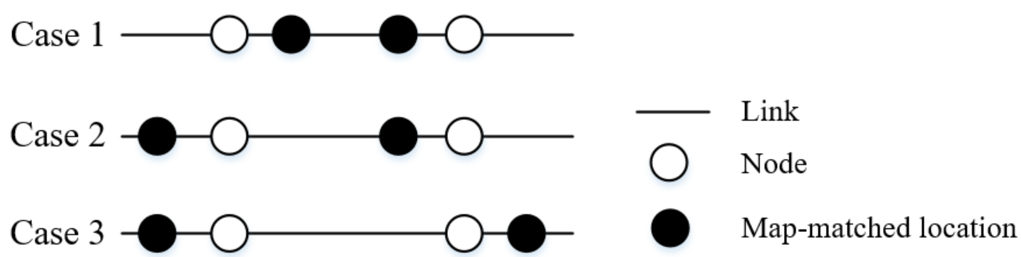


FIGURE 4.1 Cases of GPS Paths

According to the number of included nodes, paths can be categorized into three cases:

- Case 1: there is no node on the travel path, that is the two GPS points are on the same link (see case 1 in Figure 4.1);
- Case 2: there is one node on the travel path, that is the two GPS points are on adjacent links (see case 2 in Figure 4.1);
- Case 3: there are at least two nodes on the travel path, that is at least one complete link exists between the two GPS points (see case 3 in Figure 4.1).

The proposed link travel speed estimation method is to first estimate the timestamp when a probe vehicle passes a node, then the link travel time can be represented by the time interval between the estimated timestamp when the probe vehicle passes the link's start node and end node.

Considering a path $p_{k,i}$ which includes at least one node (e.g. case 2 and 3 in Figure 4.1), by assuming that the average travel speed of each link is not substantially different, the timestamp when the probe *k* passes the node n_m can be calculated by

$$t(k, n_m) = t_{k,i} - \frac{d(n_m, \tilde{g}_{k,i})}{leng(p_{k,i})}\left(t_{k,i} - t_{k,i-1}\right) \quad (4.1)$$

where

$t(k, n_m)$	Timestamp when probe *k* passes node n_m
$d(n_m, \tilde{g}_{k,i})$	Traveled distance between node n_m and position $\tilde{g}_{k,i}$
$leng(p_{k,i})$	Length of path $p_{k,i}$

Then the estimated travel time of probe *k* on link $l(n_m, n_{m+1})$, termed as $t\big(k, l(n_m, n_o)\big)$, is then obtained by calculating the time interval between the timestamp when the probe enters and leaves the link, and the individual link travel speed $v\big(k, l(n_m, n_{m+1})\big)$ of probe *k* is calculated using the following equations:

$$t\big(k, l(n_m, n_o)\big) = t(k, n_o) - t(k, n_m) \quad (4.2)$$

$$v\big(k, l(n_m, n_o)\big) = \frac{leng\big(l(n_m, n_o)\big)}{t\big(k, l(n_m, n_o)\big)} \quad (4.3)$$

where

$t\big(k, l(n_m, n_o)\big)$	Travel time of probe *k* on link $l(n_m, n_o)$
$v\big(k, l(n_m, n_o)\big)$	Travel speed of probe *k* on link $l(n_m, n_o)$

Given a time interval S_u, if there are in total *K* probes passes link $l(n_m, n_{m+1})$ during S_u, the mean speed of these *K* probes is used to represent the travel speed of link $l(n_m, n_{m+1})$ during S_u,

$$V\big(S_u, l(n_m, n_o)\big) = \frac{\sum_K v\big(k, l(n_m, n_o)\big)}{K} \quad (4.4)$$

where

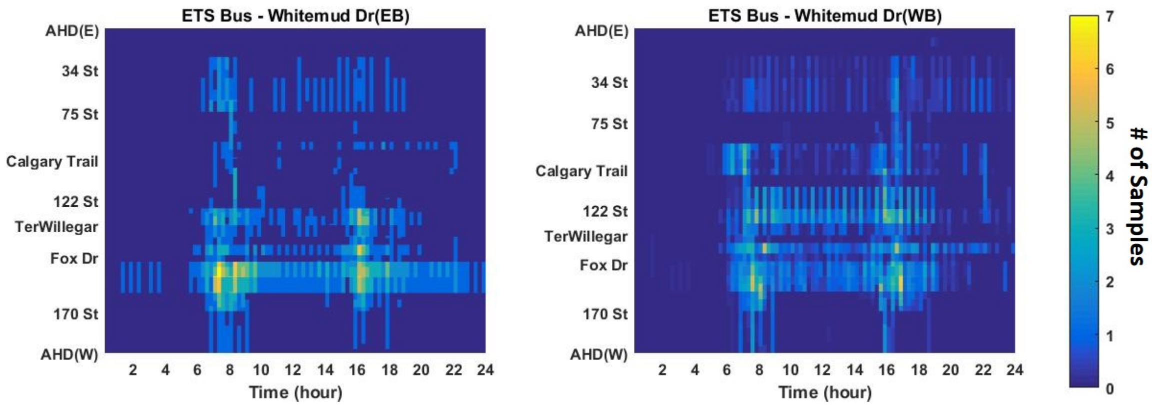
S_u	The uth time interval for speed estimation
$V\big(S_u, l(n_m, n_o)\big)$	Travel speed on link $l(n_m, n_o)$ during time slot S_u
K	Number of probes that travel through a link

4.2 Field Test

To evaluate the performance of the proposed link travel speed estimation method, a field test was conducted on an urban four-lane freeway, Whitemud Drive, in Edmonton (see Figure 4.2).

FIGURE 4.2 Selected Freeway for Case Study

The transit GPS data was collected from December 5 to 16, 2016, including 10 weekdays. Figure 4.3 illustrates the daily average sample size on Whitemud Drive for every 15-minute time interval. The X axis denotes the time of day and the Y axis denotes landmarks along the corridor, as shown in Figure 4.2. It can be clearly seen that the transit GPS data generates more samples on the freeway segments between 170 Street and Fox Drive, especially during AM and PM peak hours. This is because there are more bus routes that operate on these freeway segments, and the departure headways of these routes are shorter during peak hours for serving more passengers.



(a) Eastbound (b) Westbound

FIGURE 4.3 Sample Sizes from Transit GPS Data on Whitemud Drive

As shown in Figure 4.4, two links on Whitemud Drive, 42896 and 2554, are chosen for the performance evaluation for three reasons. First, they are between 170 Street and Fox Drive, and according to the above sample size analysis, there are more transit buses run on these links every day. Second, there are two dual-loop detectors, 1034 and 1035, deployed on each link respectively, which can provide another travel speed measurement for comparison. Finally, recurrent congestions have been observed on these links, hence we can examine if the transit bus-based link speed estimates can well capture congestions and speed drops.

In this test, the point speed from loop detectors are used as the reference for evaluating the accuracy of speed estimation from the proposed method. The loop detectors constantly record the speeds of passing vehicles in a 20-second interval for all lanes. If more than one vehicle passing a loop detector, their average speed will be noted as the estimated speed within this interval. In this study, the speed data from loop detectors are aggregated into 1-minute time interval, which means that the average speed of all vehicles passing through one loop detector within 1 minute is noted as the estimated speed. Furthermore, a 5-minute moving average window is implemented to further smooth out the curve, otherwise the speed profile will be very difficult for identifying speed drops.

FIGURE 4.4 Locations of Dual-Loop Detector on Whitemud Drive

The link travel speed estimated from transit GPS data is aggregated into 15-minute time interval. For every 15 minutes, the average speed of all the sampling records is noted as the estimated speed. This time window for aggregation considers the fact that most bus routes passing the selected links have a scheduled 30-minute headway, and during morning and evening peak hours some routes decrease headways to 15 minutes.

In evaluating the speed estimation, the Mean Absolute Speed Difference (MASD) and Mean Absolute Percentage Speed Difference (MAPSD) are used to evaluate the accuracy of speed estimation. The reason to use MASD is that the positive and negative speed difference can offset the absolute difference between the speed estimations. MAPSD, on the other hand, can help to demonstrate the percentage of the deviation given the reference speeds.

$$MASD = \frac{1}{K}\sum_{k=1}^{K}\left|v_{bus} - v_{loop}\right| \quad (4.5)$$

$$MAPSD = \frac{1}{K}\sum_{k=1}^{K}\left|\frac{v_{bus}-v_{loop}}{v_{loop}}\right| \times 100\% \quad (4.6)$$

where

$MASD$	Mean absolute speed difference
$MAPSD$	Mean absolute percentage speed difference
v_{bus}	Estimated link travel speed from Transit GPS data
v_{loop}	Travel speed from loop detector data

4.3 Travel Speed Estimation Results

The transit GPS data collected on link 25544 and 42896 contains 2,407 samples within 10 weekdays. there are in total 1,280 15-minute time intervals, 1,046 of which have at least one sample (see Table 4.1). One thing should be noticed is that, the general traffic flow on the target links is usually around 2,000 vehicles per hour, and can be over 3,000 vehicles per hour during congestion times, meaning that the transit bus penetration rate is very small, far less than 1%. This could damage the estimation accuracy as the probe speeds may fail to represent the general traffics. In this thesis, the impact of probe penetration rate is not discussed because the limited data is unable to support the analysis, but its influence should be taken into consideration when analyzing the estimation results.

TABLE 4.1 Sample Sizes of 15-Minute Time Intervals

Sample Size	Number of Time Intervals	
0	234	(18%)
1	362	(28%)
2	343	(27%)
3	176	(14%)
4	68	(5%)
5	44	(3%)
6+	53	(4%)
Total	1,280	

In the following Figure 4.5 to 4.7, the travel speeds from transit GPS data and loop detector data on December 5, 6, and 16 on link 42896 have been chosen as the examples to show the comparison results. I select the estimated speed between 6 AM and 10 PM to do the comparison. The black solid lines represent the travel speeds from loop detector data, and the black dot lines represent the link travel speeds from transit GPS data. As the figures show, the travel speed estimated from transit GPS data can represent the general trend of speed profile compared to the loop data with some variations. For instance, during the AM peak hours on December 6 (Figure 4.6), the GPS speed estimation results do capture the significant speed drop between 8 AM and 9 AM On December 5 (Figure 4.5) and December 16 (Figure 4.7), during the PM peak hours, the GPS speed can also capture the congestions. Nevertheless, there exist some discrepancies in speed estimation at specific times, such as pinnacles of transit bus speed profiles during 10 AM to 12 PM on December 5 (Figure 4.5), which may due to human factors and the specialty of transit bus. But in general, this transit GPS data can provide a valid estimation of link travel speed.

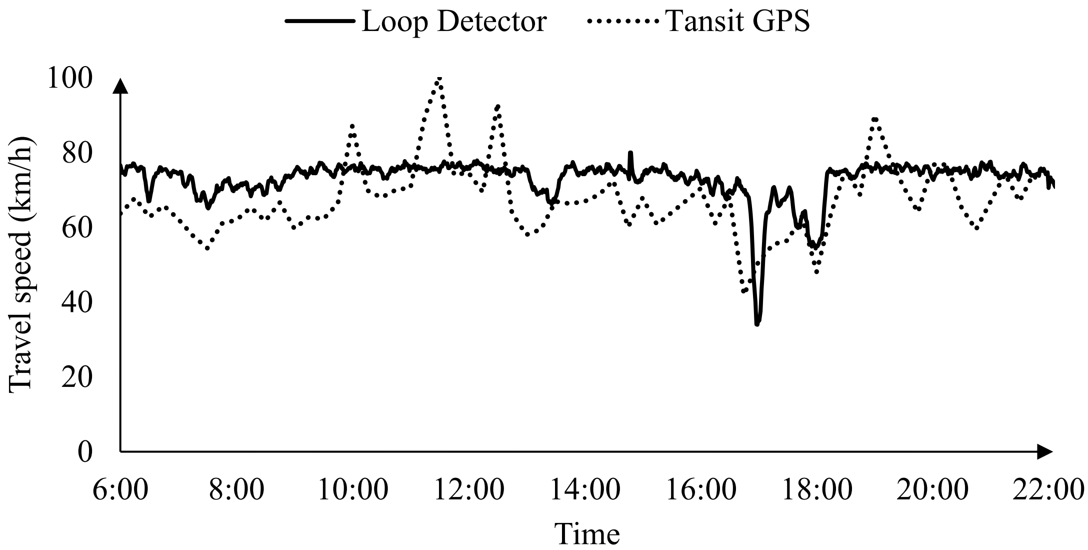


FIGURE 4.5 Speed Comparison on Link 42896 (December 5, 2016)

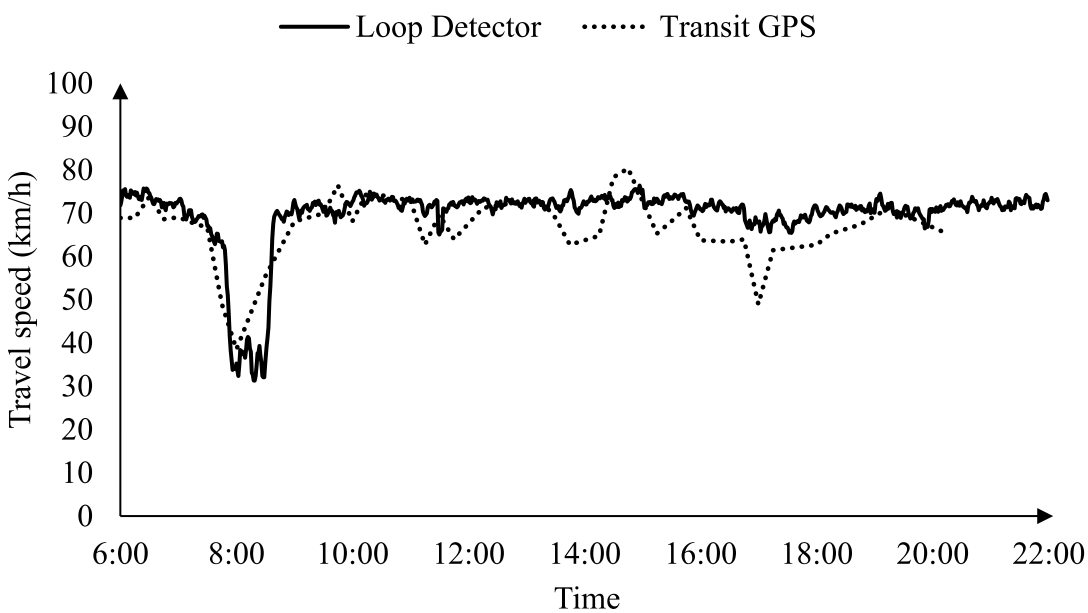


FIGURE 4.6 Speed Comparison on Link 42896 (December 6, 2016)

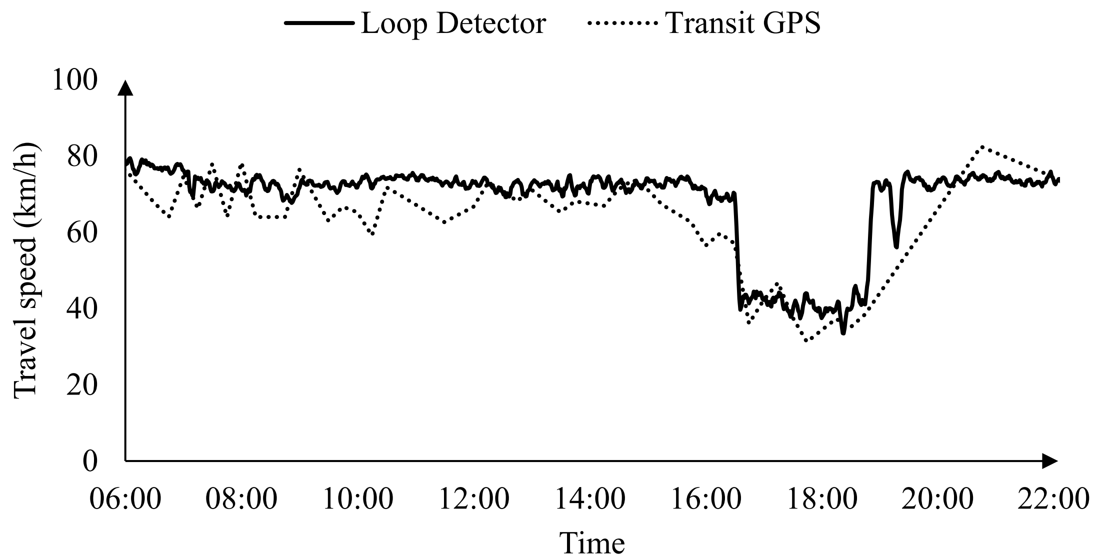


FIGURE 4.7 Speed Comparison on Link 42896 (December 16, 2016)

The results of MASD and MAPSD are shown in Table 4.2. The overall MASD is 7.0 km/h, and the MAPSD is 9.2%, which is acceptable considering that the free-flow speed on the selected freeway is usually around 80 km/h. During AM and PM peak hours, both MASD and MAPSD are higher, and a possible reason for it is that during peak hours traffic congestions are more likely to occur on the links, which makes it harder to accurately capture the speed of traffic flows with small sample size (i.e. less than 1% per interval). Nevertheless, the difference is not significant, and the MASD for both peak hour periods are under 8 km/h. To improve the current speed estimates without changing the estimation method, we can either increase the number of bus probes to reduce the variance of aggregated link travel speeds, or apply post-processing algorithm to smooth the speed profiles.

TABLE 4.2 Speed Estimation Results for All Samples

	Period	Observations	MASD (km/h)	MAPSD (%)
AM Peak	**(7 a.m. - 10 a.m.)**	715	7.3	9.7
PM Peak	**(4 p.m. - 7 p.m.)**	556	7.5	10.4
Total	**(6 a.m. - 10 p.m.)**	2,407	7.0	9.2

4.4 Impact of Probe Vehicle Type

Transit bus is a special type of vehicle, and previous researches suggest that the travel speeds obtained from transit buses are different from the travel speeds of general traffic flow (Pulugurtha *et al.*, 2014; Kieu, Bhaskar and Chung, 2015). Hence, it is necessary to examine the relationship between the speed estimated from transit buses and the speed from loop detectors (considered as the speeds of general traffic flow), aiming to reduce the bias of link travel speed estimated from transit probes.

The speed difference between the speed from transit GPS data and that from loop detector data is shown in Figure 4.8. Speed difference larger than zero means that the estimated speed from transit probes is less than the speed from loop detector data. The speed differences between the two data sources are shown in a standard normal distribution where the mean difference value is 7.0 km/h. This could be due to the bus traffic speed, in general, is slower than the overall traffic speed for safety reasons. And the general distribution is not significantly skewed to the right or left, which means that the variance of speed difference is mostly due to other factors, such as people's driving behaviors.

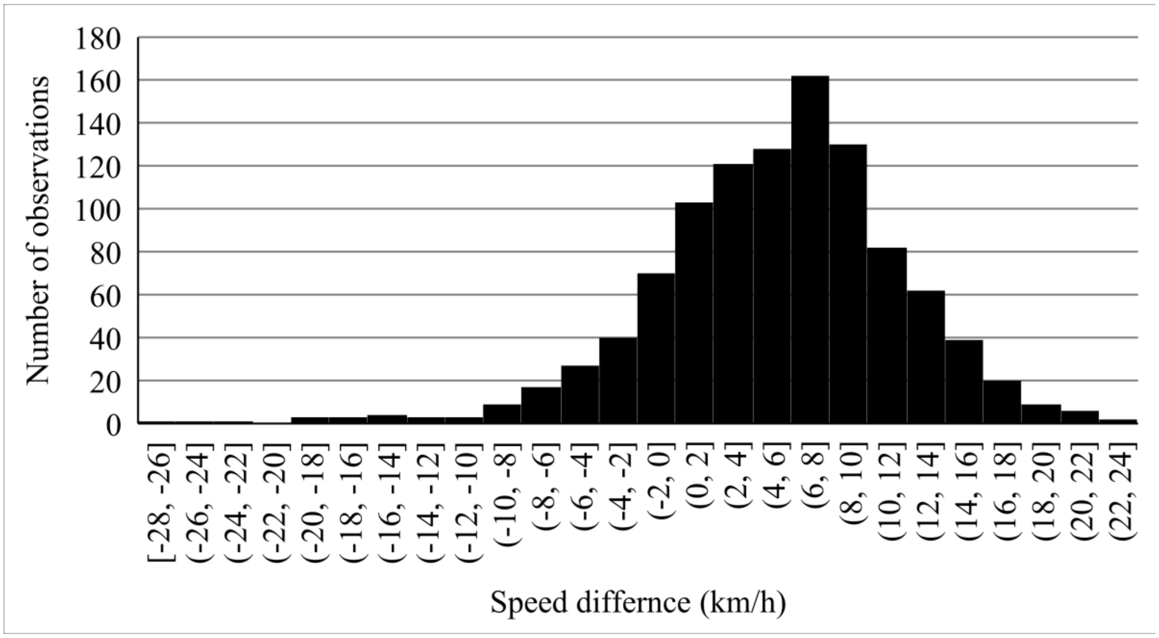


FIGURE 4.8 Distribution of Speed Differences

A one-sample Kolmogorov-Smirnov Test (K-S Test) is then conducted to further testify if the speed difference follows a normal distribution. The one-sample K-S Test is a nonparametric test of the equality of continuous, one-dimensional probability distributions that can be used to compare a sample with a reference probability distribution.

The result of the one-sample K-S test is shown in Table 4.3. The most important measurement of the test is the asymmetric significance; the lower value of it means the tested sample is more likely follows the hypothetical distribution (normal distribution in this case). As the asymmetric significance in the table is less than 0.000, it proves that the distribution of the speed difference follows a good normal distribution, and the mean and the standard deviation of the followed normal distribution are 5.43 and 6.41 respectively.

TABLE 4.3 Result of One-Sample Kolmogorov-Smirnov Test

One-Sample Kolmogorov-Smirnov Test		
		Speed Difference
N		1046
Normal Parameters[a,b]	Mean	5.436
	Std. Deviation	6.414
Most Extreme Differences	Absolute	0.041
	Positive	0.024
	Negative	-0.041
Test Statistic		0.041
Asymmetric significance (2-tailed)		.000[c]

a. Test distribution is Normal.

b. Calculated from data.

c. Lilliefors Significance Correction.

4.5 Impact of GPS Update Interval

GPS update interval can influence the accuracy of estimated sample speed. With longer GPS update interval, probe vehicles are more likely to travel a significant distance between two neighbor GPS points, which creates difficulties in inferring the true path of the vehicles. Furthermore, the fraction of the reported travel time that is spent on each individual road link is not observed, which creates challenges for travel speed estimation.

Because the GPS update interval of the transit GPS data is relatively long (around 30 seconds), it is difficult to measure the influence of GPS update interval using transit GPS data directly. In this section, the SmartTravel data of five weekdays (from September 19 to September 23, 2016) is used to evaluate the impact of GPS update interval. SmartTravel is a mobile application aimed to provide various road and traffic information for drivers and improve road safety. The customers can choose to be a volunteer and let the application collects data from their mobile phones, including encrypted user ID, timestamp, coordinates, instantaneous speed, direction and else, while the application is active. When the mobile phones are connected to the Internet via Wi-Fi, the collected data will be uploaded to the data server.

The SmartTravel mobile application records vehicle position every 1 second, which offers very accurate vehicle trajectories. Due to environmental impacts or network connectivity, however, sometimes the GPS update interval of SmartTravel probes could be longer than 1 second. To build up a reference dataset and provide samples as errorless as possible, the original vehicle trajectories with long GPS update interval are split into several sub-trajectories with reassigned vehicle ID. Figure 4.9 gives an example demonstrating this process: for a complete vehicle trajectory, when there are two GPS points with GPS update interval longer than the predefined threshold (in this case, the threshold is set as 10 seconds), this trajectory is split into two shorter trajectories. Each trajectory is assigned with a new virtual vehicle ID, hence in the processed data the GPS update intervals of all virtual vehicle trajectories are shorter than the threshold value. Besides, the total travel time of the virtual vehicle trajectory have to be longer than 5 minutes, and those with total travel time less than 5 minutes are removed. After such data processing, the processed SmartTravel data is applied as the reference dataset, and link travel speed generated from the reference dataset is considered as the ground truth for comparison.

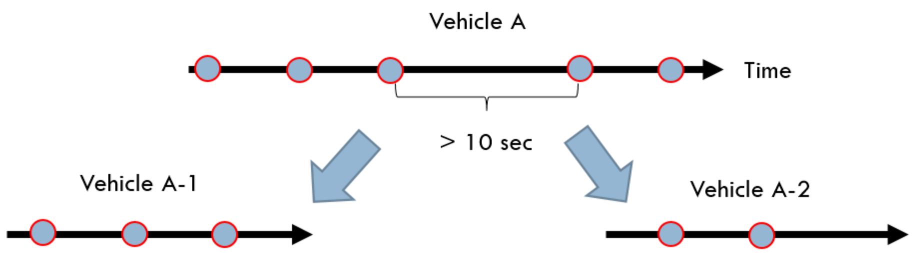


FIGURE 4.9 Process to Obtain Reference Dataset

To evaluate the impact of GPS update interval on the accuracy of link travel speed estimation, by removing partial GPS points of each SmartTravel probe from the reference dataset, we can obtain several GPS datasets with different GPS update intervals, e.g. 10 seconds or 60 seconds. These datasets are considered as the test groups and the travel speeds estimated from each test dataset using the proposed link travel time estimation method will be compared with the speed from the reference dataset.

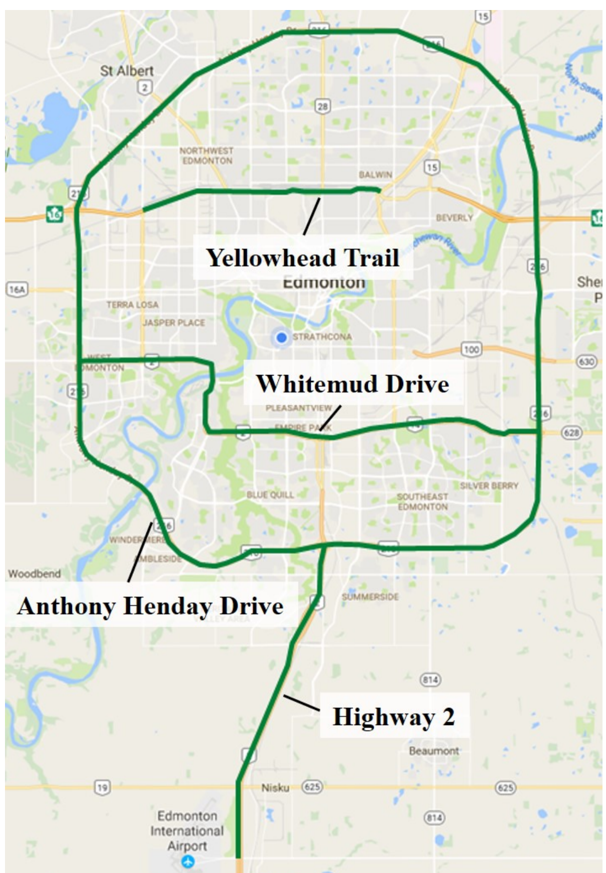
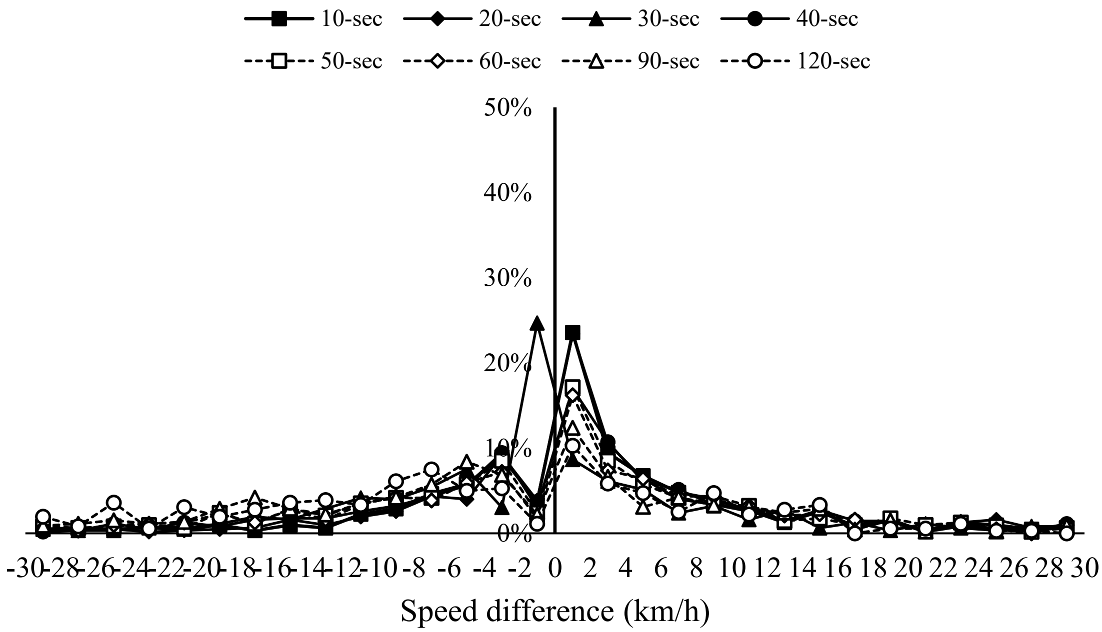


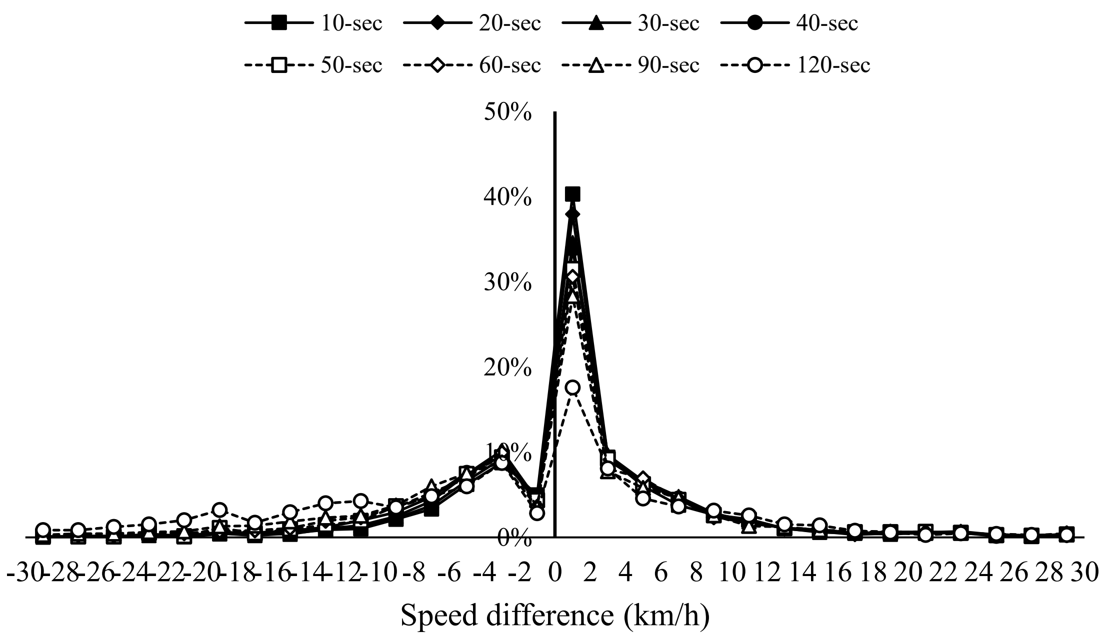
FIGURE 4.10 Scope of SmartTravel Data Collection

The SmartTravel data is collected on four corridors: Anthony Henday Drive, Whitemud Drive and Highway 2 and Yellowhead Trail (see Figure 4.10). The first three corridors are freeways, and the last one is an urban arterial road with 5 signalized intersections.

Figure 4.11 shows the distribution of speed difference for each test datasets, and Figure 4.12 shows the standard deviation of speed differences for each test datasets. For both freeway and arterial, the speed differences of most samples are within -2~2 km/h, and as the GPS update interval increases, the standard deviation of speed difference tends to increase, meaning the variance of the sample speed error increases as the GPS update interval increases. This is reasonable because as the update interval becomes longer, paths are more likely to include more links. In reality, the traffic conditions on links may be different, so the homogeneous travel speed assumption become less reliable, resulting in worse estimation accuracy. We can also see from Figure 4.12 that, the standard deviation of speed differences on freeways are generally lower than that on arterials for all tested GPS update intervals. This can be explained that the traffic conditions on arterials are more complicated than on freeways due to traffic signals, and the basic assumption of the proposed method, that the travel speeds of traversed links on a path are similar, becomes less reasonable.



(a) Arterial



(b) Freeway

FIGURE 4.11 Distribution of Speed Differences of Test Datasets

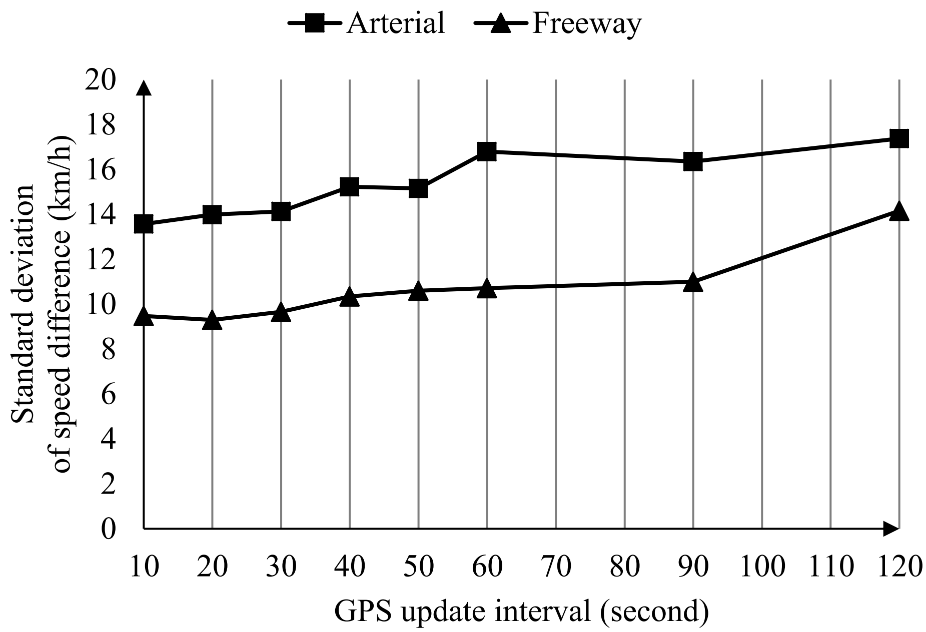


FIGURE 4.12 Standard Deviation of Speed Differences of Test Datasets

Figure 4.13 illustrates the MASD for each test dataset. As the sampling interval increases from 10 seconds to 60 seconds, the MASD increases from 3.9 km/h to 6.1 km/h on freeways and from 5.2 km/h to 8.0 km/h on arterials; when compare the MASD of 60-second and 90-second update interval, even though the GPS update interval increases by 30 seconds, the MASD does not increase significantly on both freeway and arterial. However, as the sampling interval rises to 120 seconds, the MASD of both freeway and arterial datasets significantly increases. This suggests that the proposed travel speed estimation method performs well for those GPS data with GPS update interval shorter than 90 seconds. Besides, generally the proposed method performs better on freeways than arterial, which, considering the difficulty of estimating travel delay caused by intersections, is reasonable.

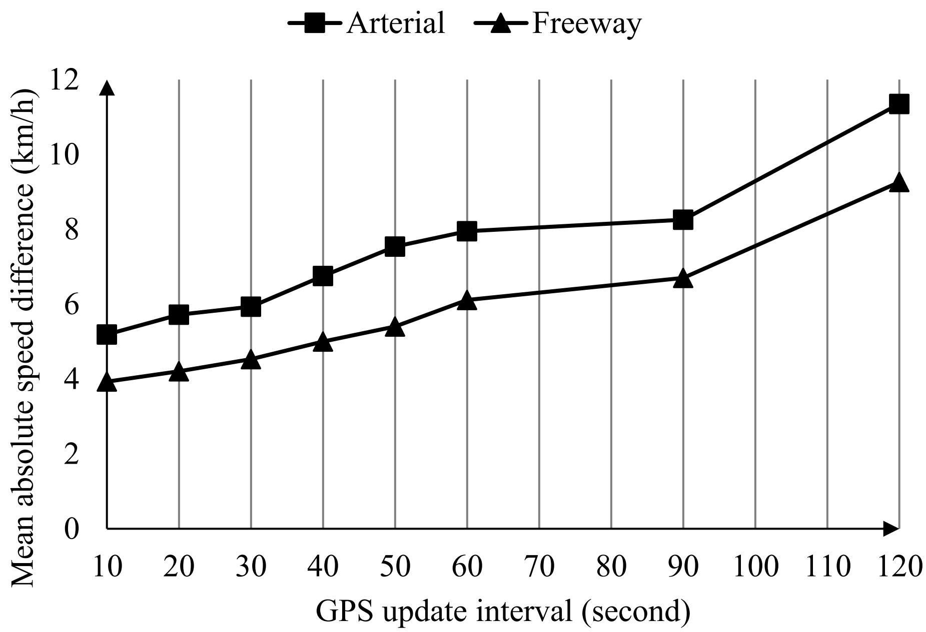


FIGURE 4.13 Mean Absolute Speed Differences of Test Datasets

4.6 Summary

This chapter presents the application of using transit buses as probes for link travel speed estimation. A length-based speed estimation method is proposed, and the performance is evaluated through a field test on urban freeway links. Results show that transit buses can provide good link travel speed estimates with an average 10% difference compared with loop detector data, which is considered acceptable. When traffic jam occurs, the speed difference increases but not significant. The impact of probe vehicle type on estimation results is significant, as transit bus speed is in average 7.0 km/h lower than the general traffic flow (represented by the loop detector speed), and the speed difference follows a good normal distribution in the field test. Besides, the impact of GPS update interval is investigated as well, and the results suggests that for the proposed link travel speed estimation method, it performs better on freeways than on arterials as the homogeneous path travel speed assumption is not reasonable for links where traffic signals or bus stops exist, and the performance of the proposed model significantly changes only when the GPS update interval is over 60 seconds. However, the penetration rate of most speed estimates in the field test is very low, as 69% estimates are from 1~3 bus probes, which could damage the estimation accuracy, which should be noticed in the future research.

5 LINK TRAVEL TIME ALLOCATION METHOD FOR INDIVIDUAL PROBES

Even though the proposed travel speed estimation method performs well on freeways, when it is applied on arterials, the existence of intersections and bus stops makes it more difficult for accurate estimation. When vehicles are driving on arterials, they may be forced to stop caused by traffic signals, pedestrian crossing streets or stop signs at intersections. Specifically, for transit buses, they have to stop at bus stops when there are passengers boarding or alighting. Hence, the assumption that transit probes are moving with similar speed on each link of a path is not reasonable for arterial. Another practical issue is that, most existing AVL systems can only provide real-time data stream with a low resolution. When the GPS update interval is relatively high, for instance 30 seconds, the probe vehicles are more likely to traverse multiple links within one interval, and the travel time on each link could be significantly different. To improve the performance of transit bus-based estimation, a link travel time allocation method for individual probes was proposed in this chapter. This method aims to identify the components of path travel times, and allocate travel time by inferring the most probable distribution of the decomposed travel times on each link, and a field test is conducted to evaluate the performance of the proposed travel time allocation method.

5.1 Basic Assumptions

The proposed link travel time allocation method is based on the following assumptions:

1. The map matching and path identification results are perfect, thus the errors produced by the two processes are not considered;

2. The free-flow travel speed of each link is known;
3. There are sufficient historical GPS data which will be used for parameter calibration;
4. A transit probe stops at most once on each path;
5. The traffic condition of each link on the same path is similar to each other;
6. The GPS update intervals of transit probes are substantially constant.

5.2 Travel Time Decomposition

Before introducing the proposed method, it is necessary to understand the general characteristics of travel times experienced by individual vehicles on arterials. Hellinga *et al.* (Hellinga *et al.*, 2008) suggested that, on arterials, travel times can be decomposed into three parts:

1. Free-flow travel time
2. Stop time
3. Congestion time

Free-flow travel time is defined as the travel time for a vehicle moving through a road section at free-flow speed plus the necessary transition times (e.g. turning at intersections). for most cases, the actual travel time is larger than free-flow travel time, and the residual time is considered as travel delay. An inverse case is that the actual travel time is smaller than the free-flow travel time, which is assumed that the vehicle is driving at the speed exceeding the free-flow speed, and the travel time can be assigned to each traversed link based on the proportion of traversed link length to the total traveled distance.

Stop time is defined as the interval that vehicles are forced to stop at a location. As the transit probe applied in this research is transit bus, there are three common causes of stop time: (1) stopping near the downstream intersections of links due to traffic control, (2) stopping at bus stops due to boarding and/or alighting passengers, and (3) stopping on the road due to irregular events such as accidents or road maintenance. It should be noted that the acceleration and deceleration time due to vehicles stopping on roads are included in stop time.

Congestion time is defined as the travel delay caused by vehicle driving at a speed lower than the free-flow speed, which is assumed to be caused by traffic congestions.

Figure 5.1 illustrates the decomposed travel time on time-space diagrams. The dashed gray line is the trajectory of a vehicle driving at free-flow speed, which is used for measuring the free-flow travel time, and the black solid line is the actual vehicle trajectory. In Figure 5.1(a), the vehicle drives at a speed lower than the free-flow speed, and it travels through the link without stopping, hence the link travel time only consists of free-flow travel time and congestion time. In Figure 5.1(b), the vehicle enters and leaves the link with free-flow speed, and it stops at a location on the link, hence the link travel time only consists free-flow travel time and stop time, noticing that the acceleration and deceleration time is included in the stop time.

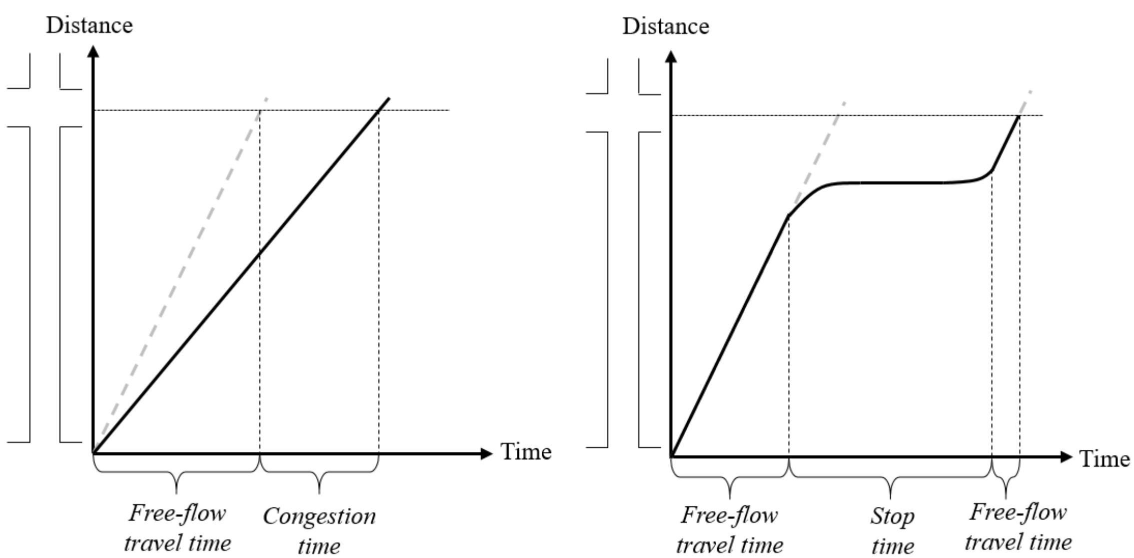


FIGURE 5.1 Example of Travel Time Decomposition

Given a path $p_{k,i}$ of a probe vehicle k, the path travel time can be decomposed into the three components mentioned above,

$$T(p_{k,i}) = \mathrm{t}_{k,i} - t_{k,i-1} = T_f(p_{k,i}) + T_s(p_{k,i}) + T_c(p_{k,i}) \text{.........................(5.1)}$$

where

$T(p_{k,i})$	Travel time of path $(p_{k,i})$
$T_f(p_{k,i})$	Free-flow travel time of path $(p_{k,i})$
$T_s(p_{k,i})$	Stop time of path $(p_{k,i})$
$T_c(p_{k,i})$	Congestion time of path $(p_{k,i})$

The path travel time $T(p_{k,i})$ can also be represented by the sum of travel times on all traversed links,

$$T(p_{k,i}) = \sum_J t(l_{k,i,j}) = \sum_J \left(t_f(l_{k,i,j}) + t_s(l_{k,i,j}) + t_c(l_{k,i,j})\right) \text{....................(5.2)}$$

where

$t(l_{k,i,j})$	Travel time on link $l_{k,i,j}$
$t_f(l_{k,i,j})$	Free-flow travel time on link $l_{k,i,j}$
$t_s(l_{k,i,j})$	Stop time on link $l_{k,i,j}$
$t_c(l_{k,i,j})$	Congestion time on link $l_{k,i,j}$

According to the second assumption in section 5.1 (the free-flow travel speed of each link is known), the link free-flow travel time can be directly calculated using the following equation:

$$t_f\left(l_{k,i,j}\right) = \frac{d\left(l_{k,i,j}\right)}{v_f\left(l_{k,i,j}\right)} \qquad (5.3)$$

where

$v_f\left(l_{k,i,j}\right)$ Free-flow travel speed of link $l_{k,i,j}$

It is hard to directly estimate the traffic condition experienced on a path, which brings the difficulty of determining link stop time and link congestion time. However, the traffic condition can be estimated by estimating the degree of congestion from probability methods. Inspired by the research of Hellinga *et al.* (Hellinga *et al.*, 2008), a term w is introduced to represent the degree of congestion experienced by probe k on path $p_{k,i}$, namely the congestion degree,

$$w = \frac{T_c(p_{k,i})}{T_c(p_{k,i}) + T_f(p_{k,i})} \qquad (5.4)$$

The value of w is between 0 and 1. When there is no congestion along the path and vehicles can pass through it with free-flow speed, the path congestion time is 0 and w reaches its minimum value; as the traffic condition becomes worse, the congestion time increases and w is getting close to 1. A special case is that, if a transit probe stops at a location over the whole path travel time, the path free-flow travel time would be 0, and the value of w would always be 1 when the congestion time is larger than 0. However, in such case the travel time experienced by the transit probe can be supposed to consist of only stop time, hence this exception case would be handled separately from the following discussion.

The maximum value of w on path $p_{k,i}$, denoted by $w_{max}(\mathrm{p}_{k,i})$, is obtained when the travel delay is composed only by congestion time, which means the stop time is 0.

$$w_{max}(\mathrm{p}_{k,i}) = \frac{T(p_{k,i}) - T_f(p_{k,i})}{T(p_{k,i})} \quad (5.5)$$

Equation (5.4) also implies that, a unique value of w can determine a unique value of the path congestion time, therefore the path congestion time and path stop time can be represented by

$$T_c(p_{k,i}) = \frac{w}{1-w} T_f(p_{k,i}) \quad (5.6)$$

$$T_s(p_{k,i}) = T(p_{k,i}) - \frac{1}{1-w} T_f(p_{k,i}) \quad (5.7)$$

According to the fifth assumption mentioned in section 5.1 (the traffic condition of each link on the same path is similar to each other), similar to Equation (5.6) and (5.7), the link congestion time can be represented by

$$t_c(l_{k,i,j}) = \frac{w}{1-w} t_f(l_{k,i,j}) \quad (5.8)$$

5.3 Link Travel Time Allocation Method

When the road network is uncongested, vehicles are assumed to be able to drive at relatively high speed, and the travel delay consists mainly of stop time, and transit probes are more likely to stop near the downstream intersections of links or near the bus stops. On the other hand, when the road network is experiencing heavy congestion, the traffic queue caused by downstream traffic control devices is expected to be longer than in uncongested condition. Besides, considering that the vehicle flow can reflect the passenger flow along the road, the transit dwell times at bus stops are supposed to be longer as well. Furthermore, the average vehicle speeds would be lower than the free-flow speed, and the proportion of congestion time increases as the traffic condition becomes worse. Therefore, under congested situations, the likelihood of transit probes stopping at locations far from link downstream intersections are larger than under uncongested situation.

However, it is difficult to directly measure the ratio of stop time and congestion time in the travel delay, as the level of congestion is still unknown. For instance, given a path which includes more than one link, the total path travel time is 30 seconds and the free-flow travel time is 20 seconds, as we do not know the types of traffic control devices neither the signal phase and timing information, it is hard to determine if the 10-second travel delay is totally stop time, totally congestion time, or the mixture of both kinds of delays. Nevertheless, a likelihood function can be applied to infer the level of congestion experienced by the transit probes, and gives an estimation of link travel times.

Two probability functions are developed for the proposed link travel time allocation method. The first one is called the congestion probability function, which represents the probability that a certain degree of congestion (*w*) is experienced by a probe vehicle on a path. The second one is called the link stopping probability function, which represents the probability that a probe stops on a certain link on a path.

5.3.1 Congestion probability

It is assumed that the likelihood of a certain degree of congestion (*w*) experienced by a transit probe k on path $p_{k,i}$, denoted by $f(w, p_{k,i})$, follows a normal distribution, $f(w, p_{k,i}) \sim N(\mu, \sigma^2)$ (see Figure 5.2 for an example). The mean value μ represents the expected degree of congestion occurred on traversed links, and the standard deviation σ measures how the congestion degree fluctuates. Then, the probability that a certain degree of congestion is experienced on path $p_{k,i}$ is given by integrating the likelihood function,

$$P_w(w, p_{k,i}) = \frac{f(w,p_{k,i})}{\int_0^{w_{max}} f(w,p_{k,i})dw} \quad (5.9)$$

where

$f(w, p_{k,i})$	Likelihood of probe k experiencing a certain congestion degree w on path $p_{k,i}$
$P_w(w, p_{k,i})$	Congestion probability on path $p_{k,i}$ given congestion degree w

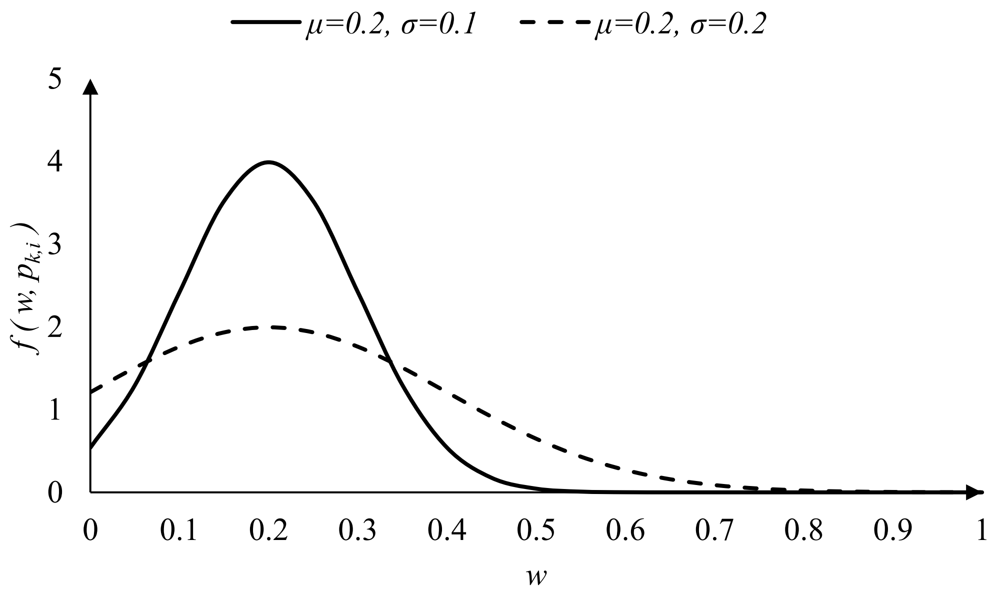


FIGURE 5.2 Example of the Congestion Probability

5.3.2 Link Stopping Probability

A point stopping likelihood function is first introduced to capture the likelihood of a transit probe stopping at a certain location on a link:

$$h_s(l_{k,i,j}, \lambda, w) = (1 - w)g(l_{k,i,j}, \lambda) + w \quad (5.10)$$

where

λ	location on a link
$h_s(l_{k,i,j}, \lambda, w)$	Likelihood of probe *k* stopping at location λ on link $l_{k,i,j}$ given congestion degree *w*
$g(l_{k,i,j}, \lambda)$	Likelihood of probe *k* stopping at location λ on link $l_{k,i,j}$ under free-flow condition (*w* = 0)

λ is a parameter used to determine the location of a probe on a certain link, and it is equal to the distance of the location to the start of the link divided by the link length, so the value of λ is between 0 and 1.

The likelihood of probe *k* stopping on link $l_{k,i,j}$ given congestion degree *w*, denoted by $H_s(l_{k,i,j}, w)$, can be determined by integrating the point stopping likelihood function along the traveled distance of the link:

$$H_s(l_{k,i,j}, w) = \frac{1}{\beta-\alpha}\int_{\alpha}^{\beta} h_s(l_{k,i,j}, \lambda, w)\, d\lambda \quad (5.11)$$

Recalling that α and β denote the locations where the probe first and last appears on a link (see Equation (3.2)), hence they are the minimum and maximum value of λ. By assuming that a transit probe stops at most once on a path (the fourth assumption in section 5.1), the probability of a vehicle stopping at link $l_{k,i,j}$ of path $p_{k,i}$ is given by

$$P_s(l_{k,i,j}, w) = \begin{cases} H_s(l_{k,i,j}, w) & J = 1 \\ H_s(l_{k,i,j}, w)\prod_{j'\neq j}\left(1 - H_s(l_{k,i,j'}, w)\right) & othewise \end{cases} \quad (5.12)$$

where

$P_s(l_{k,i,j}, w)$	Link stopping probability on link $l_{k,i,j}$ given congestion degree *w*

5.3.3 Allocating link travel times

The link free-flow travel time can be calculated using Equation (5.3). As the congestion probability and link stopping probability is given, the link stop time can be estimated by integrating the whole range of possible congestion degree (w) on the link,

$$t_s(l_{k,i,j}) = \int_0^{w_{max}(p_{k,i})} T_s(p_{k,i}) \frac{P_w(w,p_{k,i}) P_s(l_{k,i,j},w)}{Q_s(p_{k,i})} dw \quad (5.13)$$

$$\mathrm{Q_s}(p_{k,i}) = \int_0^{w_{max}(p_{k,i})} P_w(w,p_{k,i}) \sum_J \mathrm{P_s}(l_{k,i,j},w)\, dw \quad (5.14)$$

In Equation (5.13), $\mathrm{Q}_s(p_{k,i})$ is a term used to normalize the probability, ensuring that the value of it is between 0 and 1. Once the link free-flow travel time and link stop time are obtained, the link congestion time can then be calculated by

$$t_c(l_{k,i,j}) = \frac{t_f(l_{k,i,j})}{T_f(p_{k,i})} \left(T(p_{k,i}) - T_f(p_{k,i}) - \sum_J t_s(l_{k,i,j})\right) \quad (5.15)$$

Equation (5.15) is based on the fifth assumption mentioned is section 5.1, that the traffic condition of each link on the same path is similar to each other. Hence, the congestion time is allocated to each traversed link weighted by the free-flow travel time of each link. Finally, the allocated link travel time is the sum of the estimated link free-flow travel time, link stop time and link congestion time,

$$t(l_{k,i,j}) = t_f(l_{k,i,j}) + t_s(l_{k,i,j}) + t_c(l_{k,i,j}) \quad (5.16)$$

5.4 Parameter Calibration

The performance of the proposed link travel time allocation method relies on the accuracy of the congestion probability and the link stopping probability. For the congestion probability, as it is assumed that the likelihood function $f(w, p_{k,i})$ follows a normal distribution, the mean and the standard deviation of the distribution are two key parameters for the congestion probability function. For the link stopping probability, the basics of it is the function $g(l_{k,i,j}, \lambda)$, which describes the likelihood that probe k stops on a certain location λ on link $l_{k,i,j}$ under free-flow condition. Currently, the standard deviation of $f(w, p_{k,i})$ is hard to obtain, but the mean of $f(w, p_{k,i})$ and function $g(l_{k,i,j}, \lambda)$ can be calibrated from historical GPS data.

A link is first split into smaller segments, and the xth segment of link $l_{k,i,j}$ is denoted by $s_{k,i,j,x}$. Supposing that there are N transit probes traveled through link $l_{k,i,j}$ during a time period, their GPS points are located randomly on the link. However, the number of GPS points of each segment could be significantly different. Figure 5.3 gives an example showing the GPS point counts of each segment on a link. It can be clearly seen that those segments near the bus stop or in the front of the downstream intersection stop line have more GPS point counts than the other segments. This is because that the transit probes are more likely to stop or slow down at these segments, and the average travel time on these segments are significantly longer than on the others.

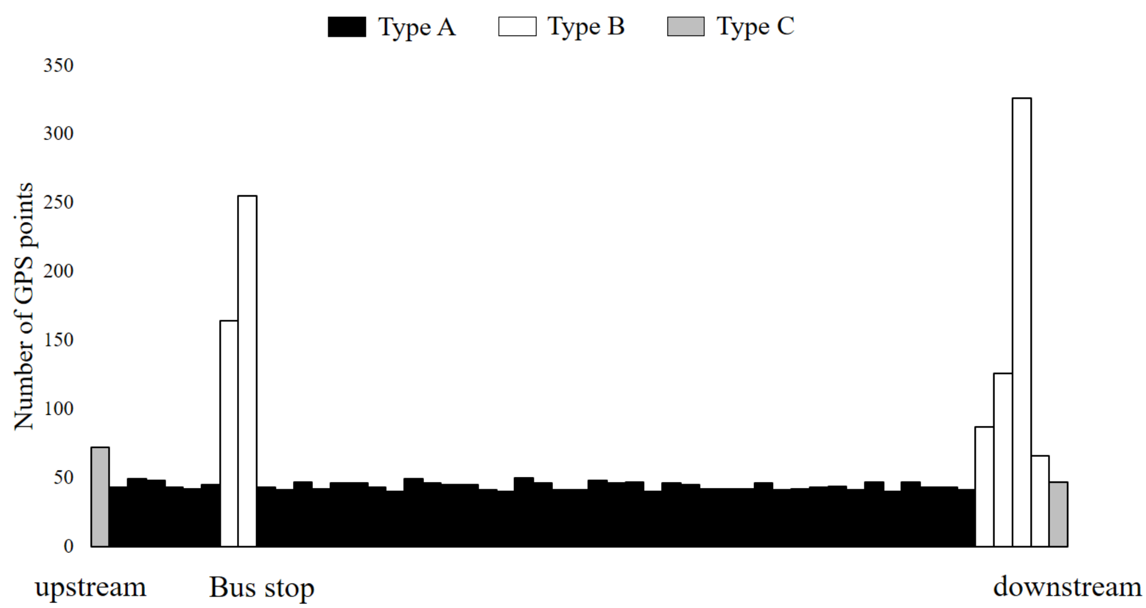


FIGURE 5.3 Example of GPS Point Counts on A Link

According to the sixth assumption in section 5.1 (the GPS update intervals of transit probes are substantially constant), denoting the average GPS update interval as T_{update}, the relationship between segment GPS point counts and average segment travel time can be represented by the following equation:

$$n(s_{k,i,j,x}) = N\frac{\tau(s_{k,i,j,x})}{T_{update}} \quad (5.17)$$

where

$s_{k,i,j,x}$	The xth segment on link $l_{k,i,j}$
$n(s_{k,i,j,x})$	Number of GPS points located on segment $s_{k,i,j,x}$
T_{update}	Average GPS update interval
N	Number of probes that travel through a link in the historical data
$\tau(s_{k,i,j,x})$	Travel time on segment $s_{k,i,j,x}$

Based on the positions and the number of GPS points, segments can be classified into three types (Figure 5.3):

- *Type A*: segments where transit probes are less likely to stop. Type A segments are usually in the middle of a link or near the upstream of a link, and their GPS point counts are relatively small.
- *Type B*: segments where transit probes are more likely to stop. Type A segments are usually near the bus stops or in the front of the stop line of downstream intersections, and their GPS point counts are relatively large.
- *Type C*: segments that are within the area of intersections. On these segments, the speeds of transit probes are not stable, as they may stop at the intersection and need to accelerate and recover the driving speed.

The segment travel time can also be decomposed as

$$\tau\left(s_{k,i,j,x}\right) = \tau_f\left(s_{k,i,j,x}\right) + \tau_s\left(s_{k,i,j,x}\right) + \tau_c\left(s_{k,i,j,x}\right) \quad (5.18)$$

where

$\tau_f\left(s_{k,i,j,x}\right)$	Free-flow travel time on segment $s_{k,i,j,x}$
$\tau_s\left(s_{k,i,j,x}\right)$	Stop time on segment $s_{k,i,j,x}$
$\tau_c\left(s_{k,i,j,x}\right)$	Congestion time on segment $s_{k,i,j,x}$

The segment free-flow travel time can be directly calculated by

$$\tau_f\left(s_{k,i,j,x}\right) = \frac{leng(s_{k,i,j,x})}{v_f(l_{k,i,j})} \quad (5.19)$$

where

$leng\left(s_{k,i,j,x}\right)$	Length of segment $s_{k,i,j,x}$

As the transit probes are more likely to stop on Type B segments, it is hard to estimate congestion times on these segments. However, for Type A segments, as probes are little likely to stop on them, it can be assumed that the stop time on Type A segments is 0, and their segment congestion time can be calculated based on Equation (5.17) and (5.18):

$$\tau_c(s_{k,i,j,x}) = \min\left(0, \frac{T_{update}}{N} n(s_{k,i,j,x}) - \tau_f(s_{k,i,j,x})\right) \text{........................(5.20)}$$

It is further assumed that the degree of congestion on Type A segments are similar to the degree of congestion on the whole link. Therefore, the segment congestion time can be extended to the link congestion time,

$$t'_c(l_{k,i,j}) = \frac{leng(l_{k,i,j})}{\sum_{x \in SEG_A(l_{k,i,j})} leng(s_{k,i,j,x})} \sum_{x \in SEG_A(l_{k,i,j})} \tau_c(s_{k,i,j,x}) \text{....................(5.21)}$$

where

$t'_c(l_{k,i,j})$	Congestion time on link $l_{k,i,j}$ estimated from historical data
$SEG_A(l_{k,i,j})$	Set of Type A segments on link $l_{k,i,j}$

After $t'_c(l_{k,i,j})$ is obtained, the stop time of Type B segments can be estimated by

$$\tau'_s(s_{k,i,j,x}) = \min\left(0, \frac{T_{update}}{N} n(s_{k,i,j,x}) - \tau_f(s_{k,i,j,x}) - t'_c(l_{k,i,j}) \frac{leng(s_{k,i,j,x})}{leng(l_{k,i,j})}\right) \text{.......(5.22)}$$

where

$t'_s(s_{k,i,j,x})$	Stop time on segment $s_{k,i,j,x}$ estimated from historical data

$t'_c(l_{k,i,j})$ can represent the average link congestion time, which can be used to calibrate the mean of $f(w, p_{k,i})$. Because $f(w, p_{k,i})$ reflects the congestion probability of a path, the mean of it can be calculated as the weighted average degree of congestion of traversed links,

$$\mu(p_{k,i}) = \frac{\sum_J\big(\mu(l_{k,i,j})d(l_{k,i,j})\big)}{\sum_J d(l_{k,i,j})} \quad (5.23)$$

$$\mu(l_{k,i,j}) = \frac{t'_c(l_{k,i,j})}{t'_c(l_{k,i,j})+t_f(l_{k,i,j})} \quad (5.24)$$

where

$\mu(p_{k,i})$	Mean of congestion degree on path $p_{k,i}$
$\mu(l_{k,i,j})$	Mean of congestion degree on link $l_{k,i,j}$

In Equation (5.23), the traveled distance on each link is used as the weight.

For the calibration of function $g(l_{k,i,j},\lambda)$, the first step is to obtain the point stopping likelihood function $h_s(l_{k,i,j},\lambda,w)$. As we already get the segment stop time from Equation (5.22), the point stopping likelihood of location λ estimated from historical GPS data can be described as

$$h'_s\left(l_{k,i,j},\lambda,\mu(l_{k,i,j})\right) = \frac{\tau'_s(s_{k,i,j,x})}{\tau'_s(S_{k,i,j,x})}, \quad \lambda \in s_{k,i,j,x} \quad (5.25)$$

where

$h'_s\left(l_{k,i,j},\lambda,\mu(l_{k,i,j})\right)$	Point stopping likelihood on location λ estimated from historical data
$S_{k,i,j,x}$	Segment with the maximum value of segment stop time on link $l_{k,i,j}$

Then $h'_s\left(l_{k,i,j},\lambda,\mu(l_{k,i,j})\right)$ and $\mu(l_{k,i,j})$ can be substituted into Equation (5.19) with $h_s(l_{k,i,j},\lambda,w)$ and w, and we can get the following equation:

$$h'_s\left(l_{k,i,j},\lambda,\mu\left(l_{k,i,j}\right)\right)=\left(1-\mu\left(l_{k,i,j}\right)\right)g\left(l_{k,i,j},\lambda\right)+\mu\left(l_{k,i,j}\right) \quad \text{..................(5.26)}$$

And $g\left(l_{k,i,j},\lambda\right)$ can be finally obtained by transferring Equation (5.26) as

$$g\left(l_{k,i,j},\lambda\right)=\left(h'_s\left(l_{k,i,j},\lambda,\mu\left(l_{k,i,j}\right)\right)-\mu\left(l_{k,i,j}\right)\right)/\left(1-\mu\left(l_{k,i,j}\right)\right) \quad \text{..............(5.27)}$$

It should be noticed that, the calibrated value of $g\left(l_{k,i,j},\lambda\right)$ is influenced by the length of segment, since $h'_s\left(l_{k,i,j},\lambda,w\right)$ is calculated using segment stop time, and the point stopping likelihood on the same segment have the same value. If the segment length is short, the calibration result is expected to be more accurate. However, when the segment length is too short, fewer GPS points are distributed to each segment when the GPS data size does not change, and the estimated segment congestion time and segment stop time may be less accurate as the sample size decreases.

5.5 Field Test

A field test was conducted on 23 Avenue in Edmonton, Canada to test the proposed link travel time allocation method. The selected corridor, 23 Avenue, is a 3.9 km long arterial, from Leger Gate NW to 111 Street NW (see Figure 5.4). The speed limit of the selected corridor is 60 km/h. There are three transit routes, 23, 30 and 36, that operates on the whole corridor, and their departure headway is around 30 minutes. The selected corridor is between two transit centers, namely Leger Gate Transit Center and Century Park Transit Center. In Figure 5.4, link 1 to 7 represent eastbound road links, and link 8 to 14 represent westbound road links. The detailed information of each link is listed in Table 5.1.

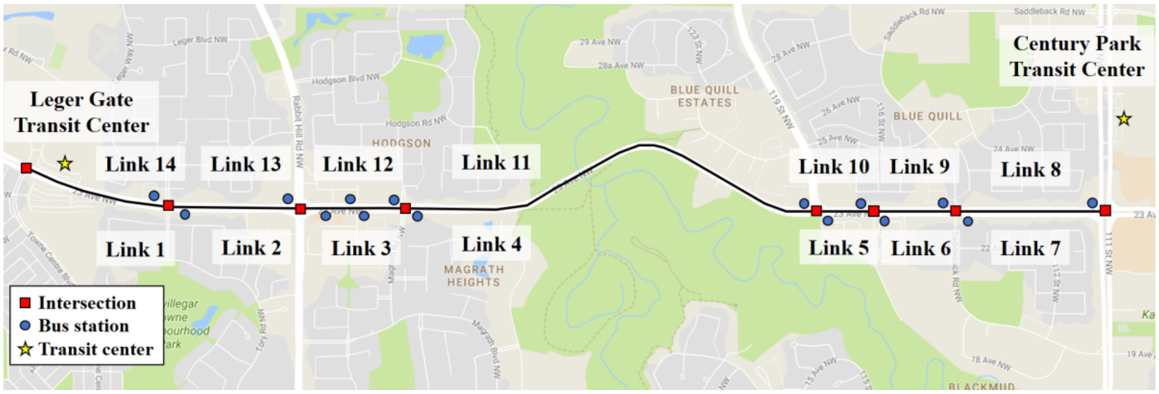


FIGURE 5.4 Selected Corridor for Field Test

TABLE 5.1 Link Information

Link ID	Direction	Length (m)	Link ID	Direction	Length (m)
1	EB	602.5	8	WB	609.6
2	EB	533.1	9	WB	328.3
3	EB	423.5	10	WB	239.0
4	EB	1794.6	11	WB	1792.6
5	EB	239.1	12	WB	423.7
6	EB	328.4	13	WB	532.3
7	EB	609.8	14	WB	594.3

5.5.1 Data description

The ground truth data was collected using GPS-enabled mobile phones. The volunteers install a GPS recording app named Geo Tracker in the mobile phones and take the transit buses from the transit centers. The mobile app records the user's location information for every 1 second, which can ensure the accuracy of the obtained link travel time and link stop time for these transit buses. The details about the collected field data was provided in Table 5.2. All field data was collected during PM peak hour, when traffic congestions are more likely to occur, especially on the westbound links.

As the timestamp when the bus enters or leaves a road link is known, the link travel time of each sample can be easily calculated. The ground truth link stop time is calculated as follows: the average travel speed between two consecutive GPS points is first calculated by dividing the traveled distance by the travel time (1 second), and if the speed is lower than 10 km/h, it is assumed that the bus is stopping and the travel time is added into the link stop time.

In the sampling procedure, 30-second GPS update interval was applied to extract GPS data from the original high-resolution dataset, which would then be used as the input of the proposed method for estimating link travel time and link stop time.

TABLE 5.2 Records of Field Collected Transit Data

Date	Vehicle ID	Direction	Start Time	End Time
2016-07-06	4666	EB	17:06:12	17:15:00
2016-07-06	4589	EB	17:48:12	17:56:32
2016-07-07	4857	EB	16:16:11	16:22:41
2016-07-07	4369	EB	17:07:47	17:16:42
2016-07-07	4758	EB	17:46:27	17:55:22
2017-06-15	4861	EB	16:51:25	16:59:14
2017-06-15	4064	EB	17:31:31	17:38:32
2017-06-15	4632	EB	18:15:14	18:22:23
2017-06-19	4486	EB	17:32:02	17:38:25
2017-06-19	4880	EB	18:15:42	18:21:14
2016-07-06	4626	WB	16:45:53	16:53:56
2016-07-06	4363	WB	17:33:46	17:40:35
2016-07-07	4861	WB	16:53:44	17:01:14
2016-07-07	4637	WB	17:35:49	17:43:15
2017-06-15	4370	WB	16:37:52	16:45:53
2017-06-15	4543	WB	17:16:08	17:28:12
2017-06-15	4488	WB	17:55:58	18:11:44
2017-06-19	4072	WB	16:46:07	16:53:50
2017-06-19	4862	WB	17:16:18	17:25:39
2017-06-19	4291	WB	18:00:17	18:10:30

5.5.2 Parameter setting

Before applying the proposed method, there are five parameters need to be set first:

1. link free-flow speeds $v_f(l_{k,i,j})$,
2. the standard deviation of the congestion likelihood function,
3. the length and classification of segments,
4. the mean of the congestion likelihood function, and
5. the link stopping likelihood function $g(l_{k,i,j}, \lambda)$.

The free-flow speed $v_f(l_{k,i,j})$ is set to be 60 km/h for all links, which is the speed limit of the selected corridor. Note that the actual free-flow speed is usually lower than the speed limit and specific to time-of-day, hence in this test the free-flow travel times may be underestimated, and the congestion time and stop time may be overestimated.

The value of σ, as mentioned in section 5.4, cannot be directly obtained due to the limitation of the proposed model. Nevertheless, by assuming that the variance of congestion levels of all links on the corridor are similar, σ is considered as a parameter and set to be 0.1 and 0.2 for the whole corridor respectively to initially test its impact.

The segment length was set to be 10 m. To simplify the process of segment classification, the first and the last segment of each link are defined as Type C segments, segments with $\left(\tau(s_{k,i,j,x}) - \tau_f(s_{k,i,j,x})\right) / \tau(s_{k,i,j,x})$ less than 0.4 are defined as Type A segments, and the remaining segments are defined as Type B segments.

$\mu(p_{k,i})$ and $g(l_{k,i,j}, \lambda)$ can be calibrated as mentioned in section 5.4. The historical GPS data used for the calibration was collected from 6 AM to 6 PM between March 28, 2017 and May 19, 2017, including 5,682 transit probe trajectories in 35 weekdays. Figure 5.5 illustrates the distribution of GPS update intervals of all collected historical GPS points.

65.8% of GPS points have update interval less than 40 seconds, and the average update interval is 40.3 seconds, which would then be applied as the average GPS update interval T_{update}. One thing should be noticed is that, due to the limited size of the transit GPS data, for this test the historical transit GPS data collected for parameter calibration was between 6 AM and 6 PM, while the field data was collected only during PM peak hours, so the calibrated parameters and probability functions may not reflect the general traffic conditions during PM peak hours. If the data is sufficient, the calibration process can be applied for a shorter time interval to capture the impact of time-of-day upon link travel times.

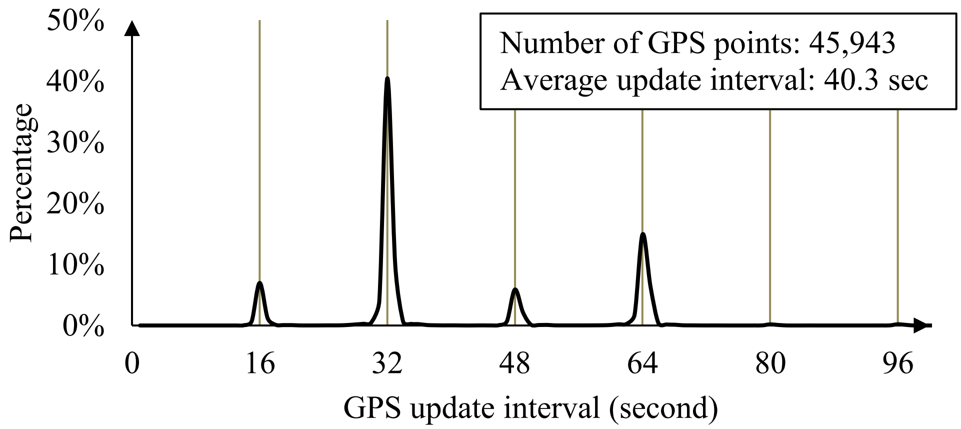


FIGURE 5.5 Distribution of GPS Update Interval

5.5.3 Test results

To quantify the performance, the mean absolute error (MAE) and mean absolute percentage error (MAPE) are applied to examine the accuracy of the link travel times and link stop times estimated by the proposed model. The link travel speed estimation method introduced in chapter 4 are chosen as the benchmark method, and the estimated link travel time results from it is used for comparison.

Table 5.3 and Table 5.4 give the results of MAE and MAPE of travel time estimation for each link respectively. The bold numbers in the tables indicate the best estimates among the estimation methods. For the eastbound links (link 1 to 7), the performance of the proposed method is slightly better than the benchmark method on link 1 to 3, with less MAE and MAPE, while after link 4 the benchmark method has better performance. A possible reason for it is that, the congestion degree used in the proposed method is adopted for all links along the corridor, while in fact the traffic conditions on each link could be different, and the estimated errors may be accumulated to the downstream links. On link 5, both methods have relatively large MAPE, even though the MAE of them are under 10 seconds. This is because that link 5 is the shortest link on the corridor (about 230 m long), hence the average travel time of this link is shorter than the others, which makes the percentage errors look larger. Furthermore, the downstream node of link 5 is an un-signalized intersection, which infers that both methods could have worse performance when the downstream nodes of links are not controlled by traffic signals.

For the westbound links (link 8 to 14), the proposed model performs better than the benchmark method on all links. Considering that during PM peak hours the westbound links have recurrent traffic congestions, the results suggest the proposed method performs better than the benchmark method under congestion condition. It should be noted that, similar to link 5, as the downstream node of link 9 is an un-signalized intersection, the estimation errors of both methods on this link are significantly larger than on the others.

TABLE 5.3 Mean Absolute Error of Link Travel Time Estimation

Link ID	Benchmark Method	Proposed Method (σ=0.1)	Proposed Method (σ=0.2)
1	1.1	**0.9**	**0.9**
2	4.1	**2.7**	**2.6**
3	5.8	**5.7**	**5.7**
4	**6.5**	7.9	7.9
5	**6.7**	7.8	7.8
6	4.3	4.4	**4.2**
7	**2.5**	2.9	2.9
8	4.3	2.8	**2.7**
9	5.9	5.0	**4.8**
10	7.3	4.4	4.4
11	**3.9**	4.9	4.8
12	8.1	5.5	**5.2**
13	7.6	7.5	**7.4**
14	4.7	4.3	**4.2**

TABLE 5.4 Mean Absolute Percentage Error of Link Travel Time Estimation

Link ID	Benchmark Method	Proposed Method (σ=0.1)	Proposed Method (σ=0.2)
1	5.9%	**4.6%**	**4.9%**
2	4.8%	**3.9%**	**3.8%**
3	11.1%	**10.1%**	**10.1%**
4	4.5%	5.6%	5.6%
5	**30.9%**	33.9%	34.3%
6	11.5%	11.7%	**11.2%**
7	**2.8%**	3.1%	3.1%
8	5.9%	3.7%	**3.5%**
9	20.3%	17.3%	**17.0%**
10	11.1%	6.8%	**6.6%**
11	**2.8%**	3.0%	3.0%
12	12.2%	7.2%	**6.9%**
13	12.8%	12.7%	**12.5%**
14	14.5%	11.4%	**11.2%**

For the proposed models with different σ values, the estimation errors of them are very similar. However, as in this study only two values of σ are applied for the test, more researches are needed in the future to examine if the estimated link travel time of the proposed method is sensitive to the value of σ.

TABLE 5.5 Mean Absolute Error of Link Stop Time Estimation

Link ID	Benchmark Method	Proposed Method (σ=0.1)	Proposed Method (σ=0.2)
1	N/A	1.0	1.0
2		5.8	**5.5**
3		7.4	**6.2**
4		11.0	**9.4**
5		7.1	**6.8**
6		4.2	4.2
7		9.5	**8.6**
8	N/A	11.5	**10.2**
9		6.9	**6.0**
10		7.0	**6.5**
11		35.2	**30.2**
12		7.8	**5.9**
13		5.0	**4.8**
14		3.2	**2.2**

Besides the link travel time estimation, another advantage of the proposed method is that it is capable to estimate link stop times while the benchmark method is not. By decomposing the travel time, the proposed method can provide a deeper view of link travel time, which can later be applied for reducing travel time estimation bias caused by bus dwell time. Table 5.5 lists the MAEs of link stop times estimated from the proposed models with different values of σ. The figure clearly depicts that the estimation error of the proposed model with σ=0.2 outperforms the model with σ=0.1 on all links, suggesting that in average the variance of congestion degree of the selected corridor has more influence on the link stop time estimation rather than the link travel time estimation.

Figure 5.6 illustrates the distribution of the estimation errors. Error larger than 0 means that link estimated stop time is larger than the ground truth stop time. Figure 5.6 suggests that, first, 51.0% and 59.7% observations of the proposed methods with σ=0.1 and σ=0.2 have estimated errors within the range of (-6,6] seconds. This result infers the promising potential of the proposed method for link stop time estimation. Second, 77.9% and 74.1% of observations of observations of the proposed models with σ=0.1 and σ=0.2 have estimated errors larger than 0, meaning that in general the proposed method tends to overestimate the link stop times.

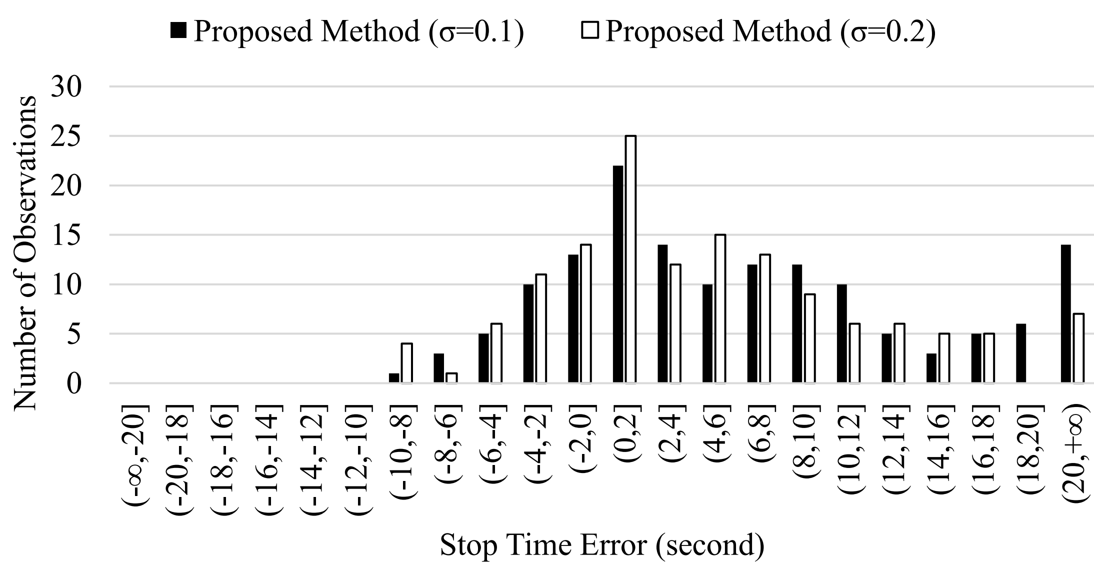


FIGURE 5.6 Distribution of Link Stop Time Error

Recalling that for the proposed method the free-flow speed is set to be the same as the speed limit, which is usually higher than the actual average free-flow speed, hence the proportion of the sum of congestion time and stop time may be overestimated, resulting in a positive average error. Another factor that may contribute to the positive estimation error is the congestion probability function. When free-flow speed is known, the sum of congestion time and stop time is constant, and inferring the proportion of the two travel time components is the key function of the proposed method. In this test, the congestion probability is assumed to follow a normal distribution, which may not be the best fit for it, as the congestion index is not linearly correlated with the congestion time. Therefore, a general overestimation of link stop times can also be described as an overall underestimation of link congestion times, hence one effort to improve stop time estimation accuracy can be replacing the current normal distribution assumption of the congestion probability, or at least testing more values of σ to find the best fit one.

5.6 Summary

A method for allocating link travel times from path travel times using low-frequency probe AVL data is proposed in this chapter. This method uses two probability functions to infer the variation of real-time traffic conditions and the delays on traversed links, and the parameters can be calibrated from historical AVL data. Results from the field test prove that the proposed method can improve the accuracy of link travel time estimation, especially when the road links are under congestion. Furthermore, this method can provide a deeper view for probe link travel delays with overall good performance, which is critical for future eliminating the estimation bias caused by bus dwell times and stopping at intersections.

Some limitations still exist in this study. First, parameters such as free-flow speeds and congestion probabilities are assumed to be the same for all links, which can be improved by setting them as link-specific. Second, the congestion probability function applied in this thesis is assumed to follow a normal distribution, yet the verity of this assumption remains unknown, and a better description of the congestion probability can be helpful for more accurate link travel time allocation. Third, the historical data used for parameter calibration does not consider temporal variation of traffic conditions due to the current limited size of data, which can be solved by using a larger historical dataset in the future.

6 CONCLUSIONS

Travel speed is one of the most commonly applied performance measurements for traffic facilities and networks. It is essential for the public understanding traffic conditions and planning for route planning and for the government improving traffic mobility. With the development of positioning technology, more vehicles are equipped with positioning devices, among which transit buses are considered as a promising probe vehicle type for real-time travel speed estimation.

In this thesis, a travel speed estimation method is first proposed for using transit buses as probes to estimate link-level travel speeds. This method is based on the assumption that the travel speed between two consecutive GPS points of a transit probe is not substantially different. A field test is conducted on a typical urban freeway, and the estimation results are compared with speed from loop detector data. the results reveal that the proposed link travel speed estimation can provide good link travel speed estimates, with a mean absolute speed difference of 7.0 km/h compared with the travel speed from loop detector data, and the traffic congestions can be well captured with relatively small sample size (less than 10 probes per time interval). The impact of probe vehicle type and GPS update interval upon estimation accuracy are also analyzed. the estimated link travel speed from transit GPS data is generally lower than the speed from loop detectors. The speed difference between transit GPS data and loop detector data on freeways follows a normal distribution, with the mean value of 5.4 km/h and the standard deviation of 6.4 km/h. In terms of the GPS update interval, it influences both the mean and the standard deviation of the speed difference, especially when the GPS update interval is longer than 90 seconds. Furthermore, the proposed link travel speed estimation method performs better on freeways than on arterials, as the basic assumption of the method is not reasonable for arterial considering the existence of intersections and bus stops.

An arterial link travel time allocation method for individual probes is then proposed to complement the link travel speed estimation method, since the basic assumption of the speed estimation method is not reliable on arterials. This method decomposes travel time between two neighbor GPS points into several components, and probability functions are used to infer the decomposed link travel times. Besides, historical transit GPS data is used for calibrating parameters, which, with sufficient data size, can capture the temporal traffic characteristics of road links. A field test is then conducted on an urban arterial for performance evaluation, and the estimated results are compared with the previously mentioned link travel speed estimation method. The test results show that the link travel time allocation method performs better especially when the traffic is congested, and it has the promising potential of estimating link stop times, which can be applied for estimating the dwell times at bus stops for transit probes and reducing speed estimation bias in signalized network.

There are several limitations existed in this thesis, which should be carefully considered in my future work. First, although the analysis results reveal the interrelation of travel speed between transit buses and general traffic, the bus-car speed relationship has not been integrated into the proposed link travel speed estimation method for improvement. Second, in the field test, the probe penetration rate is lower than 1%, hence the bus probes' speed variance due to driver behavior or other factors can have significant negative effect on the speed estimation accuracy; however, because the available data in this research is limited, the impact of probe penetration rate upon estimation accuracy is not investigated. Third, for the proposed link travel time allocation method, the congestion likelihood function is assumed to follow a normal distribution, which has not been verified yet. There might be other statistical distributions that can better fit the congestion likelihood function. Furthermore, although the link travel time allocation method can estimate link stop time, how to use this advantage to estimate bus dwell times at bus stops and to improve the speed estimation accuracy is not discussed. More researches are required in the future for improving the accuracy of the proposed link travel speed estimation method using transit GPS data, especially when applying on arterials.

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