University of Alberta

Traffic State Estimation Integrating Bluetooth Adapter and Passive Infrared Sensor

by

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Abstract

Active traffic control and management requires traffic state estimation with high accuracy. Although an inductive loop detector can achieve high accuracy in terms of volume, speed and occupancy estimation, it cannot provide accurate segment-based traffic parameters, such as segment speed and travel time. Additionally, its intrusive nature makes it not cost-effective for large scale deployment. This thesis first proposes a traffic detection method using passive infrared (PIR) sensors that generate point-based volume and speed data. Since Bluetooth is a promising technology, a Bluetooth-based segment speed estimation algorithm is also introduced. Finally, this research proposes a method to estimate arterial segment speed using both PIR sensors and Bluetooth adapters through the data fusion technique. All proposed algorithms have been validated and implemented in the field on urban arterials in Edmonton, Alberta, Canada. The final results show that traffic data fusion can greatly improve traffic state estimation accuracy.

Acknowledgement

I would never have been able to finish my thesis without the guidance of my committee members, help from friends, and support from my family.

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List of Abbreviations

ATDA	Adaptive Threshold Detection Algorithm
AVI	Automatic Vehicle Identification
CBD	Central Business District
CRM	Coordinated Ramp Metering
DOD	Department of Defense
ESAL	Equivalent Single Axle Loading
ETC	Electronic Toll Collection
FTDI	Future Technology Devices International
GPS	Global Positioning System
IEEE	Institute of Electrical and Electronics Engineers
ILD	Inductive Loop Detector
ISM	Industrial, Scientific and Medical
ITS	Intelligent Transportation System
MAC	Media Access Control
MLE	Maximum Likelihood Estimator
MOM	Max-Of-Max
MSE	Mean Squared Error
nesC	Network Embedded Systems C
OD	Origin-Destination
OUI	Organizationally Unique Identifier
PDF	Probability Density Function
PIR	Passive Infrared
RE	Relative Error
RF	Radio Frequency
RMSE	Root Mean Squared Error

(Continued)

SMS	Space Mean Speed
SPI	Serial Peripheral Interface
SSE	Sum of Squares due to Error
TPHTA	Traffic Platoon based Headway Threshold Algorithm
VIP	Video Image Processing
VSL	Variable Speed Limit
WIM	Weigh-In-Motion
WSN	Wireless Sensor Network

Chapter 1

1 Introduction

This chapter introduces the background of the traffic detection industry and the necessity for traffic state estimation from traffic detection systems. It provides information about the present state and problems of currently used traffic detection technologies and motivations for this study. The structure of this thesis is presented in the last section.

1.1 Background

Active traffic control and management requires traffic state estimation with high accuracy. Traffic state estimation, which usually includes the estimation of traffic flow, speed, occupancy and density, requires traffic data input from the traffic detection system. Different traffic detection technologies can provide different traffic data at different accuracy levels and resolutions. Currently, inductive loop detector (ILD) is the most widely used technology, which provides traffic state estimation of flow, point-based speed and occupancy. Similar to other point-based traffic detection technologies, ILD cannot provide segment-based traffic parameters, for example, segment-based travel time and speed. The general approach is to estimate segment-based traffic parameters from point-based traffic parameters. However, it is difficult and inaccurate because point-based traffic parameters cannot truly present the traffic state of a road segment.

Segment speed and travel time are fundamental traffic state parameters, which are basic inputs for Intelligent Transportation Systems (ITS). They are good indications of the traffic state along a road segment, so the accurate estimation of them can provide information for traveler information system, real-time traffic control and management and incident detection [1]. If drivers know the real-time segment speed of the roadway network in advance to their departure, they would tend to choose the route that has a higher segment speed. At a signalized intersection, if one approach is experiencing a lower speed, real-time traffic signal control can be implemented to improve the traffic conditions. Also, when one road segment has very low speed compared to historical data, one can infer that an incident might have happened on that road segment. Based on all these factors, accurate segment speed estimation is critical to the ITS development.

1.2 Problem Statement

Traffic detection technologies can be classified into three categories: intrusive, non-intrusive and off-roadway technologies [2][3]. The most commonly used technology is inductive loop detector (ILD), which is an intrusive sensor. Although it can provide vehicle detection with high accuracy (generally believed to be more than 97%) [4], it has certain disadvantages as follows:

- It is not an ideal candidate for large scale deployment on major freeways and arterials because of its high life-cycle installation and maintenance cost, and large traffic delay during the sensor installation and maintenance [5][6];
- It is a point-based sensor, so it cannot provide accurate estimation of segment-based speed. However, that is required in modern traffic management strategies, such as Coordinated Ramp Metering (CRM) and Variable Speed Limit (VSL) control [7];
- Although it is believed to be highly accurate in terms of traffic volume estimation, field testing has shown results of only 85.7% accuracy [3].

Because of the issues associated with current traffic detection technologies, especially with ILD, researchers are working towards several approaches:

1. Researchers are trying to integrate wireless sensor network (WSN) into traffic detection system to make it more cost-effective. Within WSN based traffic detection, different traffic sensors can be used and integrated, such as acoustic, magnetic and PIR sensors;
2. Because point-based sensors cannot provide accurate estimation of segment-based traffic parameters, researchers are exploring other new technologies, among which Bluetooth is

promising;

3. Because no single traffic detection technology can provide all the needed traffic state data, multi-source data fusion is being explored. It can integrate and utilize traffic data from both point-based and segment-based traffic detection technologies.

1.3 Research Motivation

Because of the above-mentioned disadvantages of inductive loop detectors, this research focuses on finding a new point-based traffic detection to provide the same traffic detection functions but at a lower cost. The PIR sensor used can provide point-based volume and speed estimation by using the proposed algorithm. It is assembled with TelosB sensor node, so it is featured with real-time wireless communication capability. They are small in size so they have high flexibility in terms of sensor deployment and the potential for large scale deployment.

As a new technology, Bluetooth is used for segment speed estimation for urban arterials. Past research on segment speed/travel time estimation has been conducted by using probe vehicles. As a mature technology, probe vehicle can provide vehicle location data, which can be further processed into speed, travel time and vehicle trajectory data. However, speed estimation accuracy lies in the penetration rate of probe vehicles within the traffic stream. Higher penetration rate can ensure higher estimation accuracy; however, it makes probe vehicle hardly a cost-effective traffic detection technology. Research has also been done on developing segment-based speed estimation algorithm using ILD [26]. But the ILD-based method still needs many calibration parameters as inputs for their proposed algorithms. Compared to these two technologies, Bluetooth does not require huge capital investments other than Bluetooth-enabled devices, such as cell phones.

In this research multi-source data fusion technique is conducted by integrating point-based PIR sensor data and segment-based Bluetooth data. The reasons why data fusion is needed are listed below. Firstly one single traffic detector cannot provide all the traffic data needed accurately. Through data fusion, more kinds of traffic data can be provided more accurately and more cost-effectively. Secondly, it is not necessarily true that one traffic detection technology is superior to another one. PIR sensor can provide the temporal coverage of the study segment and Bluetooth adapter can provide the spatial coverage. They both have their capabilities and limitations. PIR sensor can provide accurate point-based speed, which cannot accurately represent the segment speed of one road segment; Bluetooth adapter can provide more accurate segment speed estimation, but at a much lower sampling rate. On this account, data generated from both point-based PIR sensors and segment-based Bluetooth adapters can be better used to derive segment speed estimation through data fusion.

1.4 Research Objectives

This study aims to develop a new traffic detection system that can provide both point-based and segment-based traffic state estimations. The proposed traffic detection system can also provide the functions of traffic data fusion to increase the accuracy of segment-based speed estimation. For this research, PIR sensors and Bluetooth adapters were chosen. Because it is a non-intrusive traffic detection technology, it has higher configuration flexibility, which makes the proposed method more cost-effective compared to ILD.

The specific objectives of this research are as follows:

1. To develop a simple but accurate vehicle detection algorithm using the PIR sensor, which can provide microscopic traffic parameters, namely flow, speed and headway;

2. To evaluate the proposed traffic detection algorithm by implementing the algorithm in the field and comparing the field PIR data with ground truth video data in terms of accuracy;

3. To examine the speed and travel time estimation by using Bluetooth adapters in the field, on urban arterials in Edmonton, Alberta, Canada;

4. Based on the PIR point-based speed data and Bluetooth segment-based speed data, a data fusion technique, called maximum likelihood estimator (MLE) is used to improve traffic state

estimation accuracy, and the result is compared with ground truth data.

1.5 Scope of Study

Field tests were implemented on urban arterials in Edmonton, Alberta to provide Bluetooth adapter and PIR sensor data for the development and validation of traffic detection algorithms. Video recording data were also used as the ground truth. This research has attempted to estimate the segment-based speed of urban arterial through data fusion.

1.6 Structure of the Thesis

The research work performed in this study is presented in six chapters.

A brief introduction to the background and problem statement is presented in Chapter One. The chapter also contains the specific objectives of this research and importance of the study along with an introduction of the structure of the thesis.

Chapter Two presents the literature review of the related topics. First it describes the traffic detection technologies that are being commonly used all around the world. They are classified into three different detection categories. It also discusses the state-of-the-art Bluetooth based and wireless sensor network (WSN) based traffic detection.

In Chapter Three, the methodology of using PIR sensor for point-based traffic detection is addressed. It covers the analysis for the PIR sensor signal, vehicle detection algorithm (traffic volume and speed estimation) based on the characteristics of the PIR signals generated. The field implementation and validation of the algorithm and its results are also shown.

Chapter Four presents the traffic detection using Bluetooth adapters. It can generate segment-based speed and travel time by using one pair of Bluetooth adapters. The field implementation of Bluetooth technology in Edmonton, Alberta is also introduced.

In Chapter Five, the proposed method of integrating Bluetooth adapter and PIR sensor data is analyzed. Data fusion technique, namely maximum likelihood estimator (MLE) is utilized for segment-based speed estimation. Compared to the results of using single traffic detection data source, it can greatly help improve the segment speed estimation accuracy.

The summary of research contribution is presented in Chapter Six. This chapter also contains the limitations of the research, as well as recommendations for future research within this topic.

Chapter 2

2 Literature Review

This chapter covers the literature review on both traditional and emerging state-of-the-art traffic detection technologies. The new technologies, such as Bluetooth-based and wireless sensor network-based traffic detection are also emphasized.

2.1 Introduction

Traffic detection is the key component of the transportation network, which can provide both historical and real-time traffic data for transportation planning, traffic control and management purpose. Based on the increasing needs of accurate and diverse traffic data, different traffic detection technologies have been developed and implemented. However, no single traffic detection technology can provide all the needed traffic data alone. Each technology has its capabilities and limitations. In this chapter, different technologies will be reviewed in terms of their mechanism and applications.

2.2 Review of Traffic Detection Technologies

Traffic detection technologies can be generally classified as intrusive, non-intrusive and off-roadway technologies based on the sensor locations. Intrusive traffic sensors are installed within or across the pavement; non-intrusive sensors can be installed above or on the side of roads with minimum disruption to traffic flow; off-roadway technologies do not need any specific equipment to be installed at the test site [3]. This chapter introduces several commonly used technologies from each category. In addition, Bluetooth and wireless sensor network based technologies are discussed respectively.

2.2.1 Traditional Detection Technologies

Traditional traffic detection technologies refer to the mature technologies that have been developed and used in both academic and industrial world. In this section, the details of these technologies will be introduced including their physical configurations, working mechanisms and traffic data collected.

2.2.1.1 Intrusive Detection Technologies

Inductive Loop Detector (ILD)

ILD, as an intrusive traffic detection technology, is the most widely used. Installed under the pavement, the wire loop is powered by electronic units at frequencies ranging from 10 to 50 kHz [8] and causes a magnetic field. The frequency baseline is established when no vehicle is within the loop area. When a vehicle stops or passes over the loop, the inductance of the loop is reduced and it forces the electronics units to output relay. If the change in frequency from baseline is over the threshold, the relay will trigger the traffic controller device, indicating the detection of a vehicle [3]. The ILD setup is shown in Figure 2- 1 [8].

As a mature technology, inductive loop can achieve more than 97% accuracy of volume estimation [5]. It can also output point-based vehicle speed estimation, which can be obtained by using either an inductive loop pair or a single loop with certain statistical algorithm [9][10][11][12]. However, because it is embedded beneath the pavement, it requires lane closure during installation and maintenance which causes serious traffic disruption. The stress of traffic and temperature also affect the loop wire performance, making its failure rate relatively high [3], especially in cold regions. Moreover, if the installation is done improperly, it can decrease pavement life significantly [8].

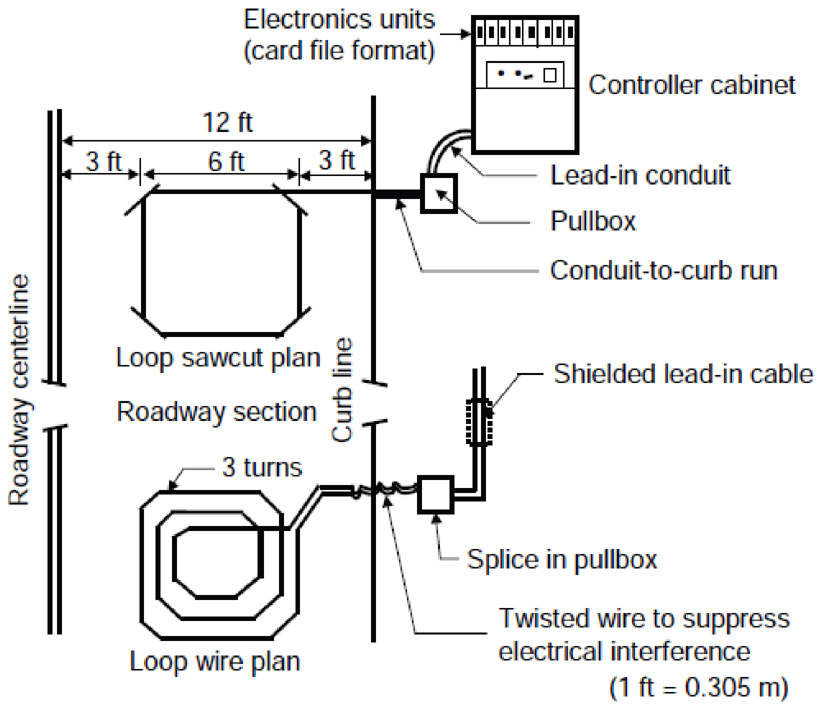

Figure 2- 1 Inductive Loop Detector Setup [8]

Weight-In-Motion (WIM)

Highway Weigh-in-Motion (WIM) systems are able to estimate the gross weight of a vehicle when the vehicle is travelling at a certain speed [13]. It has been widely applied in tolling, weight enforcement and traffic data collection, especially on trucks [14]. Because WIM system does not require vehicles to pull over and test for gross weight, it can increase the capacity of weight stations and improve the highway performance especially when heavy truck volumes are high. Because it can provide highway designers information of volume, vehicle classification and the equivalent single axle loading (ESAL) of trucks, it can greatly help with pavement design [2].

The WIM system usually contains two main parts: one provides the power for the system to collect and store data; the other one consists of sensors and cables to transmit data. The sensors record the pressure on the sensor, which is related to the dynamic load. Finally the static load of a truck is estimated from the dynamic load through calibration system.

Currently, four technologies are commonly used in WIM system, namely bending plate, piezoelectric, load cell, and capacitance mat [2]. Their working mechanisms are different: bending plate system records the strain measured by the strain gauges when a vehicle passes over; piezoelectric system detects the change in voltage caused by pressure; load cell system contains hydraulic fluid that captures the pressure caused by the axles; capacitance mat system detects the resonant frequency caused by increased capacitance when vehicles pass over.

2.2.1.2 Non-Intrusive Detection Technologies

Although intrusive sensors, especially ILD, can provide highly accurate traffic detection, they also deteriorate the pavement and cause traffic disruption and delay during installation and maintenance, which means huge indirect social costs. In this section, three common non-intrusive detection technologies are introduced, namely infrared-based system, acoustic system and video image processing system (VIP).

Infrared-based System

There are two kinds of infrared sensors, namely active and passive infrared sensor. Infrared sensors are usually mounted overhead to view approaching or departing traffic. They can be used for vehicular volume, speed and pedestrian detection.

1. Active Infrared Sensor: Active infrared sensors provide themselves low power infrared energy for illumination. The sensor emits radiation supplied by laser diodes operating in the near infrared region of the electromagnetic spectrum at 0.85m [2]. The times when the radiation is transmitted and reflected from the target are respectively measured. If the time difference between transmit and receive of the reflected signal is shorter, it indicates the presence of a vehicle [3].

2. Passive Infrared Sensor: Passive sensors detect the energy that is emitted from vehicles, road surfaces, and any other objects in the detection range. The source of the energy detected by passive infrared sensors is gray-body emission, which can occur at all frequencies by objects not at absolute zero (-273.15℃), shown in Figure 2- 2 [2].

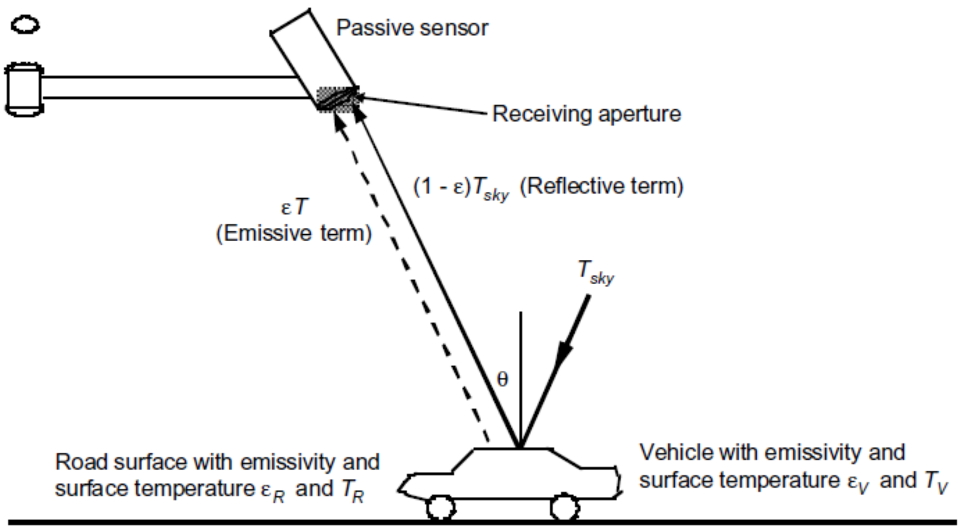

Figure 2- 2 Emission and Reflection of Energy by Vehicle and Road Surface [2]

Acoustic System

Acoustic sensors measure the acoustic energy or audible sounds produced from vehicles on the road. When a vehicle passes through the detection zone, the sound energy will increase, and it will be transferred into digital signal. A signal processing algorithm will be implemented to determine the vehicle presence [2].

A real-time traffic detection algorithm using acoustic sensor, called adaptive threshold algorithm (ATA) was developed [15]. It computes the time-domain energy distribution curve and outputs the final traffic count based on adaptive threshold. This algorithm was validated in the field by using Panasonic WM-62A microphone. In the process, the environmental noise, such as wind noise, is first removed by filtering the data through a band-pass filter. The final vehicle detection decision is made from a state machine based on the relationship between the signal and adaptive threshold, and the time it takes for the signal to stay consecutively above and below the threshold.

Video-Image-Processing (VIP)

Video image processing (VIP) was used for traffic detection purpose because it can detect vehicles through certain algorithms by analyzing the imagery. Currently VIP can automatically analyze the traffic detection zone to determine the changes between successive frames. It can examine the variation of gray levels of video frames by analyzing black and white imagery. A VIP system usually consists of three components: cameras for video recording; processor for image digitizing and processing; software for imagery analysis and traffic detection [2].

Two types of VIP systems are introduced, namely tripline system and tracking system:

1. Tripline system defines several detection zones within the view of the video camera. When a vehicle crosses the detection zones, changes in the pixels are generated compared to that when no vehicle is in the detection zones, which will be identified as the vehicle presence. Vehicle speed is estimated by measuring the time it takes a vehicle to travel through the detection zone, whose length is known [16].

2. Tracking system is used to track a particular vehicle or a group of vehicles continuously through the field of view of the video camera. The unique connected areas of pixels are identified and tracked by the system [17]. The tracking data are produced frame by frame [18].

2.2.1.3 Off-Roadway Detection Technologies

Automatic Vehicle Identification (AVI)

In transportation field, AVI technologies are primarily used for electronic toll collection (ETC). It can also be used for vehicle tracking and data collection of performance measures, such as segment travel time.

The AVI components are demonstrated in Figure 2- 3 [19]. Each detected vehicle is equipped with an electronic transponder, which can be identified by its unique ID. Typically every two to five kilometers, there will one antenna transceiver station. When the vehicle is within the roadside antenna’s detection range, the radio signal from the antenna will record the transponder’s unique ID, timestamp and antenna’s ID. These data will be sent back to the central computer through the reader unit on the roadside. The central computer will process and store all these data. If several AVI stations are available on the freeways, not only vehicle travel time can be calculated, individual vehicles can also be tracked along the freeway [19].

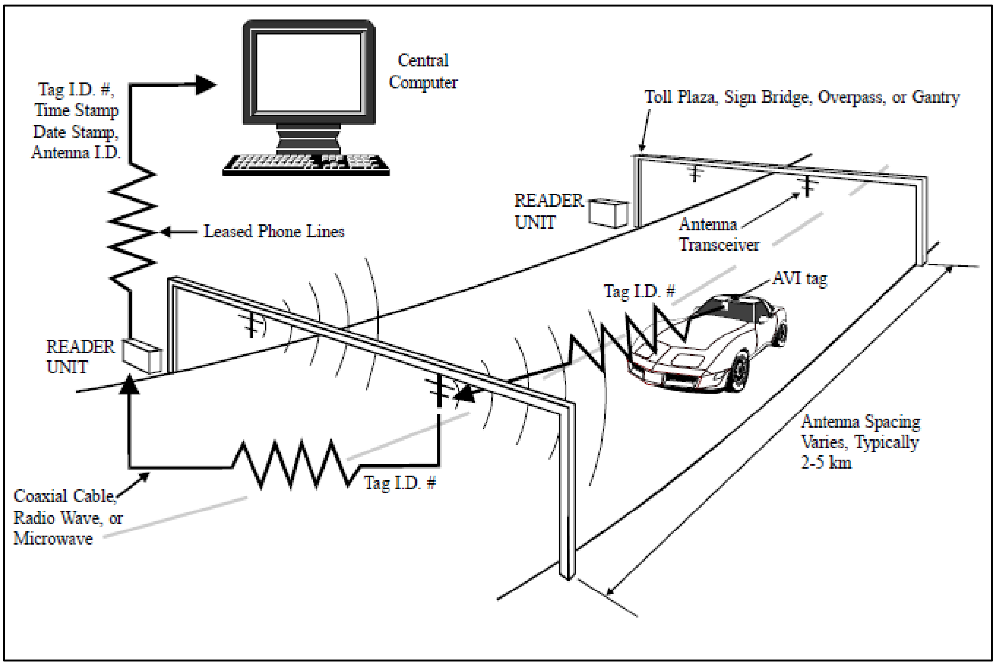

Figure 2- 3 AVI Vehicle-To-Roadside Communication Process [19]

Probe Vehicle equipped with Global Positioning System (GPS)

Global Positioning System (GPS) was originally developed by the United States Department of Defense (DOD) to track military vehicles and now it is available for public use. Signals are sent from the 24 satellites orbiting the earth.

For traffic detection purpose, probe vehicles equipped with GPS will drive through the study segment and their location and speed information will be recorded. The probe vehicles are capable of receiving GPS signals from the satellites. These signals can be utilized to monitor location, direction, and speed anywhere in the world [20]. For example, for taxi and transit applications, the technology allows users to know the location of buses and the estimated arrival time at transit stops [19].

2.2.2 Bluetooth-based Technologies

For both freeway and arterial study, segment speed is an important traffic parameter as it is a better indication of the roadway traffic condition than point-based speed. But ILD cannot provide accurate segment-based speed; instead it can only provide point-based speed estimation, either by using speed trap concept from dual loop detectors or by using speed estimation algorithm based on single loop detector data [21]. Although vehicle reidentification algorithms are being developed to track vehicles within traffic network [3], it is still not mature and it requires frequent and complex calibration.

However, the working mechanism of Bluetooth is completely different from ILD that tracks vehicles by using vehicle reidentification algorithm. Bluetooth data collection units record the timestamps of unique MAC addresses identical to the consumer electronic within passing vehicles. MAC addresses are unique 48-bit addresses that are assigned by manufacturers of wireless devices of many electronic devices such as cell phones, laptops, headsets, iPhones and iPods, and GPS devices that have Bluetooth capability [22].

These time-stamped MAC addresses can be matched between Bluetooth detection stations to obtain the segment travel time. If the segment length is known, segment speed can then be calculated accordingly. Figure 2- 4 shows how the Bluetooth based traffic detection works. Because it records any Bluetooth MAC address that is within the detection range, it might contain outlier data such as Bluetooth devices that are possessed by pedestrians. Despite that, Bluetooth-based traffic detection still shows accurate results [23].

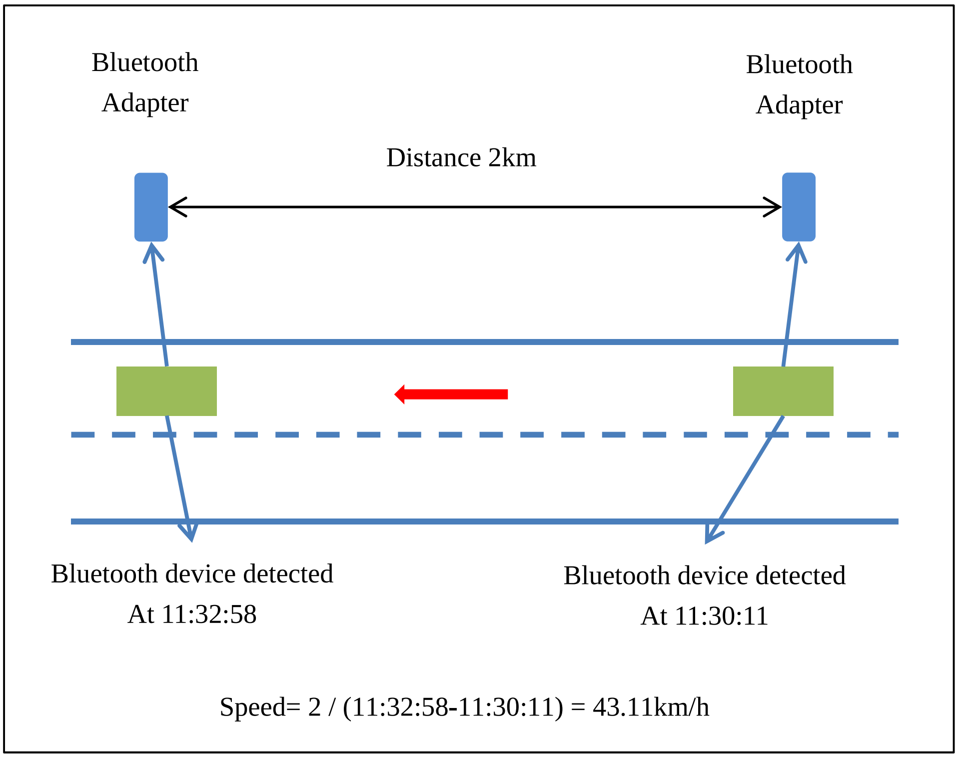

Figure 2- 4 Traffic Detection using Bluetooth Adapters

In addition, Bluetooth can be used for dynamic origin-destination (OD) estimation, which is of great use for transportation planning study [23]. The Bluetooth monitoring station is generally set up along the roadside with cable, antenna and Bluetooth reader [22]. The Bluetooth reader is used to detect Bluetooth devices along the roadway and the antenna can help increase the detection range and thus increase the detection rate.

2.2.3 Wireless Sensor Network based Technologies

Traffic detection using wireless sensor network (WSN) technology has been researched to replace the ILDs considering their disadvantages [24]. Sing-Yiu Cheung and Pravin Varaiya provided the prototype design, analysis and performance evaluation of WSN for traffic detection using magnetic sensors (Acoustic sensors are tried out as well, but magnetic sensors are finally chosen because it shows better performance).

The authors developed the WSN based traffic detection providing vehicle detection, vehicle classification and vehicle reidentification functions. Each of these functions is further discussed below.

Vehicle Detection

A robust real-time vehicle detection algorithm called "Adaptive Threshold Detection Algorithm" (ATDA) for magnetic sensor was developed and it can achieve above 97% accuracy in the field. The algorithm processed the raw magnetic data from the sensor, including the X-axis and Z-axis signal outputs. It justified vehicle detections by examining the time of magnetic signal staying above and below the adaptively defined threshold. The main objective of using adaptive threshold is to filter out spurious signals that are not caused by vehicles and to output binary detection flag without calling any complicated statistical function [3].

The algorithm can be described as three steps as follows:

1. Signal smoothing: A smoothing filter is used to avoid the frequent up-and-down fluctuation of the magnetic signal by taking a running average of the signal;

2. Adaptive Baseline: The signal outputs from the magnetic sensor are fluctuating during the day because they are installed under the pavement and are affected by pavement temperature. So the adaptive baseline is set up to track the background magnetic reading and used to determine the adaptive threshold level for the detection state machine.

3. Detection State Machine: It is used to generate the detection flag indicating vehicle presence. The times of magnetic signal staying above and below the threshold are measured. If the times have reached the critical value, the detection flag is outputted.

Since the Adaptive Threshold Detection Algorithm (ATDA) can reach high accuracy, the speed estimation algorithm is developed as well. Two methods are proposed in this research regarding speed estimation.

One is to assume a fixed, pre-defined magnetic vehicle length and calculate the speed from occupancy by using one single magnetic sensor, which is called median speed estimation. It estimates the median speed of the traffic platoon instead of the speed of each individual vehicle. Another way is to estimate speed in a manner similar to dual ILDs by using a magnetic sensor pair. However, in this method, the sensors have to be synchronized, which means their clocks must have identical timestamps. Based on the assumption that the vehicle signature measured by one sensor is identical to that by the other one, the vehicle arrival times at these two sensors can be obtained. Therefore the travel time between these two sensors can be easily calculated. Since the distance between two sensors is known, the speed can be calculated accordingly.

Vehicle Classification

Vehicle classification refers to the process to classify a vehicle's signature into a pre-defined vehicle class. Totally six types of vehicle classes are defined, namely, passenger car, SUV, van, bus, minitruck and truck [3]. A simple classification algorithm based on a single dual-axis magnetic sensor is presented. The earth's magnetic field in both the vertical direction and along the travelling direction is sampled at 64 Hz. The vehicle signatures of both directions are processed into a hill pattern. The process compares the rate of change of consecutive samples to the predefined threshold. If the rate is positive and larger than the threshold, it is declared to be +1; if it is negative and the magnitude of the rate is larger than the threshold, it is declared to be -1; or if the magnitude of the rate is smaller than the threshold, it is declared to be 0. Figure 2- 5 shows the raw samples and its hill pattern of a passenger car [3]. The field experiments suggest that a single dual-axis sensor can classify vehicles with above 60% accuracy [25].

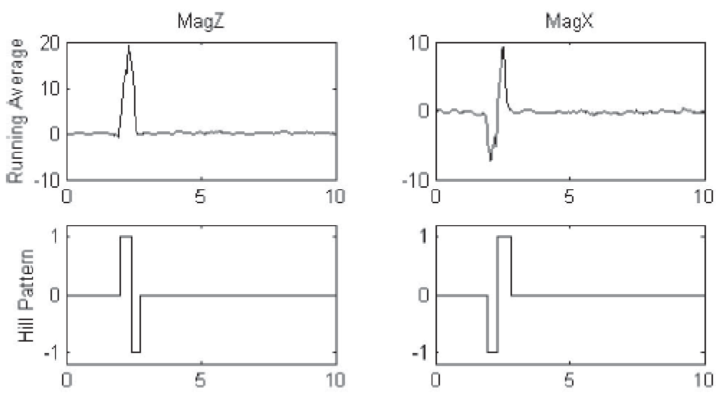

Figure 2- 5 Raw Samples and Hill Pattern from Typical Passenger Vehicles [3]

Vehicle Reidentification

Vehicle reidentification is the process of tracking vehicles at different locations along a traffic detection network. Since traditional point-based traffic detectors cannot provide segment-based traffic parameters, the developed vehicle reidentification algorithm can help provide segment-based speed and travel time.

The algorithm can be described as two steps as follows:

1. The raw data is passed through the Average-Bar process first. Because the raw signal data is fluctuating, average-bar is a process designed to smooth the magnetic signal. During the process, the magnetic signal vector is grouped into several sub-vectors of a smaller size and within each sub-vector the fluctuating signal is replaced by its average value.

2. The Max-Of-Max (MOM) reidentification scheme is proposed to further process the average-bar data. The maximum combined correlation coefficient of the 3-axis signals between different sensors along the roadway is calculated. If it is larger than a pre-defined threshold, a positive reidentification result is issued.

The field test shows that an overall reidentification rate of 72.5% can be achieved. However, in this research, only a few field tests were implemented and more tests were needed to further validate the method.

Chapter 3

3 Traffic Detection by Passive Infrared (PIR) Sensor

This chapter mainly addresses the details of traffic detection by using PIR sensors. It includes the sensor node configuration, PIR sensor and its signal characteristics analysis, and traffic volume and speed estimation algorithm based on signal characteristics. The developed algorithm is also verified through real-world field tests in Edmonton, Alberta, Canada.

3.1 Sensor Node Configuration

Due to the fast development in sensor, processor and power technologies, sensor nodes now can be integrated into a small millimeter-cubic size at low cost [27]. In this section, the sensor node used in the research is briefly introduced in terms of its physical configuration and its capabilities as well as its applications for traffic data collection, transmission, processing and storage.

3.1.1 Components

TelosB

Telos is an ultra-low power IEEE 802.15.4 complaint wireless sensor module. Its components usually include sensor, radio, antenna, microcontroller and power [28], each of which will be discussed in further details.

There are two kinds of TelosB sensors, namely TPR2420CA and TPR2400CA (A TPR2420CA is shown in Figure 3- 1 [28]). The only difference between the two is that TPR2400CA does not include any embedded sensors, and if needed, the sensors can be connected via the 6-pin and 10-pin expansion connectors [28]. In this research, TPR2400CA is used, and the PIR sensor is connected through the 6-pin and 10-pin connectors.

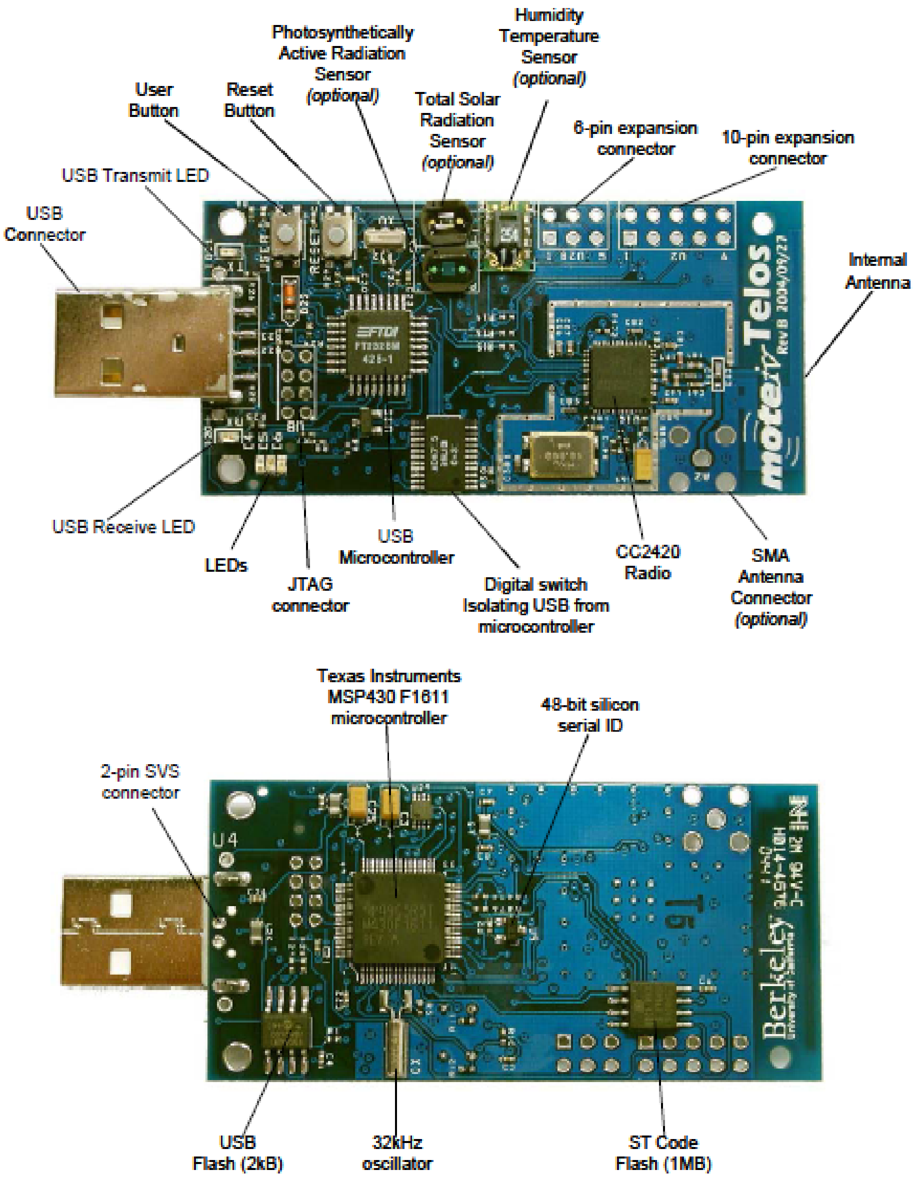

Figure 3- 1 Front and Back of TelosB TPR2420CA [28]

Power Source: TelosB can be powered by two AA batteries when there is no other alternative power source. When it is plugged into the USB port of a computer for programming or communication, it will receive power directly from the host computer.

Microprocessor: The Texas Instruments MSP430 F1611 microcontroller features extremely low current consumption during both active and sleep mode, especially during the sleep mode. It permits TelosB module to operate for years even with a pair of AA batteries being the only power source [28].

Radio: The Chipcon CC2420 is featured on TelosB module as it is designed for low power and low voltage wireless communications [28]. CC2420 is a single-chip 2.4 GHz IEEE 802.15.4 compliant radio frequency (RF) transceiver, which can be controlled by the TI MSP430 microcontroller through the Serial Peripheral Interface (SPI) port [29].

Antenna: Telos has two antenna options, an internal antenna and an external antenna. Built into the module, the internal antenna is an Inverted-F microstrip design; the external antenna can be connected through a SMA connector [28]. A simple TelosB communication test has been done and it is found that TelosB antenna may reach 100 meters communication range outdoors.

3.1.2 TinyOS

TinyOS is an open-source component-based, event-driven operating system, started as the collaboration work between the University of California, Berkeley and Crossbow Technology [30]. It is written in nesC (network embedded systems C), a component-based, event-driven programming language used specifically to build TinyOS applications [31]. Because it is an open-source system, many commonly used programming codes, such as codes for network protocols can be found from the component library for TinyOS and they can be further edited to suit a custom application. Since TinyOS is event-driven execution architecture, the sensor node can switch between the sleep mode and active mode, meaning the sensor node can remain in the sleep mode until an event is triggered [3].

3.1.3 Communication

TinyOS can provide two types of communication, namely radio communication and serial communication. In this research, both two types of communication are used. The TelosB communication setup is shown in Figure 3- 2. The node programmed with SenseToRadio collects and transmits PIR signal and the node programmed with BaseStation transfers data from radio network to serial port for PC to process and store.

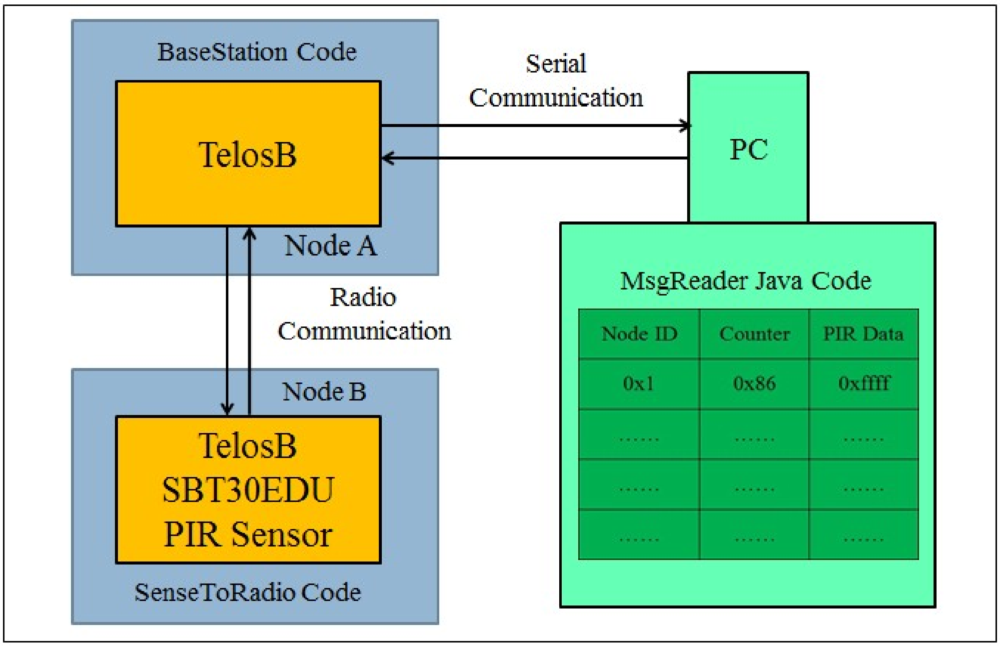

Figure 3- 2 TelosB Communication Setup

Radio Communication

In TinyOS, radio communication uses a common message buffer abstraction, called message_t, which is implemented as a nesC struct.

In the communication scheme, the node programmed with SenseToRadio needs to provide two functions:

1. It needs to collect the PIR signal from the PIR sensor periodically;

2. It needs to send the PIR signal to PC periodically for data collection and processing.

The partial coding is shown in Figure 3- 3. (The complete original coding can be found at http://www.easysen.com/support/TinyOS_2/, but coding used is customized for this research.)

```
/* - - - - - - - - EVENT: Acceleration channel X sampling done
 - - - - - - - - - - - - - - - - */
event void ReadACCx.readDone(error_t result, uint16_t ACCx_data)
{
        SenseToRadioMsg* ptrpkt = (SenseToRadioMsg*)(call
Packet.getPayload(&pkt, len));
        ptrpkt - >data[ChannelNo] = ACCx_data;
        sdata[ChannelNo++] = ACCx_data;
```

Reading one PIR sensor data: ACCx_data

```
/*  - - - - - - - -  EVENT: Acceleration channel Y sampling done
 - - - - - - - - - - - - - - - - */
event void ReadACCy.readDone(error_t result, uint16_t ACCy_data)
{
        SenseToRadioMsg* ptrpkt = (SenseToRadioMsg*)(call
Packet.getPayload(&pkt, len));
        ptrpkt - >data[ChannelNo] = ACCy_data;
        sdata[ChannelNo++] = ACCy_data;
        call Leds.led0Off();
        if (sampleCounter==4)
        {
                ptrpkt - >nodeid = TOS_NODE_ID;
                ptrpkt - >counter = pktCounter++;
                        if (!busy)
                        {
                                if (call
                        AMSend.send(AM_BROADCAST_ADDR, &pkt,
                        sizeof(SenseToRadioMsg)) == SUCCESS)
                                {
                                busy = TRUE;
                                }
                        }
```

Reading another PIR sensor data: ACCy_data; Node_ID; Counter

Sending data of both PIR sensors: ACCx_data; ACCy_data; Node_ID; Counter

Figure 3- 3 Partial Coding of PIR Signal Collection and Transmission

Serial Communication

TelosB uses a USB controller from Future Technology Devices International (FTDI) to communicate with the host computer. The basic abstraction for serial communication is a packet source, which is the platform over which a TinyOS application can receive packets from and send packets to [32].

BaseStation is a basic TinyOS utility application, which acts as a communication bridge between the serial port and radio network. When it receives a packet from the serial port, it transmits it on the radio; when it receives a packet over the radio, it transmits it to the serial port. Because it includes queues in both directions of packet transmission, once a message enters the queue, it will eventually leave on the other interface [33].

With BaseStation to generate and send packets to a node over a serial port, PC can directly communicate with sensors. In this research, when the node programmed with BaseStation is plugged into a PC, it can receive SenseToRadio packets and send them to the serial port. On the PC, the Java tool MsgReader can read and print out the contents of any packet it receives.

3.2 PIR Sensor

In this research, PIR sensor with wireless communication capability is used. Because of the flexibility of TelosB module, PIR sensor can be connected to TelosB board via the 6-pin and 10-pin expansion connector. In this section, the hardware specification and traffic detection signal output of PIR sensor are discussed. In the next section, the traffic detection algorithm based on PIR sensor signal output is presented.

3.2.1 Hardware Specification

TelosB provides the wireless communication platform, on which PIR sensor can collect PIR sensor data and send them back to the traffic control center for data processing and storage. The same as other traffic detection technologies, hardware specification of the technology has a huge impact on the traffic detection system performance, for example, the sensor detection range and its sampling frequency could affect the detection accuracy. In this research, a SBT30EDU board and PIR sensor are used for traffic detection.

SBT30EDU

SBT30EDU is a low power sensor board, specifically designed for use with TelosB platform through TelosB external connector. It is provided with supporting TinyOS and Java code that can be used to gather data from all associated sensor channels and display readings on a computer. SBT30EDU has several sensors on it, such as visual light sensor and acoustic sensor, but it is also provided with a prototyping area, where three additional channels can be added, shown in Figure 3- 4 [34].

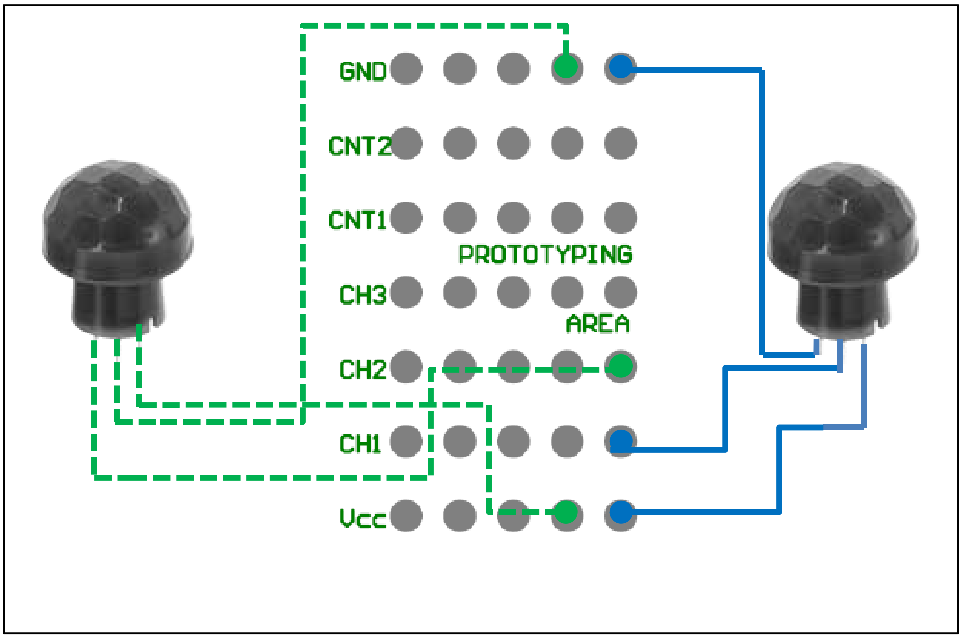

Figure 3- 4 Prototyping Area and Connecting with PIR Sensors [34]

PIR Sensor

PIR sensor used in this research is a Panasonic MP Motion Sensor “NaPiOn” [35] with detection range of ten meters, shown in Figure 3- 4 [34]. It has the ability to detect movements based on PIR signal generated from the moving object. It can detect temperature differences between the detection target and its surroundings as small as 4°C [36].

3.2.2 PIR Signal

The output of PIR sensor is shown in Figure 3- 5. When no object is within the detection range, the PIR signal would stay close to zero. The moment an object is detected, PIR signal would jump immediately from zero to maximum PIR reading and stay at the maximum value until the object is no longer within the detection range. Then PIR signal would decay exponentially at a certain rate after.

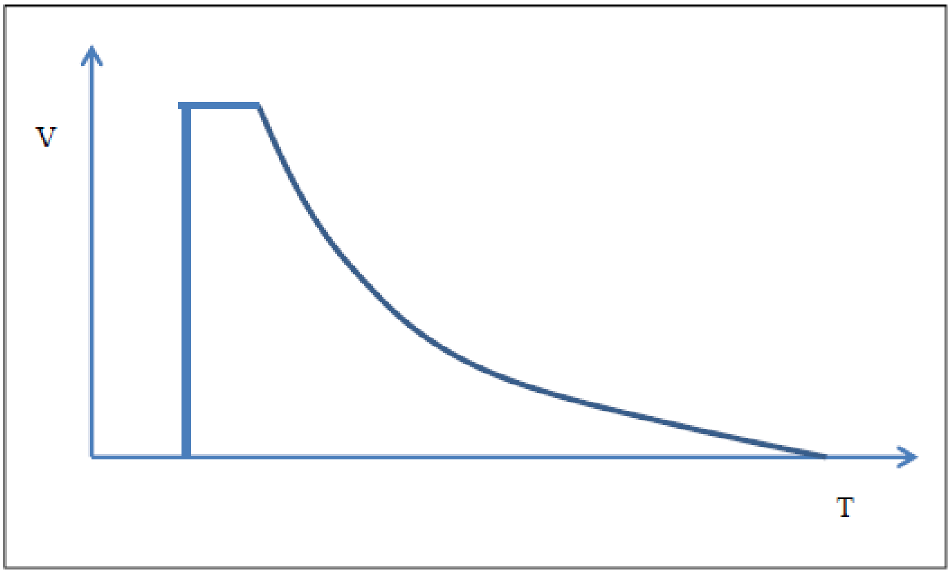

Figure 3- 5 PIR Signal Example of Single Vehicle Detection

Figure 3- 6 shows one minute of PIR signal output from a field test conducted on urban arterials in Edmonton.

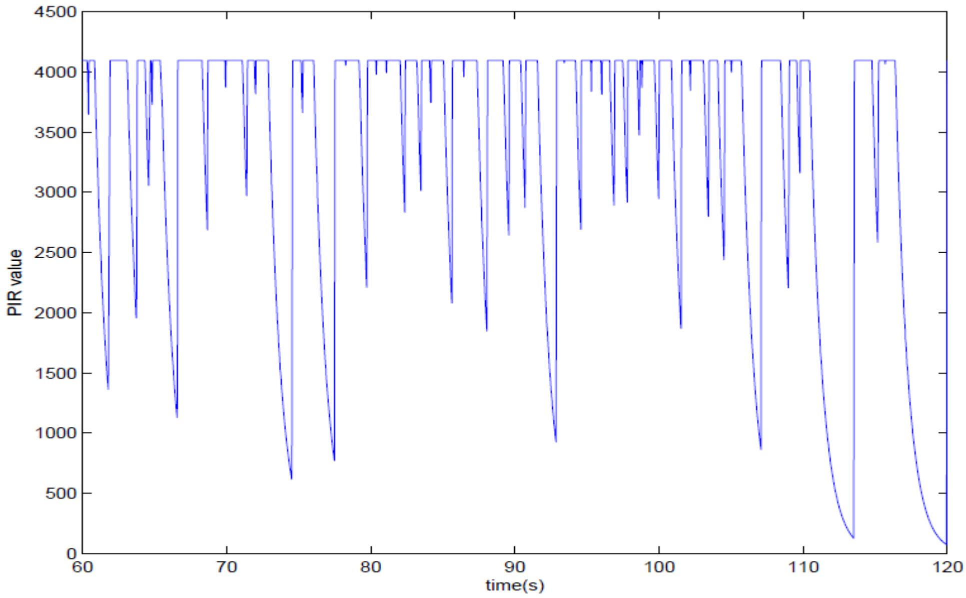

Figure 3- 6 Vehicle Signature from PIR Output in a Field Test

Signal Feature Analysis

In Figure 3- 6, some important signal features are shown. Generally, each peak represents the presence of one vehicle within the detection range. During the vehicle's presence, the PIR signal would ideally stay at the maximum value until vehicle leaves the detection range. But in reality, because the raw analog output is fluctuating, it might not pass the upper predefined threshold, so the PIR signal output would start to decay slowly (Figure 3- 5). That is why during one vehicle's presence, we can see some points staying below the maximum value. However, the signal decreasing from the maximum value can also mean that no vehicle is within the detection range. So the focus of the algorithm design is to judge when a vehicle leaves the detection range and when the following vehicle enters the detection range.

In order to do that, several PIR signal features are extracted, such as the timestamp when the vehicle enters the detection range (the timestamp when the signal reaches the maximum), the timestamp when the vehicle leaves the detection range (the timestamp when the signal decreases from the maximum), and the time one vehicle spent within the detection range (the time duration of the signal staying at the maximum). Vehicle detection algorithm design in section 3.3 is based on these PIR signal features.

3.3 Vehicle Detection Algorithm

Based on the analysis from section 3.1 and 3.2, the features of PIR signal can be extracted for vehicle detection. The PIR signal is generated periodically and can be transmitted back to the computer in real-time. The output from PIR sensor would include PIR sensor node ID, counter and PIR signal.

3.3.1 Traffic Volume Estimation

The vehicle detection algorithm has to be sufficiently accurate and computationally simple for traffic detection purpose. Based on these two objectives, a vehicle detection algorithm named Traffic Platoon based Headway Threshold Algorithm (TPHTA) was designed for detecting vehicles in moving traffic. The main reason to use a headway threshold detection approach instead of other statistical algorithms is that, drivers usually follow the two-second following distance rule, which would work at any speed, except that four-second following distance rule is used when large commercial vehicles are involved or extreme weather or road conditions are encountered [37].

The algorithm consists of five components, signal feature, signal grouping, signal smoothing, headway threshold, and final detection output. The detail of each step is discussed in the following section. Figure 3- 7 shows the block diagram of the proposed algorithm.

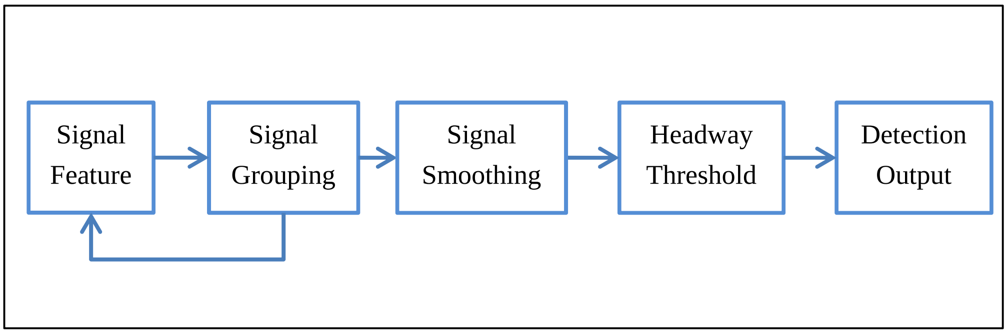

Figure 3- 7 Block Diagram of the Traffic Platoon based Headway Threshold Algorithm

Step 1: Signal Feature

The output from PIR sensor includes sensor node ID, counter and PIR value at every timestamp. The data is expressed as an array of $S_i = \{ j, T(j) \}$, in which j stands for the timestamp obtained from counter data and $T(j)$ stands for the PIR value at j timestamp. In the algorithm development process, several points were extracted from PIR signal and utilized to correctly identify the vehicle arrival. They are explained as follows:

$t(k)_{i,start}$: the starting timestamp of the k_{th} vehicle detection, the starting point of the threshold value (m), $t(k)_{i,start} = j \quad if \ T(j-1) < m \ \forall \ T(j) = m$;

$t(k)_{i,end}$: the ending timestamp of the k_{th} vehicle detection, the ending point of the threshold value (m), $t(k)_{i,end} = j \quad if \ T(j) = m \ \forall \ T(j+1) < m$;

$t(k)_{i,threshold}$: the duration time of the k_{th} vehicle detection, the duration of the PIR signal staying at the threshold value (m), $t(k)_{i,threshold} = t(k)_{i,end} - t(k)_{i,start}$;

$t(k)_{i,below\_threshold}$: the duration time of the no-vehicle detection, the duration time of the PIR signal staying below the threshold value (m), $t(k)_{i,below\_threshold} = t(k+1)_{i,start} - t(k)_{i,end}$;

Where:

m is the maximum PIR threshold;

i is the group index that is used in the signal grouping process;

k is the sequence number of vehicle detection in each signal group, and it can be expressed as follows:

$$k = \begin{cases} 0 & if \ T(j) < l \ \forall \ \mathrm{T}(j+1) \geq l \\ k+1 & if \ T(j) < m \ \forall \ \mathrm{T}(j+1) = m \end{cases};$$

Where:

l is the predefined threshold for signal grouping.

The output is $F_i(k)=\{\ t(k)_{i,start}, t(k)_{i,end}, t(k)_{i,threshold}, t(k)_{i,below\_threshold}\} \quad k=1,2,\cdots N$.

Step 2: Signal Grouping

In most urban areas, because of the existence of traffic signals, vehicles usually follow each other very closely in a platoon. Thus the traffic platoon concept is applied in this algorithm by dividing continuous traffic flow into different short segments. By doing so, vehicles with similar traffic state (vehicle speed) will be grouped into the same traffic platoon, which could greatly help improve the traffic detection accuracy when determining vehicle arrival within each signal group. If PIR signal goes below the predefined threshold l , we believe vehicles are not following each other closely and they belong to different traffic platoons. The signal grouping procedure is given by the following equations:

$$i=\begin{cases}0 & if\ \ j=0\\ i+1 & if\ T(j)<l\ \ \forall \mathrm{T}(j+1)\geq l\end{cases}$$

Where:

i is the group index to indicate the signal group that $T(j)$ belongs to;

l is the predefined threshold for signal grouping.

The output from signal grouping procedure is $S_i=\{\ i, j, T(j)\}$.

Step 3: Signal Smoothing

As the PIR signal shown in Figure 3- 6 indicates, the PIR signal during the presence of a moving vehicle within the detection range is not always staying at the maximum value because the PIR analog signal is fluctuating. So a preliminary “Signal Smoothing” procedure is proposed to help correctly identify the vehicle detection even though the PIR analog output is temporarily below the predefined threshold, based on the value of $t(k)_{i,below\_threshold}$. If $t(k)_{i,below\_threshold}$ is smaller than a threshold, the PIR signal between $t(k)_{i,end}$ and $t(k+1)_{i,start}$ is regarded as the signal of one moving vehicle. So the predefined $t(k+1)_{i,start}$ is no longer the starting timestamp of next vehicle detection and $t(k+2)_{i,start}$ is instead. The signal smoothing procedure is given by the following equations:

$$\begin{cases} t(k+1)_{i,start} = t(k)_{i,start} & if\ t(k)_{i,below\_threshold} \le \sigma \\ t(k)_{i,end} = 0 & if\ t(k)_{i,below\_threshold} \le \sigma \end{cases}$$

Where: σ is the threshold value for $t(k)_{i,below\_threshold}$.

The output is $N_i(k)=\{\ t(k)_{i,start}, t(k)_{i,end}\}\ \ if\ t(k)_{i,end} \ne 0\ \ \ k=1,2,\cdots M\,(M \le N)$

Step 4: Headway Threshold

The fourth step called "headway threshold" is done within each signal group. As discussed before, vehicles travelling in traffic platoon have relatively low headway, and traffic within each segment share similar traffic state (vehicle speed). So the minimum headway is used as the threshold. The advantage of using minimum headway is that it is not sensitive to various traffic states. Within one particular traffic stream, a minimum headway exists, which is confirmed by the field tests for headway studies implemented at urban arterials in Edmonton. The headway threshold procedure is given by the following equations:

$$\begin{cases} t(k+1)_{i,start} = t(k)_{i,start} & if\ t(k+1)_{i,start} - t(k)_{i,start} \le \tau \\ t(k)_{i,end} = 0 & if\ t(k+1)_{i,start} - t(k)_{i,start} \le \tau \end{cases}$$

Where:

τ is the headway threshold value.

Using minimum headway threshold can greatly help distinguish vehicles that travel with small headway, but within the same traffic platoon, vehicles that travel with larger headway may not be distinguished or misjudged because of the existence of disturbance in the PIR signal. In this case, using only minimum headway threshold could cause vehicle double-counting. So within each traffic platoon, the difference of the durations of vehicle detections of two consecutive vehicles is checked. If it is larger than the predefined threshold η, it is reported as vehicle double-counting and these two sets of PIR signals will be regrouped as the PIR signal of one vehicle. But the duration of vehicle detections should also be lower than a certain threshold δ. The headway threshold procedure is updated based on the following equations:

$$\begin{cases} t(k+1)_{i,start} = t(k)_{i,start} & if \left| t(k+1)_{i,threshold} - t(k)_{i,threshold} \right| > \eta \ \forall \ t(k+1)_{i,end} - t(k)_{i,start} \le \delta \\ t(k)_{i,end} = 0 & if \left| t(k+1)_{i,threshold} - t(k)_{i,threshold} \right| > \eta \ \forall \ t(k+1)_{i,end} - t(k)_{i,start} \le \delta \end{cases}$$

Where:

η is the threshold value of the difference of two consecutive vehicle detections;

δ is the threshold value of the time duration of one vehicle detection.

The output is $T_i(k)=\left\{ t(k)_{i,start}, t(k)_{i,end} \right\} \ \ if \ t(k)_{i,end} \neq 0 \ \ k=1,2,\cdots K(K \le M)$

Step 5: Final Detection Output

After step 1-4 are done, vehicle detection output is provided. Either aggregated or disaggregated traffic detection outputs are available. K is the traffic count data within certain time period. Five-minute aggregated traffic volume data can also be obtained, which are usually used by different transportation management agencies and researchers. $T_i(k)=\left\{ t(k)_{i,start}, t(k)_{i,end} \right\}$ shows the detailed vehicle detection results with timestamp. This could greatly help traffic engineers to conduct traffic studies for signalized intersections in terms of its volume characteristics, its traffic signal timing plan and others.

3.3.2 Speed Estimation

When using a single ILD for speed estimation, we usually assume a fixed, predefined magnetic vehicle length and calculate the speed based on the occupancy and the vehicle length. So the speed estimation accuracy lies in the difference between the actual vehicle length and the pre-defined one. However, by using dual ILDs, more accurate speed estimation can be obtained. Figure 3- 8 shows the field setup of speed estimation by a pair of synchronized PIR sensors similar to dual ILDs. Two sensors were placed on the sidewalk facing the traffic lane with a known separation along the travelling direction.

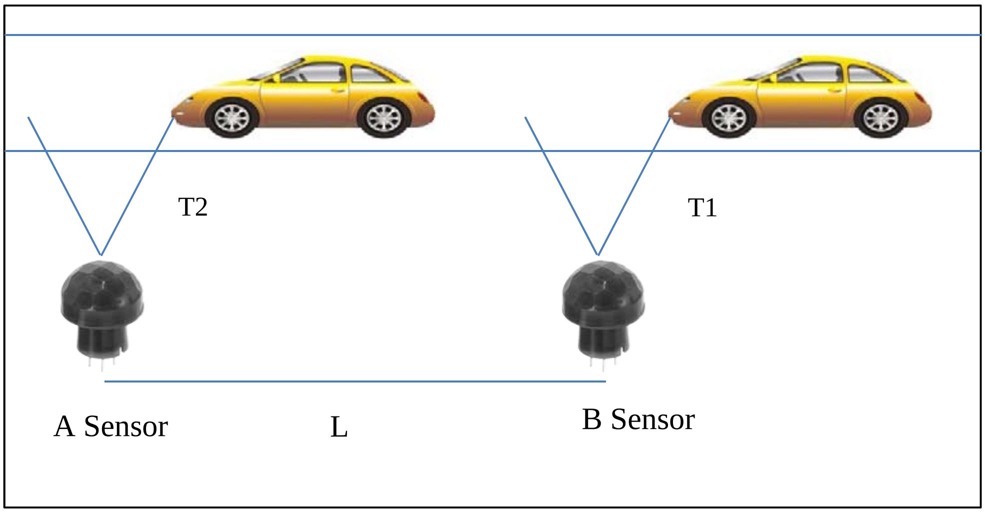

Figure 3- 8 Example of Speed Estimation by using a Sensor Pair

Assuming the vehicle has negligible lateral offset and acceleration within the distance between these two sensors, the vehicles signature measured by sensor A should be identical to the one measured by sensor B. As a result, the time difference between A and B reporting vehicle detection is the travel time across the separation distance.

The vehicle speed is estimated by the following equations:

$$v = \frac{L}{T_2 - T_1}$$

Where:

T_1, T_2 are the times when the vehicle enters into the detection range of sensor B and A respectively;

v is point-based speed;

L is the distance between two sensors.

3.4 Experimental Results and Analysis

This section describes in detail the preparation and data analysis of the field experiments conducted on 109 Street in Edmonton, AB. Section 3.4.1 explains the rationale behind the selection of the field experiment location and its characteristics. Section 3.4.2 presents the details of data analysis regarding using one single PIR sensor for traffic detection. Section 3.4.3 shows the details of data analysis regarding using two PIR sensors as a sensor pair for speed estimation.

3.4.1 Field Experiment Setup

Site Location

For traffic detection study, one location meeting the following requirements needs to be selected:

1. It has to provide intermediate to high level of traffic volume so that the detection algorithm can be better evaluated, which means it cannot be a local road or a collector;

2. There must be enough room to set up the necessary traffic detection equipment, such as PIR sensors, video camera and others;

3. Because the PIR sensor is deployed facing the traffic from the sidewalk, ideally it should be a one-way street;

4. Because this PIR sensor is used for arterial traffic performance study, ideally it should be located at an urban arterial.

The test site is chosen based on the above-mentioned requirements, and the exact location is shown in Figure 3- 9, close to the Legislature Assembly of Alberta. The geometry characteristics of the roadway are shown in Figure 3- 10.

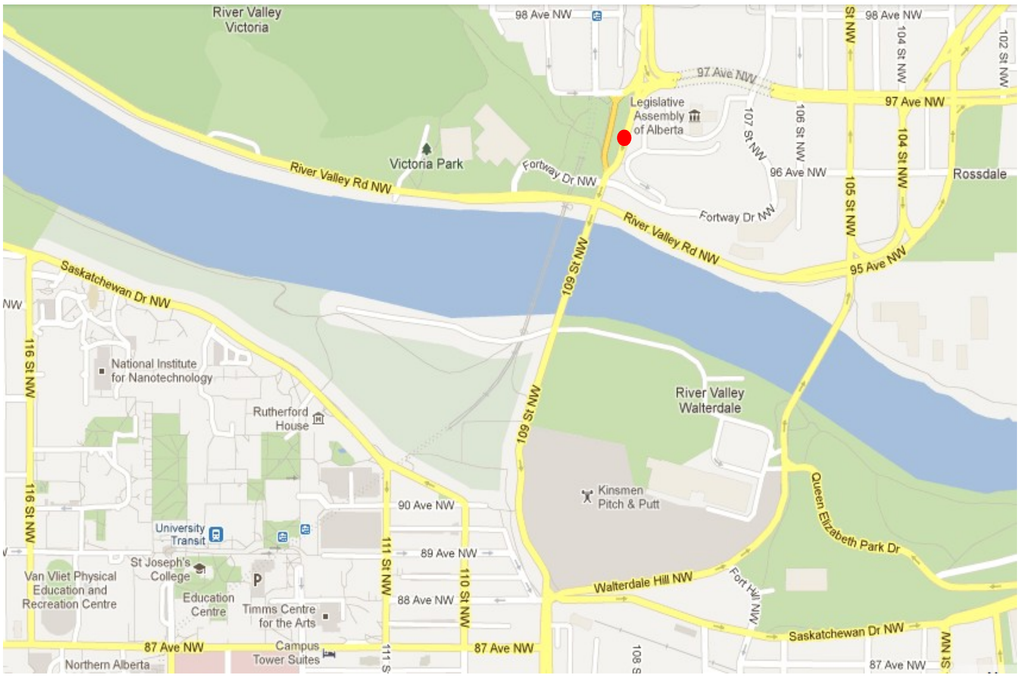

Figure 3- 9 Test Site for PIR Sensor Traffic Detection Algorithm

(Source: Google Map, http://maps.google.com/, accessed on August 01, 2011)

The details about the test site are shown below:

1. The test site is located on 109 Street, north of the North Saskatchewan River in Edmonton;

2. It is a one-way street with one travelling lane, functioning as an important urban arterial as it connects the north and south region of Edmonton;

3. Because it is close to the central business district (CBD) and it is adjacent to the High Level Bridge across the river, it has annual average weekday traffic (AAWT) of 27000 in 2007 [38].

4. The traffic passing through the field test site is coming from two directions, mainly from 109 Street Southbound and partially from 97 Avenue Westbound turning left.

Both of the approaches that traffic comes from are pretimed signalized intersections, controlled by traffic lights.

PIR Sensor and Video Camera Deployment

Two PIR sensors were placed on the sidewalk of 109Street in Edmonton, AB, shown in Figure 3-10. The sensors were placed close to the curb so it will not get disturbed from potential pedestrians and cyclists on the sidewalk.

The video camera was set up to provide ground truth data for traffic volume and vehicle speed. It was set up further back so that it will not distract the drivers and collect true traffic data. It would also provide a larger field of view of the detection zone, which would help determine the ground truth of vehicle speed.

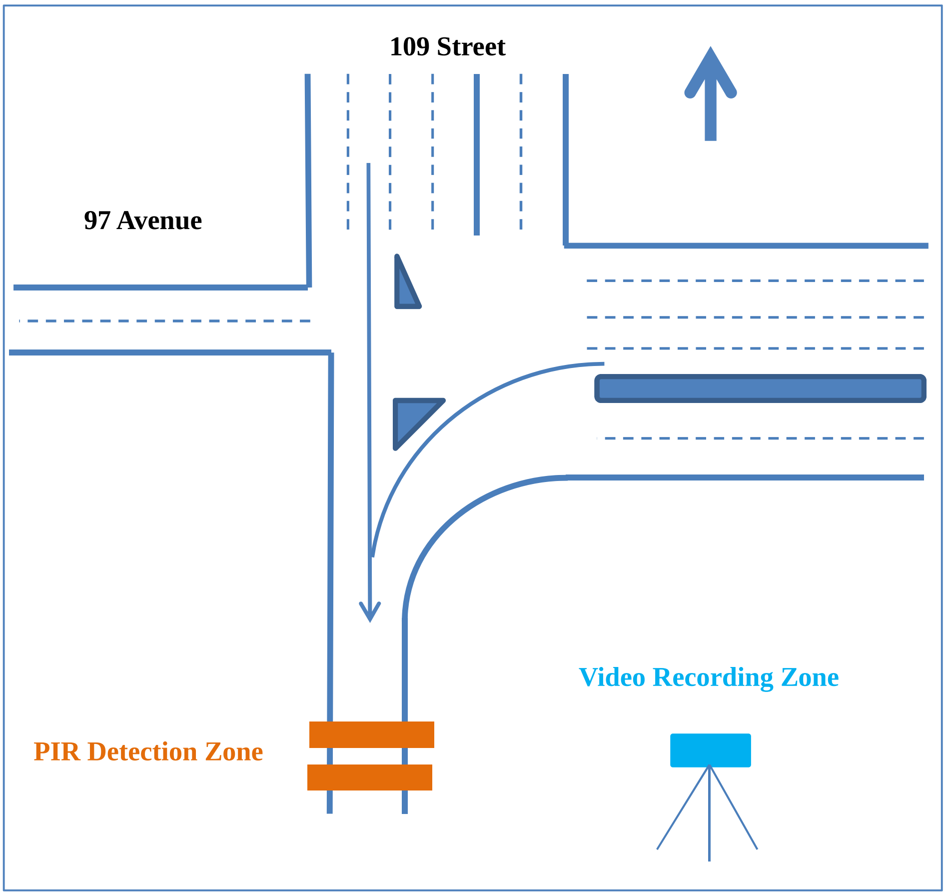

Figure 3- 10 Layout of the Field Experiment Site

3.4.2 Traffic Volume Estimation Using One PIR Sensor

To determine the traffic volume, one PIR sensor was placed facing the traffic. For the PIR sensor, the sampling rate was set at 40Hz while its data transmission rate was set at 10Hz. The configuration of vehicle detection and data transmission is shown in Figure 3- 11. The ground truth was established by the usage of video recording data. A total of 173 vehicles were observed during the time period, with the vehicle classification distribution as shown in Table 3- 1.

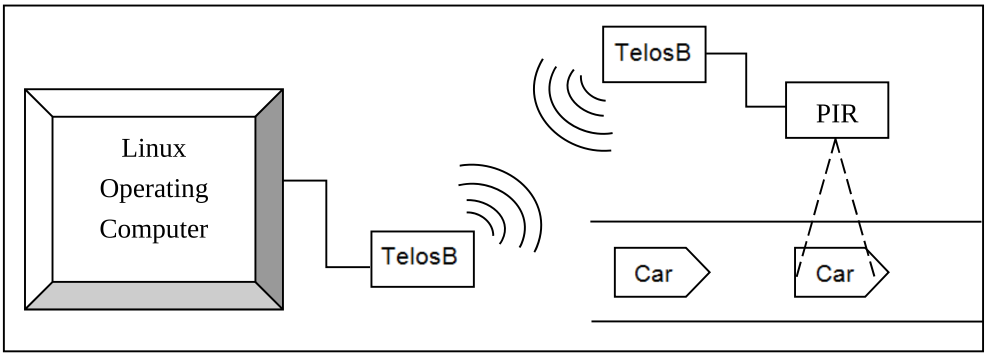

Figure 3- 11 Configuration of Data Collection and Data Transmission

PIR Signal Output

The generated PIR signal is transmitted back to the Linux-operating computer, which has TinyOS installed. PIR signal is shown in the following figures for the first 4 minutes.

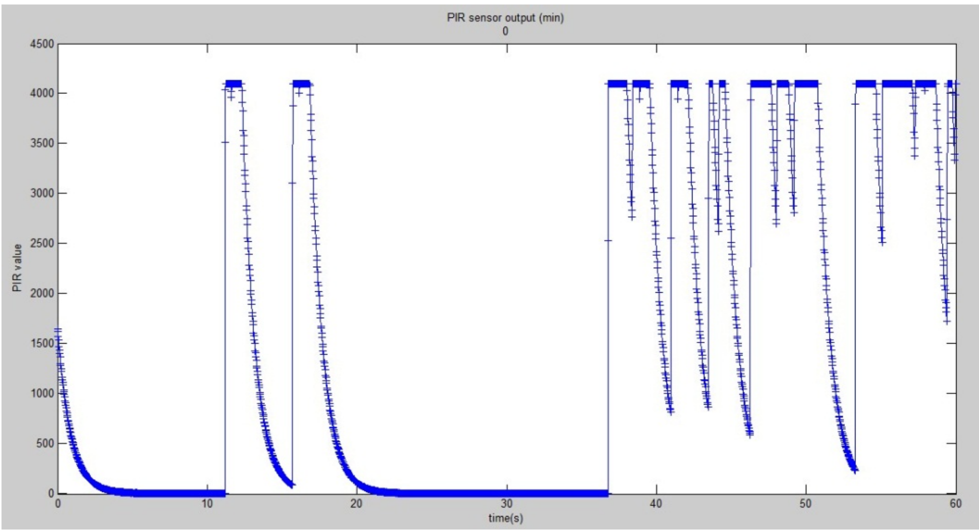

Figure 3- 12 PIR Signal Output – First Minute

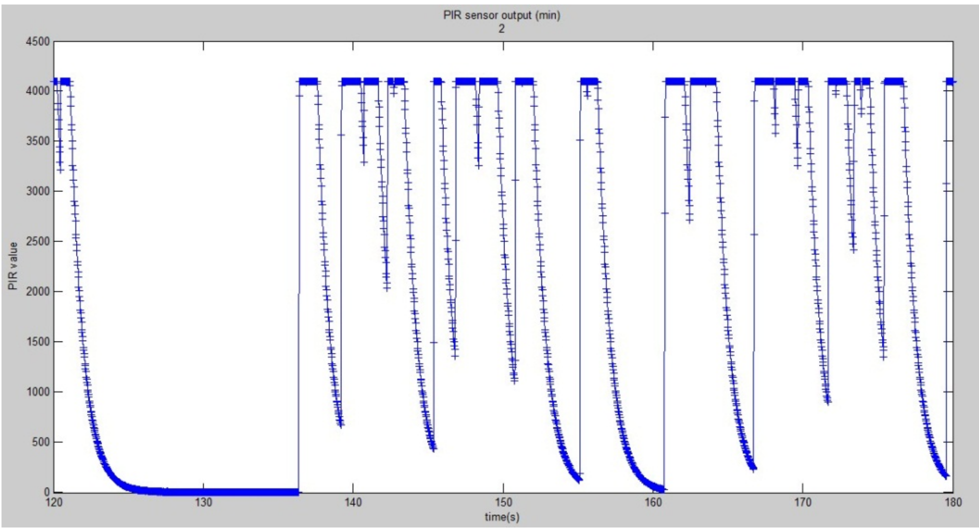

Figure 3- 13 PIR Signal Output – Second Minute

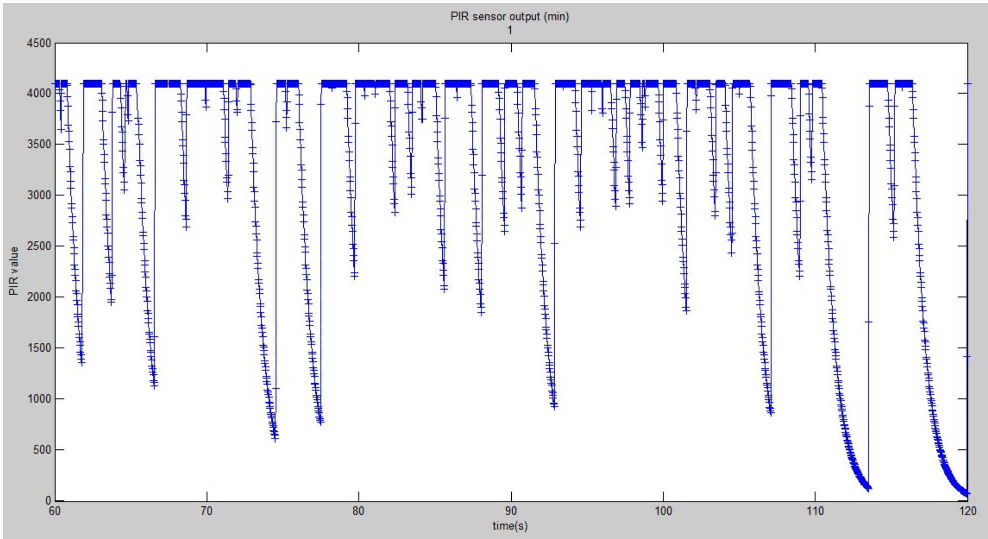

Figure 3- 14 PIR Signal Output – Third Minute

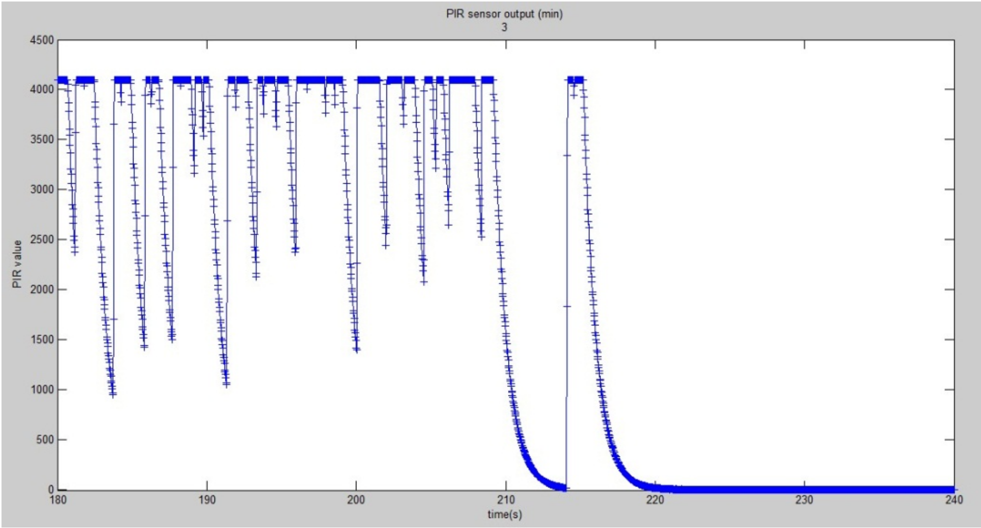

Figure 3- 15 PIR Signal Output – Fourth Minute

After the traffic detection algorithm is implemented offline, the traffic count data and detailed vehicle arrival data are obtained.

Traffic Volume Detection and its Accuracy

As expected, the passenger cars and SUVs are the majority of the traffic flow at the test site. The detailed vehicle classification of 173 vehicles is shown in Table 3- 1.

Table 3- 1 Distribution of Vehicle Types

Type	Passenger Car	SUV	Pickup	Bus	Jeep	Total
Counts	86	56	25	2	4	173
Percent (%)	49.7%	32.4%	14.5%	1.2%	2.3%	100%

PIR signals were generated periodically at the predefined frequency. A total of 176 out of 173 (98.3%) vehicles were detected. The processed PIR sensor data was compared with the video processed data, and we found there were totally three double-counting and no under-estimations were encountered. This means that PIR sensor with ten meters detection range is very sensitive to vehicular movement and it is very suitable for traffic detection since it can obtain such high detection accuracy (98.3%).

Traffic Characteristics Analysis

Other than the basic traffic flow data, more information regarding traffic flow characteristics and signal control characteristics at the signalized intersection can be extracted since each vehicle is individually measured. Because the PIR sensor is located at the downstream of the intersection, it can be used for intersection study.

Figure 3- 16 shows the vehicle arrival time and each dot stands for one vehicle arrival. Between the time periods of 0 second to 220 seconds, it clearly shows that the cycle length at this intersection is around 100 seconds. When the signal turns red for an approach, the queue would start to build up backwards at that approach. Once the signal turns green, vehicles will start to move, closely following the front vehicle, which makes the headway consistent and stay at a lower value.

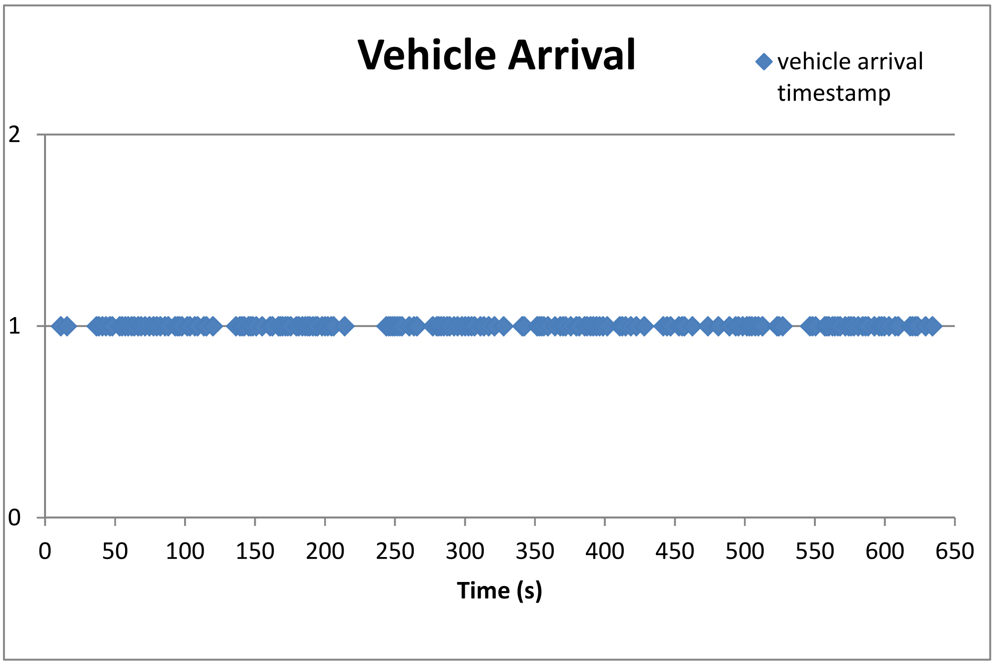

Figure 3- 16 Vehicle Arrival Time for the Field Test

Figure 3- 17 shows the headway statistics of the field test. Since the algorithm only utilizes the minimum headway concept, in this figure, we only study the headway range of 1.0 second to 2.7 seconds, which is obtained from the ground truth video data. It clearly shows that out of 173 vehicles, 53 vehicles (30%) have the headway of smaller than 2 seconds, which is the suggested headway for vehicle's following distance under good traffic conditions [37]. Only one vehicle

(0.58%) was found travelling with headway of smaller than 1.2 seconds, which is negligible. So a minimum headway threshold can be established based on this headway field test, which validated the traffic detection algorithm using the headway concept.

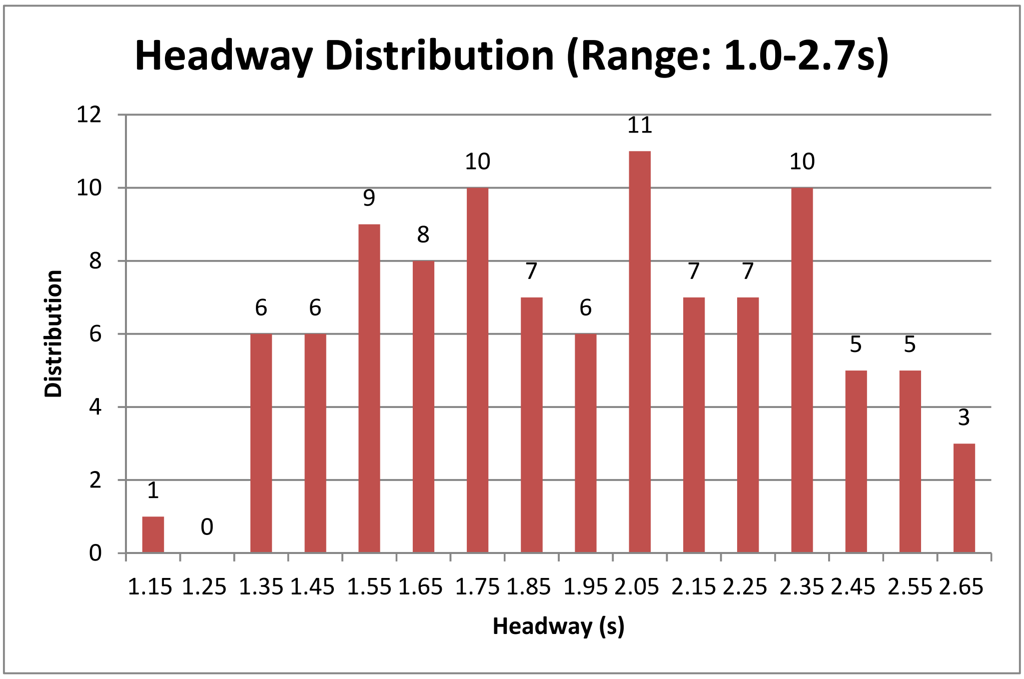

Figure 3- 17 Headway Distribution of Field Test

The data also gives further detail about the relationship between headway and arrival time. Figure 3- 18 plots the headway in seconds for the time period against the time. The large headway followed by several consecutive small headways would indicate that the green phase is shifted to the other approach within the intersection. The several large headway points are separated around 100 seconds apart, which coincides with the cycle length of the traffic signal at the intersection.

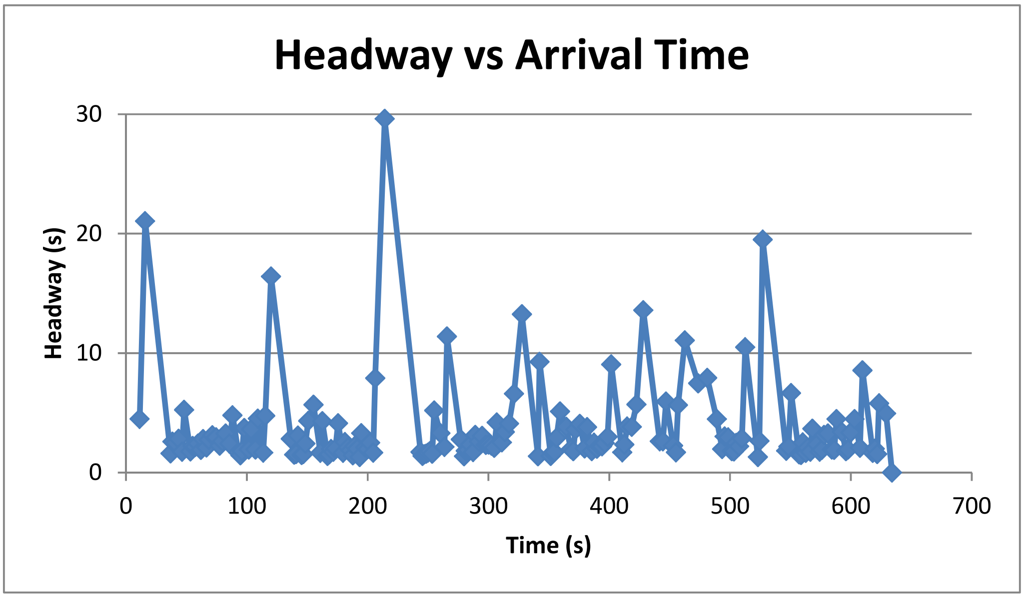

Figure 3- 18 Arrival Time of Vehicles against Headway during the Field Test

3.4.3 Speed Estimation using PIR Sensor Pair

Other field tests were done for speed estimation algorithm validation. It was conducted at the same place as the field test for traffic volume detection algorithm validation but the field test setup was slightly different, shown in Figure 3- 19. Two PIR sensors were placed facing the traffic, separated by 2.25 meters. The PIR sensor data was collected for 30 minutes long and the ground truth was established from the video recording data. A total of 455 vehicles were counted during the time period from the ground truth. Using the traffic volume detection algorithm, a total of 469 vehicles were detected and it reported 96.9% estimation accuracy.

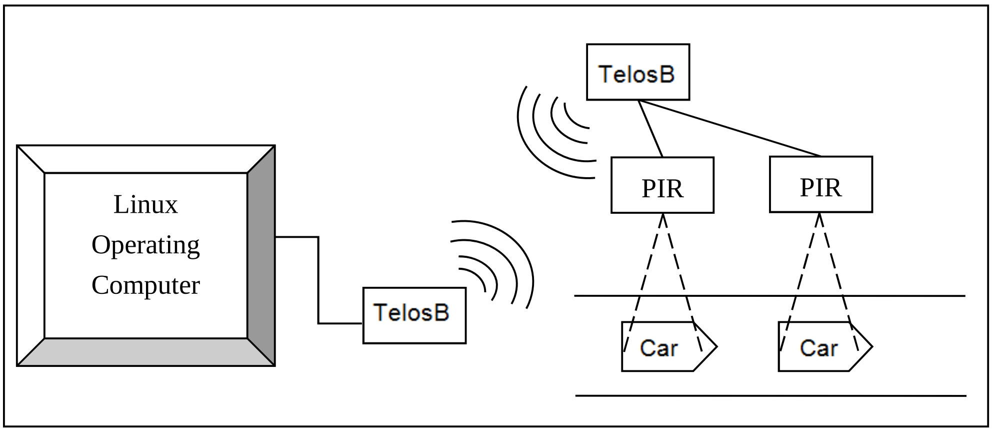

Figure 3- 19 Configuration of Data Collection and Data Transmission

Speed Profile

For estimating speed with the PIR sensor pair, only the samples whose timestamps were aligned between two PIR sensors were chosen. The reason why some samples from two PIR sensors are unaligned is because of the relatively low sampling rate. The final estimated speed profile is shown in Figure 3- 20.

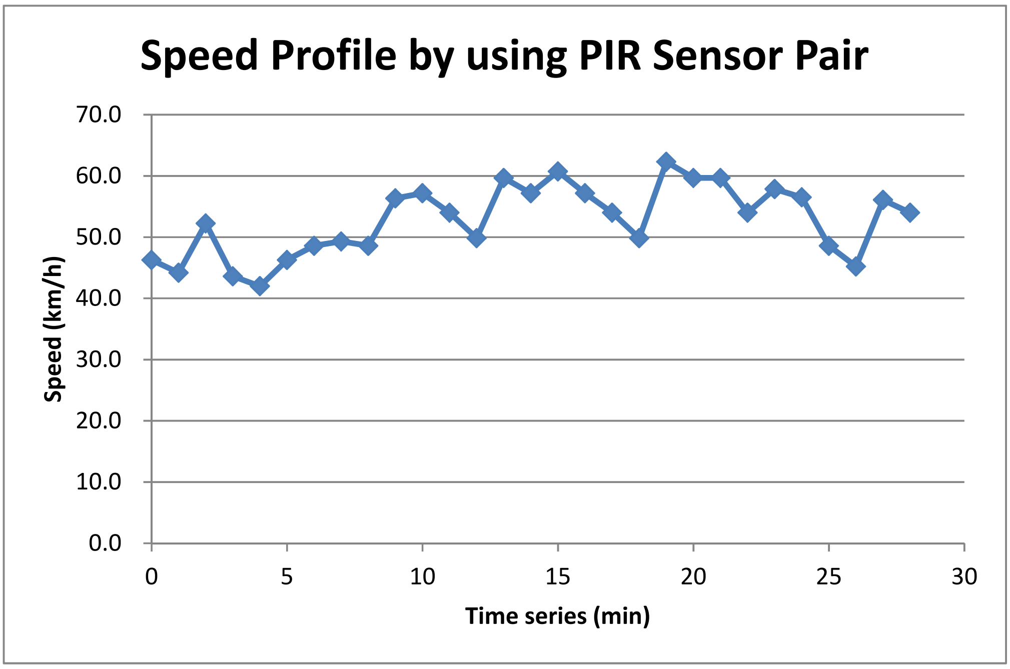

Figure 3- 20 Speed Profile by using PIR Sensor Pair

Speed Ground Truth

In the speed estimation experiment, two PIR sensors were placed 2.25 meters apart on 109 Street. Two locations on the sidewalk with 6.56 meters apart were chosen as landmarks for video processing as the ground truth of speed, shown in Figure 3- 21. The speed estimation by the sensor pair and the video data was compared and shown in Figure 3- 22.

Figure 3- 21 Picture of Video Recording

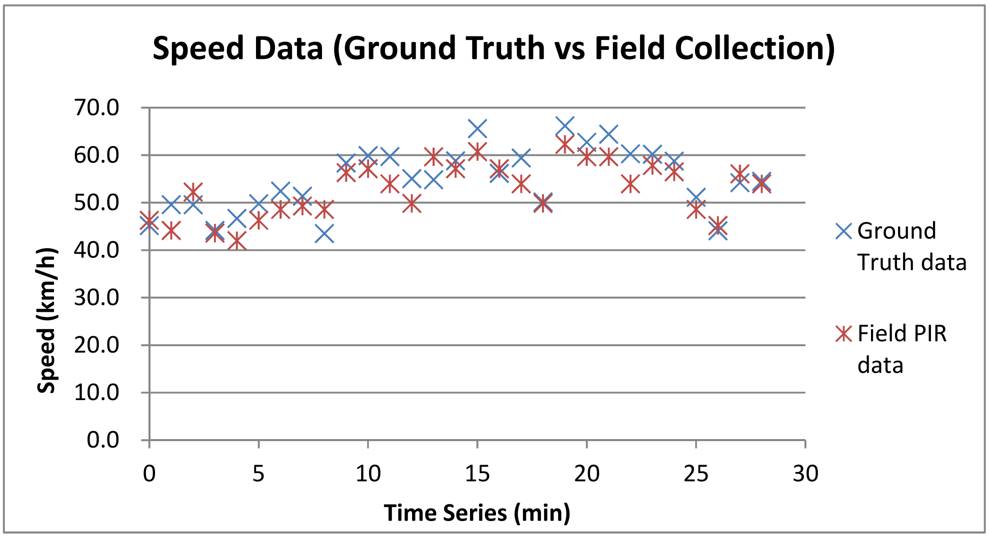

Figure 3- 22 Comparison of Estimated Speed Data and Video Data

The statistics of the speed estimation by using two PIR sensors are compared to the ground truth and tabulated in Table 3- 2. The high accuracy indicates that the method using two PIR sensors can be used to estimate point-based space mean speed (SMS).

Table 3- 2 Summary of Speed Estimation and Ground Truth Statistics

	Average	Minimum	Maximum
Video (km/h)	54.7	43.5	66.2
PIR Sensor (km/h)	52.8	42.0	62.3

3.4.4 Method Validation

To validate the traffic volume and speed estimation result, other field test datasets were used. A 30-min field data were used for vehicle volume algorithm validation. During the field test period, a total of 455 vehicles were observed from the video, used as ground truth; a total of 469 vehicles were detected based on the proposed algorithm and 96.9% vehicle detection accuracy was achieved. The arrival time of vehicles against headway during the field test is shown in Figure 3-23.

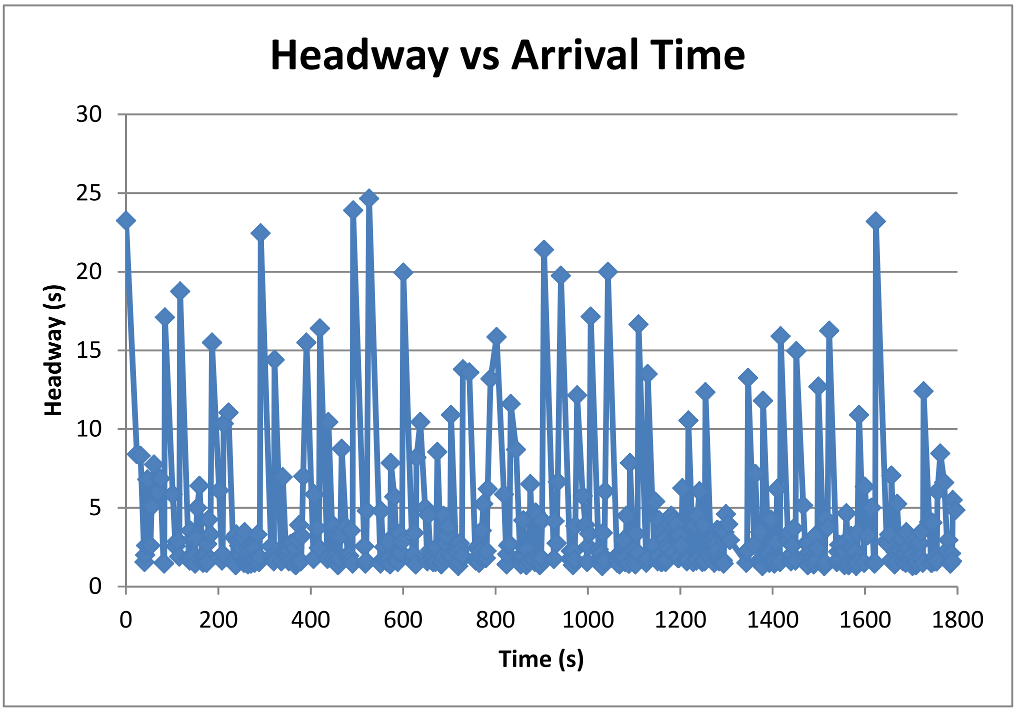

Figure 3- 23 Arrival Time of Vehicles against Headway during the Field Test

Speed algorithm was also validated with new field data. Five-minute aggregated space mean speed was presented in Figure 3- 24. It shows that the PIR detected speed follows the ground truth closely.

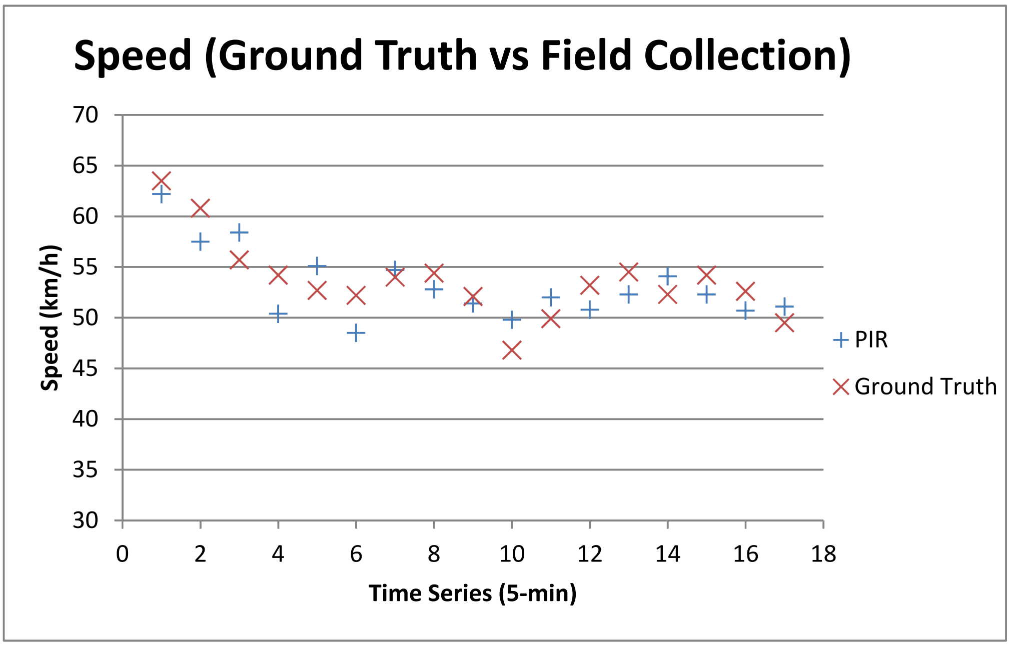

Figure 3- 24 Comparison of Estimated Speed Data and Video Data

The summary of speed estimation and ground truth is shown in Table 3- 3. High accuracy of speed estimation can be observed.

Table 3- 3 Summary of Speed Estimation and Ground Truth Statistics

	Average	Minimum	Maximum
Video (km/h)	55.0	43.4	67.6
PIR Sensor (km/h)	54.1	42.2	66.4

Chapter 4

4 Traffic Detection by Bluetooth Adapter

This chapter introduces the Bluetooth traffic detection technology. First Bluetooth traffic detection mechanism is discussed and then the methodology is verified in the real-world field test in Edmonton, AB.

4.1 Bluetooth Adapter Configuration

Recently, researchers have started to use Bluetooth as an alternative for segment speed and travel time estimation on both freeways and arterials. In this section, Bluetooth technology and specification, and its application on segment speed and travel time estimation are discussed in details.

4.1.1 Bluetooth Technology and Specification

Originally created by Ericsson in 1994, Bluetooth is a wireless technology for exchanging data over short distances from different devices, which uses short-wavelength radio transmissions in the ISM band from 2400–2480 MHz [39]. It can connect electronics equipped with Bluetooth devices to share music, images and other data.

Bluetooth Signals

Bluetooth can send and receive radio signals over short distances from one meter to more than 100 meters [40] (the distance can be increased to larger than 100 meters if required). Bluetooth sends radio waves at frequencies from 2.402 GHz to 2.480 GHz as internationally agreed for the use of industrial, scientific and medical (ISM) devices [41]. Radio frequency is defined as the rate at which radio signals are transmitted. Bluetooth device signal range, determined by its antenna class, is the distance at which other Bluetooth devices can be discovered.

Radio Classes

Bluetooth range is different based on the specific application and a minimum range is mandated by the Core Specification. Range may vary depending on the class of radio used in the implementation [40]:

- Class 3 radio – has a range of up to 1 meter;
- Class 2 radio – most commonly found in mobile devices and must provide a range of 10 meters;
- Class 1 radio – used primarily in industrial cases and must offer a range of 100 meters.

4.1.2 Bluetooth Media Access Control (MAC) Address

Typically manufacturers provide the choice of enabling or disabling Bluetooth on their devices. If they are turned on the “discovery mode”, their devices with Bluetooth capabilities will be detected by other Bluetooth devices within the range.

Bluetooth technology uses the MAC-48 identifier format as defined by the Institute of Electrical and Electronics Engineers (IEEE), so every Bluetooth device is uniquely identified by a 48-bit MAC address, which consists of six pairs of hexadecimal digits [42]. The first three groups of numbers are used to identify the organization which issued the identifier, called organizationally unique identifier (OUI). OUI is specific to the device manufacturer, while the following three are unique to the device.

4.2 Bluetooth Adapter

In this research, the Bluetooth USB Adapter used is SENA Parani-UD 100, which is a Bluetooth 2.0+EDR Class 1 type USB adapter, shown in Figure 4- 1. The advantage of using this Bluetooth adapter with a longer working distance is that more vehicles equipped with Bluetooth devices can be detected to increase the detection rate and match rate.

Figure 4- 1 Bluetooth USB Adapter Picture

4.3 Speed Estimation Algorithm

This section describes the vehicle speed estimation mechanism by using Bluetooth adapters. First, how Bluetooth adapter can estimate vehicle speed/travel time is introduced; and then the error sources of Bluetooth adapter for speed estimation are discussed; finally, the performance metrics, the detection rate and match rate are presented.

Segment Speed/Travel Time Estimation

In segment speed and travel time estimation, the Bluetooth adapter records the unique MAC address of any consumer electronics detected along with a timestamp within moving vehicles (timestamp is in Epoch time format). Thus, a MAC address detected at more than one Bluetooth sites represents a unique Bluetooth device which travelled from one site to another, and its travel time was determined by calculating the timestamp difference [43].

So if one unique MAC address was observed at both Bluetooth stations, we would estimate the link travel time based on the time difference of two timestamps assuming these two timestamps are valid data (The possible sources of invalid data are discussed in the next section of Error Sources). Based on the sequence of two timestamps at two stations, we would know the travelling direction of vehicles. Additionally, if the travel length between two Bluetooth stations is known, segment speed of each vehicle can be calculated accordingly.

With such information available, Bluetooth adapter can be used to assess vehicle travel time, segment-based speed and individual vehicle route choice. Compared to traditional techniques such as the videotaping of license plates, it is more cost effective [22].

Error Sources

As Bluetooth can only record the timestamps of vehicles when they are presented within the detection range of the test site, it cannot provide detailed information of vehicle's exact location within the segment, which can cause errors in Bluetooth speed estimation. The error sources can be classified as follows:

1. Errors may appear as a result of traffic signal existence. If Bluetooth adapter is placed close to the signalized intersection and vehicles are waiting for the green light, the MAC addresses associated with the vehicles will be recorded multiple times. The multiple records would create errors since there is no way to know which one best represents the link travel time of such vehicles.

2. Prior to the communication between two Bluetooth devices, they must discover each other via two steps: inquiry and paging [44]. The inquiry process needs at least 10.24 seconds to discover all Bluetooth devices within range [45], which may cause errors. Because during the 10.24 seconds, the vehicle can be detected anywhere within the range (Figure 4- 2), which means the travel distance is not exactly equal to the link travel distance between two Bluetooth stations. However, if the predefined travelling distance between two Bluetooth stations is larger, this error will decrease because the variation of travelling distance is relatively smaller [46][47]. So Class 1 type Bluetooth adapter with a detection range of at least 100 meters can result in larger errors compared to class 2 and class 3 type Bluetooth

adapters. However Class 1 Bluetooth adapter is still used on freeways and arterials to increase the detection rate and match rate between two Bluetooth stations.

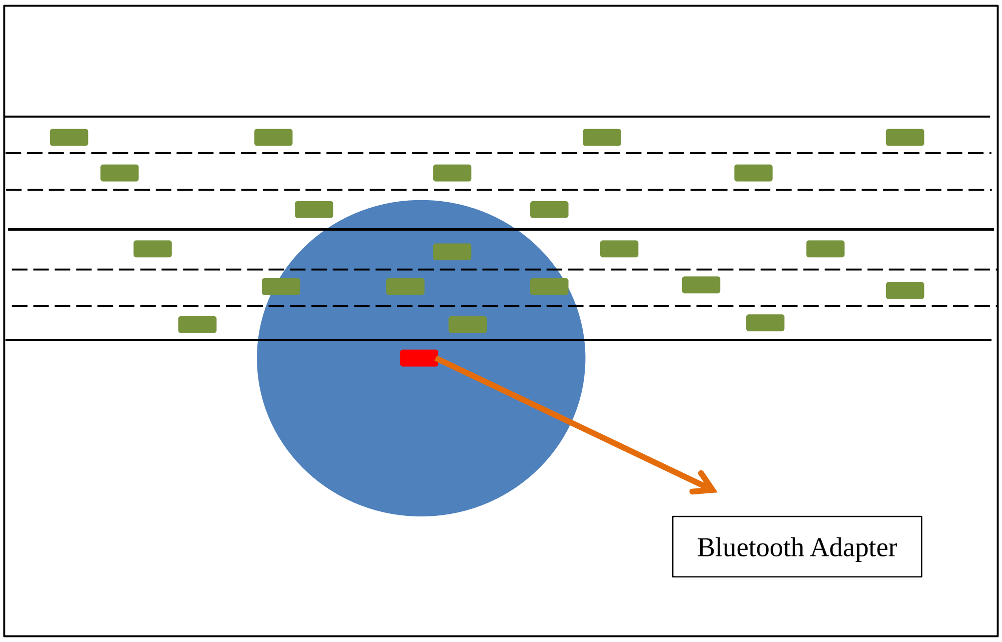

Figure 4- 2 Bluetooth Segment Speed Error caused by Large Detection Range

3. There are certain sets of Bluetooth records that do not truly represent the segment travel time. Since Bluetooth can exist both within vehicles and on pedestrians and cyclists, it might present the travel time of pedestrians and cyclists between two Bluetooth stations. Even if Bluetooth device is located within vehicles, it still might not truly represent segment travel time. Several possible scenarios are listed as follows: a) vehicles might travel past the first station, and then go to other destinations for other activities before they travel past the second station later; b) transit buses might run past both Bluetooth stations which will represent the travel time of transit buses; c) vehicles might stop temporarily on the shoulder of freeways or at the roadside of urban arterials for vehicle maintenance or to pick up people from sidewalks.

Detection Rate and Match Rate

Because not every single vehicle contains a discoverable Bluetooth device, it is critical to know the detection rate and match rate for Bluetooth detection. Detection rate refers to the percentage of Bluetooth devices within the passing vehicles which are detected by one particular Bluetooth adapter. The match rate is defined as the percentage of Bluetooth devices which are detected at two Bluetooth stations out of the total traffic volume that pass through both Bluetooth detection stations. Because detection rate and match rate are varied at most locations, field tests have been done for Bluetooth-based detection on freeways and arterials in the past. The match rate is found to be less than 5 percent [48][49][50].

4.3.1 Field Experiment Setup

Site Locations and Study Segment

To study the possibility of using Bluetooth adapters for urban arterial segment speed estimation, one roadway segment meeting the following requirements needs to be selected:

1. The chosen segment must be an urban arterial that provides moderate to high traffic volume, which can make sure the data sample size is sufficient;
2. The chosen segment must include intersections (either signalized or un-signalized) so that urban traffic characteristics can be evaluated;
3. To further study the data fusion technique on improving traffic state estimation using Bluetooth adapters and PIR sensors, the chosen site should also include the PIR test site;
4. There must be enough room to set up the necessary traffic detection equipment, such as Bluetooth adapters, video cameras and others;
5. To achieve a large detection range, there should be no obvious obstruction placed in front of the Bluetooth adapters at the test site;
6. The chosen site has to be safe for the roadside operators to record video and Bluetooth data.

The study road segment is chosen based on the above-mentioned requirements, and the exact segment is shown in Figure 4- 3, from south of the intersection of 109 Street and 100 Ave to the south end of High Level Bridge, the intersection of 109 Street and Walterdale Hill. It is totally 1.7

km long (The dot in between is the PIR test site).

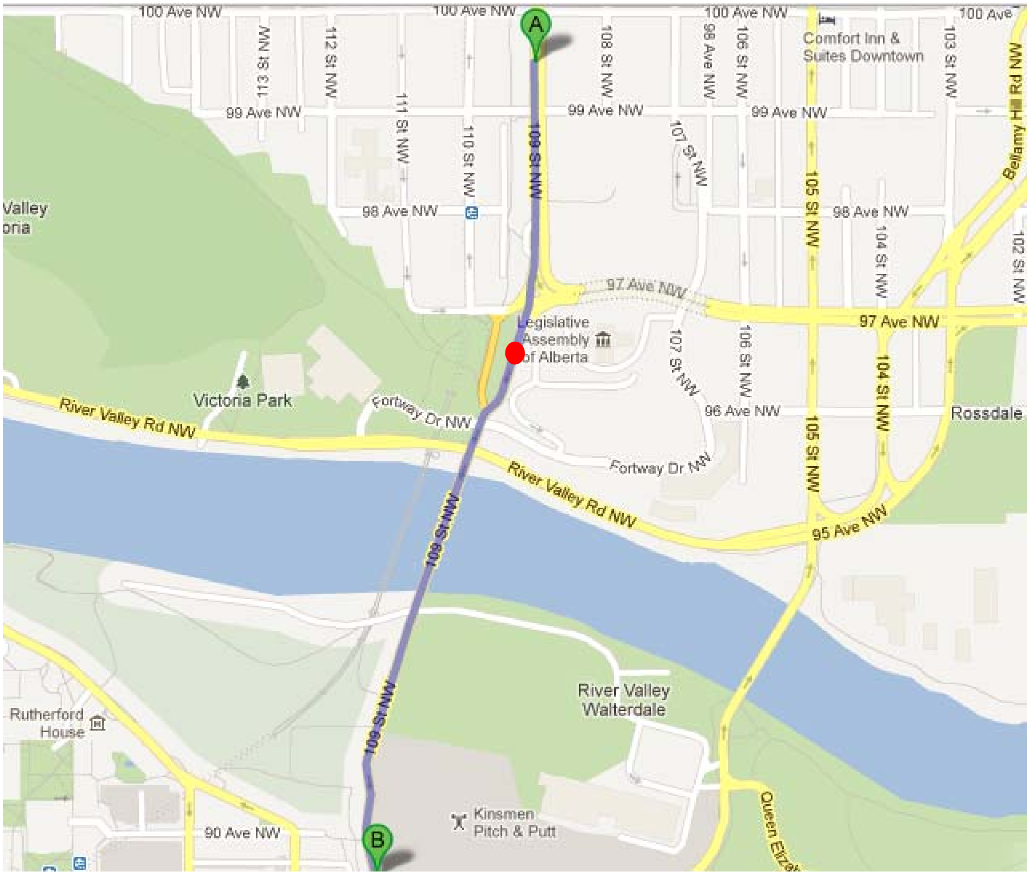

Figure 4- 3 Test Site for Bluetooth Adapter Traffic Detection Algorithm

(Source: Google Map, http://maps.google.com/, accessed on August 01, 2011)

The details about the study segment are shown below:

1. It is a two-way street north to the 97 Ave on the north of the river, a one-way street south to the 97 Ave with two traffic lanes, functioning as an urban arterial;

2. Because it connects the north and south regions of Edmonton and it is close to CBD, it has moderate to high traffic volume.

3. Because the bridge is a one-way street and has moderate to high traffic volume, relatively high Bluetooth detection rate can be ensured. Since this is the most direct way for vehicles to travel from point A to point B, a relatively high Bluetooth match rate can be ensured as well.

4. There are totally two signalized intersections along the study segment at 100 Ave and 97 Ave. But compared to 109 Street, 109 Street is the main approach, so this approach is provided with more green time.

4.4 Experimental Result and Analysis

4.4.1 Traffic Volume

To determine Bluetooth detection rate and match rate, traffic volume data at these test sites are required for the study period. As Figure 4- 3 shows, two cross streets, 99 Avenue and 97 Ave, exist in between the study segment, which means the vehicles that pass point A will not necessarily pass point B. A total of 715 vehicles (1,430 vph) travelled past point A, while 783 vehicles (1,566 vph) passed point B. Figure 4- 4 and Figure 4- 5 show the traffic volumes at these two sites of one-minute aggregation, respectively.

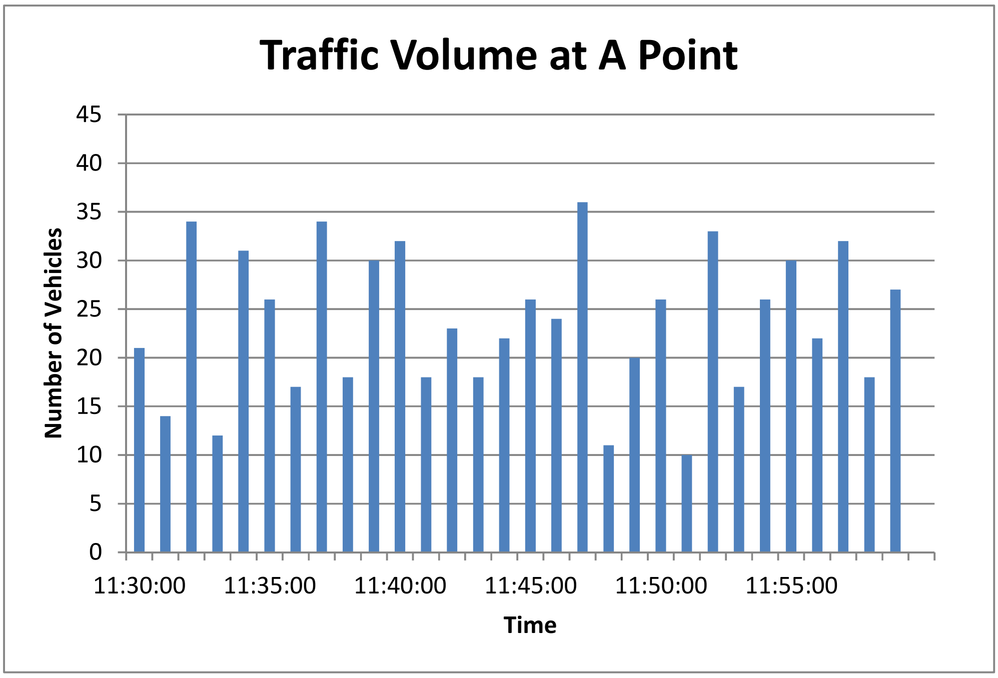

Figure 4- 4 Traffic Volume at A Point

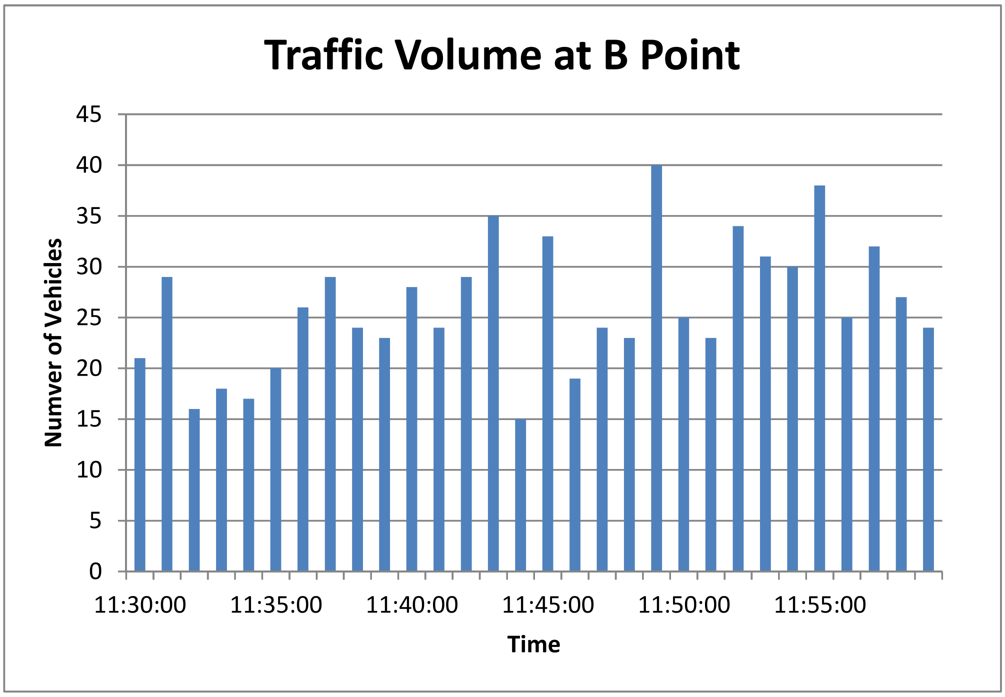

Figure 4- 5 Traffic Volume at B Point

The traffic volumes at these sites change every minute due to the fact that the test sites are close to signalized intersections. So whenever the vehicles encounter red light, traffic volume changes significantly.

4.4.2 Detection Rate

During the field test, the MAC addresses were continuously scanned and recorded using Bluetooth USB adapters, laptop running Debian (a Linux-operating system) and Bluetooth detection scripts. The script can detect Bluetooth devices within its detection range and log their MAC addresses with timestamps. It is programmed not to log the same MAC address repeatedly if it has been detected within three-minute timeframe. Based on the field test results and video data, no traffic congestion was experienced, so vehicles travelling on the road segment should not be detected more than once. This means Bluetooth MAC addresses that were recorded more than once should not be included in the detection rate calculation.

The detection rate is defined as the percentage of unique MAC addresses out of the total traffic volume over the study period. Because the Bluetooth adapter used in the field test is class 1 type, the detection rate calculated should be larger than the true value since at both test sites, there are opposite traffic lanes within the detection range. The detection rate calculation results are shown in Table 4- 1.

Table 4- 1 Detection Rates for Test Site A and B

Test Site	Unique MACs Address	Traffic Volume	Detection Rate
A	93	715	13.0%
B	129	783	16.5%

4.4.3 Match Rate

The match rate is defined as the number of unique MAC addresses detected and recorded at both test sites A and B, out of the number of vehicles that travelled through the study segment. The match rate is a key performance indicator of Bluetooth usage for arterial speed estimation. The number of matched MAC addresses influences the accuracy of speed estimation. The match rate calculation results are shown in Table 4- 2.

During the field test, totally 31 MAC addresses were matched for the study period, and four of them were outlier data, which were not valid (outlier data is explained later). Because there are two signalized intersections and several access roads along the roadway, there is no way to know the exact traffic volume that travel through both A and B points. The maximum possible traffic volume that passes through both sites is 715 vehicles. But in reality not all vehicles that pass through point A will pass point B. Based on the characteristics of the road segment, it is estimated that 60% to 100% vehicles passing through point B passes point A. The corresponding match rates are calculated and shown in Table 4- 2.

Table 4- 2 Match Rate Result

Scenario	Number of Matched MAC Addresses	Traffic Volume Passing the Study Segment	Match Rate
1	27	715	3.8%
2	31	715	4.3%
3	27	715×90%=644	4.2%
4	27	715×80%=572	4.7%
5	27	715×70%=501	5.4%
6	27	715×60%=429	6.3%

4.4.4 Outlier Data

The outlier data is presented in Table 4- 3. The first three datasets are outlier data because the Bluetooth devices within vehicles are first recorded at point B and later at point A, which means the vehicles are travelling at the other direction, shown in Figure 4- 6.

Table 4- 3 Outlier Bluetooth Data

No.	Site A Timestamp	Site B Timestamp	Travel Time (s)	Speed (km/h)
1	11:52:17	11:48:00	257	--
2	11:57:14	11:53:28	226	--
3	11:42:01	11:38:15	226	--
4	11:41:41	11:57:03	922	6.64

In terms of the last record shown in Table 4- 3, the explanation is that the vehicle might stop in the middle of the road segment to go to a fast food drive-through or gas station or coffee shop since 109 Street is one urban arterial with lots of shops nearby. It is determined as an outlier data because it takes enormously more time to cross the study segment than other vehicles and its average speed is only 6.64km/h, which is much lower than the speed limit (50km/h) or the speed of traffic flow during the field test time period. However, it is important to understand that there is no way to tell the exact reason for such long travel time or low travel speed. Although Bluetooth can be used as a segment-based traffic detector, it cannot record the details of vehicle trips within the study segment. By increasing the number of Bluetooth adapters within the study segment, more detailed vehicle travel information can be obtained and the reason for outlier data might be better explained.

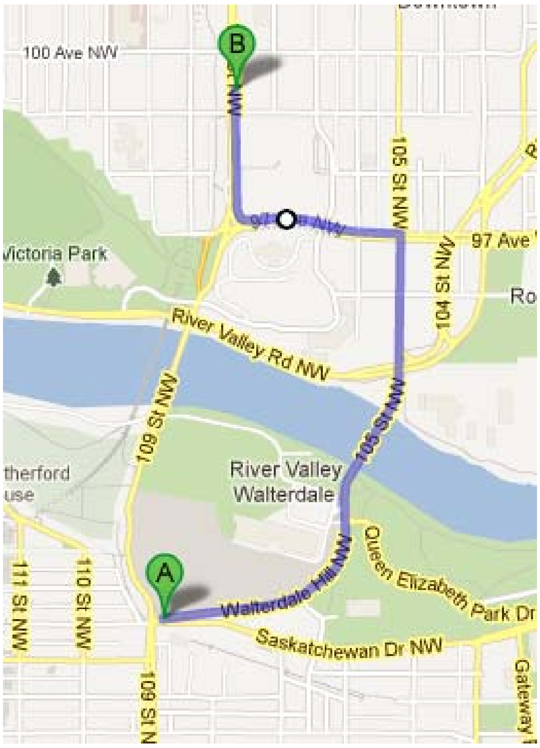

Figure 4- 6 Travel Route of Outlier Data 1-3

(Source: Google Map, http://maps.google.com/, accessed on August 01, 2011)

4.4.5 Segment Speed Estimation

Segment speeds for the study corridor were calculated using the matched MAC addresses. A total of 27 data records were valid for segment speed estimation within the study period. Two probe vehicles travelling through the study segment and video data were used as ground truth segment speed data. The segment speeds by using Bluetooth adapters to detect vehicles equipped with

Bluetooth devices are shown in Figure 4- 7.

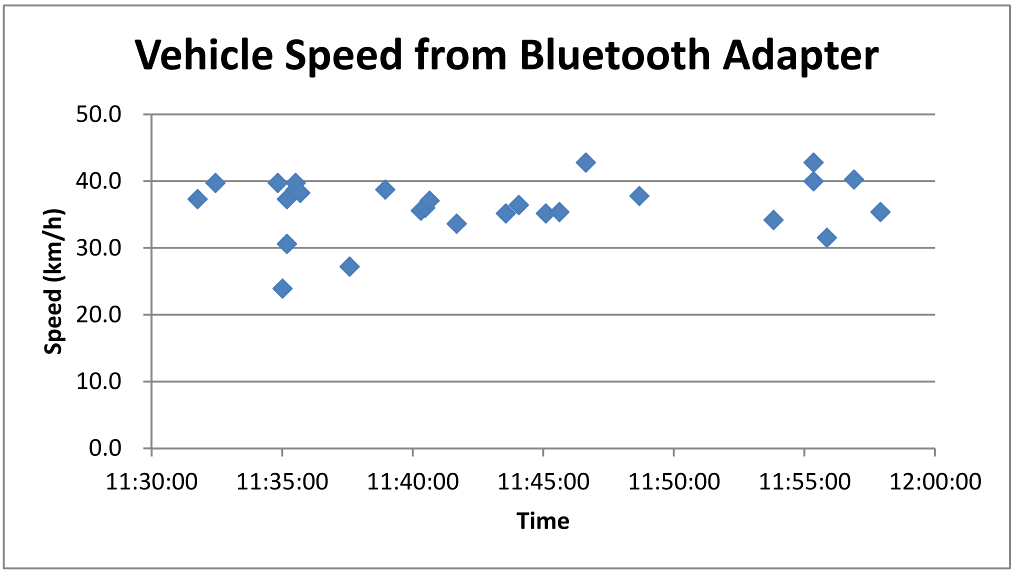

Figure 4- 7 Vehicle Speed from Bluetooth Adapters

As previously mentioned, probe vehicle data and video data were used as ground truth for segment speed estimation. A total of 73 data records were chosen as ground truth data. The segment speeds obtained via matched MAC addresses were compared to the ground truth. Figure 4- 8 shows segment speed data from both data sources.

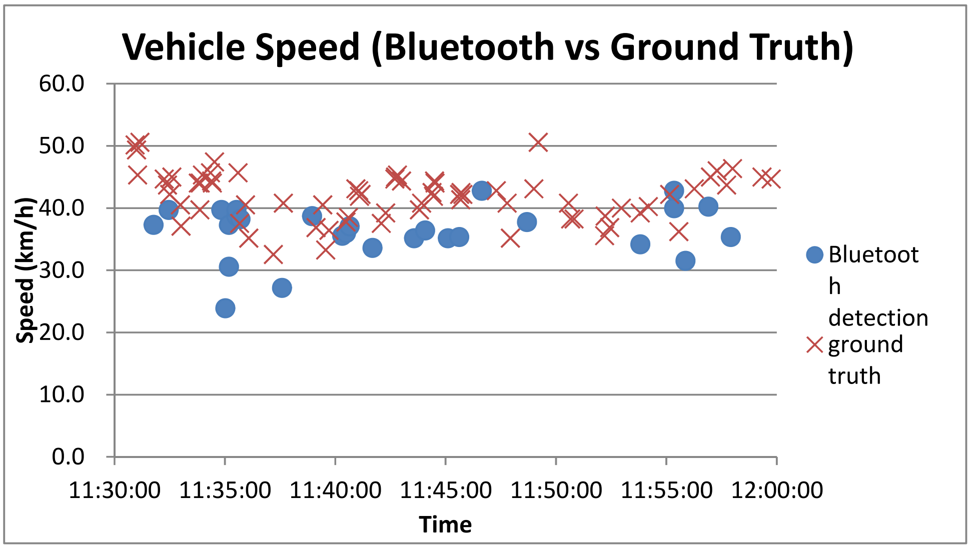

Figure 4- 8 Bluetooth and Ground Truth Speed

Chapter 5

5 Multi-Source Data Fusion

Based on the research work done in Chapter 3 and 4, this chapter proposed the traffic data fusion method by integrating both PIR sensor and Bluetooth adapter data, which can provide point-based and segment-based speed respectively. It includes the introduction and literature review on data fusion techniques and the methodology used in this research; it the end, the proposed method is implemented and validated in the field in Edmonton, AB.

5.1 Data Fusion Introduction

There is a common understanding that no single perfect source of information exists at present, as every sensor has limitations in terms of accuracy as well as coverage, and the single sensor cannot offer all types of information necessary for various applications. Therefore, data fusion is necessary to derive the desired information from the collected data of various sources. Data fusion is defined as the integration of information from multiple data sources to produce specific unified data about an entity [51]. There are many benefits by using data fusion systems [52][53][54][55], which include robustness, accuracy, completeness, cost effectiveness, representation, timeliness and others.

Transportation engineering is continuously motivated to obtain reliable traffic state estimation for traffic management, transportation planning and others. With the development of advanced technologies, heterogeneous sources of information have become available; therefore, transportation engineering faces the data fusion problem for many applications. Data fusion technique used in the transportation field mostly focuses on traffic state estimation and traffic condition identification. In most cases, desired outputs are derived by using the data from multiple traffic detectors. Speed, travel time estimation and/or prediction by applying various data fusion methods remains the most popular study area [56][57][58]. Incident detection is another popular area by applying data fusion [59][60][61].

5.2 Literature Review

Different methodologies, which include statistical estimation, artificial intelligence, pattern recognition and others, have been proposed in the literature for the purpose of fusing outputs from multiple traffic detection sensors. All these methods try to make superior estimation or multiple estimates by using data fusion, but the mathematical details and the logic varies greatly in terms of fusion operation and calibration procedures. In addition, their performances also vary greatly under different circumstances [62]. In general, these methods are divided into three types.

The first type is the statistical method. The convex combination, which relies only on the variance of the estimators' errors, is one simple approach. The Bar-Shalom/Campo combination is the optimal track-to-track fusion technique. As it is a maximum likelihood estimator of the state, it is used to consider the situation that the measurement noises are correlated [63]. These two methods simply require the covariance matrix of the estimators for calibrating the model. The matrix can be obtained from the training set of measurements data and true value data. The Kalman filtering approaches, which consider the statistical properties of the estimators, use an underlying process model to estimate the state at the next time step. A set of mathematical equations are used to provide an efficient computational recursive means for estimating the state of a process. The Kalman filtering approaches try to minimize the mean squared error (MSE) for superior estimation [64].

Another type is the probabilistic-based approach. Bayesian approach with Bayesian network and state-space models are the commonly used theories [65]. The Bayesian method deals with uncertainty associated with sensor outputs, but it requires the evaluation of high-dimensional integrals. It is necessary to numerically approximate these integrals; however, conventional numerical integration techniques are of limited use when the dimension of the integrand is large.

Possibility theory [66], evidential reasoning and more specifically evidence theory [67][68] are also important modeling frameworks under multi-source information.

The third type is the neuromimetic networks and artificial cognition based methodology, which are possible because of the advances in computing and sensing to enable them to emulate the natural data fusion capabilities of humans. For example, neural networks are composed of simple elements operating in parallel, which are inspired by biological nervous systems. As in nature, the network function is determined by the connection between elements. By adjusting the values of the connections between elements, a particular function can be performed. It has been used to perform complex functions in various fields [69].

5.3 Methodology

We consider the classic regression model $y_t = x_{t1}\beta_1 + x_{t2}\beta_2 + ... + x_{tk}\beta_k + \varepsilon_t$

Where:

t stands for the index for successive observations;

$x_{t1}, x_{t2}, ..., x_{tk}$ stands for the model inputs for each observation;

y_t stands for the true value;

ε_t stands for the disturbance for each observation.

In the linear function, the maximum likelihood estimators are defined as the values that maximize the likelihood function, denoted as β [70].

Normally, the disturbances ε_t are assumed to be distributed independently and identically following a normal distribution $\varepsilon_t \sim N(0, \sigma^2)$. The probability density function (PDF) of each disturbance is $\frac{1}{\sqrt{2\pi\sigma^2}}\exp\left\{\frac{-1}{2\sigma^2}{\varepsilon_t}^2\right\}$.

Since in this research two data sources were fused, k=2. So PDF can be written as

$$L=\prod_{t=1}^{T} f(y_t \mid \beta_0,\beta_1,\beta_2,\sigma^2)$$
$$=(\frac{1}{2\pi\sigma^2})^{-\frac{T}{2}}\exp\left\{\frac{-1}{2\sigma^2}\sum_{t=1}^{T}(y_t-\beta_0-\beta_1 x_{t,1}-\beta_2 x_{t,2})^2\right\}$$

The logarithm of this function is

$$\log L=-\frac{T}{2}\log(2\pi)-\frac{T}{2}\log(\sigma^2)-\frac{1}{2\sigma^2}\sum_{t=1}^{T}(y_t-\beta_0-\beta_1 x_{t,1}-\beta_2 x_{t,2})^2$$

To find the maximum-likelihood estimators, we need to find the first-order derivatives of $\log L$ with respect to $\beta_0,\beta_1,\beta_2,\sigma^2$, which gives

$$\sum_{t=1}^{T}(y_t-\beta_0-\beta_1 x_{t,1}-\beta_2 x_{t,2})=0$$

$$\sum_{t=1}^{T}x_{t,1}(y_t-\beta_0-\beta_1 x_{t,1}-\beta_2 x_{t,2})=0$$

$$\sum_{t=1}^{T}x_{t,2}(y_t-\beta_0-\beta_1 x_{t,1}-\beta_2 x_{t,2})=0$$

$$\sum_{t=1}^{T}(y_t-\beta_0-\beta_1 x_{t,1}-\beta_2 x_{t,2})=n\sigma^2$$

The solutions of the equations are the estimators.

5.4 Field Experiment Setup

The test site chosen for PIR and Bluetooth segment speed estimation is the same as the test site for

Bluetooth segment speed estimation, shown in Figure 5- 1. The segment is 1.7 km long and it is comprised of two signalized intersections at 99 Avenue and 97 Avenue crossing the 109 Street. The PIR sensor is located right downstream of a signalized intersection and Bluetooth sites A and B are located in the mid-block.

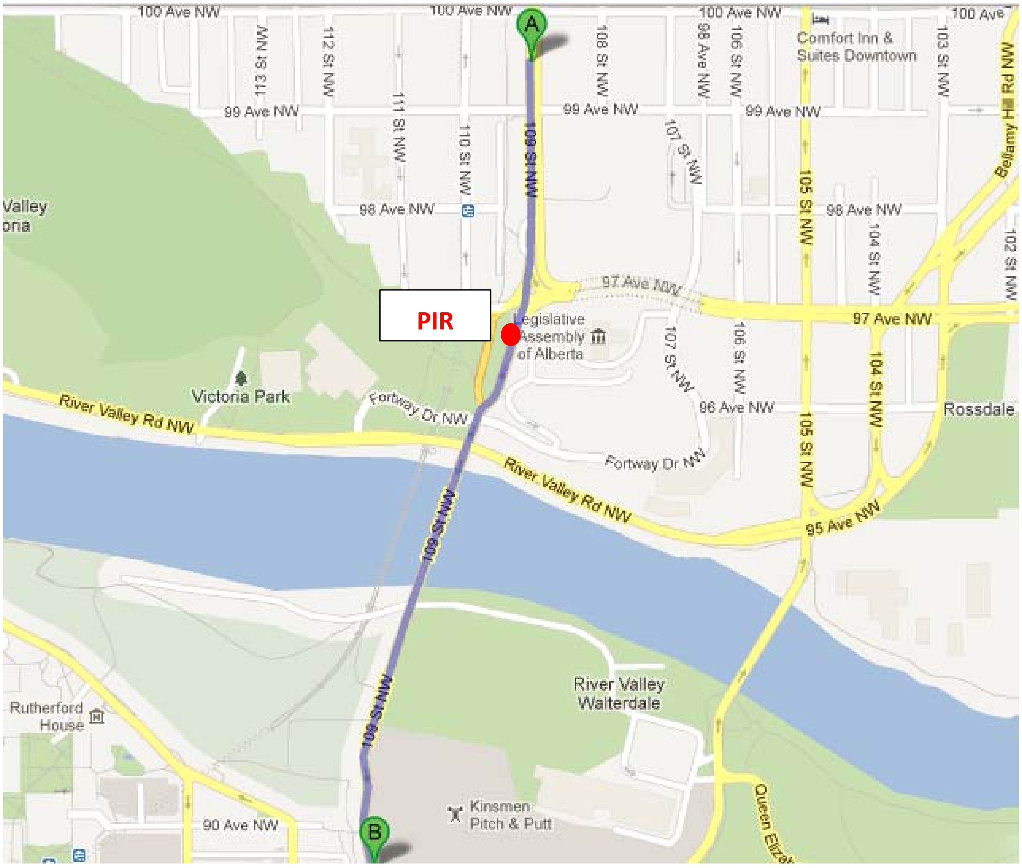

Figure 5- 1 Test Site for PIR and Bluetooth Adapter Data Fusion

(Source: Google Map, http://maps.google.com/, accessed on August 01, 2011)

The configurations of the field test sites for Bluetooth site A, site B and PIR sensors are shown in Figure 5- 2 and Figure 5- 3 respectively.

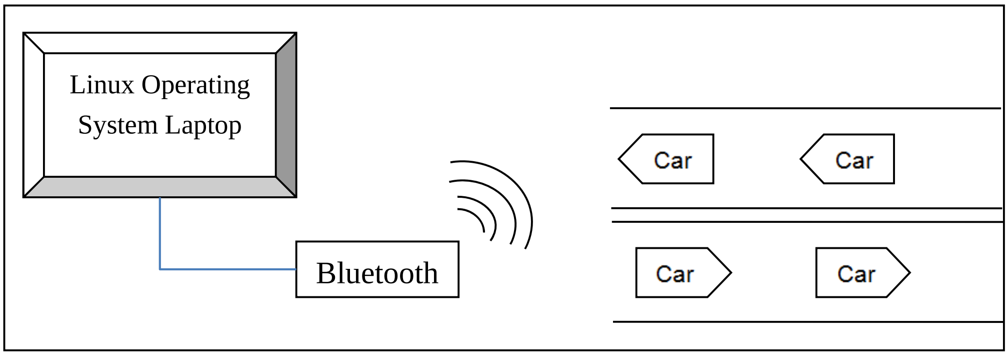

Figure 5- 2 Configuration of Field Test Site A and B

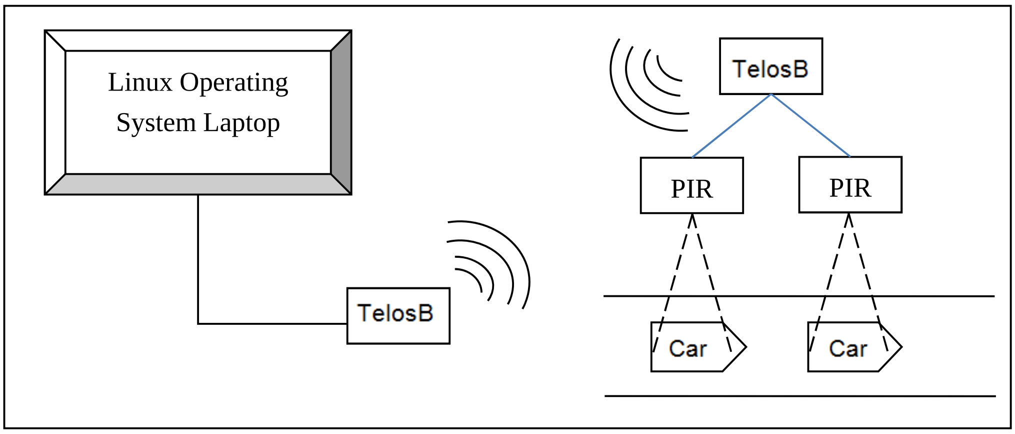

Figure 5- 3 Configuration of PIR Field Test Site

5.5 Experimental Results and Analysis

5.5.1 Segment Speed Data Processing

During the study period, a total of 27 Bluetooth MAC address matches were found, while totally 205 PIR speed data were obtained by using one PIR sensor pair. 73 segment speed data were obtained as ground truth by using probe vehicles and video data. 5-minute aggregated SMS was used for data fusion, the MLE algorithm.

Speed in traffic flow is defined as the distance covered per unit time and SMS is the speed measured by taking the whole roadway segment into account. Space mean speed is the harmonic mean of speeds passing a road segment during a time period. Its calculation is shown below:

$$\bar{v}_s = (N / \sum_{i=1}^{N} 1 / v_i) = NL / \sum_{i=1}^{N} t_i$$

Where,

N represents the number of vehicles passing the roadway segment;

L represents the roadway segment length;

t is the individual vehicle travel time along the roadway segment;

v is the individual vehicle segment speed along the roadway segment.

5.5.2 Model Calibration

A field test was done and the both Bluetooth adapter and PIR sensor data were collected. They were processed into 5-min aggregation SMS and used as the input for MLE model calibration, shown in Table 5- 1.

Table 5- 1 5-Min Aggregation SMS for Model Calibration

Time	Ground Truth (km/h)	Bluetooth (km/h)	PIR (km/h)
11:30:00	44.4	38.9	50.3
11:35:00	37.6	33.2	48.6
11:40:00	41.8	35.6	55.4
11:45:00	42	37.5	53.1
11:50:00	38.6	34.2	55.2
11:55:00	43.4	37.5	52.2

We assume a multivariable linear regression relationship among Bluetooth, PIR and ground truth data, as shown below:

$$y = \beta_0 + x_1\beta_1 + x_2\beta_2 + \varepsilon_t$$

Where,

β_0 , β_1 , β_2 are the regression coefficients;

$x_1 = \{38.9\ 33.2\ 35.6\ 37.5\ 34.2\ 37.5\}$, is the input of Bluetooth data;

$x_2 = \{50.3\ 48.6\ 55.4\ 53.1\ 55.2\ 52.2\}$, is the input of PIR data;

$y = \{44.4\ 37.6\ 41.8\ 42\ 38.6\ 43.4\}$, is the input of ground truth data.

Using MLE algorithm, we get the output shown below:

$\beta_0 = -5.2475 \quad \beta_1 = 1.1778 \quad \beta_2 = 0.0756 \quad \sigma^2 = 0.37$

$y = -5.2575 + 1.1778 x_1 + 0.0756 x_2$

$r^2 = 0.9330$, close to 1, which means the established relationship is significant.

Table 5- 2 shows that by using the MLE data fusion technique, the maximum variance of segment speed estimation for each 5-min aggregation can be reduced to 0.9km/h.

Table 5- 2 Comparison between Estimated and Ground Truth Data

Time	Estimation by MLE (km/h)	Ground Truth (km/h)	Variance (ε_t) (km/h)
11:30:00	44.4	44.4	0.0
11:35:00	37.5	37.6	0.1
11:40:00	40.9	41.8	0.9
11:45:00	42.9	42.0	-0.9
11:50:00	39.2	38.6	-0.6
11:55:00	42.9	43.4	0.5

Variance Analysis

The analysis of variance is also calculated and shown in Table 5- 3. It contains the degrees of freedom, the sum of squares, the mean squares, an F-statistic and a corresponding p value.

Table 5- 3 Analysis of Variance Table

Source	Degree of Freedom	Sum of Squares	Mean Square	F-value	p-value
Model	2	33.34	16.67	20.88	0.0174
Error	3	2.40	0.80		
Total	5	35.74			

$F = 20.88$, $p = 0.0174 < 0.05$, so it verifies the multivariable linear regression relationship among Bluetooth, PIR and ground truth data.

An error-bar plot of the confidence intervals on the residuals (variances) from the regression was displayed, shown in Figure 5- 4. The intervals of all six residuals (variances) contain zero. This indicates that each residual (variance) is smaller than expected in 95% of new observations, suggesting that all data points are valid.

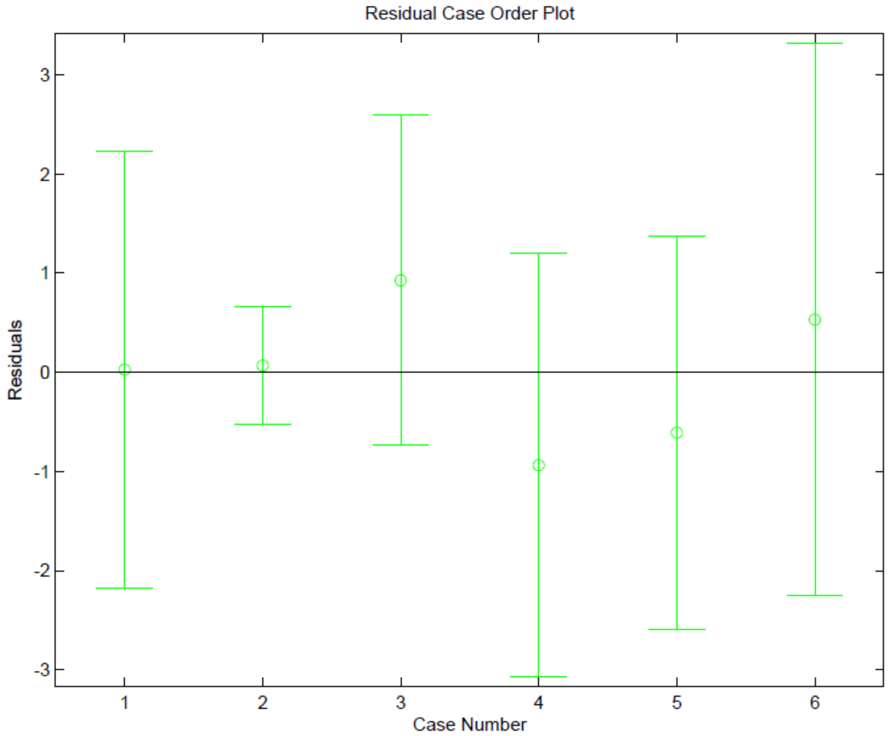

Figure 5- 4 Residual Case Order Plot

The comparison between estimated segment speed and the ground truth is presented in Figure 5- 5. It shows that the estimated value follows closely with the ground truth. The line in the middle indicates that the detected Bluetooth value has a stronger linear relationship with ground truth than the PIR value (the line on the right). This makes sense because PIR value as a point-based speed cannot always accurately represent the segment-based speed. It supports the point that although point-based traffic sensors, such as ILDs, are widely used, they show limitations when it comes to estimating segment speed on urban arterials.

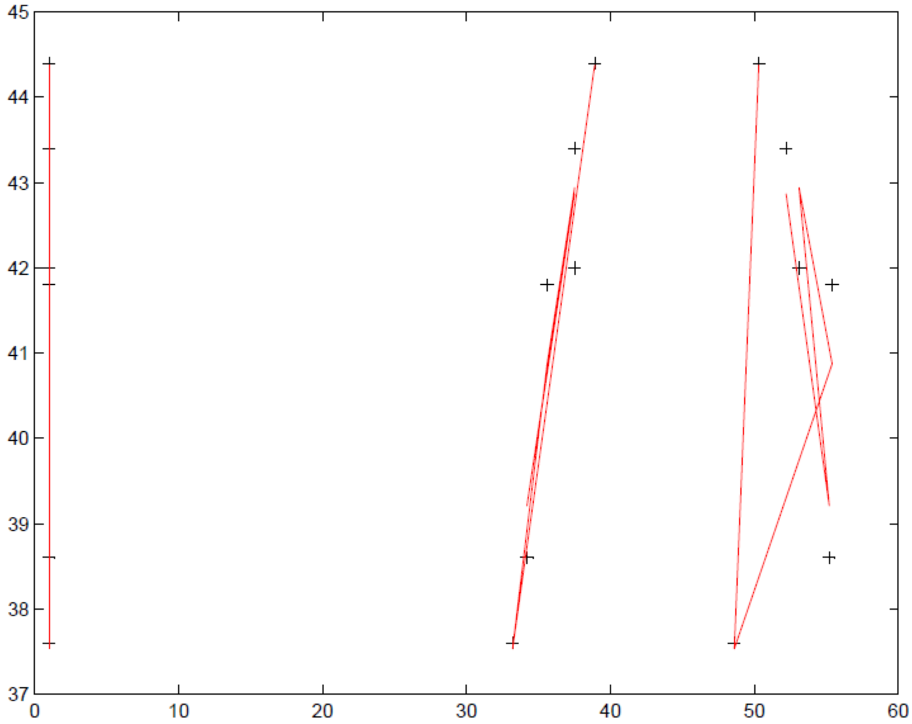

Figure 5- 5 Segment Speed Comparison of Estimation and Ground Truth

Compared to the segment speed estimations from using only PIR sensors or Bluetooth adapters, data fusion provides superior estimation with higher accuracy. Table 5- 2 and Figure 5- 6 both show the difference between several speed estimation results. Figure 5- 6 shows that Bluetooth based speed estimation can achieve a better result than the PIR sensor, but still the estimation using data fusion technique of both PIR sensors and Bluetooth adapters outperforms the result by using only Bluetooth.

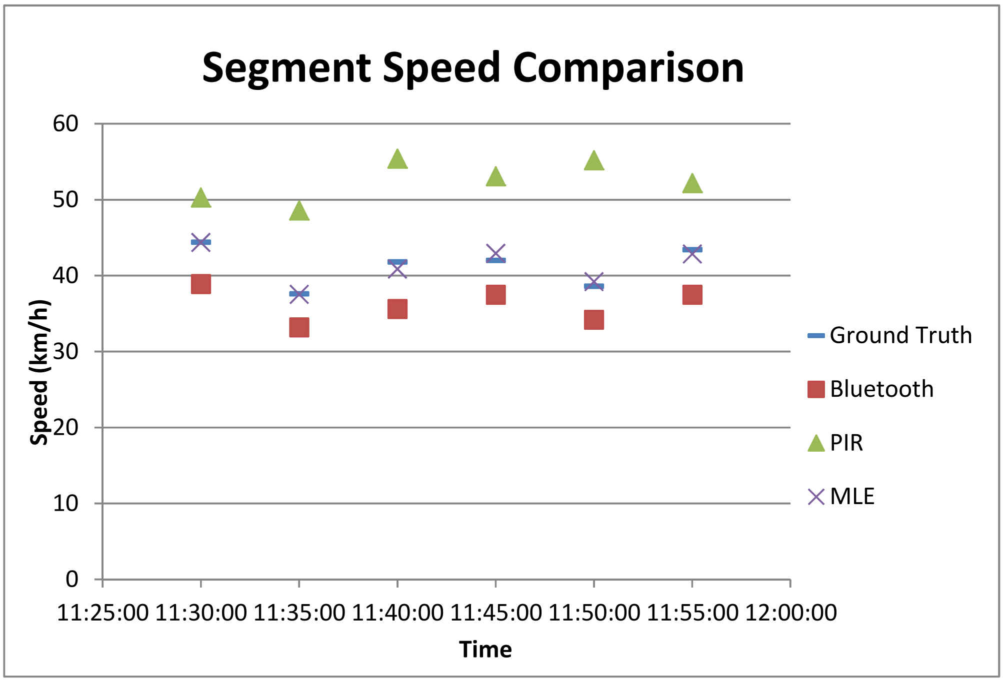

Figure 5- 6 Segment Speed Comparison among Single Sensors, Estimation and Ground Truth

5.5.3 Model Validation

Another dataset was used to validate the calibrated model in Section 5.5.2. The speed data obtained from Bluetooth adapters and PIR sensors, and video ground truth were used and they were aggregated into 5-min intervals.

The proposed model is shown below, where the segment-based speed is estimated.

$$y = -5.2575 + 1.1778x_1 + 0.0756x_2$$

Where,

x_1 is the input of Bluetooth data;

x_2 is the input of PIR data;

Table 5- 4 shows the Bluetooth adapter and PIR sensor data, video ground truth data and

estimated segment speed data using the data fusion technique at 5-minute time intervals.

Table 5- 4 5-min SMS Speed Data Input for Model Validation

No.	Ground Truth	Bluetooth	PIR	Data Fusion Output
1	45.8	40.8	62.2	47.5
2	45.5	36.0	57.5	41.5
3	48.2	36.0	58.4	41.6
4	44.1	36.5	50.4	41.6
5	41.6	37.9	55.1	43.5
6	40.8	36.9	48.5	41.9
7	45.8	40.8	54.7	46.9
8	40.6	41.3	52.8	47.4
9	43.1	40.4	51.4	46.3
10	43.2	39.3	49.8	44.8
11	42.9	35.5	52	40.5
12	38.9	36.6	50.8	41.7
13	41.7	42.8	52.3	49.1
14	40.9	35.2	54.1	40.3
15	42.1	37.7	52.3	43.1
16	38.1	29.6	50.7	33.4
17	44.8	41.0	51.1	46.9

The statistics parameters chosen to evaluate the model are sum of squares due to error (SSE), mean squared error (MSE), root mean squared error (RMSE), and relative error (RE). The details of the results are shown in Table 5- 5 and the corresponding figure is shown in Figure 5- 7.

Table 5- 5 Statistics Parameters

Parameters	Bluetooth	PIR	Data Fusion Output
SSE	597.23	1952.62	230.55
MSE	35.13	114.86	13.56
RMSE	5.93	10.72	3.68
RE	11.98%	24.18%	7.10%

In Table 5- 5, the results from single sensor estimations of using Bluetooth and PIR and from the data fusion technique are compared. Data fusion shows better estimation results in terms of SSE, MSE, RMSE, and RE. It means that segment speed estimation from data fusion can best represent true segment speed. It also shows that point-based sensors (PIR sensors) within urban road segments cannot truly represent the segment speed.

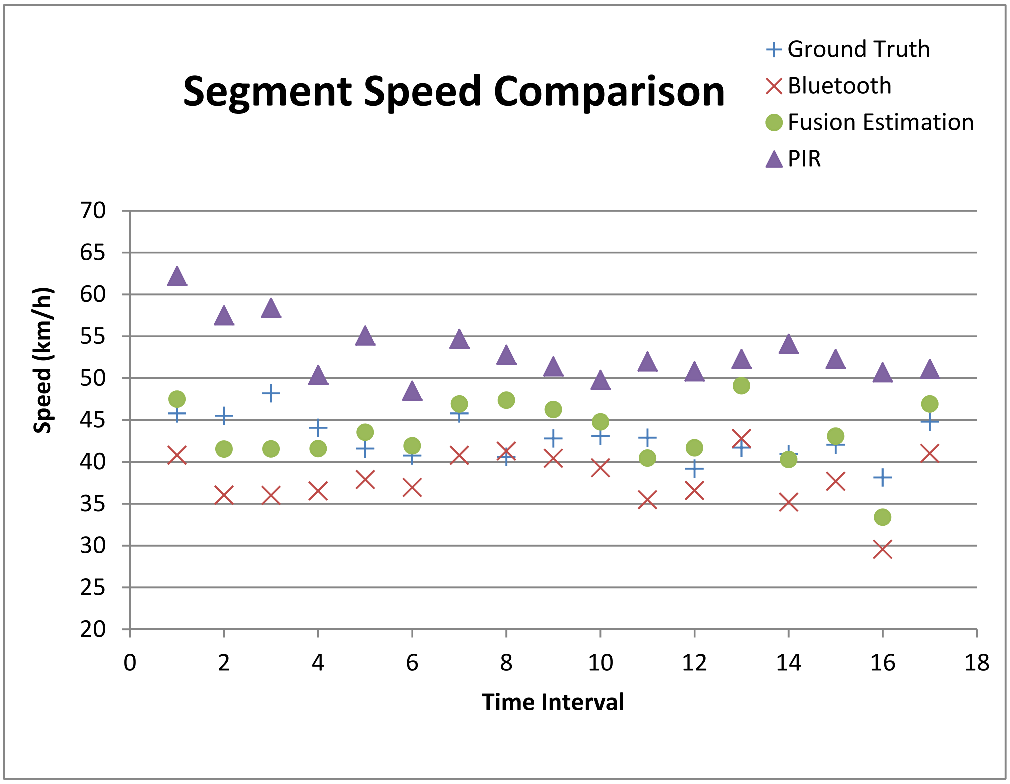

Figure 5- 7 Segment Speed Comparison using Different Sensors and Data Fusion Technique

Chapter 6

6 Conclusions and Recommendations

This chapter is composed of two parts, the summary of research contributions and the discussion of future work. This section discusses the significance of the study using Bluetooth adapters and PIR sensors. More work can be done in terms of traffic state estimation accuracy and data fusion technique.

6.1 Summary

In this research, a new method to integrate the non-intrusive PIR sensor and Bluetooth adapter was developed and tested in the field to estimate traffic state on urban arterials in Edmonton, AB. Flow estimation was generated by using the point-based PIR sensor with 97% accuracy, the same accuracy level as ILD. PIR sensor is non-intrusive in nature and can be powered by two AA batteries, which makes it more cost-effective and less disruptive to the traffic during installation and maintenance. The PIR sensor can also detect point-based speed and headway. By using Bluetooth adapters, segment-based speed estimation can be obtained. Although Bluetooth is more accurate than point-based sensors in terms of providing segment-based traffic parameters, it has a much lower sample rate, around 4% found in this research. Finally, by using traffic data fusion technique of PIR sensor and Bluetooth adapter data, more accurate segment-based speed estimation can be achieved.

6.2 Conclusions

From the results of this study, it can be concluded that:

- PIR sensors can provide accurate volume and point-based speed estimation. Compared to

ILDs, PIR sensors with wireless communication capability are non-intrusive in nature and are less disruptive to the traffic during the installation and maintenance process.

- Bluetooth adapter can provide relatively accurate segment-based speed estimation but at a much lower sampling rate. It does not require other on-vehicle units other than commonly used Bluetooth-enabled devices, such as cell phones and laptops, meaning that it can provide segment speed more cost-effectively. It is a valid method for arterial speed estimation.
- Segment-based speed estimation can be obtained either by using only Bluetooth adapters or through integrating both Bluetooth and PIR data. Although using only Bluetooth adapters can provide relatively accurate segment speed estimation, it has a much lower penetration rate among the traffic flow. This shortcoming leads to the fusion of different traffic detection sensors.
- Traffic data fusion using MLE shows a promising application in traffic state estimation. As more traffic sensors get installed and implemented within the roadway network, traffic data fusion can provide more detailed and reliable traffic data. It is easily implemented in practice as it is not computationally intense.

6.3 Limitations of the Study

For the study segment, only two Bluetooth adapters were placed at the ends of the study segment and only one PIR test site was located between the two Bluetooth adapters. Although the proposed algorithm shows good results only using this field test configuration, we certainly expect to have better results if more Bluetooth adapters and PIR sensors were added along the study segment. More Bluetooth adapters can provide a better and more detailed segment speed profile, and PIR sensors can identify point-based speeds of more intermediate points along the study segment.

This research only focuses on data fusion techniques for segment-based speed estimation on urban arterials. But the past research has tested Bluetooth adapters on freeway segment-based speed estimation [71]. Due to the undesired field implementation environment, no tests were done on freeways in Edmonton, AB. With the ILD data available on freeways, data fusion using PIR sensors, Bluetooth adapters and ILDs can be explored for the possibility of providing more accurate and reliable speed estimation and possibly other functions.

The proposed method was validated after the experiments were done in the field. However, the PIR sensor connected with TelosB is capable of wireless data transmission; also the Bluetooth adapters are connected to the computer through USB ports. These provide the possibility of real-time implementation of the traffic detection algorithm and data fusion technique. For example, a method to automatically transfer and match detected MAC addresses in real-time can be developed with Linux programming.

6.4 Future Research

This research led to several useful conclusions for urban arterial traffic state estimation, namely the estimation of segment-based speed, point-based volume, speed and headway. Using data fusion technique, speed data from both PIR and Bluetooth adapters can be utilized to improve the segment-based speed estimation accuracy. This method using state-of-the-art technology is superior to the current method of only using one single sensor for speed estimation.

There are a number of opportunities for further research. Since TelosB can provide wireless communication capability and is equipped with extension that can integrate sensors other than PIR, research can be done in terms of how to integrate different sensors and perform data fusion, such as with magnetic or acoustic sensors, and probe vehicles. Then their performances can be compared with the proposed method.

An in-depth investigation can be performed to determine how to deploy the PIR and Bluetooth adapters to achieve higher detection rate and better speed estimation. In reality, the sensor deployment has an effect on the traffic detection system performance, so several field tests can be conducted to investigate how to achieve optimum sensor deployment plan.

Additionally, a major improvement to the Bluetooth detection system can be done. For example, an algorithm to calculate travel times from the Bluetooth adapter data in real-time can be developed. Potential improvements in the travel time algorithm should also be explored, such as a filter design to omit the outlier data.

In this research data fusion using MLE is explored, as it has the advantages of easy implementation and integrating several traffic state parameters into the estimator. In the future, research can be done to evaluate other data fusion techniques, such as Kalman Filtering.

As previously mentioned, future research needs to be done for estimating the traffic state using PIR and Bluetooth adapters and ILDs on freeways and arterials. Also other traffic state parameters, such as density, queue length on urban arterials might be estimated using such traffic detection configuration.

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