Measuring Signalized Intersection Performances with Traffic Sensors

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Abstract

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In recent years, the Intelligent Transportation Systems (ITS) have gained more and more attention from researchers and are widely applied in many transportation fields. Since ITS focuses on processing transportation information and data, data collection is fundamental and essential for the whole system. Most of the data, especially traffic data in real-time, are collected with traffic sensors. Compared with freeways, signalized intersections have much more complicated traffic conditions and deserve more research on data collection. Intersection traffic analysis parameters, such as control delay, queue length, and signal cycle failure, are difficult to directly capture with traffic sensors. In this research, an algorithm is developed to measure these traffic parameters at signalized intersections with traffic count data collected with traditional traffic sensors. Control delay and queue length are measured in a zone with traffic sensors on both ends. A system using video image processing was also developed for

locations with no other traffic sensors but video cameras. Performances of these systems were demonstrated with both real-world and simulation data. With the method and system developed by this research, intersection performance can be quantitatively monitored in real-time and this can benefit many transportation applications. One application example of the system discussed in this dissertation is to evaluate the Transit Signal Priority (TSP) system based on traffic sensor inputs.

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DEDICATION

To my family.

Chapter 1 Introduction

Background

In recent years, the rapidly developing technologies, especially the information technology, have provided many more opportunity and capacity to solve transportation problems that were difficult to deal with before and to supply better transportation services. Intelligent Transportation Systems (ITS), which are defined as: "the application of advanced sensor, computer, electronics, and communication technologies and management strategies—in an integrated manner—to improve the safety and efficiency of the surface transportation system," have gained more and more attention from researchers and are widely applied in many transportation fields (National ITS Architecture Team, 2001). Based on the Transportation Equity Act for the 21st Century (TEA-21), the ITS programs received $1.282 billion financial support from the United States Department of Transportation (USDOT) from 1998 to 2003 (USDOT, 1998).

ITS can be divided into 16 subsystems: arterial management, freeway management, transit management, incident management, emergency management, electronic payment and pricing, traveler information, information management, crash prevention and safety, roadway operations and maintenance, road weather management, commercial vehicle operations, intermodal freight, collision avoidance systems, driver assistance systems, and collision notification systems (USDOT, 2007).

The trend of research and development in ITS was studied and it was found that about 56% of ITS publications and 32% of patents were related to the traffic management, which includes traffic surveillance, device control, incidents, travel demand, emissions, and highway rail intersections (Khattak, 2007).

Since ITS focuses on processing transportation information and data, data collection is fundamental and essential for the whole system. In a typical ITS architecture shown in Figure 1-1 (Federal Highway Administration, 2003), all the advanced transportation applications, such as the traffic management and the traveler support services, are built up on data collected by the system. Most of the data, especially traffic data in real-time, are collected with traffic sensors.

Current research on traffic sensors is mostly focused on freeways, rather than intersections. However, traffic conditions at intersections are much more complicated than those on freeways. At an intersection, traffic flows are controlled by traffic signals or signs, moving in multiple directions with many conflicting points, and traffic flow can also be interrupted by transit vehicles, pedestrians and cyclists. Furthermore, the total traffic volume through all the signalized intersections in an urban or suburban area is much higher than that through freeways of the same area. Of the total vehicle miles traveled (VMT) on national roadways, interstate freeways only accounted for about 24.4% (or 732 billion VMT), while other arterials, collectors, and locals carried the remaining 75.6% (about 2,268 billion VMT) in 2004 (Federal

Highway Administration and Federal Transit Administration 2006). Therefore, it is of practical significance to measure intersection performance.

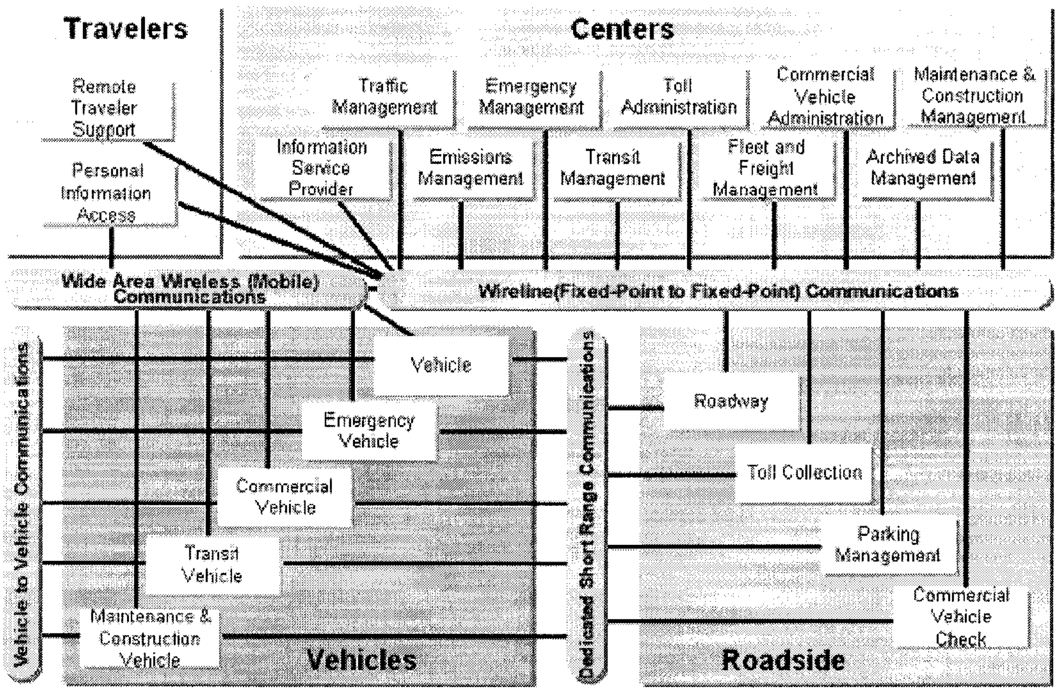


Figure 1-1 ITS Architecture Diagram

Source: Freeway Operation Handbook. *FHWA Report No. FHWA-OP-04-003*. Federal Highway Administration, 2003

There are several traffic parameters for performance evaluation at signalized intersections. Based on the Highway Capacity Manual 2000 (HCM 2000), the three criteria for this task are: Level of Service (LOS or the control delay per vehicle), queue length, and cycle failure (or overflow). Control delay is the delay for a vehicle approaching and entering a signalized intersection that is contributable to traffic signal operation. Queue length is the maximum number of vehicles that are queued during a signal cycle. Cycle failure occurs when a number of queued vehicles are not able to depart the intersection due to insufficient capacity during a signal cycle.

These traffic parameters, such as control delay, queue length, and signal cycle failure, are difficult or even impossible to be directly captured by traditional traffic sensors. However, most of these detectors have the ability to capture traffic count data. With the traffic count data provided in real-time, it is possible to estimate the traffic parameters of control delay, queue length, and signal cycle failure using special algorithms.

Research Objective

In this research, algorithms are designed to measure traffic parameters at signalized intersections using traffic counts collected by traditional traffic sensors, such as inductive loops or traffic cameras. A computer system is developed to implement these algorithms. The traffic parameters measured by this system include average control delay, queue length, and signal cycle failure. The intersection performance can be quantitatively measured in real-time by this system.

Originality of This Research

The algorithm for control delay measurement is based on an innovative idea that captures control delays with two sets of detectors, one for entering detection and the other for exit detection. This algorithm utilizes currently available traffic sensors and provides quantitative intersection performance measures in real-time. Therefore it enables the measurement of arterial performance in real-time. As we know, there are lots of similar applications developed for freeways, but till now there are not such an applications known for arterials or intersections. Thus, this research complements the state of the art in this area and may trigger some follow-on research and applications.

A major contribution of this research is that it successfully developed the system based on the algorithm for automatically and quantitatively measuring intersection performance in real-time. All of the functions of the system were tested with both real world and simulated traffic data.

System Boundary

The research is limited to measure control delay, queue length, and signal cycle failure at a typical signalized intersection equipped with properly installed traffic sensors such as Video Image Processors (VIPs). Traffic sensors, which provide input data for this study, are assumed to be sufficiently accurate and reliable. The VIPs used in the field test are those installed in the City of Lynnwood, Washington State. Traffic detection in nighttime or under extreme weather conditions will not be studied in this research. The shadows' impact on video image processing will be dealt with using existing algorithms from other studies and thus is not studied either in this dissertation. Also, it is assumed that traffic queue will not extend beyond the camera's field of view in this study.

Notes to Chapter 1

1. Federal Highway Administration, (2003) Freeway Operation Handbook. *FHWA Report No. FHWA-OP-04-003*. United States Department of Transportation, Washington, D.C.

2. Federal Highway Administration and Federal Transit Administration, (2006) *2006 Status of the Nation's Highways, Bridges, and Transit: Conditions and Performance*. United States Department of Transportation, Washington, D.C.

3. *Highway Capacity Manual 2000* (2000) Transportation Research Board, National Research Council, Washington, D.C.

4. Khattak, Asad, Yingling Fan, and Elizabeth Shay. (2007) 'What Do ITS Publications and Patents Tell Us?' *Journal of Intelligent Transportation Systems,* Vol. 11 No. 2, pp. 91-103.

5. National ITS Architecture Team, (2001) *Regional ITS Architecture Guidance: Developing, Using and Maintaining and ITS Architecture for Your Region*. Executive Summary, United States Department of Transportation, Washington, D.C.

6. USDOT (United States Department of Transportation), (1998) *Transportation Equity Act for the 21st Century: A Summary*. United States Department of Transportation, Washington, D.C.

7. USDOT, (2007) *Federal Intelligent Transportation Systems (ITS) Program*. [Online], Available: http://www.itsoverview.its.dot.gov. [June 2007].

Chapter 2 State of the Art

Current Research on Traffic Data

To acquire and to apply traffic data in real-time has been a quickly developing business in North America. Figure 2-1 shows the economics behind ITS and corresponding data flow (Seymour and Carvell 2005). Inrix, Inc., for example, partnered with Clear Channel and Tele Atlas to develop a real-time traffic information system with traffic data mainly from Globe Positioning System (GPS) probes on about 650,000 vehicles (Mistele 2007).

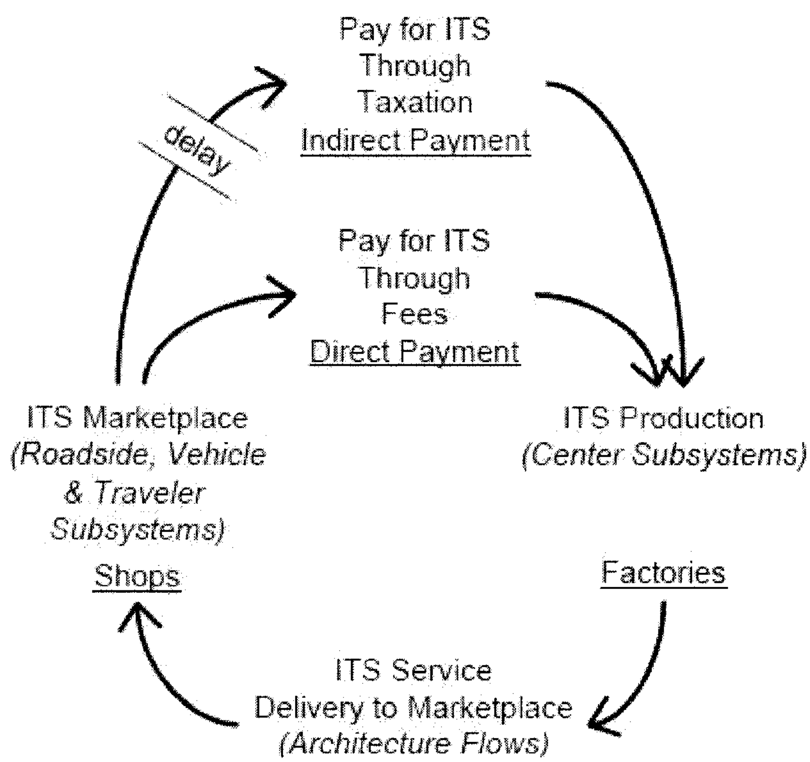


Figure 2-1 ITS Market

Source: Interim Guidelines for Data Access for Texas Traffic Management Centers. *FHWA Report No. FHWA/TX-05/Report 0-5213-P1*, Texas Department of Transportation and United States Department of Transportation, 2005

Traffic volume is the most fundamental data in transportation. Traffic volume is "the total number of vehicles that pass over a given point or section of a lane or roadway during a given time interval" (HCM 2000). For the purpose of describing traffic demand, two parameters are commonly used: Annual Average Daily Traffic (AADT) and directional design-hour volume (DDHV). Many other traffic parameters are related to traffic volume. For example, roadway capacity is defined as "the maximum flow rate that can be accommodated by a given traffic facility under prevailing conditions" (HCM 2000). The relationship between traffic volume and traffic safety has been widely studied and several Accident Prediction Models (APMs) were built up based on these studies (for example, Joksch and Kostyniuk 1997; Davis 1998). Traffic signal controls also rely on volume. For example, special traffic control strategies cannot be utilized under low traffic-volume conditions (Abdelghany and Connor 2006). Pavement performance is significantly impacted by traffic load, which can be determined by traffic volume of each vehicle class (Skerritt 1993; Hajek *et al* 2005). Traffic calming, which is to mitigate the impact of vehicle volume of a given roadway section, is of big interests among traffic professionals (Reardon 2001). Traffic volume is stochastically distributed and dynamically evolves with other factors. To predict traffic volume, researchers have applied mathematical methods, such as the Empirical Bayes methods, to model the distribution of traffic volume (Davis and Yang 2001).

Along with traffic volume, speed is considered to be one of the most desirable traffic parameters for multiple ITS applications, such as real-time traffic control and traveler information systems (Wang and Nihan, 2000). Based on the research by Evanchik *et al* (2006), the speed index is a viable performance measure for state operations because it can be measured with existing traffic sensors, can be easily understood by most individuals, can be applied to varied classes of roadways, is suitable from the lane level up to a regional or statewide measurement, and is reliable without principle assumptions or estimating techniques. Vehicle speed can be directly measured or estimated with inductive loop, calibrated camera, Remote Traffic Microwave Sensor (RTMC), etc. (Wang and Nihan, 2003; Schoepflin and Dailey, 2003; Weber, 1999).

Occupancy is the proportion of time a roadway cross section is occupied by vehicles. Since it is easier to measure, roadway occupancy is often considered as a surrogate for density of vehicles (HCM, 2000). In research on freeway usage and performance, occupancy and vehicle volume are the two principle measurements from traffic sensors, because occupancy can be used to indicate level of congestion and can also be used to estimate vehicle speeds with vehicle volume and classification data (Ishimaru and Hallenbeck 1999; Wang and Nihan 2003).

Density is the number of vehicles occupying a given length of a lane or roadway at a particular instant. It is a critical parameter for freeway or highway performance evaluation and is the criterion determining the Level of Service (LOS) of uninterrupted traffic flows (HCM, 2000). Research on freeway bottlenecks found that the level of density corresponding to capacity drop was reproducible at various locations (Chung *et al*, 2007). High vehicle density is found to increase drivers' mental work load and significantly change response time and detection accuracy in both visual and auditory modalities (Baldwin and Coyne, 2003).

Travel time may include the delays from traffic congestion or fixed interruptions, such as traffic signals. Travel time-based measures are believed to be the most useful for the needs of a wide range traffic congestion measurement (Lomax *et al*, 1995). Travel time can be measured by re-identifying vehicles with multiple inductance loops (Coifman and Krishnamurthy 2007), license plate matching (Shuldiner 1996), tracking probe vehicles with cell phone (i.e., Turner 1996; Wunnava *et al* 2007), or Automatic Vehicle Location (AVL) system (Schafer *et al* 2002), etc.

All these above listed traffic parameters can be applied to both un-interrupted flow and interrupted flow. There are several traffic parameters that are often used for interrupted flow, which is much more complicated. Control delay is such a parameter that is defined as the part of delay attributed to signal control. Control delay includes decelerating delay, stopped delay, and accelerating delay. It has been the principle measure of service and determines the LOS at intersections (HCM, 2000). HCM 2000 provides a methodology to estimate control delay with input data of traffic movements, traffic composition, geometric characteristics, and signal configuration. Compared with the stopped delay, which is a widely used intersection performance indicator before the mid 1990's, the control delay is difficult to measure directly. Hoeschen *et al* (2005) proposed to estimate control delay by subtracting mid-block delay from the segment delay. The mid-block delay occurs at the mid-block and is independent of signal controls, and the segment delay is the total delay between the center of the upstream intersection and the center of the downstream one. Probe vehicles installed with GPS devices (i.e., Hoeschen *et al* 2005; Quiroga and Bullock 1999) or speed measuring devices (Colyar and Rouphail, 2003) were utilized to measure control delay at intersections using this technology.

Queue forms when the demand exceeds capacity at the beginning of a green period at a signalized intersection (HCM, 2000). The characters of queuing are determined by three major factors: arrival rate, service rate, and signal timing plan. Larson (2001) developed a video image processing system with inputs from surveillance and detection cameras to estimate queue length at signalized intersections. Queue length can be estimated by modeling the characteristics of speed ~ density relationship with parameters updated in real-time (Yi, 2001). Chang and Su (1995) applied neural network models trained with simulated data to predict queue length and found that they can achieve 90% accuracy if one-vehicle difference is acceptable error.

Cycle failure (or overflow) is the situation that occurs when queued vehicles are not cleared during a given green phase. The number of queued vehicles that fail to pass through the intersection during a green indication is called cycle failure (HCM, 2000). Zheng *et al* (2006) developed a system to capture cycle failure with video image processing by tracking the location of the end-of-queue. A model based on the principle of flow conservation was developed to estimate the overflow queue (or cycle failure) and was implemented and tested in a simulation model by Fu *et al* (2001).

Current Research on Traffic Sensors

Middleton *et al* (1999) pointed out that the inductive loop is the most common traffic detector used today. An inductive loop detects vehicles by their ferromagnetic effect, which would decrease the inductance of the loop when a vehicle is over or near a loop (Kell *et al*, 1990). A single loop can measure traffic volume and occupancy. With the algorithm developed by Wang and Nihan, a single loop can also detect vehicle speed (2000) as well as vehicle type (2003). Dual loops, or speed traps, can be used to measure speed directly. The sensitivity difference of the two single loops in the dual loop, as well as unsuitable sensitivity levels of a single loop, may cause errors in detection. Loops not working properly can be identified with historical loop data and the relationships between volume, speed, occupancy, and vehicle length (Al-Deek and Chandra, 2004). In most practices, the volume and occupancy data provided by a loop are aggregated every 20 or 30 seconds. Although such interval data are convenient to transfer and store, the event data of each individual vehicle are lost in this process. To capture the event data for individual vehicles, the Advanced Loop Event Data Analyzer (ALEDA) was developed by Cheevarunothai *et al* (2005). With the event data, the sensitivity of both single loops can be adjusted to a reasonable level with the smallest sensitivity discrepancies (Cheevarunothai *et al*, 2006). Coifman (1999) proposed to detect errors of the dual loop by simply comparing the occupancies difference of the same vehicle on the two single loops.

In recent years, Video Image Processors (VIPs) have became most popular because they have the ability to capture not only traffic volumes, but also speeds, bin volumes, queue length, control delay, and other traffic parameters. These parameters can be obtained through detecting and tracking vehicles based on their features (Beymer *et al*, 1997) or profiles (Kim and Malik, 2003). Another popular approach to obtain these parameters is called "image subtraction." It subtracts background image from current image to detect objects moving across a constant scene (Shapiro and Stockman, 2001). The constant scene is referred to as the background, which contains merely static objects (e.g. road pavement, roadside buildings, etc.) and is clear of moving vehicles or pedestrians. There are several ways to extract background images from traffic video streams. Avery *et al* (2004) introduced a background image extraction algorithm based on the changes of pixel colors from frame to frame. Zheng *et al* (2006) introduces a method that can quickly extract the background image from traffic video streams for both freeways and intersections under a variety of prevailing traffic conditions

RADAR technology is widely used in traffic engineering to measure vehicle volume, speed, and length. A RADAR antenna generates and transmits radio wave into the space. When the radio wave strikes an object, it reflects back to the detector and the object gets detected. Based upon the radio wave travel time, the distance from the sensor to the object can be calculated. The speed of the object can be calculated with the change of reflected radio signal's frequency based on the Doppler Principle (National Highway Traffic Safety Administration 1983). With the calculated speed and the duration of vehicle being detected, the vehicle length and classification can be measured by a calibrated RADAR sensor (Zwahlen et al 2005). RADAR sensors are non-intrusive. Compared with intrusive sensors, such as inductive loops, the non-intrusive sensors are safe for installation, non-disruptive to traffic, and free from pavement environment (Minnesota Department of Transportation and SRF Consulting Group, Inc. 2001). RADAR sensors also have the ability to monitor traffic on several lanes at the same time with only one device. This method can drastically reduce implementing cost compared with inductive loops. South Dakota Department of Transportation used the Remote Traffic Microware Sensor (RTMS), which is one kind of RADAR sensor, to count vehicles. The test showed that for the 45,062 vehicles passed by, the result from the RTMS was about 3% lower than ground-truth data (Weber 1999). Field tests also showed that compared with inductive loop, RADAR sensor is less accurate in speed measurement, and some RADAR sensors can only provide averaged speed data, rather than the speed of individual vehicle (Zwahlen et al

2005; Weber 1999). Reflective surface for the radio signal may introduce errors. Vehicles may be missed due to occlusions introduced by larger vehicles in the path of RADAR waves (Wald 2004; Coifman 2006).

GPS is a worldwide radio-navigation system with a constellation of operating satellites and their ground stations and enables the receiver almost anywhere on the earth to compute position, velocity, and time (Grewal *et al*, 2001). Many factors, such as ionosphere delay, troposphere delay, and multipath propagation of GPS signals, can cause errors in position calculation by GPS. For example, in forest GPS position error and data update frequency would significantly deteriorate as forest canopy level increases (Zheng *et al*, 2005). With the Differential GPS (DGPS) technology, accuracy can reach to centimeter level. DGPS can take out most of the GPS bias errors with a DGPS reference receiver that observes the bias of each satellite and transmits the corrections based on the differences between observed signals and predicted signals to any remote GPS receiver within its communication coverage. GPS position error can also be reduce by integrating GPS with other position systems. For example, GPS can be integrated with the Inertial Navigation System (INS), which can provide reliable position data for a relative short period when the GPS signal is blocked, such as in tunnels (Weiss, 1998). Another example is to integrate GPS with Dead Reckoning (DR), which uses a magnetic compass and wheel odometers to determine the vehicle's route and position ((Vlcek, 1993). GPS-enabled transit Automatic Vehicle Location (AVL) systems can help spot chronic bottlenecks, provide navigation information to the transit agency, and provide public bus arrival times, service and routes. These systems are implemented at multiple locations in the United States, such as Milwaukee County Transit, Central Ohio's Transit Authority (COTA) in Central Ohio, Blacksburg Transit in Virginia, and Bus Dispatching System (BDS) in Portland (Carter, 2002). GPS can be installed on transit vehicles to provide positioning data that are critical for calculation of transit travel time and Transit Time Match (TTM), which is the difference between actual transit arrival time and scheduled arrival time at each timing point on the transit routes (Zheng *et al*, 2008).

The traffic sensor technologies are developing very fast and it is difficult to discuss every kind of sensor in detail in this dissertation. There are several other sensors, such as pneumatic tubes, transponders, cell phones, infrared detectors, acoustic detectors, etc., are not introduced here because they are less widely deployed at the current stage.

Current Research on Intersection Performance Measurement

Performance measures can be generated from archived ITS data. The California Department of Transportation (Caltrans), for example, developed the Performance Measurement System (PeMS) that provides a comprehensive assessment of freeway performance based on loop detector data (Chen *et al*, 2001). The TranStar in Houston provided vehicle delays, which were calculated based on travel time data that are collected by an Automatic Vehicle Identification (AVI) system (TTI, 2000).

Several studies have been conducted to collect intersection traffic data using video image processing. For example, Yin *et al* (2004) used virtual loops to measure traffic parameters. The position and size of each loop can be adjusted by users for collecting volume, speed, occupancy, and vehicle classification data. A video image processing system, called SPatial Image processing Traffic flow Sensor (SPITS), was developed by Higashikubo *et al* (1997) to detect traffic queue length. SPITS measures a queue length in meters, but cannot provide the number of vehicles in a queue. Fathy and Siyal (1995, 1998) also developed image processing systems to measure volume, speed, vehicle length, and queue length. The profiles used to detect queue length were divided into sub-profiles, each with approximately the same length per vehicle, thereby making it possible to estimate the number of vehicles in the queue. Zheng *et al* (2006) developed a system to detect traffic signal cycle failure using video image processing by tracking the location of the end of the queue. Gupte *et al* (2002) proposed a method to track vehicles by matching regions with vehicles in the video stream. Vehicle parameters such as location, length, and speed can be extracted from images captured by a properly calibrated camera. They also proposed to use a dynamically updated threshold to separate vehicles from the background. In a study conducted by Saito *et al* (2001), average stopped vehicle delays were estimated by image analysis. The total delay was calculated by adding all the stopped vehicle delays in a sampling time interval. The average stopped vehicle delay was then estimated by dividing the total delay by the total volume.

This literature review has not found a comprehensive algorithm to measure the traffic parameters at signalized intersections using traffic count data collected by currently available traffic sensors.

Notes to Chapter 2

1. Abdelghany, Ahmed and Billy Connor. (2006) Guidelines for Operating Traffic Signals during Low-Volume Conditions. *Report No. INE/autc 06.21,* Transportation Northwest (TransNow), Seattle, Washington State.

2. Al-Deek, Haitham M. and Chilakamarri Venkata Srinivasa Ravi Chandra. (2004) 'New Algorithms for Filtering and Imputation of Real-Time and Archived Dual-Loop Detector Data in I-4 Data Warehouse'. *Transportation Research Record*, No. 1867, Transportation Research Council, Washington D.C., pp. 116-126.

3. Avery, R. P., Y. Wang, and S. G. Rutherford. (2004) 'Length-Based Vehicle Classification Using Images from Uncalibrated Video Cameras'. *Proceedings of the 7th International IEEE Conference on Intelligent Transportation Systems,* October 2004, pp. 737-742.

4. Baldwin, C L and J T Coyne. (2003) 'Mental Workload as a Function of Traffic Density: Comparison of Physiological, Behavioral, and Subjective Indices'. *Proceedings of the Second International Driving Symposium on Human Factors in Driver Assessment, Training and Vehicle Design*, Park City, Utah State, pp. 19-24.

5. Beymer, D., P. Mclauchlan, B. Coifman, and J. Malik. (1997) 'A Real Time Computer Vision System for Measuring Traffic Parameters'. *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition*, pp 495-501.

6. Carter, A. (2002) 'GPS KEEPS TRANSIT AGENCIES ON TRACK'. *Metro Magazine*, Vol. 98, No. 3.

7. Chang, Gang-Len and Chih-Chiang Su. (1995) 'Predicting Intersection Queue with Neural Network Models'. *Transportation Research Part C: Emerging Technologies*, Vol. 3, No. 3, pp. 175-191.

8. Cheevarunothai, Patikhom, Yinhai Wang, and Nancy L. Nihan. (2005) 'Development of Advanced Loop Event Data Analyzer (ALEDA) System for

Dual-Loop Malfunction Identification'. *Proceedings of the 12th World Congress on ITS*, San Francisco, California State.

9. Cheevarunothai, Patikhom, Yinhai Wang, and Nancy L. Nihan. (2006) 'Identification and Correction of Dual-Loop Sensitivity Problems'. *Transportation Research Record*, No. 1945, Transportation Research Council, Washington D.C., pp. 73-81.

10. Chen, Chao, Karl Petty, Alexander Skabardonis, Pravin Varaiya, Jia Zhanfeng. (2001) 'Freeway Performance Measurement System: Mining Loop Detector Data'. *Transportation Research Record,* No. 1748, National Research Council, Washington, D.C., pp. 96-102.

11. Chung, K, J Rudjanakanoknad, and M J Cassidy. (2007) 'Relation between Traffic Density and Capacity Drop at Three Freeway Bottlenecks'. *Transportation Research. Part B: Methodological*, Vol. 41, No. 1, pp. 82-95.

12. Coifman, Benjamin. (2006) 'Vehicle Level Evaluation of Loop Detectors and the Remote Traffic Microwave Sensor'. *Journal of Transportation Engineering*, Vol. 132 No. 3, pp. 213-226.

13. Coifman, Benjamin. (1999) 'Using Dual Loop Speed Traps to Identify Detector Errors'. *Transportation Research Record*, No. 1683, Transportation Research Council, Washington D.C., pp. 47-58.

14. Coifman, Benjamin and Sivaraman Krishnamurthy. (2007) 'Vehicle Reidentification and Travel Time Measurement across Freeway Junctions Using the Existing Detector Infrastructure'. *Transportation Research Part C: Emerging Technologies,* Vol. 15, No. 3, pp. 135-153.

15. Colyar, JD and NM Rouphail. (2003) 'Measured Distributions of Control Delay on Signalized Arterials'. *Transportation Research Record*, No. 1852, Transportation Research Council, Washington D.C., pp. 1-9.

16. Davis, G A. (1998) 'Method for Estimating Effect of Traffic Volume and Speed on Pedestrian Safety for Residential Streets', *Transportation Research Record,* No. 1636, National Research Council, Washington, D.C., pp. 110-115.

17. Davis, Gary and Shimin Yang. (2001) 'Accounting for Uncertainty in Estimates of Total Traffic Volume: An Empirical Bayes Approach'. *Journal of Transportation and Statistics,* Vol. 4, No. 1, pp. 27-38.

18. Evanchik, Daniel M, Matthew G Best, Brian L Smith, and William T Scherer. (2006) 'Speed Index: Scalable Operations Performance Measure Based on Available Data'. *Transportation Research Record*, No. 1956, National Research Council, Washington, D.C., pp. 14-20.

19. Fathy, M. and M. Y. Siyal. (1995) 'Real-time Image Processing Approach to Measure Traffic Queue Parameters'. *IEE proceedings: Vision, image, and signal processing,* Vol. 142, No. 5.

20. Fathy, M. and M. Y. Siyal. (1998) 'A Window-Based Image Processing Technique for Quantitative and Qualitative Analysis of Road Traffic Parameters'. *IEEE Transactions on Vehicular Technology,* Vol. 47, No. 4.

21. Fu, Liping, Bruce Helling and Yongliang Zhu. (2001) 'An Adaptive Model for Real-time Estimation of Overflow Queues on Congested Arterials'. *2001 IEEE Intelligent Transportation Systems Conference Proceedings*, Oakland, California State.

22. Grewal, Mohinder S., Lawrence R. Weill, and Angus P. Anderews. (2001) *Global Positioning Systems, Inertial Navigation, and Integration.* New York, NY: John Wiley & Sons, Inc.

23. Gupte, Surendra, Osama Masoud, Robert F. K. Martin, and Nikolaos P. Papanikolopoulos. (2002) 'Detection and Classification of Vehicles'. *IEEE Transactions on Intelligent Transportation Systems,* Vol. 3, No. 1.

24. Hajek, Jerry J., Olga I. Selezneva, Goran Mladenovic, and Y. Jane Jiang. (2005) Estimating Cumulative Traffic Loads, Volume II: Traffic Data Assessment and Axle Load Projection for the Sites with Acceptable Axle Weight Data, Final Report for Phase 2. *FHWA Report No. FHWA-RD-03-094*, United States Department of transportation, Federal Highway Administration, Washington, D.C.

25. Higashikubo, Masakatsu, Toshio Hinenoya, and Kouhei Takeuchi. (1997) 'Traffic Queue Length Measurement Using an Image Processing Sensor'. *Sumitomo Electric Technical Review,* No. 43, pp. 64-68.

26. *Highway Capacity Manual 2000* (2000) Transportation Research Board, National Research Council, Washington, D.C.

27. Hoeschen, Brian, Darcy Bullock, and Mark Schlappi. (2005) 'Estimating Intersection Control Delay Using Large Data Sets of Travel Time from a Global Positioning System'. *Transportation Research Record,* No. 1917, National Research Council, Washington, D.C., pp. 18-27.

28. Ishimaru, John M., and Mark E Hallenbeck. (1999) Flow Evaluation Design Technical Report. *Technical Report WA-RD 466.2*, Washington Department of Transportation, Washington State.

29. Itoh, T. (1986) 'Navigation system using GPS for vehicles'. *Society of Automotive Engineers Transactions*, pp. 5.236–5.248.

30. Joksch, H C and L P Kostyniuk. (1997) Modeling Intersection Crash Counts and Traffic Volume. *FHWA Report No. FHWA-RD-98-096,* United States Department of transportation, Federal Highway Administration, Washington, D.C.

31. Kell, James H., Iris J. Fullerton, and Milton K. Mills. (1990) Traffic Detector Handbook. Second Edition. *FHWA Report No. FHWA-IP-90-002*, United States Department of transportation, Federal Highway Administration, Washington, D.C.

32. Kim, Z. and J. Malik. (2003) 'Fast Vehicle Detection with Probabilistic Feature Grouping and its Application to Vehicle Tracking'. *Proceedings of IEEE International Conference on Vision,* vol. 1, pp 524-531.

33. Klein, Lawrence A. (2001) *Sensor Technologies and Data Requirements for ITS*, Boston: Artech House.

34. Larson, B. (2001) Real-Time Signal Control Using Queue Length Information Deployed at an Intersection. *ITS-IDEA Project 71, Final Report*, Transportation Research Board, Washington, D.C.

35. Lomax, T., S. Tumer, G. Shunk, H. Levinson, R. Pratt, P. Bay, and G. Douglas. (1997) Quantifying Congestion. Volume 1: Final Report. *NCHRP Report No. 398*, National Cooperative Highway Research Program, Transportation Research Board, Washington, D.C.

36. Middleton, D., D. Jasek, and R. Parker. (1999) Evaluation of Some Existing Technologies for Vehicle Detection. *FHWA Report No. FHWA/TX-00/1715-S*, Texas Transportation Institute, College Station, Texas State.

37. Minnesota Department of Transportation and SRF Consulting Group, Inc. (2001) Evaluation of Non-Intrusive Technologies for Traffic Detection, Volume One Report. United States Department of transportation, Federal Highway Administration, Washington, D.C.

38. Mistele, Bryan. (2007) 'Here and Now: How the North American Traffic Data Market Has Evolved'. *Traffic Technology International*. pp 46-50.

39. National Highway Traffic Safety Administration. (1983) 'Basic Training Program in RADAR Speed Measurement: Trainee Instructional Manual'. United States Department of transportation, Federal Highway Administration, Washington, D.C.

40. Quiroga, C. and D. Bullock. (1999) 'Measuring Control Delay at Signalized Intersections'. *Journal of Transportation Engineering*, ASCE, Vol. 125, No. 4, pp. 271-280.

41. Reardon, L. (2001) 'Traffic Calming: Creatively Mitigating Traffic Speeds and Volume'. *Civil Engineering News,* Vol. 13, No. 10, pp. 52-56.

42. Saito, Mitsuru, Jaylen Walker, and Alan Zundel. (2001) 'Using Image Analysis to Estimate Average Stopped Delays per Vehicle at Signalized Intersections'. *The 80th Annual Meeting of the Transportation Research Board (CD-ROM), National Research Council,* Washington, D.C.

43. Schafer, R., K. Thiessenhusen and P. Wagner. (2002) 'A traffic information system by means of real-time floating-car data'. *Proceedings of 9th World Congress on Intelligent Transport Systems information*, ITS America, Berlin, Germany.

44. Schoepflin, Todd N and Daniel J Dailey. (2003) 'Dynamic Camera Calibration of Roadside Traffic Management Cameras for Vehicle Speed Estimation'. *IEEE transactions on intelligent transportation systems,* Vol. 4, No. 2, pp. 90-98.

45. Seymour, Edward J. and James D. Carvell. (2005) Interim Guidelines for Data Access for Texas Traffic Management Centers. *FHWA Report No. FHWA/TX-05/Report 0-5213-P1*, Texas Department of Transportation and United States Department of Transportation, Federal Highway Administration, Washington D.C.

46. Shapiro, L.G. and G.C. Stockman. (2001) *Computer Vision.* Prentice Hall, New Jersey.

47. Shuldiner, P W, S A D'Agostino, and J B Woodson. (1996) 'Determining Detailed Origin-Destination and Travel Time Patterns Using Video and Machine Vision License Plate Matching'. *Transportation Research Record,* No. 1551, National Research Council, Washington, D.C., pp. 8-17.

48. Skerritt, W H. (1993) 'Aggregate Type and Traffic Volume as Controlling Factors in Bituminous Pavement Friction'. *Transportation Research Record,* No. 1418, National Research Council, Washington, D.C., pp. 22-29.

49. Texas Transportation Institute (TTI). (2000) 'Houston TranStar Annual Report – 1999'. Texas Department of Transportation.

50. Turner, S M. (1996) 'Advanced techniques for travel time data collection'. *Transportation Research Record,* No. 1551, National Research Council, Washington, D.C., pp. 51-58.

51. Vlcek, Charles, Patricia McLain, and Michael Murphy. (1993) 'GPS/Dead Reckoning for Vehicle Tracking in the 'Urban Canyon' Environment'. *Proceedings of the IEEE Vehicle Navigation & Information Systems Conference*, Ottawa-VNIS'93.

52. Weber, Nathan A. (1999) Verification of RADAR Vehicle Detection Equipment. *Study SD98-15*, final report, South Dakota Department of Transportation, Pierre, South Dakota.

53. Wald, W. M. (2004). Microwave vehicle detection. *Final report*, Caltrans, Office of ITS Development and Support, HQ Traffic Operations. [Online], Available: http://www.dot.ca.gov/hq/traffops/elecsys/reports/FinalMVDS104.pdf. [August 2007].

54. Wang, Yinhai, and Nancy L. Nihan. (2003) 'Can Single-Loop Detectors Do the Work of Dual-Loop Detectors?' *Journal of Transportation Engineering*, ASCE, 129(2), pp. 169-176.

55. Wang, Yinhai, and Nancy L. Nihan. (2000) 'Freeway Traffic Speed Estimation Using Single Loop Outputs'. *Transportation Research Record,* No. 1727, National Research Council, Washington, D.C., pp. 120-126.

56. Weiss, J. David and Frank Shields. (1998) 'GPS/INS Integration in a Severe Urban Environment'. *Proceedings of IEEE 1998*.

57. Wunnava, Subbarao V, Kang Yen, Tadeusz Babij, Richard Zavaleta, Rafael Romero, and Christian Archilla. (2007) Travel Time Estimation Using Cell Phones

(TTECP) for Highways and Roadways. *Contract BD015-12, Final Report*, Florida Department of Transportation, Tallahassee, Florida State.

58. Yi, Ping, Clara Xin and Qiang Zhao. (2001) 'Implementation and Field Testing of Characteristics-Based Intersection Queue Estimation Model'. *Networks and Spatial Economics*, Vol. 1, No. 1, pp. 205-222.

59. Yin, Zhaozheng, Fan Yang, Henry X. Liu, and Bin Ran. (2004) 'Using Image Sensors to Measure Real-time Traffic Flow Parameters'. *The 83rd Annual Meeting of the Transportation Research Board (CD-ROM), National Research Council,* Washington, D.C.

60. Zheng, Jianyang, Yinhai Wang, and Nihan, L. Nihan. (2005) 'Quantitative evaluation of GPS performance under forest canopies', *2005 IEEE International Conference on Networking, Sensing and Control (IEEE Cat. No.05EX967)*, pp. 777-782.

61. Zheng, Jianyang, Yinhai Wang, Nancy L. Nihan, and Mark E. Hallenbeck. (2006) 'Detecting Cycle Failures at Signalized Intersections Using Video Image Processing', *Computer-Aided Civil and Infrastructure Engineering*, Vol. 21, No. 6, pp. 425–435.

62. Zheng, Jianyang, Yinhai Wang, Nancy L. Nihan, and Mark E. Hallenbeck. (2006) 'Extracting Roadway Background Image: a Mode-Based Approach', *Transportation Research Record,* No. 1944, National Research Council, Washington, D.C., pp.82-88.

63. Zheng, Jianyang, Guohui Zhang, Yinhai Wang, and Peter M. Briglia Jr. (2008) 'Comprehensive Evaluation of a Transit Signal Priority System Using Observed and Simulated Traffic Data', *The 87th Annual Meeting of the Transportation Research Board (CD-ROM), National Research Council,* Washington, D.C.

64. Zwahlen, Helmut T, Andrew Russ, Erdinc Oner, and Meghna Parthasarathy. (2005) 'Evaluation of Microwave RADAR Trailers for Nonintrusive Traffic Measurements'. *Transportation Research Record,* No. 1917, National Research Council, Washington, D.C., pp. 127-140.

Chapter 3 Methodology

The flow chart of the methodology is shown in Figure 3-1. The first step is to detect and count vehicles. There are several detection systems that are available for this task and most of them provide good performance and have been commercialized for years. In this research, the author did not spend time on repeating their work. Instead, this study directly utilized their count results that are the most reliable outputs available from the implemented systems including commercial software. In the test, the Traficon VIP3D.2 detector was chosen to capture the traffic volume and speed data. The reason for using this device to capture data was that it has been deployed at many locations, including the test locations and proven to be reliable by local traffic engineers.

Based on the vehicle count data, the queue lengths can be estimated with a model developed in this study. With the estimated queue length, an innovative algorithm can be applied to calculate the corresponding control delays. Signal cycle failures can be calculated with the estimated queue length. The author also proposed another algorithm to detect cycle failures by tracking the end of traffic queue (Zheng et al 2005). This algorithm is proven to be robust with an accuracy rate of about 98%. A mode-based background extraction method was employed for this task.

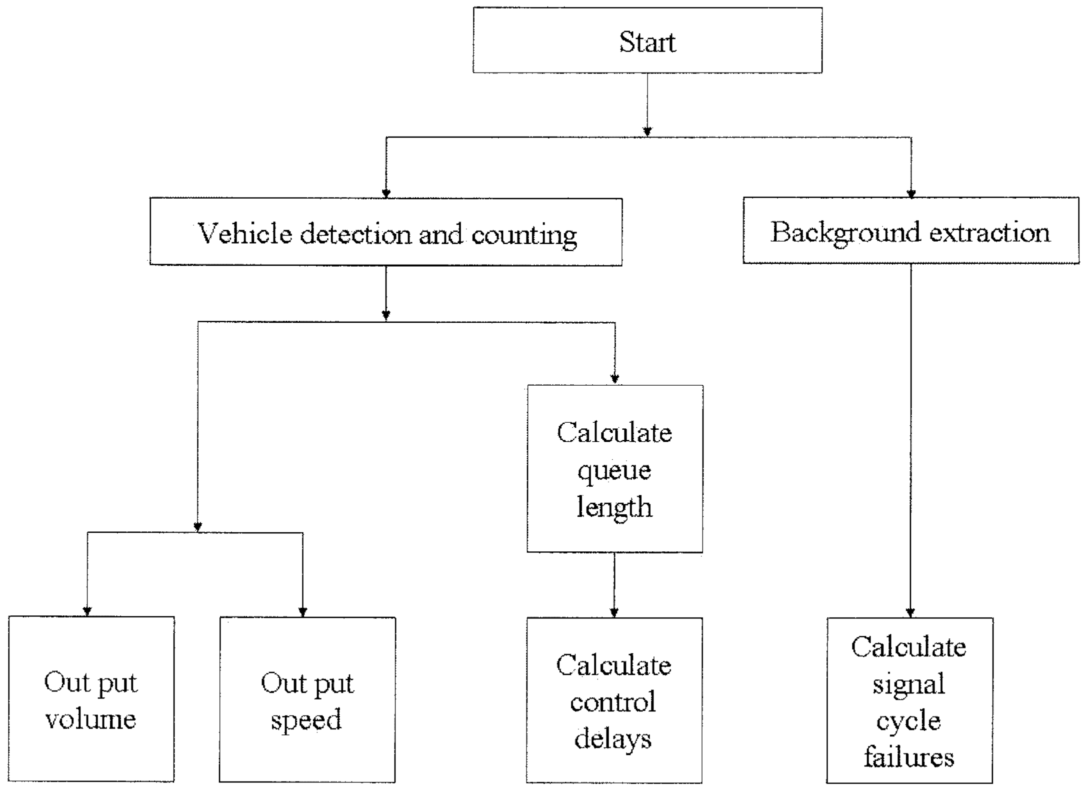


Figure 3-1 Flow Chart of the Methodology

Input Data and Layout of Intersection with Sensors

Figure 3-2 shows the ideal layout of an approach of an intersection. In the scenario shown in the figure, it is assumed that:

1. Right-turn vehicles will use the first lane (right-turn only lane);

2. Left-turn vehicles will enter the fourth lane (left-turn-only lane); and

3. Through vehicles will use the second and third lanes and are evenly distributed in the two lanes (through movement only).

4. All four lanes are in the same signal phase group, i.e. protected left-turn green, through, and right-turn green signals are concurrent.

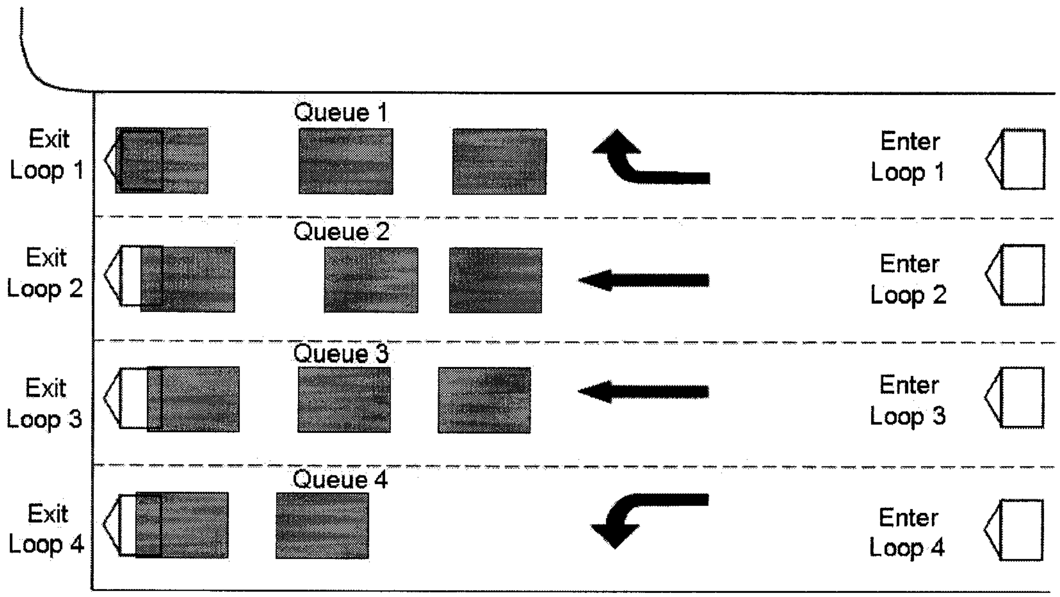


Figure 3-2 Configuration of an Approach with Virtual Loops

Figure 3-2 also shows a typical configuration of traffic detectors. In my algorithm, traffic detectors are required to provide only vehicle count data. Therefore, the traffic sensors may be inductive loops, video cameras, RTMS etc. These kinds of traffic detectors have been widely implemented across the county and are capable of providing reasonably reliable traffic count data.

Modeling Queue Length

Queue length data can be straightforwardly derived from vehicle count data. Figure 3-2 shows a typical configuration of traffic detectors for queue length detection at an ideal intersection approach. The analysis starts at the beginning of a red phase $t_r(1)$. Assume that the queue length on lane i at $t_r(1)$ is Q_i, where i = 1, 2, 3, and 4 (lane is numbered from right to left as shown in Figure 3-2). At the end of the red phase, i.e. the beginning of the first green phase $t_g(1)$, the entry loops detected a total of $IV_r(1)$ vehicles entered the detection zone and the right-turn loop detected $OV_r(1,1)$ vehicles completed right turn during the first red phase. Then a total of $IV_r(1)$-$OV_r(1,1)$ vehicles added to the initial queues through the first red phase. Depending on the intended movements (i.e. through, left turn, and right turn), these vehicles enter different queues. For the purpose of queue modeling, the author assumes that a vehicle will follow the lane layout for its intended movement and join the shortest queue whenever choices are available.

Assume that the right-turn to total volume ratio is rr and the left-turn to total volume ratio is lr. The queue lengths at the end of the $(k+1)^{th}$ (k>1) red phase are

Right turn lane: $Q_r(k+1,1) = Q_g(k,1) + IV_r(k+1) \cdot rr(k+1) - OV_r(k+1,1)$ (1)

Through lanes: $Q_r(k+1,2) = Q_g(k,2) + IV_r(k+1) \cdot (1 - rr(k+1) - lr(k+1))/2$ (2)

and: $$Q_r(k+1,3) = Q_g(k,3) + IV_r(k+1) \cdot (1 - rr(k+1) - lr(k+1))/2$$ (3)

Left turn lane: $$Q_r(k+1,4) = Q_g(k,4) + IV_r(k+1) \cdot lr(k+1)$$ (4)

Where $OV_r(k+1,1)$ represents number of vehicles detected by the exit loop at the right-turn lane during the $(k+1)^{th}$ red phase and $IV_r(k+1)$ represents number of vehicles detected by all entry loops during the $(k+1)^{th}$ red phase. $Q_g(k)$ represents the queue length at the end of the k^{th} green phase and can be calculated as follows:

Right turn lane: $$Q_g(k,1) = Q_r(k,1) + IV_g(k) \cdot rr(k) - OV_g(k,1)$$ (5)

Through lane: $$Q_g(k,2) = Q_r(k,2) + IV_g(k) \cdot (1 - rr(k) - lr(k))/2 - OV_g(k,2)$$ (6)

and: $$Q_g(k,2) = Q_r(k,3) + IV_g(k) \cdot (1 - rr(k) - lr(k))/2 - OV_g(k,3)$$ (7)

Left turn lane: $$Q_g(k,4) = Q_r(k,4) + IV_g(k) \cdot lr(k) - OV_g(k,4)$$ (8)

Where $OV_g(k,i)$ represents number of vehicles detected by the exit loop at lane i, $i \in [1, 4]$, during the green phase of interval k and $IV_g(k)$ represents number of vehicles detected by all entry loops during the green phase of interval k. Right-turn and left-turn volume ratios can be estimated with historical data and updated periodically using Equation (9) and (10), respectively.

$$rr(k+1) = \frac{OV_r(k,1) + OV_g(k,1)}{\sum_{i=1}^{4} OV_g(k,i) + OV_r(k,1)}$$

(9)

$$lr(k+1) = \frac{OV_r(k,4)}{\sum_{i=1}^{4} OV_g(k,i) + OV_r(k,1)}$$

(10)

When k=1, the queue lengths are

$$Q_r(1,1) = Q_1 + IV_r(1) \cdot rr(1) - OV_r(1,1)$$

(11)

$$Q_r(1,2) = Q_2 + IV_r(1) \cdot (1 - rr(1) - lr(1))/2$$

(12)

$$Q_r(1,3) = Q_3 + IV_r(1) \cdot (1 - rr(1) - lr(1))/2$$

(13)

$$Q_r(1,4) = Q_4 + IV_r(1) \cdot lr(1)$$

(14)

$$Q_g(1,1) = Q_r(1,1) + IV_g(1) \cdot rr(1) - OV_g(1,1)$$

(15)

$$Q_g(1,2) = Q_r(1,2) + IV_g(1) \cdot (1 - rr(1) - lr(1)) - OV_g(1,2)/2$$

(16)

$$Q_g(1,3) = Q_r(1,3) + IV_g(1) \cdot (1 - rr(1) - lr(1)) - OV_g(1,3)/2$$

(17)

$$Q_g(1,4) = Q_r(1,4) + IV_g(1) \cdot lr(1) - OV_g(1,4)$$

(18)

As shown in the equations above, the initial queue lengths on all four lanes should be known to start the process. Considering that cycle failure do not exist during off-peak hours at most intersections, I can assume $Q_1=Q_2=Q_3= Q_4=0$ if the process is started during off-peak hours. As for the initial turning volume ratios, $rr(1)$ and $lr(1)$, we can estimate values from historical data. The cost for incorrect initial values is diminishing and after first few cycles, the turning volume ratios should adapt to their correct values because these ratios are continuously updated using virtual loop measured volumes.

Although equations are given to only the scenario shown in Figure 3-2, the same logic can be extended to other scenarios. When shared lanes exist, probability theory will be employed to model the vehicle lane arrivals and real-time feed back information will be needed to tune up the probability models for modeling accuracy. However, as a study to initiate and demonstrate the idea, this study will not investigate the details of such shared lane scenarios.

Measuring Control Delay

Based on the calculated queue length, together with vehicle count data, average control delay can be estimated. The area between the entrance loop and the exit loop is called the measuring zone. Assume the distance from the entrance loops to the exit loops is L and the speed limit on the approach is s_{df}. The time needed to traverse the length of L with s_{df} is

$$tt_{df} = \frac{L}{s_{df}}$$

(19)

When a vehicle i enters the measuring zone, its entry is time-stamped as en_i and recorded in a log file. Similarly when a vehicle j exits the measuring zone, its departure time-stamp de_j is also recorded. By comparing the entry time and the departure time of vehicle i, its control delay can be calculated as

$$cd_i = en_i - de_i - tt_{df}$$

(20)

In reality, however, it is difficult to match the entry and departure time for each vehicle. Therefore, only average delay data can be collected using this approach.

Assume that we start to collect control delay data at time t_0 when the total number of vehicles in the measuring zone is N. Because I do not know when the N vehicles entered, we cannot provide control delay measurements for these vehicles. After all the N vehicles have checked out at t_s, we can start to calculate control delay. To estimate the average control delay from t_s to t_e, we need to know the number of vehicles exited from the detection zone N_{de}. N_{de} should be the sum of all the exit loops detected vehicles from t_s to t_e. Then the average control delay of the N_{de} vehicles can be calculated using Equation (21).

$$D(t_s, t_e) = \frac{\sum_{i=1}^{N_{de}} (en_i - de_{i+N})}{N_{de}} - tt_{df}$$

(21)

Although the logged en_i and de_{i+N} may not be for the same vehicle, mismatch is not an issue for calculating the average control delay as far as all the timestamps of the N_{de} vehicles are included in the calculation.

Detecting Cycle Failure

Cycle failure data can be derived from the calculated queue lengths and the real-time signal control status. The maximum queue length in a red phase will be recorded. If the maximum queue length for a lane at the end of a red phase is larger than the number of vehicles passed the exit detector at the following green phase, there is at least one vehicle failed to pass the intersection in one signal cycle, which means a cycle failure happened. The number of vehicles that experienced cycle failure can also be detected. The flow chart for cycle failure detection is shown in Figure 3-3.

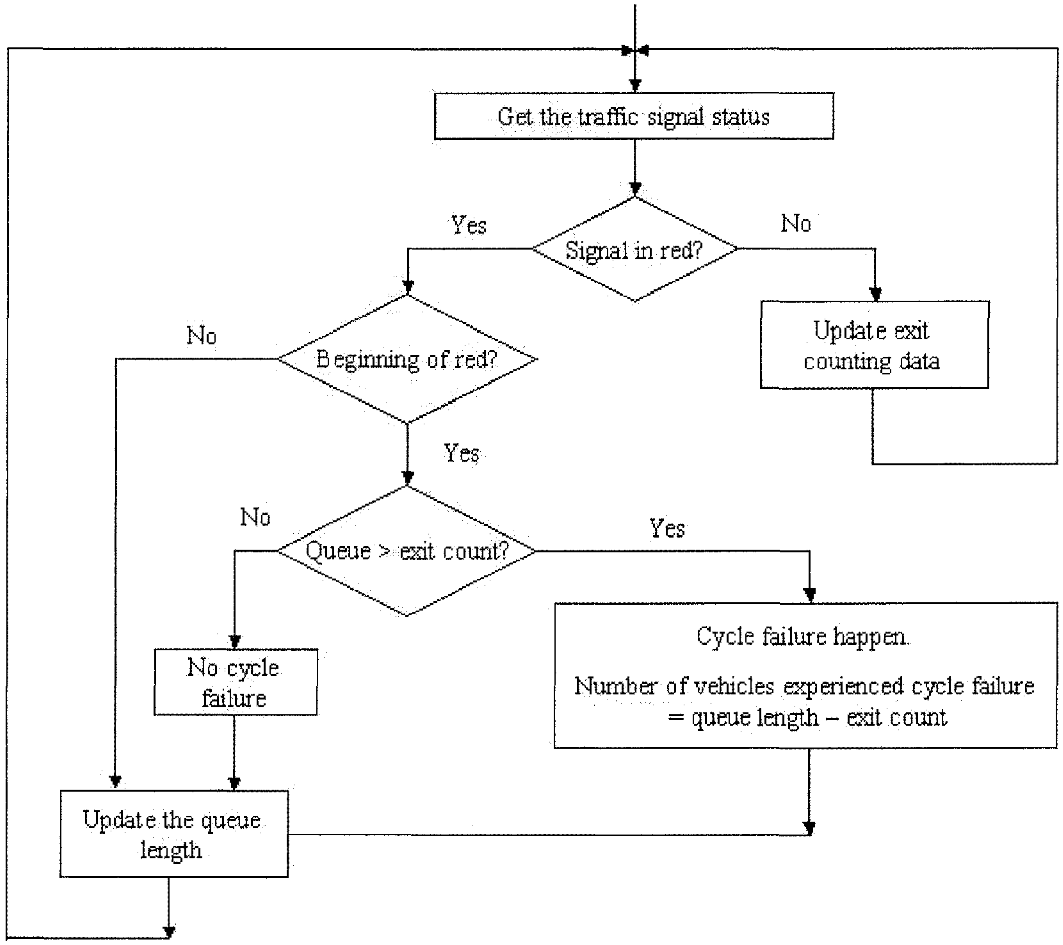


Figure 3-3 Flow Chart of the Determination of Cycle Failure

Chapter 4 A Prototype System with Input from Counting Sensors

A Prototype System in Real-Time Operations

To demonstrate and test my algorithm that measures intersection performance, a prototype system, which is called InterPer, is developed and tested with field data. Figure 4-1 shows the flow chart of the prototype system. To demonstrate the feasibility of InterPer, it was tested with VIPs, which is increasingly deployed for traffic detection in the field. As mentioned before, the InterPer system is also capable of receiving input data from other traffic sensors, such inductive loops.

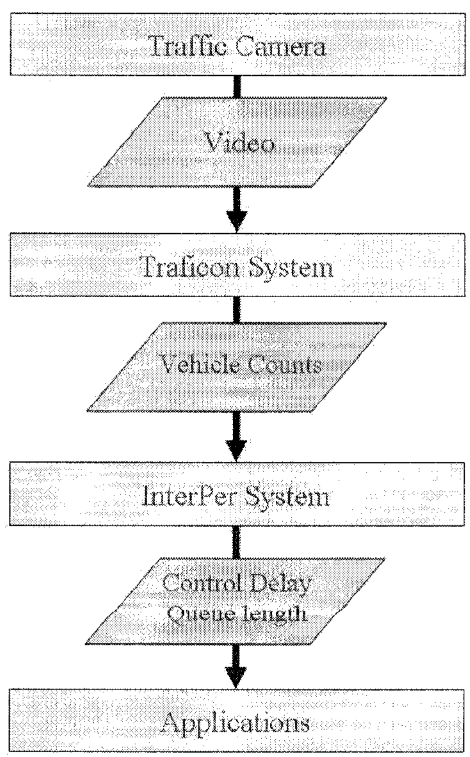


Figure 4-1 Flow Chart of the Prototype System

Two traffic cameras, one at the entrance and one at the exit of the approach, were connected to the Traficon device, which is a VIP3D.2 VIP. The VIP3D.2 card can process video images from two cameras at the same time. Figure 4-2 show a screen shot of the user interface of VIP3D.2 card. The black boxes are virtual loops that count the number of vehicle passing over them.

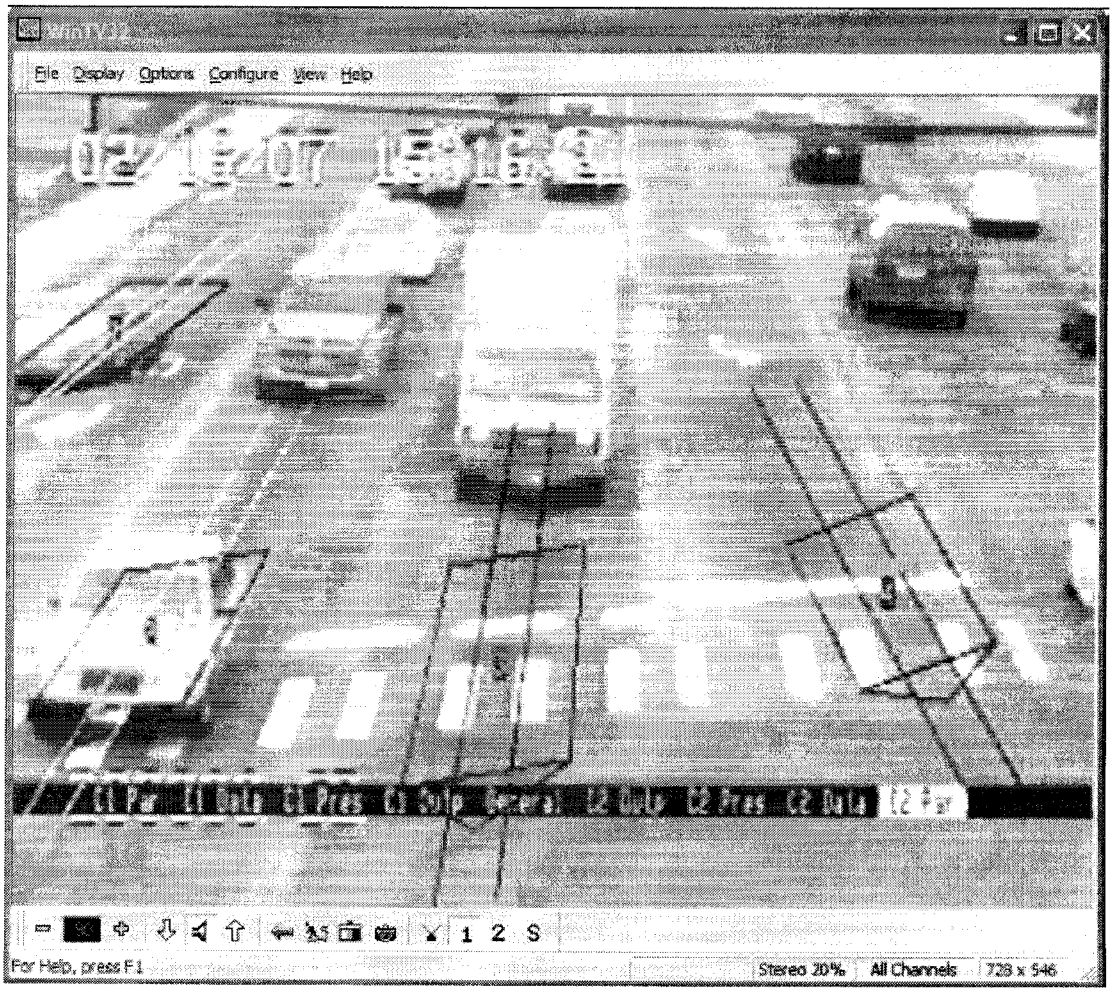


Figure 4-2 Screen shot of the User Interface of VIP3D.2 Card

The traffic count data were transferred to a computer in an html file through an Ethernet cable. Currently the Traficon device updates data once every five seconds. The InterPer system, which was developed by using MICROSOFT VISUAL C#, was installed on the computer and read the vehicle count data from the .html file. Using the algorithm introduced in Chapter 3, the queue length and control delay were estimated. Figure 4-3 shows the user interface, with output and input data presented, of the prototype system.

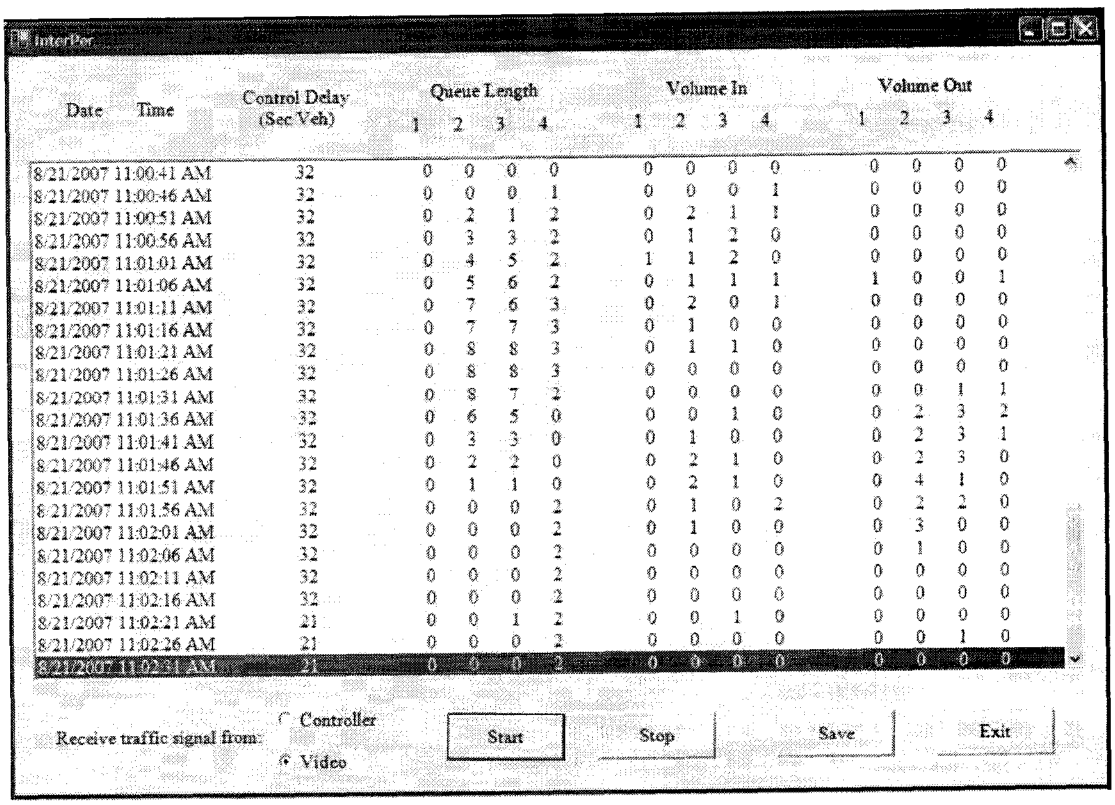


Figure 4-3 User Interface of the Prototype System

There are two ways to acquire the traffic signal status. The first one is to connect the InterPer system with the traffic controller and directly read signal status from the controller. This way is accurate but requires extra hardware. The second one is to estimate the traffic signal status based on the video data. There are no extra hardware requirements in the method. However, it would be less accurate compared with the first method. Users can specify either of the two options based on the hardware available and the accuracy level required.

Test on Field Data

The test site was located at the intersection of SR 99 and 200th Street SW, Lynnwood, Washington State. This intersection is one of the busiest in the City of Lynnwood and its layout is very close to the ideal intersection discussed in Chapter 3. City of Lynnwood installed traffic cameras at both the stop line and an upstream location to monitor and manage traffic. Two VCRs were installed to record the traffic video for the field test. The test was performed for the northbound approach for about 100 minutes during afternoon peak hours. The queue length and control delay measured by the InterPer system were compared with the ground truth data measured manually. The ground truth data of control delay were collected using the HCM field measurement technique (HCM 2000). The test results were summarized in Table 4-1.

Table 4-1 Test Results of InterPer System

Signal Cycle	Volume In		Volume Out		Queue Length		Control Delay	
	Measured	Ground Truth	Measured	Ground Truth	Measured	Ground Truth	Measured	Ground Truth
1	54	57	54	56	11	12	32	35
2	33	36	35	35	8	9	21	22
3	40	47	45	47	10	11	28	32
4	42	48	47	47	11	11	35	40
5	37	52	52	52	8	11	30	32
6	52	58	57	58	9	11	28	33
7	66	70	65	69	11	12	23	25
8	37	37	44	38	10	10	42	43
9	41	43	42	42	10	11	25	28
10	46	47	40	48	11	11	32	33
11	33	36	34	34	11	10	43	48
12	66	70	55	69	10	12	31	34
13	35	36	33	39	7	10	50	54
14	29	30	30	30	9	10	80	82
15	55	60	57	57	9	11	36	37
16	39	40	31	44	10	11	50	53
17	38	48	46	48	13	11	74	77
18	64	65	62	65	10	11	41	43
19	40	40	35	38	10	11	54	57
20	45	46	40	48	11	11	64	68
21	47	49	40	49	10	11	45	48
22	41	53	50	53	9	11	49	58
23	41	43	24	43	12	11	67	70
24	34	35	34	35	12	10	90	91
25	47	48	47	48	11	11	34	36
26	46	58	55	58	8	12	23	24
27	35	38	38	38	8	10	41	46
28	43	57	55	57	10	11	45	46
29	49	50	50	50	10	11	37	37
30	50	55	54	55	10	12	39	42
31	47	47	42	47	10	11	49	53
32	32	36	35	36	12	10	39	44
33	80	83	76	83	11	12	38	41
34	8	8	6	8	3	3	13	15
35	57	57	50	57	11	11	37	40
36	59	62	45	62	13	12	85	90
37	53	55	51	55	9	12	37	40
38	47	51	49	51	10	11	37	41
39	29	34	33	34	8	10	29	31
40	49	50	41	49	8	11	49	54
Average	44.7	48.4	44.5	48.3	9.9	10.8	42.6	45.6

The traffic volumes were under-counted at both entrance and exit of the detection zone. T-test showed that the t-ratio values for the entrance volume and exit volume were -6.04 and -4.79, respectively (t-critical = 2.02). As discussed above, we would not repeat other researches on counting vehicles. Instead, we borrowed commercially available traffic counting results and assumed that they are accurate enough. However, if the traffic counts were not sufficiently accurate, the accuracy levels of the estimated queue length and control delay would be decreased. The test results showed that the estimated queue length was also underestimated, with the t-ratio value of -4.04 (t-critical = 2.02) compared with ground truth data. One reason for the underestimation was that the length of detection zone was limited. Queued vehicles beyond the field of view of the entrance detector cannot be detected and would not be counted into the queue. The average control delay therefore was underestimated as well, with the t-ratio value of -11.24 (t-critical = 2.02) compared with ground truth data. One of the reasons for the underestimated control delay was that the queue length was underestimated. In average the error of estimated control delay was about 3 second/vehicle, which is accurate enough from practical perspective and would still predict the right Level of Service in most cases.

Test on Simulated Data

The test with field collected data showed that the control delay estimation algorithm is practical but its accuracy depends largely on the accuracy of traffic count. As described earlier the field test involved errors from traffic sensors that were beyond the system boundary of this research. Therefore, the accuracy of our algorithm may be underestimated in the field test. To test the algorithm in an ideal system, a simulation model has been developed using the software of VISSIM. The same simulation model was also applied to evaluate the impact of the Transit Signal Priority (TSP) system in south Snohomish County. Details of the simulation model and the TSP system can be found in Chapter 6 – "Application Example for Practice: Evaluating Transit Signal Priority". Table 4-2 shows the test results of the control delay estimation algorithm using data from the simulation model.

Table 4-2 Test Results of Simulated Data

Signal Cycle	Queue Length		Control Delay		Signal Cycle	Queue Length		Control Delay	
	Measured	Ground Truth	Measured	Ground Truth		Measured	Ground Truth	Measured	Ground Truth
1	0	0	0.0	0	24	1	1	6.6	10.7
2	1	2	6.1	4.9	25	1	2	0.0	0
3	1	0	1.1	0	26	1	0	2.1	1.4
4	3	0	0.8	0	27	1	0	0.0	0
5	1	0	0.0	0	28	1	1	0.0	0
6	0	0	0.0	0	29	1	1	3.1	0
7	1	0	0.0	0	30	2	2	7.6	5.7
8	1	0	2.1	0.9	31	2	0	1.6	0
9	1	0	1.1	0	32	3	1	1.9	0
10	2	1	1.6	0	33	2	1	0.0	0
11	3	2	20.8	14.9	34	3	2	26.6	8.4
12	1	1	0.0	0	35	2	2	9.1	0
13	2	1	0.0	0	36	1	0	0.0	0
14	3	2	20.8	6.1	37	2	1	26.1	14
15	1	1	2.9	1.6	38	1	1	0.0	0
16	1	2	1.1	6.2	39	4	2	13.8	8.5
17	4	2	15.9	27.8	40	2	0	17.4	0.5
18	2	1	1.8	0.8	41	1	0	0.0	2.1
19	1	2	4.1	14.8	42	1	1	0.0	0
20	0	1	0.0	0	43	2	1	0.0	3.6
21	1	1	2.1	3.3	44	1	1	3.1	3.8
22	3	2	4.7	9.3	45	1	1	0.0	0
23	2	2	1.1	4.7	Average	1.6	1.0	4.6	4.3

Since VISSIM tracks each vehicle's movement in the simulation model, it can measure control delays and queue length nearly perfectly. The ground truth values in Table 4-2 were directly provided by the VISSIM's delay and queue length evaluation tools. The author also set up vehicle counting detectors in the simulation model. The vehicle counts provided by VISSIM were saved in a data file and post-processed with the algorithm.

A t-test was conducted to evaluate the difference between the algorithm produced queue lengths and simulation model measure queue lengths. The t-ratio value was 4.40 with the t-critical value of 2.02 (two-tails). This indicates that the two series of queue length data are statistically different. However, this difference was caused by the definition disparity of queue length. In VISSIM, queue length is defined as vehicles stopped before the red light while, in the control delay estimation algorithm, queue length is referred to as the number of vehicles added to the detection zone during the red phase, regardless of their speeds. Therefore, the simulated queue lengths were slightly lower than the calculated queue lengths using the algorithm. Taking the definition difference into account, the results from simulation were just as expected and proved that the control delay estimation algorithm can produce reasonably accurate traffic queue length. The average of simulated control delay was 4.6 second per vehicle, with the average of ground truth data of 4.3 second per vehicle. The simulation result of control delays also showed that the algorithm is robust in measuring intersection performance.

Chapter's Conclusion

A prototype system for intersection performance measurement named the InterPer has been developed and tested with field data to demonstrate and test the control delay estimation algorithm. In this test, the Traficon VIPs were applied to provide traffic count data. Field data were collected at the intersection of SR 99 and 200th Street SW in City of Lynnwood, Washington State. The test results based on the field-collected data showed that the estimated queue length and control delay was slightly lower than the ground truth data. One of the reasons for the error was that the traffic was undercounted by the VIPs. The other reason was that the length of the detection zone was limited in length which caused overflowed vehicles dropped out from queue length calculations. This problem is more likely to occur during peak hours.

To test my algorithm under ideal situations, a simulation model was built up with the software of VISSIM. The same simulation model was also applied to evaluate the traffic impact of the TSP system in south Snohomish County. The simulation results of queue length and control delay were more accurate, compared with those based field-collected data. The simulation test shows that our algorithm is reliable and robust in measuring intersection performances, especially when traffic detectors provide reliable counts.

Notes to Chapter 4

1. *Highway Capacity Manual 2000* (2000) Transportation Research Board, National Research Council, Washington, D.C.

Chapter 5 Measuring Intersection Performance with Video Image Processing

An ideal video image processing system

The control delay estimation algorithm and the InterPer system are based on the assumption that the layout of the traffic sensors is in the ideal situation discussed in Chapter 3. This algorithm requires input data of two sensors per lane one at the entrance and the other at the exit of the detection zone. The algorithm also assumes that the sensors can count vehicles accurately. However, at many locations there may be only one camera installed at each approach and operates as presence detectors, which can not provide reliable traffic counting data. To measure intersection performance at these intersections, a system using video image processing has been also proposed and partially developed. Figure 5-1 shows the flow chart of the intersection performance measurement system using video image processing.

In Figure 5-1, each block represents a functional module. The first module is to extract background image from traffic video stream. By comparing the background image with current traffic image, vehicles can be detected by image processing algorithms. With the extracted background image, the module of "Feature-Based Vehicle Detection and Tracking" would detect and track each individual vehicle. With each vehicle tracked, the control delay, the queue length, and the cycle failure can be measured. The cycle failure can also be detected by tracking the position of the end-of-queue. Currently, only the modules of "extracting background image" and "detecting cycle failure" have been completely developed. Other modules are scheduled to be developed at the Smart Transportation Applications and Research Laboratory (STAR Lab) at the University of Washington.

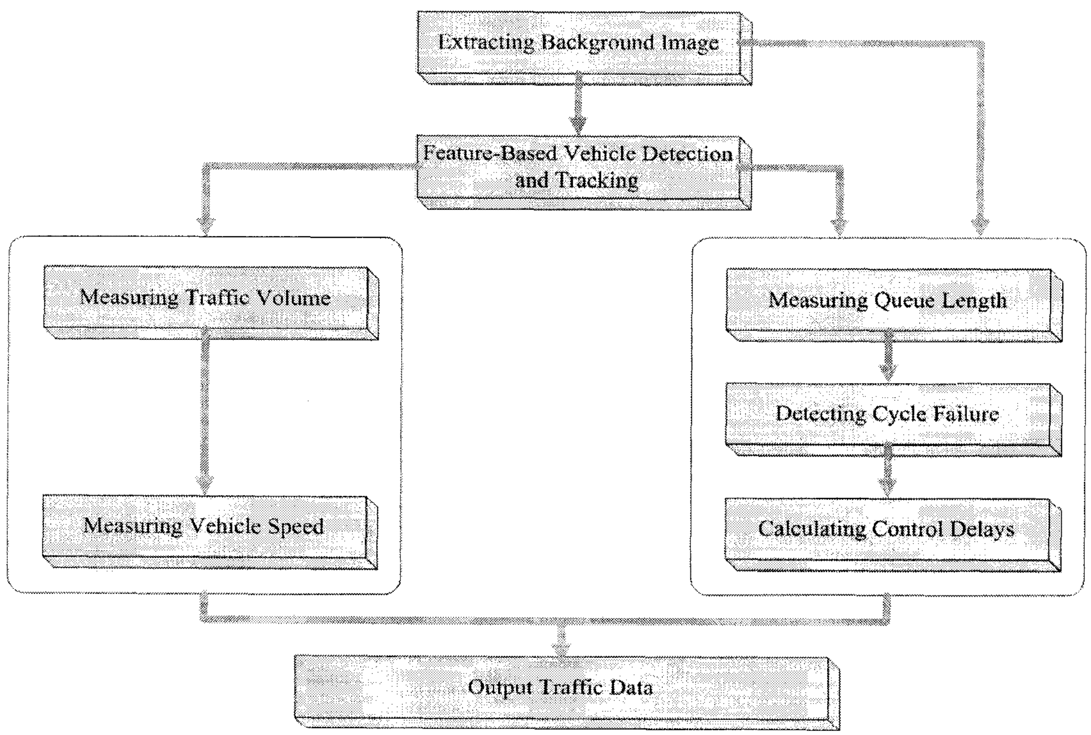


Figure 5-1 Flow Chat of an Ideal Video Image Processing System

Extracting background image

Introduction

A popular approach to obtain traffic parameters is called "image subtraction." It subtracts background image from current image to detect objects moving across a constant scene (Shapiro and Stockman, 2001). The constant scene is referred to as the background, which contains merely static objects (e.g. road pavement, roadside buildings, etc.) and is clear of moving vehicles or pedestrians. Some of the methods detect vehicles by directly comparing the three color values (measures of red, green, and blue). To eliminate the effects from the changes of illumination, Rojas and Crisman (1997) proposed to compare color in the chromaticity plane, where the measured colors of the same object under different illuminations will concentrate to one value. The color values in the chromaticity plane can be easily transformed from the RGB color space (Rojas and Crisman, 1997). The background image can also be updated with a Kalman filter-based adaptive model to accommodate the change of lighting conditions (Malik and Russell, 1997). Therefore, the background image must be known to run the image subtraction algorithm efficiently. To get the background image of a scene, I need to use video image processing to extract the background information from a series of traffic images, because it is nearly impossible to find a frame in a traffic video stream without a single moving vehicle or pedestrian on a busy urban road.

There are several ways to extract background images from traffic video streams. Avery *et al* (2004) introduced a background image extraction algorithm based on the changes of pixel colors from frame to frame. Each pixel in the previous frame was compared with the same pixel in several consecutive frames. If their color values stayed the same, it was assumed that this pixel was not occupied by moving vehicles and the color values were assigned to the corresponding pixel on the background image. This process was iterated until color values for all pixels in the background image were determined. This algorithm proved to work well on freeways under non-congested conditions. Gupte *et al* (2002) used a similar method to extract background images. They first calculated a binary motion mask, which is the subtraction of two successive frames. Any pixel with different color values between these two frames was assumed to be part of a moving object. A motion mask was used as a gating function to extract the background image from traffic images by filtering out moving objects. After a sequence of frames is processed, the entire background image could be extracted. Elgammal *et al* (1999) studied each pixel's value in the three color channels (red, green, and blue) in an image sequence, and tried to find the distribution of these values. They assumed that the values formed a Gaussian distribution, where the probability of a pixel being a background pixel could be estimated. Then the decision on whether it is a background or a foreground pixel is made by comparing the estimated probability with a given threshold. This method can be used for both freeways and intersections. Cucchiara *et al* (2003) also looked at pixel values in an image series, but they suggested using the medians of color values in the series as the background values. This method can also be applied to both freeways and intersections. Zheng *et al* (2006) used median background extraction in a video image application for detecting signal-cycle failure at urban intersections. The background extraction method requires sorting the image series to obtain the median values and hence demands more computing time.

In this research, a new method that can quickly extract background images by finding the mode of the pixel value series is developed and introduced. The details of this method are presented in the following section. Then field tests on this method are described and the test results are discussed. Summary about the utility of this method are provided at the end of this section.

Methodology

In a series of traffic image frames, the color values of a pixel at location (x, y) at time t are I(x, y, t). In most cases the pixel's color values are in the Red, Green, and Blue (RGB) color space, and I(x, y, t) is a vector with three elements: $I_R(x, y, t)$, $I_G(x, y, t)$, and $I_B(x, y, t)$. For a given pixel (x, y), its color values from time t_i to time t_{i-n} are represented by matrix M(x, y) as follows:

$$M(x, y) = \{I(x, y, t_i), I(x, y, t_{i-1}), I(x, y, t_{t-2}), \ldots, I(x, y, t_{i-n})\} \quad (1)$$

This given pixel has only two possible states in the traffic image: obstructed by a moving vehicle or clear from obstruction. If it is obstructed by a moving vehicle (common referred as foreground), the observed color values are actually from the obstructing vehicle. The pixel's color values in the periods of being obstructed can be expressed as:

$$M_F(x, y) = \{I(x, y, t_{F1}), I(x, y, t_{F2}), I(x, y, t_{F3}), ..., I(x, y, t_{F.j})\} \quad (2)$$

where t_{F1}, t_{F2}, t_{F3}, …, and $t_{F.j}$ are the times when the pixel is occupied by the foreground.

If this pixel is not obstructed by a moving object, its observed color values should be those of the background. The pixel's color values in this case are in the following set:

$$M_B(x, y) = \{I(x, y, t_{B1}), I(x, y, t_{B2}), I(x, y, t_{B3}), ..., I(x, y, t_{B.k})\} \quad (3)$$

where t_{B1}, t_{B2}, t_{B3}, …, and $t_{B.k}$ are the times when the pixel is not occupied by the foreground.

$M_F(x, y)$ and $M_B(x, Y)$ have the following relationships:

$$M(x, y) = M_F(x, y) \cup M_B(x, y) \text{ and } \phi = M_F(x, y) \cap M_B(x, y)$$

(4)

where ϕ represents an empty set.

Since the background is motionless, the color values of this pixel would approximately be the same during the entire analysis time (here I assume the analysis time is short enough to ignore the luminance change of the scene):

$$I(x, y, t_{B1}) = I(x, y, t_{B2}) = I(x, y, t_{B3}) = \ldots = I(x, y, t_{B.k})$$

(5)

For the foreground, however, since the moving vehicles occupying the pixel may be in different colors and shapes at different times, we cannot expect that:

$$I(x, y, t_{F1}) = I(x, y, t_{F2}) = I(x, y, t_{F3}) = \ldots = I(x, y, t_{F.j})$$

(6)

Therefore, I assume that it should be the background-pixel color vector that occurs the most frequently in M(x, y) and this concludes that:

$$I(x, y, t_{Bi}) = Mode\ (M(x, y)) \quad (7)$$

where t_{Bi} is the time when the pixel is not occupied by the foreground and Mode(M(x, y)) represents the mode of color values in M(x, y).

By calculating the mode of the M(x, y), the background color values at location (x, y) can be determined. After applying the same process to each pixel in the image, a background image will be extracted.

The assumption may be violated when the analysis time period, $t_A = (t_i - t_{i-n})$, is not long enough and a stopped vehicle occupies the pixel during most of the period t_A. The possibility to violate the assumption can be lowered by increasing t_A to a reasonable level. For some applications (e.g. image extraction at a congested intersection) that require a longer t_A, we can use a lower sampling rate to balance the computing work load. With a lower sampling rate, the system can process fewer amount of frames over even a longer period t_A. In the field test I used a sampling rate of 1 fps (frame per second).

Although the background is motionless, the background color values are not always the same because of disturbances in lighting, atmosphere, cameras, etc. Consequently, Equation (5) is not usually 100% true. This is illustrated in Figure 5-2, which shows the histograms of a given pixel's background color values over a two minute interval.

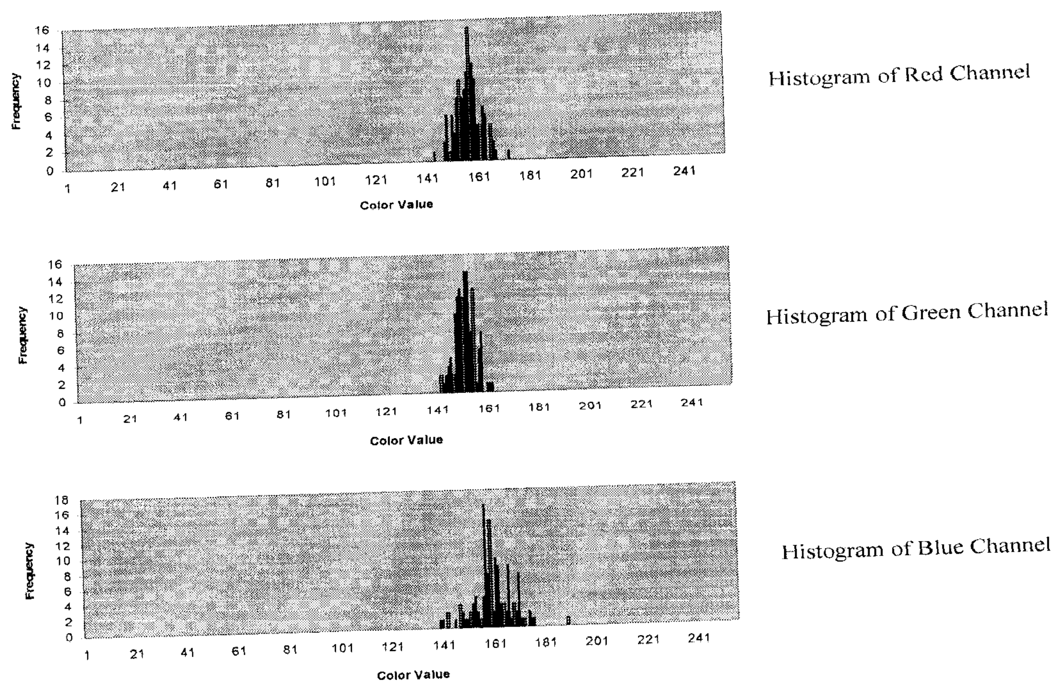


Figure 5-2 Background Variance in Two Minutes

To accommodate the small variations of background pixel values due to these disturbances and make the proposed algorithm more robust, I introduce a function to aggregate several color value in a small range into one bin. The function in my algorithm is:

$$h_i = \sum_{j=i\times s}^{(i+1)\times s-1} frequency_j \quad , \quad i = 0, 1, 2, \ldots, (256/s-1) \tag{8}$$

Where frequencyj is the frequency of color value j in the series M(x, y), s is the size of the range, and hi is the aggregated bin value. With the function (8), 256 color levels can be regrouped into 256/s bins. Using the frequencies of these regrouped bins, the impacts of disturbances are reduced. This robustness is not at the cost of reduced color resolution. If bin i is identified to be the mode, then we do a secondary mode operation to find the best color value of the pixel. That is I calculate the mode again for the s color values: $i \times s, i \times s + 1, i \times s + 2, \ldots, (i + 1) \times s - 1$. This secondary mode is considered the best background color value.

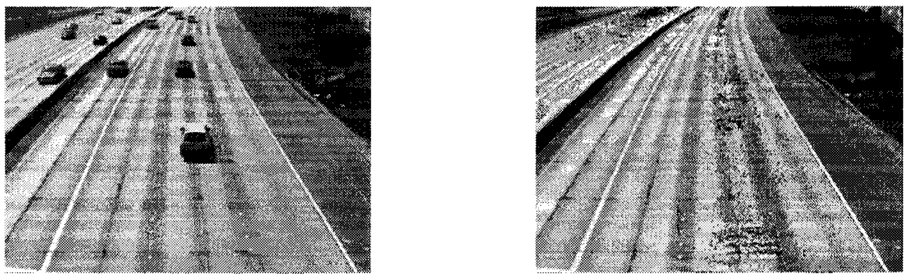
In this study, I used $s = 4$ according to the quality of my images. This corresponds to a total bin number of 64.

Test and discussion

All the field test data were obtained from traffic monitoring cameras that were not specifically installed and calibrated for video image processing. Although such cameras may not generate the best video data for traffic analysis purposes, they are already widely deployed across the country for day-to-day traffic management operations, and are, therefore, a potentially robust source of traffic video data. Image processing algorithms that can be proven to be sufficiently accurate in extracting traffic data from such cameras will be more robust and have a much larger application domain than those that require data from specially placed and specially calibrated cameras. Consequently, the field test data were all taken from cameras that were already in the field for traffic detection or other traffic management purposes. The STAR Lab at the University of Washington has a fiber optic line connected to the Traffic System Management Center (TSMC) at the Washington State Department of Transportation (WSDOT). This fiber optic line brings full motion video to the STAR Lab from nearly 300 surveillance video cameras deployed in the Greater Seattle area. My freeway test video images were captured at the STAR Lab from these surveillance video cameras.

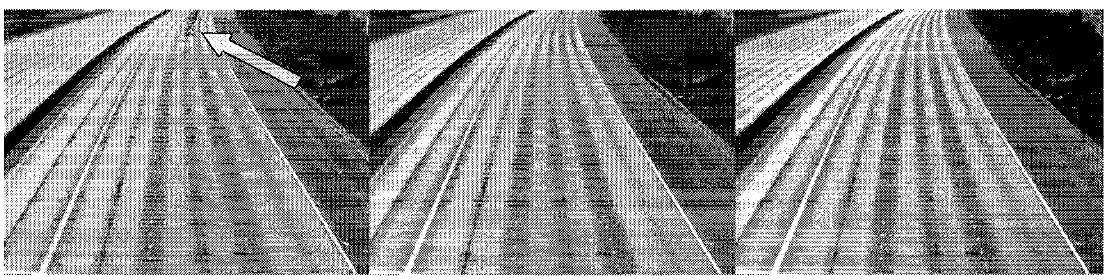
The first field test was conducted on a freeway with free-flow traffic. Figure 5-3 shows the extracted backgrounds for this test. Figure 5-3 (a) is a typical snapshot of the traffic stream at this test site. It shows that there was no traffic congestion during the test period. Figure 5-3 (b) ~ (e) shows the extracted backgrounds for the same video stream using different analysis time periods, t_A. Figure 5-3 (b) shows that when t_A = 10 seconds, the extracted background contained wrong pixel values for a significant portion of the background image. When t_A was increased to 30 seconds, most background pixels received the correct color values except for some locations at the far side of the image, identified by the author-added arrow in Figure 5-3 (c). When

t_A was further increased to 60 seconds, the extracted background image (Figure 5-3 (d)) was almost perfect. As shown in Figure 5-3 (e), when t_A was three minutes, the results were nearly the same as when t_A was one minute. The test shows that, for a t_A longer than one minute, the algorithm will work well for freeway applications in free flow conditions.



(a) Traffic Image

(b) Background extracted in 10 seconds



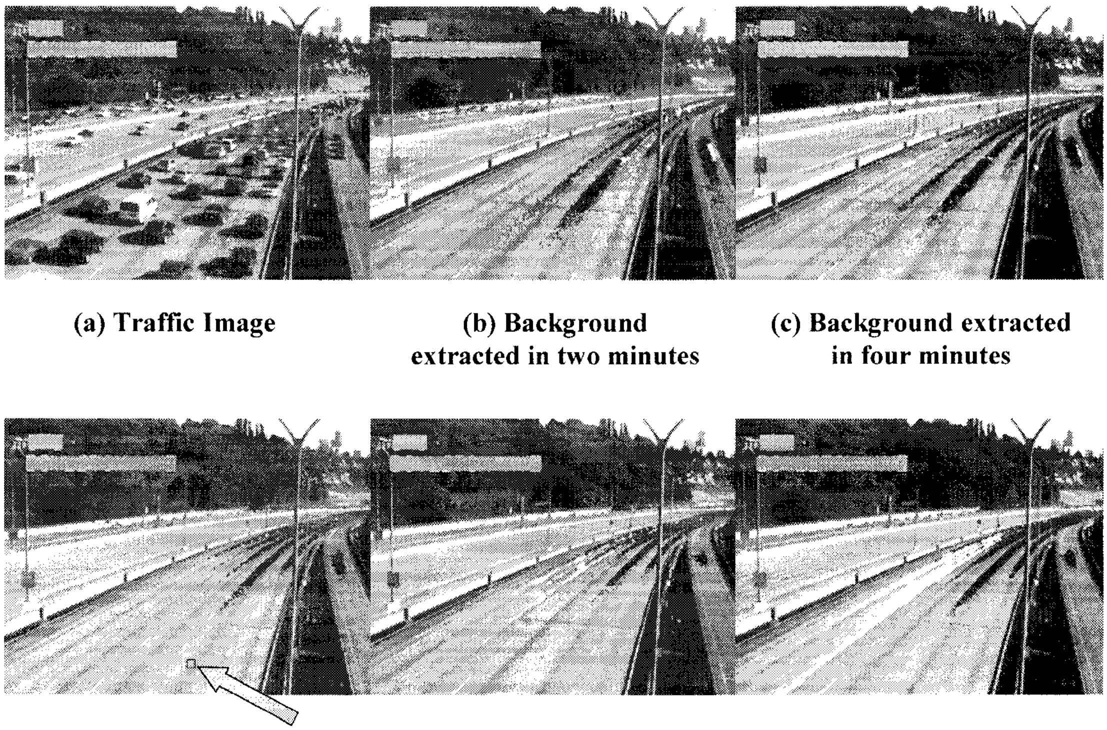
(c) Background extracted in 30 seconds

(d) Background extracted in one minute

(e) Background extracted in three minutes

Figure 5-3 Background extraction on freeway in free flow

The second field test was performed on a section of congested freeway. The traffic condition for this test site is shown in Figure 5-4 (a). Obviously, traffic density is higher at this site than at the fist test site. Therefore, a longer t_A is desired. Figure 5-4 (b) ~ (f) shows the background images extracted when t_A = 2 minutes, 4 minutes, 6 minutes, 10 minutes, and 20 minutes, respectively. The figures indicate that, when traffic is congested, the extracted background will not be as good as that for free flow condition, especially on the far side of the image. Figure 5-4 (e) and (f) show that, when t_A was greater than 10 minutes, the quality of the extracted background did not increase. The fact that the background quality does not improve and may even become worse as t_A grows to too long may be a result of changing factors such as the position of the sun that can, over time, affect pixel colors significantly. The quality of the background image appeared to be best when t_A was six minutes. Though the colors for the far side background pixels were not correct, they may not hurt follow-up image processing steps because traffic detections are most likely done at the near side where image resolution is better. Therefore, this method can also extract useful background image under congested conditions.



(a) Traffic Image

(b) Background extracted in two minutes

(c) Background extracted in four minutes

(d) Background extracted in six minutes

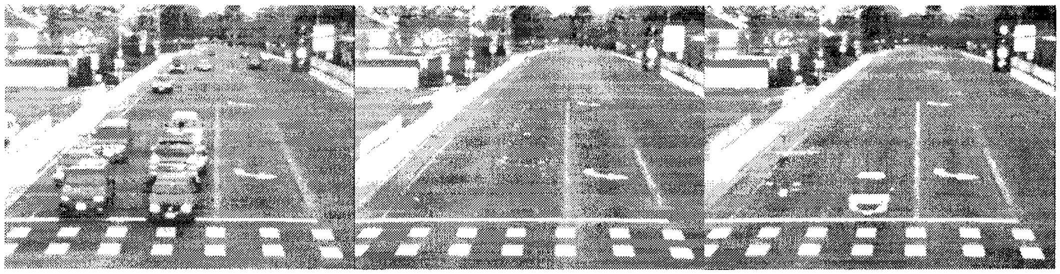
(e) Background extracted in 10 minutes

(f) Background extracted in 20 minutes

Figure 5-4 Background extraction on congested freeway

The location of the last field test was at a signalized intersection. At a signalized intersection, a vehicle may stay still for minutes even though there is no congestion. Figure 5-5 shows the results for this final test with different values of t_A. Figure 5-5 (a) shows a snapshot of the traffic when the signal was red. Figure 5-5 (b) shows the extracted background image when the analysis period t_A was one minute and about half of t_A had a red signal and the other half had green or yellow signals. Figure 5-5 (c) ~ (e) shows the extracted background when t_A was two minutes, five minutes, and 10 minutes, respectively. These images provide most of the background with good quality, especially as t_A gets longer. However, these are not perfect background images, and flawed pixels are located near the stop line, where most of the image processing is performed. Conversely, Figure 5-5 (f) shows a perfect background image extracted from the same traffic video stream with t_A = 1 minute. The only difference is that this image was extracted when the traffic signals were green for most of the time period t_A. Therefore, if the user can select an analysis period in the video stream that has a sufficient amount of green time, the algorithm can quickly extract a perfect background image.

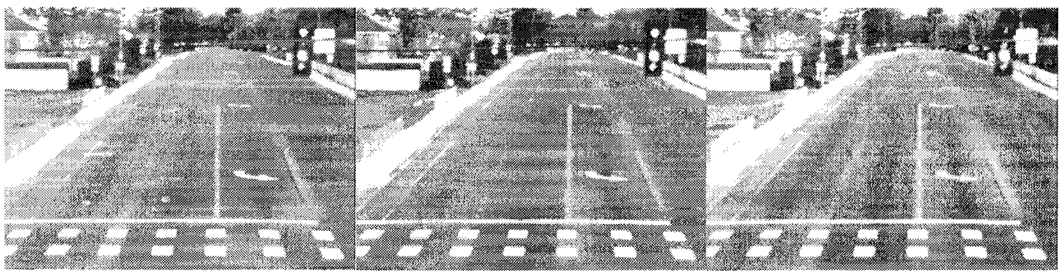
The field test data can also demonstrate the effectiveness of the proposed background-extraction method. A pixel in the congested freeway images was studied for this purpose. Position of the pixel was identified by the author-added square and arrow in Figure 5-4 (d). The pixel's histograms of three color channels in one minute were shown in Figure 5-6. Traffic video showed that in the test period 23 vehicles passed over the pixel, with eight vehicles in black, six in gray, five in red, and four in white. All of these vehicles were passenger cars or pickups. The frame rate was 4 frame/second in the test, and the manual counting showed that of the 240 frames in the test minute, the pixel was not obstructed by any vehicles in 116 frames, covered by black vehicles in 37 frames, by gray vehicles in 31 frames, by red vehicles in 29 frames, and by white vehicles in 27 frames. Because of these vehicles, the pixel's color histograms extended to a wider range.



(a) Traffic Image

(b) Background extracted in one minutes

(c) Background extracted in two minutes



(d) Background extracted in five minutes

(e) Background extracted in 10 minutes

(f) Background extracted in one minutes with green lights

Figure 5-5 Background extraction for a signalized intersection

The distribution of pixel color histograms was close to multiple Gaussians, as identified by Stauffer and Grimson (1999). Based on the scenario described, the highest columns showed the correct background color values, and the lower curves showed the colors of vehicles. As shown in Figure 5-6, the modes of each color channel were the colors that correspond to the highest columns. The median color values were interfered by vehicle colors and did not sit in the right ranges of the true background colors. The mean color values were the least accurate because they were interfered the most by the vehicle colors. This example indicated that the proposed background extraction algorithm using color modes was more robust than the background extraction algorithm using color medians. However, the comparison is only based on the data I collected, and I cannot conclude that the proposed method performs better in all conditions.

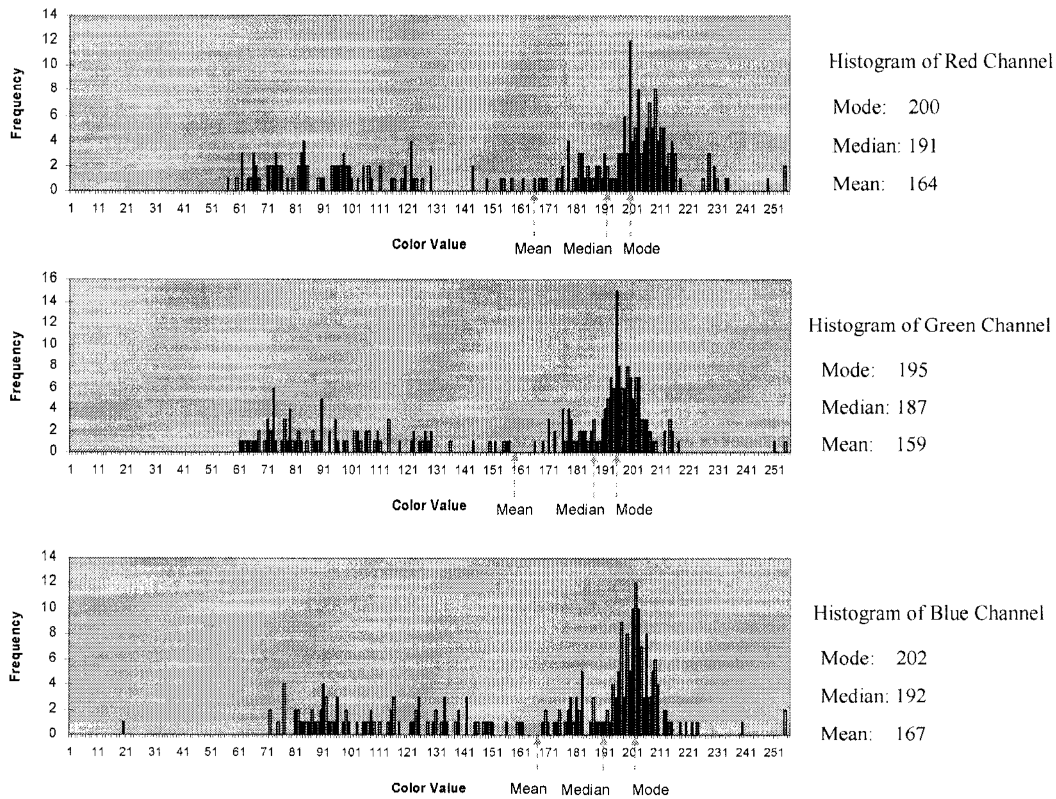


Figure 5-6 Illustration of Background Extraction Using Mode

The proposed algorithm is not only more robust, but also faster than the median background extraction algorithm. To find the median value of a data set, the data need to be sorted first. There are several sorting algorithms, such as bubble, insertion, selection, shell, heap, merge, and quick sorts (please refer to (Carrano *et al*, 1998) for details of these sorting algorithms). For bubble, insertion, selection, and shell sorts, the algorithmic complexity, or relative efficiency, is O (n^2), where O (Big

O notation) is a mathematical notation used in computer science to measure the complexity of an algorithm and n represents the size of the data set. If an algorithm has O (n^2) on average, then its execution time increases quadratically with n. These sorting algorithms are the least efficient, especially when the size of the data set is large. For heap, merge, and quick sorts, the algorithmic complexity is O ($n \times \log(n)$), which is relatively faster than other sorting algorithms (Carrano *et al*, 1998). The algorithmic complexity of the mode algorithm, however, is only O (n) because it takes just one scan to find the mode of a data set. Therefore, the mode background extraction algorithm will be faster than the median algorithm, no matter which sorting algorithm is used to find the median values. This performance difference between the median algorithm and the mode algorithm proposed in this study has been demonstrated with the field data. Table 5-1 summarizes the computing times consumed by the two algorithms to extract background from the same video data sets. The experiments were conducted on a DELL personal computer (Pentium 4 at 3.0 GHz, 1.00GB of RAM, Windows XP). Three test video data sets, each recorded at a different location, were used for this test. The median background extraction algorithm was implemented based on the quick sort algorithm. As can be seen in Table 5-1, the mode algorithm performed approximately the same when the data set is small. However, when the number of processed frames gets bigger, the saving of computing time with the mode algorithm becomes more significant.

Table 5-1 Comparison of Computing Time

Test Location	Number of Frames Processed	Computing Time (seconds)	
		Mode Algorithm	Median Algorithm
Freeway with free flow traffic	6	2	2
	60	20	22
	600	219	284
Congested freeway	6	2	2
	60	20	21
	600	222	251
Signalized intersection	6	2	2
	60	20	22
	600	231	253

Summary

In this research, a new algorithm to extract background images from traffic video streams is introduced. This algorithm analyzes each pixel's color values in a series of frames captured during a particular time period, and then uses the mode of the series as the correct color value for the background image. To handle small disturbances of background color over a short time period, a function is used to aggregate neighbor color values into one bin for mode calculation. With this function, the algorithm is more robust and lowers the impact of the disturbances resulted from environmental factors. This algorithm does not require sorting and hence is easy to implement and fast to extract background images.

Field tests were performed with video data from traffic monitoring cameras that were not specifically configured for video image processing. The test results showed that the algorithm could extract nearly perfect backgrounds on freeways when traffic was in free flow condition. For congested freeways, the algorithm could still generate background images for image processing using the near side of the image. Test results also demonstrated that the algorithm is effective to generate clear and nearly perfect backgrounds at urban signalized intersections.

Detecting Cycle Failure

Introduction

Cycle failure happens when one or more queued vehicles are unable to depart due to insufficient capacity during a signal cycle. The HCM provides methodologies to estimate LOS and queue length using roadway geometry, traffic volumes, and signal timing data. Another approach to estimate these measures of effectiveness is through simulation models that simulate the movement of each vehicle. These models require input data similar to that used by the HCM methodologies. Obviously, both types of methodologies depend on quality inputs to estimate the measures of effectiveness. If the inputs do not fully represent the actual diversity in traffic demand, the results from these methods may not properly reflect the performance of a signal control system.

Furthermore, approaches other than the aforementioned ones are needed for evaluating the performance of modern traffic control applications, which aim to adapt signal timing plans to changing traffic volumes and conditions. Control technologies, such as the Adaptive Signal Control (ASC) and the TSP systems, require evaluations under actual traffic conditions because they are specifically designed to respond varying traffic conditions.

For example, because a TSP system impacts control delay for both transit vehicles and general purpose vehicles, several traffic parameters must be measured onsite in order to evaluate the benefit of the TSP system through comparisons of the before and after scenarios. The number of cycle failure is considered one of the most useful parameters for measuring drivers' frustration toward a signal control system. Real-time cycle failure data can also be used to improve dynamic signal control. The occurrence of signal cycle failure on a phase indicates that the flow rate exceeds the capacity of the phase. If this information is available in real time in a traffic controller, the traffic signal control system may be able to optimize signal timing to provide more green time for the over-flowed phase. Another example concerns Advance Traveler Information Systems (ATIS). A key evaluation question is whether an ATIS is correctly describing the current performance of an arterial. The performance can be measured in terms of LOS, queue length, and/or cycle failure. Being able to detect and broadcast the occurrence of cycle failure (that implies "this intersection is currently congested") will help the pubic to perceive traveler information more specifically. Therefore, detection of cycle failure in real-time is of practical significance.

In this research, cycle failure is defined from a drivers' perspective, i.e., cycle failure occurs when a driver joining a specific movement queue during the green time interval is forced to wait through more than one red light to complete the intended movement via the intersection. A computer system for cycle failure detection was developed based on this algorithm. The system was tested with field data collected from VIPs deployed for signal control at two intersections in the City of Lynnwood, Washington. Test results will be presented and discussed in detail in this section.

Methodology

A VIP deployed for signal control at an intersection is typically mounted at a fixed location above the intersection facing down toward an intersection approach. In the camera's field of view, everything is relatively stable except moving objects such as vehicles and pedestrians. In a video image, moving objects are regarded as foreground and the rest as background. When no moving objects appear in an image, the image shows the complete background scene.

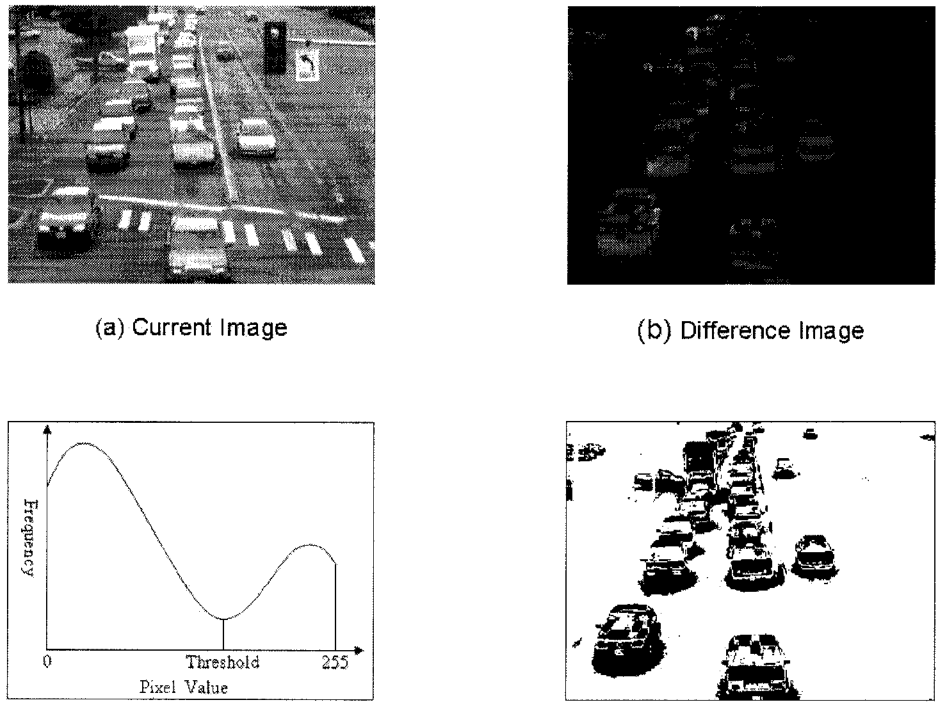
In ordinary full-motion video streams, the frame rate is from 24 frames per second (fps) to 30 fps. To increase the computational efficiency, the frame rate used in the proposed algorithm is four frames per second. Due to the relatively low speed at intersections, this frame rate is sufficient to capture the continuous movements of vehicles for my analysis.

In this study, I developed a motion detection algorithm for cycle failure detection. This video image processing algorithm for cycle failure detection contains three steps: (1) dynamic threshold determination for segmenting foreground objects from background images; (2) locating the end-of-queue with motion images; and (3) determining whether a cycle failure occurred for each lane in each cycle. Details of the four steps are described in the following sections.

Dynamic Threshold

The background image is extracted based on the algorithm introduce above. Each frame is compared with the background image. Non-background pixels are considered to be part of the moving objects such as an automobile, motor cycle, bicycle, or pedestrian. To determine whether a pixel is a background pixel, we need to establish a threshold. For a given pixel, if its value difference from the background value is larger than the threshold, it will be determined as a non-background pixel. Otherwise, it is confirmed as a background pixel. The threshold may be a constant value chosen by trial and error or by experience. However, with a dynamically updated background, a fixed threshold for each frame may not yield satisfying results. Therefore, a dynamic threshold was employed for this study.

A dynamic threshold value is calculated for each frame using a difference image that represents the differences between the background image and the current image. Each pixel value on the difference image is the absolute difference of pixel values between the current frame and the background. Therefore, the foreground pixels in the difference image will have higher values, and the background pixels will have lower values. Figure 5-7 (b) shows a difference image generated from the current image shown in Figure 5-7 (a). The grayscale histogram of all pixels in a typical difference image is shown in Figure 5-7 (c). Since most of the pixels in the difference image are part of the background, the histogram has a higher peak on the left. The other peak on the right of the histogram represents the grayscale distribution for foreground pixels. The threshold will probably be located at the bottom of the valley between the two peaks. Gupte *et al* (2002) assumed that the threshold should be at the first point from the left with a significant pixel value difference (90% of the peak value, for example) corresponding to that of the left peak. However, since the histogram of the difference image is bimodally distributed, the author prefers using Otsu's method (Otsu, 2001) to find the threshold between the two peaks. Otsu's method has been widely adopted for threshold searching in image processing studies. The threshold determined by Otsu's method minimizes the intra-group variance and works well for many applications.



(a) Current Image

(b) Difference Image

(c) Histogram of a Typical Difference Image

(d) Binary Image

Figure 5-7 Dynamic Threshold

With a specifically identified threshold, the difference image can be transferred into a binary image, where the pixel value "0" means background and "1" means foreground. The following analysis is based on this binary image. Figure 5-7 (d) shows the binary image generated from the current image shown in Figure 5-7 (a).

The End-of-Queue

In order to detect cycle failure, one must keep tracking the end of queue when the traffic signal turns green. If the vehicle at the end of a queue clears the intersection, there is no cycle failure; otherwise, a cycle failure is recorded. In this program, the user needs to interactively input the position of the stop line and the longitudinal line of each lane. To determine the end of a queue, motion images were used. A motion image is the absolute difference of two contiguous frames in a video stream and shows only the moving objects between the two frames. A fully stopped vehicle in a queue cannot be reflected in the motion image, but can be shown in the difference image. By comparing a motion image with the corresponding difference image, a stopped vehicle can be confirmed. Figure 5-8 shows the flow chart for identifying stopped vehicles and finding the queue end for a lane. Since there is noise in both the motion image and difference image, the determined queue end sometimes changes noticeably, although not because of an approaching vehicle. To make the result more stable, a median filter was used for the position of the queue end in the time domain. The positions of the queue end in the last several frames were recorded and their median was used as the queue end of the current frame. In this study, I chose to use seven frames for calculating the median. This number of frames produced a smooth performance of queue-end detection and a quick reaction to the change of queue length. Figure 5-9 shows a snapshot of the user interface with the identified end-of-queues. In this picture, the image box on the right shows the motion image. The reader can see that all stopped vehicles in the two left lanes are not shown in the motion image, but vehicles moving under the left-turn green signal in the third lane from the left are visible. The short horizontal bars at the end of the longitudinal lines were automatically drawn by the software to mark the detected positions of the end-of-queues.

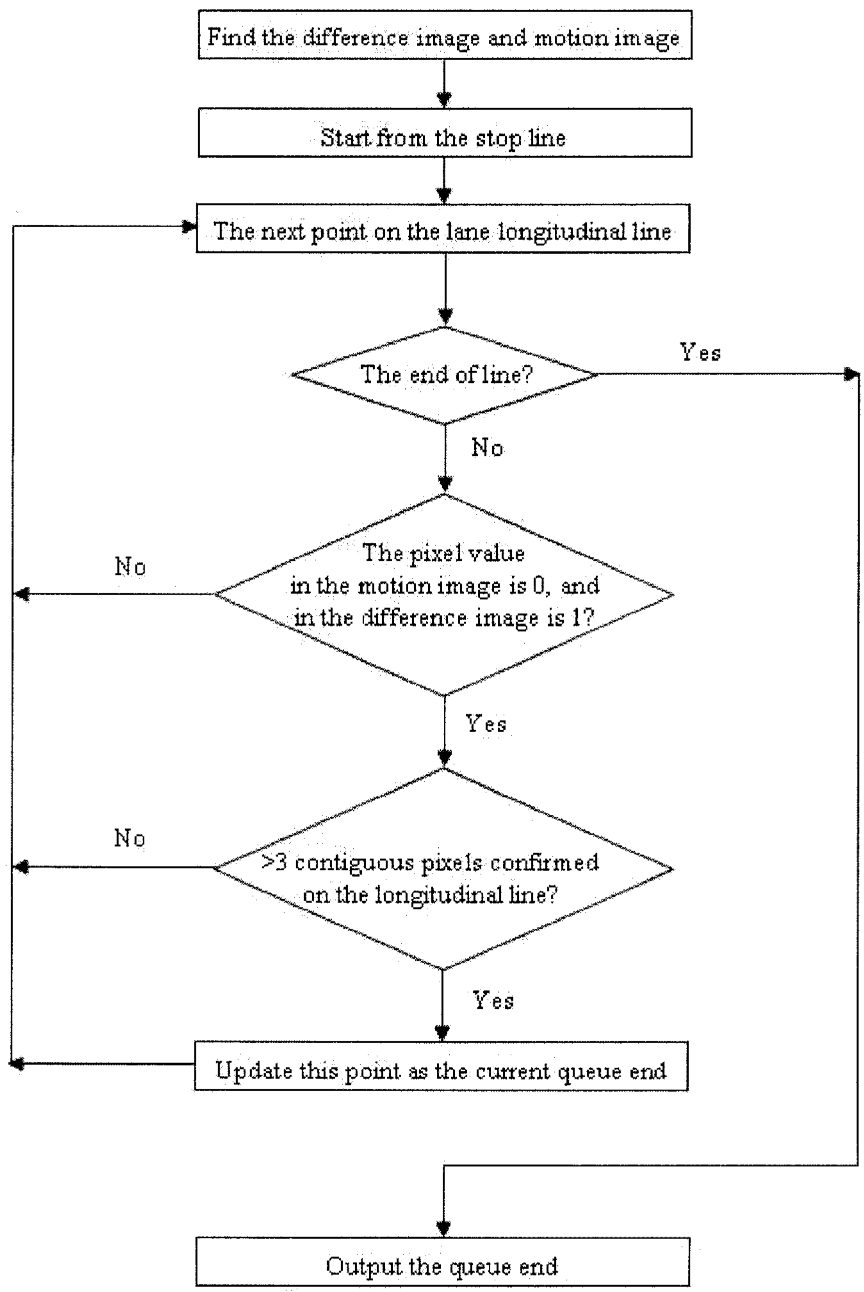


Figure 5-8 Flow Chart for Detecting the Queue End

Signal data at an intersection can be obtained from the signal controller when the system runs online. At the current offline development and test stage, however, signal controller data are unavailable. The status of signal lights is estimated from the movements of vehicles in the video stream. To detect vehicle movements, a virtual loop is created near the stop line for each lane as shown in Figure 5-9. Such a detector loop is called a motion loop. Once the stopped vehicle closest to the stop line is detected as in-motion, it is assumed that the signal light for the lane has just turned green. Similarly, if the vehicle is detected stopping, the corresponding signal light is considered turning red.

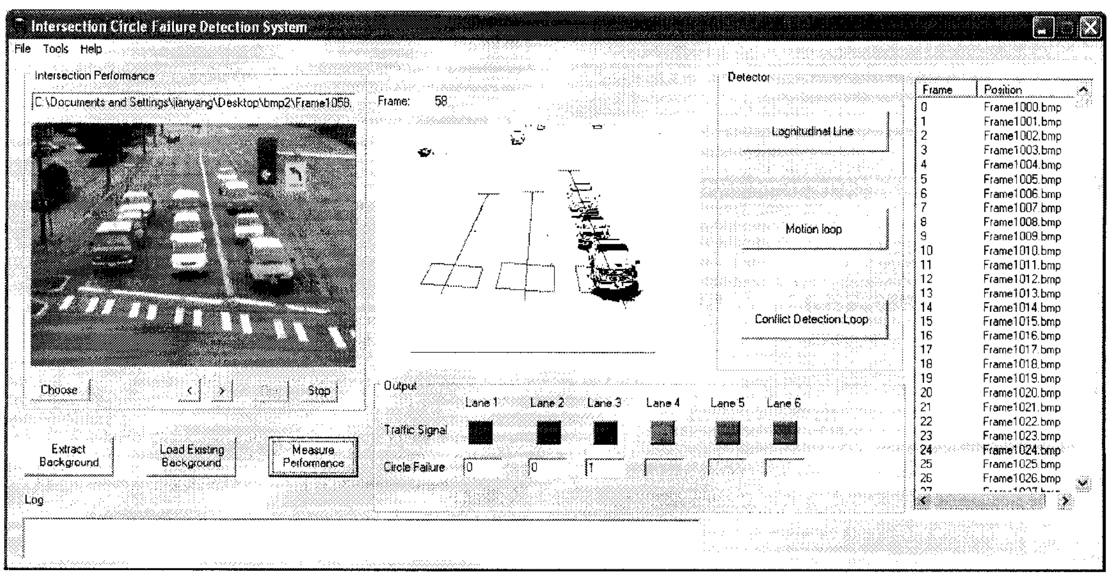


Figure 5-9 A Snapshot of the User Interface

When a long and tall vehicle such as a bus runs through the intersection from the cross streets, it may be projected to the virtual motion loops and trigger false alarms. To avoid this problem, another virtual loop was placed in the core area of the intersection to detect long vehicles from cross streets. This is called conflict detection loop. If this loop is occupied, all the motion loops are disabled because signals at conflict approaches cannot be green simultaneously. Compared with the signal data directly from the signal controller, the signal timing estimated by this algorithm is less accurate.

Determine the Cycle Failure

Once the signal light is determined to be changing from red to green, the current position of the queue end for a lane is stored. The queue length is expected to decrease under the green signal and the end-of-queue for each lane is tracked along the longitudinal line and updated from frame to frame. Figure 5-10 shows the flow chart for cycle failure detection for one lane in one frame of the video stream. The end-of-queue position is updated in the current frame and stored for usage in the next frame. If the end-of-queue reaches the stop line before the signal turns back to red, all vehicles accumulated in the queue during the previous cycle have been fully discharged and no cycle failure will occur during this signal cycle. If, when the signal light turns back to red, the queue end is still behind the stop line, the accumulated queue have not been fully cleared during the green interval and a cycle failure is detected for the lane during this signal cycle. During the red signal time, a queue length grows and the system sets the end of queue to the last vehicle in the queue and updates its position with new arrivals. At the end of each signal cycle, detection results are preserved in a data file.

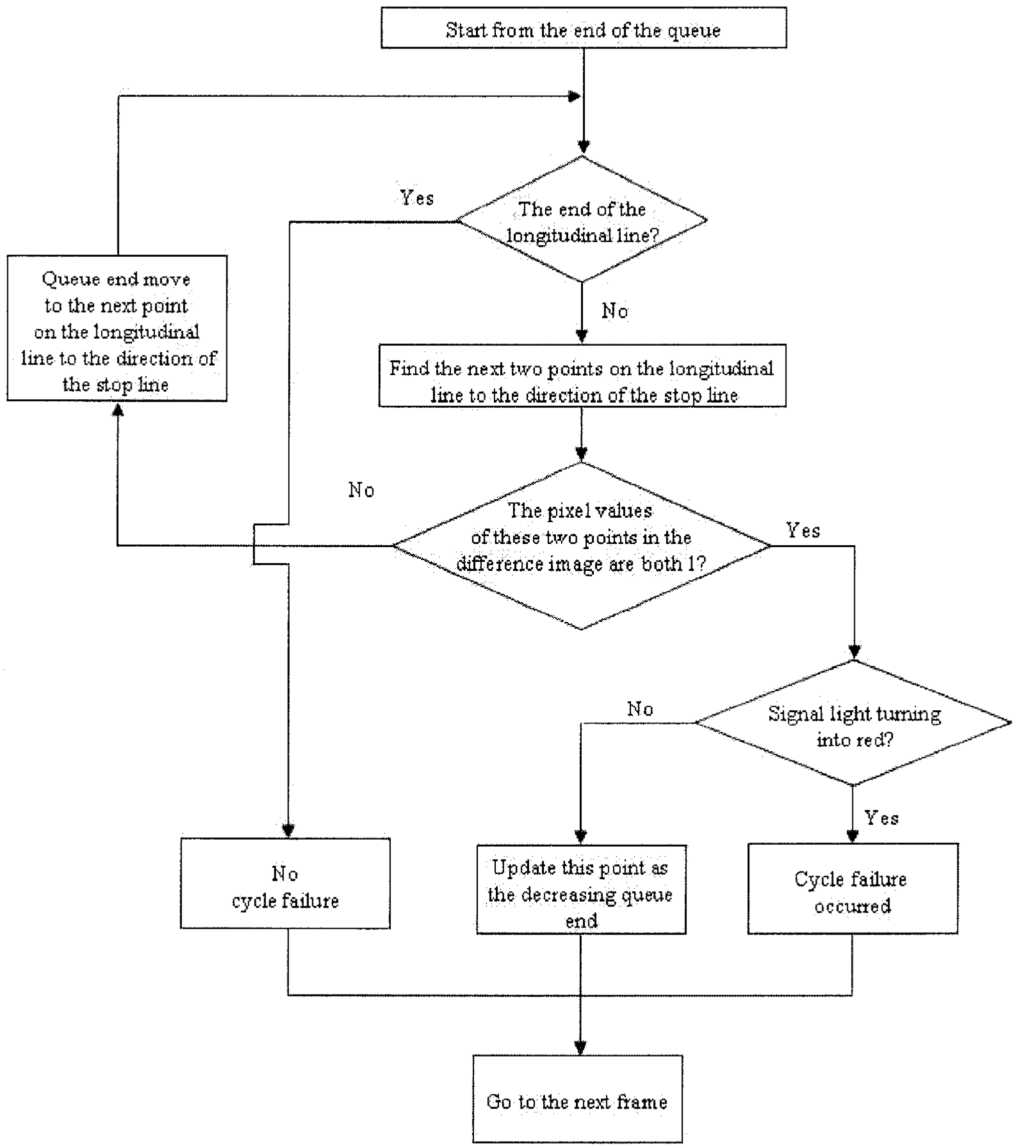
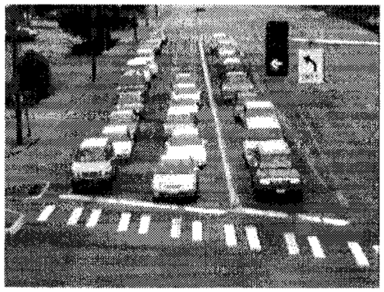


Figure 5-10 Flow Chart for Detecting Cycle Failure

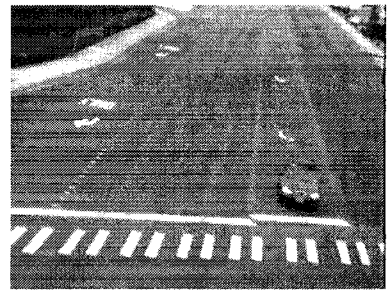
System Test and discussion

A video image processing-based cycle failure detection system implementing the proposed algorithm was developed using Microsoft Visual C#. Video data recorded by Trafficon VIPs were used to test the system. The VIPs are currently used as traffic detectors for signal control at two intersections in Lynnwood, Washington. At the intersection of SR-99 and 196th Street SW, the cameras are mounted approximately 8.5 meters above the ground and aligned approximately 30 degrees below horizontal. The VIPs were configured for general-purpose detection rather than cycle failure detection. Based on the researchers' visual count, the maximum queue length visible in the VIPs' field of view was 18 vehicles under this configuration. Since the maximal number of queued vehicles visible in a camera's field of view is determined by the camera's lens, height, and posture, a VIP may be reconfigured to accommodate longer vehicle queues when there is a need to do so. At the intersection of 164th Street SW and 36th Ave W, the cameras' installation height and pointing angle are slightly different. The sample images captured from cameras at these two intersections are shown in Figure 5-11.

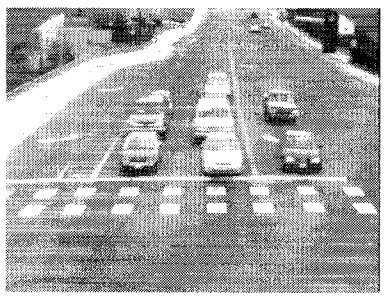
For the intersection of SR-99 and 196th Street SW, the test video data sets were recorded during the afternoon peak period on June 23, 2004 (Wednesday). The eastbound approach and the southbound approach at this intersection were selected for the test. Each approach has three lanes including one left-turn lane. Approximately 50 minutes of video data for each approach were tested. Since SR-99 is one of the most important and busiest highways in the Greater Seattle area and 196th Street SW is also a busy local arterial, the selected intersection is oversaturated during peak hours, especially for the left-turn movements. It was obvious that cycle failure occurred frequently at left-turn lanes during the test period. For the intersection of 164th Street SW and 36th Ave W, test video data sets were recorded during morning peak hours on April 2, 2005 (Wednesday). The eastbound approach and the westbound approach were selected for this test. The eastbound approach has two through lanes, one left-turn lane, and one right-turn lane (the traffic on the right-turn lane is not closely related to this research and was not studied). The westbound approach has two through lanes and one left-turn lane. Approximately 50 minutes of video data for each approach were tested in this study.



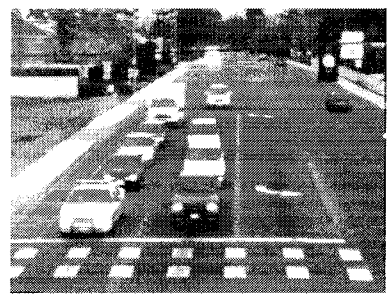
SR-99 and 196th Street, Eastbound



SR-99 and 196th Street, Southbound



164th Street and 36th Ave, Eastbound



164th Street and 36th Ave, Westbound

Figure 5-11 Sample Images Captured at Test Intersections

A total of approximately 200 minutes of video data were tested and the test results are encouraging. Of the 106 signal control cycles tested, 318 lane-based test results were recorded. All the test results were manually checked. These test results are summarized in Table 5-2.

Table 5-2 Test Results

Test Location		Number of Test Cycles	Cycle failure Occurred	Number of Correct Detections	Cycle failure Detected	False Dismissals / Alarms
SR-99 and 196th ST,	Lane 1 (through)	21	1	21	1	0 / 0

Eastbound	Lane 2 (through)	21	0	20	1	0 / 1
	Lane 3 (left turn)	21	7	20	8	0 / 1
SR-99 and 196th ST, Southbound	Lane 1 (through)	20	0	20	0	0 / 0
	Lane 2 (through)	20	0	20	0	0 / 0
	Lane 3 (left turn)	20	12	20	12	0 / 0
164th ST and 36th Ave, Eastbound	Lane 1 (through)	33	0	33	0	0 / 0
	Lane 2 (through)	33	0	32	1	0 / 1
	Lane 3 (left turn)	33	0	33	0	0 / 0
164th ST and 36th Ave, Westbound	Lane 1 (through)	32	1	32	1	0 / 0
	Lane 2 (through)	32	0	32	0	0 / 0
	Lane 3 (left turn)	32	0	32	0	0 / 0
Summation		318	21	315	24	0 / 3

For the intersection of SR-99 and 196th Street SW, there were 12 cycle failures occurred on the southbound approach during the test period. All of these cycle failures were on the left-turn lane. The left-turn signal had a 24.5-second protected green interval and a 3.5-second yellow interval. Through-lane traffic had a combined time of approximately 60 seconds for green and yellow intervals. The cycle failure detection system worked favorably for the southbound approach: it captured all 12 cycle failures and made no false dismissal (a false dismissal means a "yes" event is overlooked) or false alarm (a false alarm refers to the mistake of recording a "no" event as "yes") mistakes. The eastbound approach experienced eight cycle failures during the same period: seven on the left-turn lane and one on the through lane. The left-turn movement at this approach was protected by a 16.5-second green interval and a 3.5-second yellow interval. The combined green and yellow time for through-lane traffic was approximately 40 seconds. All eight cycle failures at this approach were successfully detected, including the only one on a through lane. However, the system generated two false alarms, one on the left lane and the other on a through lane.

For the intersection of 164th Street SW and 36th Ave W, the traffic volume was lower and fewer cycle failures occurred. At the eastbound approach, the green interval was 90 seconds and the yellow interval was 3.5 seconds. No cycle failure occurred on this approach during the test period. However, the system generated a false alarm on a through lane. At the westbound approach, the green and yellow interval lengths are exactly the same to the eastbound approach. One cycle failure occurred on the through lane during the test period. The system successfully detected this cycle failure and did not generate any false alarms or false dismissals for this approach.

The three false alarms were further examined. Two false alarms were caused by the failure of the conflict detection loop. Since the conflict detection loop did not capture the long vehicle that triggered the motion loops, the red signal light was considered to be green and consequently resulted in a false alarm. Such a mistake can be eliminated when the system is operated online and signal control data are obtained from controllers rather than through estimation. The other false alarm occurred when the volume was very close to the critical volume for a cycle failure. Actually the last vehicle in the queue had just passed the intersection when the signal turned red, but the system mistakenly captured the vehicle behind it as the last vehicle in the queue. If there had been one more vehicle in the queue, this could have been a correct detection. The chances of such false alarms occurring can be lowered by using higher frame rates and real-time signal control information in that vehicle-queue status can be evaluated in a more accurate and timely manner.

In summary, all 21 cycle failures from the 318 test cycles were successfully captured by the system. No false dismissals occurred, but there were three false alarms, which is approximately 0.9% of the total cycles tested. The overall detection accuracy was 99.1%. However, all test data were collected in daytime under sunny conditions. Like most video detection algorithms, the performance of this algorithm is expected to degrade when applied to bad weather or lighting conditions, such as rain, fog, snow, nighttime, etc. Further research will be conducted to address the impacts from these unfavorable conditions.

Conclusions

In this study, an algorithm was proposed to detect cycle failures at signalized intersections using video data from traffic surveillance cameras. The algorithm includes three steps: (1) determining dynamic threshold for segmenting foreground objects from background images; (2) locating the end-of-queue with the motion image; and (3) determining whether a cycle failure occurred in each lane in each cycle. This algorithm was implemented in the cycle failure detection module of the intersection performance measurement system using Microsoft Visual C#. This module was tested with four sets of video data captured at two intersections.

The test results showed that the proposed algorithm for cycle failure detection is encouraging. During the nearly 200 minutes of test periods, the cycle failure detection system captured all 21 cycle failures, and detection accuracy was approximately 99.1%; the system generated only three false alarms, which is approximately 0.9% of the total cycles tested. This accuracy will probably be sufficient for most practical applications. Two of the three false alarms came from mistakes made by the system in estimating the status of signal lights. If the program can take signal status data directly from the signal controller, the accuracy level can be further improved. The algorithm, which extracts stopped vehicles from the video stream, tracks the end-of-queue, and determines if a cycle failure is occurring, has proven to be effective for the test locations over the test periods. The cycle failure detection system has the potential to provide reliable real-time cycle failure information to many traffic management and operation applications.

Notes to Chapter 5

1. Avery, R. P., Y. Wang, and S. G. Rutherford. (2004) 'Length-Based Vehicle Classification Using Images from Uncalibrated Video Cameras'. *Proceedings of the 7th International IEEE Conference on Intelligent Transportation Systems*, October 2004, pp. 737-742.

2. Carrano, Frank M., Paul Helman and Robert Veroff. (1998) *Data Abstraction and Problem Solving with C++*, 2nd edition, Addison Wesley Longman.

3. Cucchiara, R., C. Grana, and M. Piccardi, and A. Prati. (2003) 'Detecting Moving Objects, Ghosts and Shadows in Video Streams'. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 25, No. 10, pp. 1337-1342.

4. Elgammal, A., D. Harwood, and L. Davis. (1999) 'Non-parametric Model for Background Subtraction'. *Proceedings of IEEE International Conference, Computer Vision '99 FRAME-RATE Workshop,* 1999.

5. Gupte, S., O. Masoud, R. F. K. Martin, and N. P. Papanikolopoulos. (2002) 'Detection and Classification of Vehicles'. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 3, No. 1, March 2002, pp. 37-47.

6. Malik, Jitendra and Stuart Russell. (1997) Traffic Surveillance and Detection Technology Development: New Sensor Technology Final report. *Research Report UCB-ITS-PRR-97-6*, California PATH Program.

7. Otsu, N. (1979). 'A Threshold Selection Method from Gray-Level Histograms'. *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 9, no. 1, pp. 62-66.

8. Rojas, Juan Carlos and Jill D. Crisman. (1997) 'Vehicle Detection in Color Images'. *Proceedings of the IEEE Intelligent Transportation System Conference*, 1997.

9. Shapiro, L.G. and Stockman G.C. (2001) *Computer Vision*. New Jersey: Prentice Hall.

10. Stauffer, C. and W. E. L. Grimson. (1999) 'Adaptive Background Mixture Models for Real Time Tracking'. *Proceedings of IEEE international conference, Computer Vision and Pattern Recognition*, pp. 246-252.

11. Zheng, Jianyang, Yinhai Wang, Nancy L. Nihan, and Mark E. Hallenbeck. (2006) 'Detecting Cycle Failures at Signalized Intersections Using Video Image Processing', *Computer-Aided Civil and Infrastructure Engineering*, Vol. 21, No. 6, pp. 425–435.

Chapter 6 Application Example for Practice: Evaluating Transit Signal Priority

Introduction

TSP is an operational strategy that facilitates the movement of in-service transit vehicles through signalized intersections. Since delays incurred by transit vehicles at signalized intersections typically account for 10 to 20 percent of transit vehicle running times, TSP promotes transit use by improving service reliability (Baker *et al*, 2004). A transit agency has two objectives for using TSP: improve service and decrease costs (Garrow and Machemehl, 1997). Through customer service enhancements, the transit agency could ultimately attract more customers. Fewer stops also mean reductions in driver's workload, travel time, fuel consumption, vehicle emissions, and maintenance costs. Local transportation agencies also can benefit from TSP strategies when improved transit service encourages more auto users to switch to public transportation. Reduced demand for personal car travel will help improve roadway level of service.

Due to the rapid population and economic growth in the greater Seattle area, traffic congestion has become an increasingly important issue. Improving transit service to reduce personal car travel demand is considered an effective countermeasure against traffic congestion. The South Snohomish Regional Transit Signal Priority (SS-RTSP) system was launched to improve the level of service for

Community Transit buses and, therefore, help solve traffic congestion problems in the greater Seattle area.

In North America, one of the main concerns about TSP is that overall traffic performance may be unduly compromised when signal timing plans intended to optimize traffic flow are overridden to provide a travel advantage to transit vehicles (Chang and Ziliaskopoulos, 2003). Several recent studies, i.e. (Abdulhai *et al*, 2002) and (Dion *et al*, 2002), have quantitatively evaluated the effect of TSP. While these studies generally agree on the benefits for transit operations, the overall impacts of TSP on local traffic networks remain unclear. Also, since the performance of a signal control strategy is closely related to traffic conditions, surrounding land use, traffic regulations, and roadway network geometry, comprehensive impacts of TSP systems on transit and other vehicles are case specific and difficult to generalize. This implies that TSP's effects on a particular network need to be evaluated based on field data. Therefore, a comprehensive evaluation of the SS-RTSP system is of both academic interest and practical significance.

The SS-RTSP system installation and evaluation comprises two phases. Phase-one involves four intersections on SW 164th Street managed by Snohomish County. Phase-two covers thirteen intersections on SR-99 managed by the City of Lynnwood.

Literature Review and Problem statement

Sunkari *et al* (Sunkari *et al*, 1995) developed a model to evaluate a bus priority strategy for one signalized intersection in a coordinated signal system. The model used the delay equation employed by the Highway Capacity Manual 2000 (HCM, 2000) for signalized intersections and adapted the equation to calculate person delays for cases with and without priority strategies. Al-Sahili and Taylor (Al-Sahili and Taylor, 1995) used the NETSIM microscopic model to analyze Washtenaw Avenue in Ann Arbor, Michigan. A decrease of 6 percent in bus travel time was the maximum benefit found. The authors suggested that the most suitable TSP plan for each intersection should be integrated and implemented as a system to maximize the benefit. Garrow and Machemehl (1997) evaluated the 4-kilometer-long Guadalupe N. Lamar arterial in Austin, Texas. The main objective of this study was to evaluate performance of different TSP strategies under peak and off-peak traffic conditions and at different saturation levels for side-street approaches (Chada and Newland, 2002).

Field evaluations reported by Chang *et al* (1995) and Collura *et al* (2006) indicated that reductions in average intersection delays ranged from 6 to 42 percent, and reductions in average bus travel times were from 0 to 38 percent. Some studies, i.e. (Yand, 2004), found that vehicles sharing the same signal phase with transit vehicles also occasionally benefited from TSP treatments. The TSP system in Los Angeles was found to reduce travel times by 19% to 25%, as well as increase ridership by 4% to 40%, depending on transit lines (Skehan, 2003). While a number of deployments produced no significant impacts on general traffic, others yielded stop and delay increases as high as 23 percent (Baker *et al*, 2004).

The Transit Capacity and Quality of Service Manual (TCQSM) (Kittelson & Associates, Inc. *et al*, 2003) provides guidance to practitioners seeking to evaluate the impact of a TSP system. The TCQSM recommends using person-delay as the unit of measurement for comparing the benefits and costs of TSP implementation. The person-delay approach assumes that the value of time for a bus passenger is the same as for an auto passenger. This assumption allows use of the same scale to evaluate the benefits and costs of TSP and provides flexibility to practitioners by allowing variable auto occupancy and bus occupancy rates.

Project and Test Overview

The SS-RTSP project applies roadside antennas to detect an oncoming transit vehicle and read information from the transponder on the bus. If the transit vehicle is qualified to receive TSP, a TSP strategy may be provided to reduce delay to the transit vehicle (McCain Traffic Supply, 2004). The components of the SS-RTSP system are very similar to a TSP project in adjacent King County (King County Department of Transportation, 2002).

Although several active TSP strategies are available, such as phase insert and phase suppression (Baker *et al*, 2004), only two commonly used transit signal priority strategies are used in the SS-RTSP system: Early Green (Early Start or Red Truncation of Priority Phase) and Extended Green (or Phase Extension of Priority Phase). The TSP treatments were only granted to transit vehicles of the test routes that were 0–30 minutes behind their schedule.

The phase-one test of the SS-RTSP project lasted two weeks, from 4/4/05 to 4/17/05, and the phase-two test was from 1/22/07 to 2/4/07. The TSP system was turned off for one week, and on for the other week. All the data were collected in both TSP on and off weeks in order to conduct a before and after analysis for the SS-RTSP project. The corridors are about 6 miles long in total with 17 signalized intersections where TSP devices are installed. The tested transit routes on the 164th Street corridor were Community Transit 114, 115, and 116. This corridor has seven bus stops and three of them are near-side stops. Near-side bus stop is located at the upstream of an intersection, whereas far-side stop is at downstream of the intersection. On the SR-99 corridor, the tested transit routes were Community Transit 100 and 101. There are 33 bus stops on this corridor and none of them are near-side bus stops.

To provide a comprehensive evaluation of TSP strategies, several Measures of Effectiveness (MOE) were used to assess impacts on traffic and transit operations. The main MOEs chosen for this evaluation are as follows:

Transit Time Match

Transit Time Match (TTM) is defined as the difference between actual transit arrival time and scheduled arrival time at each timing point on the test routes. The actual arrival times were extracted from Global Positioning Systems (GPS) installed on transit vehicles.

Transit Travel Time

Transit travel time data are collected to evaluate whether the TSP system has caused a significant change in travel time on the test routes. In-vehicle GPS devices recorded vehicle locations periodically for transit travel time comparisons.

Traffic Queue Length

A major concern about TSP systems is whether they cause excessive delay for other intersection movements. In this study, sample traffic queue length data was manually collected from recorded video images at TSP-enabled project intersections.

Signal Cycle Failures

Signal cycle failure refer to the specific delay condition in which vehicles must sit through at least one complete signal cycle to pass through an intersection. Signal cycle failure were manually collected from recorded video data.

Frequency of TSP Calls

This MOE monitors how frequently the TSP system requests signal priority and how often those calls result in a denied priority request. This information was used along with the intersection delay information to determine the need for any changes to the TSP policy. The frequency of TSP calls was calculated from the TSP requests logged by the TSP device of Transit Priority Request Generator.

Average Person Delay

This MOE is commonly adopted to reflect the performance of a roadway system. A microscopic traffic simulation model was used to derive this MOE.

Vehicle Delays and Stops

The average delay per vehicle is the MOE used for intersection level of service evaluation in HCM 2000. A microscopic traffic simulation model was used to derive this MOE.

VISSIM (version 4.10) traffic simulation software was used to model traffic operations with or without the functions of the TSP system. VISSIM is a microscopic, behavior-based, traffic simulation tool that can model integrated roadway networks and various modes including general-purpose traffic, buses, high-occupancy vehicles (HOV), light rail, trucks, bicyclists, and pedestrians. VISSIM can also implement advanced traffic systems and control strategies such as TSP, provide effective measures to assess their benefits and costs, and then further optimize system operations (PTV, 2004).

The section of 164th Street SW between 36th Avenue W and 25th Avenue W and the SR-99 corridor between 238th Street SW and 164th Street SW in Snohomish County, Washington were modeled to simulate the corresponding test sites. The simulation model was configured using the actual layout of the corridor and traffic control parameters. Observed traffic volumes, transit ridership estimates, and vehicle occupancy data were used to calibrate the model.

The emulated NEMA controller provided by VISSIM can function as a standard NEMA controller. The feature was utilized on the 164th Street corridor to satisfy the requirements of actuated signal control and basic TSP operations. However, the traffic controllers on the SR-99 corridor are Naztec, which provide some different TSP functions compared to those of the NEMA controllers. Therefore, an external controller was established for each intersection using the vehicle actuated programming (VAP) function. The control logic and transit priority strategies of the phase-two test intersections could be implemented by using the VAP programming language.

Arterial geometric characteristics and transit stop coordinates were obtained from construction designs and the GPS systems used by Snohomish County, in addition to actual observations (Community Transit and David Evans and Associates, Inc., 2003). Traffic volumes for the approaches were set based on actual volumes observed by traffic sensors. Some traffic volume data were checked by ground-truth video recorded at the test intersections to enhance the reliability of the model calibration process. The passenger ridership on buses was estimated from the annual ridership of Community Transit (National Transit Database, 2004). For this model, 12 passengers per vehicle (ppv) was selected as the ridership. The average vehicle occupancy for general-purpose vehicles was estimated to be 1.2 occupants per vehicle, as determined by King County Metro based on field observations (King County Department of Transportation, 2002). Additionally, the generation rate of passengers was set as 10 persons per hour (pph) based on the number of boardings at each stop (Community Transit, 2005). Other parameters, such as bus headways, locations of bus stops and so on, were calibrated according to the real values.

The traffic control settings of the simulation model were calibrated by using actual traffic operations parameters and control plans. Internal parameters for the simulation model were properly adjusted to ensure the model's appropriateness to the corresponding application. After the simulation model was properly calibrated, simulation tests were conducted.

Due to the stochastic features of the simulation model, multiple simulation iterations are essential to enhance the reliability of simulation results. By changing the VISSIM simulation random seeds, the random vehicle generation feature can be used. In this analysis, 20 iterations were conducted, ten scenarios with TSP functions and ten without TSP functions. The test period was 3 hours for each scenario.

Results and Discussion

Transit Time Match

The average transit time match results at bus stops are shown in Table 6-1. The transit time match results show that when TSP was on, transit vehicles were more reliable.

For the phase-one test, the increase of on-time performance varied from 18 seconds to 3 minutes and 24 seconds, or 3.9 percent to 27.4 percent, compared to the scenario when TSP was off. The overall, average improved time match at all the stops was 1.56 minute, or about 16.3 percent. For the phase-two test, the increase in on-time performance varied from location to location, with the maximum of 5 minutes and 51 seconds at stop 1013, which is located near the 220th Street intersection. The average improvement of transit time match for all the bus stops was 15 seconds, or about 6 percent, compared with scenario when TSP was off.

Table 6-1 Transit Time Matches at Bus Stops

	Stop ID	TSP off (min:sec)	TSP on (min:sec)	Stop ID	TSP off (min:sec)	TSP on (min:sec)
Phase-one	197	10′12″	8′06″	1101	9′42	9′18″
	189	7′36″	7′18″	1573	12′24″	9′00
	196	7′54″	6′30″	1575	10′12″	9′12″
Phase-two	1499	9′30″	3′48″	1003	4′09″	4′34″
	1500	4′04″	3′06″	1004	4′09″	5′29″
	1501	4′27″	3′30″	1005	4′50″	4′42″
	1502	5′47″	4′02″	1006	3′53″	3′25″
	1503	3′58″	3′28″	1007	3′02″	4′21″
	1504	3′16″	4′10″	1008	2′31″	2′30″
	1506	4′17″	4′22″	1010	3′06″	5′04″
	1507	4′59″	4′08″	1012	2′41″	2′43″
	1508	3′56″	4′25″	1013	8′33″	2′42″
	1509	3′56″	4′58″	1016	6′49″	2′13″
	1510	4′43″	4′35″	1517	3′59″	2′05″

Transit Travel Time

Table 6-2 shows the transit travel times for the test corridors. For the phase-one test, the average travel time for eastbound trips granted TSP was 6.8 seconds (or 5.0 percent) shorter when TSP was on compared with the average travel time of eligible trips with TSP off. For the westbound trips, the average travel time was longer when the TSP was on, and even longer for the trips with granted priorities. Since two of the three westbound bus stops are near-side stops, they may be the reason for the negative impact. Near-side bus stops are known to decrease the transit benefits from TSP and even introduce extra delays to transit vehicles under certain situations (Zheng *et al*, 2007). This research found that these extra delays can be avoided by disabling TSP treatment of extended green.

For the phase-two test, the average transit travel time of eligible trips with TSP on was 13 seconds (northbound) and 32 seconds (southbound) shorter than that when TSP was off. Northbound and Southbound together, the TSP saved an average of 26 seconds of transit travel time per trip, which was about 2.5 percent of the total corridor travel time. The average transit travel time for the granted trips was longer than that for all eligible trips with TSP off. Considering that only late trips would be granted TSP treatment, this result is not beyond my expectation. Another comparison between late trips with TSP on and off was conducted. The result showed that TSP saved 54 seconds of transit travel time (northbound and southbound together) for late trips, which was about 4.9 percent of the total corridor travel time.

Table 6-2 Transit Corridor Travel Times

			Eligible Trips with TSP off	Eligible Trips with TSP on	TSP Granted Trips
Phase-one	Average travel time	Westbound	2′23″	2′24″	2′27″
		Eastbound	2′15″	2′12″	2′8″
	Standard deviation	Westbound	0′29″	0′30″	0′29″
		Eastbound	0′33″	0′33″	0′30″
	Maximum	Westbound	3′30″	3′53″	3′53″
		Eastbound	4′29″	4′47″	3′25″
	Minimum	Westbound	1′35″	1′27″	1′30″
		Eastbound	1′25″	1′19″	1′22″
Phase-two	Average travel time	Northbound	17′36″	17′23″	18′24″
		Southbound	17′39″	17′07″	17′35″
	Standard deviation	Northbound	2′08″	3′12″	3′12″
		Southbound	2′34″	2′20″	2′20″
	Maximum	Northbound	22′47″	25′13″	25′13″
		Southbound	24′23″	24′16″	24′16″
	Minimum	Northbound	12′13″	9′43″	9′43″
		Southbound	10′23″	12′26″	12′26″

Traffic Queue Length

Table 6-3 shows the average of traffic queue length on cross streets per signal cycle and other descriptive statistics. Only data from major intersections with heavy traffic during typical weekdays were analyzed and summarized. As shown in Table 6-3, when the TSP was on, the queue length decreased in some cases and increased in others. Paired t-tests were applied to compare the average queue length at the test intersections before and after TSP implementation. The t ratios were -1.578 and -1.663 for phase-one and phase-two tests, respectively, with the critical t ratios of 2.920 and 1.962, respectively, at $p=0.05$ level. Therefore, the change of the average queue length on cross streets after the SS-RTSP implementation was not significant.

Signal Cycle Failures

Table 6-4 shows the frequency of signal cycle failure per cycle as well as other descriptive statistics on cross streets at busy intersections on typical weekdays. The frequency of signal cycle failure slightly increased or decreased, depending on flow and signal control conditions, after TSP was enabled. Paired t-tests show that t ratios were 0.044 and 0.450 for phase-one and phase-two tests, respectively, with the critical t ratios of 2.920 and 1.962, respectively, at $p=0.05$ level. TSP implementation did not result in significant changes in the average number of signal cycle failures. This is consistent with the cross-street queue length analysis.

Frequency of TSP Calls

The number of granted TSP trips differed from day to day and from intersection to intersection. The average number of granted TSP trips per intersection per day was 16.96, or about 18.2 percent of all scheduled trips for the phase-one test, and 14.4, or about 9.9 percent for the phase-two test.

Table 6-3 Traffic Queue Length on Cross Streets

Intersection	Cross Street	TSP	Queue Length	Standard Deviation	Maximum	Median
Alderwood Mall Parkway	Northbound	Off	2.655	2.415	14	2
		On	2.643	2.431	12	2
Alderwood Mall Parkway	Southbound	Off	1.567	1.316	7	1
		On	1.637	1.403	7	1
36th Ave	Eastbound	Off	3.201	2.581	16	3
		On	3.271	2.769	16	3
164th Street	Eastbound	Off	4.412	2.377	12	4
		On	3.829	2.172	10	4
164th Street	Westbound	Off	4.877	3.116	14	4
		On	4.471	3.229	13	3
196th Street	Eastbound	Off	9.582	4.087	20	9
		On	10.343	3.726	20	9
196th Street	Westbound	Off	10.875	5.159	23	11
		On	10.737	5.230	23	11
200th Street	Eastbound	Off	4.405	3.310	15	4
		On	5.308	3.595	18	5
200th Street	Westbound	Off	7.394	4.681	22	6
		On	7.217	4.655	21	6
220th Street	Eastbound	Off	6.776	3.321	15	6
		On	6.463	3.608	16	6
220th Street	Westbound	Off	7.764	4.756	18	8
		On	8.484	4.710	20	8

Table 6-4 Signal Cycle Failures on Cross Streets

Intersection	Cross Street	TSP	Cycle Failure	Standard Deviation	Maximum
Alderwood Mall Parkway	Northbound	Off	0.01121	0.12492	2
		On	0.00909	0.19069	4
Alderwood Mall Parkway	Southbound	Off	0.00229	0.04789	1
		On	0.00000	0.00000	0
36th Ave	Eastbound	Off	0.00000	0.00000	0
		On	0.00413	0.11134	3
164th Street	Eastbound	Off	0.02941	0.27056	3
		On	0.02857	0.26668	3
164th Street	Westbound	Off	0.00769	0.08771	1
		On	0.06429	0.36404	3
196th Street	Eastbound	Off	0.35802	0.47991	14
		On	0.38784	0.48777	10
196th Street	Westbound	Off	0.36129	0.48089	15
		On	0.43249	0.49594	13
200th Street	Eastbound	Off	0.01220	0.10992	1
		On	0.03030	0.17194	1
200th Street	Westbound	Off	0.05625	0.23076	6
		On	0.11491	0.31941	5
220th Street	Eastbound	Off	0.10029	0.30084	6
		On	0.15021	0.35764	1
220th Street	Westbound	Off	0.10417	0.30654	3
		On	0.39959	0.49032	5

Average Person Delay

As shown in Table 6-5, the average person delay was reduced by the SS-RTSP system. Over all the intersections, the TSP system saved an average of 0.05 second for all passengers in the phase-one test and 0.02 second in the phase-two test. Although the 0.05 or 0.02-second time saving seems negligible to each person, the overall benefit of more than 10.2 person-hours over a three-hour period (peak hours) on all of the test corridors is significant. This indicates a total peak-hour time saving of 20.4 person-hours (assuming six peak hours per day) per day or 5,100 person-hours per year (assuming 250 working days per year). The overall person delay saved by the SS-RTSP system is remarkable. Considering that the number of granted TSP trips was not high and the negative impact on cross street not significant, more transit routes and vehicles could become eligible for the TSP system and more person delay could be avoided.

Vehicle Delays and Stops

Table 6-6 presents the average vehicle delays and the number of stops observed from the simulation scenarios. TSP impacts on average vehicle delays were controversial: in some scenarios, the impacts increased, while in others, the impacts decreased. Observations on the number of vehicle stops in the ten simulation scenarios were similar. Paired t-tests concluded that the TSP implementation did not generate significant changes in average vehicle delay and number of vehicle stops for local traffic.

Table 6-5 Simulation Results of Personal Delays

		Average Personal Delay		Person Number	
	Simulation	TSP on	TSP off	TSP on	TSP off
Phase-one	1	8.5	8.5	7177	7166
	2	8.7	8.7	7275	7285
	3	8.6	8.6	7238	7242
	4	8.7	8.7	7290	7288
	5	8.6	8.7	7113	7119
	6	8.6	8.7	7315	7315
	7	8.8	8.9	7337	7321
	8	8.5	8.6	7261	7264
	9	8.6	8.7	7135	7146
	10	8.6	8.6	7187	7189
	Average	8.62	8.67	7233	7234
	Paired t-test	Not significant			
Phase-two	1	24.0	24.0	134245	134204
	2	24.0	24.2	134947	134952
	3	23.8	24.0	134377	134378
	4	23.7	23.6	133622	133627
	5	24.5	24.2	133942	133891
	6	24.3	24.3	135750	135769
	7	23.9	24.1	134499	134519
	8	23.9	24.0	135140	135167
	9	23.8	23.7	134016	134004
	10	23.7	23.7	134909	134914
	Average	23.96	23.98	134545	134543
	Paired t-test	Not significant			

Table 6-6 Simulation Results of Traffic Delays and Stops

		AVD[1] (sec/veh)		ANS[2]		VN[3]	
	Simulation	TSP-on	TSP-off	TSP-on	TSP-off	TSP-on	TSP-off
Phase-one	1	8.4	8.4	0.33	0.33	5937	5938
	2	8.2	8.2	0.32	0.32	5826	5825
	3	8.3	8.3	0.33	0.33	5905	5907
	4	8.5	8.5	0.33	0.34	5925	5924
	5	8.3	8.4	0.33	0.33	5818	5818
	6	8.5	8.4	0.33	0.33	5974	5973
	7	8.7	8.6	0.34	0.34	5951	5951
	8	8.2	8.2	0.32	0.32	5869	5869
	9	8.4	8.4	0.33	0.33	5809	5809
	10	8.3	8.2	0.33	0.33	5880	5881
	Average	8.4	8.4	0.33	0.33	5889	5890
	Paired t-	Not significant		Not significant			
Phase-two	1	24.2	24.1	0.77	0.77	131165	131134
	2	24.2	24.3	0.78	0.78	131877	131882
	3	24.0	24.1	0.77	0.78	131307	131308
	4	23.9	23.7	0.77	0.76	130552	130557
	5	24.6	24.4	0.82	0.79	130872	130831
	6	24.5	24.5	0.81	0.80	132680	132699
	7	24.1	24.2	0.78	0.79	131429	131459
	8	24.1	24.1	0.77	0.78	132060	132087
	9	24.0	23.8	0.76	0.75	130936	130934
	10	23.9	23.8	0.78	0.77	131839	131844
	Average	24.2	24.1	0.78	0.78	131472	131474
	Paired t-	Not significant		Not significant			

[1] *denotes Average Vehicle Delay;* [2] *denotes Average Number of Stops;* [3] *denotes Vehicle Count*

Conclusions

In this study, the SS-RTSP system was evaluated with field data. Simulation models were also use to compute MOEs that could not be obtained from field data. With the simulation models and field data, the impacts of the SS-RTSP system on both transit and local traffic operations were quantitatively evaluated.

The evaluation results showed that the SS-RTSP system introduced remarkable benefits to transit vehicles with insignificant negative impacts to local traffic on cross streets. With the SS-RTSP system transit vehicles can be operated more reliably. The MOE of Transit Time Match indicated improvements of 1.56 minutes, or about 16.3 percent, in the phase-one test and 15 seconds, or about 6 percent, in the phase-two test. In the phase-one test, the average eastbound corridor travel time of transit vehicles was 6.8 seconds, or 5.0 percent shorter for than the average corridor travel time without TSP. In the phase-two test, the average saved transit corridor travel time was 26 seconds, or 2.5 percent. Because of the saved transit travel time, the SS-RTSP system decreased the overall person delays. For all passengers who used the TSP-enabled intersections, the average person delay was reduced by 0.05 second in the phase-one test and 0.02 second in the phase-two test. Taking phase-one and phase-two together, the overall saved person delay was 5100 person-hours per year for peak-period travel.

The simulation runs indicated that the SS-RTSP system sometimes increased and sometimes decreased local traffic delay at an intersection. Paired t-tests on average vehicle delay and the number of vehicle stops did not find any significant impacts from the SS-RTSP system at the p=0.05 level. Similarly, the SS-RTSP system impact on cross-street traffic was also analyzed. The test data showed slight changes in vehicle delay, queue length, and signal cycle failure frequency on cross streets after TSP implementation. However, t tests indicated that these changes were not significant at the p=0.05 level.

To improve the performance of the current SS-RTSP system, more transit vehicles can be provided with TSP eligibility. The average number of granted TSP trips per day per intersection was only 16.96 in the phase-one test and 14.40 in the phase-two test. Considering that the negative impact of the SS-RTSP on local traffic was not significant, more transit trips could be granted TSP priority and the frequency of TSP requests could be increased to generate more benefits from the SS-RTSP system.

This research found that extra transit delays may be introduced by TSP, compared with non-TSP, at an intersection with a near-side bus stop under certain conditions. Avoiding these extra delays by moving near-side bus stops to the far side of the intersection, or disabling TSP treatment of extended green at intersections with near-side bus stops, is recommended.

Notes to Chapter 6

1. Abdulhai, B., A. Shalaby, J. Lee, and A. Georgi. (2002) 'Microsimulation Modeling and Impact Assessment of Streetcar Transit Priority Options: the Toronto Experience'. *The 81st Annual Meeting of the Transportation Research Board (CD-ROM), National Research Council,* Washington, D.C.

2. Al-Sahili, K.A., and W.C. Taylor (1995) 'Evaluation of Bus Priority Signal Strategies in Ann Arbor, Michigan'. *Transportation Research Record,* No. 1554, National Research Council, Washington, D.C., pp. 74-79.

3. Baker, R.J., J. Collura, J.J. Dale, L. Head, B. Hemily, M. Ivanovic, J.T. Jarzab, D. McCormick, J. Obenberger, L. Smith,, and G.R. Stoppenhagen. (2002) *An Overview of Transit Signal Priority.* Intelligent Transportation Society of America, Washington, D.C., 2002.

4. Chada, S., and R. Newland. (2002) Effectiveness of Bus Signal Priority – Final Report. *Report NCTR-416-04,* National Center for Transit Research, University of South Florida, FL.

5. Chang, E., and A. Ziliaskopoulos. (2003) 'Data Challenges in the Development of a Regional Assignment-Simulation Model to Evaluate Transit Signal Priority in Chicago'. *The 82nd Annual Meeting of the Transportation Research Board (CD-ROM), National Research Council,* Washington, D.C.

6. Chang, G.-L., M. Vasudevan, and C.C. Su. (1995) 'Bus preemption under adaptive control environments'. *Transportation Research Record,* No. 1494, National Research Council, Washington, D.C., pp. 146-154.

7. Collura, J., H. Rakha, and J. Guifford (2006) Guidelines for the Planning and Deployment of Emergency Vehicle Preemption and Transit Priority Strategies. Research Report, Virginia Tech Transportation Institute.

8. Community Transit. (2005) Addendum to Results of Service Quality Monitor On-Board Survey Data: September 2004 – February 2005.

9. Community Transit and David Evans and Associates, Inc. (2003) South Snohomish Regional Transit Signal Priority Intersection Inventory.

10. Dion, F., H. Rakha, and Y. Zhang. (2002) 'Evaluation of Potential Transit Signal Priority Benefits along a Fixed-Time Signalized Arterial'. *The 81st Annual Meeting of the Transportation Research Board (CD-ROM), National Research Council,* Washington, D.C.

11. Garrow, M., and R. Machemehl. (1997) Development and Evaluation of Transit Signal Priority Strategies. *Research Report SWUTC/97/472840-00068-1*, Southwest Region University Transportation Center, Center for Transportation Research, University of Texas, Austin, Texas.

12. King County Department of Transportation. (2002) 'An Evaluation of Transit Signal Priority on Aurora Avenue North'. King County Department of Transportation, Transit Speed and Reliability Program.

13. Kittelson & Associates, Inc., KFH Group, Inc., Parsons Brinckerhoff Quade & Douglas, Inc., and Hunter-Zaworski, Katherine. (2003) Transit Capacity and Quality of Service Manual, 2nd Edition. *TRB, National Research Council, TCRP Report 100*, Washington, D.C.

14. McCain Traffic Supply. (2004) AVITSP System Operations Manual – Including System Enhancements.

15. National Transit Database. (2004) Transit Profiles All Reporting Agencies. Federal Transit Administration.

16. PTV Planung Transport Verkehr AG. (2004) 'VISSIM User's Manual'. Version 4.00. Karlsruhe, Germany.

17. Skehan, S. (2003) 'Traffic Signal Priority's Role in Bus Rapid Transit'. *Proceedings of 2003 Annual Meeting and Exhibit, Institute of Transportation Engineers.*

18. Sunkari, Srinivasa R., Phillip S. Beasley, Thomas Urbanik II, and Daniel B Fambro. (1995) 'Model to Evaluate the Impacts of Bus Priority on Signalized Intersections'. *Transportation Research Record,* No. 1494, National Research Council, Washington, D.C., pp. 117-123.

19. *Highway Capacity Manual 2000* (2000) Transportation Research Board, National Research Council, Washington, D.C.

20. Yand, M.C. (2004) 'Effective Transit Signal Priority'. *Proceedings of 2004 Annual Meeting and Exhibit, Institute of Transportation Engineers.*

21. Zheng, Jianyang, Yinhai Wang, Hongchao Liu, and Mark E. Hallenbeck. (2007) 'Modeling the Impact of Near-Side Bus Stop on Transit Delays at Transit Signal Priority Enabled Intersections'. *The 86st Annual Meeting of the Transportation Research Board (CD-ROM), National Research Council,* Washington, D.C.

Chapter 7 Summary and Future Research

Summary of Research

In this research, we developed a comprehensive strategy that quantitatively measures intersection performance in real-time with traffic counting data collected with traditional traffic sensors. The strategy contains several algorithms for measuring important traffic parameters including average control delays, queue length, and signal cycle failures.

Based on the vehicle count data collected at the entrance and exit of the detection zone, the control delay estimation algorithm estimates the queue lengths inside the zone at right-turn, through, and left-turn lanes. With the estimated queue length, this algorithm calculates the corresponding control delays. Signal cycle failures can be calculated with the estimated queue length. A real-time system, which is called InterPer, was developed to demonstrate the algorithms and was tested with field data. A simulation model was also built up and applied to test the algorithm under ideal situations.

A system for intersection performance measurement using video image processing was also proposed for locations with no other traffic sensors except for one video camera for each approach. An innovative video image processing algorithm for detecting cycle failure by tracking the end-of-queue in traffic was also developed in this study. Background subtraction was used for this task. To make the background extraction process more robust, a mode-based background extraction algorithm was developed and proven to be effective using field collected videos.

Since this research is closely related to the project of evaluating SS-RTSP system, the author also introduced part of his work on this project. To evaluate the impact of the SS-RTSP system on local traffic, intersection performances were quantified and compared with TSP on and off. This SS-RTSP system evaluation serves as an example of potential applications of the intersection performance measurement system described in this study.

Conclusion

The InterPer system was tested with field data. The test results showed that the estimated queue lengths and control delays were slightly lower than the ground truth data. These errors were largely due to count errors with the VIPs. In average, the estimation error for control delay was about 3 second/vehicle. In practice, estimation error of control delay in a couple of seconds range is certainly acceptable. Its impact on determination of the intersection's LOS would be marginal. To further evaluate the performance of the proposed control delay estimation algorithm, simulation experiments were conducted. The simulation tests showed that the algorithm is reliable and robust in measuring intersection performances under ideal situations. The queue length measured in simulation model was very close to the ground truth value. The average of simulated control delay was 4.6 seconds per vehicle, with the average of ground truth data of 4.3 second per vehicle. The control delay estimation algorithm is proven to be reasonably accurate when detector errors are eliminated.

The author also developed and tested a video image processing system that detects signal cycle failures. The system was evaluated using field collected video slips. The test results showed that the proposed video image processing algorithm for cycle failure detection is encouraging. During the nearly 200 minutes of test periods, the cycle failure detection system captured all 21 cycle failures, and detection accuracy was approximately 99.1%; the system generated only three false alarms, which was approximately 0.9% of the total cycles tested.

Future Works

The current algorithm assumed that the layout of the intersection and traffic sensors is ideal, which limits its application at many locations. In the future, the algorithm will be improved to enhance its ability to measure intersection performance at locations with non-ideal layout, such as at intersections with shared through-right or shared through-left lanes.

The ideal video image processing system needs to be completed. In this research, only two modules were developed: extracting background image and detecting cycle failure. Other modules, such as the feature-based vehicle detection and tracking, measuring queue length, and calculating control delay modules need be developed to complete the proposed system for intersection performance measurements.

LIST OF REFERENCES

1. Abdelghany, Ahmed and Billy Connor. (2006) Guidelines for Operating Traffic Signals during Low-Volume Conditions. *Report No. INE/autc 06.21,* Transportation Northwest (TransNow), Seattle, Washington State.

2. Abdulhai, B., A. Shalaby, J. Lee, and A. Georgi. (2002) 'Microsimulation Modeling and Impact Assessment of Streetcar Transit Priority Options: the Toronto Experience'. *The 81st Annual Meeting of the Transportation Research Board (CD-ROM), National Research Council,* Washington, D.C.

3. Al-Deek, Haitham M. and Chilakamarri Venkata Srinivasa Ravi Chandra. (2004) 'New Algorithms for Filtering and Imputation of Real-Time and Archived Dual-Loop Detector Data in I-4 Data Warehouse'. *Transportation Research Record*, No. 1867, Transportation Research Council, Washington D.C., pp. 116-126.

4. Al-Sahili, K.A., and W.C. Taylor (1995) 'Evaluation of Bus Priority Signal Strategies in Ann Arbor, Michigan'. *Transportation Research Record,* No. 1554, National Research Council, Washington, D.C., pp. 74-79.

5. Avery, R. P., Y. Wang, and S. G. Rutherford. (2004) 'Length-Based Vehicle Classification Using Images from Uncalibrated Video Cameras'. *Proceedings of the 7th International IEEE Conference on Intelligent Transportation Systems*, October 2004, pp. 737-742.

6. Baldwin, C L and J T Coyne. (2003) 'Mental Workload as a Function of Traffic Density: Comparison of Physiological, Behavioral, and Subjective Indices'. *Proceedings of the Second International Driving Symposium on Human Factors in Driver Assessment, Training and Vehicle Design*, Park City, Utah State, pp. 19-24.

7. Baker, R.J., J. Collura, J.J. Dale, L. Head, B. Hemily, M. Ivanovic, J.T. Jarzab, D. McCormick, J. Obenberger, L. Smith,, and G.R. Stoppenhagen. (2002) *An Overview of Transit Signal Priority.* Intelligent Transportation Society of America, Washington, D.C., 2002.

8. Beymer, D., P. Mclauchlan, B. Coifman, and J. Malik. (1997) 'A Real Time Computer Vision System for Measuring Traffic Parameters'. *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition*, pp 495-501.

9. Carrano, Frank M., Paul Helman and Robert Veroff. (1998) *Data Abstraction and Problem Solving with C++*, 2nd edition, Addison Wesley Longman.

10. Carter, A. (2002) 'GPS KEEPS TRANSIT AGENCIES ON TRACK'. *Metro Magazine*, Vol. 98, No. 3.

11. Chada, S., and R. Newland. (2002) Effectiveness of Bus Signal Priority – Final Report. *Report NCTR-416-04*, National Center for Transit Research, University of South Florida, FL.

12. Chang, E., and A. Ziliaskopoulos. (2003) 'Data Challenges in the Development of a Regional Assignment-Simulation Model to Evaluate Transit Signal Priority in Chicago'. *The 82nd Annual Meeting of the Transportation Research Board (CD-ROM), National Research Council,* Washington, D.C.

13. Chang, Gang-Len and Chih-Chiang Su. (1995) 'Predicting Intersection Queue with Neural Network Models'. *Transportation Research Part C: Emerging Technologies*, Vol. 3, No. 3, pp. 175-191.

14. Chang, G.-L., M. Vasudevan, and C.C. Su. (1995) 'Bus preemption under adaptive control environments'. *Transportation Research Record,* No. 1494, National Research Council, Washington, D.C., pp. 146-154.

15. Cheevarunothai, Patikhom, Yinhai Wang, and Nancy L. Nihan. (2005) 'Development of Advanced Loop Event Data Analyzer (ALEDA) System for Dual-Loop Malfunction Identification'. *Proceedings of the 12th World Congress on ITS*, San Francisco, California State.

16. Cheevarunothai, Patikhom, Yinhai Wang, and Nancy L. Nihan. (2006) 'Identification and Correction of Dual-Loop Sensitivity Problems'. *Transportation Research Record*, No. 1945, Transportation Research Council, Washington D.C., pp. 73-81.

17. Chen, Chao, Karl Petty, Alexander Skabardonis, Pravin Varaiya, Jia Zhanfeng. (2001) 'Freeway Performance Measurement System: Mining Loop Detector Data'. *Transportation Research Record,* No. 1748, National Research Council, Washington, D.C., pp. 96-102.

18. Chung, K, J Rudjanakanoknad, and M J Cassidy. (2007) 'Relation between Traffic Density and Capacity Drop at Three Freeway Bottlenecks'. *Transportation Research. Part B: Methodological*, Vol. 41, No. 1, pp. 82-95.

19. Coifman, Benjamin. (2006) 'Vehicle Level Evaluation of Loop Detectors and the Remote Traffic Microwave Sensor'. *Journal of Transportation Engineering*, Vol. 132 No. 3, pp. 213-226.

20. Coifman, Benjamin. (1999) 'Using Dual Loop Speed Traps to Identify Detector Errors'. *Transportation Research Record*, No. 1683, Transportation Research Council, Washington D.C., pp. 47-58.

21. Coifman, Benjamin and Sivaraman Krishnamurthy. (2007) 'Vehicle Reidentification and Travel Time Measurement across Freeway Junctions Using the Existing Detector Infrastructure'. *Transportation Research Part C: Emerging Technologies,* Vol. 15, No. 3, pp. 135-153.

22. Collura, J., H. Rakha, and J. Guifford (2006) Guidelines for the Planning and Deployment of Emergency Vehicle Preemption and Transit Priority Strategies. Research Report, Virginia Tech Transportation Institute.

23. Colyar, JD and NM Rouphail. (2003) 'Measured Distributions of Control Delay on Signalized Arterials'. *Transportation Research Record*, No. 1852, Transportation Research Council, Washington D.C., pp. 1-9.

24. Community Transit. (2005) Addendum to Results of Service Quality Monitor On-Board Survey Data: September 2004 – February 2005.

25. Community Transit and David Evans and Associates, Inc. (2003) South Snohomish Regional Transit Signal Priority Intersection Inventory.

26. Cucchiara, R., C. Grana, and M. Piccardi, and A. Prati. (2003) 'Detecting Moving Objects, Ghosts and Shadows in Video Streams'. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 25, No. 10, pp. 1337-1342.

27. Davis, G A. (1998) 'Method for Estimating Effect of Traffic Volume and Speed on Pedestrian Safety for Residential Streets', *Transportation Research Record,* No. 1636, National Research Council, Washington, D.C., pp. 110-115.

28. Davis, Gary and Shimin Yang. (2001) 'Accounting for Uncertainty in Estimates of Total Traffic Volume: An Empirical Bayes Approach'. *Journal of Transportation and Statistics,* Vol. 4, No. 1, pp. 27-38.

29. Dion, F., H. Rakha, and Y. Zhang. (2002) 'Evaluation of Potential Transit Signal Priority Benefits along a Fixed-Time Signalized Arterial'. *The 81st Annual Meeting of the Transportation Research Board (CD-ROM), National Research Council,* Washington, D.C.

30. Elgammal, A., D. Harwood, and L. Davis. (1999) 'Non-parametric Model for Background Subtraction'. *Proceedings of IEEE International Conference, Computer Vision '99 FRAME-RATE Workshop,* 1999.

31. Evanchik, Daniel M, Matthew G Best, Brian L Smith, and William T Scherer. (2006) 'Speed Index: Scalable Operations Performance Measure Based on Available Data'. *Transportation Research Record*, No. 1956, National Research Council, Washington, D.C., pp. 14-20.

32. Fathy, M. and M. Y. Siyal. (1995) 'Real-time Image Processing Approach to Measure Traffic Queue Parameters'. *IEE proceedings: Vision, image, and signal processing,* Vol. 142, No. 5.

33. Fathy, M. and M. Y. Siyal. (1998) 'A Window-Based Image Processing Technique for Quantitative and Qualitative Analysis of Road Traffic Parameters'. *IEEE Transactions on Vehicular Technology,* Vol. 47, No. 4.

34. Federal Highway Administration, (2003) Freeway Operation Handbook. *FHWA Report No. FHWA-OP-04-003.* United States Department of Transportation, Washington, D.C.

35. Federal Highway Administration and Federal Transit Administration, (2006) *2006 Status of the Nation's Highways, Bridges, and Transit: Conditions and Performance*. United States Department of Transportation, Washington, D.C.

36. Fu, Liping, Bruce Helling and Yongliang Zhu. (2001) 'An Adaptive Model for Real-time Estimation of Overflow Queues on Congested Arterials'. *2001 IEEE Intelligent Transportation Systems Conference Proceedings*, Oakland, California State.

37. Garrow, M., and R. Machemehl. (1997) Development and Evaluation of Transit Signal Priority Strategies. *Research Report SWUTC/97/472840-00068-1*, Southwest Region University Transportation Center, Center for Transportation Research, University of Texas, Austin, Texas.

38. Grewal, Mohinder S., Lawrence R. Weill, and Angus P. Anderews. (2001) *Global Positioning Systems, Inertial Navigation, and Integration*. New York, NY: John Wiley & Sons, Inc.

39. Gupte, Surendra, Osama Masoud, Robert F. K. Martin, and Nikolaos P. Papanikolopoulos. (2002) 'Detection and Classification of Vehicles'. *IEEE Transactions on Intelligent Transportation Systems,* Vol. 3, No. 1.

40. Hajek, Jerry J., Olga I. Selezneva, Goran Mladenovic, and Y. Jane Jiang. (2005) Estimating Cumulative Traffic Loads, Volume II: Traffic Data Assessment and Axle Load Projection for the Sites with Acceptable Axle Weight Data, Final Report for Phase 2. *FHWA Report No. FHWA-RD-03-094*, United States Department of transportation, Federal Highway Administration, Washington, D.C.

41. Higashikubo, Masakatsu, Toshio Hinenoya, and Kouhei Takeuchi. (1997) 'Traffic Queue Length Measurement Using an Image Processing Sensor'. *Sumitomo Electric Technical Review,* No. 43, pp. 64-68.

42. *Highway Capacity Manual 2000* (2000) Transportation Research Board, National Research Council, Washington, D.C.

43. Hoeschen, Brian, Darcy Bullock, and Mark Schlappi. (2005) 'Estimating Intersection Control Delay Using Large Data Sets of Travel Time from a Global Positioning System'. *Transportation Research Record,* No. 1917, National Research Council, Washington, D.C., pp. 18-27.

44. Ishimaru, John M., and Mark E Hallenbeck. (1999) Flow Evaluation Design Technical Report. *Technical Report WA-RD 466.2*, Washington Department of Transportation, Washington State.

45. Itoh, T. (1986) 'Navigation system using GPS for vehicles'. *Society of Automotive Engineers Transactions*, pp. 5.236–5.248.

46. Joksch, H C and L P Kostyniuk. (1997) Modeling Intersection Crash Counts and Traffic Volume. *FHWA Report No. FHWA-RD-98-096,* United States Department of transportation, Federal Highway Administration, Washington, D.C.

47. Kell, James H., Iris J. Fullerton, and Milton K. Mills. (1990) Traffic Detector Handbook. Second Edition. *FHWA Report No. FHWA-IP-90-002*, United States Department of transportation, Federal Highway Administration, Washington, D.C.

48. Khattak, Asad, Yingling Fan, and Elizabeth Shay. (2007) 'What Do ITS Publications and Patents Tell Us?' *Journal of Intelligent Transportation Systems,* Vol. 11 No. 2, pp. 91-103.

49. Kim, Z. and J. Malik. (2003) 'Fast Vehicle Detection with Probabilistic Feature Grouping and its Application to Vehicle Tracking'. *Proceedings of IEEE International Conference on Vision,* vol. 1, pp 524-531.

50. King County Department of Transportation. (2002) 'An Evaluation of Transit Signal Priority on Aurora Avenue North'. King County Department of Transportation, Transit Speed and Reliability Program.

51. Kittelson & Associates, Inc., KFH Group, Inc., Parsons Brinckerhoff Quade & Douglas, Inc., and Hunter-Zaworski, Katherine. (2003) Transit Capacity and Quality of Service Manual, 2nd Edition. *TRB, National Research Council, TCRP Report 100*, Washington, D.C.

52. Klein, Lawrence A. (2001) *Sensor Technologies and Data Requirements for ITS*, Boston: Artech House.

53. Larson, B. (2001) Real-Time Signal Control Using Queue Length Information Deployed at an Intersection. *ITS-IDEA Project 71, Final Report*, Transportation Research Board, Washington, D.C.

54. Lomax, T., S. Tumer, G. Shunk, H. Levinson, R. Pratt, P. Bay, and G. Douglas. (1997) Quantifying Congestion. Volume 1: Final Report. *NCHRP Report No. 398*, National Cooperative Highway Research Program, Transportation Research Board, Washington, D.C.

55. Malik, Jitendra and Stuart Russell. (1997) Traffic Surveillance and Detection Technology Development: New Sensor Technology Final report. *Research Report UCB-ITS-PRR-97-6*, California PATH Program.

56. McCain Traffic Supply. (2004) AVITSP System Operations Manual – Including System Enhancements.

57. Middleton, D., D. Jasek, and R. Parker. (1999) Evaluation of Some Existing Technologies for Vehicle Detection. *FHWA Report No. FHWA/TX-00/1715-S*, Texas Transportation Institute, College Station, Texas State.

58. Minnesota Department of Transportation and SRF Consulting Group, Inc. (2001) Evaluation of Non-Intrusive Technologies for Traffic Detection, Volume One Report. United States Department of transportation, Federal Highway Administration, Washington, D.C.

59. Mistele, Bryan. (2007) 'Here and Now: How the North American Traffic Data Market Has Evolved'. *Traffic Technology International.* pp 46-50.

60. National ITS Architecture Team, (2001) *Regional ITS Architecture Guidance: Developing, Using and Maintaining and ITS Architecture for Your Region.* Executive Summary, United States Department of Transportation, Washington, D.C.

61. National Highway Traffic Safety Administration. (1983) 'Basic Training Program in RADAR Speed Measurement: Trainee Instructional Manual'. United States Department of transportation, Federal Highway Administration, Washington, D.C.

62. National Transit Database. (2004) Transit Profiles All Reporting Agencies. Federal Transit Administration.

63. Otsu, N. (1979). 'A Threshold Selection Method from Gray-Level Histograms'. *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 9, no. 1, pp. 62-66.

64. PTV Planung Transport Verkehr AG. (2004) 'VISSIM User's Manual'. Version 4.00. Karlsruhe, Germany.

65. Quiroga, C. and D. Bullock. (1999) 'Measuring Control Delay at Signalized Intersections'. *Journal of Transportation Engineering*, ASCE, Vol. 125, No. 4, pp. 271-280.

66. Reardon, L. (2001) 'Traffic Calming: Creatively Mitigating Traffic Speeds and Volume'. *Civil Engineering News,* Vol. 13, No. 10, pp. 52-56.

67. Rojas, Juan Carlos and Jill D. Crisman. (1997) 'Vehicle Detection in Color Images'. *Proceedings of the IEEE Intelligent Transportation System Conference*, 1997.

68. Saito, Mitsuru, Jaylen Walker, and Alan Zundel. (2001) 'Using Image Analysis to Estimate Average Stopped Delays per Vehicle at Signalized Intersections'. *The 80th Annual Meeting of the Transportation Research Board (CD-ROM), National Research Council,* Washington, D.C.

69. Schafer, R., K. Thiessenhusen and P. Wagner. (2002) 'A traffic information system by means of real-time floating-car data'. *Proceedings of 9th World Congress on Intelligent Transport Systems information*, ITS America, Berlin, Germany.

70. Schoepflin, Todd N and Daniel J Dailey. (2003) 'Dynamic Camera Calibration of Roadside Traffic Management Cameras for Vehicle Speed Estimation'. *IEEE transactions on intelligent transportation systems,* Vol. 4, No. 2, pp. 90-98.

71. Seymour, Edward J. and James D. Carvell. (2005) Interim Guidelines for Data Access for Texas Traffic Management Centers. *FHWA Report No. FHWA/TX-05/Report 0-5213-P1*, Texas Department of Transportation and United States Department of Transportation, Federal Highway Administration, Washington D.C.

72. Shapiro, L.G. and G.C. Stockman. (2001) *Computer Vision.* Prentice Hall, New Jersey.

73. Shuldiner, P W, S A D'Agostino, and J B Woodson. (1996) 'Determining Detailed Origin-Destination and Travel Time Patterns Using Video and Machine Vision

License Plate Matching'. *Transportation Research Record,* No. 1551, National Research Council, Washington, D.C., pp. 8-17.

74. Skehan, S. (2003) 'Traffic Signal Priority's Role in Bus Rapid Transit'. *Proceedings of 2003 Annual Meeting and Exhibit, Institute of Transportation Engineers.*

75. Skerritt, W H. (1993) 'Aggregate Type and Traffic Volume as Controlling Factors in Bituminous Pavement Friction'. *Transportation Research Record,* No. 1418, National Research Council, Washington, D.C., pp. 22-29.

76. Stauffer, C. and W. E. L. Grimson. (1999) 'Adaptive Background Mixture Models for Real Time Tracking'. *Proceedings of IEEE international conference, Computer Vision and Pattern Recognition*, pp. 246-252.

77. Sunkari, Srinivasa R., Phillip S. Beasley, Thomas Urbanik II, and Daniel B Fambro. (1995) 'Model to Evaluate the Impacts of Bus Priority on Signalized Intersections'. *Transportation Research Record,* No. 1494, National Research Council, Washington, D.C., pp. 117-123.

78. Texas Transportation Institute (TTI). (2000) 'Houston TranStar Annual Report – 1999'. Texas Department of Transportation.

79. Turner, S M. (1996) 'Advanced techniques for travel time data collection'. *Transportation Research Record,* No. 1551, National Research Council, Washington, D.C., pp. 51-58.

80. United States Department of Transportation, (1998) *Transportation Equity Act for the 21st Century: A Summary.* United States Department of Transportation, Washington, D.C.

81. United States Department of Transportation, (2007) *Federal Intelligent Transportation Systems (ITS) Program.* [Online], Available: http://www.itsoverview.its.dot.gov. [June 2007].

82. Vlcek, Charles, Patricia McLain, and Michael Murphy. (1993) 'GPS/Dead Reckoning for Vehicle Tracking in the 'Urban Canyon' Environment'.

Proceedings of the IEEE Vehicle Navigation & Information Systems Conference, Ottawa-VNIS'93.

83. Weber, Nathan A. (1999) Verification of RADAR Vehicle Detection Equipment. *Study SD98-15*, final report, South Dakota Department of Transportation, Pierre, South Dakota.

84. Wald, W. M. (2004). Microwave vehicle detection. *Final report*, Caltrans, Office of ITS Development and Support, HQ Traffic Operations. [Online], Available: http://www.dot.ca.gov/hq/traffops/elecsys/reports/FinalMVDS104.pdf. [August 2007].

85. Wang, Yinhai, and Nancy L. Nihan. (2003) 'Can Single-Loop Detectors Do the Work of Dual-Loop Detectors?' *Journal of Transportation Engineering*, ASCE, 129(2), pp. 169-176.

86. Wang, Yinhai, and Nancy L. Nihan. (2000) 'Freeway Traffic Speed Estimation Using Single Loop Outputs'. *Transportation Research Record,* No. 1727, National Research Council, Washington, D.C., pp. 120-126.

87. Weiss, J. David and Frank Shields. (1998) 'GPS/INS Integration in a Severe Urban Environment'. *Proceedings of IEEE 1998.*

88. Wunnava, Subbarao V, Kang Yen, Tadeusz Babij, Richard Zavaleta, Rafael Romero, and Christian Archilla. (2007) Travel Time Estimation Using Cell Phones (TTECP) for Highways and Roadways. *Contract BD015-12, Final Report*, Florida Department of Transportation, Tallahassee, Florida State.

89. Yand, M.C. (2004) 'Effective Transit Signal Priority'. *Proceedings of 2004 Annual Meeting and Exhibit, Institute of Transportation Engineers.*

90. Yi, Ping, Clara Xin and Qiang Zhao. (2001) 'Implementation and Field Testing of Characteristics-Based Intersection Queue Estimation Model'. *Networks and Spatial Economics*, Vol. 1, No. 1, pp. 205-222.

91. Yin, Zhaozheng, Fan Yang, Henry X. Liu, and Bin Ran. (2004) 'Using Image Sensors to Measure Real-time Traffic Flow Parameters'. *The 83rd Annual Meeting*

of the Transportation Research Board (CD-ROM), National Research Council, Washington, D.C.

92. Zheng, Jianyang, Guohui Zhang, Yinhai Wang, and Peter M. Briglia Jr. (2008) 'Comprehensive Evaluation of a Transit Signal Priority System Using Observed and Simulated Traffic Data', *The 87th Annual Meeting of the Transportation Research Board (CD-ROM), National Research Council,* Washington, D.C.

93. Zheng, Jianyang, Yinhai Wang, Hongchao Liu, and Mark E. Hallenbeck. (2007) 'Modeling the Impact of Near-Side Bus Stop on Transit Delays at Transit Signal Priority Enabled Intersections'. *The 86st Annual Meeting of the Transportation Research Board (CD-ROM), National Research Council,* Washington, D.C.

94. Zheng, Jianyang, Yinhai Wang, and Nihan, L. Nihan. (2005) 'Quantitative evaluation of GPS performance under forest canopies', *2005 IEEE International Conference on Networking, Sensing and Control (IEEE Cat. No.05EX967)*, pp. 777-782.

95. Zheng, Jianyang, Yinhai Wang, Nancy L. Nihan, and Mark E. Hallenbeck. (2006) 'Detecting Cycle Failures at Signalized Intersections Using Video Image Processing', *Computer-Aided Civil and Infrastructure Engineering*, Vol. 21, No. 6, pp. 425–435.

96. Zheng, Jianyang, Yinhai Wang, Nancy L. Nihan, and Mark E. Hallenbeck. (2006) 'Extracting Roadway Background Image: a Mode-Based Approach', *Transportation Research Record,* No. 1944, National Research Council, Washington, D.C., pp.82-88.

97. Zwahlen, Helmut T, Andrew Russ, Erdinc Oner, and Meghna Parthasarathy. (2005) 'Evaluation of Microwave RADAR Trailers for Nonintrusive Traffic Measurements'. *Transportation Research Record,* No. 1917, National Research Council, Washington, D.C., pp. 127-140.

CURRICULUM VITAE

EDUCATION

Ph.D. **University of Washington**
Transportation Engineering, March 2008 (expected)
Dissertation Topic: *Measuring Signalized Intersection Performances with Traffic Sensors.* (Supervised by Yinhai Wang and Nancy L. Nihan)

M.S. **University of Washington**
Transportation Engineering, December 2002
Thesis: *Performance Evaluation of the GPS/INS Integrated System in Forest Environment and Urban Area.* (Supervised by Nancy L. Nihan)

B.Eng. **Tsinghua University, Beijing, China**
Civil Engineering, July 1997
Thesis: *Interactive Graphic Geologic Information Input System.* (Supervised by Aizhu Ren)

AWARDS AND HONORS

First place in scholarship awards competition of Institute of Transportation Engineers (ITE) Washington State Section, 2006

CERTIFICATIONS

Professional Engineer, Washington State, 2007

Certificate in Global Trade, Transportation, and Logistics, University of Washington, 2004

RESEARCH INTERESTS

- Video image processing
- Traffic signal control
- Transit priority
- Vehicle tracking
- Transportation simulation

- Pedestrian and bicycle transportation
- Advanced traveler information system
- Traffic safety

PUBLICATIONS

Peer Reviewed Journal Papers:

1. Zheng, Jianyang, Yinhai Wang, Nancy L. Nihan, and Mark E. Hallenbeck. (2006) 'Detecting Cycle Failures at Signalized Intersections Using Video Image Processing', *Computer-Aided Civil and Infrastructure Engineering*, Vol. 21, No. 6, pp. 425–435.
2. Zheng, Jianyang, Yinhai Wang, Nancy L. Nihan, and Mark E. Hallenbeck. (2006) 'Extracting Roadway Background Image: a Mode-Based Approach', *Transportation Research Record,* No. 1944, National Research Council, Washington, D.C., pp.82-88.

Peer Reviewed Conference Papers:

1. Zheng, Jianyang, Guohui Zhang, Yinhai Wang, and Peter M. Briglia Jr. (2008) 'Comprehensive Evaluation of a Transit Signal Priority System Using Observed and Simulated Traffic Data', *Proceedings of Transportation Research Record (CD-Rom).*
2. Malinovskiy, Yegor, Jianyang Zheng and Yinhai Wang. (2007) 'A Simple and Model-Free Algorithm for Real-Time Pedestrian Detection and Tracking', *Proceedings of Transportation Research Record (CD-Rom).*
3. Zheng, Jianyang, Yinhai Wang, and Nihan, L. Nihan. (2005) 'Quantitative evaluation of GPS performance under forest canopies', *2005 IEEE International Conference on Networking, Sensing and Control (IEEE Cat. No.05EX967)*, pp. 777-782.
4. Zheng, Jianyang, Yinhai Wang, and Nancy L. Nihan. (2003) 'Tracking Vehicles: Is GPS a Sufficient Solution?' Proceedings of *the 13th Annual Meeting of ITS America (CD-Rom).*

Conference Presentations:

1. Zheng, Jianyang, Guohui Zhang, Yinhai Wang, and Peter M. Briglia Jr. 'Comprehensive Evaluation of a Transit Signal Priority System Using Observed and Simulated Traffic Data', presented at the 87th Annual Meeting of the Transportation Research Board, Washington, D.C., January 2008.

2. Zheng, Jianyang, Yinhai Wang, Hongchao Liu, and Mark E. Hallenbeck. 'Modeling the Impact of Near-Side Bus Stop on Transit Delays at Transit Signal Priority Enabled Intersections', presented at the 86^{th} Annual Meeting of the Transportation Research Board, Washington, D.C., January 2007.

3. Yinhai Wang, Jianyang Zheng, Guohui Zhang, and Yegor Malinovskiy. 'Traffic Detection Using Video Image Processing', presented at the ITS Washington Annual meeting, Bellevue, Washington, October 2006.

4. Zheng, Jianyang Zheng. 'How Did the Transit Signal Priority Work in Our Neighborhood?' presented at the Institute of Transportation Engineers (ITE) Washington State Section student night, Seattle, Washington, April 2006.

5. Zheng, Jianyang, Yinhai Wang, Nancy L. Nihan, and Mark E. Hallenbeck. 'Extracting Roadway Background Image: a Mode-Based Approach', presented at the 85^{th} Annual Meeting of the Transportation Research Board, Washington, D.C., January 2006.

6. Zheng, Jianyang, Yinhai Wang, and Nihan, L. Nihan. 'Quantitative evaluation of GPS performance under forest canopies', presented at the 2005 IEEE International Conference on Networking, Sensing and Control, Tucson, Arizona, March 2005.

7. Zheng, Jianyang, Yinhai Wang, Nancy L. Nihan, and Mark E. Hallenbeck. 'Detecting Cycle Failures at Signalized Intersections Using Video Image Processing', presented at the 84^{th} Annual Meeting of the Transportation Research Board, Washington, D.C., January 2005.

Report:

1. Zheng, Jianyang, Guohui Zhang, and Yinhai Wang. (2006) Comprehensive Evaluation on Transit Signal Priority System Impacts Using Field Observed Traffic Data (Phase One). *Research Report TNW2006-10*, Transportation Northwest (TransNow), the US Department of Transportation University Transportation Center for Federal Region 10, at the University of Washington, Seattle, Washington State.

RESEARCH EXPERIENCE

1. Evaluation of the South Snohomish Regional Transit Signal Priority (SS-RTSP), January 2003 ~ December 2006 (expected)

   Test and analysis the impact of transit signal priority to transit and local traffic. Research is support by the Washington State Department of Transportation (WSDOT) with funding of about $300,000. (Supervisor: Yinhai Wang)

2. Navigation with Inertial Navigation Systems, October 2001 ~ December 2002

   Test of the Applanix POS LS inertial positioning system for the collection of terrestrial coordinates under a heavy forest canopy. This research is supported by the Precision Forestry Cooperative, University of Washington. (Supervisor: Yinhai Wang and Kamal M. Ahmed)

TEACHING EXPERIENCE

Transportation Data Management and Analysis (CEE 412/599), autumn 2005

Responsibility: grade homework, projects and exams, assist students through lab practices, give brief lectures about students' performance.

INDUSTRIAL EXPERIENCE

1. Transportation Engineer, State Highway Administration, Maryland Department of Transportation, 2007~current

   Responsibility: review traffic impact study; provide solutions to traffic operation and safety concerns.

2. Intern, Seattle Department of Transportation, 2007

   Responsibility: monitor traffic operation; troubleshoot traffic signal control system; analyze and optimize traffic signal system operation and reliability; present and analyze traffic data.

3. Civil Engineer, Beijing 1st Construction Engineering Co., Beijing, China, 1997~2001

   Responsibility: monitor and control schedule, quality and budget of construction projects; provide technical support and detailed design for construction projects

REVIEWER

Reviewer of IEEE International Conference on Intelligent Transportation Systems (ITSC), 2005~2006

Reviewer of Transportation Research Board (TRB), 2005~2007

SERVICE

Coordinator of the STAR Lab, University of Washington, 2006

Volunteer at the Engineering Open House, University of Washington, 2002 ~ 2007

PROFESSIONAL AFFILIATION

Transportation Research Board (TRB), 2004 ~ present

Institute of Transportation Engineers (ITE), 2001 ~ present

American Society of Civil Engineers (ASCE), 2001 ~ present

PROFESSIONAL TRAINING

Training at the Future Trends in Energy, Technology and Transportation Workshops, Cascadia Discovery Institute, 2006

Training on traffic signal control in the City of Lynnwood, 2005

Training on ACTRA and i2TMS by Siemens, 2005 and 2006