University Transportation Research Center - Region 2

Final Report

Heterogeneous Regional Signal Control

Performing Organization: State University of New York (SUNY)

March 2017

Sponsor:
University Transportation Research Center - Region 2

University Transportation Research Center - Region 2

The Region 2 University Transportation Research Center (UTRC) is one of ten original University Transportation Centers established in 1987 by the U.S. Congress. These Centers were established with the recognition that transportation plays a key role in the nation's economy and the quality of life of its citizens. University faculty members provide a critical link in resolving our national and regional transportation problems while training the professionals who address our transportation systems and their customers on a daily basis.

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16. Abstract

The goal of this project is to develop a comprehensive framework with a set of models to improve multi-modal traffic signal control, by incorporating advanced floating sensor data (e.g. GPS data, etc.) and traditional fixed sensor data (e.g. loop detectors, etc.). In order to accomplish this goal, we completed five tasks. First, we conduct a comprehensive survey with transportation professionals, who can bring up existing state-of-practice, open issues and future challenges in multi-modal traffic signal control. This survey also identifies the weights of travel modes under different scenarios. Second, by leveraging floating sensors (smartphones), we develop an online travel model identification algorithm and a smartphone app to automatically recognize people's travel modes, including passenger cars, transit buses, light rail as well as bicycles and pedestrians (including both jogging and walking). Third, by analyzing large scale of 15,000 fixed sensors (loop detectors) in a transportation network, we build a compression theory based approach to identify the spatial and temporal anomaly condition in the traffic network, caused by day-to-day commuting or traffic incidents. Fourth, by using multi-modal trajectory data, we develop multi-modal signal control models with dynamic programming and leverage the results derived from previous tasks. Further, the proposed control model is evaluated by microscopic simulation VISSIM and externally developed signal control modules.

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EXECUTIVE SUMMARY

The goal of this project is to develop a comprehensive framework with a set of models to improve multi-modal traffic signal control, by incorporating advanced floating sensor data (e.g. GPS data, etc.) and traditional fixed sensor data (e.g. loop detectors, etc.). In order to accomplish this goal, we completed five tasks. First, we conduct a comprehensive survey with transportation professionals, who can bring up existing state-of-practice, open issues and future challenges in multi-modal traffic signal control. This survey also identifies the weights of travel modes under different scenarios. Second, by leveraging floating sensors (smartphones), we develop an online travel model identification algorithm and a smartphone app to automatically recognize people's travel modes, including passenger cars, transit buses, light rail as well as bicycles and pedestrians (including both jogging and walking). Third, by analyzing large scale of 15,000 fixed sensors (loop detectors) in a transportation network, we build a compression theory based approach to identify the spatial and temporal anomaly condition in the traffic network, caused by day-to-day commuting or traffic incidents. Fourth, by using multi-modal trajectory data, we develop multi-modal signal control models with dynamic programming and leverage the results derived from previous tasks. Further, the proposed control model is evaluated by microscopic simulation VISSIM and externally developed signal control modules.

Major findings and recommendations are summarized as follows:

1. According to the survey among experienced practitioners, multi-modal signal control is very importation for signal operations. However, when it comes to implementation, there exist multiple major challenges, including funding support, human resources and related training.
2. The survey also first reveals the rank for different travel modes. For day-to-day operations, the descending rank of travel modes (including emergency vehicles and passenger cars) is emergency vehicles > light rail > buses > pedestrians > bicycles > trucks > passenger cars. Compared to peak hour, the truck weights increase during off-peak hours, whereas the weights for all other modes decrease. It indicates that we should encourage off-peak truck delivery and assign proper truck signal priority for off-peak hours. For a planned special event (e.g. sporting games, concerts, running races, etc.) with massive pedestrians, the descending rank of travel modes is emergency vehicles > pedestrians > light rail > buses > bicycles > trucks > passenger cars. Given

safety concerns with massive pedestrians, pedestrians are assigned with the highest weight except for emergency vehicles.

3. This research proposes a real-time and network-free method to detect a user's travel mode using smartphones, as floating sensors. Our application is built on the latest Android phones and iPhones with multimodality sensors. By carefully designing the time domain and frequency domain features; together with a hierarchical classification model, we achieve 100% accuracy in a binary classification wheeled/non-wheeled travel mode, and an average of 97.1% in all the six travel modes.
4. This study develops an online updating method for smartphone-based travel mode identification to achieve superior performance in time cost and it does not rely on data scale. In contrast to from previous work, the proposed solution is designed with energy concerns (small sampling frequency for mobile phones), fast server response (slide window segmentation) and quick start (a small portion of initial training dataset). These advantages ensure our method is practical in realistic applications.
5. This project, as a first attempt, leverages dictionary-based compression theory for the regional traffic pattern identification and anomaly detection based on fixed traffic sensors within a large-scale of traffic networks. Three different levels of the network are considered: sub-region, intersection, and detector.
6. An anomaly degree index is derived to describe and quantify both spatial and temporal traffic pattern. The spatial pattern identification shows meaningful results of concurrent traffic patterns: Over a certain time period, the regional spatial pattern shows a clear geographic distribution of abnormal traffic locations. The temporal traffic pattern identification shows that the occurrences of temporal abnormal places are quite random, and detectors in the same intersections may have quite different anomaly degrees from each other. It can detect the non-concurrent traffic anomalies compared to historical time-of-day periods. Different from spatial regional traffic pattern, no identical trend from AM peak, Noon, and PM peak can be found in different sub-regions. A case study for newly opened subway stations validates the proposed methodologies.
7. This study develops a Multi-modal Hierarchically Responsive Signal system, called *MARS*, which grants hierarchical priority for multiple travel modes during traffic signal control. MARS adopts a hierarchical optimization framework with lexicographic

dynamic programming to handle mixed traffic with hierarchical priority levels. The superiority of MARS stems from the fact that the optimal signal plan is not unique (He et al. 2011). By optimizing each travel model hierarchically, the developed signal plan are better tuned from all levels of travel modes. The proposed optimization model explicitly considers each vehicle' trajectory approaching an intersection. Therefore, each vehicle's real-time delay has been addressed in the model. In addition, the low computation time (0.1 sec) identifies the feasibility of the implementation in a real-world intersection.

8. The test of MARS is conducted along a mixed multi-modal traffic corridor (with passenger cars, trucks, buses and trains) at downtown Buffalo network. Compared with state-of-practice actuated Transit Signal Priority control, MARS decreases average bus delay for 68% and average car and truck delay for 16%, while maintaining the similar delay of light rail. Compared with state-of-practice actuated control, MARS improves average delay for light rail by over 51%, average bus delay by 10%, while achieving similar cars and trucks delay. Therefore, MARS achieves reliable and efficient real-time multi-modal signal control.

The results have been disseminated to TRB annual meetings, INFORMS annual meetings, KDD (a top data mining conference), Buffalo/Niagara Traffic Signal Committee Meetings. The project also leads to three journal papers (e.g. Chapter 3 was published in IEEE Transactions on Intelligent Transportation (X. Su et al. 2016), Chapter 4 was published by Transportation Research Part C (Z. Zhang et al. 2016), and Chapter 5 will be submitted soon) and two conference papers (one TRB (X. Su et al. 2015) and one KDD (Cai et al. 2015)).

1 INTRODUCTION

Modern urban transportation networks involve complex traffic dynamics composed of multiple travel modes, including passenger cars, buses, predestinations, bicycles, trucks, light rail, emergency vehicles, and other commercial and private modes of transportation. Although different traffic modes have their own characteristics, traffic signal control systems traditionally treat each mode separately, as summarized in Table 1-1. For example, signal coordination aims to generate a "green wave" for passenger cars; signal preemption ensures the high priority requests from emergency vehicles are served in a timely fashion, and transit signal priority (TSP) is widely used to favor bus and light rail movements.

Table 1-1 Traffic signal control treatments for different traffic modes in current state-of-practice systems in the U.S. (He et al. 2014)

Traffic Modes	**Traffic Characteristics**	**State-of-Practice Treatment**
Passenger cars	Mass volume and very low priority	Signal coordination
Buses	Low volume and medium priority	Transit signal priority
Pedestrians	Variant volume and priority increasing when volume increasing; low speed and high vulnerability	Pedestrian dedicated phases
Bicycles	Variant volume and priority increasing when volume increasing; medium speed and high vulnerability	Bike dedicated phases
Trucks	Medium volume and low priority	Freight signal priority
Light rail	Low volume and high priority	Signal preemption and Transit signal priority
Emergency vehicles	Very low volume and extremely high priority	Signal preemption

Treating each mode separately is likely to result in sub-optimal system performance (He et al. 2012). Different travel modes have their own specific characteristics including travel speed, volume, priority level, and vulnerability. Yet very little is understood about the links among signal control strategies for different modes. The environment of enriched traffic data makes optimal multi-modal traffic control a real possibility (Research and Innovative Technology Administration 2013). With the technological advance of vehicle-based positioning and communications, it is possible to know where the vehicles are and to plan traffic signal control to best serve all vehicles

Figure 1-1. A CV environment with V2V and V2I communications

in the entire network, simultaneously. According to US Department of Transportation (USDOT), *multi-modal traffic signal control is the next generation of traffic signal systems that seeks to provide a comprehensive traffic information framework to service all modes of transportation, including general vehicles, transit, emergency vehicles, freight fleets, and pedestrians and bicyclists in a Connected Vehicle (CV) environment* (US Department of Transportation 2014).CV includes communications paradigms such as Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I). The basic elements of a CV system consist of Roadside Equipment (RSE) and On-Board Equipment (OBE) devices, as shown in Figure 1-1. Usually installed within the infrastructure, RSE supports 5.9G HZ Dedicated Short Range Communications (DSRC) (Society of Automotive Engineers 2006), and serves as an interface between vehicles and the backhaul network. Contrary to RSE, OBE is installed onboard the vehicles and also supports DSRC to communicate with either other OBEs or RSEs.

In addition to CV, nowadays, smartphones become ubiquitous and provide much more than GPS location information. They are usually equipped with accelerometer, gravity sensor, barometer, light sensor, gyroscope, compass and more. The advanced sensors equipped on the smartphone chips enable us to detect details of people's travel activities, including travel modes (Xing Su et al. 2014a). Compared to recent Connected Vehicles (CV) technologies (U.S. Department of Transportation 2014), smartphones provide an almost cost-free solution to gain tremendous real-time data in our current urban city, shown as Table 1-2. Furthermore, unlike CV designed mainly for motor vehicles, smartphone based sensors are able to provide an entire data picture for multi-dimensional transportation systems including non-motorized traffic (e.g., pedestrians and bicycles), which is critical for large metropolitan areas (e.g., New York City). In additional to such floating sensors, traditional fixed sensors (e.g., loop detectors and cameras) will continue serving as a major vehicle detection method in near future due to well-established current Intelligent Transportation System (ITS) practices.

Table 1-2 Comparing floating sensors from Connected Vehicles (DSRC) and smartphones

	Connected Vehicles	Smartphones
Cost	\$2,000~\$4,000 for aftermarket devices (Savari 2014)	Almost cost-free for existing smartphone users
End-to-end delay	10 milliseconds, perfect for collision avoidance	100~1000 millisecond, good enough for traffic signal control
Range	100s meters	10 km
Market penetration (now)	Almost zero	69.4% of the global population (eMarketer 2014)
Travel modes	Motorized vehicles only	All travel modes

In additional to such floating sensors, traditional fixed sensors will continue serving as a major vehicle detection method in the near future due to well-established current Intelligent Transportation System practices. Therefore, there is a pressing need to make fundamental changes from unimodal traffic control to multi-modal traffic control. In pursuit of this goal, not only should new signal control algorithms be developed, but also new multi-modal and multi-source data fusion and mining should be explored and accommodated for future implementation.

Given an environment of enriched multi-source and multi-modal data, there are two critical challenges for effective signal control as follows. First (C1. Model Complexity), different from the existing work which aims to estimate the *overall* traffic condition (i.e., aggregated for all types of vehicles and for all lanes) of a given road segment or intersection based on both fixed and floating sensor data, in our setting, we aim to take it at a much finer granularity, that is, to estimate and diagnose the traffic condition for different types of vehicles (e.g., emergency, bus, taxi, etc.) of different directions (e.g., straight, left, right, etc.). Given a road segment or intersection, we conjecture that the traffic condition for different types of vehicles of different directions might be correlated with each other. Moreover, the traffic conditions of the adjacent segments are likely to dependent on each other. This requires us to build multiple inter-correlated prediction and diagnosis models simultaneously. Second (C2. Computation Efficiency), in order to provide a reliable input for traffic signal control, both the prediction and diagnosis models need to respond and further adapt itself over time in real-time or at least near real-time. This puts an extra challenge in terms of the computation, given the large, heterogeneous, highly dynamic/volatile, noisy, and incomplete raw fixed and floating sensor data.

2 SURVEY OF TRANSPORTATION PROFESSIONALS

We have developed a survey recently to understand the state-of-practice in multi-modal signal control. The design and results of the survey are summarized and attached as **Appendix A** and **Appendix B**, respectively. The objective of this survey is to

- Learn field practice with multi-modal signal control
- Identify the existing challenges for multi-modal signal control
- Get potential solutions for multi-modal signal control
- Identify data sources available for multi-modal signal control
- Rank travel modes in multi-modal signal control
- Rank problems/challenges in multi-modal signal control

We reached out different transportation agencies to obtain feedbacks. Most of the participants are members and friends of TRB Traffic Signal Control Committee. In total, we received 21 responses, from government (23.81%), industry (42.86%) and university (28.57%). Most of participants have 10-19 years (52.38%) of experiences in signal operations. Therefore, the results of the survey reflect the state-of-the-practice in multi-modal signal control.

2.1 State-of-the-Practice and Challenges in Multi-modal Signal Control

This survey considers the following seven travel modes:

1. Emergency Vehicles
2. Light rail/trains
3. Buses/BRT
4. Bicycles
5. Pedestrians

6. Trucks
7. Passenger cars

Among travel modes other than passenger cars, most of the participants have experiences working with “Pedestrians” (85.71%), whereas least of them with “Truck” (38.10%). 60-75% of the participants have experiences with “Emergency Vehicles”, “Light Rail/Trains”, “Buses/BRT”, and “Bicycles”.

Most of the responses indicate that multi-modal signal control is very important (4.62/5.0). However, they disagree that multi-modal signal control is well implemented (2.14/5.0). They also believe it is challenging to implement multi-modal signal control (3.33/5.0). The survey provides six kinds of challenges, including “Funding”, “Technologies”, “Human resources”, “Staff training”, “Jurisdiction boundary”, and “Policy support”. According to the responses, all above items are challenging. the most challenging item is “Funding” (3.95/5.0), followed by “Human resources” (3.52/5.0), “Staff training” (3.38/5.0), and “Policy support” (3.19/5.0). The relatively less challenging items are “Technologies” (2.86/5.0), and “Jurisdiction boundary” (3.05/5.0). Therefore, when it comes to implementation of multi-modal signal control, the major challenges exist, including funding support, human resources, and related training.

The difficult level of adding treatment of travel modes vary a lot according to the response. The results show that adding signal priority for light rail (3.33/5.0) and buses (3.29/5.0) are most difficult, whereas it is relatively less difficult to add signal preemption for emergency vehicles (2.33/5.0) and pedestrian operations (2.62/5.0).

2.2 Weights for Different Travel Models under Different Scenarios

We assume the weight of emergency vehicles is 10 and the weight of passenger car is 1 for the survey. The participants were asked to report the weights from 1 to 10 for different travel modes under three different scenarios, day-to-day peak hour, day-to-day off-peak hour, and planned special events with massive pedestrians.

Table 2-1 summarizes the average weights for different travel modes under different scenarios. For day-to-day operations, the descending rank of travel modes (including emergency vehicles and passenger cars) is emergency vehicles > light rail > buses > pedestrians > bicycles > trucks > passenger cars. Compared to peak hour, the truck weights increase during off-peak hours, whereas the weights for all other modes decrease. It indicates that we should encourage off-peak truck delivery and assign proper truck signal priority for off-peak hours. For a planned special event (e.g. sporting games, concerts, running races, etc.) with massive pedestrians, the descending rank of travel modes is emergency vehicles > pedestrians > light rail > buses > bicycles > trucks > passenger cars. Given safety concerns with massive pedestrians, pedestrians are assigned with the highest weight except for emergency vehicles. Surprisingly, under special events, trucks' weight is lowered to 2.43/10.0 compared with 4.0/10.0 under peak hours.

Table 2-1 Average weights/variance for different travel modes under different scenarios

Scenarios		Light rail	Buses	Bicycles	Pedestrians	Trucks
Day-to-day peak hour	Average	7.25	6.52	4.14	4.95	4
	Variance	5.09	3.26	4.93	7.25	4.1
Day-to-day off-peak	Average	6.57	5.71	5.24	5.48	4.95
	Variance	6.46	4.81	7.19	6.96	6.25
a planned special event with massive pedestrians	Average	7.62	7.24	5.10	7.67	2.43
	Variance	7.55	4.89	6.99	4.13	3.96

The results of this survey will help existing traffic signal agencies identify the existing practice and challenges of multi-modal signal control. In addition, the average weights of each travel model provide guidance to configure priority treatments for different competing travel modes under different scenarios. As one can see from the table, although the average weights among light rail, buses and pedestrians are very close, the variances of the weights in different travel modes vary dramatically in different scenarios. Therefore, there is no consistent agreement in the weights for each travel mode. There is a pressing need for a different approach to model the competitions among travel modes.

3 FAST ONLINE TRAVEL MODE IDENTIFICATION WITH SMARTPHONES

3.1 Background

Personal trips in modern urban society usually involve multiple travel modes, including passenger cars, buses, subway, pedestrian, bicycles, etc. Different travel modes have their own specific characteristics, ranging from the travel speed, the volume, the fuel consumption, the emission use, the priority level, to the vulnerability. Not only is recognizing transportation mode critical to understand people's travel behavior (Bamberg et al. 2003), but also such information helps improve transportation planning, management, and operations. Travel mode detection is a natural extension of vehicle classification. Traditional vehicle classification aims to identify motorized transportation with fixed sensors such as pneumatic tubes, inductive loop detectors, infrared sensors, acoustic sensors and computer vision-based sensors (Sun and Ban 2013b). The limitations for the fixed sensors are: i) high installation and maintenance costs, ii) limitations under specific situations (e.g. inclement weather) and iii) failure to obtain travel mode information in a complete trip rather than in few fixed locations. A Global Positioning System (GPS) sensor as a floating sensor provides an alternative solution. It can record individual trip-chain data with extremely low costs. The drawback is that GPS only provides location and speed information, and it becomes inapplicable in certain scenarios (e.g., underground subways).

Another emerging type of floating sensors to obtain travel mode information is the smartphone. As an integral part of our wearable devices, smartphones become more and more sophisticated, with ever-growing computing, networking and sensing powers. They are usually equipped with accelerometer, gravity sensor, barometer, light sensor, gyroscope, compass and other sensors. These advanced sensors enable a rich variety of smartphone data mining applications such as users' activity recognition, including travel activities (see (Xing Su et al. 2014b) for a complete survey). Therefore, the smartphone is one of the best sources for crowdsourcing real-time dynamics while traveling.

In this chapter, we are particularly interested in using smartphones to automatically classify six different travel modes: ***driving a car, walking, jogging, bicycling, taking a bus and taking a***

subway. The existing challenges for using smartphones to classify travel mode are: i) most methods that use smartphone sensors for travel mode detection use GPS/GSM data (Sun and Ban 2013a; Rasmussen et al. 2013; Bolbol et al. 2012; L. Zhang et al. 2011; Reddy et al. 2010; Liang et al. 2014). These data sources are unstable due to urban area reception status; ii) the battery capacity and computing resources are the main bottlenecks for long-term sensing and classification (Liang et al. 2014; Yan et al. 2012); iii) the smartphone's mobility introduces noise when it moves with human body or it is placed at different positions. In this chapter, we present a solution to tackle these problems. Our method uses network-free data from the latest smartphone sensors like barometer and magnetometer. We adopt a hierarchical classification framework that uses different sensors' data at different phases of the learning and classification process in order to save both computing resources and battery cost. We explore other sensors besides traditional motion sensors such as acceleration to ensure the method is phone-gesture independent. The main contributions of this research effort are:

1) In this chapter, we formulate the problem in addressing the challenges in travel mode detection with smartphone sensors and then give the design principles for this classification problem.
2) We explore environment sensors in multimodality sensing and reduce the weight of motion sensors in the overall sensing process.
3) Our solution is designed to be user-friendly that it is smartphone-position independent and the online learning algorithm ensures the model is adaptive to each user's specific pattern.
4) Our system is designed with energy concern (small sampling frequency for mobile phones), fast response time (slide window segmentation) and quick start (a small portion of initial training dataset). These advantages ensure our method is practical in realistic applications.
5) The classification model maintains a promising accuracy (97.1%) while updating the model with online learning fashion.

3.2 Literature Review

There is rich literature in travel mode identification (including vehicle classifications). Recently, more and more studies focus on travel mode identification with floating sensors, due to their various advantages over fixed sensors. Therefore, in this chapter, we only consider floating sensor based approaches (see (Sun and Ban 2013b) for a detailed review for fixed sensor-based methods). According to the types of sensors adopted, most of the previous work could be categorized as either GPS-based or smartphone-based classification methods.

The vast majority of the early literature in travel survey, which leverages only GPS information (location, speeds, and derived acceleration data) belong to GPS-based classification methods (Chung and Shalaby 2005; Draijer et al. 2000; Stopher et al. 2008; Chen et al. 2010; C. Xu et al. 2010). Support Vector Machine (SVM) is one of the most popular methods for classification. Zhang et al. (2011) performed a two-stage classification with SVMs. The first stage identified three main travel-mode classes: pedestrian, bicycle, and motorized vehicles. The second stage further classified different categories of vehicles into cars, buses, trains and trams. Bolbol et al. (2012) developed a moving window SVM to classify six travel modes from sparse GPS data. Another study used SVMs with quadratic kernel functions for binary classification, which only considered passenger cars and trucks. Several studies leveraged Geographic Information Systems (GIS) for better detection accuracy. GIS and GPS data were combined to detect five travel modes (walk, car, bus, subway, and commuter rail) in New York City (Gong et al. 2012). Moreover, another study proposed a combined fuzzy logic and GIS-based algorithm to process raw GPS data. The algorithm was applied to GPS data collected in the highly complex Greater Copenhagen Area network in Denmark and detected trip legs and distinguished between five modes of transportation (Bolbol et al. 2012). A similar study with fuzzy pattern recognition was conducted in Shanghai, China (C. Xu et al. 2010). Many algorithms presented in this category usually involve heavy data processing and transmission load on mobile devices that may exceed its capacity.

Emerging trends in smartphone-based methods are observed in recent literature (Ustev et al. 2013; Feng and Timmermans 2013; Shin et al. 2014; Manzoni et al. 2010; Xiao et al. 2012). Manzoni et al. (2010) developed an algorithm that automatically classifies the traveler's transportation mode into eight classes using a decision tree. The input features were computed from the Fast Fourier Transform (FFT) coefficients of the total acceleration measured by the accelerometer. A trip analysis system that consisting of mobile apps and a centralized analyzer was developed to identify the travel mode and the travel purpose using smartphone GPS and accelerometer (Li et al. 2011). It was deployed to the smartphones of the volunteers in Dubuque, IA, to serve both the volunteers and the transit agencies. Another study leveraged the same two types of sensors to classify six different travel modes in the region of Vienna, Austria (Nitsche et al. 2012). Authors proposed multivariate parametric models that are fitted to the distribution of feature vectors extracted from the training set.

Very few studies employ a complete list of smartphone sensors for better classification results. Frendberg (2011) designed a smartphone app to detect transportation modes by applying a Boosted Naive Bayes classifier to the data collected from GPS, accelerometer, orientation, and magnetic sensors. However, the data were collected from a single user and only two travel modes, walk and automobile, were considered in that study. Another recent work collected multi-modal travel data in New Delhi, India, from a variety of sensors, including accelerometer, linear acceleration, gyroscope, orientation, magnetometer, light intensity meter, proximity, sound level and GPS (Garg and Singh 2014). They focused on two-wheeler and three-wheeler classification with a threshold-based heuristic. However, no pedestrian, cyclist, or subway is considered in that work. Jahangiri and Rakha (2014) explored the solutions with different combinations of sensors such as accelerometer, gyroscope and GPS. They used a Gaussian kernelled SVM as the learning model and obtained high accuracy. However, they did not include subway as the travel mode. Although much progress has been made, several key challenges remain open, including (1) dynamic model update and (2) reducing battery consumption.

Problem Definition and Terminology

This chapter aims to address the problem of real-time travel mode detection with an online classification model. The travel modes we discuss here are ***walking, jogging, bicycling, taking a bus, driving a car*** and ***taking a subway***. The system takes mobile sensing data as the input and the identified travel mode as the output. The whole scenario consists of three phases. The first phase is the initial classification model training phase when labeled data is collected by volunteers while traveling. A multiclass classification model is learned as the output. In this phase the data collected is not user specified. The second phase is the model updating phase when the previously trained model is updated to adapt to the current user's personal patterns during traveling. The inputs are the initial classification model and user-specific traveling data (labeled). The general model from the first phase is updated using an online learning method, and the output is an adaptive model corresponding to the user. The third phase is the travel mode identification and logging phase. User-specific model is ready for various situations such as travel mode detection, travel logging, public transportation survey, etc. The extraction of the discriminative features from the raw smartphone data is the critical part of the proposed systems. In the following, we summarize the limitations (e.g. battery life) and the challenges in relation to coping with the extraction of useful information from smartphone data for mobility analysis and choice modeling. We begin with the terminology and problem settings.

3.2.1 Terminology

Sampling Frequency. The sampling frequency is the frequency at which the smartphone app senses and records data. E.g. a sampling rate of $5Hz/s$ means we use related sensors every $200ms$ to sense the motion and environment. We denote it by F.

Data Sample. A data sample is the sensors' readings at a single time. It is the unit data that is sent to the server from a smartphone. We denote a data sample by I_i, where $i = 1, 2, 3, \ldots$

Instance/Segment. A training instance or a data segment (in some literature it is also called a training sample), consists of one or more data samples. For example, if we say the segment length is 8, which means the data segment contains 8 data samples. We denote a segment by $S_i, i = 1,2,3, \ldots N$, N is the segment length.

Time-Window. *A T*ime-window is the length of time required to collect data for one instance/segment. We denote it by T. If a data segment consists of N_e data samples, and the data is collected with a sampling frequency of F_e, the time-window $T_e = N_e/F_e$.

Feature Vector. A feature vector is a vector that describes the characteristics of each data segment (e.g., the maximum of barometer readings, the average acceleration along Y axis, etc.). We denote a feature vector by $\boldsymbol{X}_i$, where $i = 1,2,3, \ldots, \boldsymbol{X}_i \in \mathbb{R}^n$. We use y_i to denote the correspondent label. A proper segment length is critical for feature vectors.

Training Set. A training set is the data set used to train the classification model. It is denoted by $\boldsymbol{S} = \{\boldsymbol{S}_i\}$, where $i = 1,2,3, \ldots$ In this chapter, there are two kinds of training sets: the initial training set and the add-up training set. The initial training set is used to train a general model in the first phase. The add-up training set is used in the second phase to update the model. Each add-up training set is collected by one user so that the updated model will adapt to his/her pattern.

Iteration. Iterations are used at the add-up training process. One iteration is one complete model updating process. It begins at the time when a new data sample is being collected on the smartphone, and ends when the model is updated with the new data sample.

3.2.2 Problem Setting

In our previous work [32], we developed methods to identify travel modes using a generally trained model. However, the general model may result in a relatively low accuracy since different travelers could behave quite differently. For example, each person has his/her own driving style, some drive with a relatively steady speed, while others drive more aggressively with a lot of accelerations and decelerations. Some people walk as fast as others jog. All these differences among users' traveling behavior increase the complexity of traveling features and introduce potential noise for the classification model. To achieve a higher accuracy, it requires the model to learn the patterns of the user's specific behavior, besides the general features of transportation modes.

In addition to classification accuracy, the battery limit of smartphone usage would be another main concern. Although sensors such as GPS are commonly used in the existing research, we aim to avoid them since they are quite battery draining. Finally, we want to lower the sensor's sampling frequency F and save more resources to speed-up the computations.

Furthermore, we would like to make the model update process as fast as possible. In each iteration, the model needs to wait $T = N/F$ to accumulate the samples for a segment. If we want to decrease F in order to maintain a small T, we also need to decrease N. The benefit of decreasing N is that with a smaller segment size the calculation would be faster. However, a shorter segment may lead to less informative/discriminative features. In the extreme case, if a segment contains only two data samples, we lose the frequency domain information. Having these concerns in mind, we would like to adhere the following principles:

1) The model can process a small batch of samples despite the data used previously. In other words, it should use online updating strategy.
2) The model updating algorithm should not put restrictions on the data scale since each update only depends on data sensed from the current traveler's behavior.

3) Avoid using battery draining sensors such as GPS sensors.
4) The method should maintain a short waiting time for the server, meanwhile keeping low sampling frequency F.
5) Maintain a reasonable segment size N to balance the computational time and the quality of the feature extraction.

3.3 A Hierarchical Framework

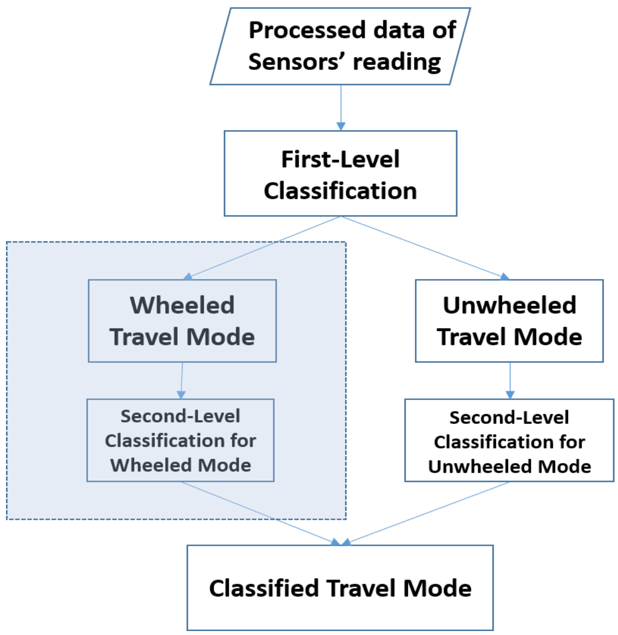


Figure 3-1 Hierarchical Classification Structure

Intuitively, during a wheeled traveling (e.g. bicycling or on a car, bus, subway), the body movement is less drastic than the unwheeled traveling (e.g. walking and jogging). This is verified by comparing accelerometer readings of wheeled and unwheeled activities in our previous work (X. Su et al. 2015). We use a hierarchical classifier to classify the six travel modes. Fig. 1 shows the flowchart of the hierarchical classifier.

3.3.1 Unwheeled Travel Mode Detection

Our previous work (Xing Su et al. 2014c) uses decision trees and Hidden Markov Model to detect activities (e.g., walking, jogging, sitting, climbing stairs, etc.), using smartphone sensors. In the traffic mode detection problem, the unwheeled modes only involve walking and jogging. Thus, we use a simplified model for the second level unwheeled mode classification. The simplified model only uses the acceleration data features: **XSTND**, **YMAX**, **ZSTND** (see (X. Su et al. 2015) for detail of the feature vector). The reason can be explained as follows. In the standard coordination system, Y axis is vertical to the surface of the earth, and X and Z form the surface that is parallel to the ground. During jogging, the body movement is more drastic. It means the movement of the smartphone movement along y-axis and x-z surface are more intense. This directly reflects in acceleration along y-axis and x-z surface. **XSTND** and **ZSTND** describe the standard deviation of acceleration along X and Z axes' reading during the time-window, and **YMAX** describes the highest acceleration along Y axis during the time-window. Although there are other differences in feature analysis, the three features cover most of the differences between walking and jogging.

3.3.2 Wheeled Travel Mode Detection

In this chapter, we will mainly focus on the online model training in identifying the wheeled travel mode, i.e., the shaded cubic part in Figure 3-1. As explained before, it contains three phases. We divide the collected data into the initial training set, the add-up training set and the test set with certain ratios. The initial training set is used to train a general model. In the initial training set, the data is a mix of multiple users' traveling data. The add-up training set for one specific model will only include one person's traveling data. At each iteration, the initial model would update with one training sample from the add-up training set. At the end of each iteration, the updated model is being evaluated with the test set. Figure 3-2 shows the process of model training and updating, and the corresponding process in the experimental simulation.

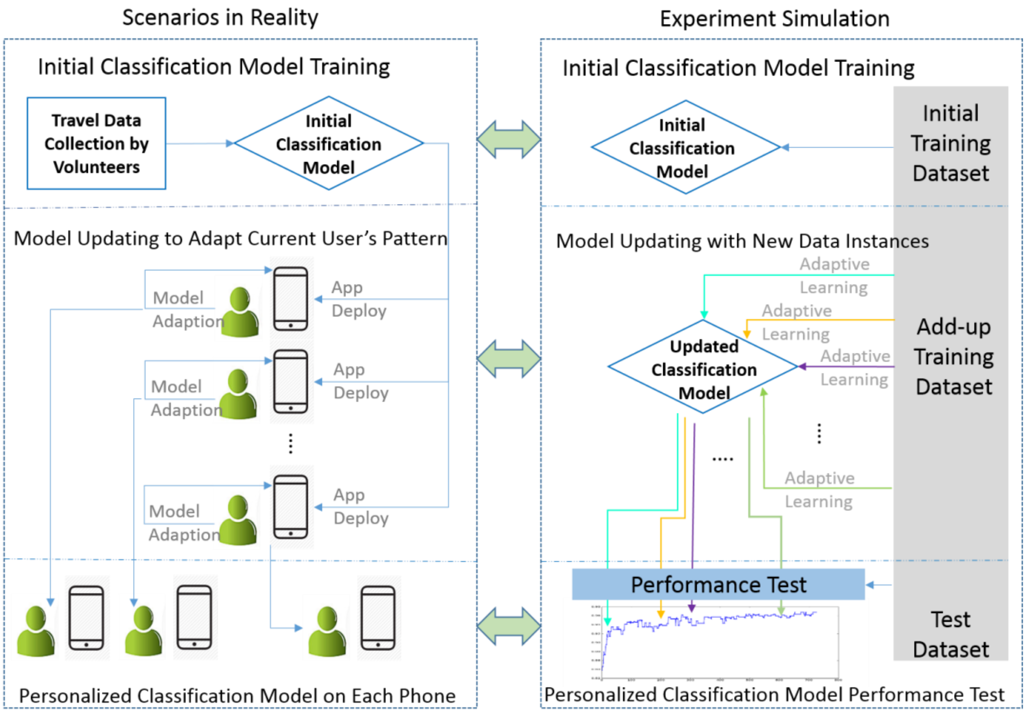


Figure 3-2 Online Training for Personalized Classification Model: The Reality Scenario and Its Simulation in Experiment

3.4 Data Processing

Data processing is critical for the model learning. In this section, we will describe the data collection and techniques for data processing.

3.4.1 Data Collection

We developed a smartphone App based on the Android and iOS systems to collect smartphone sensors' data while traveling. The smartphones we used are:

- iPhone 5s and 6
- Samsung Galaxy Note3, S4
- Google Nexus 4

The data was collected in both summer and winter times. Since the traffic patterns are quite different at different time-of-day, e.g. rush hours VS midnight, in order to minimize the time pattern difference, both summer and winter data are collected around the same time period, 5:00 pm to 6:00 pm period, and morning around 10:00 am. Five volunteers were asked to carry the smartphones with the App installed and traveled in different modes as designated (walking, jogging, driving a car, taking a bus, taking a subway, bicycling). The data duration that we used for each travel mode training was roughly 30 minutes. The details of data collection are shown in Table 3-1. Below is the description of some of the important sensors in our experiment.

Accelerometer. Accelerometer readings return the acceleration as measured along each axis of the cell phone. Acceleration data is an important reference to detect the pattern of a user's body movement.

Gravity Sensor. Gravity sensor readings return the gravity as measured along each axis of the cell phone. If the phone is put on the table with Y axis facing the sky, the reading on Y axis would be roughly $-9.8m/s^2$ while the readings on other 2 axis would be around $0.0m/s^2$.

Barometer. Barometer readings return the detected ambient air pressure. Muralidharan et al. (2014) conducted an experiment showing that the pressure detected by the smartphone barometer would change with the building structure and type, and such a pattern is able to learn. In our experiment, we also verified that the barometer reading is discriminative with different transportation modes.

Table 3-1 Data Collection Details

Sensor Used	Data Name	Frequency	Dimensions
Accelerometer	Acceleration (m/s^2)	15 Hz	x, y, z
Gravity Sensor	Gravity (m/s^2)	5 Hz	x, y, z
Gyroscope	Rotation Rate (rad/s)	5 Hz	x, y, z, $x\_calibration, y\_calibration$, $z\_calibration$
Magnetometer	Magnetic Field (μT)	5 Hz	x, y, z, $x\_calibration, y\_calibration$, $z\_calibration$
Barometer	Ambient Air Pressure (hPa)	5 Hz	1

3.4.2 Data Preprocessing

The travel mode detection model is trained using data from multiple sensors. Among which, the acceleration and rotation are important parts for motion profiling. Noise is introduced into these data by activities such as suddenly picking up the phone, walking inside a subway/bus and similar activities that are irrelevant to the travel mode. Also, the sensors generate internal noise such as a single data point spike. Therefore, we implemented methods to clean the sample data before model training.

3.4.2.1 Data Rotation

Among all the sensors' readings we collected, acceleration is measured along phone axes which depends on the phone's position and heading direction. Since it is difficult to coordinate all the volunteers to have the same phone position and heading direction to collect data, the acceleration data needs to be rotated back from the phone coordinate system to a specific coordinate system prior to any calculation. Here we define the standard coordinate system as Y axis vertical to the earth pointing to the sky and Z axis pointing to the magnetic north. Magnetic field reading and the gravity reading are used to rotate the readings from the phone's coordinates to the standard coordinates. We denote the magnetic field vector and gravity vector in standard coordinates by $\boldsymbol{G_s}$ and $\boldsymbol{M_s}$, and gravity vector and magnetic field from raw sensor reading by $\boldsymbol{G_0}$ and $\boldsymbol{M_0}$. By the definition of standard coordination above, $\boldsymbol{M_m}$ is pointing to earth with same magnitude as $\boldsymbol{G_0}$, and $\boldsymbol{M_g}$ is pointing to the magnetic north with same magnitude as $\boldsymbol{M_g}$. We then calculate the rotation matrix RM_1 and RM_2 using Equation (3-1) and (3-2).

$$RM_1\boldsymbol{G_0^T} = \boldsymbol{G_s^T} \quad (3\text{-}1)$$

$$RM_2\boldsymbol{M_0^T} = \boldsymbol{M_s^T} \quad (3\text{-}2)$$

Now assume we have the raw reading of acceleration $\boldsymbol{A_s}$ at the same time. We can rotate the acceleration into the standard coordinates value $\boldsymbol{A_s}$ by $RM_1 RM_2\boldsymbol{A_0^T} = \boldsymbol{A_s^T}$.

3.4.2.2 De-noising

Winsorization is used to reduce the possible spurious outliers in the data. In our data cleaning, we use 95% of the data range, so 2.5% of the data would be cut off on both sides of the data distribution. The outlier of the data is replaced with the upper/lower limit values. A Gaussian filter is then applied for data smoothing. A Gaussian filter works as a low-pass filter and attenuates high-frequency signal periods in the data. The filtration drops all the high-frequency oscillations most of which are white noises, and leaves only the main increase and decrease trends.

3.4.3 Data Segmentation

Data segmentation slices the time series of data into segments. The critical part is to define the length of a segment. If the time span is too short, we may cut off the data inside its cycle of the certain pattern that would make the learning less effective. On the other hand, if the time span is too long, we may end up calculating more numbers which are more time consuming. And furthermore, it delays the prediction since it needs more data to come in and construct the segment. We learned through observations that the minimum segment of any travel mode would be no less than 4 seconds (e.g. from jogging to walking), and a period of 10 - 15 seconds is safe for any travel mode detection. In our experiment, we start with the segment length of 32 and 64 (which is for the convenience of Frequency domain analysis). The data sampling frequency is set to $5\ Hz$ initially, so the corresponding time-windows are $6.4s$ and $12.8s$, respectively. The segment length will get tuned later according to its performance. We aim to find a proper segment length that contains as much information as possible, which also ensuring that the server doesn't need to wait for a long time to collect the data for one segment.

3.5 Model Development

To train a learning model is the core task. The travel mode detection problem is to solve a multiclass classification problem.

3.5.1 SVM Model

Support vector machine (SVM) is a supervised classification tool that provides the largest margin between two hyperplanes of the classes in the multi-dimensional feature space. In a binary classification problem, we have a training set $S = \{(\boldsymbol{X_i}, y_i)\}_{i=1}^{m}$, where $\boldsymbol{X_i} \in \mathbb{R}^n$ and $y_i \in$

$\{+1, -1\}$. The pair $(\boldsymbol{X_i}, y_i)$ is composed of an arbitrary input $\boldsymbol{X}$ and the prediction label y. To train a SVM is to find the minimizer of the following problem:

$$\min_{\boldsymbol{W},\xi} \left(\frac{\lambda}{2} \|\boldsymbol{W}\|^2 + \frac{1}{m} \sum_{(\boldsymbol{X},y)\in S} l(\boldsymbol{W}; (\boldsymbol{X}, y)) \right) \tag{3-3}$$

Where,

$$l(\boldsymbol{W}; (\boldsymbol{X}, y)) = \max(0, 1 - y < \boldsymbol{W}, \boldsymbol{X} >)$$

We denote the objective function in Equation (3-3) by $f(\boldsymbol{W})$. Gradient descent has been often proposed to find a solution for the approximate objective functions like $f(\boldsymbol{w})$ (Rumelhart et al. 1985). A simplification for gradient descent is stochastic gradient descent (SGD). SGD allows the update on batch gradient descent with randomly picked samples at each iteration (Saad). At each iteration, the update is given by:

$$\boldsymbol{W_{t+1}} \leftarrow \boldsymbol{W_t} + \eta \nabla_{\boldsymbol{w}} f \tag{3-4}$$

Since the stochastic algorithm does not need to remember which examples were visited during the previous iterations, it can process examples on the fly in a deployed system (Bottou 2012).

In the travel mode identification problem, on the other hand, different users could behave very differently in traveling. Therefore, it is possible that certain user's behavior shows an enormous difference from the data we used to train the general model. Meanwhile, different users may need a different size of new data for the model updating in order to reach a stable performance. Thus, the model updating requires user-specific samples and the yields should be user-specific parameters. As in our principles, we require a model updating algorithm that doesn't restrict the data scale and can process with a small batch of samples despite the previous data. The SGD algorithm fit our requirements well.

3.5.2 Online Learning

Shalev-Shwartz et al. (2011) proposed an SGD algorithm: Primal Estimated sub-GrAdient SOlver (Pegasos) for SVM. Pegasos works solely on the primal objective function at each iteration, thus its running time does depend linearly on the training set size. The sub-gradient of the approximation in Equation (3-3) is then given by:

$$\nabla_t = \lambda\, \boldsymbol{w_t} - \mathbb{1}\left[y_{i_t} < \boldsymbol{w_t}, \boldsymbol{X}_{i_t} > \, < \, 1\right] y_{i_t}\, \boldsymbol{X}_{i_t} \qquad (3\text{-}5)$$

Where $\mathbb{1}\left[y_{i_t} < \boldsymbol{w_t}, \boldsymbol{X}_{i_t} > \, < \, 1\right]$ is the indicator function that takes a value of 1 if $\boldsymbol{w}$ yeilds non-zero loss on the example $(\boldsymbol{X}, y)$. Substituting ∇_t in Equation (3-3) with Equation (3-6), and using learning rate $\eta_t \; = 1/\lambda t$, the update of $\boldsymbol{w}$ is

$$\boldsymbol{w}_{t+1} \leftarrow \; \boldsymbol{w}_t \, + \eta_t\, \nabla_{\boldsymbol{w}}\, \mathbb{1}\left[y_{i_t} < \boldsymbol{w_t}, \boldsymbol{X}_{i_t} > \, < \, 1\right] y_{i_t}\, \boldsymbol{X}_{i_t} \qquad (3\text{-}6)$$

In our model updating mechanism, in order to minimize the server's response time we use Pegasos as our online model updating method and update with single training sample. The following pseudo-code shown in

is the algorithm of the online model updating process. Note that the updating process is based on a pre-trained model. Therefore the input $\boldsymbol{w}_0$ in the model updating process is the output of the general model in the first phase training, which is different from the original input in (Shalev-Shwartz et al. 2011).

3.5.3 Experiment Process/Data Analysis

In this section, we explain the development of the experiment methodology, and then analyze the results and discuss the solutions as well as existing problems. We will take (X. Su et al. 2015) as the baseline for performance analysis. Our goal is to find an online updating solution that follows the principles in section 3.3.2 and performs as well as the baseline. To begin with, we first raise the following questions which we aim to find an answer in the following part:

Table 3-2 Online Learning with Pegasos Updating

Require: $\boldsymbol{w}_0$ *, the weight vector of the general model.*
λ*, the regularization parameter.*
T*, the maximum training epoch.*
S*, the training set.*
Begin: $t \leftarrow 0$
while $t < T$ $\boldsymbol{do}$:
$$\eta_t = \frac{1}{\lambda t}$$
choose $i_t \in \{1,2,\ldots,|S|\}$ *uniformly at random*
if $y_t < \boldsymbol{w}_t, \boldsymbol{X}_t > < 1$ ***then:***
Set $\boldsymbol{w}_{t+1} \leftarrow (1 - \eta_t \lambda)\boldsymbol{w}_t + \eta_t\, y_t \boldsymbol{X}_t$
else*:*
Set $\boldsymbol{w}_{t+1} \leftarrow (1 - \eta_t \lambda)\boldsymbol{w}_t$
end if
$$\boldsymbol{w}_{t+1} \leftarrow min\left\{1, \frac{1/\sqrt{\lambda}}{\|\boldsymbol{w}_{\boldsymbol{t+1}}\|}\right\}\boldsymbol{w}_{\boldsymbol{t+1}}$$
$t \leftarrow t + 1$
end while
return $\boldsymbol{w}_{T+1}$

1) The baseline in (X. Su et al. 2015) uses Bayes Net learning model. Here we demonstrate the online learning model with Pegasos (SVM). Before developing the online model, we need to fill the comparison gap between the method in (X. Su et al. 2015) and our online learning method: the performance of offline learning with Pegasos (SVM) as the learning algorithm. Would the offline learning with Pegasos perform as well as the results in (X. Su et al. 2015)? Our expectation is that the Pegasos updating with the whole dataset, as offline learning, should achieve similar performance in classification accuracy as in (X. Su et al. 2015).

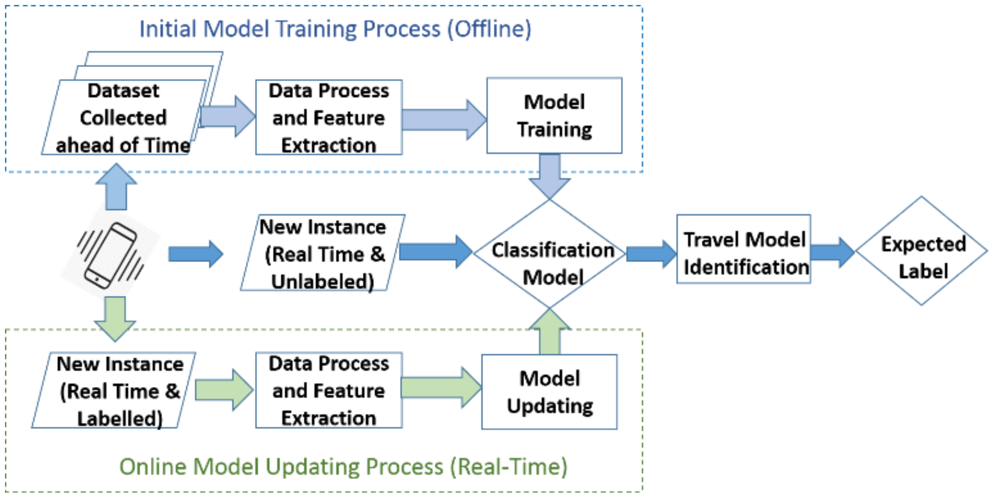
2) We would further promote the learning algorithm to online mode that updates the pre-trained classification model with a single instance. Based on the expected results of the first question, would the online updating give promising results compared to the offline method?
3) Since the online model updates itself using the single instance, would it excel the offline training mode in computation time?

In the following subsections, we will describe our experiments in the effort to answer the questions above. We will focus on the second level classification process. First, we will compare the baseline with both online and offline updating models using the configuration in (X. Su et al. 2015). Then we describe the methods to improve the system's performance in terms of (i) energy consumption, (ii) response time, (iii) the total data needed for training an adaptive model for smartphones users.

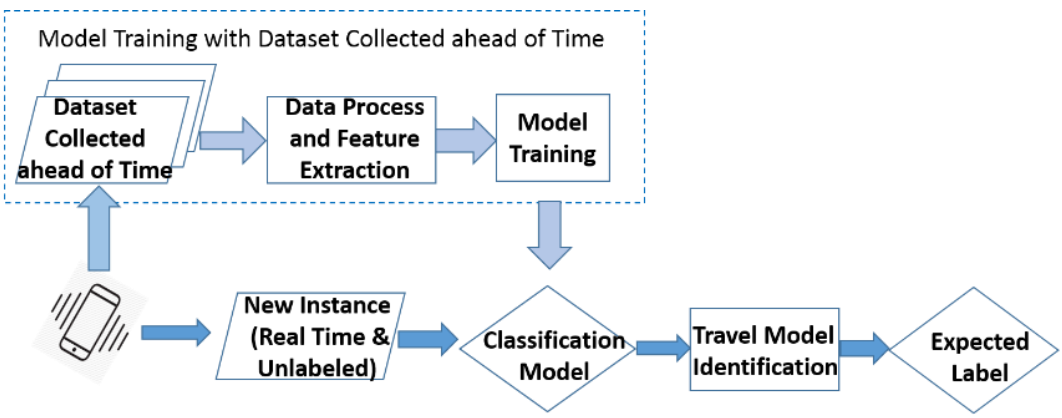
3.6 Online Learning vs. Offline Learning

To compare the online updating strategy with the traditional offline training method, we use Pegasos batch updating method in the offline training and take the whole training set as the batch size. In the online mode, we update the model with each single instance. In the offline mode, the dataset used to train a new model is the combination of the existing dataset and the new instance, (the old model is abandoned). (b)

Figure 3-3 shows the process of online and offline updating. In order to compare the performance of online learning with offline learning, we repeat the offline learning with the whole updated dataset every time after the new data sample comes in. By doing so, we guarantee the offline model we compare with is trained with same data as our online model.



(a)



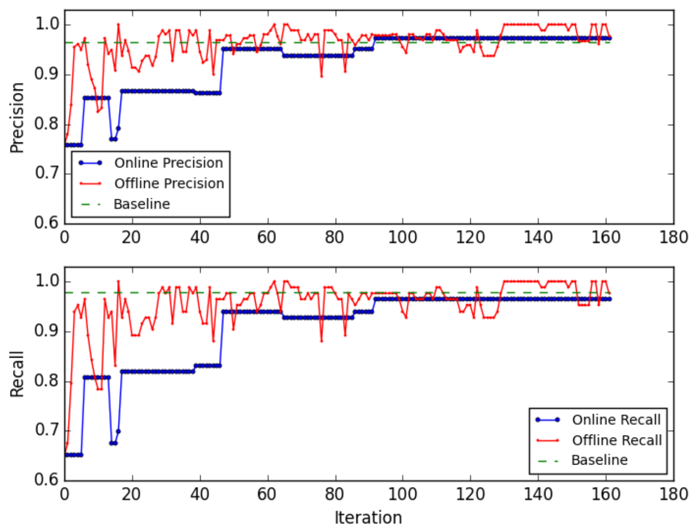
(b)

Figure 3-3 (a) Online learning Process, (b) Offline Learning Process

We compared the two updating process in prediction performance and time cost. In both experiments, we use the segment length of 64 with sensors' sampling rate $5Hz/s$, which is the configuration in (X. Su et al. 2015). The time-window is $64 * 0.2s = 12.8$ s for each data instance.

The baseline we compare to is the best results in (X. Su et al. 2015) using Bayes Net Model. Figure 3-4(a) shows that both online updating and offline updating using SVM with gradient descent solver achieve promising results. The accuracy of offline learning model is as good as the baseline, this answers our first question. The online updating model begins with lower accuracy:

65% recall and 75% precision in prediction. The performance improves significantly after about 50 iterations. And the accuracy of online and offline updating model converge as more data is used for training. This answers the second question. Figure 3-4 (b) shows the time cost of online and offline updating.



(a)

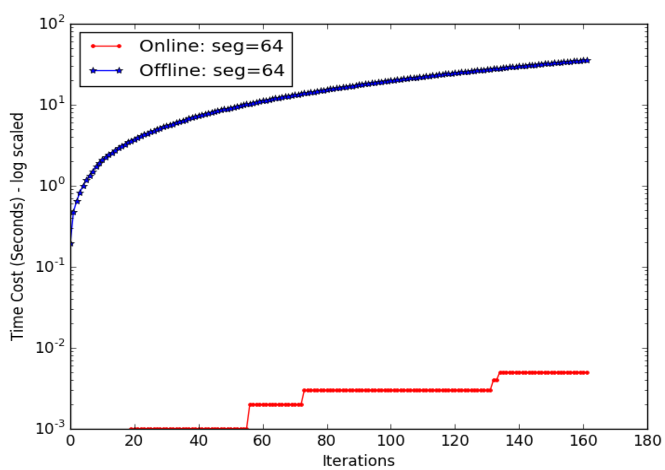


Figure 3-4 (a) Performance Comparison of Online and Offline Learning (b) The Time Cost of Online and Offline Updating

The time cost of online updating is relatively stable and accumulated to less than 0.01 second for nearly 250 iterations (data generated in about 53 minutes) of updating, while the time cost of offline updating increases faster and it reaches 85 seconds around the $250th$ iteration. So the online updating performance is superior to the offline updating mode. So far we've answered all the three questions at the beginning of this section.

3.7 The Sliding Window in Segmentation

According to the principles in 3.2, we would like to keep the segment size small to decrease the response time. Ideally, the smaller, the better. However, extremely small segment size invites fundamental issues in the recovery of the frequency domain features. For example, if the segment length is 2, it doesn't make sense to do frequency analysis with only 2 data samples. We propose the solution of using slide window for current time-window. That is, we don't have to wait until the server gets enough new data for segmentation. Instead, the segmentation will use both current data and cached data that occurs adjacent to the current data sample. Whenever the latest data sample comes, the server will segment it with the cached data to prepare the new training instance. The process is shown in

Figure 3-5. At time t, the training instance is segmented with current data sample: $Sample_t$ and the historical data: $Sample_{t-1}, Sample_{t-2}$ that are cached on the server. By using sliding window mechanism, we decrease the time-window without shortening the segment length, thus guaranteeing short response times. As for denotation, for example, if the server waits the time of 2 data samples and segment it with the 6 previous cached data samples, we say "the segment length is 2 with slide window (+3)". Figure 3-6 shows the performance for configuration of segment length 2 with slide window (+3) and segment of length4 with slide window (+1). Their performance doesn't show much difference, and both converges around 95% precision after 60 iterations of updates.

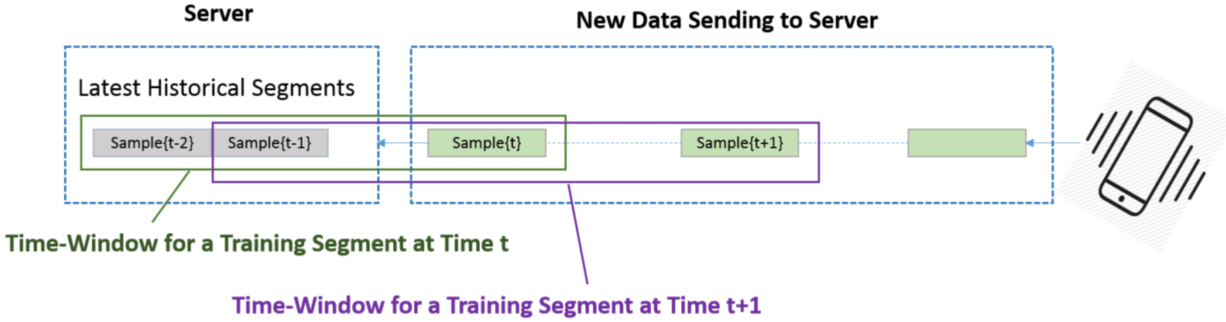


Figure 3-5 Using Slide Window for Data Segmentation

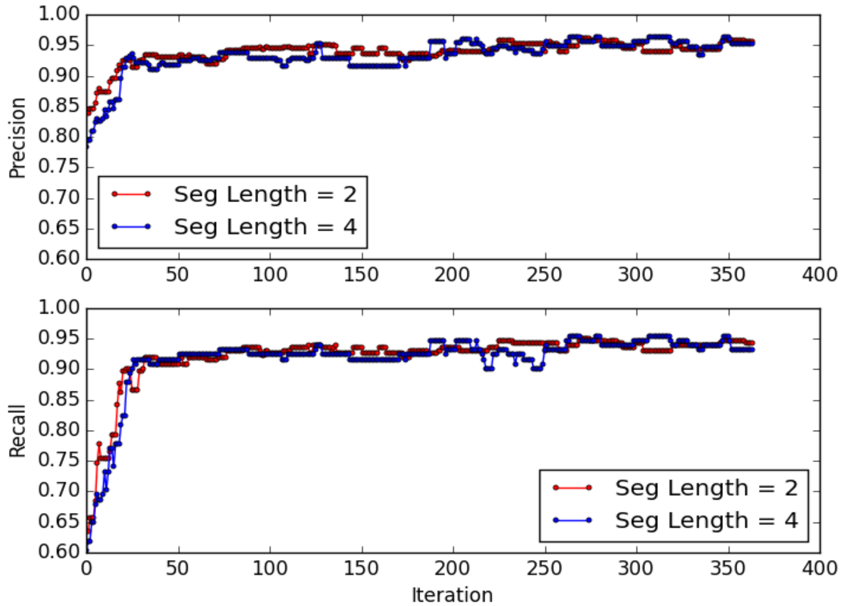


Figure 3-6 Performance with Very Small Time-Window and Slide Window Mechanism

The potential problem of using cached data is that the more historical data we use, the more latency we get for the current event. If current travel mode is in a transition period (e.g. the user just stopped biking and begins to walk), the change will be detected with a time delay. This would be an interesting problem for the future work.

3.7.1 How much data is enough for the initial model training?

In machine learning problems, in general, the size of training dataset is also critical. Smaller dataset usually results in less accurate models. In this chapter, since we are updating our model with new data samples, the whole mechanism should depend less on the initial training set. In order to see how much data is necessary to train the initial dataset, we did experiment with different initial training set (we take 20%, 30%, 40%, 50% of the whole training set as initial training set and the rest is the add-up training set). Figure 3-7 shows the performance comparison with different initial training sets. It is found that smaller initial training datasets have lower accuracy at the beginning. However, as the model is updated with new instances, the accuracies increase and tend to converge after several iterations. It reaches as high as 90% even if only 20% of the data is taken as initial training set. This result promises a quick start for the online learning model.

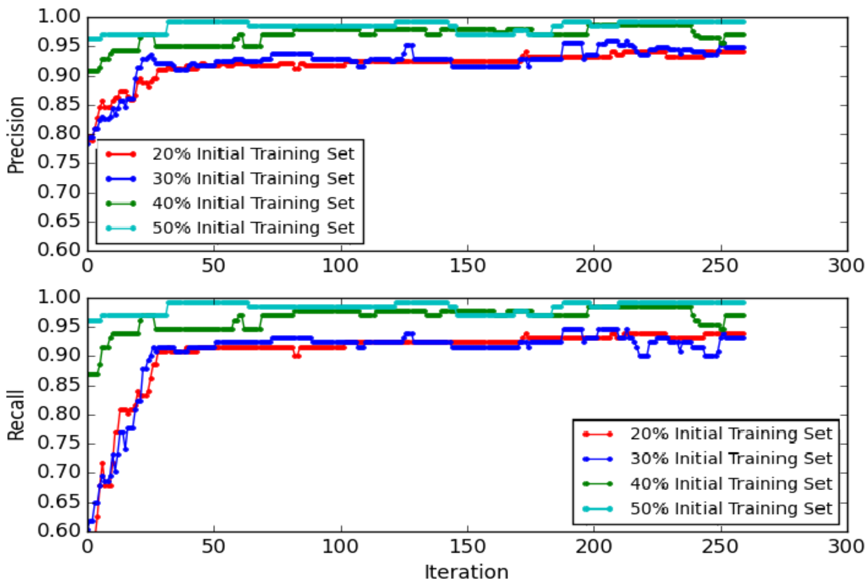


Figure 3-7 Prediction Performance with Different Initial Training Set

3.8 A Summary of Performance

Table 3-3 Classification Results

First Layer	Accuracy	Second Layer	Confusion Matrix			
Unwheeled Transportation	100%	Classified as →	Walk	Jog		
		Walk	47	0		
		Jog	0	17		
Wheeled Transportation		Classified as →	Bike	Bus	Subway	Car
		Bike	23	0	0	1
		Bus	0	14	0	0
		Subway	0	0	27	0
		Car	1	2	0	63

The experiment result is promising. We use the slide window mechanism with 50% cached data and 50% new data as a training sample in the experiment. The length of a training sample is

8 segments, and the sampling rate is $2s$. The training set is divided into half initial training set and half add-up training set and the learning rate is set to be $1.0e-5$. The first layer classification accuracy reaches100%. Second layer classification accuracy is 100% for unwheeled travel mode and 97.1%. The confusion matrix is shown in Table 3-3.

3.9 Chapter Conclusions

In this chapter, we propose a real-time and network-free method to detect a user's travel mode using smartphone sensors. Our application is built on the latest Android phones and iPhones with multimodality sensors. By carefully designing the time domain and frequency domain features; together with a hierarchical classification model, we achieve 100% accuracy in a binary classification wheeled/non-wheeled travel mode, and an average of 97.1% in all the six travel modes. The online updating method achieves superior performance in time cost and it does not rely on data scale, which is an important aspect in transportation application. In contrast to from previous work (X. Su et al. 2015), the proposed solution is designed with energy concerns (small sampling frequency for mobile phones), fast server response (slide window segmentation) and quick start (a small portion of initial training dataset). These advantages ensure our method is practical in realistic applications. Future work includes (1) the generalization of the classification model to detect more complicated travel modes (e.g., Federal Highway Administration's 13 different vehicle classes), (2) transition mode detection, (3) Highway safety and driving analysis (e.g. detecting the dangerous speed when making turns, detecting wrong-way movements, etc.), (4) Mining more information such as time, and location by using environmental sensors such as a magnetometer, a light sensor, etc.

4 TRAFFIC ANOMALY DETECTION IN A LARGE-SCALE URBAN NETWORK

4.1 Background and Literature Review

Studies on traffic patterns within a certain scale of road facilities have aroused increasing attentions in recent years. The traffic pattern can be taken as those characteristics of vehicle groups passing a point or short segment during a specified span or traveling over longer sections of highway (Lan et al. 2008) and it can be explained in different ways and serve different purposes. For instance, White (2007) focused on the impact of the daily visitor transportation on the public infrastructures; Ramaswami and Sivarajan (1996) studied the proper design of network physical topology and traffic pattern to minimize the network congestion. Despite the different emphasis and purposes of these studies, the traffic pattern identification usually performs as an initial step of the entire research process in transportation management, and there are still research gaps to explore further.

First, the definition of the traffic pattern is not so clear as it should be. The metrics to describe the traffic pattern are various including traffic flow (M. J. Cassidy and Bertini 1999; D. Zhang et al. 2001; Shen and Zhang 2009), density (Treiber and Kesting 2012; M. Cassidy and Mauch 2001), speed (Banaei-Kashani et al. 2011), etc. This is mainly because the researchers usually have so different purposes that their problems intentionally shape the definition of the traffic pattern. However, only traffic related data are not sufficient. Other information such as time and link locations should also be taken into consideration and incorporating more information can enrich and clarify the connotations of traffic pattern identification.

Second, in recent years, the high-resolution and large-scale floating or fixed sensors are extensively utilized to collect the traffic data and the size of traffic data booms both in time and space. For example, traditional studies mainly focused on traffic patterns within intersections (Teodorovic et al.) or corridors (Schoenhof and Helbing 2007). With the expansion of geographic scope, there is a pressing need to conduct a hierarchical analysis for traffic pattern in larger geographic scales. The traffic pattern identification can expand from links to a district or even a county. This is much more difficult and has aroused increasing attentions. How to archive and summarize massive historical data effectively and extract meaningful traffic patterns from accumulated data to support decision making has become a significant challenge, considering the huge size of the dataset (L. Xu et al. 2013).

Third, the spatial-temporal features of traffic patterns need to be taken into account separately and further explored. This is mainly because the time and geographic information can help identify the recurrent and non-recurrent traffic patterns in separate ways and thus provide some straight-forward results in revealing the characteristics of traffic patterns. Traditional studies focus mostly on the time-of-day features, such as the fluctuation of traffic metrics over different time periods (Anbaroglu et al. 2014). However, this feature should be further explored in different geographic and time perspective. That is how the traffic pattern in one location performs as compared to its nearby locations and how it performs as compared to its historical records. A systematic study should be also conducted to reveal the day-to-day feature, geographic-located feature, etc.

To address the above research gaps, we employed a method based on the compression theory in traffic pattern identification. Compression-based approaches have been successfully implemented in pattern recognition and anomaly detection in different domains, such as image processing (Akoglu et al. 2012), system query processing (Binnig et al. 2009), etc. Previous research even argues that this approach is competitive or superior to many of the state-of-the-art approaches in anomaly and interestingness detection, classification, and clustering with empirical tests on time series, DNA, text, XML, and video datasets (Keogh et al. 2007). This method is capable of recognizing the frequent traffic patterns through effective interpretations of multi-dimensional data, and the least frequent item sets are the abnormal ones that can be taken as anomalies. The method can quantitatively distinguish traffic patterns with the similar traffic flow rate located in different intersections or districts, or the patterns in the same locations but with different time-of-day traffic occupancy.

The contributions of this chapter lie in: First, we propose to employ compression theory to effectively interpret the large collections of multi-dimensional traffic data. The study area and method are fully detailed in Section 4.2 and 4.3; Second, we reveal the geographic distribution features, time-of-day features of traffic patterns by spatial and temporal traffic pattern identifications which are in Section 4.4; Findings of our method are concluded in Section 4.5 with a series of thoughtful discussions.

4.2 Data Description

Our study builds on massive traffic loop detector datasets collected in the urban network of Northern Virginia (NOVA), located to the northwest bank of Potomac River and adjacent to the District of Columbia. Most of this area can be taken as parts of the Washington Metropolitan Area. Owing to high population density and the geographic advantages, the area has long been known for its heavy traffic (Cervero 1994). The area is further manually divided into more than 21 sub-regions by the Virginia Department of Transportation (VDOT) for traffic operation purposes, shown in Figure 4-1. Our study only focuses on urban streets, including arterials, collectors and local roads, whereas freeways are not included in the scope of this study. The signalized intersections on these road facilities usually have 3 to 4 approaches and lane-based traffic detectors are fixed on each approach. In each detector, the traffic flow and occupancy are recorded every 15 minutes. The study period contains 8 months from January 1, 2014 to August 31, 2014. The study area and the road networks are shown in Figure 4-1.

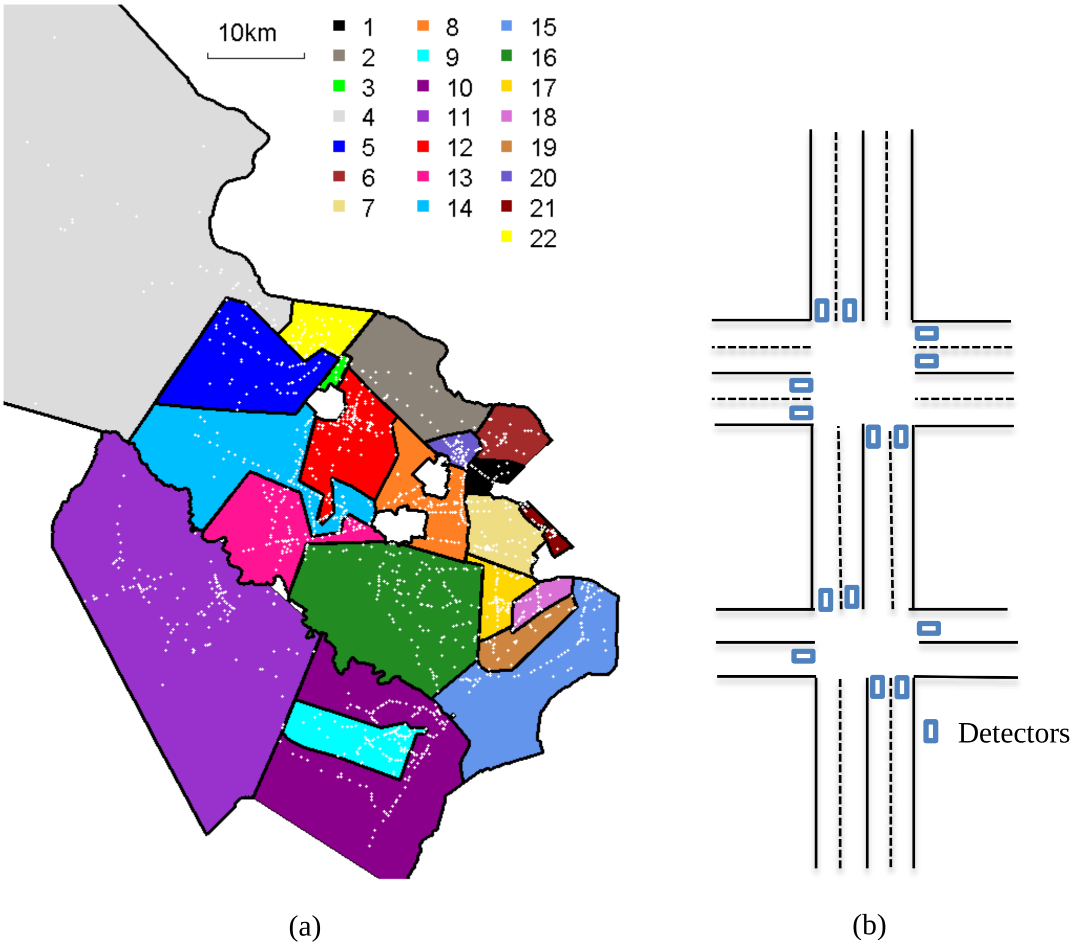


Figure 4-1 (a) Locations of the intersections (white dots), and the boundaries of sub-regions, and (b) Layouts of the detectors in signalized intersections

4.3 Methods

4.3.1 Feature categorization

The first task is to discretize the traffic-related features which requires the pre-definition of the bounds of the features, shown in Table 4-1.

For geographic information, we studied the county, sub-region and intersection level. Both the county and sub-region are discretized information. The county that a detector belongs to has three levels: Loudoun County, Prince William County, Fairfax County. The sub-region information is what we mentioned in Section 4.2. As to the intersection level, there are two levels: “Major” and

“Non-Major”. The “Major” intersections are those whose major roads are arterials and the “Non-Major” intersections are those whose major roads are collectors or local roads.

For the traffic information, the traffic flow can be categorized in three levels: Level A: [0, 700), Level B: [700, 1200), Level C: [1200, 2000) according to the service flow rate (*20-22*). The unit is vehicles per hour (vph). The occupancy is linearly related to the density, and the categorization should not only refer to (*20-22*) but also the study of the flow-density relationship in the past few decades. According to the definition of level of service from A to E, the traffic occupancy is categorized into five different levels: Level 1: [0, 1/17), Level 2: [1/17, 1/9), Level 3: [1/9, 1/7). After occupancy reaches 1/7, the traffic flow capacity is reached and we introduce another 2 categories to distinguish traffic jams: Level 4: [1/7, 1/2), Level 5: [1/2, 1].

For the time information, we do not include any of them as features into the compression database. Instead, we try to aggregate the database according to the different time scales to identify the traffic pattern differences in different time periods. Also, the differences between weekdays and weekdays are an interesting topic and will be discussed in section 4.4.

Table 4-1 Feature table

Features	**Categories**
County	Loudoun County; Prince William County; Fairfax County;
Sub-region	Divided into 22 as shown in Figure 4-1
Intersection level	Major; Non-major;
Traffic flow	[0, 700); [700, 1200); [1200, 2000);
Traffic occupancy	[0, 1/17); [1/17, 1/9); [1/9, 1/7); [1/7, 1/2); [1/2, 1];

4.3.2 Dictionary-based compression

After categorization, the traffic pattern of each 15-minute has been discretized according to their features. Assume we have a database D with 3 different features: *Flow (F), Occupancy (O), Intersection level (I)*. In each feature, there is a domain of possible values: $dom(F)=\{F_1 \ldots F_3\}$, $dom(O)=\{O_1 \ldots O_5\}$, $dom(I)=\{I_1 \ldots I_2\}$. The combination of all features in each 15-minute time period is taken as a database (DB) pattern: $DF_i=\{F_j, O_k, I_l\}$. Theoretically, the domain of DF_i: $dom(DF_i)$ is all the possible combinations of features of the database.

Table 4-2 An illustrative example of database table and pattern table

Database table				Pattern table	
DB pattern (DF_i)			PT pattern included	PT pattern (PF_i)	usage of PT pattern
F	O	I			
Level A	Level 2	Major	PF_1	PF_1: Level A, Level 2, Major	4
Level A	Level 2	Major	PF_1	PF_2: Level A, Non-major	2
Level A	Level 2	Major	PF_1	PF_3: Level 3	1
Level A	Level 2	Major	PF_1	PF_4: Level B, Non-major	2
Level A	Level 2	Non-major	PF_2, PF_6	PF_5: Level 4	1
Level A	Level 2	Non-major	PF_2, PF_6	PF_6: Level 2	2
Level B	Level 4	Non-major	PF_4, PF_5		
Level B	Level 3	Non-major	PF_4, PF_3		
……			……	……	……

The next step is to build a suitable pattern table (PT) to compress and encode the features of the database. Table 4-2 shows an illustrative example of the database and its PT. There are two columns in a PT. The first column is the PT pattern column. The domain of PT pattern: $dom(PF)$ can be different from that of DB pattern $dom(DF)$. The PT patterns can be the combination of any feature values but PT patterns are included by DB pattern: $\forall PF \in DF$. The second column is the number of occurrences of each PT pattern in the database. The PT then performs as a code dictionary and the process of converting the DB patterns into combination of PT patterns is called dictionary-based compression. One can see that after conversion, the previous larger database are compressed and encoded into a smaller one. In the table the usage of PT patterns differs with each other in the table. One can assume that different pattern tables result in different PT patterns and thus different usages.

For DB pattern encoding, given the usage, one can compute the optimal lengths of the code words to encode the patterns according to optimal prefix code (Rissanen 1978). The length of PT pattern ($P\mathcal{F}_i$) in a certain pattern table is defined as:

$$L(usage\ (PF)|PT) = -\ log\left(\frac{usage\ (PF)}{\sum_{PF_i \in PT} usage\ (PF_i)}\right) \tag{4-1}$$

It is worth mentioning that the base of all logarithms in this chapter is 2. Then, the length of DB pattern (DF_i) is calculated as the sum of the lengths of all PT patterns it contains. We find the best set of PF that can make up DF. In one DF, any component PF cannot cover other PF.

$$L(DF|PT) = \sum_{PF \in DF} L(usage\ (PF)|PT)$$

The length of DB is the sum of the lengths of all DB patterns the database contains.

$$L(DB|PT) = \sum_{DF \in dom(DF)} L(DF|PT)$$

For encoding the pattern table, we still need optimal prefix code (Akoglu et al. 2012). There are two parts involved in the length of PT. The first part is the sum of lengths of all PT patterns; the second part is the sum of lengths of all singleton items in each category in DB. Define I as all the singleton items in DB, c as the total count of singleton items and r_i is the count of the ith singleton item. For example, in Table 4-2, c is equal to 24, r_i of the singleton item "Level A" is 6.

The length of the PT table is defined as:

$$L(PT) = \sum_{PF \in PT} L(usage\ (PF)|PT) + \sum_{r_i \in I} -r_i log(\frac{r_i}{c})$$

The length of a DB pattern code plays a significant role in anomaly detection. To save storage space, patterns that occur more frequently result in smaller $L(PT)$, which are regarded as the normal ones, whereas those occurring less frequently are taken as the abnormal ones. For example, in transportation study, the unexpected non-recurrent traffic congestions are treated as anomalies and the severity of the anomalies can be quantified by the length of the DB patterns.

4.3.3 Minimum Description Length principle and Dictionary-based compression algorithm

One can see from Section 4.3.2 that given a database of observations, the lengths of both DB and PT are totally decided by the selection of PT. One principle, called Minimum Description Length (MDL), should be followed to select a suitable pattern table to compress and encode the database. The MDL principle identifies the best PT which minimizes the description length:

$$\mathcal{L} = L(DB|PT) + L(PT) \tag{4-2}$$

The MDL principle requires us to find the description length of the shortest codes for the actually observed sequence (data), rather than a mean length (Barron et al. 1998). Also, one can see that a complex PT with diverse PT patterns can compress the DB very well and thus leads to a small $L(DB|PT)$. The side effect is that it will also result in a large $L(PT)$. MDL principle attempts to balance the complexity of PT and its fit to DB. Therefore, the PT that can provide the shortest description length of Eq. (4-2) is the best pattern table that compresses the database.

To find the best PT Table, we employ a heuristic search algorithm as follows.

Algorithm: Dictionary-based compression

Input: Database with *n* rows and *m* categories
Output: A PT table and the length of each pattern
Build the initial PT table and all PT patterns $\boldsymbol{PF_i}$ are singleton items of features in DB
Compute the initial description length $\boldsymbol{\mathcal{L}_0}$, the optimal length $\boldsymbol{\mathcal{L} = \mathcal{L}_0}$
Implement the Apriori algorithm to find all frequent items $\boldsymbol{FI}$ whose frequency is higher than a threshold $\boldsymbol{T}$, these frequent items constitute a set $\boldsymbol{S}$
Repeat
    for $\boldsymbol{FI_i}$ in $\boldsymbol{S}$
        Put $\boldsymbol{FI_i}$ into the PT table
        Compute the current description length $\boldsymbol{\mathcal{L}_i}$
        If $\boldsymbol{\mathcal{L}_i < \mathcal{L}}$
            $\boldsymbol{\mathcal{L} = \mathcal{L}_i}$
            remove $\boldsymbol{FI_i}$ from $\boldsymbol{S}$
            add $\boldsymbol{FI_i}$ into PT table
        else
            remove $\boldsymbol{FI_i}$ from $\boldsymbol{S}$
until $|\boldsymbol{S}| = 0$

The proposed search algorithm can be interpreted in the following steps:

- Step 1: All possible singleton items in DB are taken as the PT patterns in the PT table. For example in Table 4-2, the PT patterns are (“Level A”, “ Level B”, “Level 2”, ”Level 3”, “Level 4”, “Major”, “Non-major”). According to these PT patterns, one can calculate the initial description length and take it as the current length.

- Step 2: We implement the Apriori algorithm (Agrawal and Srikant 1994) to find all frequent items that are the combinations of one or more singleton items. We order the items according to their frequency and choose those whose frequency is higher than a threshold. These "frequent" items are the potential candidates for PT patterns. For example, in Table 4-2, the combination of "Level A" and "Level 2" has the highest frequency of 6 and they are put into the list of candidates.
- Step 3: We add the most frequent combination from the list of candidates into the PT table and recalculate the description length. If the recalculated length is smaller than the current one, we add the new item into the PT table and change the length of each pattern. If the recalculated length is larger, we keep the previous PT table and score. For example, in Table 4-2, after calculation, it is found that adding the item "Level A/Level 2" to the PT table can reduce the description length. Therefore, the item "Level A/Level 2" is chosen and added to the PT table.
- Step 4: We remove the item in Step 3 from the candidate list and continue with the next candidate until there is no candidate left in the list.

It is worth mentioning that the threshold $\boldsymbol{T}$ for the candidate item is chosen as 30% of the total count of DB patterns in this chapter. One can still lower the threshold but this may lead to much more computation and relatively less improvement.

4.3.4 Anomaly degree

In Section 4.3.3, the MDL principle finds the best pattern table, and we proceed to derive a normalized anomaly degree that can characterize the traffic patterns.

Given a PT, the length of a traffic pattern is:

$$L(DF|PT) = \sum_{PF \in DF} L(usage\ (PF)|PT)$$

$L(DF|PT)$ indicates the anomaly degree of a traffic pattern. The higher the length is, the closer the traffic pattern length is to the upper bound, and consequently the more abnormal the traffic pattern should be. Theoretically, when the DB table has only one kind of DF, there should also exist only one kind of PF equal to DF in PT. The lower bound of $L(DF|PT)$ is inevitably 0. However, the upper bound should be bounded by a certain value.

Definition 1: Given the number of DB patterns, the approximate upper bound of $L(DF|PT)$ is defined as:

$$U = \tau \cdot \sum_{i \in dom(i)} -log\left(\frac{1}{N}\right)$$

Where N is the total number of rows in DB, τ is a discount factor.

Remark 1:

$$L(DF|PT) = \sum_{PF \in DF} L(usage\ (PF)|PT)$$

$$= \sum_{PF \in DF} max\{L(usage\ (PF)|PT)\}$$

$$= \sum_{PF \in DF} max\left\{-log\left(\frac{usage\ (PF)}{\sum_{PF_i \in PT} usage\ (PF_i)}\right)\right\}$$

Two cases need to be considered separately.

Case 1: If there exist only singleton items in PT table, then the highest values of $-log\left(\frac{usage\ (PF)}{\sum_{PF_i \in PT} usage\ (PF_i)}\right)$ for each PT feature in DF should be $usage\,(PF) = 1$ and $\sum_{PF_i \in PT} usage\ (PF_i) = N$ that is $-log\left(\frac{1}{N}\right)$.

Case 2: If there exist PT patterns that are combinations of 2 or more singleton items. For PT patterns with more than one singleton items, $-log\left(\frac{usage\ (PF)}{\sum_{PF_i \in PT} usage\ (PF_i)}\right) = \sum_{i \in dom(i)} -log\left(\frac{1}{N - \sum_{i \in dom(i)} M_i}\right)$ where M_i equals to the number of combined PT patterns that contain the singleton items in *i*th feature. Also, $\sum_{i \in dom(i)} -log\left(\frac{1}{N - \sum_{i \in dom(i)} M_i}\right) \leq \sum_{i \in dom(i)} -log\left(\frac{1}{N}\right)$.

However, this value is too large for most of DB table and to make comparable the anomaly degrees from different DB. To make it less conservative, we introduce τ as a discount factor. Therefore:

$$L(DF|PT) \leq \tau \cdot \sum_{i \in dom(i)} - log\left(\frac{1}{N}\right)$$

Defining U allows us to normalize the anomaly index to be a fraction number. We further derive the anomaly degree to evaluate the performance of traffic patterns:

$$D(DF_i|PT) = L(DF_i|PT)/U \qquad \textit{(4-3)}$$

where $D(DF_i|PT)$ is the normalized anomaly degree of the *i*th traffic pattern in the database. As one can see, the anomaly degree is the index that characterizes the traffic patterns in the DB. Note that since U is approximated, $D(DF_i|PT)$ could possibly exceed 1.0. In this chapter, τ is set as 0.85.

We employ this index to quantify the traffic patterns from two different perspectives: spatial anomaly degree and temporal anomaly degree. For spatial anomaly degree, we check the pattern differences across locations over the same time period, and the DB table is the set of traffic patterns in the whole region. For temporal anomaly degree, we check the pattern differences in the same location over different time periods, and the DB table is the set of traffic patterns in one location in different time-of-day periods. For anomaly index in Eq.(4-3), the lower the value is, the less abnormal the traffic condition should be. From a spatial perspective, over a large road network, it is true that only a small portion of road links or intersections may suffer from either heavy traffic, bottleneck locations or even traffic incidents as compared to most of the others. From a temporal perspective, over a certain time period, it is also true that only on few days there exists an unexpected traffic incident, whereas the traffic runs as usual on the other days. These rare conditions may contribute to a higher anomaly degree. Thus, the anomaly degree defined in Eq. (4-3) can access the overall traffic performance of an intersection in different spatial and temporal perspective.

4.4 Numerical examples

4.4.1 Spatial regional traffic pattern identification

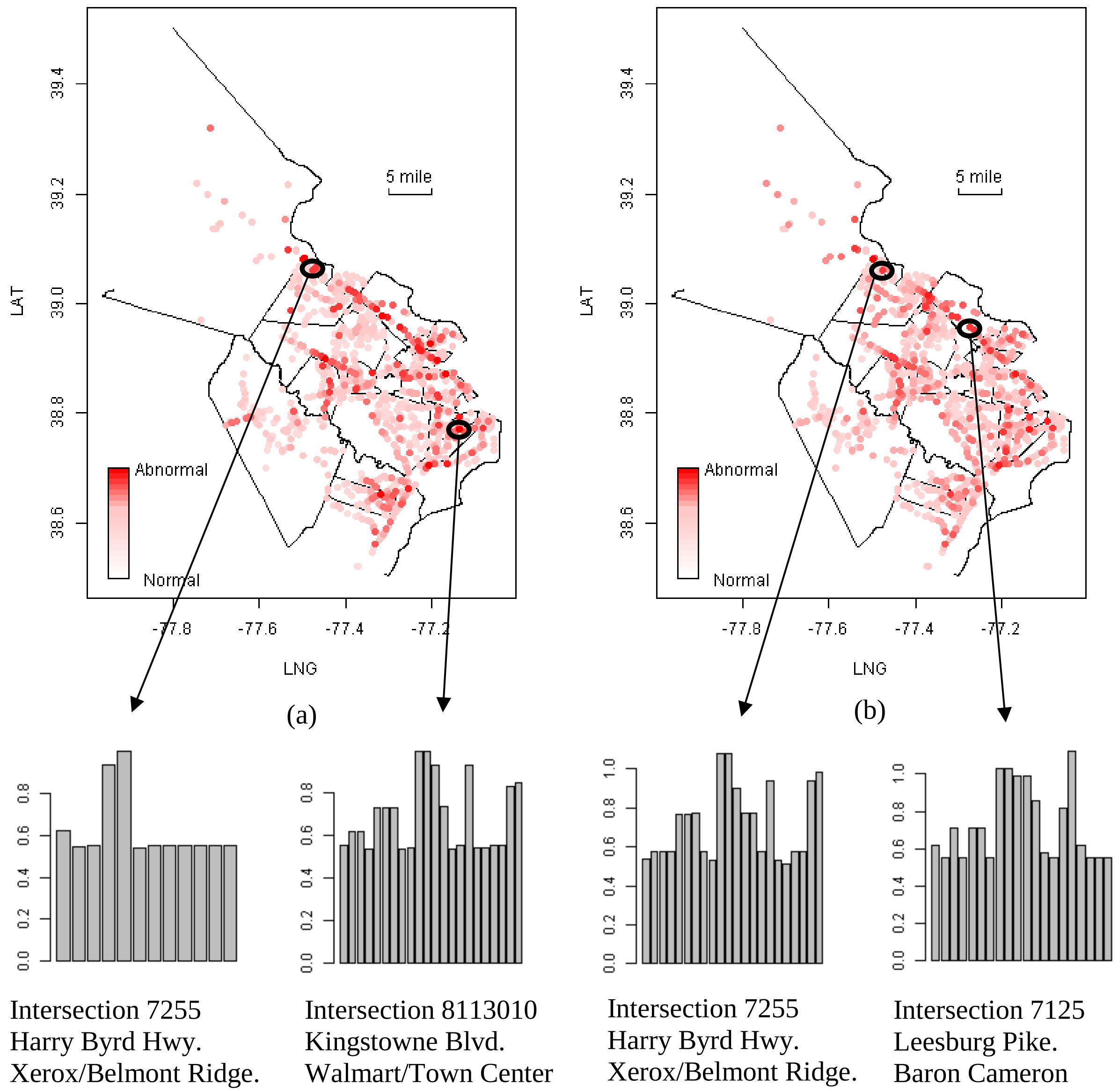


Figure 4-2 spatial regional traffic pattern identification during PM peak (5:00-6:00 p.m.) on (a) Feb 20, 2014 (Weekday) and (b) Mar 22, 2014 (Weekend). The anomaly degrees of detectors in two most abnormal intersections and their locations are shown in the bottom of

The DB table of the spatial regional traffic pattern is the set of traffic patterns in the whole region over the same time period. We first calculate the anomaly degrees of the traffic patterns in the detectors and further derive the anomaly degrees of the intersections by taking the 90th percentile of anomaly degrees of all detectors that belong to the intersection. Figure 4-2 shows the heat map of spatial regional traffic pattern at intersection level in PM peak (5:00-6:00 p.m.) separately on weekday (Feb 20, 2014) and weekend (Mar 22, 2014). One can see some distinct red corridors, such as Leesburg Pikes, which goes from northwest to southeast. This indicates that certain roads in the network experience more severe conditions than that of others. Also, one can say that certain regions are more likely to be jammed together (Banaei-Kashani et al. 2011). Also, there is almost no difference in geographic distributed features of anomaly locations on weekdays or weekends during PM peak.

We further selected three sub-regions and averaged the anomaly degrees of the intersections within the sub-regions. From Figure 4-3, one can see a clear trend of regional anomaly degrees, decreasing from AM peak to noon, and increasing back to PM peak. In addition, the ranks of the sub-region remain almost the same.

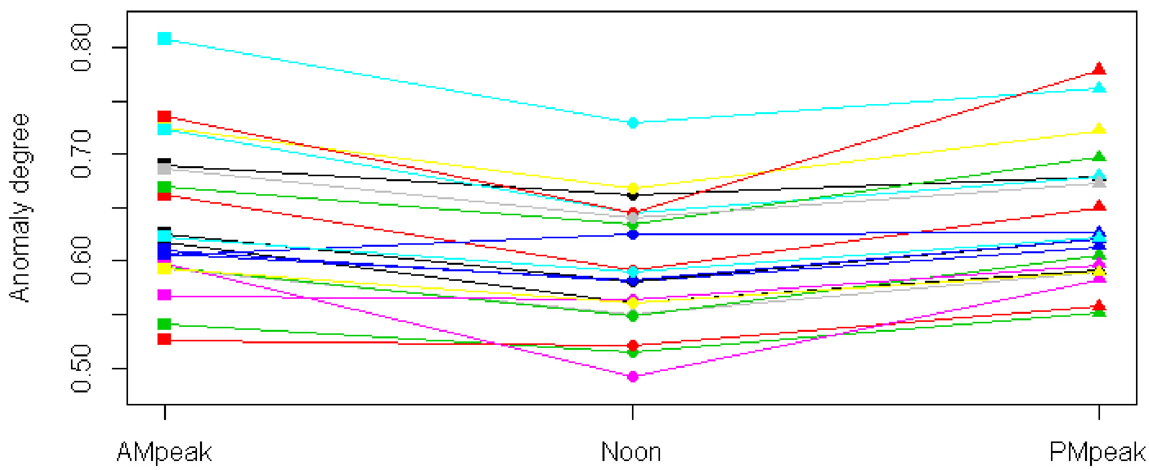
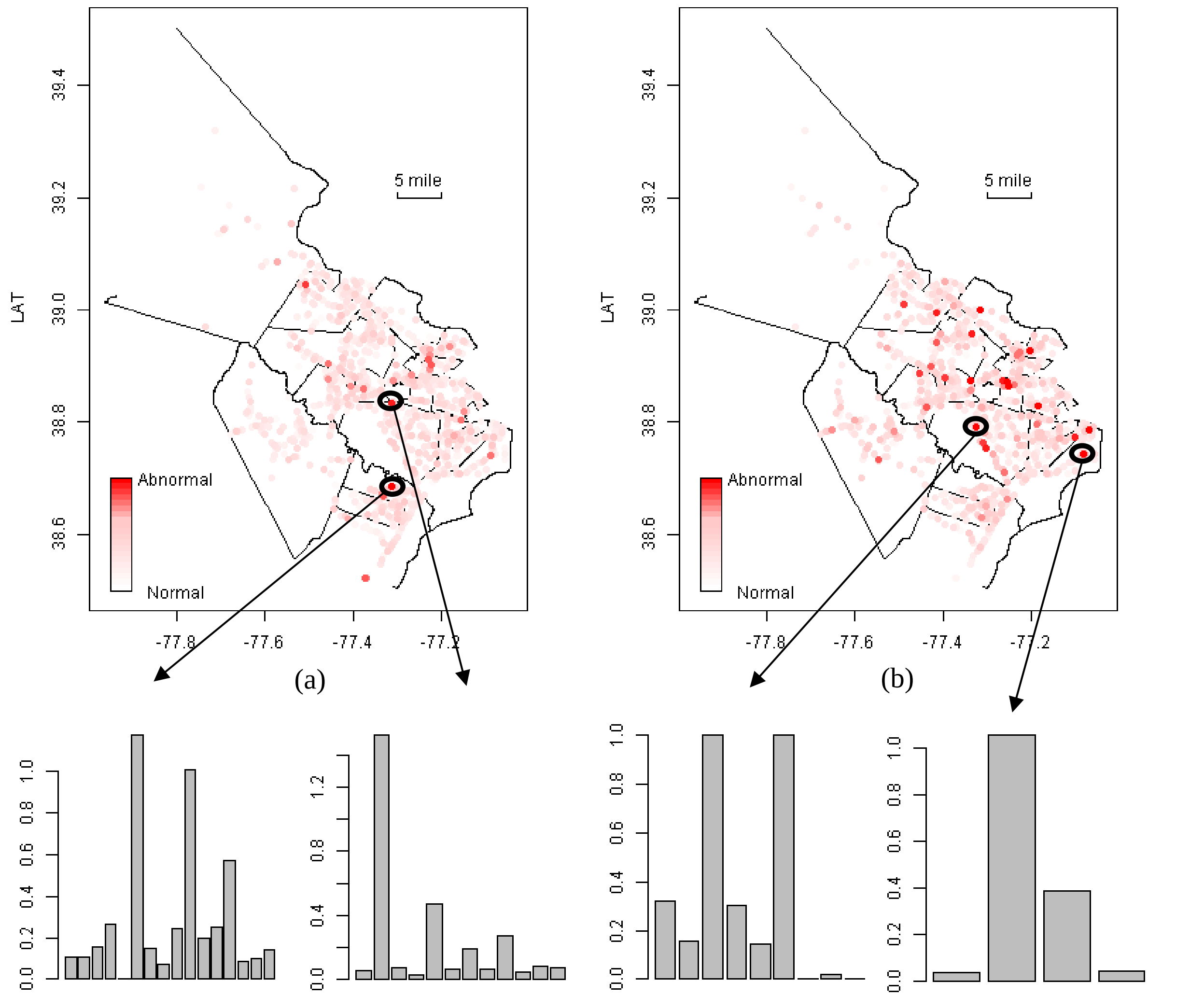


Figure 4-3 Spatial anomaly degrees in three different time periods for different sub-regions (each link represents a sub-region).

4.4.2 Temporal regional traffic pattern identification



Intersection 641035
Old Bridge Rd.
Hedges Run Dr.

Intersection 123115
OX Rd.
University Dr.

Intersection 123146
OX Rd.
Ramp B.

Intersection 626005
Sherwood Hall Lane
Fordson

Figure 4-4 Temporal regional traffic pattern identification during PM peak (5:00-6:00 p.m.) on (a) Feb 20, 2014 (Weekday) and (b) Mar 22, 2014 (Weekend). The anomaly degrees of detectors in two most abnormal intersections and their locations are shown in the bottom of the

The DB table is the set of traffic patterns in one location over different time periods. Same as the spatial traffic pattern identification, we first calculate the anomaly degrees of the detectors and aggregate them to that of intersections by taking the 90th percentile. We also consider weekdays and weekends separately. Figure 4-4 shows an entirely different heat map of temporal traffic pattern than that of spatial traffic patterns. As one can see, there is no clear corridor pattern of abnormal intersections as shown in Figure 4-4. The occurrences of abnormal traffic patterns are quite random. If the criterion of anomaly degree is set as 0.8, less than 10 percent of the intersections are abnormal, whereas more than 90% of the intersections operate pretty much the same as most of the other days. For two most abnormal intersections, the anomaly degrees of the detectors in the intersection differ greatly from each other, and the traffic patterns of an intersection may deteriorate by one or two abnormal detectors.

Unlike the spatial pattern, the temporal anomaly degrees in the sub-regions do not show a clear trend in different time periods, shown in Figure 4-5. This observation is expected since the temporal pattern has little to do with geography information.

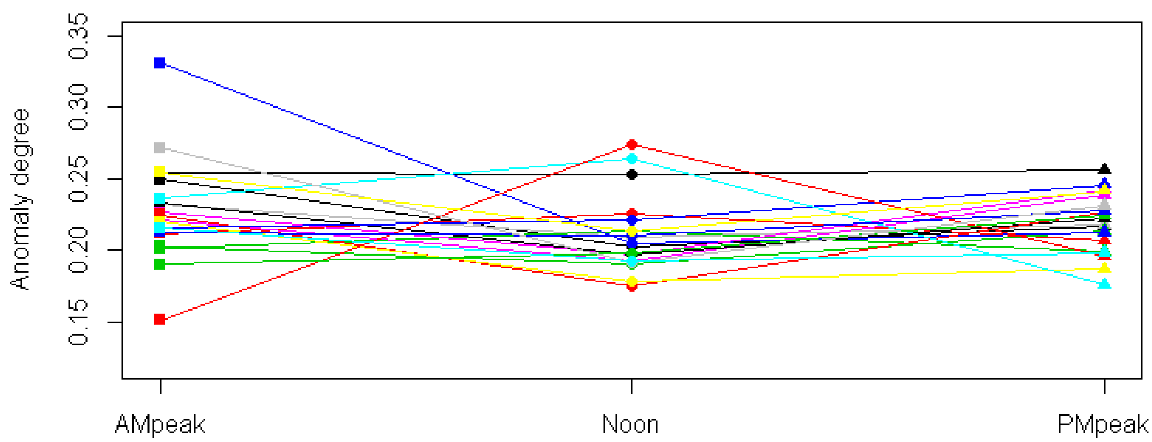
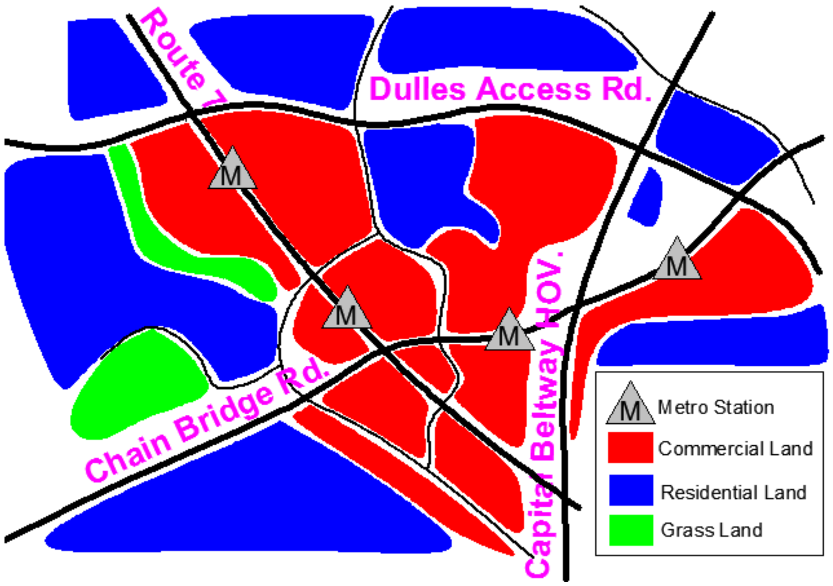


Figure 4-5 Temporal anomaly degrees in three different time periods for different sub-regions (each link represents a sub-region).

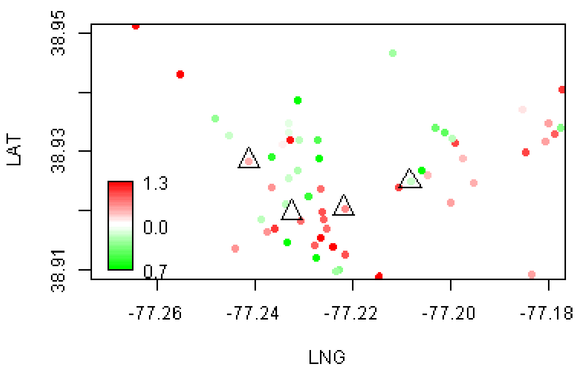
4.4.3 A case study

In this sub-section, we implement the proposed method to study the traffic impact of the new 11-mile extension of Sliver Line, a subway line of Washington Metro. The extension consists of 5 exclusive new stations, which began service on July 26, 2014. We only studied the sub-region that contains 4 metro stations, shown in Figure 4-6 (a). The metro stations are evenly distributed along the road line of Route 7, Chain Bridge Rd, and one metro station (Greenboro metro station) is almost located at the intersections of two roads. We divide the entire time span into two ranges, before and after the day of service. We conduct the spatial-temporal traffic pattern identifications on PM peak separately on weekdays and weekends before and after Sliver Line extension. A ratio of anomaly degrees between after and before the Sliver Line extension is calculated, as shown in Figure 4-6 (b)-(e).

It will be helpful to examine the anomaly degrees together with the geographic-distributed feature of the study areas. On both arterials, one can see an overall increase of anomaly degrees both in spatial and temporal traffic patterns on weekdays and weekends after the Silver Line extension. It should be due to that new metro stations attract more commute traffic and entertaining traffic (for Tysons Corner Center in the red area). Besides these two arterials, other intersections, especially those collectors and local roads located within the commercial land, do not show an identical increase or decrease in different spatial-temporal perspectives. For the spatial traffic pattern part, it should be noted that the metro stations are coupled with several newly-built transit lines designed to connect new Silver line rail travel (WMATA 2014). Most of the transit lines stop at the arterials instead of collectors or local roads. What is more, new parking lots are open together with the metro station and their locations are mostly near the arterials. The newly-built metro station may change both the land-use features and the trip mode and in turn change the spatial traffic patterns. For the temporal traffic pattern part, these changes are even more apparent. The after-case traffic pattern can be taken as the minority and detected just because the time period of the after-case traffic pattern is from July 26th to August 31st that is only a small portion of the total record period. Unlike spatial traffic patterns, temporal traffic patterns capture the sudden changes of traffic as with the changes of land use and travel mode. In sum, the spatial and temporal traffic identification reach conclusions in different ways and support decision making for transportation planning and management.



(a)



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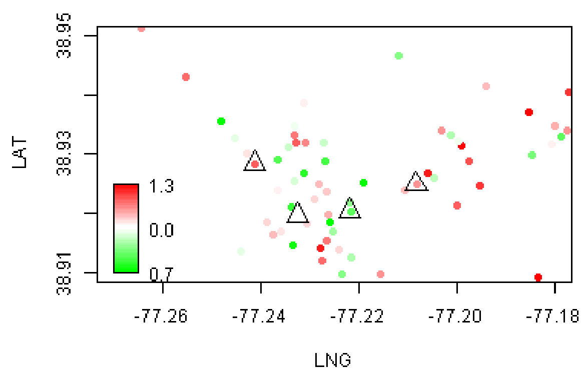

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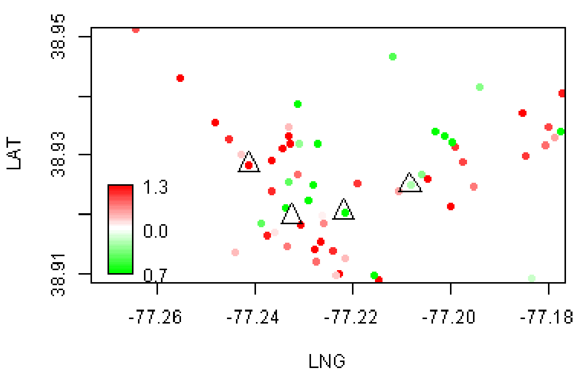

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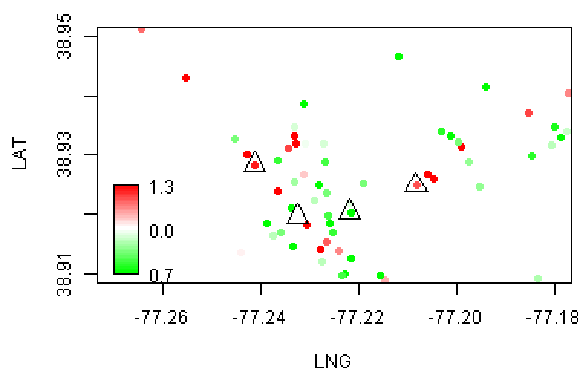


(e)

△ Metro stations ● Signalized intersections

Figure 4-6 (a) Map of the sub-region; ratio of spatial anomaly degrees between after and before Sliver Line extension on (b) weekdays and (c) weekends; Ratio of temporal anomaly degrees between after and before Sliver Line extension on (d) weekdays and (e) weekends.

4.5 Chapter Conclusions and discussions

This chapter focuses on the regional traffic pattern identification and anomaly detection within a certain scale of traffic networks. The dictionary-based compression techniques are fully exploited and an anomaly degree index is derived to describe and quantify both spatial and temporal traffic pattern. The spatial pattern identification shows meaningful results of concurrent traffic patterns: Over a certain time period, the regional spatial pattern shows a clear geographic distribution of abnormal traffic locations. Two most abnormal intersections in the plots show that if one detector suffers a higher anomaly degree, other detectors in the same intersection are more probable to be abnormal. If we focus on the traffic patterns in different time-of-day on the same day, an identical "high-low-high" trend for AM peak, Noon, and PM peak can be found in different sub-regions.

The temporal traffic pattern identification shows that the occurrences of temporal abnormal places are quite random, and detectors in the same intersections may have quite different anomaly degrees from each other. It can detect the non-concurrent traffic anomalies compared to historical time-of-day periods. Different from spatial regional traffic pattern, no identical trend from AM peak, Noon and PM peak can be found in different sub-regions.

5 MULTI-MODAL TRAFFIC SIGNAL CONTROL WITH SMARTPHONES UNDER MIXED TRAFFIC FLOW

5.1 Background and Literature Review

As a first attempt, this chapter aims to develop Multi-modal Hierarchically Responsive Signal, called *MARS*, which grants hierarchical priority for multiple travel modes during traffic signal control.

As one can see from Table 1-2, existing practice of smartphones can provide near 70% penetration of multi-modal travelers. Given high penetration rates of smartphones and additional vehicle index estimation technique, it is anticipated to obtain real-time 100% of vehicle trajectories soon in the real-world. Therefore, in order to leverage the trajectory of each vehicle, this paper makes the **assumption** that the vehicle penetration rate is 100%.

This paper develops a hierarchically multi-modal signal control model, in which each travel mode is solved by a dynamic programming hierarchically with the consideration of the delay and budget from upper-level modes. The key contributions of this paper lie on

1) Estimate the delay based on the trajectory of each vehicle. Such feature could be used for trajectory control of automated vehicles.
2) Develops a weight-free hierarchical optimization model to deal with different travel modes. Previous studies showed that there is no straightforward method to determine the appropriate weight for each mode.
3) The proposed model is European style stage-based phasing scheme. But it is fully compatible with any U.S. phase configuration, including NEMA dual right eight phase setting. Also, it allows phase omitting, rotation and insertion.

The literature on adaptive traffic signal control, traffic signal priority control, multi-modal signal control and event-based traffic signal control, bears relevance to this research.

5.1.1 Adaptive Traffic Signal Control

Nowadays, the most advanced and sophisticated traffic signal control systems are adaptive traffic signal control systems. With advanced traffic sensors, adaptive signal control systems can make real-time incremental changes in terms of green splits, offsets and cycle time, corresponding to the existing traffic conditions. Therefore, several attempts to develop proactive (or prediction based) adaptive control systems have occurred. Representative adaptive traffic signal control systems, including SCOOT (Hunt et al. 1982), SCATS (Cornwell et al. 1986), RHODES (Head and Mirchandani 1992; Sen and Head 1997), UTOPIA (Mauro and Taranto 1989), and PRODYN (Henry et al. 1983), have been developed in the past decades. At first glance, such adaptive system seems very applicable for event traffic management. However, there are some limitations for these systems:

- Typically these adaptive systems depended on elaborate communications, computation, and detection system that are difficult to maintain and require highly specialized knowledge and understanding to operate. Various practical limitations have restricted the practicability of adaptive signal control systems. Only less than 100 out of 300,000 traffic signals in U.S are implemented with adaptive signal control systems (Selinger and Schmidt 2009; National Transportation Operations Coalition 2012).
- It is well known that adaptive signal control systems still cannot manage traffic in an oversaturated network, which widely exists in event-induced traffic conditions. To avoid queue spillover, human-involved traffic control, such as turn restrictions, lane group reallocation and reversible lanes are more effective than automatic signal control.
- Large scale planned events usually involves multimodal traffic, including pedestrians, buses, trucks and passenger cars. Current adaptive traffic signal systems, which are not able to detect different traffic modes, fail to provide effective multimodal control.
- Severe unplanned events, such as traffic incidents and natural disasters, often result in road closures and turn restrictions, which could fundamentally change the traffic pattern, such as volume capacity ratio, can degrade the performance of adaptive traffic signal control systems.

5.1.2 Traffic Signal Priority Control

Traditional priority control systems in the United States can be categorized into emergency vehicle preemption and Transit Signal Priority. An emergency vehicle requests signal preemption treatment by using either optical, acoustic, special inductive loop technology, or based on Global Positioning System (GPS) positions (Nelson and Bullock 2000). Preemption generally involves a control strategy that immediately switches from current phase to a pre-selected phase for the first request received. Transit signal priority has been adopted using similar technology, but can be served by minor modifications to traffic signal plan parameters (offset adjustment, green split reallocation, phase insertion or phase rotation) to favor the movements of transit vehicles (Evans and Skiles 1970; Yagar and Han 1994; Balke et al. 2000; Furth and Muller 2000; Skabardonis 2000; Baker et al. 2002; Head 2002; Liu et al. 2003; Smith et al. 2005; Skabardonis and Geroliminis 2008; Ma et al. 2010; He et al. 2011).

In current emergency vehicle preemption systems, only one request is served at a time. Therefore, if multiple vehicles are approaching an intersection at one time and they request conflicting phases the first request received would be served even if a safer and more efficient solution could be achieved by considering all active request simultaneously. While emergency vehicle operators are trained to be observant and vigilant, there have been cases where two emergency vehicles have collided in an intersection (ABC13 2009). Roadway safety has been noted as a significant emergency responder issue (The Transportation Safety Advancement Group 2010). Traffic accidents account for over 13% of all emergency first responder deaths (Donoughe, Whitestone, Gabler, 2012). This is a startling statistic that needs to be addressed and can be addressed using technological advances that are available.

Transit Signal Priority is a popular tool for improving transit performance and reliability (Smith et al. 2005). However, state-of-practice TSP is designed for one priority request at a time. Existing priority control systems are not capable of handling conflicting priority requests or multi-modal priority requests. For example, when two buses and a group of pedestrians arrive on conflicting approaches at an intersection during a cycle, there is a pressing need to simultaneously consider the multiple and multi-modal priority requests in a way that is not disruptive, or inefficient, to other traffic such as other transit vehicles and passenger cars. The questions about how to balance signal priority for different modes and balance signal priority and signal coordination remain open.

5.1.3 Multi-modal Traffic Signal Control

Multi-modal traffic signal control originates from traditional traffic signal priority control, which usually deals with one priority travel mode over passenger cars (e.g. preemption for the priority of emgergency vehicles over cars, and TSP for the priority of buses over cars), but extends the concept of priority control to multiple travel modes, including but not limited to emergency vehicles, light rail, buses, pedestrains, bicylcies, and trucks. Multi-modal traffic signal control was raised recently because of the adevent of CV (He 2010) and expanded first from multi-priority signal control (He et al. 2011), which considers multiple priority requests from the same mode for transit buses. Further, He, Head, and Ding (2012) proposed a multi-modal signal control formulation called PAMSCOD, in which bus and pedestrian priorities as well as passenger cars are explicitly considered by mathematic programming. However, PAMSCOD relies only on the significant level penetration of V2I communications, which ignore the fact that current traffic field data is heterogeneous in terms of its source. Later, a more practical model was developed (He et al., 2014), which assumes multiple traffic modes with priority (such as emergency vehicles, buses, and pedestrians) are equipped with V2I communication systems. And the proposed algorithm for bus multi-priority control has been successfully implemented in a real-world arterial, composed of six intersections in Anthem, Arizona (Ding et al., 2013). A unified decision framework was proposed by Zamanipour, Head, and Ding (2014) for multi-modal traffic signal control that simultaneously considered the need of different modal users based on wireless communication, as well as traditional detection methods. However, the previous work in multi-modal signal control was built upon weighted averages of objective function among different modes, and did not directly address the specific challenge on how to choose weights for each travel mode under different scenarios, such as the massive amount of pedestrians, saturated traffic conditions, and so on. In this research, to resolve this challenge, we introduce a hierarchical priority control framework for multiple travel modes.

5.1.4 Event-based traffic signal control

Large-scale planned events, such as sporting games, concerts, parades and conferences, and unplanned events, such as traffic incidents, disasters, inclement weather and infrastructure failures, either attract high-volume multi-modal traffic, or reduce the existing network capacity, both of which result in significant non-recurrent traffic congestion (Latoski, Dunn Jr, Wagenblast, Randall, & Walker, 2005). Over the years, a large amount of effort has been invested in studying how to alleviate non-recurrent congestion with automatic signal control methods. Sheu (2002) presented a fuzzy clustering approach to automatically identify and characterize freeway incidents for reducing non-recurrent traffic congestion on freeways. A stochastic optimal-control-based approach was proposed to realize real-time incident-responsive coordinated ramp control (Sheu & Chang, 2007). Lu, Xu, Hou, and Zhang (2011) focused on reducing incident-induced congestion in urban traffic network via intersection signal control strategies. A bi-level programming model was presented by Zhang, Gao, and Ren (2011) to alleviate the incident-based congestion. The proposed model included the upper level to minimize the total travel cost and the low level to present travelers' dynamic route choice behavior. Hossain, Kattan, and Radmanesh (2011) proposed a responsive control strategy called RESSICA, which was based on Case-based reasoning (CBR), a technique in artificial intelligence (AI), to accommodate non-recurrent traffic congestion and high traffic fluctuations caused by unexpected events. Additionally, there also exist a few studies focused on manual control operation. Mahalel, Gur, and Shiftan (1991) collected field data at a single intersection to understand the differences between automatic and manual signal control. Lassacher, Veneziano, Albert, and Ye (2009) examined traffic management strategy for a large football game and concluded that signal retiming and manual traffic control strategies allowed for dramatic improvements in the traffic level of service.

Different with previous approaches, Ding et al. interviewed Traffic control agencies (TCAs), including police officers, firefighters or other traffic law enforcement officers, who can override automatic traffic signal control and manually control the traffic at an intersection (Ding et al. 2014). They modeled TCA-based manual traffic signal control and showed that such control methods can mitigate non-recurrent oversaturated congestions very effectively (Ding et al. 2015).

5.2 Multi-modal Traffic Signal Control with Lexicographic Dynamic Programming

The objective of this chapter is to build a hierarchical optimization framework to achieve reliable and efficient real-time multi-modal signal control. To achieve this objective, we develop a lexicographic dynamic programming approach to handle mixed traffic with hierarchical priority levels.

Table 5-1 Hierarchical priority levels of travel modes and their control objectives

Priority level	Level 1	Level 2	Level 3	Level 4
Travel modes	Emergency vehicles	Massive pedestrians or bikers	Transit buses and light rail	Trucks, passenger cars, pedestrians and bikers
Objective	Minimize delay	Maximize throughput	Minimize schedule deviations (or Maximize reliability)	Minimize delay or number of stops, or Maximize throughput or Minimize emission
Applications	Emergency response operations	Planned special event management	Reliable transit vehicle operations	mixed traffic control in central business areas

Table 5-1 classifies the existing modes into four hierarchical priority levels according to our previous survey with traffic control agencies (Ding et al. 2014). The objectives of travel modes within different levels are arranged in the order of importance, whereas the objectives of travel modes within the same level are considered in a competing manner. In this chapter, we first use lexicographic optimization (non-scalarizing method) to solve the Multi-Objective Optimization (MOO) problem for travel modes in different hierarchical levels (Marler and Arora 2004). In lexicographic optimization, we consider the lexicographic order when comparing objective for each travel mode in criterion space. In general, the lexicographic optimization of a series of objective functions is to optimize the first objective function and then among the possible alternative optima optimize for the second objective function and so on.

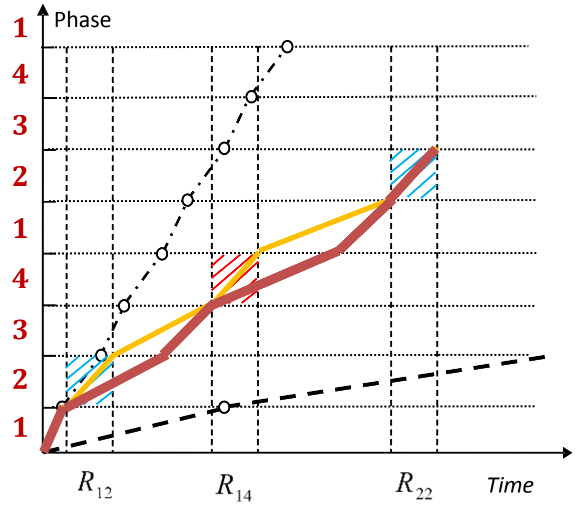


Figure 5-1. A phase-time diagram showing that multiple optimal signal timing plans exist for serving three priority requests

According to our previous work, it is worth mentioning the fact that multiple optimal solutions always exist at a certain priority level of travel modes (He et al. 2011). We developed the phase-time diagram to illustrate multiple optimal solutions in Figure 5-1. A phase-time diagram showing that multiple optimal signal timing plans exist for serving three priority requests. Given three priority interval requests, multiple optimal signal plans can achieve zero priority delay. This fact builds the foundation for applying lexicographic optimization for hierarchical multi-modal signal control.

Objectives of travel modes within the same priority level, will be handled with a dynamic programming model, incorporating smartphone-based floating sensors. Each traveler makes a request (with its travel mode and arrival time) to get through the intersection with its own objective.

A dynamic programming model is developed based on breaking a decision into manageable decision stages which are solved recursively. In our approach, we developed a formulation that performs the recursion in a forward manner.

Much like the COP formulation (Sen and Head 1997), our model uses phases as stages in the dynamic program, the length of a phase as a decision variable and the total number of time-steps that have been allocated as state variable. One of our contributions is to consider the inclusion of additional state variables that track the trajectories of vehicles through the road, both before and after the intersection and provided that the initial position of every vehicle is known at the beginning of the optimization process. To track the vehicle makes it possible to calculate any desirable performance measure that one wishes to optimize. For this study, we consider total delay as our performance measure. Another contribution of this study, unlike COP formulation only designed for stage-based operations, the proposed model can support NEMA 8 phase dual ring operations.

We hereby study the single mode and multi-modal problem separately. Majority of the definition of the first problem is maintained in the second problem.

5.2.1 Single Mode Model

Before presenting the model of MARS, we need to provide the notations of the model:

- $P -$ set of phases.
- $\phi -$ index of the phases.
- $T -$ total number discrete time-steps.
- $t -$ index for each time period in T.
- $\gamma -$ minimum green time.
- $r -$ effective clearance interval.
- $j -$ index for stages of the dynamic program.
- $k -$ index for vehicles arriving at the intersection.
- $l -$ index in P that denotes the initial phase.
- $\delta_1 -$ minimum distance between vehicles in the queue.
- $x_j -$ control variable denoting the amount of green-time allocated to stage j .
- $s_j -$ total number of time-steps that have been assigned at stage j.
- $D_{jk}-$ the delay of vehicle k at stage j.
- $f_j(s_j, x_j)$ the performance measure of each stage j given control variable x_j.
- $h_j(x_j) -$ the length (in time-steps) of phase j.
- $X_j(s_j) -$ set of feasible control decisions, given state s_j.
- $\omega_f > 0 -$ average free flow speed.

- $\omega_c < 0 -$ average shock wave speed.

We define the recursive function (or value function) as follow:

$$v_j(s_j) = \min_{x_j \in X_j(s_j)} \{f_j(s_j, x_j) + v_{j-1}(s_{j-1})\} \tag{5-1}$$

where the transition of the state variable is defined as

$$s_{j-1} = s_j - h_j(x_j) \tag{5-2}$$

where $h_j(x_j)$ represent the length of phase j and obtained as follow,

$$h_j(x_j) = \begin{cases} 0 & if\ x_j = 0 \\ x_j + r & if\ x_j > 0 \end{cases} \tag{5-3}$$

The performance measure function $f_j(s_j, x_j)$ defined in Eq. (5-1) can be represented by total delay as follows,

$$f_j(s_j, x_j) = \sum_k D_{jk} \tag{5-4}$$

On each stage j of the dynamic program, a decision is made concerning the length x_j of the current phase $\phi(j)$. For a given length of the phase is possible to update the position of the vehicles d_k and compare it to the position they could have been if they were to maintain free ow at all times. This difference provides the delay for each vehicle, and the aggregation the total delay for that particular stage. Figure 5-2 illustrates the space-time diagram of the proposed model. The horizontal axis is time and the vertical axis is space. Vehicles are approaching the signal from bottom to top.

If $\phi \neq \phi(j)$, meaning the requested phase of the vehicles is different to that one to the current stage, the delay of each vehicle is obtained as follows,

$$D_{jk} = \begin{cases} 0 & if\ d_{j-1,k} > 0 \\ max\{h_j(x_j) - \frac{l_k - d_{j-1,k}}{\omega_f}\} & if\ \ d_{j-1,k} \leq 0 \end{cases} \tag{5-5}$$

where the projected position, relative to the intersection, of a vehicle in the queue is calculated as follows,

$$l_k = \delta_1 - \sum_{l=1,\, d_l \le 0}^{k} \delta_1 \tag{5-6}$$

and the updated position of each vehicle is

$$d'_k = \min\{l_k, d_k + \omega_f(h_j(x_j))\} \tag{5-7}$$

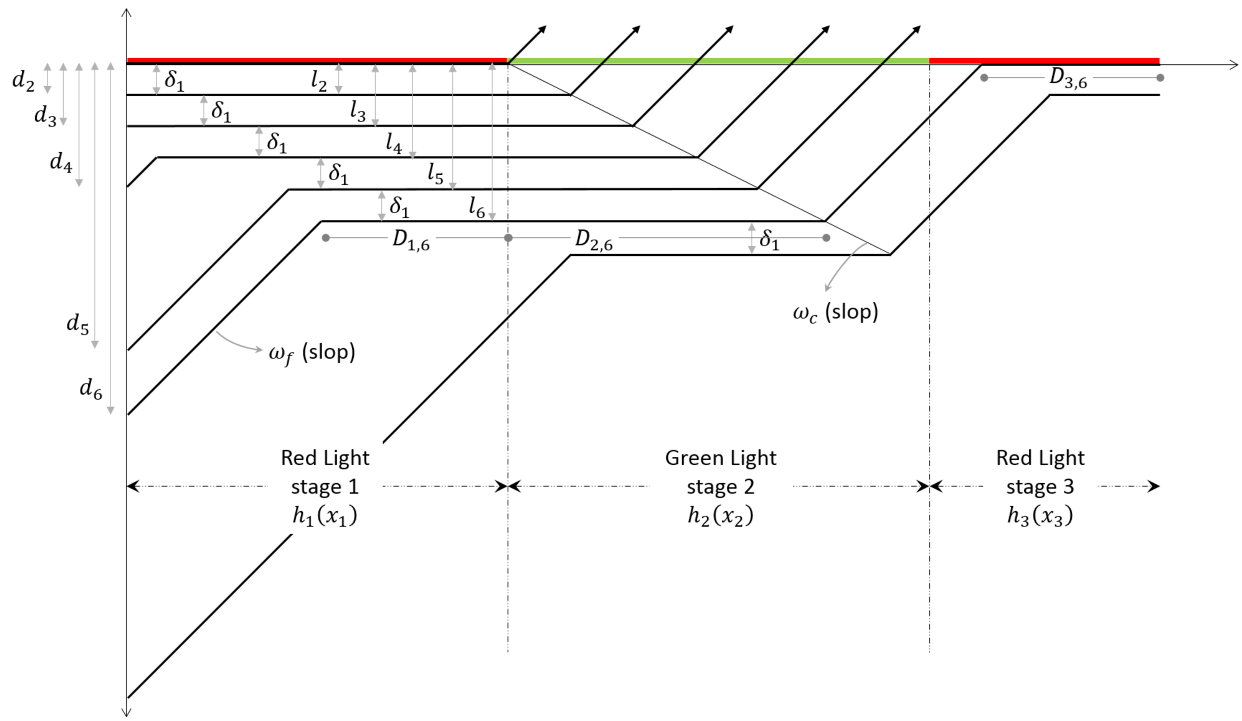


Figure 5-2 Space-time diagram of the proposed model, where the red bar represents red time, and the green bar green time, and each black line represents the trajectory of an arriving vehicle.

If $\phi = \phi(j)$, meaning the requested phase of the vehicles is the same as the one from the current stage, the delay of each vehicle is obtained as follows:

$$D_{jk} = \begin{cases} 0 & if\ d_j > 0 \\ min\left\{max\left\{\frac{l_k}{\omega_c} - \frac{l_k - d_k}{\omega_f}, 0\right\}, h_j(x_j)\right\} & if\ \ d_j \le 0 \end{cases} \tag{5-8}$$

where the projected position, relative to the intersection, of a vehicle in the queue is calculated with Eq. (5-6), and the updated position of each vehicle is calculated as follows,

$$d'_k = d_k + \omega_f(h_j(x_j) - D_{jk}) \tag{5-9}$$

5.2.2 Multiple Mode Model

Based on the single mode model, we proceed to solve the multi-level priority model iteratively starting from the mode with the highest priority (assuming the objective is minimization). Let ρ be the priority (or mode) of vehicle *k*. In a iteration, when optimizing for a priority $\hat{\rho}$, we will only add up in the value function the delays for those vehicle with $\rho = \hat{\rho}$. However, in the case when a certain configuration yields for a vehicle with $\rho > \hat{\rho}$ a delay greater than the one obtained in its corresponding iteration, the value function will equal ∞. Since the problem is minimization, the decision that makes the value function equal to ∞ will always be avoided.

Then, the model reads as follows,

$$f_j^{\hat{\rho}}(s_j, x_j) = \begin{cases} \sum_k D_{jk\hat{\rho}} & if\ D_{jk\rho} \leq max\{D^*_{jk\rho}, B_{jk\rho}\}\ \forall k{:}\ \rho > \hat{\rho} \\ \infty & otherwise \end{cases} \tag{5-10}$$

$$v_j^{\hat{\rho}}(s_j) = \min_{x_j \in X_j(s_j)} \{f_j^{\hat{\rho}}(s_j, x_j) + v_{j-1}^{\hat{\rho}}(s_{j-1})\} \tag{5-1}$$

To find the solution, we follow these steps

1. Set $\hat{\rho}$ to the highest priority.
2. Solve the model for $v_j^{\hat{\rho}}(s_j)$.
3. Save $D^*_{jk\hat{\rho}}$.
4. While $\hat{\rho} > 1$, make $\hat{\rho} \leftarrow \hat{\rho} - 1$, and go to step 2.

5.3 Numeric Examples

We evaluate the proposed multi-modal traffic signal control models at Buffalo downtown area. The City of Buffalo, Niagara Frontier Transportation Authority (NFTA), New York State Department of Transportation (NYSDOT) and the office of Congressman Brian Higgins are working on returning vehicular traffic to Main Street in downtown Buffalo, where passenger car traffic was removed since 1980s due to light rail operations. The mixed traffic operations, which introduce passenger car traffic again and allow light rail track bed to be shared with cars, are expected to start in spring 2014, as shown in Figure 5-3.

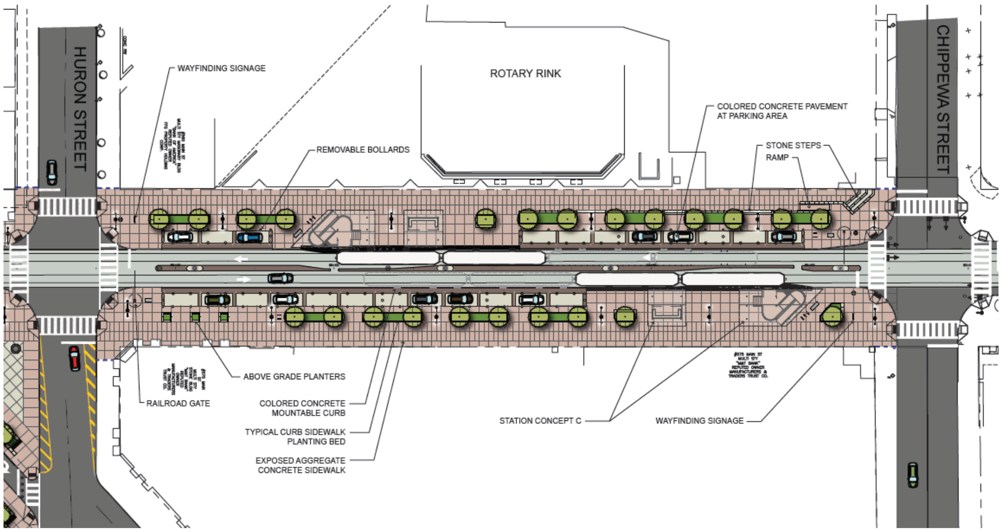


Figure 5-3 Multi-modal traffic operations of light rail, passenger car and pedestrian on Main St in downtown Buffalo

We have modeled such unique multi-modal traffic operation scenario in VISSIM, considering light rail trains, cars, and pedestrians concurrently. To retrieve the real-world traffic demand, the O-D trip estimation, and simulation calibration process are accomplished with relatively high accuracy, shown as Figure 5-4. Two numbers are labeled for each link in Figure 5-4. The first number represents the real-world traffic counts data and the second number represents the simulation traffic counts data. For example, 89/137 means 89 is the real-world count data and 137 is the simulated data. A logit path flow estimator (LPFE) originally proposed by Bell and Shield (1995) is adopted in this research for inferring both steady and time-dependent O-D trip tables. LPFE is chosen because: 1) it incorporates the logit-based route choice model while avoiding several difficulties encountered in the conventional bi-level formulation; 2) it avoids the difficult dynamic traffic assignment problem through decomposes the dynamic O-D estimation problem into a sequence of static problems, yet takes into account of queuing by linking the static problems across time with residual queues which can be carried over from one period to subsequent periods; and finally, 3) it has been validated in a number of scenarios as a potential tool to determine O-D flows and path travel times in various transportation networks.

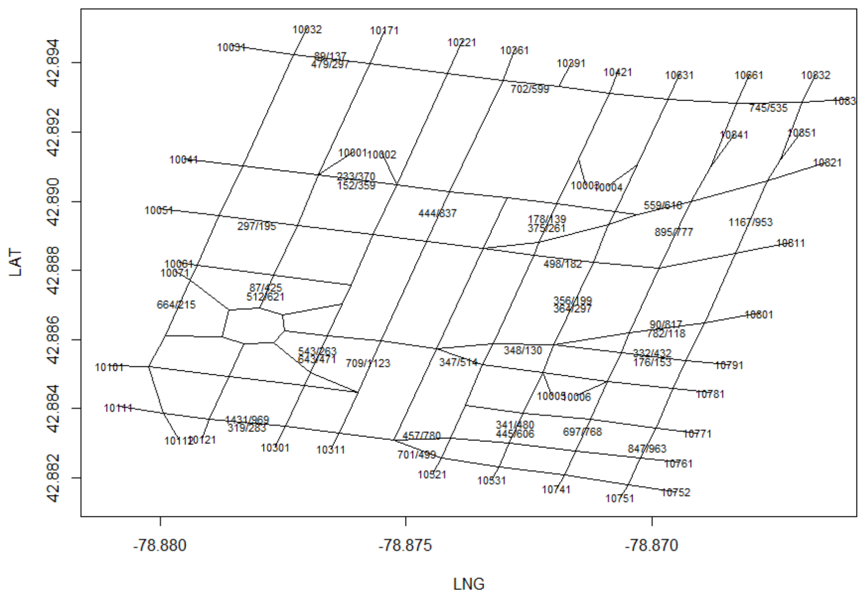
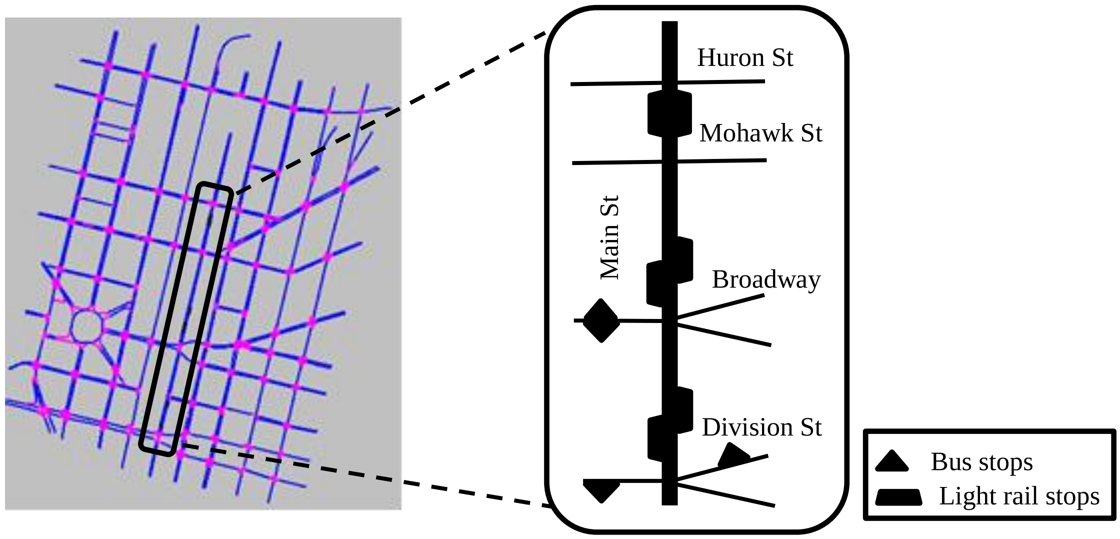


Figure 5-4 OD trip calibration results in Buffalo downtown network

Figure 5-5(a) shows the entire VISSIM network at Buffalo downtown, which includes total 67 signalized intersections. We only test the develop signal control algorithm on four intersections (See Figure 5-5(b)) on Main St, where the light rail is located. We consider four different travel modes: passenger cars, trucks, buses and light rail. Three priority levels are assigned to these four travel modes, shown in Table 5-2. Two light rail lines (every 6 minutes) travels along Main St, whereas there are 18 buses lines (every 15 minutes) only travels across Main St along side streets. Cars and trucks travel with their fixed route given by the dynamic traffic assignment model.

In the simulation, far side stops and near side stops are treated differently. Priority vehicles (light rail and buses) generate priority requests within 200 meters for far side stops. For near side stops, priority vehicles generate priority requests when entering stops, and the dwell time is considered normally distributed with mean 20 seconds and a relatively small variance in this study. One may refer to Zeng et al. (2014) for stochastic modeling of dwelling time. The developed algorithms are implemented through Java 8 and VISSIM COM interface. Travel demand is peak hour volume estimated by LPFE method. Note that this chapter does not consider coordinated signal control, since the coordination is disrupted by light rail stops between intersections. Future research could further investigate the coordination given stochastic dwell time at stops and transit signal priority.



(a) The entire VISSIM network (b) Tests on four intersections on Main St

Figure 5-5 VISSIM simulation model of Buffalo down area with 67 traffic signals

Table 5-2 Travel modes considered in one-hour simulation run

Travel modes	Priority level	Travel locations	Vehicle Counts
Light rail	3	Only on Main street	20
Buses	2	Only on side streets	75
Trucks	1	On both Main street and side streets	104
Passenger cars	1	On both Main street and side streets	5500
Pedestrians	(not considered)	On both Main street and side streets	1759

The entire simulation lasts 3600 seconds with extra 600 seconds warm-up period. We run simulation 5 times and take the average. Each controller runs its own optimization model every 20 seconds with a rolling horizon scheme. The optimization time for each instance varies from 0.01 to 0.1 seconds, on a personal laptop with Intel i7 CPU 2.9GHZ and 8 GB RAM. Therefore, the proposed optimization model is ready to be implemented in the real-world intersections.

The proposed signal control algorithm is compared to two benchmark signal timing plans. The first benchmark plan (denoted as "*Synchro*") is directly derived from Synchro, a popular commercial signal optimization tool. On the basis of the first plan, the second benchmark plan (denoted as "*Synchro-TSP*") implements Transit Signal Priority (TSP) at each controller, only for light rail. Both signal plans are deployed in VISSIM with RBC controller (PTV 2016), which is a dual ring actuated signal controller, very similar to US NEMA eight phase dual ring controller (Head et al. 2006). Therefore, both benchmark plans are fully-actuated control, which is able to extend green time for real-time vehicle arrivals. The shortcomings of "Synchro" are: 1) treat each travel mode the same as others, 2) The shortcomings of "Synchro-TSP" are: 1) it follows first-come-first-serve rule, which is sub-optimal, 2) it does not consider multiple levels of priority.

Table 5-3 Comparisons of average delay by three different methods for three different travel modes.

Methods	Average delay (seconds)		
	Car+Truck	Bus	Light rail
Synchro	20.90	21.59	34.22
Synchro-TSP	24.67	61.28	16.50
MARS	20.49	19.26	16.54
Delay changes (%) of MARS compared to Synchro	-1.99%	-10.82%	-51.68%
Delay changes (%) of MARS compared to Synchro-TSP	-16.94%	-68.58%	0.23%

Table 5-3 summarizes the average vehicle delay across different travel modes under different methods. Compared with Synchro, state-of-practice actuated control without priority, MARS demonstrates the following advantages: 1) extremely reducing delay for light rail (by 51.68%), 2) significantly reducing delay for buses (by 10.82%), 3) slightly reducing delay for passenger cars and trucks (1.99%). Without damaging the benefit of the majority of passenger cars, MARS extends huge benefit for high priority travel mode (light rail) and significant middle priority travel mode (buses).

Compared with Synchro-TSP, state-of-practice actuated control with priority added for light rail, MARS also demonstrates advantages: 1) Achieving the same level of delay for light rail (with 0.23% differences), 2) extremely reducing delay for buses (by 68.58%), 3) significantly reducing delay for passenger cars and trucks (by 16.94%). These advantages can be attributed to the following reasons:

1. Synchro-TSP grants absolute priority for light rail, same as MARS, which considers light rail as the highest priority (since emergency vehicles are not considered in the example).
2. Without damaging the delay for light rail, MARS further optimizes signal timing plans for all buses. Given large occurrences of buses in the simulation, accumulated reduction of bus delay is huge.
3. Further, MARS also considers delay minimization for passenger cars and trucks, although their priority is the lowest. However, a large portion of passenger cars and trucks greatly benefits while traveling with buses and trains under mixed traffic conditions.

Figure 5-6 illustrates the delay comparisons as well as the error bar. Under light rail, the delay standard deviation of MARS (2.6 sec) is slightly higher than the one (1.1 sec) of Synchro-TSP. The randomness of treatment for light rail can be accounted for the uncertain dwell time at near side stops, though the variation is not significant. If one can better estimate the dwell time using real-time OD information, the delay variations can be further reduced.

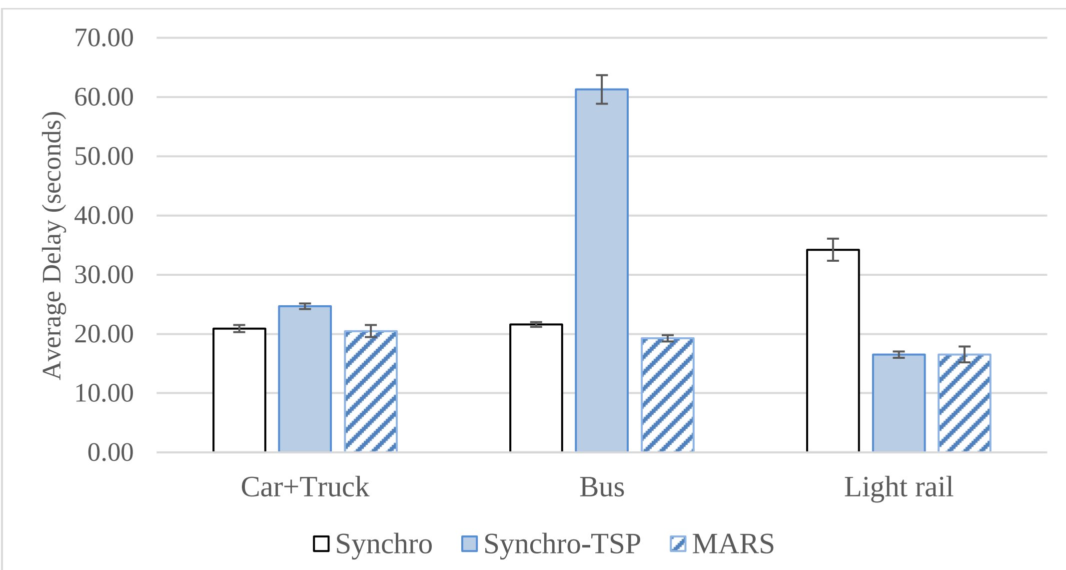


Figure 5-6 Comparisons of average delay by three different methods for three different travel modes.

5.4 Chapter Conclusions and Future Research

This chapter develops a Multi-modal Hierarchically Responsive Signal system, called *MARS*, which grants hierarchical priority for multiple travel modes during traffic signal control. MARS adopts a hierarchical optimization framework with lexicographic dynamic programming to handle mixed traffic with hierarchical priority levels.

The superiority of MARS stems from the fact that the optimal signal plan is not unique (He et al. 2011). By optimizing each travel model hierarchically, the developed signal plan are better tuned from all levels of travel modes. The proposed optimization model explicitly considers each vehicle' trajectory approaching an intersection. Therefore, each vehicle's real-time delay has been addressed in the model. In addition, the low computation time (0.1 sec) identifies the feasibility of the implementation in a real-world intersection.

The test is conducted along a mixed multi-modal traffic corridor (with passenger cars, trucks, buses and trains) at downtown Buffalo network. Compared with state-of-practice actuated Transit Signal Priority control, MARS decreases average bus delay for 68% and average car and truck delay for 16%, while maintaining the similar delay of light rail. Compared with state-of-practice actuated control, MARS improves average delay for light rail by over 51%, average bus delay by 10%, while achieving similar cars and trucks delay. Therefore, MARS achieves reliable and efficient real-time multi-modal signal control.

Future research includes the following directions: 1) Add signal coordination with MARS, 2) Consider different objectives in the optimization model, such as fuel consumptions, emissions, number of stops, etc. 3) add trajectory control for automated vehicles, 4) Add adjustable delay constraints from higher level of priority control so MARS could adjust the priority according to the real-time conditions (e.g. schedule adherences).

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APPENDIX A: THE SURVEY OF STATE-OF-PRACTICE IN MULTI-MODAL SIGNAL CONTROL

1. How many years of experiences in traffic signal operations?

○ How many years of experiences in traffic signal operations? 1-4
○ 5-9
○ 10-19
○ 20-29
○ 30+

2. What sector are you working in?

○ What sector are you working in? Government
○ Industry/Consulating
○ University/Education
○ Other (please specify)
○

3. Which travel modes and its signal control technologies you have worked with, except for passenger cars?

○ Which travel modes and its signal control technologies you have worked with, except for passenger cars? Emergency Vehicles
○ Light Rail/Trains
○ Buses/BRT
○ Bicycles
○ Pedestrians
○ Trucks
○ Other (please specify)

4. Please evaluate the following statements.

	Strongly Disagree	Disagree	Neither Disagree Nor Agree	Agree	Strongly Agree
Multi-modal signal control is very important	○	○	○	○	○
Multi-modal signal control is well implemented in U.S.	○	○	○	○	○
Multi-modal signal control is very challenging	○	○	○	○	○

5. Please indicate under what circumstances multi-modal signal control should be considered?

○ Please indicate under what circumstances multi-modal signal control should be considered? Central Business District
○ Residential areas
○ Major arterial
○ Truck corridor
○ Stadium area
○ Other (please specify)

6. Please identify the challenge level (1-5, 1-not challenging, 5- very challenging) of the following items for implementing multi-modal signal control

	1	2	3	4	5
Funding	○	○	○	○	○
Technologies	○	○	○	○	○
Human resource	○	○	○	○	○
Staff training	○	○	○	○	○
Jurisdiction boundary	○	○	○	○	○
Policy support	○	○	○	○	○

7. Please rate the difficult level of adding treatment of this travel mode in signal control?

	Very easy	Easy	Normal	Difficult	Very difficult
Emergency Vehicles	○	○	○	○	○
Light Rail/Trains	○	○	○	○	○
Buses/BRT	○	○	○	○	○
Pedestrians	○	○	○	○	○
Trucks	○	○	○	○	○

8. Please rate the priority weights of following travel modes during <u>day-to-day peak hour traffic</u>, assuming the weight of emergency vehicles 10 and the weight of passenger cars 1.

	1	2	3	4	5	6	7	8	9	10
Light Rail/Trains	○	○	○	○	○	○	○	○	○	○
Buses/BRT	○	○	○	○	○	○	○	○	○	○
Bicycles	○	○	○	○	○	○	○	○	○	○
Pedestrians	○	○	○	○	○	○	○	○	○	○
Trucks	○	○	○	○	○	○	○	○	○	○

9. Please rate the priority weights of following travel modes in a planned special event with massive pedestrians, assuming the weight of emergency vehicles 10 and the weight of passenger cars 1.

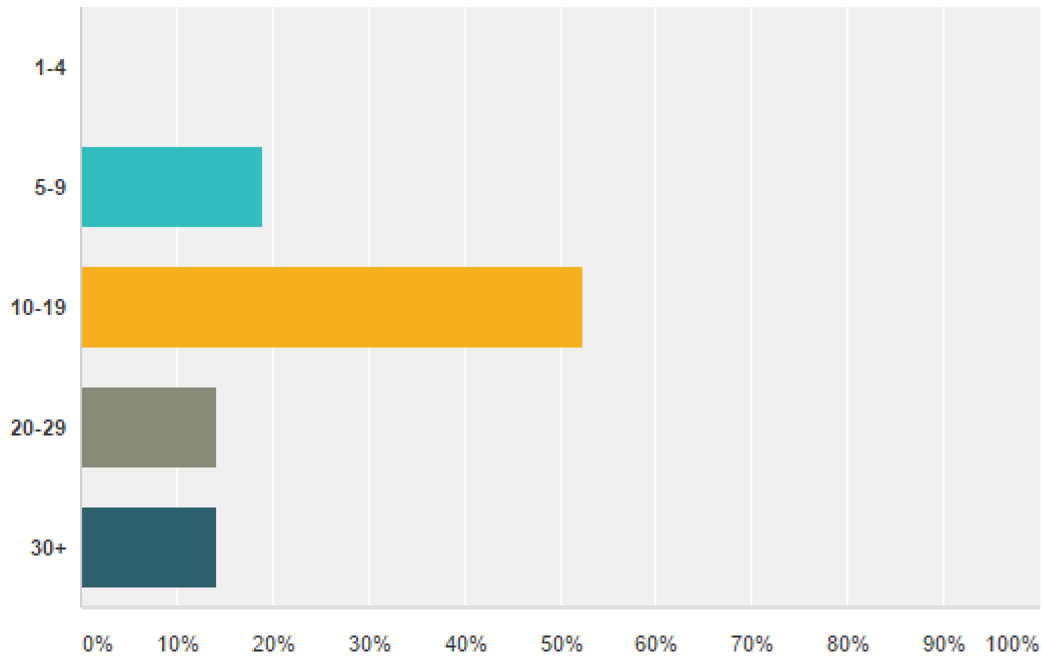
	1	2	3	4	5	6	7	8	9	10
Light Rail/Trains	○	○	○	○	○	○	○	○	○	○
Buses/BRT	○	○	○	○	○	○	○	○	○	○
Bicycles	○	○	○	○	○	○	○	○	○	○
Pedestrians	○	○	○	○	○	○	○	○	○	○
Trucks	○	○	○	○	○	○	○	○	○	○

10. Please rate the priority weights of following travel modes during off-peak traffic, assuming the weight of emergency vehicles 10 and the weight of passenger cars 1.

	1	2	3	4	5	6	7	8	9	10
Light Rail/Trains	○	○	○	○	○	○	○	○	○	○
Buses/BRT	○	○	○	○	○	○	○	○	○	○
Bicycles	○	○	○	○	○	○	○	○	○	○
Pedestrians	○	○	○	○	○	○	○	○	○	○
Trucks	○	○	○	○	○	○	○	○	○	○

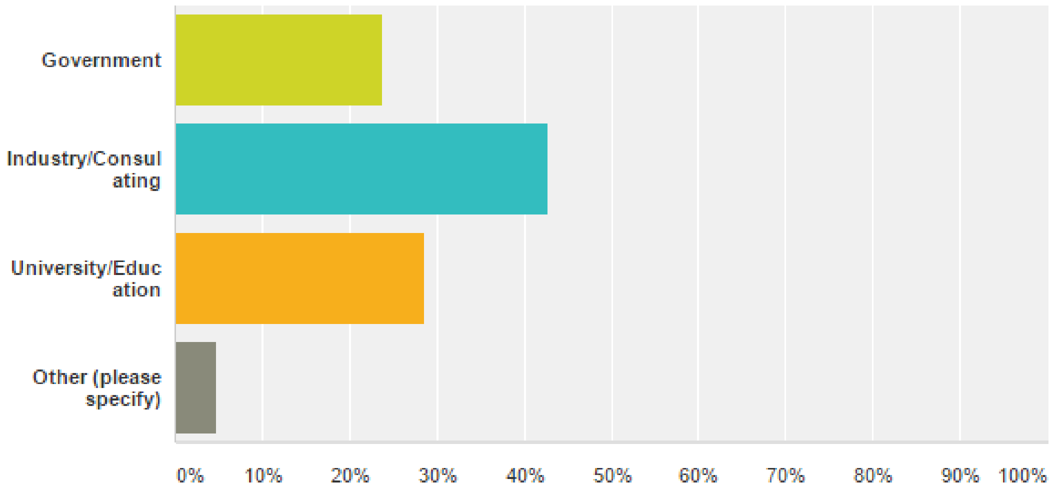
APPENDIX B: THE SURVEY RESULTS

1. How many years of experiences in traffic signal operations?



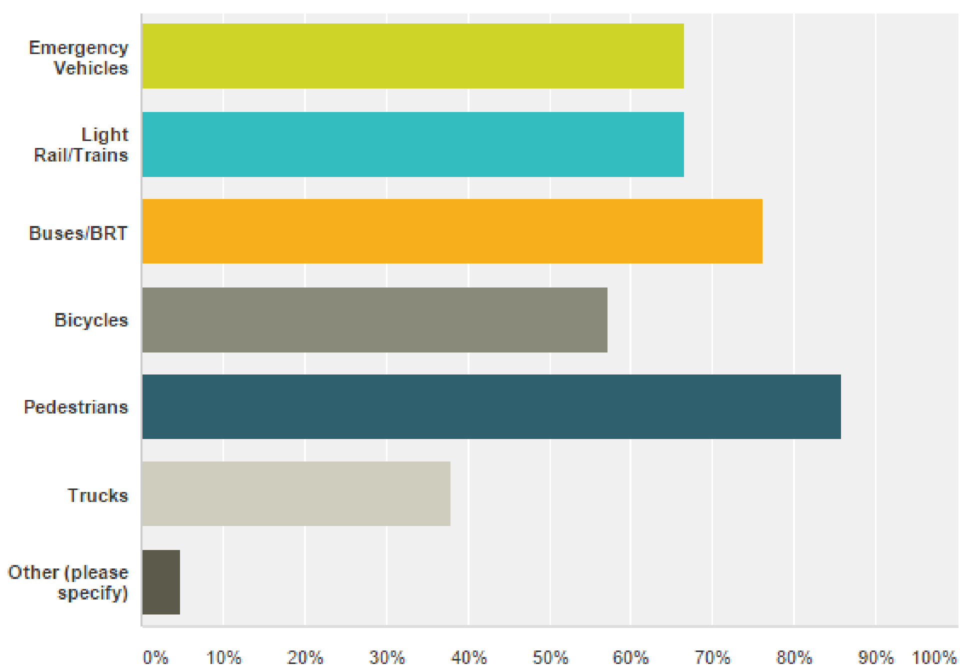
Answer Choices	Responses
1-4	**0.00%** 0
5-9	**19.05%** 4
10-19	**52.38%** 11
20-29	**14.29%** 3
30+	**14.29%** 3
Total	21

2. What sector are you working in?



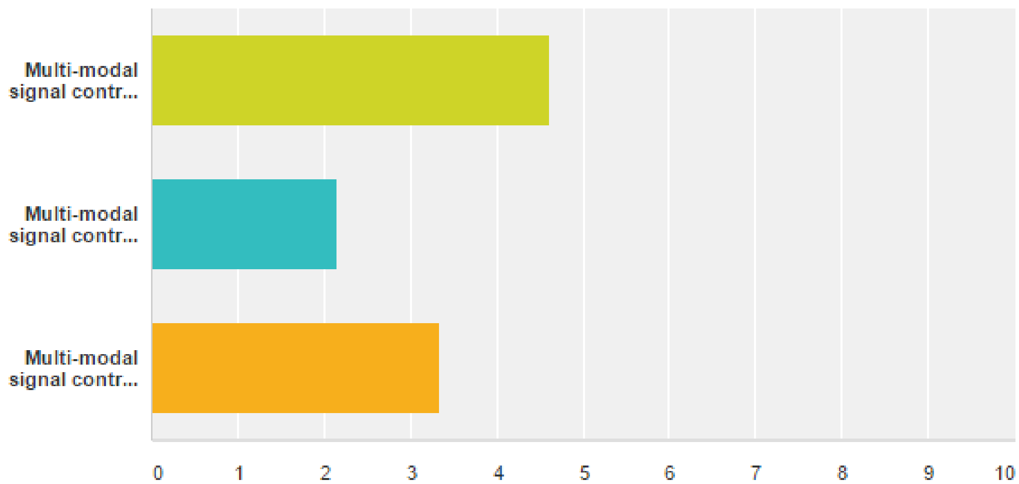
Answer Choices	Responses
Government	**23.81%** 5
Industry/Consulating	**42.86%** 9
University/Education	**28.57%** 6
Other (please specify)	**4.76%** 1
Total	21

3. Which travel modes and its signal control technologies you have worked with, except for passenger cars?



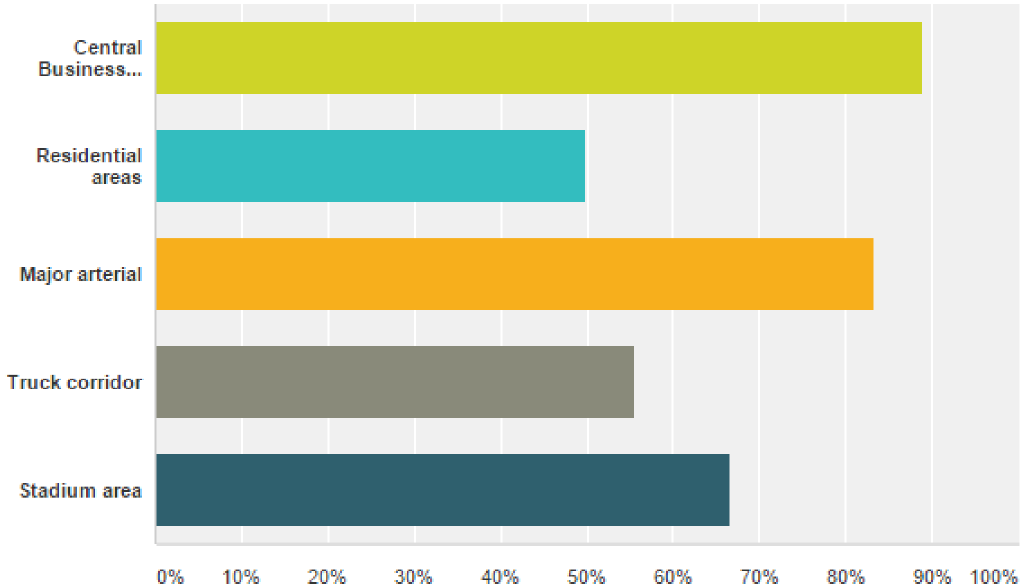
Answer Choices	Responses
Emergency Vehicles	**66.67%** 14
Light Rail/Trains	**66.67%** 14
Buses/BRT	**76.19%** 16
Bicycles	**57.14%** 12
Pedestrians	**85.71%** 18
Trucks	**38.10%** 8
Other (please specify)	**4.76%** 1
Total Respondents: 21	

4. Please evaluate the following statements.



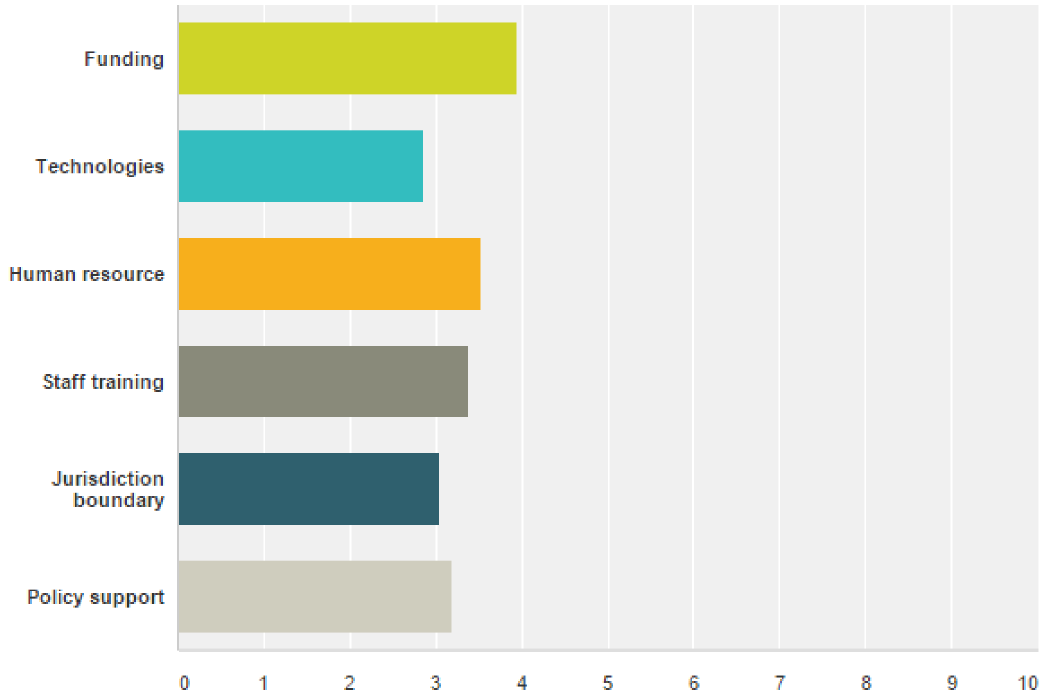
	Strongly Disagree	Disagree	Neither Disagree Nor Agree	Agree	Strongly Agree	Total	Weighted Average
Multi-modal signal control is very important	0.00% 0	0.00% 0	4.76% 1	28.57% 6	66.67% 14	21	4.62
Multi-modal signal control is well implemented in U.S.	19.05% 4	52.38% 11	23.81% 5	4.76% 1	0.00% 0	21	2.14
Multi-modal signal control is very challenging	4.76% 1	23.81% 5	28.57% 6	19.05% 4	23.81% 5	21	3.33

5. Please indicate under what circumstances multi-modal signal control should be considered?



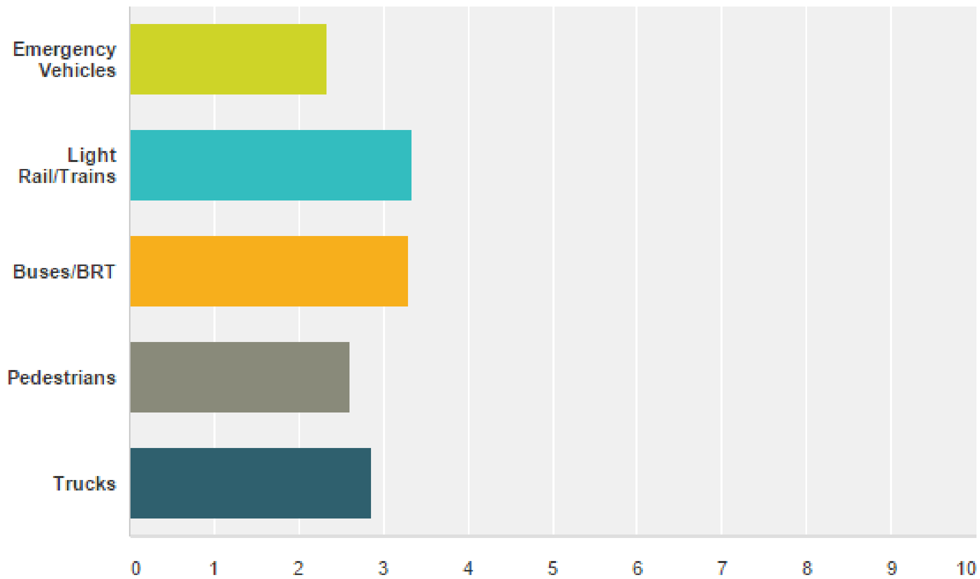
Answer Choices	Responses
Central Business District	**88.89%** 16
Residential areas	**50.00%** 9
Major arterial	**83.33%** 15
Truck corridor	**55.56%** 10
Stadium area	**66.67%** 12
Total Respondents: 18	

6. Please identify the challenge level (1-5, 1-not challenging, 5- very challenging) of the following items for implementing multi-modal signal control



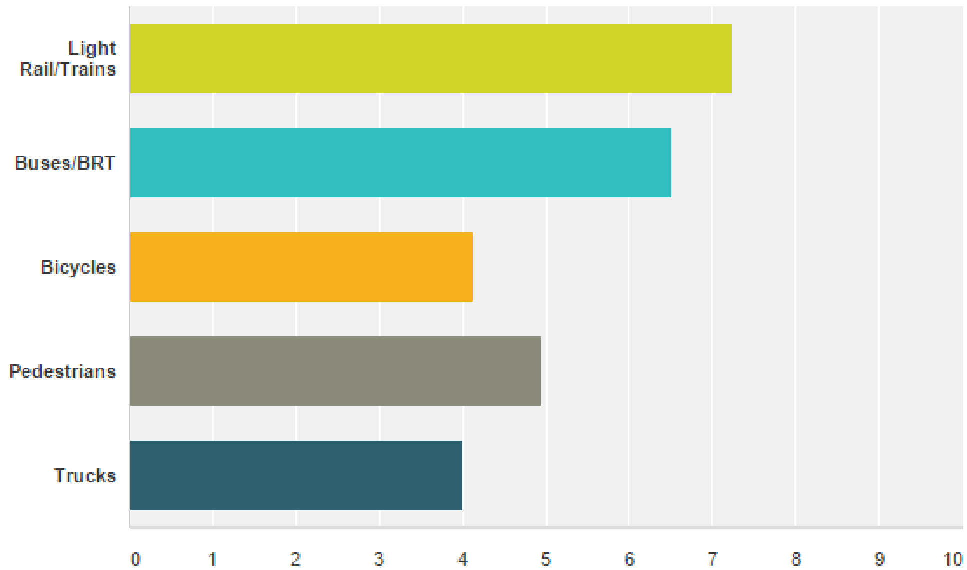
	1	2	3	4	5	Total	Weighted Average
Funding	0.00% 0	9.52% 2	14.29% 3	47.62% 10	28.57% 6	21	3.95
Technologies	9.52% 2	28.57% 6	38.10% 8	14.29% 3	9.52% 2	21	2.86
Human resource	9.52% 2	9.52% 2	23.81% 5	33.33% 7	23.81% 5	21	3.52
Staff training	4.76% 1	19.05% 4	38.10% 8	9.52% 2	28.57% 6	21	3.38
Jurisdiction boundary	23.81% 5	9.52% 2	14.29% 3	42.86% 9	9.52% 2	21	3.05
Policy support	9.52% 2	19.05% 4	23.81% 5	38.10% 8	9.52% 2	21	3.19

7. Please rate the difficult level of adding treatment of this travel mode in signal control?



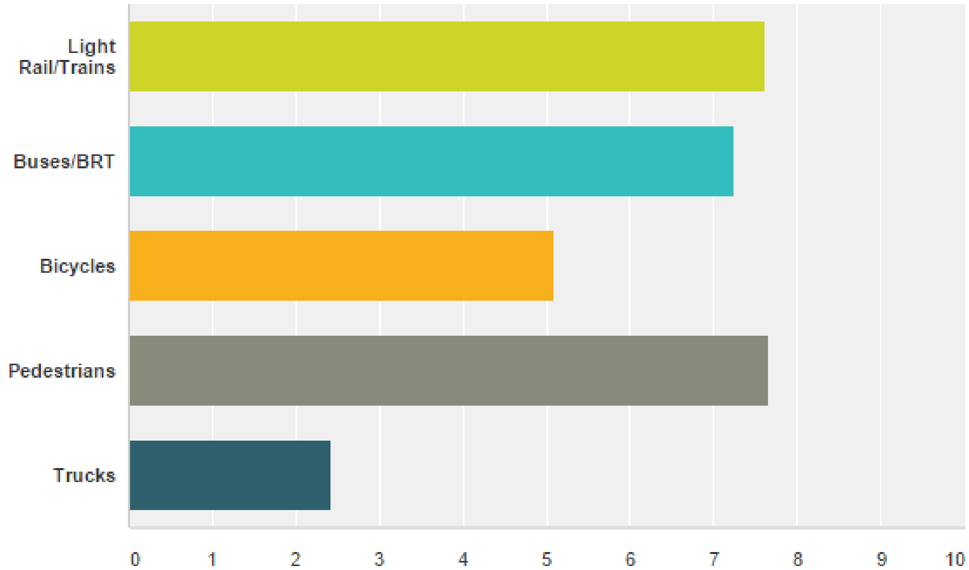
	Very easy	Easy	Normal	Difficult	Very difficult	Total	Weighted Average
Emergency Vehicles	23.81% 5	19.05% 4	57.14% 12	0.00% 0	0.00% 0	21	2.33
Light Rail/Trains	0.00% 0	14.29% 3	47.62% 10	28.57% 6	9.52% 2	21	3.33
Buses/BRT	0.00% 0	14.29% 3	47.62% 10	33.33% 7	4.76% 1	21	3.29
Pedestrians	14.29% 3	33.33% 7	28.57% 6	23.81% 5	0.00% 0	21	2.62
Trucks	9.52% 2	19.05% 4	47.62% 10	23.81% 5	0.00% 0	21	2.86

8. Please rate the priority weights of following travel modes during <u>day-to-day peak hour traffic</u>, assuming the weight of emergency vehicles 10 and the weight of passenger cars 1.



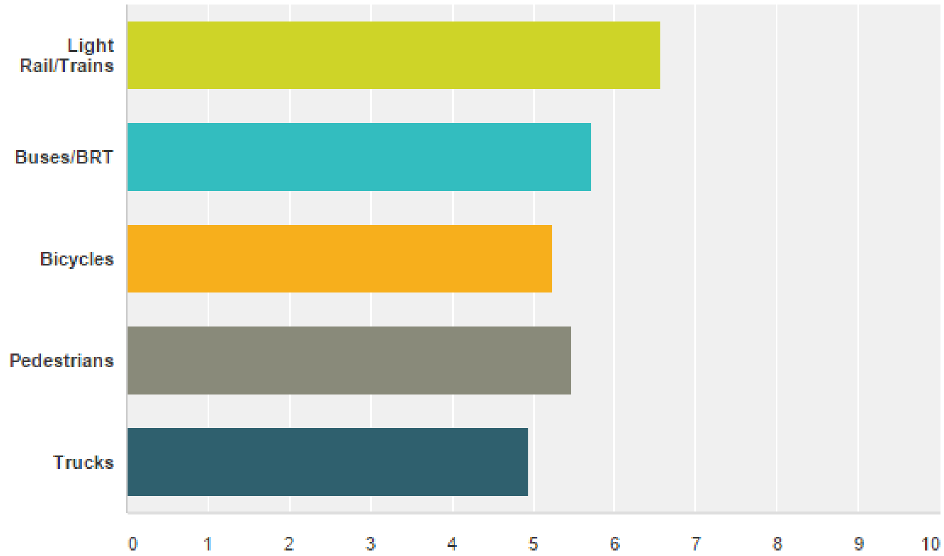
	1	2	3	4	5	6	7	8	9	10	Total	Weighted Average
Light Rail/Trains	4.76% 1	0.00% 0	4.76% 1	0.00% 0	9.52% 2	4.76% 1	23.81% 5	19.05% 4	23.81% 5	9.52% 2	21	7.24
Buses/BRT	4.76% 1	0.00% 0	0.00% 0	0.00% 0	14.29% 3	33.33% 7	14.29% 3	28.57% 6	0.00% 0	4.76% 1	21	6.52
Bicycles	14.29% 3	14.29% 3	9.52% 2	19.05% 4	14.29% 3	14.29% 3	9.52% 2	0.00% 0	4.76% 1	0.00% 0	21	4.14
Pedestrians	9.52% 2	14.29% 3	14.29% 3	4.76% 1	14.29% 3	9.52% 2	14.29% 3	9.52% 2	4.76% 1	4.76% 1	21	4.95
Trucks	14.29% 3	14.29% 3	14.29% 3	9.52% 2	23.81% 5	9.52% 2	14.29% 3	0.00% 0	0.00% 0	0.00% 0	21	4.00

9. Please rate the priority weights of following travel modes in <u>a planned special event with massive pedestrians</u>, assuming the weight of emergency vehicles 10 and the weight of passenger cars 1.



	1	2	3	4	5	6	7	8	9	10	Total	Weighted Average
Light Rail/Trains	4.76% 1	4.76% 1	4.76% 1	0.00% 0	4.76% 1	4.76% 1	9.52% 2	14.29% 3	23.81% 5	28.57% 6	21	7.62
Buses/BRT	4.76% 1	0.00% 0	4.76% 1	0.00% 0	4.76% 1	14.29% 3	14.29% 3	28.57% 6	19.05% 4	9.52% 2	21	7.24
Bicycles	19.05% 4	4.76% 1	4.76% 1	4.76% 1	19.05% 4	4.76% 1	19.05% 4	23.81% 5	0.00% 0	0.00% 0	21	5.10
Pedestrians	0.00% 0	0.00% 0	4.76% 1	4.76% 1	9.52% 2	4.76% 1	9.52% 2	28.57% 6	19.05% 4	19.05% 4	21	7.67
Trucks	52.38% 11	14.29% 3	9.52% 2	4.76% 1	4.76% 1	9.52% 2	4.76% 1	0.00% 0	0.00% 0	0.00% 0	21	2.43

10. Please rate the priority weights of following travel modes during off-peak traffic, assuming the weight of emergency vehicles 10 and the weight of passenger cars 1.



	1	2	3	4	5	6	7	8	9	10	Total	Weighted Average
Light Rail/Trains	4.76% 1	4.76% 1	4.76% 1	0.00% 0	19.05% 4	9.52% 2	19.05% 4	14.29% 3	9.52% 2	14.29% 3	**21**	**6.57**
Buses/BRT	4.76% 1	0.00% 0	14.29% 3	9.52% 2	14.29% 3	23.81% 5	4.76% 1	19.05% 4	9.52% 2	0.00% 0	**21**	**5.71**
Bicycles	14.29% 3	9.52% 2	4.76% 1	0.00% 0	23.81% 5	9.52% 2	14.29% 3	19.05% 4	0.00% 0	4.76% 1	**21**	**5.24**
Pedestrians	9.52% 2	14.29% 3	4.76% 1	0.00% 0	19.05% 4	4.76% 1	9.52% 2	38.10% 8	0.00% 0	0.00% 0	**21**	**5.48**
Trucks	14.29% 3	9.52% 2	9.52% 2	0.00% 0	19.05% 4	9.52% 2	28.57% 6	4.76% 1	4.76% 1	0.00% 0	**21**	**4.95**

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