Self-Powered Intelligent Traffic Monitoring Using IR Lidar and Camera

Yi Tian

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Tomonari Furukawa, Chair
Alan Asbeck
Pinhas Ben-Tzvi

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ABSTRACT

This thesis presents a novel self-powered infrastructural traffic monitoring approach that estimates traffic information by combining three detection techniques. The traffic information can be obtained from the presented approach includes vehicle counts, speed estimation and vehicle classification based on size. Two categories of sensors are used including IR Lidar and IR camera. With the two sensors, three detection techniques are used: Time of Flight (ToF) based, vision based and Laser spot flow based. Each technique outputs observations about vehicle location at different time step. By fusing the three observations in the framework of Kalman filter, vehicle location is estimated, based on which other concerned traffic information including vehicle counts, speed and class is obtained. In this process, high reliability is achieved by combing the strength of each techniques. To achieve self-powering, a dynamic power management strategy is developed to reduce system total energy cost and optimize power supply in traffic monitoring based on traffic pattern recognition. The power manager attempts to adjust the power supply by reconfiguring system setup according to its estimation about current traffic condition. A system prototype has been built and multiple field experiments and simulations were conducted to demonstrate traffic monitoring accuracy and power reduction efficacy.

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GENERAL AUDIENCE ABSTRACT

This thesis presents a novel traffic monitoring system that does not require external power source. The traffic monitoring system is able to collect traffic variables including count, speed and vehicle types. The system uses two types of sensors and implements three different measuring techniques. By combining the results from the three techniques, higher accuracy and reliability is achieved. A power management component is also developed for the system to save energy usage. Based on current or predicted system power state, the power manager selectively deactivates or turns off certain part of the system to reduce power consumption. A system prototype has been built and multiple field experiments and simulations were conducted to demonstrate traffic monitoring accuracy and power reduction efficacy. The experiments have shown that the system achieves high accuracy in every variable estimation and large portion of energy is saved by adopting power management.

Dedication

I would like to dedicate this thesis to my dear parents, Tian Wenhai and Wu Wenyan, and my sister, Tian Yu, for their loving support and guidance, and putting me through the best education possible. I would not be able to get to this stage without them.

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Chapter 1

Introduction

1.1 Background

Intelligent Transportation System (ITS) has been developing for several decades with solid theoretical basis and is gaining increasing attention from both industry and academia. By improving transportation safety and mobility, providing real-time route guidance and adaptive infrastructures control and advising traffic planning and relative policy making, ITS provides effective solutions to rapidly growing traffic challenges. In the structure of ITS, traffic monitoring system plays an important role by constantly providing traffic flow data to administrations and individual drivers and makes the base for full function of system. As a result, the output of traffic monitoring system fundamentally influences the overall performance of ITS.

Although currently multiple options for traffic monitoring are available, most of them have problems in different respects. First, most of sensors rely on single physical process. Since sensors are to function in uncontrolled environment, most of these processes have unstable performance in different circumstances. Another major problem lies in installment and power supply. For most stationary traffic monitoring system, large power consumption is always required for 24X7 operation. To meet such requirement, road surface needs to be cut open for power cable connection and organization. And if infrastructural power supply is not available, a large solar panel and battery would be required. These requirements significantly increases the installation cost and influences system portability. These problems seriously constrain the expansion and applicability of ITS and must be addressed.

1.2 Objectives

The primary objectives of this thesis are as follows:

- To propose a traffic monitoring method that could provide stable and reliable traffic flow data including vehicle counting, individual traveling speed and vehicle class.
- To propose a dynamic power management strategy that reduces energy cost of system.
- To build a system prototype capable of demonstrating and evaluating the performance of proposed techniques

1.3 Traffic Monitoring

This thesis presents a novel infrastructural traffic monitoring approach which estimates traffic information by combining outputs of three sensing techniques based on two categories of sensors. The approach uses input from an IR camera and an array of laser range finder sensors such as Lidar and output traffic flow information including passed vehicle counting, estimated vehicle speed and vehicle classification based on its size (length). The first technique uses local background subtraction algorithm to process video frames from camera and perform traffic monitoring. The second technique, at the same time, achieving the same goal by constantly measuring the distance from laser transmitter to the multiple target ground region. The third technique on the other hand attempts to track IR laser points from laser range finders in camera frame and check if a vehicle is in the field of view. All of the three methods output different traffic state observations based on different physical process. And by fusion of these observations, the system updates traffic flow states in the framework of Kalman filter and stably provides reliable traffic information.

1.4 Power Management

This thesis also presents a dynamic power management strategy for traffic monitoring. The strategy attempts to reduce the energy consumption of system by turning system into a relatively inactive power state when active state is not necessary. In the development, a system power state machine is defined based on hardware power consumption property in different configuration or transition. And based on traffic flow theory, the power manager tries to distinguish certain traffic state that does not require top power state and if valid transit system into a proper power state. State attempted to recognize here in DPM mainly includes traffic congestion state, inter-vehicle state and inter-group state.

1.5 Summary of Principle Contributions

The technical contributions of this thesis are summarized as follow:

- A traffic monitoring approach that provides reliable traffic information
- Formulation of traffic monitoring problem in Kalman Filter framework
- A dynamic power management approach based on traffic flow theory that reduces energy cost of traffic monitoring.

1.6 Publications

- Hangxin Liu, **Tian, Yi**, Tomonari Furukawa. Design of a Highly Reliable Infrastructural Traffic Monitoring System using Laser and Vision sensors. *International Design Engineering Technical Conferences/Computers and Information in Engineering Conference.* American Society of Mechanical Engineering, 2016.
- **Tian, Yi**, Hangxin Liu, Tomonari Furukawa. Reliable Infrastructural Urban Traffic Monitoring Via Lidar and Camera Fusion, *WCX17, SAE World Congress Experience.* Society of Automotive Engineering International, 2017. Submitted
- **Tian, Yi**, Tomonari Furukawa. Dynamic Power Management for Infrastructural Urban Traffic Monitoring. In preparation

1.7 Outlines

This thesis is organized as follows:

- Chapter 2 describes the past and emerging traffic monitoring techniques.
- Chapter 3 gives an overview of fundamentals and common principles in traffic monitoring.

- Chapter 4 presents the traffic monitoring approach based on three different techniques using two categories of sensors.
- Chapter 5 presents the dynamic power management approach based on traffic flow theory that is used to reduce system power consumption.
- Chapter 6 presents the developed traffic monitoring system prototype.
- Chapter 7 presents the experimental and simulation results for both traffic monitoring and energy reduction.
- Chapter 8 summarizes conclusions and proposes future work.

Chapter 2

Literature Review

2.1 Introduction

In this chapter, a summary of approaches to traffic monitoring is presented with an emphasis on infrastructural traffic monitoring. And a review of dynamic power management techniques in traffic monitoring is also provided. Traffic monitoring approaches reviewed include pneumatic tube sensor, inductive loop sensors, microwave radars, machine vision sensors, etc. With the principles of each technique explained, the advantages and disadvantages are then investigated.

2.2 Traffic monitoring

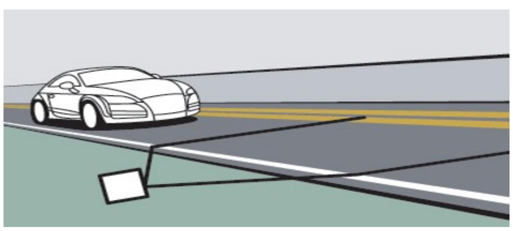
2.2.1 Current traffic monitoring techniques

Traffic monitoring systems that have been widely used till today mostly are stationary sensors that are installed in a specific location, either permanently or temporarily. They measure local traffic data and reflect overall traffic condition in whole traffic system. Infrastructural traffic monitoring sensors can be categorized into two group based on how they interact with passing vehicles: Contact sensors and non-contact sensors.

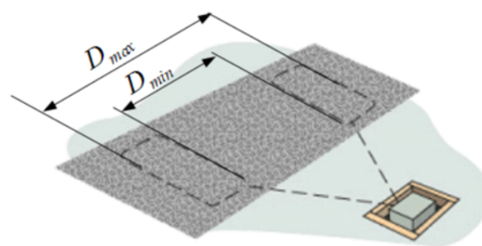
Pneumatic Tube

Pneumatic tube sensor is among the earliest traffic monitoring solutions and is still one of the most-used technique in practice. Made with rubber, the sensor send air pressure burst along tube while vehicle tires pass over. The pressure pulse then triggers a switch off which leads to a count. Using short section measurement procedure, speed and length can be measured. Nowadays, research in pneumatic tube sensors mostly is focused on its application and integration in the the whole intelligent transportation system as well as performance improvement [1, 2, 3]. Krista Nordback et al. [1] share findings and recommendations for how to minimize error for bicycle counting from tests conducted with different types of pneumatic tube detectors. Factors that have great influence on the detection and classification reliability are analyzed and summarized. Bohang Liu et al. [2] proposed a design of pressure tube traffic data acquisition and analysis device that is suitable for mixed traffic conditions. The device is able to accurately identify motor vehicles, motorcycles and bicycle. Martin Brosnan et al. [3] reports findings from research in Minnesota to validate the use of commercially available pneumatic tube counters to count bicycles in mixed traffic flows on urban roadways.

As one of the most widely used techniques used in traffic monitoring, the advantages of pneumatic tube lies in its inexpensive installation, portability and robustness in different conditions. But the problems of this technique are as follows: 1) In nature, the detectors are trying to detect tires and in most cases cannot provide enough information for the system to tell whether the neighboring tires should be considered as one vehicle. As a result, vehicles with large size or more than two pairs of tires such as bus or truck may confuse the system in all respects. 2) Since the tubes are physically in contact with passing vehicles, sensors may get destructed due to vandalism and tire wear. Due to these reasons, pneumatic tube sensors are mostly used as a temporary solution for road with non-intense traffic condition.



(a) Pneumatic tube detector



(b) Inductive Loop Detector (ILD)

Figure 2.1: Traffic monitoring sensors

Inductive loop detector

Inductive loop detector (ILD) is currently one of the most common traffic monitoring sensor[4]. In installation, a loop wire is buried in a shallow saw-cut in roadway. Multiple sets of loop wires in a short section enable the system to measure vehicle speed and length. The loop act as an inductive element and is excited by signals with certain frequencies. While a vehicle passes over the loop, inductiveness changed and the frequency also becomes different, which causes an electronic unit to send a pulse to the system to indicate passage of a vehicle. Research about ILD these days has been focused on different respects including collision analysis, vehicle tracking and classification,etc [5, 6, 7, 8, 9]. Carlos Sun et al. [10] discussed the process of developing feature extraction and vehicle pattern matching algorithms and the subsequent derivation of section-related measures based on conventional inductive loops. J. Gajda et al. [6] presents a discussion concerning the influence of loop length (in direction of vehicle movement) on differences between characteristics describing the magnetic profiles of the vehicles belonging to the different classes. Cheol Oha [7] proposed a method that attempts to capture rear-end collision potentials from the analysis of inductive loop detector data which is applied for monitoring individual vehicle information on freeways to estimate safe stopping distances in car-following situations. Janusz Gajda [8] presents the findings of model and field research into narrow inductive loop used as vehicle wheels detector in normal traffic conditions and confirmed that narrow inductive loops can be successfully applied as wheel detectors. Shin-tin Jeng [9] proposed an innovative approach for heavy vehicle tracking that combines the use of both WIM data and the inductive loop signature data. By fusing both inductive loop signatures and WIM data, promising tracking performance is achieved.

The advantage of ILD in traffic monitoring is: 1) As a mature technology, ILD sensors output robust results and can be used in large variety of applications; 2) Equipment cost is inexpensive compared with other solutions. On the other hand, drawbacks of the method fall into the following respects: 1) Installation and maintenance disrupt the traffic and are costly; 2) Very hard in relocation; 3) Resurfacing of the road may affect the function of ILD; 4) Buried in road, loop wires are directly exposed to pressure from passing vehicles, which may lead to damage to the detector.

Radar

Microwave radars have been developed decades ago for object detection. In traffic monitoring, the mounted microwave radar sensors transmit energy to area of interest from antenna.

In passage of vehicle through this area, the amount of energy reflected from the area is changed, which is considered as a detection event and vehicle data includes speed and length can be calculated. J. Sanchez-Oro et al. [7] presents a novel approach to object detection and tracking in urban environments using images obtained from a radar network, deployed in an urban environment. The proposed system detects, tracks and computes the speed of vehicles and generates alerts when vehicles exceed the predefined road speed limit. P. Samczynski et al. [11] presents a feasibility study on using passive radar signals for traffic control in different environments including urban areas, highways and small agglomeration roads and the initial analysis shows that such system can be successfully used to extract traffic parameters such as the average speed of vehicles and road capacity.

Microwave radar normally is insensitive to inclement weather conditions for short range monitoring. And compared with in-roadway sensors such as ILD, radars do not have issue of damage from direct contact with vehicles and can be used as a long term traffic monitoring solution.But the problem of this technique is that Doppler microwave radars are not able to detect stopped vehicles.

2.2.2 Emerging traffic monitoring techniques

Probe vehicle measurement

In probe vehicle measurement, vehicles act as roving traffic detectors and are not bound to specific and fixed locations along road infrastructure. Different strategies have been developed and adopted to derive traffic data from these measurement.

Currently, mainstream probe vehicle systems include Signpost-based Automatic Vehicle Locartion (AVL)[12, 13], Automatic Vehicle Identification (AVI), Ground-based Radio Navigation System[14, 15, 16], Cellular Geo-location[17, 18, 19] and Global Positioning System

(GPS)[20, 21, 22, 23, 24]. Juan et al. [20] presented a traffic monitoring technique using on-board GPS-enabled smart phone and presented a proof of concept experiment to evaluate such technique. R. Zito et al. [21] proposed an approach that uses GPS information to obtain the information on position, speed and direction of the traveling vehicles. Multiple field tests have been conducted to picture the reliability and usefulness of such technique in traffic monitoring. Wang et al. [14] proposed a design of traffic monitoring and management system based on RFID. A simulation is done to demonstrate the efficacy of the design in loss reduction from accidents. Don Nash [15] investigates the effect of speed, tag and reader location, vehicle speed, and over-shadowing on RFID performance. Fabio Ricciato [18] proposed a method to infer vehicle travel times on highways and to detect road congestion in real-time, based solely on anonymized signaling data collected from a mobile cellular network.

Most of these sensor systems share the following advantages:

1. Low cost per unit of data. Once installed, data is collected at very low cost.
2. Continuous data collection. As long as the system is permanently installed, the system keeps collecting traffic data when vehicle travels.
3. No disruption of traffic. Since the sensor is traveling with traffic flow, the measurement does not have any direct influence on traffic flow.

However, such techniques have following major problems that prevent their wide application:

1. High installation fee. Probe vehicle system normally has high initial cost for necessary equipment and installation.
2. Privacy issues. As this technique involves tracking vehicles, concerns that privacy of drivers is exposed have been raised.
3. Not recommended for small scale data collection.

Vision-based traffic monitoring method

Vision-based traffic monitoring as a major emerging technique in this field has been attracting increasing attention and effort in academia [25, 26, 27, 28, 10]. In practice, vision based methods monitor traffic with different strategy including edge-based detection, background differencing, lane-region recognition, feature-driven approach, model-driven approach, etc [25]. Benjamin Coifmana [29] proposed a real time computer vision system for vehicle tracking and traffic surveillance. In recent years, learning-based approach is also being developed rapidly. Janne Heikkila et al [30] proposed a camera based automatic system that utilizes Kalman filtering in tracking and Learning Vector Quantization for classifying the observations to pedestrians and cyclists. Using a feature-based tracking system, the system is able to function in light changing conditions. Carlo Migel Bautista et al. [10] presented a vehicle detection algorithm using convolutional neural network and low resolution video frames. And the field test has shown that the algorithm works in real time and achieves high accuracy in normal condition. Mariano Gallo et.al [28] also present an artificial neural network approach for spatially extending road traffic monitoring measures. D. Beymer et al. [31] and Norbert Buch [32] both have a review over the application of vision-based technique in traffic monitoring.

Vision-based techniques use cameras monitoring road section of interests. The most important advantage of vision-based technique lies in that unlike most other techniques, imaging sensors provide 2D information which is theoretically informatively enough to reconstruct whole traffic condition. Such ability of providing rich array of data makes vision-based technique one of the most promising traffic monitoring solution. The major weakness for such technique however is that performance of the sensors is affected by many external factors such as inclement weather condition, illumination variance, etc. Although such problems could be overcome by applying certain advanced algorithms, it always requires processors with better performance, increases computational complexity, and indirectly causes much more energy cost and processing time.

2.2.3 Summary

Table 2.1: Comparison of different traffic monitoring techniques.

Technique	Advantage	Disadvantage
Pneumatic tube	Inexpensive equipment and installation; Stable performance; Accurate in small vehicles.	Only short-term use; Inaccurate for large vehicle; Not portable.
Inductive Loop Detectors (ILD)	Reliable in counting; Stable performance.	Inaccurate speed measure; Disruption of traffic; Hard relocation; Expensive installment; Not portable.
Radar	Long term use; Accurate speed measure.	Cannot detect stop vehicle; Affected by weather; Not portable.
Probe-vehicle	Long term use; Low equipment cost; Robust against environment; Portable.	Unstable output; Privacy issue.
Vision-based method	Long term use; Rich information.	Unstable in weather and illumination change; Affected by weather; Not portable.

Table 2.1 presents a summary of the techniques discussed above by comparing their advantages and disadvantages. In comparison it is found although most of available solutions meet the requirement of traffic monitoring in certain circumstances, they have issues in aspects such as stability, reliability, portability or installment. All of these issues limit the extension of traffic monitoring sensors in traffic system and need to be resolved.

2.3 Dynamic Power Management

2.3.1 Different DPM strategies

Dynamic Power Management has gained growing attention during the last few years. Dynamic Power Management in core is a power supply policy that constantly configures system performance and minimize system power consumption according to system workload. Based on policy generating process, DPM could be categorized into the following groups: greedy DPM method, time-out DPM and predictive DPM. For devices with different power consuming property and workload changing behavior, different DPM method could be applied.

Greedy DPM

Greedy DPM method basically is a system that only provides service when a service requester has sent a request [33, 34]. As a simple policy, this method is easy to implement and in many cases has best performance regarding power saving. However, for application that takes long time to prepare for service provision, such policy may greatly reduce the system performance.

Time-out DPM

Time-out DPM is also a simple policy where a device is shut down after it has been idle for a certain threshold of time period [35]. The time-out policy can be classified into static time-out DPM and adaptive time-out DPM [36]. Adaptive time-out DPM would readjust the time-out threshold based on the history idle period. This method compared with greedy method balances the system performance and power consumption. But still a large portion of service is not provided in time.

Predictive DPM

Predictive DPM better address the problem by attempting to understand service request dynamic [37, 38]. The basic idea in predictive DPM is to predict the length of coming idle periods and shut down the device when the predicted idle period is longer than a certain threshold time period. The limitation of this method lies in its dependence on a good prediction model. If such prediction mode is hard to obtain, the DPM method may not work.

2.3.2 DPM in traffic monitoring

In dynamic power management, works have been done on its application in traffic monitoring. Jatupom Chinrungrueng [39] proposed power efficient traffic monitoring approach by optimizing communication process among the network. In [40, 41], Umair Ali Khan proposed two dynamic power management framework based on reinforcement learning and on-line learning respectively. In these works, it is attempted to predict the arrival time of next vehicle based on history data. And based on the estimated arrival time, certain power supplying policy is generated. As a learning-based method, the proposed method has the following problems: 1) Learning-based method attempts to model the dynamics of traffic system by certain feature descriptors and history data. But traffic system as a highly complicated system require very customized feature descriptor and large training data. This significantly increases the training cost. 2) As traffic system itself is very randomized, even a good learning-based predictor is very likely to output inaccurate estimations.

2.3.3 Summary

Table 2.2 presents a summary of the three different basic DPM strategies. As suggested, the three strategies are all built based on the understanding of system power consumption and workload property. And for the same system in different functioning stage, different strategies can be implemented.

Table 2.2: Comparison of different DPM strategies.

DPM strategy	Applied case	Effect
Greedy DPM	Service requester required; Service request time longer than system wake-up time.	Maximum power saving; More performance degradation risk.
Time-out DPM	Service requester preferred; Clearer workload changing pattern.	Limited power saving; Smaller performance degradation risk.
Predictive DPM	Service requester preferred; Predictive workload changing.	Good power saving; Smaller performance degradation.

Chapter 3

Fundamentals of Traffic Monitoring

This chapter presents fundamentals about traffic monitoring. Components and their characteristics about urban transportation system are discussed and leads to the formulation of urban traffic monitoring problem. Following that, common traffic monitoring methods are presented and analyzed.

3.1 Fundamental elements in urban traffic monitoring

In traffic monitoring, traffic system infrastructure, system user and external factors as such weather conditions are three of the key elements needs to be considered. These three elements constructs the environment where traffic monitoring systems function and influence system reliability and accuracy by their interaction with monitored target, traffic flow, and monitoring system itself.

3.1.1 Traffic system infrastructure

System infrastructure plays fundamental role in the whole transportation system. The availability and property of the existing infrastructures practically constrains what traffic monitoring solution could be adopted in that local area. Major infrastructures in the urban transportation system includes the following:

1. Roads: Roads are the most important infrastructure in the transportation system. As roads directly interact with system users, their shape and property to a large extent decide the behavior of the conveyed traffic flow. For traffic monitoring, it also physically constrains what kinds of sensors can be used in this specific road.

   Normally, the road parameters need to be considered in traffic monitoring include lane number, lane width, speed limit, etc, and most of these parameters are correlated with each other.

   (i) Lane number and lane width. For a road with many lanes and large lane width, sensors with large field of detection are preferred. Otherwise, multiple sets of same sensor may be required to monitor all of the lanes. Also, long total road width will raise other problems. Problem of occlusion occurs while sensors can only be installed on roadside. To get rid of occlusion, the installing height of the sensors need to be increased. In urban area, normally a road have 1 to 3 lanes for one direction. Some road in large cities will have more than 5 lanes for one direction. Lane width varies for different speed limit and traffic volume, from 9 to 15 feet (2.7m to 4.6m)

   (ii) Speed limit. Inside urban districts, most states have set the maximum speed limit lower or equal to 55mph. Although many study has shown that speed limit has been disregarded by most drivers, it is still correlated with the average speed of the road, except for congestion case. Empirically, the prevailing traveling speed in a road is 8 to 12 mph higher than the posted speed limit. As traffic flow speed reflects the vehicle traveling speed, it helps to optimize the sampling frequency of traffic monitoring sensor.

2. Traffic signals: As the key control input of traffic system, traffic signals have great influence on traffic flow behavior, especially for neighboring road segment. Special traffic flow pattern resulted from traffic signals can potentially help to optimize the configuration of certain traffic monitoring solutions.

3. Light pole or other pole structures: In traffic monitoring, light poles have influence in two respects. First, light poles change the illumination conditions of the road at night, which is crucial for optical sensors such as video cameras. Without light pole, or if the light pole does not provide good illumination, optical sensors at night can only rely on vehicle's head light or tail light, which can be extremely confusing and unreliable. Another role light pole or other pole structures play in traffic monitoring is in system installation. Figure 3.1 shows an example of a traffic monitoring camera installed on a light pole. As most available infrastructure in transportation system, pole structure provides an inexpensive installation choice for many traffic monitoring system.

4. Overpass or other above-road structure: Compared with pole structures, above-road structure is not as common. But it provides a better installing site which fundamentally solve the problem of vehicle occlusion mentioned before.

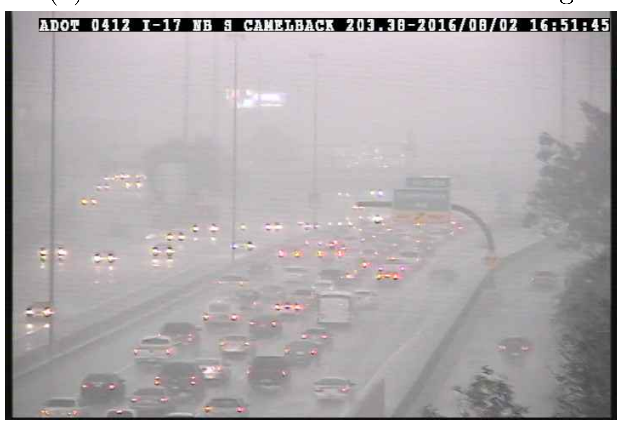
Figure 3.1: Traffic monitoring sensor installed on a light pole

3.1.2 Traffic system user

Transportation system users include different types of motor vehicles and pedestrians and are the measuring targets for most traffic monitoring systems. As active components in transportation system, how vehicles and pedestrians use the road segment of interest must be considered in traffic monitoring. For motor vehicles, size, especially height of vehicles that are allowed to use the road helps to predict potential occlusion condition in monitoring. Pedestrians, on the other hand, are one of the major factors that influence the monitoring accuracy in roads with low speed limit. As most of current traffic monitoring methods does not directly detect motor vehicles by recognizing them, the monitoring system may not be able to distinguish all pedestrians that pass the monitored region from motor vehicles.

3.1.3 External factor

(a) Influence of rain on traffic monitoring



(b) Influence of fog on traffic monitoring

Figure 3.2: Influence of external factors on traffic monitoring

As traffic flow is affected by different external factors, these factors also have great influence on the performance of traffic monitoring system. The factors with significant impact include weather and sunshine conditions.

1. Weather: Most sensors have different performance in different weather condition due to the physical essence of their measuring methods. For sensors rely on optical measurement or other non-contact measurement such as video camera, rain, snow or fog make disturbance in imaging and may create trouble in vehicle detection if the detect-

ing algorithm is not robust. In the case of heavy rain, fog and snow, many non-contact sensors totally fail in measurement. Contact measurement sensors like pneumatic tube are comparably more robust regarding different weather conditions.

2. Illumination condition: Illumination condition is another important factor that decides the performance of certain category of sensors. Optical sensors that use environmental light highly rely on sunshine or light poles and any unstable light condition such as shadow from a cloud could jeopardize the performance of such sensors. During night, especially while there is no light pole available, the accuracy of optical sensors are extremely decreased.

3.2 Urban traffic monitoring

Property of the traffic flow is described by different variables and these variables fall into two categories based on in what scale these variables describe traffic flow, i.e microscopic descriptors and macroscopic descriptors. While macroscopic variables are more concerned about the "big image" of traffic condition and describe behavior of whole traffic flow, microscopic variables evaluates each individual vehicles. Since traffic flow is composed of individual vehicles, microscopic variables are the basis to derive macroscopic information and normally are the directly measured variables in traffic monitoring. Microscopic information about traffic now also play important roles in fields such as intelligent transportation system and autonomous navigation.

Generally, the most used and important microscopic descriptors include vehicle counting, individual speed and corresponding vehicle size. These microscopic information presents a detailed image about traffic flow and also reflects other microscopic information and macroscopic knowledge for different practical applications. Based on this, variable of interests the developed systems make measurement of is:

$$x_k = \{t_k, v_k, l_k\} \tag{3.1}$$

where k is the time step when measurement is made, t is detection time, v is vehicle speed and l is the vehicle length.

3.3 Traffic measurement procedures

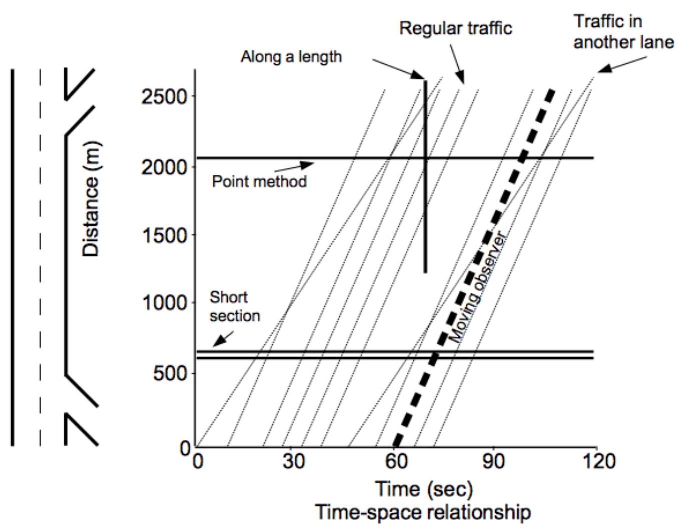


Figure 3.3: Traffic measurement procedures

Figure 3.3 shows four different traffic flow measurement principles that are mostly used in traffic engineering. While the vertical axis represents road distance from arbitrary starting point along road in travel direction and the horizontal axis represents time difference from an arbitrary starting time, the diagram describes space-time relationship of the four methods and shows how the measurement is interacting with traffic flow. The four methods are:

1. Measurement at a point. Illustrated as a single horizontal line in the diagram in the diagram, measurement location remains constant during traffic monitoring. This procedure is mostly used in vehicle counting. It can measure vehicle speed and length only if sensor has high measure frequency, such as radar.

2. Measurement over a short section [normally less than 10 meters (m)]. This method is represented as two parallel horizontal lines with a short distance apart in the diagram. In implementation, a pair of traffic detectors or more are used to measure speed and length of vehicles.

3. Measurement over a length of road [mostly at least 0.5 kilometers (km)]. Represented as the vertical line in the diagram, monitoring sensor has a constant monitored area in different time. Its difference compared with the second procedure lies in its large field of view, normally as far as 300   1000 meters. This is mostly realized by installing sensor like cameras on top of tall buildings. Good at obtaining macroscopic information of traffic flow, it is not recommended in individual vehicle measurement.

4. Moving observer method. As shown in the figure, sensor location does not remain constant and changes with traffic flow. In measurement, one or multiple observer vehicles travel in the measured traffic flow and are regarded as an average vehicle in the flow. From the recorded state of the observer vehicle, traffic flow state is estimated.

All of the procedures discussed above have been realized with different types of sensor systems and some of them are becoming the mainstreams in the field of traffic monitoring.

3.4 Summary

In this chapter, fundamental elements in traffic monitoring are analyzed as the base to develop a reliable traffic monitoring system. After that, urban traffic monitoring problem is formulated by defining what variables are to be measured and estimated. In third section, four traffic measurement procedures that are used in traffic engineering are first presented, followed by how these procedures are realized using different types of sensors. Properties of these two categories of sensors are discussed. The next chapter will present the measuring technique that is used in the developed system.

Chapter 4

Traffic Monitoring by IR Lidar and Camera

Traffic monitoring system in Intelligent Transportation System (ITS) are expected to constantly provide more informative and reliable traffic data compared with the conventional application. As ITS is highly data-driven system, the amount and class of the feed-in traffic information directly determines the system's functionality and applicability. And the data's reliability fundamentally decides the performance of the system. To meet such requirements, the proposed approach produces traffic information including passing vehicle counts, corresponding travel speed and vehicle classification, for each individual vehicles. Using these data, more information can be derived such as traffic flow speed, road occupancy, etc. The proposed approach is based on the fusion of three techniques realized by two types of sensors, a Lidar array and a near infrared (NIR) camera sensor. With statistical knowledge about the performance of all measurements, the data fusion produces best estimation based on the collected data.

4.1 Multipoint short-section measurement with Lidar/camera for traffic monitoring

4.1.1 Measurement with Lidar

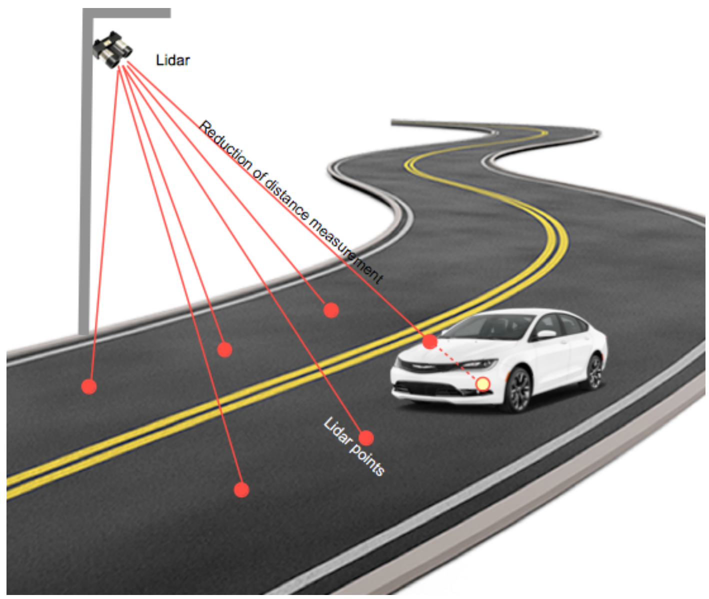


Figure 4.1: Lidar measurement in traffic monitoring

Figure 4.1 illustrates how Lidar measurement is working in the developed traffic monitoring system. In traffic monitoring, each Lidar measures the distance between the transmitter and projecting point on the road or other obstacles and provides point information about the road plane. As shown in the figure, a reduction of the distance measurement indicates a possible vehicle or pedestrian occupying the detecting point on the road. Based on this, an line of Lidars that provides multi-point distance measurement can be used to sample a 2D region of interest on the lane and acquire information of vehicle counts. By calibration of the sampling point, vehicle speed and size classification can also be estimated. To monitor multiple lanes, an array of Lidars that have projecting points on different lanes are required.

4.1.2 Measurement with camera

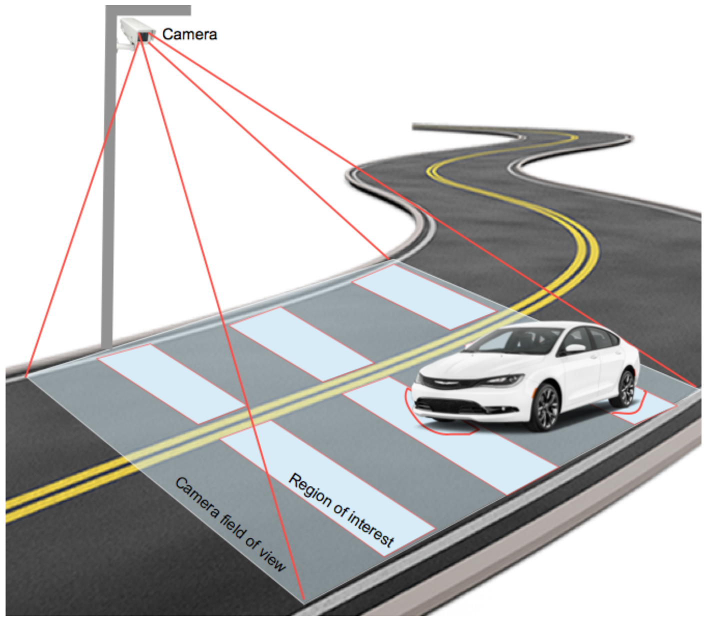


Figure 4.2: Camera measurement in traffic monitoring.

Vision-based traffic monitoring is based on video frame information and can be achieved through different approaches. To minimize the computation complexity while remaining reliability, background subtraction is implemented in the developed system. As presented in Figure 4.2, one single camera sensor is able to monitor multiple road lanes as long as the lanes' part of interest is in the field of view of the camera. The camera collects optical information of lanes on a per pixel basis and provides 2D information about the lanes. Similar to Lidar measurement, multiple regions of interest (ROI) are selected as shown in the figure. On each individual ROIs, independent background models are built to represent the state of non-occupancy.

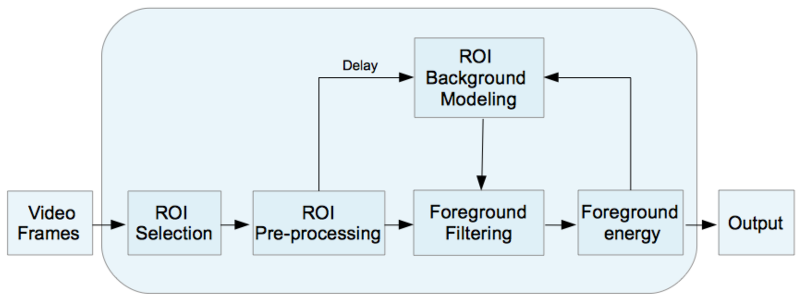


Figure 4.3: Background subtraction algorithm working flow.

Figure 4.3 shows the working flow of background subtraction algorithm for traffic monitoring. While a vehicle is passing through the ROI, background subtraction has following major steps:

1. ROI Selection. Since the algorithm is based on local information, global modeling is not necessary. ROIs are selected based on real location of the image region.

2. Pre-processing. This step is used to remove noise and resize the ROI images. Each incoming frame will be preprocessed using Gaussian filter or other filters based on image quality.

3. Background modeling. Model of the ROI can be initialized by obtaining different statistical measures such as mean value of a pixel of the first n incoming frames, where the number n is selected based on the quality of the camera, ranging from 10 to 20. The model needs to be updated due to the changing background in real world. While the incoming frame triggers a non-vehicle-detection event, the corresponding ROI will be considered as new background and have higher influence in the background model update. If a vehicle-detection event is triggered, although the model is still updating, the new frame's weight will be much smaller.

4. Foreground filtering and foreground energy. With the updated ROI background model, the foreground energy is obtained by comparison between new frame and the model. A high foreground energy value indicates a possible vehicle or pedestrian occupation in the ROI, which is similar to Lidar measurement.

Multiple ROIs improve the reliability of vehicle counting and enable the system to conduct vehicle speed estimation and size classification.

4.1.3 Measurement with Laser points in frame

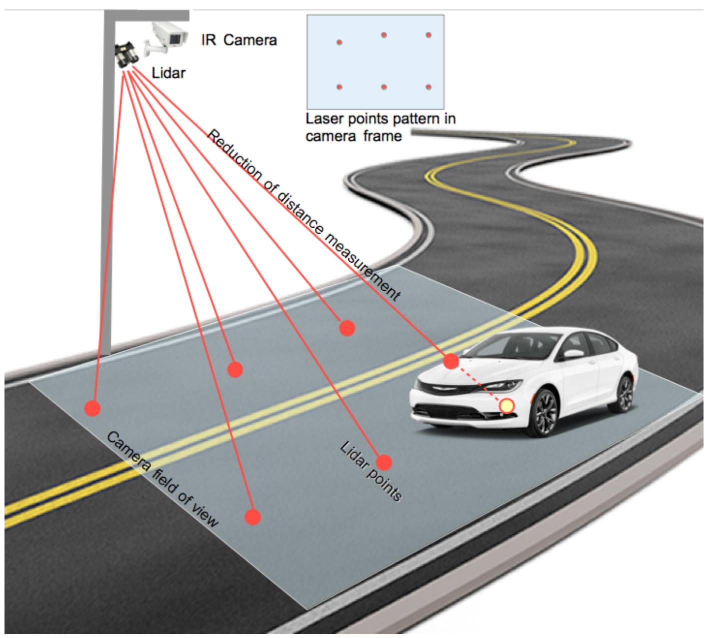


Figure 4.4: Measurement with Laser points in camera frame

Figure 4.4 shows measurement with Laser points in the frames of camera video. As illustrated, this method uses Lidar as Laser transmitter and IR camera as receiver. Lidar projects Laser points array onto the monitored area and the location of each points in video frames are constantly being checked. During passage of a vehicle, laser points on that lane will have their location altered successively and then restore. Through this, a location measurement of vehicle similar to direct Lidar measurement is achieved.

4.1.4 Comparison between different measurements

All of the three methods can be categorized into short section measurement procedure in traffic engineering. Each of them attempt to detect passing vehicles in multiple location within a short section and measure vehicle speed and length. Individually, these techniques have the following properties:

1. Lidar. Compared with other measurements, the strongest advantage of the Lidar measurement lies in its independence from sunlight or any other external light source. As a result, Lidar provides consistent measurement regardless of time of day, shadow or other illumination problems. The problem of Lidar measurement is the limited detecting zone. As a point-measurement, assumption has to be made that all objects pass through the detecting line between transmitter and projecting point on road, are a passing vehicle; and every passing vehicle passes through this line. Depending on the road condition and sensor installation, more Lidars are possibly required to make the assumption hold.

2. Camera. In regards to camera measurement, its biggest advantage is the provision of large amount of information. Normally, vision sensors like cameras have a large field-of-view, which makes it possible to distinguish small object from large ones that are considered as passing vehicles. A large field-of-view enables the selection of more ROIs, which improves the overall reliability of the output, including vehicle counting, speed estimation and length measurement. On the other hand, camera provides RGB information, which makes the detection more easy and reliable. The major disadvan-

tage of the vision-based method is its dependence on external illumination, which is hard to be controlled or known ahead. As a result, illumination variation and shadow are always potential factors decreasing the performance of system. At night, vision sensors have to rely on illumination from light poles or sometimes only from headlights of vehicles and that significantly reduced the detecting accuracy.

3. Laser points in frame. Because this technique does not require additional sensor units, it provides "bonus" information about the monitored road section. Not relying on external illumination, it works better in low illumination environment. While in very dark environment and camera measurement cannot provide reliable data, this technique helps increase system reliability as a backup. The problem of this measurement is its sensitivity to external illumination. In daytime, since sunlight brings large amount of noise, the camera is not able to distinguish the laser point and the measurement fails. At night, light poles with strong power may also fail this method.

Concluding from the discussion above, these three methods in many respects have complementary performance and a combined approach can potentially lead to more reliable and accurate output. The next section will describe the proposed approach that fuses the measurement output from the three techniques.

4.2 Vehicle state estimation with Kalman Filter and grid-based sensor fusion

In the developed traffic monitoring system, Kalman Filter(KF) is used to estimate the state of each passing vehicle. Since the measurement procedure of the system involves multiple observations in a sequence of time steps, KF offers a computationally inexpensive framework to incorporate prior knowledge from both previous and new observations. On the other hand, fusion of observations from different sensor measurements is not conducted in the framework of KF, as all the sensor models of each measurement are neither linear nor with Gaussian uncertainty. Alternatively, sensor fusion is achieved using grid-based likelihood fusion, and will be regarded as a part of sensor measurement.

4.2.1 Kalman Filter formulation for vehicle state estimation

In this section, the formulation of Kalman Filter for vehicle state estimation is presented. In the formulation, vehicle state is firstly defined, followed with motion model and sensor model building.

State definition

The objective of the developed system is to conduct vehicle count, speed estimation and vehicle length measurement. Since all three measurement techniques sample data between known constant time interval, these three required output can be derived from an estimation of the vehicle location in each time step. And the state of the vehicle in RBE framework is defined as:

$$x_k^t = \begin{bmatrix} d_k^t \\ v_k^t \end{bmatrix}, x_k^t \in \chi \tag{4.1}$$

where x is the vehicle state, k is kth time step, t is the current vehicle, d is estimated vehicle head distance from first sampled area and v is the vehicle velocity. For other variables, f is the motion model, h is the sensor model, z represents observations made from measurements, u is the control input in sensor model and w and v are the noise in motion model and sensor model respectively.

Motion model and sensor model in traffic monitoring

Consider a vehicle t of concern, whose motion is given by:

$$x_k^t = f^t(x_{k-1}^t, u_{k-1}^t, w_{k-1}^t) \tag{4.2}$$

where $x_k^t \in \chi$ is the vehicle state at time step k. In the developed system, since information about control input u cannot be obtained, the input is assumed to be 0 for simplicity. The system noise in the formulation is assumed to be Gaussian. In other words, the vehicle is assumed to travel with constant speed during the time interval under some noise. In Kalman Filter, it is assumed that the estimated state is linear. So motion model, or in another name the prediction equation, is:

$$x_k^t = Ax_{k-1}^t + w_{k-1}^t \tag{4.3}$$

In the example of vehicle state, speed v and distance d are directly related, and the model can be explicitly expressed as:

$$x_k^t = \begin{bmatrix} 1, t \\ 0, 1 \end{bmatrix} x_{k-1}^t + \begin{bmatrix} \frac{t^2}{2} \\ t \end{bmatrix} a_{k-1}^t \tag{4.4}$$

here, t is the time interval between two time steps and a is the acceleration.The acceleration is assumed to be a Gaussian distribution, which reflects the Gaussian system noise. As suggested in Equation 4.4, the 2D Gaussian distribution is correlated, and a non-diagonal covariance Q is expected:

$$Q = \begin{bmatrix} \frac{1}{2}\Delta t^2 a_v, \frac{1}{2}\Delta t^3 a_v \\ \frac{1}{2}\Delta t^3 a_v, \Delta t a_v \end{bmatrix} \tag{4.5}$$

where a_v is the variance of acceleration.

In observation, sensors after fusion output the measured targeting vehicle location after each time interval t. Since the speed of vehicle cannot be directly observed, speed variable is derived by the observed distances, and distance is the only variable being observed. Given the current state x_k^t, sensor model gives the expected observation that is likely to be made:

$$z_k^t = h^t(x_k^t, \hat{x}_k^s, n_k^t) \tag{4.6}$$

where z_k^t is the fused observation. In Kalman Filter, sensor model is also formulated linearly and Equation 4.6 can be written as:

$$z_k^t = Bx_k^t + n_k^t \tag{4.7}$$

And the covariance of n is a one-by-one matrix built based on how detecting region is distributed.

State initialization

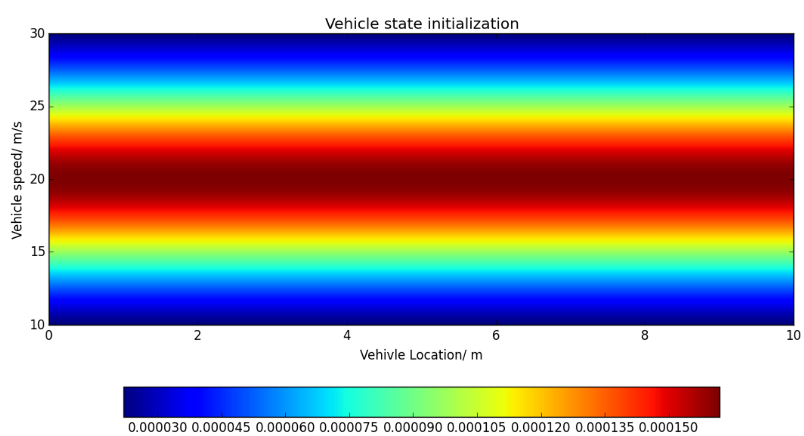


Figure 4.5: Vehicle state initialization (average speed 20m/s)

In the initialization stage, prior knowledge about current traffic flow can be used to build a initial guess about the state of next vehicle. Figure 4.5 shows an example of the initial state for a new vehicle. For initial speed, it is assumed that the speed of next vehicle follows Gaussian distribution with mean value equal to previous vehicle speed (20m/s in figure) or road speed limit. For vehicle's initial location, since no sensor input is available before the first detection, chance of the vehicle present at any point site in sensor field of view (FOV) is equally distributed. Concretely, the initial state can be written as:

$$x_0^t = \begin{bmatrix} d_0^t \\ \bar{v}^{t-1} + u^t \end{bmatrix}, d_0^t \sim unif(0, L), v_0^t \sim \mathcal{N}(0, \omega) \tag{4.8}$$

where $\bar{v}^{t-1}$ is the average speed of the previous vehicle in FOV, ω is a parameter that describes how much the vehicle speed varies in history.

4.2.2 Grid-based sensor observation fusion

Grid-based representation of sensor observation

In the developed traffic monitoring system, the grid-based method is used to handle the non-Gaussian sensor fusion problem. Normally, grid-based method is computationally expensive since it requires operation in every single cell. But in the case of the developed system, observation is of one dimension and it turns out that grid-based fusion can be conducted in real time. As shown in 4.6, grid-based method represents distance domain of vehicle state observation by normally aligned rectangle grid cells. In the figure, Δd represents the size of cell, $Dist$ represents the last observed region, and χ^{dist} is system field of view.

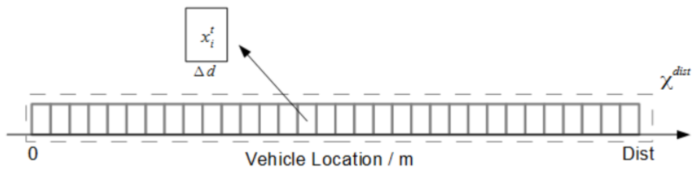


Figure 4.6: Grid-based representation of observation domain

Sensor observations in traffic monitoring

For all three measurement techniques, each one has an output of:

$$^{s}\hat{z}_k^t = \{b_0, ..., b_m, ...b_n\} \tag{4.9}$$

where s is the measurement technique, b_m is a binary variable indicating the detection event at m_{th} detecting site, and n is total number of detecting site for measurement technique s.

Table 4.1: Confusion matrix of measurement technique s.

s	Measured: Detection	Measured: Non-detection
Actual: Detection	α	β
Actual: Non-detection	$1-\alpha$	$1-\beta$

In modeling sensor observation likelihood, accuracy and property of each measurement technique need to be well understood. Such property can be described using confusion matrix. Table 4.1 shows how confusion matrix is formulated. As indicated by the table, sensors in the system naturally may prone to produce one category of results due to both internal and external reasons. In other words, one group of outputs is more "trusted" than another. With $\alpha = 0.85$, $\beta = 0.98$ and uniformly distributed observation region, when the measurement is made that ${}^{s}\hat{z}_k^t = \{1, 1, 0, 0\}$, sensor model outputs a likelihood map shown in Figure 4.7. For measurement $\{1, 1, 0, 0\}$ it is intuitive to conclude that the vehicle head is most likely to be at a site between the second and third detecting point, which is represented as the red area in the figure. From the figure, it can also be inferred that compared with third region represented as light blue, vehicle is more likely to be at deep blue area. This is because that normally sensors are more easy to fail when a detection occurred in the developed system. For all three measurement techniques, each of them attempts to check a variable that is logically related with vehicle existence. In other words, the variable in theory should remain unchanged when no vehicle is passing. Assuming that all hardwares are functioning normally, this nature can be analyzed in two aspects: 1) When sensors through measurement reads that the variable is unchanged, it is extremely unlikely that in physical world the property described by that variable has been modified but some factors else properly compensate that modification; 2) When the variable is changed, while it could be a result from a passing vehicle, it could also be other random factors. Reflecting in confusion matrix shown in Table 4.1, α should always be smaller than β. This property of sensor measurement accuracy significantly improve the reliability of hybrid measurement in traffic monitoring.

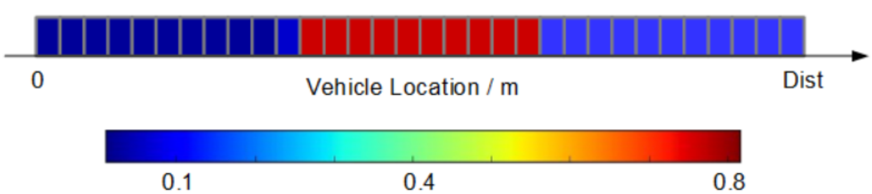


Figure 4.7: Multipoint short-section sensor observation likelihood in traffic monitoring

Sensor observation fusion

As shown in the previous sections, grid-based representation of the observations discretize the variable space and each single cell is numerically evaluated independently. Given the observations from the three measurement, $l^i_{x^t_k}(\theta_0)$, $l^i_{x^t_k}(\theta_1)$ and $l^i_{x^t_k}(\theta_2)$, the fused observation is:

$$l^i_{x^t_k}(\theta) = \frac{l^i_{x^t_k}(\theta_0) \cdot l^i_{x^t_k}(\theta_1) \cdot l^i_{x^t_k}(\theta_2)}{\sum_{\alpha=0}^{l_d} l^i_{x^t_k}(\theta_0) \cdot l^i_{x^t_k}(\theta_1) \cdot l^i_{x^t_k}(\theta_2)} \tag{4.10}$$

where $l^i_{x^t_k}(\theta)$ is the fused likelihood and l_d is the number of cells.

This fused likelihood $l_{x^t_k}(\theta)$ cannot be directly fed into Kalman Filter. As Kalman Filter requires all uncertainty be Gaussian, the fused likelihood needs to be Gaussianized. In other words, the original likelihood distribution is replaced by a Gaussian distribution approximation.

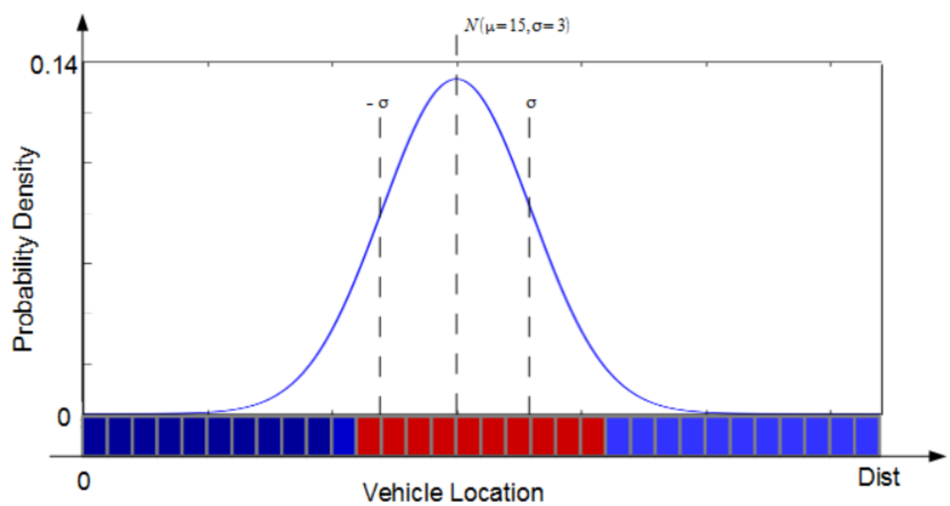


Figure 4.8: Gaussianization of fused likelihood

Figure 4.8 shows the Gaussian approximation of the observation represented in Figure

4.7. As a Gaussian distribution has two parameters, mean and standard deviation. To simplify the computation, the mean value is set as the expectation of the original likelihood. Standard deviation can be derived based on pairing of confidence interval.

4.3 Traffic monitoring process

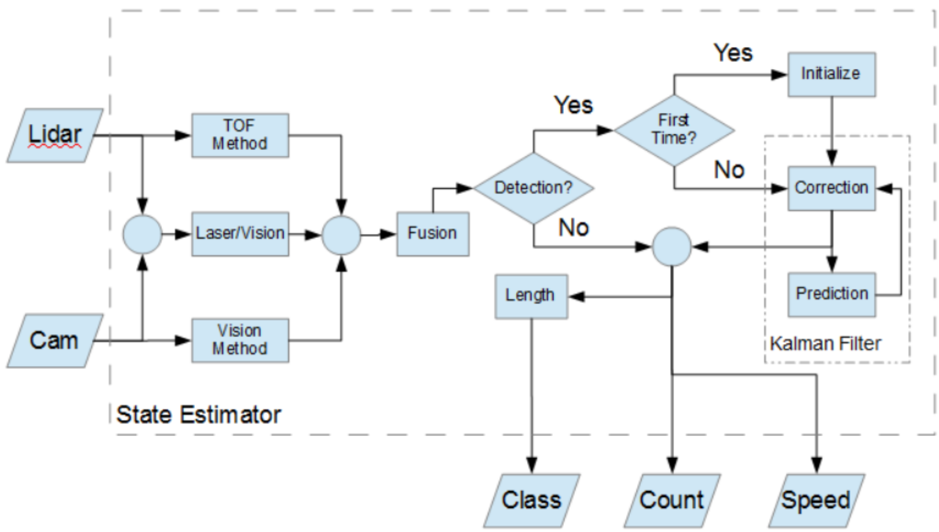


Figure 4.9: Recursive Bayesian Estimation (RBE) in traffic monitoring

Figure 4.9 shows the full process of traffic monitoring in the system. As a start, Lidar array and IR camera collect raw data. These data then are fed into system and processed by three different techniques. After that, the produced likelihood distributions are joint together by grid-based method and produce the fused observation with Gaussian uncertainty. At this stage, the system is able to tell if a vehicle detection event has occurred. On occurrence, if this is the first detection, a new vehicle variable is initialized and passed to Kalman Filter. During the following observations, Kalman Filter updates the state variable using new inputs until system believes the vehicle has completely left the monitored area. After a vehicle event has finished, the latest updated speed value is outputted as estimated vehicle speed. Combined with passing time, vehicle length is calculated, based on which the vehicle class is identified. And of course, passing vehicle count is also updated.

4.4 Summary

In this chapter, the traffic monitoring approach is described in detail. The three detection techniques are firstly introduced. Then, formulation of traffic monitoring in Kalman filter is presented, including state definition, motion model and sensor model. After that, sensor fusion by grid-based method is introduced, followed by how non-Gaussian uncertainty is handled. Finally, the whole traffic information estimation process is summarized and comprehensively explained. The following chapter will discuss about the dynamic power management approach developed for traffic monitoring.

Chapter 5

Dynamic Power Management of Traffic Monitoring

Since development of ITS requires large number of traffic monitoring systems installed over the whole traffic system, self-powered traffic monitoring systems are more preferred in that they make installation easier and operation more inexpensive. The developed system adopts a power management strategy called Dynamic Power Management (DPM) based on the established traffic theory and lower the total system power consumption by optimizing system power supply. This chapter presents how DPM is combined with traffic flow theory and describes the working process of DPM.

5.1 Power management based on traffic flow behavior prediction

Traffic system as a complex non-linear system still has not been fully understood. But in different scale and from different perspective, traffic flow has shown its nature of regularity and predictability. As the first step of traffic monitoring is to detect the next passing vehicle, such regularity and predictability can potentially help to improve the system detecting efficiency. In other words, based on history data, long term or short term, system can have a reasonable estimation about incoming vehicle parameters such as speed, time interval, etc.

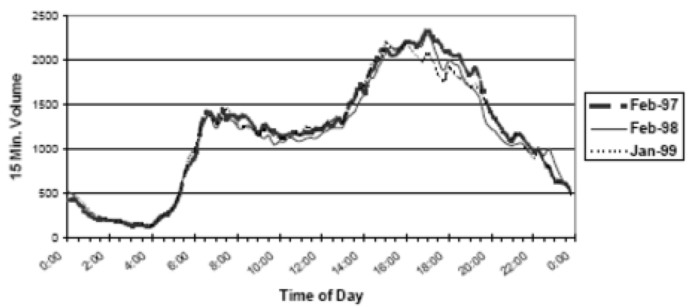


Figure 5.1: Predictive pattern of traffic flow

Figure 5.1 shows the traffic trends at certain location in different time of a day distribution in 3 days counted in an experiment conducted by U.S. Department of Transportation. As shown in the figure, traffic volume that have passed this location has repetitive shape and a prediction purely based on history data can achieve fairly high accuracy. As traffic volume in a time period is closely correlated with the average speed of vehicles travel through that location, predicted traffic volume helps system to optimize sensor parameters include camera frame rate and Lidar sample frequency. Since these parameters directly decide system power consumption and also have influence on measurement accuracy, this optimization balances performance-power ratio.

Like the property demonstrated in Figure 5.1, the established traffic flow theory describes such predictability of traffic flow in different aspects and scenario. So intuitively, some portion of knowledge about future traffic flow that can be predicted does not need to be practically measured, and energy that is used for such measurement somehow can be seen as a waste. If prediction about incoming traffic can be made or partially made, functioning and measurement in normal mode is not necessary and system can be turned off or reconfigured to reduce the energy usage. Such strategy in power management is referred as Dynamic Power Management (DPM), which in core is a power management design that selectively turn off or reduce performance of system component based on the status of component [42]. Combining DPM and traffic flow theory, a power management strategy is used in the developed system targeting reducing system power consumption by cutting unnecessary usage.

5.2 Dynamic power management for traffic monitoring system

5.2.1 Adaptive preemptive DPM

In the developed traffic monitoring system, an adaptive preemptive DPM strategy has been built. And the power management architecture is shown in Figure 5.2. As demonstrated in figure, after system initiated, power state manager first find the predefined power state and then send a command to service provider to make the power mode transition. In this state, service provider feed measurement into traffic state estimator once the configuration is finished. The estimator produce traffic flow data and these data are used by power state manager to make prediction about recent future workload. Based on this prediction, power state is paired again, and the power management is processed recursively. In power state manager, a service requester is used and can force a power state mode transition against command from power state pairing. In real world, service requester corresponds to a Lidar that is observing ahead of the monitored zone. Since workload predictor could make mistake, observations of this special Lidar could negate the prediction and is designed for stop-loss. As part of service provider, service requester is to function all the time and its observation is also used by traffic state estimator as indicated in the figure.

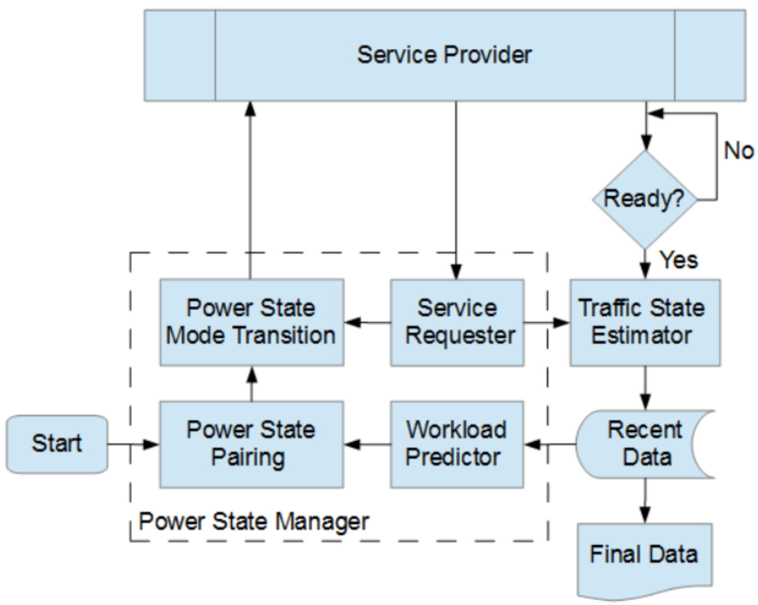


Figure 5.2: DPM power management architecture

5.2.2 Power State Manager: Power state transition

Power State Machine

Power State Machine (PSM) is the abstraction of DPM realization and is a state machine that describes operating modes of the system. PSM has two major categories of components, system state and transition between states, and is characterized by system performance ($Perf$) and power consumption ($Power$).

Power state and transition

In system power management, ideally it is expected that a system element will be switched to more active state and consume more energy only if it is required; switched off or to a less active state and consume much less energy when it is not used.However, this strategy only considers the effect of power state and disregards the influence of state transition period. In reality most electronic components take time and much energy than in normal situation to get back to more active status from inactive. Figure 5.3 demonstrates an example of power state transition for a PSM with two states defined, ACTIVE and IDLE. As shown in figure, when service requester has requested system to provide service, it takes a time of TR to get system state switched from IDLE to ACTIVE. During this transition time, the power consumption increased rapidly and the energy cost is called wake-up energy E_{Wake}. After that, power consumption drops back to normal power P_{ON}. Influence from this mainly fall into two aspects including system performance degradation and energy cost. With respect to performance, as shown in the figure, if the system starts to switch after power manager receives the request, there would be a gap of TR until service could be fully provided. For most systems, a small time gap between request and provision is acceptable but large gap can result in a total failure. Energy-wise, in third service request period from Figure 5.3, because the time interval between second request and third is quite short, system is waked up only after a small amount of energy E_{SAVE} has been saved, which is marked by yellow region. And the energy consumed in transition period TR, which is the red region, is actually more than the saved. In other words, the total energy cost in this switch-off-on operation is more than the amount from when system stays the same.

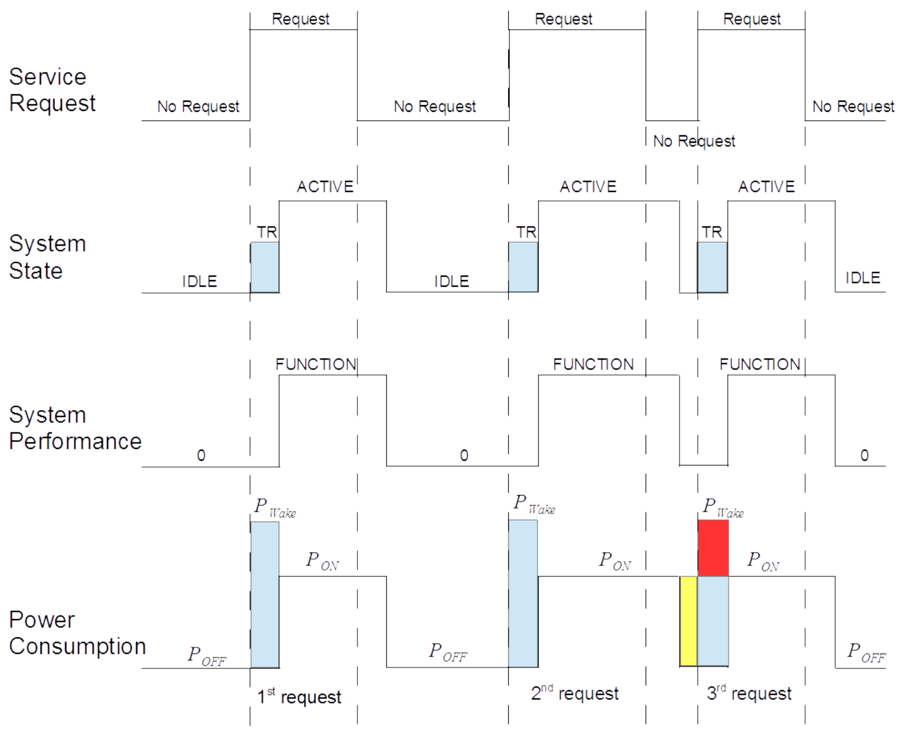


Figure 5.3: Power state transition property

Due to this reason, before state transition it has to be assured that:

$$E_{WAKE} < E_{SAVE} \tag{5.1}$$

and the performance degradation is acceptable.

In DPM, Power State manager attempts to detect the idleness of service requester. If detected, power manager first predict the time length of this idle period and will issue a shut-down command to switch power state into IDLE if predicted time length is valid for energy deduction. And after the estimated time length, power manager wakes up power state from IDLE to an active state to eliminate service delay and avoid performance degradation. In this process, judging whether the predicted idle time length is valid requires knowledge about break-even time, which can be calculated with the defined PSM. Break-even time is a property of power state transition and is defined as the minimum idle period it will take to compensate the energy cost in state transition. In other words, if the idle time is longer than the break-even time, this transition can be triggered and an energy cost deduction can be expected. Break-even time can be calculated as:

$$T_{BE} = T_{TR} + T_{TR} \cdot \frac{P_{TR} - P_0}{P_0 - P_1} \tag{5.2}$$

which is derived from:

$$(T_{BE} - T_{TR})(P_0 - P_1) = T_{TR}(P_{TR} - P_0) \tag{5.3}$$

Here, T_{BE} is the break-even time, T_{TR} is transition time from current state to target state, P_0 is the power consumption of current power state, P_1 is the power consumption of the target state and P_{TR} is the power consumption in state transition period.

Power State Machine for traffic monitoring

For the developed traffic monitoring system, while system power consumption can be directly measured, system performance can be quantified by the number of functioning measurement methods and sampling frequency of each methods. As different hardwares are likely to have very different operating and power consuming property, a complicated power state definition for one specific hardware realization cannot be generalized to others. Because of this, PSM built for the developed traffic monitoring system is built in a way that the DPM strategy can be applied to most hardware realizations of the same concept.

For the proposed method, two categories of sensors are implemented and normally, imaging sensors like cameras have a longer wake-up time compared with Lidars. Based on this, power state of the system is roughly defined in Table 5.1. In the table, S means SLEEP, I means IDLE and A represents ACTIVE.

Table 5.1: Traffic monitoring system power state definition.

State Name	Lidar State	Camera State
S&S	OFF	0 fps, Not configured
S&I	OFF	0 fps, Configured
I&I	0 Hz, Configured	0 fps, Configured
A&A	10 Hz	10 fps

Corresponding to the table, Power State Machine could be defined, as shown in Figure 5.4. In the PSM, power consumption in each state and the transition time is to be measured.

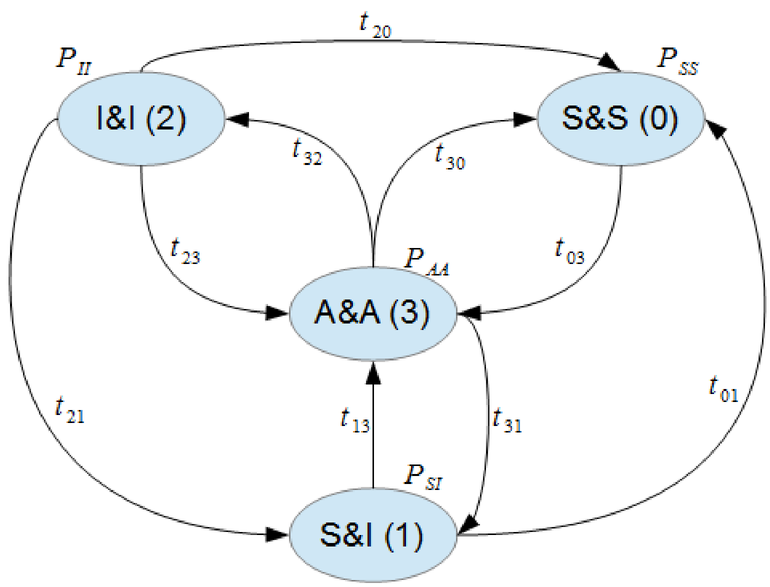


Figure 5.4: Proposed system power state machine

Power consumption details and dynamics are studied in the developed prototype and a Power State Machine is built and presented in Chapter 6.

5.2.3 Power State Manager: Power policy

In power state manager, it requires good prediction about future workload to make correct decision in power state transition. In the built DPM, the workload predictor is based on recent local traffic data and theoretical explanation from traffic flow theory. In the developed system, workload prediction is made in two levels: multi-lane level and single-lane level.

Multi-lane level: Power state transition in congestion

Multi-lane level power management estimates traffic condition of multiple lanes in same direction and the policies generated are applied to all sensors monitoring the corresponding lanes.

In traffic flow theory, many models regard vehicles traveling in the same direction on the road as a "flow" and shares common properties in different respects. For one traffic flow at the same time period, each individual vehicles in it have very close travel speed. And in DPM, theoretically if the speed of current traffic flow could be estimated, total energy cost could be deducted by minimizing the necessary sampling frequency of all the sensors while still remaining reliable measurement when traffic flow speed has decreased.

In real world traffic, speed of free flow fluctuates around an average number and achieving large amount of energy saving requires notable speed drop compared to normal and that scenarios mostly are related red light or traffic congestion. Due to this reason, in multi-lane level power management, a red-light/congestion detector is implemented in workload predictor. Once a red-light event or congestion event is detected, the predicted workload rapidly decreased to near zero as the vehicles are either moving extremely slow or completely stopped, and significant amount of energy could be saved in this time period.

This strategy works more efficiently in urban traffic monitoring. In urban road, as traffic lights are distributed in most sections, traffic flow would every other time be paused for a predictable time period. And also in modern city traffic during certain time of a day, traffic congestion is very common. Both of the traffic flow behaviors have predictable property and in most roads are likely to occur frequently enough to lead to a large amount of energy saving if exploited.

The detector basically makes two estimations. On one hand, it attempts to measure the current speed and if the speed of vehicles in most lanes has been very low or close to zero more than the threshold time, a red-light/congestion event would be triggered. On the other hand, the estimator summarizes history data and predicts how long would the red-light state stay in that time of a day. Normally such prediction about time length is not made for congestion, because congestion time statistically is not easy to predict and the service requester for one lane in Power State Manager is solely used to wake up the system.

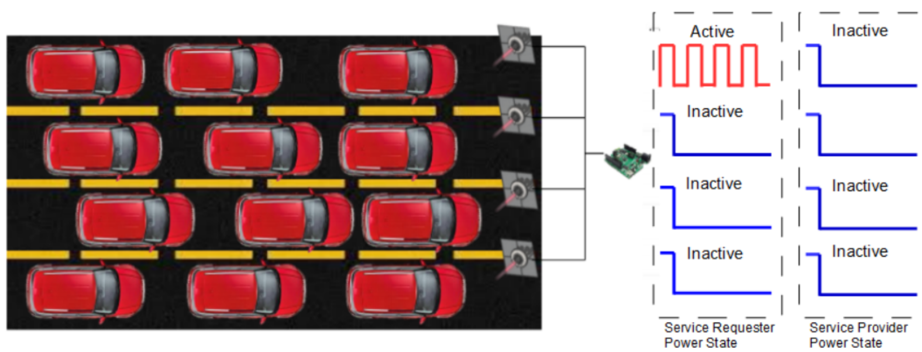


Figure 5.5: Power state in congestion or red light

Figure 5.5 shows the power state of system when congestion or red light event is triggered. As demonstrated, after the detection, sensors act as service providers are all shut down as the idle time from red light or congestion is far more than break-even time. For sensors act as service requesters, only one of them needs to stay active and monitor the traffic because as mentioned before, vehicles of the whole traffic flow have very close speed, and one lane's condition is enough to reflect whether red-light or congestion has ended. Empirically, service requester in the most inner lane is preferred to stay active. So when inner lane's vehicle starts moving, the corresponding service requester wakes up both the lane's service providers and service requesters of other lanes. And other service requesters will then wake up their service providers if they find their monitored vehicle has also started moving. As vehicles in red light and congestion could not speed up rapidly, performance degradation in this process is also trivial.

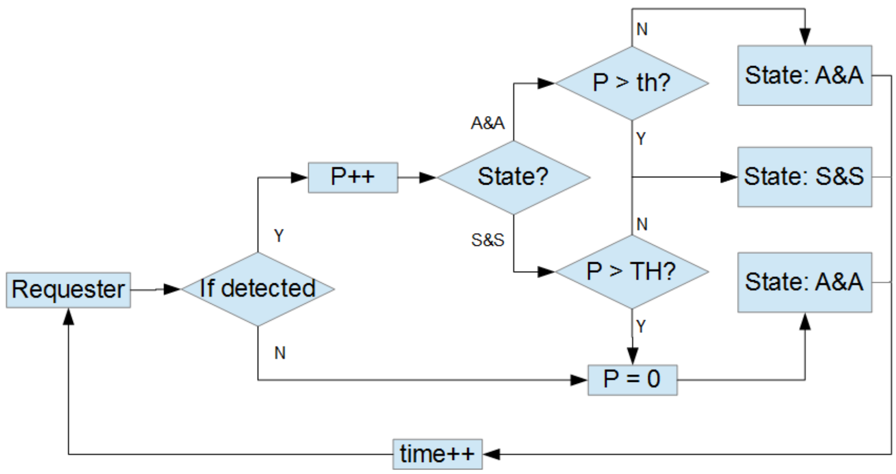


Figure 5.6: Power state transition process in congestion or red light

Figure 5.6 shows how service requester and history data together generates power state transition decision based on red light or congestion detection. In the figure, th and TH are two parameters derived from history data and decide whether the system has stayed in the same state for long enough time to switch. As illustrated, red light or congestion time is expected to be long and system will directly get into A&A state once red light or congestion event is triggered.

Single-lane level: Inter-arrival power state transition

In traffic flow theory, traffic flow also has predictable patterns in different level. In single-lane level workload prediction, vehicle inter-arrival time is attempted to estimate with two classical models, car following model and signal effect model.

1. Inter-vehicle power state transition

Most traffic monitoring system samples the detecting response from filed of view in a certain frequency. Sampling frequency needs to be set high enough to ensure an accurate measurement and theoretically higher sampling frequency results in more precise results. However, high sampling frequency brings higher energy cost from sensor power supply and more computation. To balance measurement accuracy and energy cost, the ideal power management would be to set high sampling frequency while some vehicle is passing and lower the frequency while there is non-occupancy. And car following model from classical traffic theory is applied to achieve such power management.

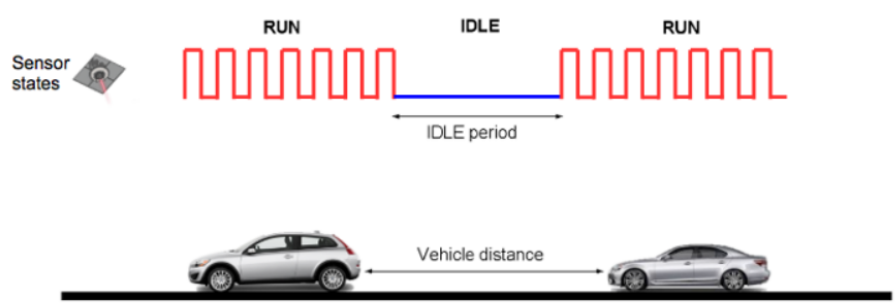


Figure 5.7: Sampling frequency adjustment under car following model

As shown in Figure 5.7, normally two neighboring vehicles on the road will remain a reasonable inter-vehicle distance and the distance is related to the flow speed, which means that after one vehicle has passed the detecting zone, it is expected that where would not be any other vehicles passing in a certain period of time following that. Using this property, the sensor system can turn into inactive mode and stay for that amount of time. Now the problem turns into the estimation of this time. In traffic theory, it is assumed there exists a correlation between vehicles in a range of inter-vehicle spacing, from zero to about 100 meters and the car following models are built to describe such coupling relation and can be used to estimate the interval. The modeling also assumes each driver in the transportation system when following a vehicle plays a role as an "active and predictable control element", which holds in most cases.

Among car following models, the speed-spacing models apply while each vehicle in the traffic flow maintains the same or close to a constant speed and every driver is attempting to maintain the inter-vehicle spacing. This model describes the relations between vehicle speeds and the inter-vehicle spacing and can be expressed using the following equation:

$$S = \alpha + \beta V + \gamma V^2 \tag{5.4}$$

where α is the effective vehicle length L, β represents the reaction time, and γ is the reciprocal of twice the maximum average deceleration of a following vehicle. Here the reaction times vary greatly with situation and from person to person. Mostly the reaction time is set from 1.5 seconds to 2.3 seconds. For γ, a typical value empirically derived would be about 0.023 $seconds^2/ft$. With the estimated spacing and the flow speed, the system sampling frequency can be optimized

With S estimated, the minimum inter-arrival time t_inter between two vehicles could be calculated. So in power management, each time when system find that one vehicle just left in free traffic, the system will immediately transmit into I&I state, stay for t_inter, and then turn back to A&A state.

2. Inter-group power state transition

Research in the theory of traffic signals have indicated that traffic signals have great influence on traffic flow not only in its upstream, but also downstream. And since such influence in downstream also potentially leads to predictable traffic pattern, it can be used as basis of dynamic power management for self-powered traffic monitoring system.

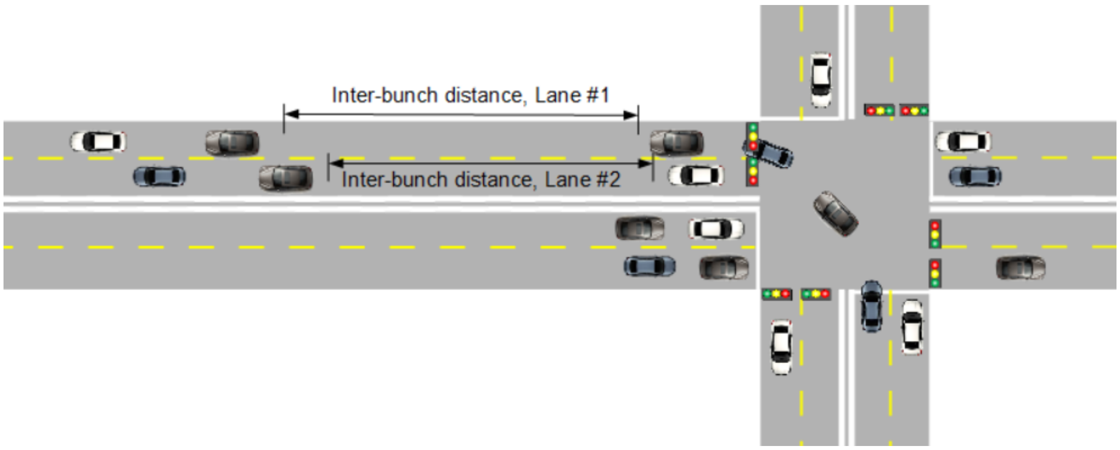


Figure 5.8: Signal effect in downstream traffic flow

Figure 5.8 shows how traffic signals in an intersection affect traffic flow in both upstream and downstream. As illustrated, when red light is on, the vehicles in corresponding load is stopped and has to wait. During this waiting time, many new vehicles come and join the queue and form a group, or a "bunch". After the light turned green, vehicles in the queue start to move and all vehicles in other roads are not allowed to get into the same road. As the vehicles travel, each individual ones maintain a distance with each other like described in the car following model. After all vehicles have passed, there will be a certain amount of time before another queue of vehicles are allowed to get in. As result, it could be observed that in each lane, vehicles are traveling in "bunch" and sometimes there will be a long distance between two bunches, marked as inter-bunch distance in the figure. Besides inter-bunch distance, there is another variable called bunch size, which described how many vehicles are in the bunch.

In traffic flow theory, there are effects from upstream traffic signals:

1. Platooning effect: Vehicles pass the signal in "bunches" that are separated by a time equivalent to the red signal.

2. Filtering effect: The number of vehicles passing the signal during one cycle does not exceed some maximum value corresponding to the signal throughout.

These two effects can be used for dynamic power management as shown in Figure 5.9. While detecting the end of a "bunch", the system turn itself into less active mode like S&I after one "bunch" of vehicles have passed and switch back to I&I mode after time TH or a service is required. The maximum number of vehicles passing from filtering effect th on the other hand helps to detect the end of a "bunch" of vehicles.

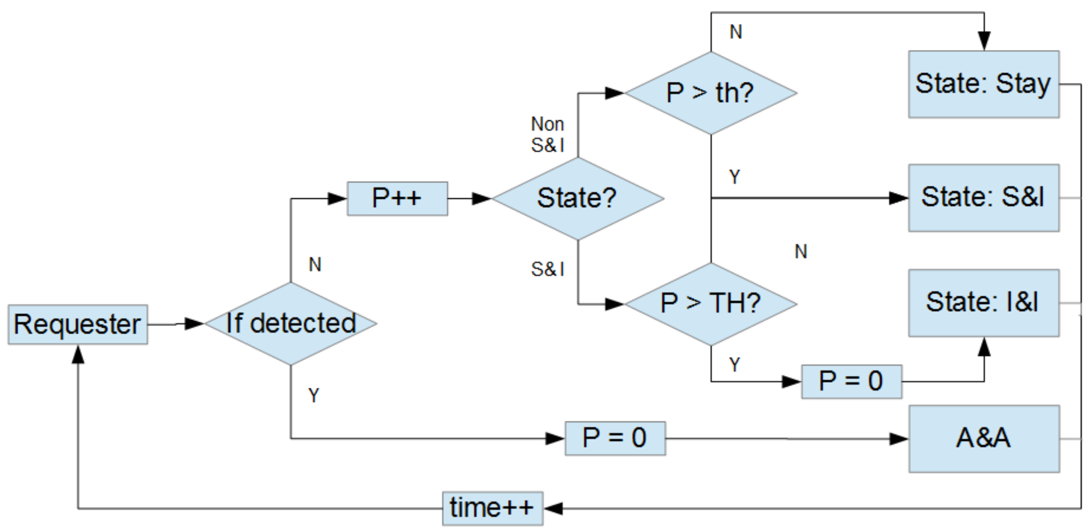


Figure 5.9: Power state transition process in bunch detection

5.3 Summary

In this chapter, the developed dynamic power management approach is explained. First, the basic idea of how energy reduction is achieved in traffic monitoring through dynamic power management is introduced. After that, the working process is demonstrated, followed by the formulation of power state machine definition. Finally, power policy of the power state manager is presented. The power policy is reflected through three power state transition. In presenting, the theoretical basis is first explained, followed by the realization in practice. The following chapter will introduce the prototype built to demonstrate both traffic monitoring accuracy and power management efficacy.

Chapter 6

System Development

In the development of the self-powered traffic monitoring system, two prototypes have been built and tested in field. As a system realization of the proposed power-efficient traffic monitoring method, the system is mainly composed of four units: computing unit with vehicle state estimator and dynamic power manager, power supply unit with energy harvesting component, sensor unit and communication unit. In this chapter, system hardware design and building are discussed, followed with system installation and calibration details in experiments.

6.1 Hardware development

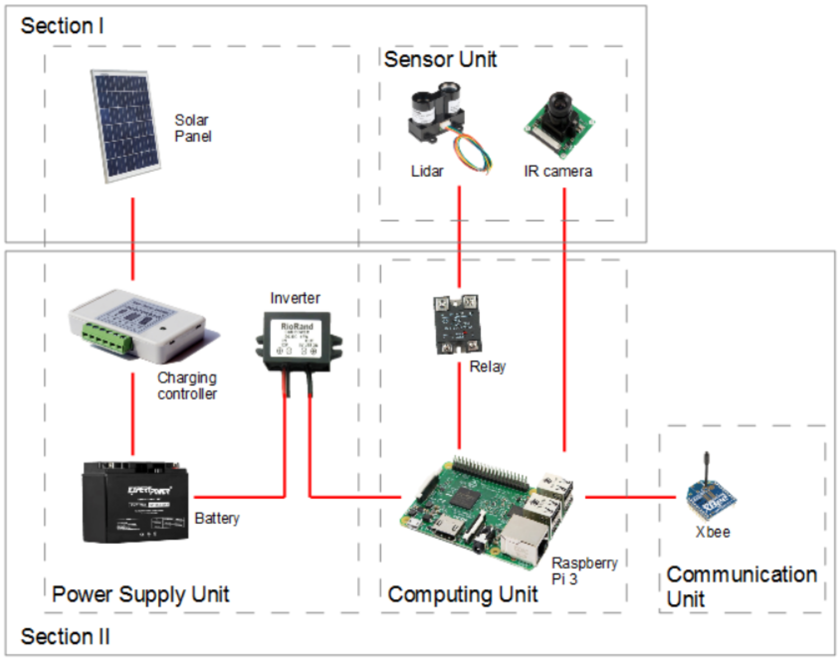


Figure 6.1: Traffic monitoring system schematic

Figure 6.1 shows the schematic of the developed traffic monitoring system prototype. The system mainly has four units including power supply unit, computing unit, sensor unit and communication unit. As a self-powered system, power supply unit harvest solar energy by solar panel and store energy in the deep cycle battery. The battery through inverter supplies stable DC power to computer and other electronics. Computing unit plays a center role in the system and interacts with all the other individual units. In computing units, a raspberry pi on-board computer is used for sensor controlling, data processing and power management. The on-board computer has very low power consumption and as a result has limited computation capacity. Due to this reason, all the algorithms are developed in a way that computation cost is minimized. Sensor unit is composed of two types of sensors including a Lidar array and an IR camera. The Lidar used in the system uses 905nm wavelength laser beam and is able to function in outdoor environment and measures distance from 0 to as far as 40m. The on-board computer interfaces with the Lidar array in I2C protocol and the measurement is made at maximum frequency of 50 Hz. In controlling the Lidars, SSR relay is used for power management purpose. For IR imaging sensor, the Pi camera that comes with Raspberry Pi is used and communicates with computer in CSI-2 interface. The camera has a frame rate of 30 and the resolution is 1920 X 1080. A Xbee module is used for communication purposes to enable between-system communication in future work.

Table 6.1: Traffic monitoring system component specs.

Part Name	Major components	Weight	Dimension
Solar panel	Solar panel, charging controller;	5.07 lbs.	36mm $\times$ 52mm
Sensor array	IR camera, 2 to 6 Lidars, sensor controller;	About 4.8 lbs.	36.5mm $\times$ 32mm $\times$ 17mm
Base	Raspberry Pi, inverter, deep cycle battery, electrical enclosure.	16.5 lbs.	23mm $\times$ 30mm $\times$ 26mm

Table 6.1 shows the specs of the developed system. Solar panel and sensor array compose the section I marked in Figure 6.1 and are both installed in high site of the pole. The base contains all the components marked in section II and is protected by an electrical enclosure. To ensure the applicability and portability, the weight and dimension are both designed as small as possible.

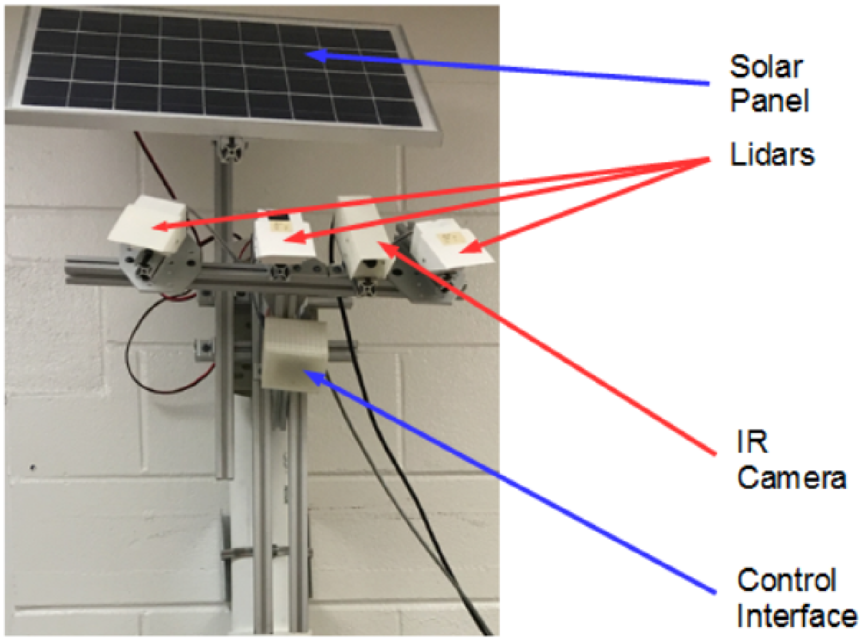


Figure 6.2: Developed traffic monitoring system prototype

Figure 6.2 shows the prototype built for field test. Corresponding parts illustrated in Figure 6.1 is the marked section I, the exposed section of the system. For this section, as the system is designed for 24X7 monitoring, all the electronic parts are sealed and protected in enclosures that are both waterproof and dust proof. Also, the system is designed to be portable and scalable. With a mounting bracket, the system could be attached to any pole structure that could be found alongside most of the roads. Structured by 80/20 material, all individual sensors including each Lidar and camera have two degrees of freedom in rotation, panning and tilting, which allows the system to be able to function in different installation setup and change the monitored zone in middle. Also, by adding more sensor modules, the system can be scaled up to monitor multiple lanes. Section II shown in the schematic figure is placed in an electrical enclosure that avoid these components from direct contact from external environment and is not shown in the figure.

6.2 Hardware component selection

The key components for building the proposed system are the sensor unit and computing unit. Their selections directly affect the traffic monitoring performance and power consumption property, which decides the selections of other components like power supply unit.

Lidar

In selection of Lidar for the proposed system, four properties are primarily considered including measuring range, accuracy, frequency and power consumption.

Because Lidars in system are used to making measurement of distance between installing site and monitored road, the Lidars used are required to have a measuring range longer than that distance. And for road-side installment like light pole installing, the measuring range decides how many lanes can be monitored. Normally, to monitor 4 lanes in two direction, a range of 30 meter is preferred. And for measuring accuracy, because the expected distance reduction is in meter level, most Lidars currently available in the market fit accuracy requirement. In regards to frequency, roads with different vehicle maximum speed require different sampling frequency. For example, in a road with speed limit of 45 mph, empirically Lidar should be able to work at 20 Hz to achieve high accuracy. Power consumption is another major concern in Lidar selection as multiple Lidars are used. As lower power consumption is always preferred, a working power that is lower than 1W is the minimum requirement.

The Lidar that is used in prototype development is LidarLite produced by Gummins. With power consumption of about 0.5W in continuous function mode, the sensor measures distance as far as 40 meters in accuracy of about 2.5cm. The Lidar achieves as high as 50 Hz in stable and accurate measurement.

Camera

IR imaging sensor to be used does not require high performance. As long as the camera responds to both visible light and near IR light and has a normal angle of view and frame rate(30fps), the imaging sensor would fit the requirement. In the developed system, a Pi camera designed for Raspberry Pi computer is used. The camera has a resolution of 2592 X 1964 and frame rate of 30 fps. Responding to both NIR and visible light, the diagonal FOV angle is about 46 degree.

Computing Unit

As mentioned before, the on-board computer used is raspberry pi, mainly in consideration of its low power consumption property. Because the algorithm is developed to be as computationally simple as possible, the system does not require very high computing capacity. The RPi 3 computer has 4 ARM Cortex-A53 processor with frequency of 1.2GHz, which is enough for the designed application. The average power consumption is about 2 Watt, which is acceptable for the self-powering requirement.

6.3 Installation and calibration

For traffic monitoring in road with different conditions and requirement, the developed system needs different installation arrangement and calibration is also required.

Installation

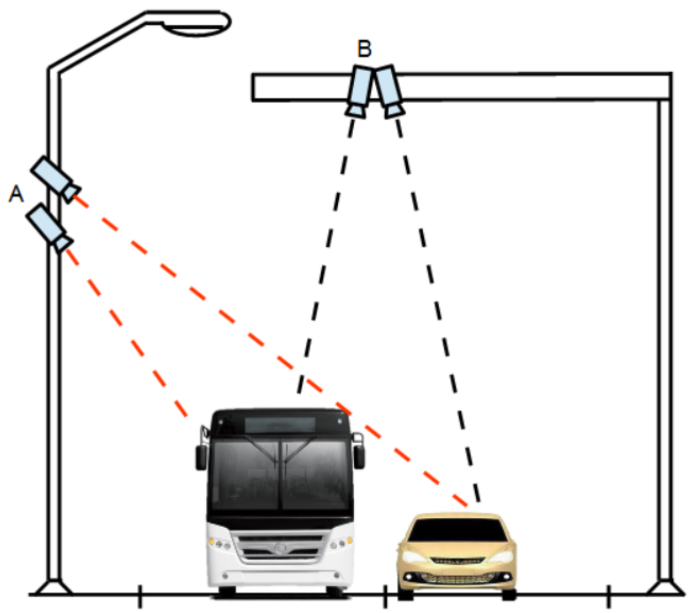


Figure 6.3: System installment

Figure 6.3 is a top view of the system monitoring one lane. As shown in the figure, the major issue needs to be considered in installation is occultation. As the system is more likely to be installed alongside the road onto a pole structure like solution A in the figure, when the system is monitoring multiple lanes, occultation from tall vehicles like a bus may occur. Due to this reason, the more lanes are to be monitored, the higher system should be installed. However, there are two constraints in this. First, some poles may not be tall enough. Also, Lidars have measurement range and if it is installed too high, the measurement will fail for far lanes. In the case that many large vehicles are expected to pass through and it's not feasible to install the system at site that is high enough, the system could be installed over the street, as the installing solution B demonstrated in the figure.

Calibration

Calibration of system is necessary each time when installation setup has changed. From this, spatial geometry of the system could be well understood and constant variables required for vehicle estimation could be derived. In this process, the constant variables of concern are the relative positions of each Laser points on the road as well as their locations in video frame.

As shown in Figure 6.4, L_0, L_1 and L_2 are three Lidars making TOF measurement. A, B and C are the three spots the Lidars targeting respectively. Cam is the IR camera with blue area marked $frame$ as its monitored road section. It is assumed here that all the Lidars have the same tilting angle and Laser beams emitted thus are in the same plane.

The aims in calibration are two:

- To find out d_1 and d_2 marked in figure;
- To locate the three Laser spots in camera frame.

For the first aim, as shown in the figure, ABL_1L_0 compose a trapezoid and s_1 distance and angle α could be directly measure once the installation setup is decided. And as a range finder, L_0 and L_1 could measure distance h_0 and h_1 respectively. With all these knowledge, the trapezoid is identified and distance d_1 could also be calculated. The same process could be used to derive distance d_2. As measurement of distance and angle in field may be troubling, aligned locating holes to attach each sensor are created on 80/20 by using standard parts. And for system structure, the major benefit of such design is that by adopting the function of Lidars, no additional manual measurement about environment is required once the spatial geometric information of system structure is known.

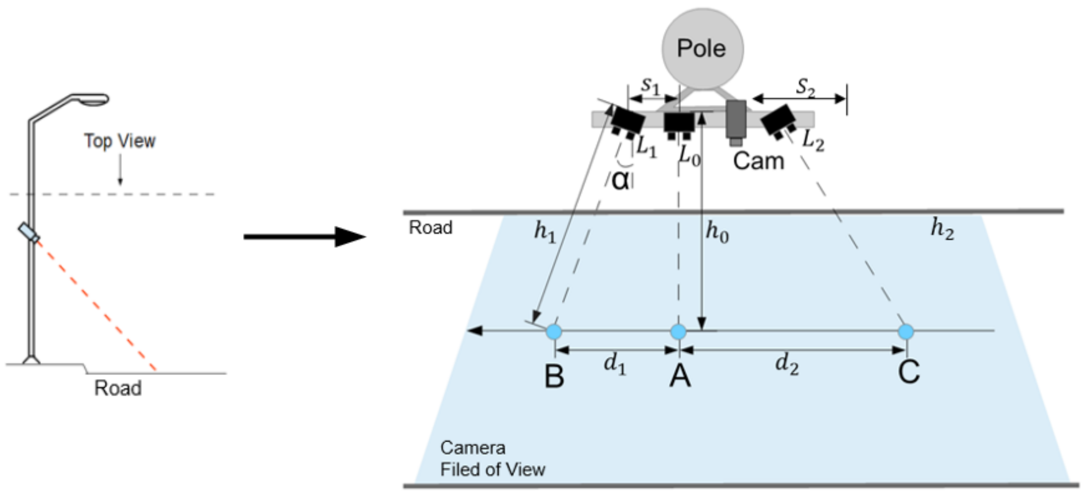


Figure 6.4: System calibration after installment

For the second aim, although the IR camera is able to see light with wavelength of the Lidar, it is very likely that during installment the camera could not find these Laser spot on road directly due to the noise from sunshine or other light source. As a result, to locate these laser spots, an object such as a human needs to pass through the monitored zone at a slow pace. While Lidar measurement finds a distance reduction, the current location of the object in the frame is then set as the location of the laser spot.

After these two steps, the detecting regions of the camera are to be defined. Figure 6.5 shows the camera view of a calibrated system with two Lidars. Red dots in the figure locate the Laser spots on road. Camera's Region of Interest then should be selected in a way that each ROI does not overlap with the laser spots, as shown in the figure. By this, more sampling points are collected and accuracy of speed estimation can be improved.

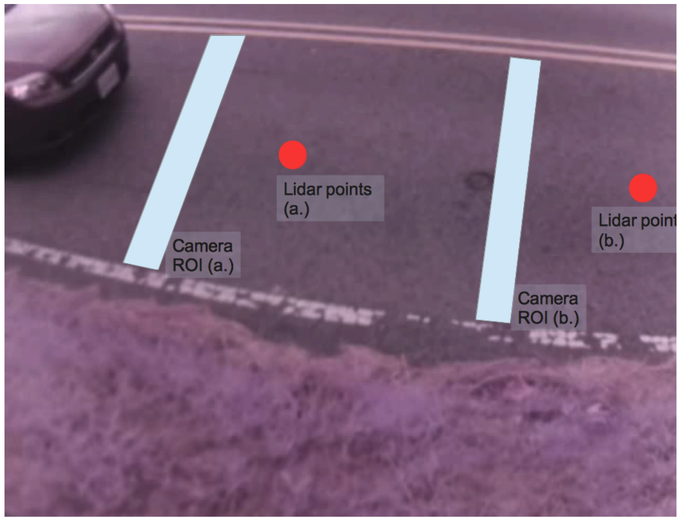


Figure 6.5: Calibrated system camera view

6.4 System Power State Machine

With the system prototype built, system power consumption property is measured and evaluated. Corresponding to power states defined in Table 5.1, power consumption in each state is analyzed in different parameter setup. From this study, information about performance degradation and power consumption during power state transitions is also expected to be learned.

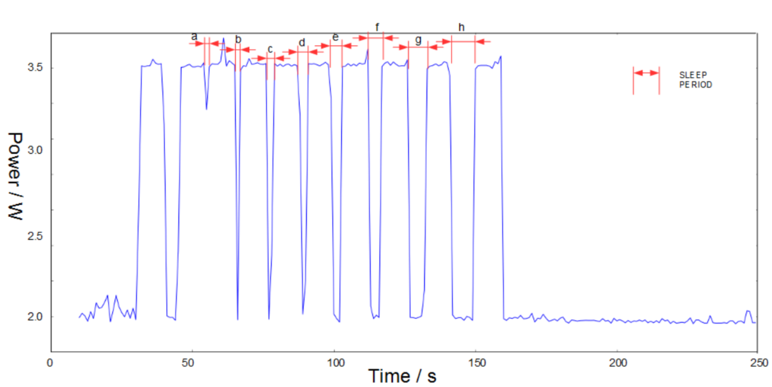


Figure 6.6: Power state transition: Lidar (4) between IDLE and SLEEP

Figure 6.6 shows power cost of a 4-Lidar array in IDLE state and SLEEP state. As defined previously, in IDLE state the Lidar array is already configured and ready to take measurement, while in SLEEP it is power off and requires reconfiguration to wake up. During testing, it is found that it takes less than 0.53 second to wake up the 4-Lidar array to IDLE state. In the figure, a, b, c, d, e, f, g and h represented 8 SLEEP periods. a period is the shortest and is 1 second plus wake-up time and h period is the longest, about 10 seconds. As for break-even time, it is found that P_Wake which is higher than normal power cost only endures for very short time and cannot even be detected by the power meter. Due to this reason, only performance degradation is considered before state transition from IDLE to SLEEP and as long as the estimated non-busy time is longer than 0.53 second, theoretically the Lidar array could be switched off. However, to avoid frequent turning-on-and-off which may make damage to sensor, this time is set as 0.8 second, twice as the theoretical value. One thing to be clarified is that while Lidar is in SLEEP, the power consumption is the power cost of computer as no other sensors are attached.

Similar to previous figure, Figure 6.7 shows a 3-Lidar array switched between ACTIVE and IDLE. In ACTIVE state, Lidar array makes measurement in certain frequency and the power increases compared with IDLE state. As shown in the figure, the measured power fluctuated a lot and to quantitatively analyze the power consumption, the curve is smoothed and presented in red line. Same process is applied to other following measurements. As presented in the figure, upper class letters represents system in ACTIVE states while lower class is IDLE. Different letters are set with different sampling frequency, and more frequently the measurement is made, more power is consumed. But the difference between different frequency is small. In test, the time it takes to wake the Lidar from IDLE to ACTIVE is less than 0.05 second. As Figure 6.6 and Figure 6.7 measures 3-Lidar array and 4-Lidar array respectively, by comparison it could be found that each Lidar in IDLE state consumes about

$0.38W$ and in ACTIVE consumes about $0.03W$ to $0.05W$ more than in IDLE, depending on sampling frequency.

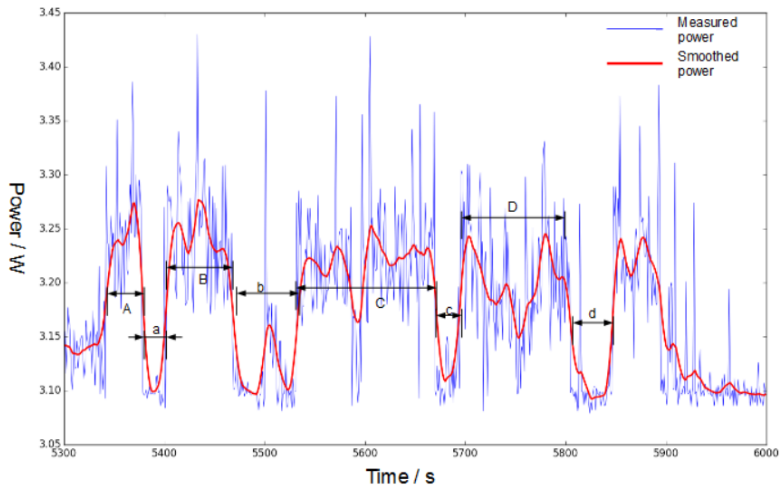


Figure 6.7: Power state transition: Lidar (3) between IDLE and ACTIVE

Figure 6.8 shows power cost change when camera is switching between ACTIVE and SLEEP. Here frame rate of camera is set to $15fps$ and while testing a 3-Lidar array is connected to system and remains in IDLE state. Figure 6.9 on the other hand shows the power cost property of camera switching between ACTIVE and IDLE. In SLEEP state, camera is closed and when waked up it requires reconfiguration. In IDLE state, camera stops feed in frames but is still configured and ready take in frames. So here it takes about 1.1 seconds for camera to switch from SLEEP to ACTIVE and less than 0.05 second for it to transit from IDLE to ACTIVE.

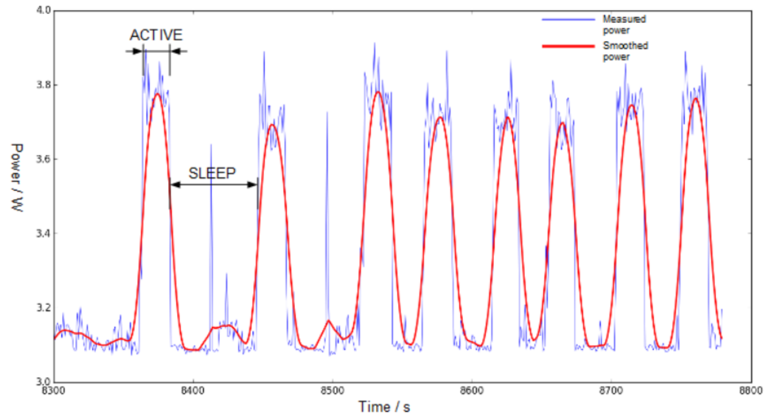


Figure 6.8: Power state transition: IR camera (1) between ACTIVE and SLEEP

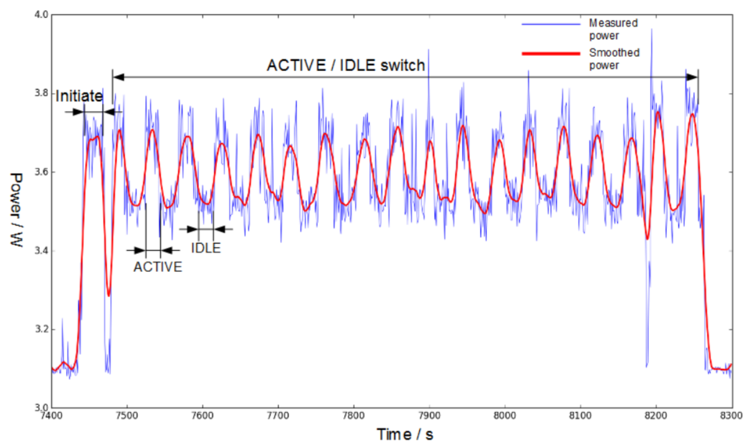


Figure 6.9: Power state transition: IR camera (1) between ACTIVE and IDLE

With all the information acquired from previous testing, the Power State Machine of the prototype with 3-Lidar array and a camera is illustrated in Figure 6.10. One addition Lidar is used as service requester and always remains in ACTIVE state in the system.

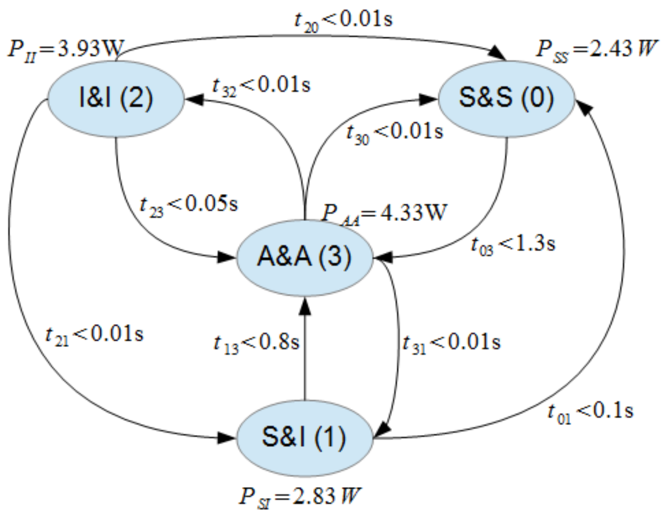


Figure 6.10: Power State Machine construction for prototype

6.5 Summary

In this chapter, the developed system prototype is presented. Hardware components and structure are first introduced. After that, the installation and calibration of the prototype is also explained. Finally, the power consumption property is measured and tested, based on which the power state machine of the prototype is defined. In the following chapter, experimental and simulation results of the built system is presented.

Chapter 7

System Experimental Results

Multiple field tests have been conducted to validate the reliability and accuracy of the system in traffic monitoring. And using collected traffic data from the tests, simulations of system power consumption are made with the power state model in built in Chapter 6. In this chapter, experiment setup, field test and simulation results and analysis are presented.

7.1 Experiment setup

Field test has been conducted in five locations in Blacksburg, VA around Virginia Tech campus. Among the 5 locations, two of them are alongside major road with speed limit of 35 MPH and the rest of roads are of 25 MPH. In North Main street, the system is installed onto a light pole and is aimed for long-term test. For the rest locations, short-term tests have been done multiple times.

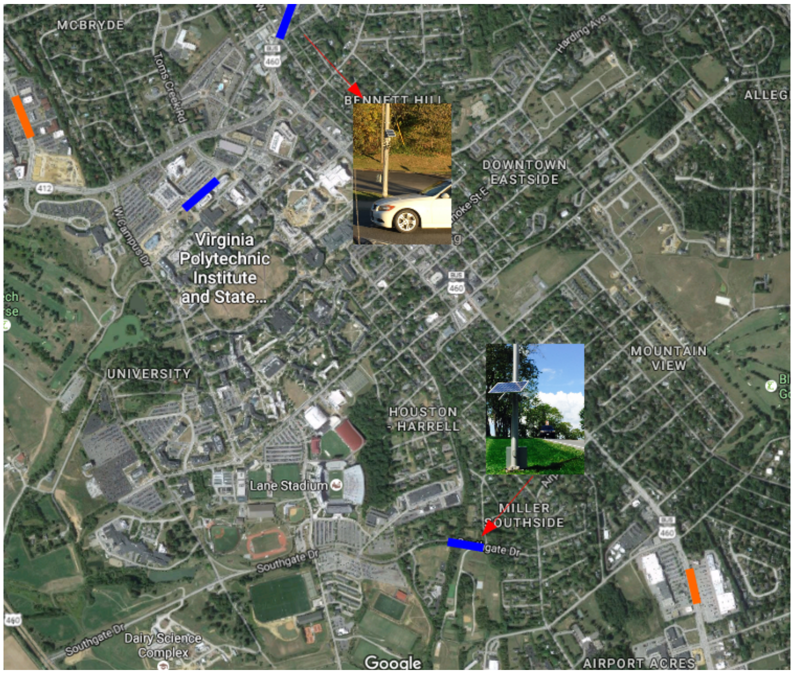


Figure 7.1: Field test locations

In these experiments, the number of Lidars that are used ranges from 2 to 4. Both Lidars and cameras have a sampling frequency of 10 Hz. Most of the tests are conducted in day time and night tests are only conducted in North Main Street site.

7.2 Traffic monitoring result

The traffic flow variables that system is attempting to estimate is vehicle count, traveling speed and vehicle size. In this section, estimated results for these variables are presented for analysis.

7.2.1 Vehicle counting result and analysis

Figure 7.2 and Figure 7.3 shows 60 second measurement of Lidar array and IR camera during the same time period.

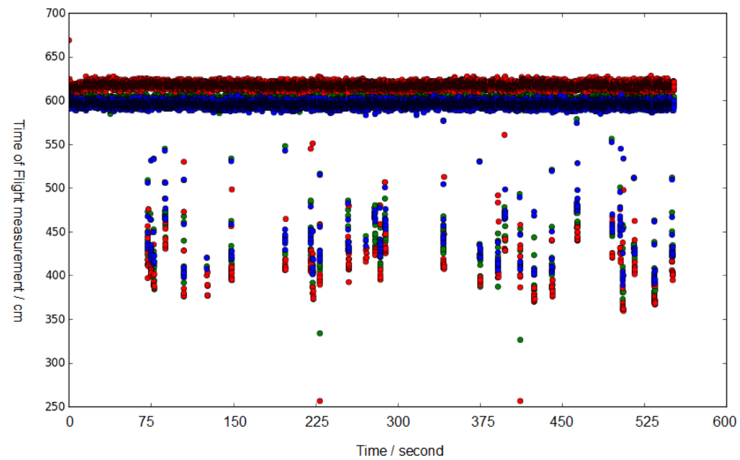


Figure 7.2: Lidar(3) measurement for 600 seconds

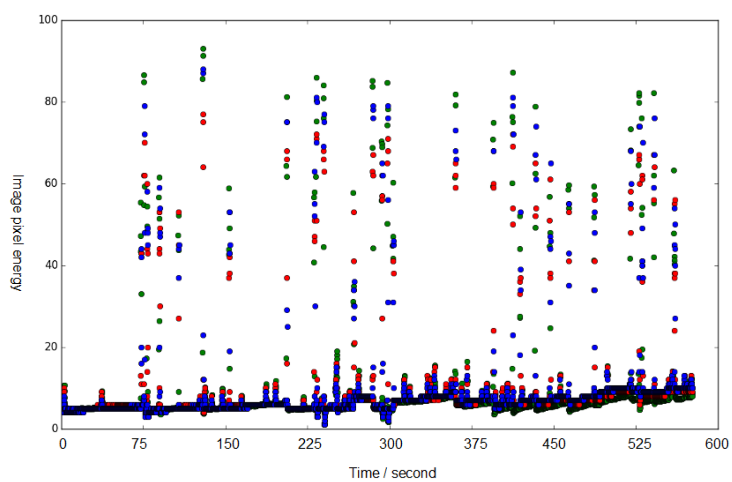


Figure 7.3: Vision ROI(3) measurement for 600 seconds

As presented in both figures, mostly the measurement result staying in a small interval. While vehicles pass through both measurement theoretically would be altered and such alternation reflects a detection. As both measurement has multiple sampling site (three in the Figure for both methods), fusion of all the individual measurement provides final estimation about detection of a vehicle.

Table 7.1: Vehicle counting accuracy with different parametric setting in daytime

Camera \ Lidar		0	1	2	3
0 ROI	F.P:	NA	6	1	0
	F.N:	NA	4	1	0
1 ROI	F.P:	11	2	0	0
	F.N:	6	1	0	0
2 ROI	F.P:	5	1	0	0
	F.N:	3	1	0	0
3 ROI	F.P:	2	0	0	0
	F.N:	2	1	0	0
Manual Total Count		97			

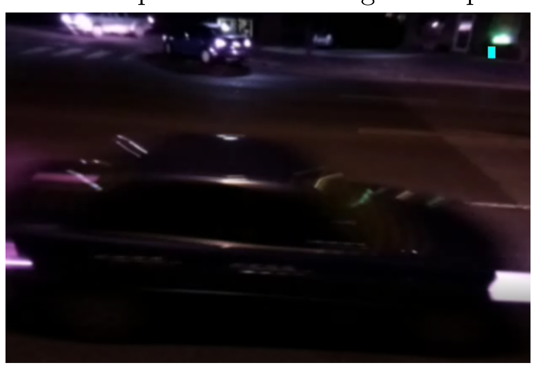
Table 7.2: Vehicle counting accuracy with different parametric setting in night

Camera \ Lidar		0	1	2	3
0 ROI	F.P:	NA	3	0	0
	F.N:	NA	0	0	0
1 ROI	F.P:	24	2	0	0
	F.N:	14	0	0	0
2 ROI	F.P:	22	2	0	0
	F.N:	14	1	1	1
3 ROI	F.P:	22	0	0	0
	F.N:	12	1	1	1
Manual Total Count		33			

Table 7.1 and Table 7.2 presents the performance of system in vehicle counting in day and night respectively. In the table F.P represents false detection and F.N represents false non-detection. With more number of camera Region of Interest and Lidar devices, output

accuracy improves rapidly. From the table, it could be concluded that in both day and night, Lidar provides more reliable detection. And for camera measurement itself, by increasing its number of ROI, the reliability of its detection is improved. Decent improvement by this could be expected only in day time and at night both FP and FN are large.

(a) Failed example due to crossing street pedestrian



(b) Failed example due to poor illumination

Figure 7.4: Failed detection examples

Fig 7.4 shows two examples of incorrect detection. Incorrect measurement of Lidar could be result of two reasons, hardware defect and environment interference. On one hand, due to internal defect of sensor, Lidar occasionally outputs incorrect measurement. On the other hand, some unexpected environmental interference such as a pedestrian crossing a street may confuse the system and lead to a false measurement. For camera measurement, most of the false measurements are result of unstable illumination. As shown in Figure 7.4(a), while the camera actually responses to the headlight and taillight, it fails to detect the vehicle body and see the two lights as two individual vehicles.

7.2.2 Vehicle speed estimation result and analysis

From the previous section, it could be observed that one Lidar set combined with one camera ROI are able to provide vehicle count measurement with decent accuracy both in day and night. However, with regards to speed estimation, more sampling from sensors are required. In speed estimation, two parameters have fundamental influence on the accuracy of the final result, field of view length and sampling site number (Lidar number and ROI number).

To conduct the parametric study, the author has drove at constant speed passing through the monitored area multiple times.

Table 7.3: Vehicle speed measurement with different parametric setting

True Speed	Cam ROI: 2 Lidar: 2			Cam ROI:3 Lidar: 3		
	4m	6m	8m	4m	6m	8m
10mph	9.46	7.15	6.26	10.42	9.12	8.7
15mph	15.83	14.09	12.5	15.74	15.52	14.22
20mph	19.31	18.8	18.72	20.02	19.28	20.62
25mph	20.61	23.09	24.78	25.24	23.81	24.8
30mph	32.66	27.97	30.33	25.52	29.05	28.57

Table 7.3 shows the experimental result for speed estimation. As demonstrated in the table, both sapling site number and field of view length have large influence on the estimation accuracy. For roads with different average speed, different parameter settings are preferred. Generally speaking, more sampling sites could always improve the accuracy. But for field of view size, an optimal length exists, and longer or shorter length both reduce the performance.

7.2.3 Vehicle class estimation result and analysis

Here the system classifies vehicles based on their lengths, and the length estimation of the vehicles relies on vehicle speed and passing time derived. Since both variables are not 100% reliable, the overlapped error may lead to inaccurate length estimation. However, in real world, size of vehicles are highly standardized and even the estimated vehicle length that is inaccurate could lead to correct classification.

Table 7.4[43] shows classification of vehicles by their length. Most of the vehicles traveling on the streets are passenger cars including sedan, SUV and even pickups, which in the table is represented as short vehicles. Medium vehicles include trucks and normal buses, whose length varies from 6.7m to 15m. Those vehicles longer than 15m are classified as large vehicles.

Table 7.4: Vehicle classification based on length

Class	Vehicle Length (m)
Bicycle	< 2
Short Vehicle	2 - 6.7
Medium Vehicle	6.7 - 15
Large Vehicle	>15

Classification result of one experiment is presented in Table 7.5. As demonstrated, the accuracy of the estimation is high, especially for vehicles larger than bicycle. Problems of bicycle classification mainly fall into two aspects. On one hand, sometimes when system fails to correctly respond to a passing vehicle continuously, system may see that one detection as two neighboring small vehicles, i.e bicycles. On the other hand, a pedestrian pass through the field of view could also lead to a bicycle estimation by system.

Table 7.5: Vehicle classification result

Class	Manual Count	Estimated
Bicycle	1	3
Short Vehicle	73	74
Medium Vehicle	5	5
Large Vehicle	0	0

7.2.4 Summary

After the experimental results and analysis, the following conclusions could be draw: 1) The developed traffic monitoring system is able to provide reliable traffic flow information including vehicle counts, speed estimation and vehicle classification. In experiments, it was found that by combining Lidar and camera, accuracy of more than 96% is achieved. And by adding the number of sensors, an accuracy close to 100% is realized. For speed estimation, by setting up system properly, the error could be reduced to within 1 mph. And for classification, the accuracy is also above 95% 2) The system functions 24 hour and provide reliable data in both day and night. But in comparison between day time and night time, performance in day is better. In daytime, the accuracy of counting is very close to 100% while at night is around 96%. 3) Factors that cause error in measurement falls into multiple categories. But as suggested in the experiment, by fusing information from multiple sensors most of the errors are eliminated. 4) Experiments also suggest that for roads with different properties, system parameter needs to be set accordingly.

7.3 Power analysis and effect of DPM

To validate the efficiency of the dynamic power management strategy developed in for the traffic monitoring system. Simulations of system energy cost in different time and location have been conducted using the collected real traffic data. Three workload predictors have been tested respectively and each have shown different performance in different circumstances.

7.3.1 Congestion predictor

Nine simulations have been conducted for the test of congestion predictor in DPM. As mentioned in Chapter 5, before prediction two parameters are required to be set, th and TH, where th decides when to transit to S&S and TH decides when to transit to A&A. To obtain the parameters, K-Means clustering is used in practice to first group the passing time of each vehicle.

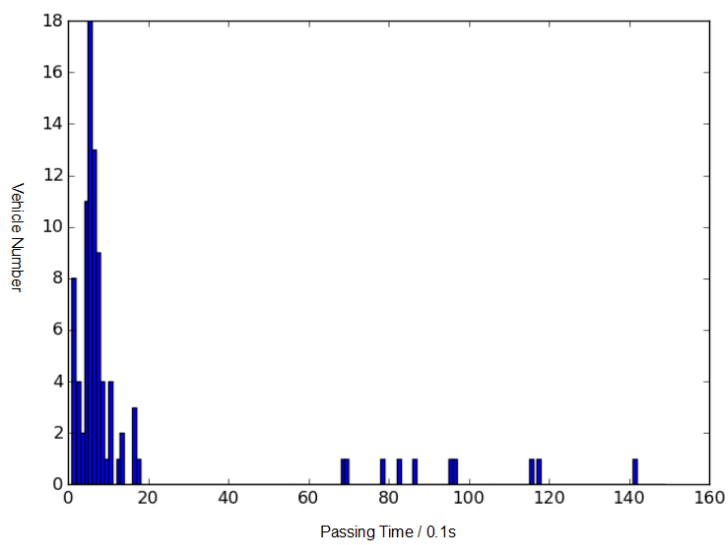


Figure 7.5: Passing time distribution, 13:28-13:41, Nov 23, UCB, Blacksburg, VA

As shown in Figure 7.5, most of vehicles passing through field of view of sensors in less than 2 seconds while a few others take considerably longer time (longer than 6 seconds). Using K-Means clustering, these passing times are grouped into two clusters and the two parameters could be set by:

$$th = max\{T_1\} \tag{7.1}$$

$$TH = max\{T_2\} \tag{7.2}$$

where T_1 is the group with smaller centroid and T_2 is the one with larger.

Testing the congestion predictor in 9 simulations, the results are presented in Table 7.6. In the table, 7_{th} and 8_{th} simulation using dataset collected at a site close to traffic light while others are not. Because the all the data are collected during a time without congestion, in the first six simulations congestion is not detected and the policy is not triggered, as expected. For 7_{th} and 8_{th}, the congestion resulted from red light is detected multiple times. Here, about 10% energy cost is deducted and only 5% detection is missed. And among these missed detections, because the vehicle after green light starts to move and the speed is very low, its influence on both vehicle count and speed estimation actually is very limited.

Table 7.6: DPM based on congestion detection simulation results.

	1	2	3	4	5	6	7	8
Time	10:00	14:00	16:00	23:30	15:00	16:00	11:00	12:00
Location	S.M	S.M	S.M	N.M	N.M.	N.M.	U.C.B.	U.C.B.
Original Sensor Energy Cost ($W \cdot h$)	0.516	0.516	0.516	0.516	0.516	0.516	0.516	0.516
Sensor Energy Saved	NA	NA	NA	NA	NA	NA	10.72%	9.33%
Total Detection	1665	1730	1704	369	651	765	1813	1645
Missed Detection	0	0	0	0	0	0	91	90
Avoided Sampling	0	0	0	0	0	0	1049	913
Original Total Sampling	7980	7980	7980	7980	7980	7980	7980	7980

7.3.2 Inter-vehicle power state transition

Table 7.7: DPM based on inter-vehicle time estimation simulation result.

	1	2	3	4	5	6	7	8
Time	10:00	14:00	16:00	23:30	15:00	16:00	11:00	12:00
Location	S.M	S.M	S.M	N.M.	N.M.	N.M.	U.C.B	U.C.B.
Original Sensor Energy Cost $(W \cdot h)$	0.516	0.516	0.516	0.516	0.516	0.516	0.516	0.516
Sensor Energy Saved	12.62%	12.50%	12.54%	15.40%	14.78%	14.50%	12.34%	12.51%
Total Detection	1661	1730	1704	369	651	765	1813	1645
Missed Detection	0	0	0	0	0	0	0	0
Avoided Sampling	6120	6060	6081	7469	7165	7028	5983	6063
Original Total Sampling	7980	7980	7980	7980	7980	7980	7980	7980

Table 7.7 shows simulation results of inter-vehicle power transition applied for three location at different time period. From Figure 6.10, it could be found that power state transition from I&I to A&A takes less than 0.05 second, which is much lower than the maximum allowed requesting time of service requester. Because of this, it is unnecessary for the system to automatically wake it up from I&I after th, and power state could stay at I&I as long

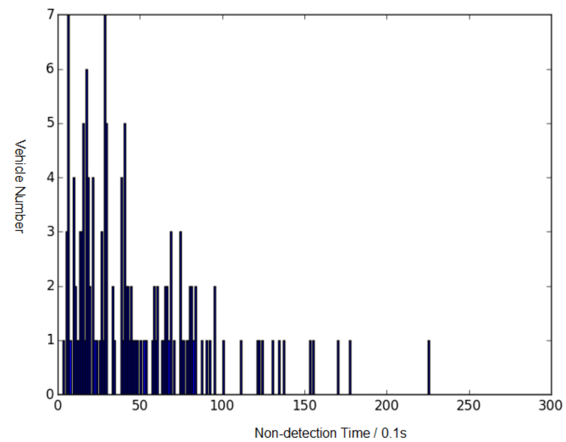
as service is not requested by the requester. Through this, theoretically such power state transition would not result in any missed detection and power state could stay at less active state, i.e I&I for much longer time. As shown in the table, system mostly stay at I&I for 3/4 of the whole time period. However, since not large portion of power is deducted from such power state transition, the total energy saved ranges from 10% to 16%, as presented in the table.

The major advantage of this transition is that it provides very reliable energy cost deduction disregards local traffic flow property and has no negative impact on traffic monitoring accuracy. How much power could be reduced directly relies on passing vehicle number and more energy could be saved for road with less vehicles, as presented in the table.

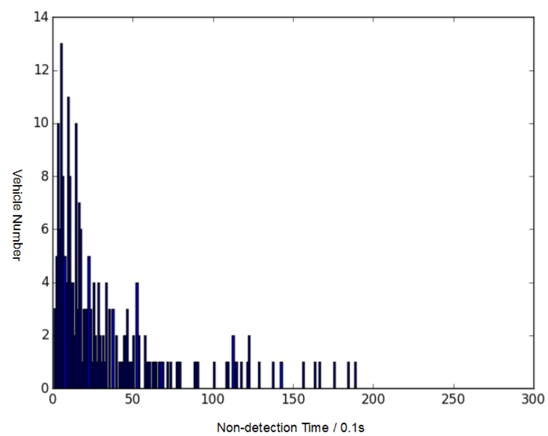
7.3.3 Inter-group power state transition

Similar to previous experiments, eight simulations have been conducted to test inter-group power state transition in DPM. To simplify the problem, parameter th here is set to infinite and the only parameter needs to be set is TH.

Figure 7.6 shows comparison of two inter-arrival time distributions draw from two sets of 13.3 minutes traffic flow data collected from two sites in Blacksburg. Compared with Fig 7.5, it could be observed that here it is hard to distinguish between inter-group time and inter-vehicle time. This is because in many cases when the traffic is not dense enough, the traffic flow pattern could not be well-reflected and traffic is flowing highly randomly. But on the other hand, from the comparison between the two figure, as North Main street is less busier than South Main, the South Main distribution is better shaped while the two have similar contour.



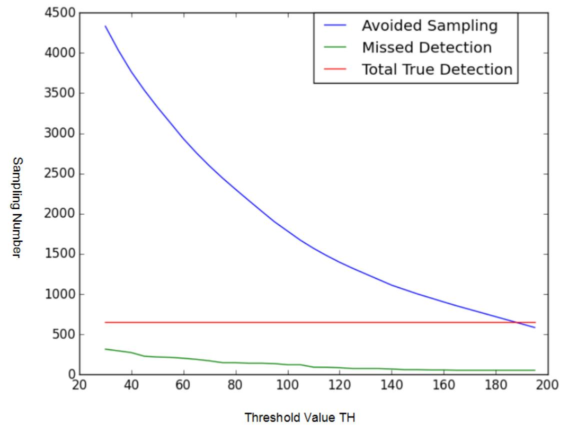
(a) Inter-arrival time distribution, 13:28-13:41, Nov 09, North Main



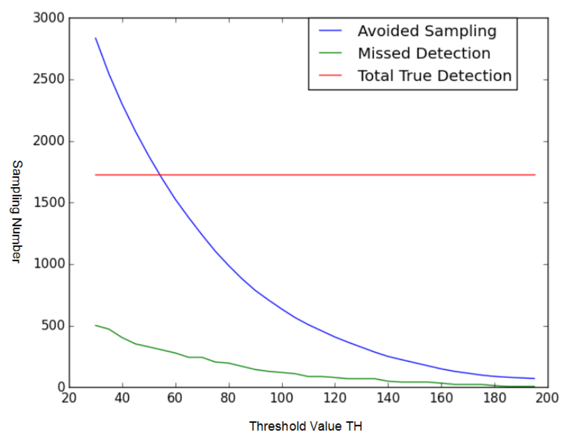
(b) Inter-arrival time distribution, 11:48-12:01, Nov 26, South Main

Figure 7.6: Inter-arrival time distribution at different site in Blacksburg, VA

To obtain proper TH value, Figure 7.7 could be derived from history traffic flow data collected at monitored site. The two figures are based on the same data sets in Figure 7.6. In practice the TH value obtained here could be used for the next 13 minutes power management. The figures demonstrate that as the threshold value TH is increasing, both energy deduction by avoided sampling and missed detection decreased. One thing to be noted is that missed detection does not directly lead to miss counting of vehicles as each vehicle passing event should cause multiple detection and some detection missed only decrease the accuracy of speed estimation and vehicle classification. And from such figures, a TH value could be found according to either power saving requirement or accuracy requirement.



(a) Effect of different inter-group power state transition, 13:28-13:41, Nov 09, North Main



(b) Effect of different inter-group power state transition, 11:48-12:01, Nov 26, South Main

Figure 7.7: Different inter-group power state transition at two sites, Blacksburg, VA

Table 7.8: DPM based on inter-group time estimation simulation result.

	1	2	3	4	5	6	7	8
Time	10:00	14:00	16:00	23:30	15:00	16:00	11:00	12:00
Location	S.M	S.M	S.M	N.M.	N.M.	N.M.	U.C.B	U.C.B.
Sensor Energy Saved	5.49%	5.6%	6.78%	19.61%	10.74%	9.09%	9.20%	10.19%
Total Detection	1661	1730	1704	369	651	765	1813	1645
Missed Detection	147	122	155	78	82	71	77	91
Avoided Sampling	681	693	841	2377	1302	1102	1115	1235
Original Total Sampling	7980	7980	7980	7980	7980	7980	7980	7980
th	96	96	96	120	120	120	172	172

Table 7.8 shows the result of inter-group power state transition in 8 simulations. The table demonstrates that although the process has strong randomness, certain regularity still exists. The first three dataset is collected on a wide street with large traffic flow. Due to this reason, it makes sense that more samplings are required and less could be avoided, which leads to lower energy reduction. The 4_{th} dataset is collected during night, and much less vehicle has passed during that time period. This fact increases the unpredictability of the traffic flow, which leads to a large portion of detection being missed. On the other hand, because th is set to infinite, much more energy reduction is achieved. 5_{th} and 6_{th} dataset is

collected from the same location but at day time. As more vehicles have passed, the traffic flow has better predictability and less portion of detection is missed. At the same time, however, less power is saved. The last two dataset is collected at a site close to traffic light and thus has good predictability even there is a large traffic flow. As a result, less portion of detection is missed while a large power reduction is still achieved.

7.3.4 Summary

In this section, multiple simulations have been conducted to evaluate the effect of the three power state transition policies used for dynamic power management. To fully analyze all the policies, parametric study has been done in both day and night, busy and free road, close and far section from traffic lights. Based on the simulations, the power management strategy in the developed traffic monitoring system has shown to be able to reduct a decent amount of energy cost and still achieve reasonable detection accuracy by proper parameter setting. (1) In power management based on congestion recognition, about 10% of energy cost is saved in sacrifice of only about 5% detection. Because multiple detection is triggered for each individual vehicle, such sacrifice is very close to a neglectable level. (2) In power management based on inter-vehicle power state transition, by properly configuring service-requester, about 12% energy reduction is achieved in sacrifice of no detection missing. (3) Power management based on inter-group state transition have various performance in different traffic condition. For example, its performance at night is much better than in daytime. And to achieve same amount of energy cost reduction, mostly more missing detection would happen.

Chapter 8

Conclusions and Future Work

8.1 Conclusion

This thesis has proposed a self-powered traffic monitoring approach with key feature of its reliability and power efficiency. The system is mainly composed of two components, sensor component and power supplying component. Sensor component hardware-wise includes a Lidar array and an IR imaging sensor. Using the input from the two sensors, the three different traffic monitoring techniques are realized using ToF measurement, 2D RGB measurement and Lidar laser point tracking respectively. In power supplying component, major effort has been made on the development of Dynamic Power Management. Power state machine has been defined based on power consumption property analysis and three different power state transition policy has been developed using traffic condition or pattern recognition. One prototype has been built and multiple field tests have been conducted in local roads near Virginia Tech campus. Through the experiments, the accuracy and reliability of the system has been evaluated and it has shown that both in day time and night the system could stably output the target traffic state variables. Parametric study has also been done to find out how parameters of the system could affect the system performance. To evaluate power consumption reduction from the developed dynamic power manager, multiple simulations have been conducted for each power state transition policy. It is found that in different locations most policies have different efficacy. But for simulations in the same location but different (neighboring) time period, the power cost reduction and system performance sacrifice are very close. By setting policy parameter using recent traffic state data, power supply and output performance could be well-controlled.

8.2 Future work

Future work could be conducted in the following directions: 1) In experiment, it has been found that due to the illumination noise from light pole or other source, the Lidar laser point tracking method could not be evaluated in the field test. One possibility solution is to apply an optical filter that could filter out the light noise. 2) In the evaluation of power manager, the simulations are conducted individually for each policy. In future work these policies could be integrated together and be tested to find the overall efficacy of the whole power management strategy. 3) In the developed power manager, two levels of DPM have been proposed. In future work, a network level DPM could be developed because mutual communication among near traffic monitoring system could help in better service request time prediction and through this much more amount of energy could be saved.

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