SURE-SE

SENSORS for UNPLANNED ROADWAY EVENTS-- SIMULATION AND EVALUATION

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ABSTRACT

The purpose of this research was to demonstrate the feasibility of using sensor networks in traffic monitoring applications, specifically a rapidly deployable *network of traffic sensors (NOTS)* for short-term monitoring and data collection. A sensor network is an array of sensors attached to small computer nodes that have communications capabilities via wireless network. Our application problem is heavy duty truck data: vehicle classification and reidentification, particularly under slow or varying speed conditions. An experimental sensor, the IST Blade sensor, is essentially a portable inductive loop sensor that provides high resolution data. We used the Blade sensor for our initial experiments. We conducted a field experiment on the USC campus in order to collect data for development of classification algorithms. Our results are encouraging; classification accuracy is comparable to that of other recent research efforts. Once we have developed acceptable classification algorithms, two directions are apparent for future research: use of multiple sensors with the goal of improving classification results, and the use of vehicle signatures to allow re-identification of vehicles across multiple sensors.

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CHAPTER ONE

INTRODUCTION

An emerging and rapidly developing field in computer science is sensor networks – many sensors attached to small, low cost computer nodes that have communications capability via wireless network. Sensor networks seek to exploit advances in computing power, battery power, and wireless communications to develop highly accurate sensing systems. The purpose of this research was to demonstrate the feasibility of using sensor networks in traffic monitoring applications, specifically a rapidly deployable *network of traffic sensors (NOTS)* for short-term monitoring and data collection. Our application problem is heavy duty truck data: vehicle classification and reidentification.

1.1 Background and Justification of Research

There is an ongoing need for traffic data to validate and calibrate regional and local transportation models. Regional models are used to test hypotheses regarding human travel behavior, transportation and land use interactions, and the effectiveness of alternative investments or pricing policies.[1] Local transportation models are used to evaluate changes in economic activity or transportation system characteristics at a more disaggregate level. Traffic management policies, congestion reduction strategies and impacts of new development (such as housing or commercial centers) are some examples of local transportation model applications (Hansen, et al, 1993; Banister and Berechman, 2000; Transportation Research Board, 1995; Transportation Research Board 2002).

Freight flows are of growing interest within metropolitan areas, due to their recent rapid increase. As the impact of commodity flows has increased, government planners and system operators have a greater demand for commodity flow information and for better methods to track, analyze, and monitor these flows as they impact transportation networks and nodes. Demand for better information and analysis tools is particularly strong at the metropolitan level, because access to disaggregate data is limited and analysis tools are not yet well developed (Gordon and Pan, 2001; Sivakumar and Bhat, 2002).

The lack of data on truck traffic is particularly problematic. We have surprisingly little information on the characteristics of truck traffic and its distribution across space and time. State highway transportation departments have "weigh-in-motion" (WIM) stations at key locations on the interstate highway systems that provide truck traffic data, but there are relatively few such stations (there are only 104 stations in all of California), mainly due to their high installation and maintenance costs. In order to meet federal reporting requirements on heavy duty vehicles, additional WIM-type sensors are

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[1] See Meyer and Miller, 2001; Miller, Kriger and Hunt, 1999; Pas, 1995; Wegener, 1994.

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emplaced at other locations on the state highway system. Data on the arterial system is almost non-existent, because there is no easy way to collect such data.

There are also more localized problems that would benefit from a rapidly deployable data collection system that provides accurate vehicle classification and identification. For example, SB 2650 may impose fines on terminal operators if trucks entering the terminal idle in queue for more than 30 minutes. The law is intended to reduce diesel emissions. At present, the law is enforced by a roving officer who estimates idle time based on his assessment of queue length. A NOTS system that could be deployed on a random basis would allow for much more effective enforcement. The system could also detect queuing on the bridges or roads in the port area. Some other potential applications include parking lots in shopping malls, freeway ramps, airports, etc.

The key problem of sampling relevant to our proposal is that current permanently installed traffic management systems (TMS) do not provide sufficient flexibility for occasional sampling needed for research and planning for goods movement. In addition, the current state of the art for portable sensors lags behind that of permanent systems. Vehicle classification capability is limited, and vehicle re-identification is just beginning to be explored. Hence the purpose of this research is to develop new, more accurate approaches to collect freight data more efficiently and more flexibly by deployable sensors. Although data collection is the primary motivation for our work, other possible transportation applications include use of networks of traffic sensors (NOTS) around construction areas to manage traffic and improve worker safety, and to assist in traffic flow in emergency situations such as during a major evacuation.

Our approach is to use an accurate, low cost and rapidly deployed *Network of Traffic Sensors (NOTS)* to improve the accuracy of vehicle information analyzing. This NOTS system will consist of a number of small, low cost computer nodes, each with one or a few sensors (such as pneumatic tubes or adhesive magnetic sensors), connected with a wireless network. Although individual sensors may be relatively inaccurate, we expect this research to develop algorithms that allow the combination of individual sensor readings in the sensor network to provide highly accurate vehicle classification and vehicle re-identification.

1.2   Research Overview

Our first task was to review the state-of-the-art in current sensor systems. Existing emplaced systems (such as inductive loops and video cameras) provide reasonably accurate vehicle counts, speed and density estimations. Using inductive loops for vehicle re-identification is under research. . The state of the art in portable traffic monitoring is far less developed. Deployable systems tend to be large and expensive, or have limited functionality, and often require data to be downloaded and analyzed after-the-fact. For vehicle classification and queuing studies, human counting is still the method of choice; human counting is labor intensive and can only be done when personal safety can be assured. In addition, portable sensors today are often not tied in to central traffic

management systems because of the cost of communication (the per-installation charges of a wired connection make regular telephone lines impossible, and the pay-per-bit cost makes cellular data connections undesirable). We also consulted with leading California researchers at the UC Institute of Transportation Studies and PATH in order to learn about current research in progress.

Our preliminary research led to the discovery of an experimental sensor, the IST Blade sensor. It is essentially a portable inductive loop sensor that provides high resolution data. The Blade sensor is far more advanced than state-of-practice portable systems (e.g. pneumatic tubes), and we therefore chose the Blade sensor for our initial experiments.

A second observation from our preliminary research is that vehicle classification and re-identification is more challenging at low speeds, because vehicles are more likely to change their speed or location as they move over the sensor, thus it is more difficult to normalize vehicle signatures. We therefore redefined our research problem as how to improve the accuracy of vehicle classification and re-identification at lower and inconstant speed by using portable blade sensors.

Our second task was a data collection experiment at the USC campus. We had expected to obtain sensor data from other sources so that we could conduct a simulation study, focusing on correlated readings from multiple sensors and algorithms for self-configuration, e.g. the potential of the network approach for improving accuracy. We were unable to obtain such data, however, and hence decided to generate our own. Working with Steven Hilliard of IST, we collected 1500 detections of vehicles at three locations on the USC campus on Aug. 6th when construction was underway on campus, allowing us to capture a mix of periodic traffic, including the USC shuttle bus, construction traffic, including cement mixers and 18-wheel trucks, and general automobile traffic. Our data collection design included multiple observations of some vehicles. We supplemented sensor data with human observers and videotape to provide "ground truth". The observation data were checked with the video data to provide a ground truth data file.

Our third task was the development of algorithms to interpret the blade sensor data, starting with simple vehicle counts, then proceeding to classification, while laying the groundwork for re-identification. Our results are encouraging; classification accuracy is comparable to that of other recent research efforts. Once we have developed acceptable classification algorithms, two directions are apparent for future research: use of multiple sensors with the goal of improving classification results, and the use of vehicle signatures to allow re-identification of vehicles across multiple sensors.

CHAPTER TWO

LITERATURE REVIEW

Various sensors have been produced to collect traffic information such as volume, occupancy, speed, vehicle classification, vehicle re-identification on freeways, arterials, ramps, parking lot, etc. The data collected are widely used in planning, research, and as the source for real-time traffic information for Intelligent Transportation Systems (ITS). Sensors can be roughly divided into two categories: emplaced and portable. Emplaced sensors are directly installed on road infrastructure and detect traffic information continuously. Once anchored, emplaced sensors are usually not removed. Portable sensors are used for short-term data collection and are moved from place to place. The use of portable sensor also typically requires lane closures, as with emplaced sensors, but the period of traffic disruption is shorter. There is no absolute boundary between these two kinds of sensors. Inductive loops sensors are known as typical emplaced sensors, but "blade" sensors, which basically are also made of inductive loops, are portable. Piezoelectric sensors, which are used flexibly from place to place, can also be used in permanently installed Weight-in-motion (WIM) systems. Another example is magnetic sensors. They can be cut into the pavement surface, but pavement cuts are not always needed.

Emplaced sensors, mainly inductive loops, are used to collect real time traffic information. See Figures 1 through 5. Inductive loop sensors are emplaced in the roadway (Figure 1) and connected to local processing units -- detection cards (Figure 2) -- which are stored in fixed cabinets (Figure 3), by underground wires. The data collected are then transferred by cable or telephone transmission to computers in the traffic surveillance and control center (Figure 5). Traffic information such as volume, occupancy, speed, etc is generated by processing the data through software (Figure 4). Emplaced sensors are more sophisticated and stable than state of practice portable sensors. However, their installation and maintenance is costly, and consequently they are usually used where long-term data collection is required, such as signalized arterial intersections and freeways.

Figure 1: inductive loop sensors

Figure 2: detection card

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Figure 3: Cabinet
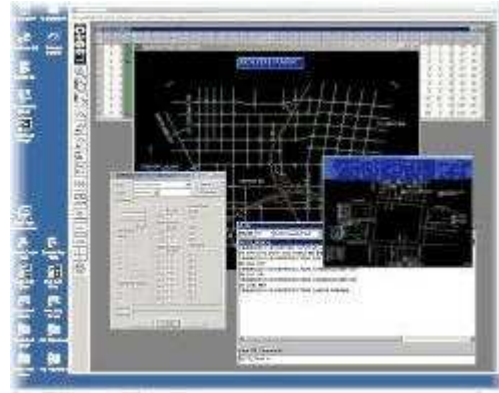
Figure4: data processing software

Figure 5: LADOT   Traffic Surveillance and Control Center

Sources: Figure 1 International Road Dynamics Inc., http://products.irdinc.com; Figure 2 SURE-SE project; Figure 3 Diamond company, http://www.diamondtraffic.com; Figures 4 and 5 City of Los Angeles, http://trafficinfo.lacity.org.

Portable sensors are typically deployed across a roadway, with the sensor data collected by a small CPU. See Figures 6 and 7. Sensor data is downloaded to a PC for processing after completion of the data collection period. Portable sensors are used for temporary data collection in locations without emplaced systems, such as un-signalized intersections or bridges. Each type of sensor has advantages and disadvantages. The following section reviews the main types of sensor used in traffic data collection.

Figure 6: Piezoelectric sensor

Figure 7: local data collection CPU

Sources: Figures 6 and 7 International Road Dynamics Inc.,http://products.irdinc.com.

2.1 Types of Sensors

2.1.1 Emplaced sensors

Inductive loops are the most widely used sensors at present. They are used singly or in pairs. Single loops provide data on vehicle passage, presence and occupancy, but speed estimation is less accurate. Several recent research efforts are aimed at improving the accuracy of speed estimation with single loops. (Ritchie Park, Oh and Sun, 2002; Lin, Dahlgren and Huo, 2004; Neelisetty and Coifman, 2004; Wang and Nihan, 2003). New inductive loop and detection technology have resulted in more capable sensors. Several algorithms have been developed to classify vehicles by analyzing the waveform signature from these advanced inductive loops. Double loops can determine speeds more easily than single loops and are more easily used for vehicle classification. However, double loops are not widely used due to their installation and maintenance costs. A major advantage of inductive loops is time-tested technology. Major disadvantages include reduced pavement life and required lane closures for installation and maintenance.

Video image processors detect vehicles by analyzing the video imagery to determine changes between successive frames. Algorithms are available to generate count, speed estimation, vehicle classification, and identification data. They are better off in clear condition for getting direct information on many vehicle characteristics. Performance depends greatly on visibility conditions, and hence is affected by weather and shadow conditions. The algorithm is data and memory intensive. Furthermore, the cost of video camera and image processing is high, and their energy requirements make battery operated imaging systems problematic.

Weight-in-motion (WIM) systems use a piezoelectric polymer sensor that produces a voltage proportional to an applied pressure or load. WIM sensors are used for vehicle classification, speed, axle count and axle weight estimation. WIMs have significant disadvantages. They are very high cost, require significant road construction to install, require regular maintenance, and their accuracy is sensitive to temperature and weather conditions and time, thus leading to larger uncertainty in data collection.[2]

Existing emplaced systems (inductive loop sensors and video image processors) can accurately count vehicles. The accuracy of speed estimation and vehicle classification has been improved through research. However, vehicle re-identification remains a challenge.

Emplaced sensors are used in Advanced Traffic Management Systems (ATMS) and Advanced traveler information systems (ATIS). For example, inductive sensors and video cameras are used in Los Angeles City's Automated Traffic Surveillance and Control (ATSAC) system. Inductive sensors and video cameras gather information electronically on congestion and flow condition from many points of a highway network and local arterials. Information is fed to a control center, where it is analyzed and used to adjust traffic signals, ramp entry controls, and lane direction controls throughout the system to reduce delays. The information can also be fed to individual drivers through websites (see figure 8) and traffic gauge, a wireless on-time traffic information receiver (See figure 9).

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[2] According to Caltrans, a recent WIM installation in District 7 cost $700,000.
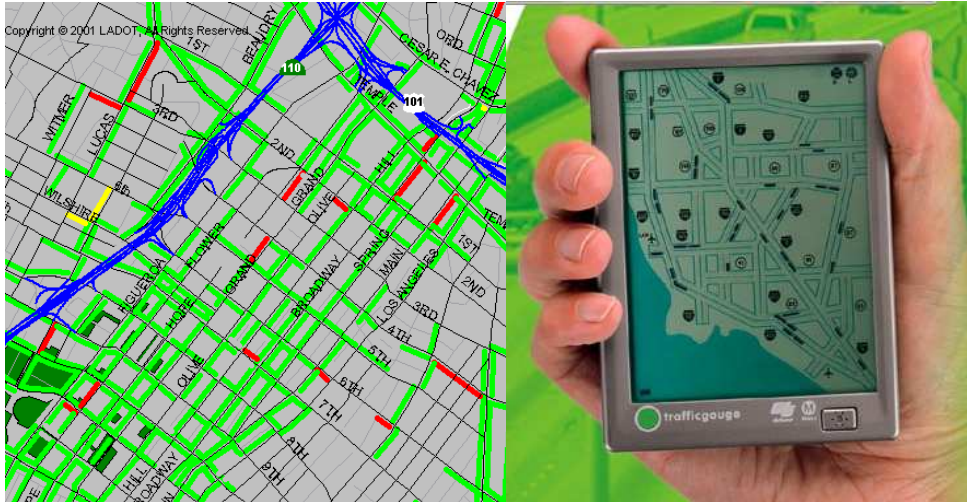
Figure 8: LADOT online traffic information   Figure 9: Caltrans Traffic gauge

Sources : Figure 8 http://trafficinfo.lacity.org, Figure 9 Trafficgauge,
http://www.trafficgauge.com/

2.1.2 Portable sensors

Pneumatic tubes remain among the most commonly used sensors for short-term traffic counting, vehicle classification by axle count and spacing. Some types gather data to calculate vehicle gaps, intersection stop delay, stop sign delay, saturation flow rate, spot speed, etc. They are installed perpendicular to traffic flow. They can be assembled quickly and have lower power usage. However, when trucks and bus volumes are high, axle counts become inaccurate. They are also prone to breakage due to vandalism and wear produced by truck tires. (Mimbela and Klein, 2000)

The **piezoelectric sensor** works by converting between mechanical and electrical energy forms. When pressure is applied to a polarized crystal, the resulting mechanical deformation results in an electrical charge. Piezoelectric sensors are used to classify vehicles by axle count and spacing to measure speed (use of multiple sensors required). They are also frequently used as part of weight-in-motion (WIM) systems (Mimbela and Klein, 2000). However, piezoelectric sensors are quite sensitive to pavement temperature and vehicle speed.

Ultrasonic sensors emit high frequency acoustic signal bursts beyond the audible range of humans and most animals. A vehicle moving into or through the detection area reflects the signals back to the detector; accurate timings of the return pulses allow determination of the distance to the target (much as bat and submarine sonar systems work). Pulse energy transmitted at two known points at a closely spaced incident angle allows vehicle speed to be calculated by recording the time at which the vehicle crosses each beam. Some models of ultrasonic sensors feature multiple lane operation (Mimbela and Klein, 2000). Problems include erratic results in turbulent air and temperature change. Large pulse repetition periods may degrade occupancy measurement on freeways with vehicles traveling at moderate to high speed.

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Acoustic sensors transmit pulses of ultrasonic energy toward the roadway. The energy is reflected back when a vehicle passes through. The pulse then is changed into electrical energy and it is sent to a controller notifying it of the presence of a vehicle. Two detection zones can be used in a speed trap mode to measure vehicle speed. Acoustic sensors are passive, unaffected by precipitation and consume every little power. When mounted over the center of the roadway and using a fully populated microphone array and adaptive spatial processing to form multiple zones, the acoustic sensor can detect the traffic information from up to 6 to 7 lanes (Mimbela and Klein, 2000). Disadvantages include effects of extreme cold weather on data quality, purchase and installation costs.

Multi-channel and multi-zone passive **infrared sensors** measure speed and vehicle length as well as the more conventional volume and lane occupancy. These models are designed with dynamic and static-thermal energy detection zones that provide the functionality of two inductive loops. Time delays between signals from the three dynamic zones are used to measure speed. Vehicle presence time from the fourth zone gives the occupancy of stationary and moving vehicles. The main disadvantage of infrared sensors is sensitivity to weather conditions, including fog, rain, or snow (Mimbela and Klein, 2000).

Two types of Magnetic sensors are used for traffic flow parameter measurement. The first type, the two-axis fluxgate magnetometer, detects changes in the vertical and horizontal components of the Earth's magnetic field produced by a ferrous metal vehicle. The second is the magnetic detector, more properly referred to as an induction or search coil magnetometer. It detects the vehicle signature by measuring the change in the magnetic lines of flux caused by the change in field values produced by a moving ferrous metal vehicle. Magnetic sensors can detect speed, traffic flow and classify vehicles. The advantage of this kind of sensor is that some models can be installed under the roadway without the need for pavement cuts. However, they can't detect stopped vehicles as they measure the change in flux (Mimbela and Klein, 2000) .

The state of the art in portable traffic monitoring is far less developed. Tube sensors continue to be widely used, because they are relatively low cost and robust, and they do a reasonable job of traffic counting. If used in double configuration, they can also estimate speed. The magnetic counters are less widely used due to higher cost and less robustness. Also, because they must be placed on the roadway, they are a potential hazard for pedestrians and bicyclists. Ultrasonic sensor and acoustic sensors are not capable of vehicle classification. They are more expensive than inductive loop sensors, especially when sufficient numbers of sensors are installed for speed estimation. Infrared sensors are expensive and sensitive to weather.

Generally speaking, portable systems tend to be large and expensive, or have limited functionality, and often require data to be downloaded and analyzed after-the-fact (Klein, 1999). Although many systems tie sensors into a central TMS, it is quite difficult to incorporate easily deployable sensors into centralized systems. Communications cost is a major barrier, since the setup costs of wire line communication (for example, telephone lines) are prohibitive, and the per-byte costs of metro-area wireless (for example, cellular

telephones, CPDP, etc.) are also quite expensive. The capabilities of each kind of sensor are summarized in Table1.

TABLE 1: Summary of Sensor Capabilities

Sensor	Function				
	Count	Occupancy	Speed	Vehicle Classification	Vehicle Re-identification
Inductive loop sensor	X	X	X2	X3	X5
Video image processor	X	X	X	X3	
Weight-in-motion (WIM)	X	X	X	X	
Pneumatic tube	X	X	X2	X4	
Piezoelectric Sensor	X	X	X2	X4	
Ultrasonic sensor	X	X	X		
Acoustic Sensors	X	X	X		
Infrared sensors	X	X	X	X	
Magnetic sensors	X	X	X2	X4	

X2: double sensors required
X3: software provided by vendors
X4: Portable vehicle traffic classifier provided by vendors
X5: Experimental
Source: adapted from Klein, 2001

2.2 Vehicle Classification

The most widely used technology for vehicle classification is double inductive loop sensors. Since a dual-loop detector system is capable of time stamping each detection, the elapsed time for a vehicle traversing the two loops can be calculated. Since the distance between the two loops is known, a dual-loop detector can calculate traffic speed fairly accurately. Vehicle classification is obtained by combining count and speed data. Accuracy breaks down under low speed/high flow density conditions, because vehicles are more difficult to distinguish when headways are short, or where speed is highly variable.

2.2.1 Vehicle Signature Approach

Because single loop detectors are more numerous, research has aimed at improving single loop capabilities. Advances in loop detector technology have resulted in higher resolution data. Several recent studies have focused on using vehicle signature data from loop detectors.

Sun, Ritchie and Oh (2000) used a Self-organizing Feature Map (SOFM) approach to classify about 300 vehicles chosen from approximately 2000 vehicles in moderate flow traffic (~1000VPHPL) drawn from a four lane section of the SR24 freeway. Ninety three equally spaced interpolations of vehicle signature were used in as input in the SOFM. Similar classes of vehicles were difficult to distinguish, because vehicles of similar size and shape have similar waveforms. Classification was least accurate for vans, SUVs, and pickup trucks, and for large pickup and panel trucks.

Ritchie, Park, Oh and Sun (2002) extended this work by testing three types of neutral networks: back propagation neutral network (BNN), probabilistic neutral network (PNN) and self-organizing map (SOM) Data were drawn from a major four-way intersection in the city of Irvine, California. Speed ranged from 5 to 30miles/hour. .Using SOM resulted in the best overall performance of 82.6% correct classification. Accuracy varies by vehicle type: bus and trailer/vehicle with boat were correctly identified in all cases. Accuracy was much lower for van/minibus, pick up truck and SUV, again because the waveform signatures of the vehicles belonging to those three groups are similar to one another.

2.2.2 Vehicle Length Approach

Another approach is to use occupancy and speed data to impute vehicle length, and classify by vehicle length categories. Neelisetty and Colifman (2004) identified heavy duty trucks by comparing occupancy time across successive vehicles. Given constant speed, occupancy is proportional to vehicle length. However, constant speed is a strong assumption, particularly under congestion. Also, vehicle length only allows broad categorization

Wang and Nihan (2003) developed a method to identify the composition of a vehicle flow so as to improve the accuracy of speed estimation by using single inductive loop data. Assuming constant speed, the ratio of effective vehicle length of one flow that contains long vehicles to that of a flow with only short vehicles can be estimated by comparing their occupancies. This ratio determined by the length distribution of short vehicles and long vehicles. A ratio greater than a given threshold value indicates a flow with long vehicles. Although the estimation error for long vehicle volume in each vehicle flow was less than 10%, the method has two limitations. First, accuracy depends largely on whether vehicle speed is constant. Second, the two category classification is generally too rough for vehicle classification purposes.

Kwon, Varaiya and Skabardonis (2003) estimated truck traffic volume from single loop detector data by using lane-to-lane speed correlation. They observed that the distribution of effective vehicle length is bimodal. Nominal representative lengths of 18.6 ft and 61.2

ft are used as the typical length of the two vehicle classes. They develop an algorithm that connects the relationship between the percentage shares of the vehicle classes, average effective vehicle length, flow and occupancy. The algorithm works for those freeway locations that have a truck-free lane and exhibit high lane-to-lane speed correlation. The overall accuracy is quite high but the accuracy of each lane is low, negative in some lanes and positive in some other lanes.

2.2.3 Video Imaging

Advances in computing power and image processing techniques make video imaging more feasible for vehicle classification. For example, Avery et al (2004) developed an image processing algorithm for length-based vehicle classification using an image stream captured by an un-calibrated video camera. Trucks were correctly identified 100 percent of the time. But the sub classification of trucks and other vehicles is still under research. The image processing program is fairly memory and processor intensive; it required a Pentium III GHz with 192 MB. The test dataset was collected on a sunny day from 11:30AM to 12:30PM on I-5 at 145th street in Seattle. Thus conditions were ideal. The extent to which imperfect weather conditions or peak hour traffic volumes would affect results is unknown.

2.2.4 State of Practice

Despite these research efforts, the state of practice for short-term vehicle classification counts among state DOTs continues to be pneumatic road tubes (Benekohal and Girianna, 2003). Vehicle classification technologies in current use by state DOTs can be grouped into three major categories:

(1) Axle based: classifiers measure the number of axles and axle spacing; Errors are caused by incorrect measurement of number of axles, a considerable change of vehicle speed over the sensors, etc;

(2) Vehicle-length-based: classifiers use vehicle length to group vehicles into classes. A single sensor or combination of different types of length sensors normally are used, including loops, piezoelectric and electrical contact closures;

(3) Machine-vision-based classifiers: a video camera is used to record video images that are taken at contiguous time instants spaced at regular time intervals. A digitizer converts the frame into digital signals that are sent to a computer for extraction of vehicle features. Visual based classifiers have problems with speed measurement and differentiating among closely spaced vehicles (Benekohal and Girianna, 2003).

The same survey asked state DOTs about their satisfaction with vehicle classification products offered by vendors. Magnetic imaging and acoustic sensor technologies got the highest score (4.0/4.0). However, only one state DOT used this kind of sensor. Loop detector plus axle sensors were rated second highest (3.41), followed by the WIM device (3.31), and pneumatic road tube (3.31), loop detector only (3.09), video image and

electrical contact closure (3.0), microwave (2.50), and fiber optic (1.50) sensors (Benekohal and Girianna, 2003). Pneumatic tuber sensors have a high failure rate (unclassified vehicles) in some jurisdictions, and they do not perform well in congested traffic conditions or where longer-term classification is needed along a high-speed section of a freeway. The main problems with the tube systems are related to installation, level of accuracy, durability, and maintenance. Use of inductive loop detectors alone in congested traffic condition frequently overestimates the number of trucks, because passenger cars with light trailers are counted as single-unit trucks. The detectors can appropriately classify large trucks, but they misclassify small trucks. Piezoelectric treadles require extensive oversight during installation and maintenance once they are installed. During operation, they are very sensitive to temperature (Benekohal and Girianna, 2003).

2.3 Vehicle Re-identification

Several techniques exist for vehicle re-identification. One can employ humans or cameras and automated image processing systems to record vehicle license plate numbers or some other identifying feature, but they are hard to read and very hard to automate.

High-resolution inductive loops can generate vehicle signatures that have been used for re-identification on arterials (Oh, Ritchie and Jeng, 2004). The basic idea of vehicle re-identification based on the inductive signature is to match a given downstream vehicle signature with an upstream vehicle signature amongst a set of candidate upstream vehicle signatures. Sun developed a lexicographic method to minimize mismatches between signature feature vector pairs (Sun, Ritchie, Tai and Jayakrishnan, 1999). Ritchie, Park, Oh and Sun (2002) added an optimization level to filter individual vehicle turning movements in order to expand the use of the lexicographic method to vehicle re-identification at arterial intersection at peak hour. A Heuristic classification algorithm or PNN algorithm was first implemented for turning filtering. Then, three feature vectors of the signature: maximum signature magnitude, slew rate and duration were used as input in PNN to do vehicle re-identification. The accuracy in the turning filtering classification phase was as high as 93.6% using the Heuristic algorithm and 95% using PNN. However, vehicle re-identification accuracy was only about 35%.

In related work vehicle re-identification was tested using two different types of sensors. Upstream inductive loop data was used in combination with downstream data from portable inductive loop blade sensors. Both a mapping procedure for input features and a genetic algorithm were incorporated into a lexicographic optimization based vehicle re-identification algorithm. Since each detector system has unique characteristics for representing vehicle images, re-identification is very challenging. The algorithm correctly matched only 50% of the vehicles, and the number of vehicles the algorithm could analyze was small due to data intensity. Blade sensors were reported to be more sensitive than other inductive loops and capable of capturing vehicle wheel locations due to their configuration and hence hold promise for improving accuracy of vehicle re-identification. (Oh, Ritchie and Jeng, 2004)

The state of practice for vehicle re-identification is the use of human observers. Workers are hired to record license plate numbers or California vehicle ID numbers at specific locations. This method has many disadvantages. First, cost is high. For example, a recent METRANS project required collection of data on truck queues at port terminal gates.[3] A team of 13 students was assigned to 6 locations at 2 terminals. Students worked 3 hours per day for 4 days. Creating data files and verifying data took several months. Second, human counting is subject to error. Worker attentiveness declines quickly after a few hours on the job; shifts of three hours are common to reduce this problem, making even one full day of data difficult to obtain. Third, manual observations are not effective at night, and can only be performed if worker safety is assured Logistics and cost constraints of deploying human observers limit this technique to only very valuable studies.

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[3] G. Giuliano and J. Maggadino, Evaluation of the Terminal Gate Appointment System and the Los Angeles and Long Beach Ports, METRANS project 04-06.

CHAPTER THREE

METHODOLOGY AND DATA

Our research problem is how to improve the performance of portable sensors in vehicle classification and re-identification. We are particularly interested in classification and re-identification under difficult conditions: low and variable speeds, variable weather and light conditions, and mixed traffic with a high proportion of heavy duty trucks. Our research goal is a rapidly deployable system, so we are interested in sensors that are easily installed and removed.

3.1 Sensor Selection

The literature review suggests that advanced inductive loop detectors (ILD) are most promising for our purposes. The unique signature data is determined by both **vehicle characteristic information** such as length, distance between axles, distribution of the metal mass along the body, etc. and **contextual information** such as speed, time, vehicle entrance angle into inductive field, etc.

Signature length and magnitude are the two most important features. Signature length is related to both vehicle length and vehicle speed. Low speed classification and re-identification is more difficult than high-speed, because vehicles are more likely to change their speed as they move over the sensor, making it more difficult to normalize vehicle signatures and compare them. Signature magnitude is related to inductance change which is proportional to the inverse of the distance of the vehicle body from the loop detector. High lateral offset (greater distance between the detector and the vehicle) results in low magnitude vehicle signatures, which leads to misclassification. We seek to improve the accuracy of vehicle classification and identification under conditions of varying vehicle speed and lane shifting.

We selected the "blade" sensor as the most promising ILD for our purposes. The blade sensor was developed by IST Corporation. It collects data from two parallel ILDs separated by a distance of 6 inches and oriented at an angle of 20° to the direction of the traffic flow. This orientation allows for information on number of axles and wheel based-vehicle length, as well as the other signature attributes described above. Axle and wheel base data should improve classification accuracy. The blade sensor is also very portable. It is easily transported and installed.

We requested test data from both IST and researchers at UC Irvine who had used the sensors in previous experimental work. Unfortunately, we were unable to obtain any test

data, and hence decided to conduct our own data collection experiment.[4] Although the data collection considerably changed the scope of work for this project, it provides a rich data set for follow-on work.

Our research approach is incremental. We first develop methods for interpreting data from a single pair of blade sensors. This involves various data processing steps to identify vehicle signatures and then use of algorithms to classify. We start with the simplest problem, counting vehicles, and then proceed to classification. Later work will focus on re-identification and on the potential of multiple sensors for improving accuracy.

3.2 Field Test

On August 6th, from 7AM to noon, we undertook a data collection experiment at the USC campus. Working with Steven Hilliard of IST, we collected 1500 detections of vehicles at three locations on the USC campus. Sensor data was supplemented with human observers and videotape to provide ground truth data. We selected the locations to get a mix of low- and moderate-speed traffic. We selected a data collection day when construction was underway on campus, allowing us to capture a mix of periodic traffic, including the USC shuttle bus, construction traffic, including cement mixers and 18-wheel trucks, and general automobile traffic. In addition to general traffic, we selected two passenger cars and ran them over each sensor 10 or more times to provide a baseline known vehicle to evaluate re-identification.

Data collection locations are shown in Figure 10. Sites A (northbound) and C (westbound) were selected because they are near the USC parking kiosks and a stoplight exiting campus, allowing us to capture low-speed traffic. Site B (both direction) was selected to provide moderate-speed traffic. The combination of the three sites was selected based on vehicle routes so as to obtain multiple readings of the same vehicle. A large share of vehicles entering at A continue along Watt Way through site B northbound. Site B also captures trucks and other vehicles in both directions. We were informed by USC Department of Transportation Services that heavy trucks would exit at Site C; however, on the survey day most trucks exited either at A or another exit not covered by the data collection effort.

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[4] IST's available datasets were from an old sensor and consisted of high-speed traffic. Stephen Ritchie declined to share his existing data until his group had completed their analysis, conducted under a research contract expected to end in late 2005.
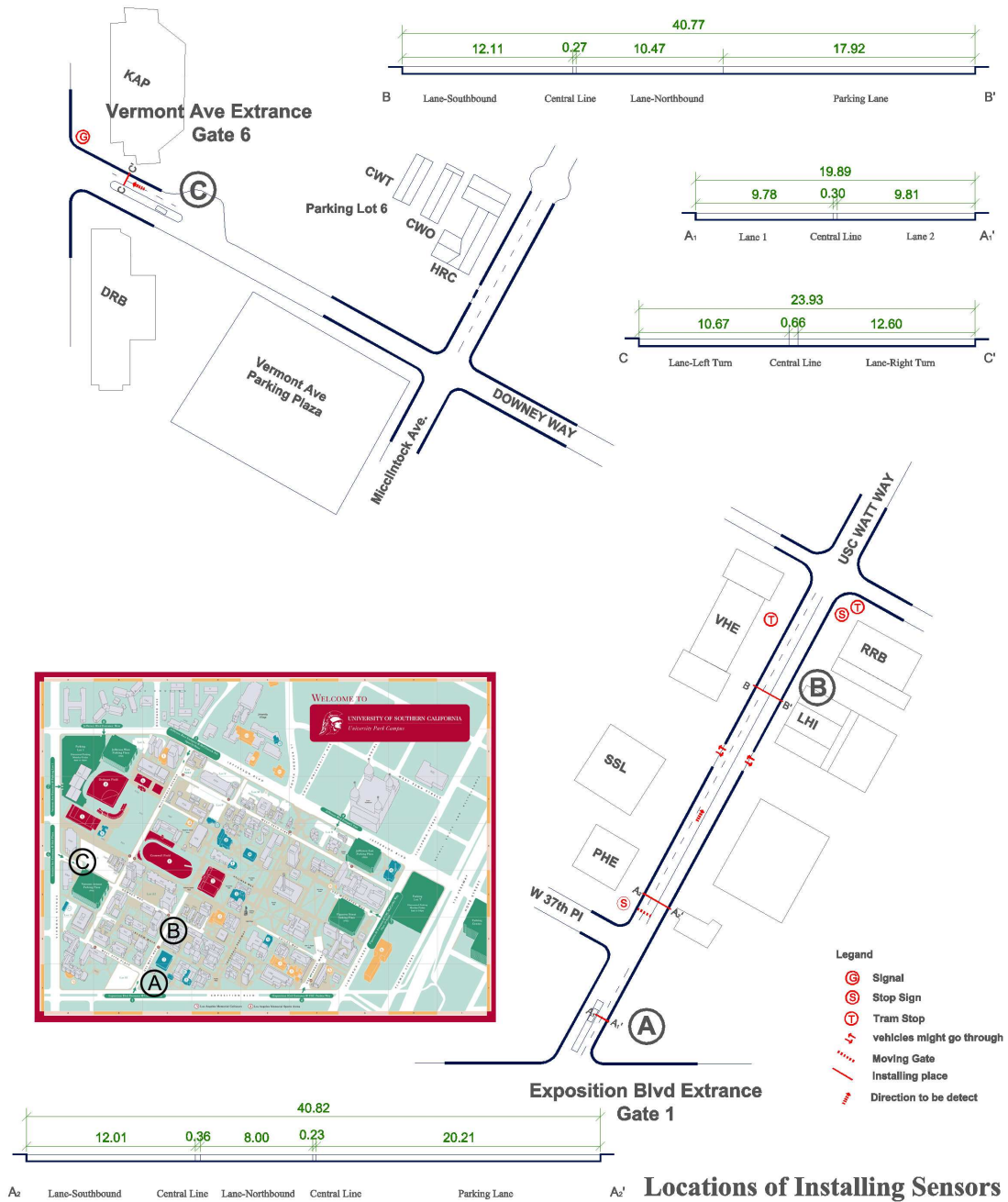
Figure 10: Sensor deployments for data collection experiment at USC.

Figure11: IST blade sensor cards (in plastic bag)

Figure 12: ILD being installed on the roadway

The IST blade sensors were installed on the roadway using standard pavement tape. Two loops 6 inches apart are laid across the roadway at approximately a 20° angle to traffic. The loops were connected to the IST detector cards, and the detector cards were connected to laptop computers (see Figures 11 and 12). Video camera recorders were set up at Sites A and B. We intended to place a camera at all three sites, but were unable to deploy the camera at Site C because of a tripod failure. At each location, students recorded the license number, vehicle type and color of each vehicle passing through the blade sensor in a single direction. Time was recorded to the nearest minute, and all watches were set to the laptop computer clocks. Student observations were input into a database file and checked with the video. Video-cross checks allowed correction of many errors and omissions.

We selected this placement of sensors with several goals in mind:

1) Observation of different vehicle speeds: Sites A and C were selected near the USC parking kiosks so that vehicles detected there would be slow-moving and stop-and-go, the most challenging conditions we expected.

2) Re-detection of similar but non-identical vehicles: We chose site B beacuse we believed it would result in repeated observations of campus shuttles, allowing exploration of re-identificaiton algorithms.

3) Many repeated observations of identical vehicles: We ran two test vehicles (passenger cars) over all sensors repeatedly. This approach allows us to compare sensor calibration across different sensors, and across the same sensor over time.

4) Detection of large trucks: In the port we must detect many similar tractor-trailer rigs. We selected experiment dates so that construction was going on on the campus, allowing detection of a number of similar cement trucks.

5) Detections of trucks before and after load removal: Similarly, we selected locations A and C so that we could detect the same cement trucks when full of

cement and after dumping their load. (Unfortunately, on the day of the experiment, the cement trucks were leaving by a different exit.)

We are just beginning to explore this data as outlined in the next section

CHAPTER FOUR

RESULTS

This section presents our results in three parts. First, we conduct an analysis of manual count accuracy, made possible by our use of both human counters and video. Second, we present our methodology for processing the raw sensor data and generating classification algorithms. Third we present results for classification.

4.1 Results of Manual Counts

To validate our sensor-based results we collected vehicle records in two additional ways: manual counts by graduate students, and video cameras. Although intended to provide "ground truth", both manual and video counts had errors that we describe below. Thus, in addition to providing an alternate count to compare sensor-based counts against, it also unexpectedly provided an alternate estimate of error rates to help put sensor-based errors into context.

4.1.1 Expected Manual and Video Deployment Issues

We did not expect any errors in our manual counts. However, in practice we found that errors crept in for several reasons. (1) At times, vehicles came too quickly to write down type, plate, and other information before the next vehicle arrived. In some cases this resulted in missing subsequent records, or incomplete prior records. (2) In some cases it was impossible to see the vehicle plate. (3) Different manual counters sometimes used different indications of different vehicle types, particularly with unusual types, or with truck/SUV/station wagons. (4) The manual counters were distracted when counters or video tapes were changed.

Video collection losses were more predictable. As described above, we were unable to deploy a video camera at Site C, and video deployments at sites A and B happened about 30 minutes after we began collecting sensor data. In addition, video resolution was not sufficient to note vehicle license plates, so we were unable to validate that data from manual counts. Note that interpretation of the video data required careful analysis (and re-analysis) by a graduate student after the fact. While essential for careful evaluation of our results, this cost is probably not warranted for typical counting experiments.

4.1.2 Preliminary Analysis of Manual and Video-based Classification

Nevertheless, both the manual counts and video data provide an important baseline to compare the sensor data. Below we summarize our analysis of the Site B Northbound dataset.

We prepared the B Northbound dataset in a manner similar to what we did for the sensor based analysis. We discarded data for before 9:15 am to ensure that we had video data that matches the manual counts. We discarded data after 10:50 am to match our analysis of the sensor data. We chose not to discard entries between 10:40 am and 11:05 am. This segment was discarded for the sensor analysis because we had not yet completed our video analysis at the time and hence lacked ground truth for this period; that analysis is now completed. We discarded 35 records of motorcycles, electric carts, and bicycles, again to match our sensor analysis. These changes left us with 263 manual observations. This count is slightly higher than the 192 sensor records we used because of the addition of the 10:40 am to 11:05 am segment (26 records), as well as some records that appear only in manual or video data (28 undercounts, 2 overcounts).

Accuracy of Manual Classification: We are examining two types of manual accuracy: vehicle classification and vehicle re-identification. Since manual counts are considered appropriate for use today, accuracy of manual counts will provide an acceptable accuracy target for our automated classification system.

Table 2 summarizes our comparison of manual classification. First, Table 2 shows that for the vehicles that are counted, accuracy is quite good: only 8% of vehicles that have a recorded classification type are mis-classified. That figure is a bit of an over-estimate as well, since it includes 10 errors where trucks (type T) had miscounted axles (6 cases) or where video revealed a different type of SUV-like vehicle (4 cases). Second, the data shows the main problem with manual counting: inability to keep up when many vehicles are present. This shows up as a large number of undercounts (28 cases, 11% of the records). This was particularly a problem in the period around 10:40 am. Finally, we observe that there are two overcounts, vehicles recorded as present that were not there. We discuss how these results compare to computer sensors in a later section.

Table 2: **Accuracy of Manual Classification Compared to Post-facto Video Analysis**

	Total Considered	Correctly Classified	Unable to Classify	Incorrectly Classified					
				Total Incorrect	Under-counts	Over-counts	Incor-rect as T	Incorrect as S*	Incor-rect as P
Total	263 (100%)	211 (80%)	0	52 (19%)	28 (11%)	2 (1%)	22 (8%)		
T	62	55	0	13	7	0	6	0	0
S*	51	44	0	17	7	0	1	4	5
P	126	112	0	22	14	2	1	5	--

S* = SUV, van, minivan, pickup truck

Accuracy of Manual Re-identification: Second, we wanted to judge the accuracy of manual recording of vehicle license plates. In a manual system of re-identification, license plate numbers or vehicle identification numbers are ideal ways to identify the same vehicle at different locations. Thus, this measure will provide an estimate on the target accuracy for a future automated re-identification system.

Unfortunately we cannot directly measure the accuracy of manually recorded license plates because our video resolution is insufficient to check our manual entries. Instead we must approximate correctness with completeness, a weaker metric since seemingly complete licenses may actually be incorrect for the given vehicle. Thus we count any "well-formed" California license number (in the format NAAANNN for non-commercial vehicles and NANNNNN for commercial vehicles, where N represents a digit and A a letter) as "complete" and any other license values as "incomplete". (We also accept custom license plates and some older patterns as complete as well.)

Table 3 summarizes our ability to record license plates. The majority of plates were completely recorded (199 records, 75%). There were several kinds of errors: a large number (44 records or 17%) were incompletely recorded, and hence could not be used for re-identification. About 5% were not counted. As with vehicle type, when traffic is busy it can be difficult for a human counter to keep up. There were two overcounts (vehicles that did not appear in the video). Finally, 5 vehicles lacked plates of any kind. Typically these were backhoes.
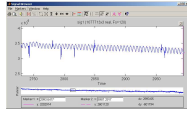
Note that we cannot judge *correctness* because we could not compare these plates to ground truth. Thus these estimates represent an upper bound on the accuracy of manual recording of license plates to re-identify vehicles. We should expect a typical human-based re-identification system based on license plates to have a 25% error rate. A challenge for future work will be to see if a computerized, sensor-based system can do better than this level.

Table 3: **Number of License Plates Completely Recorded by Manual Counting**

	Total Considered	Complete Plates	Incomplete Plates	Under-counts	Over-counts	No Plates on Vehicle
Total	263 (100%)	199 (75%)	44 (17%)	14 (5%)	2 (1%)	5 (2%)

4.2 Algorithms and Data Processing

Our vehicle classification system has a typical architecture, consisting of preprocessing, segmentation, normalization, feature extraction, and matching, as shown in Figure 13.

Figure 13 Structure of vehicle classification system

4.2.1 Noise Removal

Preprocessing in our system must eliminate crosstalk and environmental noise from multiple sensors. In some cases we found the strength of crosstalk was much larger than the actual signal from the vehicle (for example, the sinusoid in Figure 14 is crosstalk while the spikes are vehicle detections); changes in temperature provide a known, low-rate drift in sensor readings (in Figure 14, a gradual downwards drift can be seen). In addition, the sensor sampled the channel at 1kHz; we observed about 14% of these samples were lost between the sensor and the PC due to interactions between the sensor card and the PC collecting data. According to IST, this level of loss is not atypical. As recommended we correct for it by interpolating the missing data.
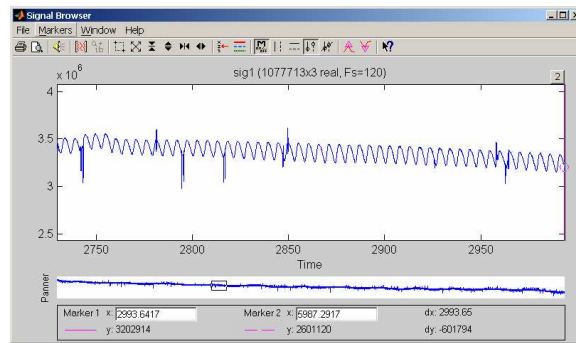

Figure 14: Section of raw sensor data illustrating
both crosstalk and environmental drift noise.

4.2.2 Segmentation Algorithm

When noise is eliminated, we are left with a continuous record of data readings. We must segment this data into individual vehicles to allow easy processing. We use a three-step approach to achieve stable segmentation.

Extract active segments: This is a threshold-based approach for extracting active areas. A sliding window (based on experimental evaluation we selected a window size of 400ms or about 120 samples, we tried window sizes from about 100 to 800ms and found the results generally insensitive to variation) passes through the input stream and the standard derivation of samples within the window is calculated. This corresponds to the energy of the signal within the window without the DC component.

The window advances one sample per iteration, and the output (standard derivation) is compared against a threshold. For simplicity we chose a fixed threshold base on our experimental data. In the long run we need to select the threshold as a function of the signal returned by the sensor, one candidate selection would be twice the baseline noise. Segments where the output is greater than the threshold are recorded as *active segments*, otherwise they are recorded as inter-vehicle gaps.

The threshold is set such that all wheel signals will be recorded as active segments and body signals may be recorded as active segments or gaps. With narrow blade sensors this criteria is easy to meet because wheels consistently show large deviation from the baseline signal. In follow-on work we plan to explore the relationship between sensor width and readings from different vehicle parts.

Combine active segments: In this step each gap segment is examined and a decision about whether the gap is part of a vehicle signal is made. By definition, the output of step 1 is an alternating series of active and gap segments. If a gap is shorter than a threshold, it is considered as part of the current vehicle signature. In our current work we set this threshold at 1.2s on the assumption that vehicles are typically more than this distance apart. This value seems appropriate for the low-speed vehicles in our experiment. This gap avoids accidentally splitting one actual vehicle into two vehicle partial signatures. This portion of the algorithm is particularly important with long vehicles (such as 18-wheel trucks) with relatively featureless signatures.

Thus we can combine several active segments and gap segments and produce a complete vehicle signature. The output of this step is a list of vehicle signature segments.

Grow the size of signature segments: For results from last step, the signature segments may not be complete enough to include the full heads and tails of vehicle signatures. In this step is each segment is enlarged by a constant factor. By default we grow the signature by half its length both at the front and the back, resulting in a signature of double overall length. Our goal here is to ensure we capture the vehicle beginning and end. One special case is where two signatures are very close. If we enlarge both segments they will overlap. For this case we only enlarge two segments up two the midpoint between them.

4.2.3 Feature Extraction

Feature extraction is an important part of the vehicle classification system. Selecting features that are least affected by noise maximizes the effectiveness of matching by highlighting true differences between vehicles rather than sensor noise. At the current

stage we use wheelbase and number of axles as basic features. In future systems we are going to add combinations of wheel timing and amplitude, and the general pattern of underbody detection. The physical meanings of the features are:

Wheelbase: Trucks should have longer wheelbase than cars. This is a straightforward choice for vehicle classification.

Number of Axles: Trucks can have more than two axles while almost all cars have two axles. Thus, signatures with more than two axles strongly suggest trucks.

In a vehicle signature from a Blade sensor, wheels can be identified as significant peaks in vehicle waveform. The wheelbase can be derived from wheel timing and vehicle speed. Vehicle speed can be derived from time differences between two sensors of a known distance. Figure 15 gives an example of a vehicle signature.
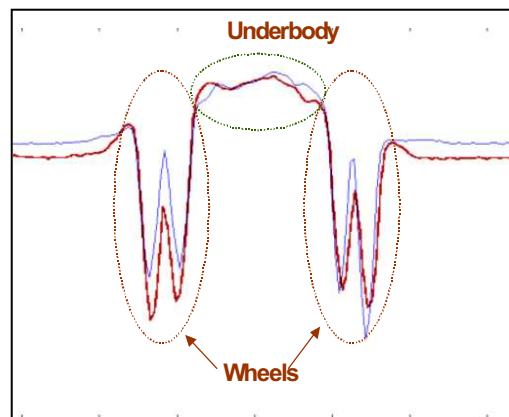

Figure 15 Vehicle Signature Example

As blade sensors are deployed at an angle to the roadway, wheel(s) on each side of an axle will be detected separately. Ideally, we can derive the number of axles by dividing number of wheel detections by two. However, sometimes peaks for corresponding wheels on different sides of an axle can merge, resulting in only one wheel detection, and we can have either one or two peaks from a single axle. Thus we want a more robust algorithm for better accuracy. We observe that with a blade sensor, the wheels show up as large negative values, and the chassis results in values above zero, while gaps between two wheels on the same axle remain below zero. Thus we can use this characteristic to distinguish different axles:

```
Detect all wheel related peaks in waveform
If number of peaks != 0  (i.e., if it's a signature that shows wheels)
Axle count = 1
For each wheel peak from 1
      Scan samples between the peak and previous peak:
            count values that are indicate presence of chassis (i.e., are > 0)
      if 20% of the values indicate chassis
            then conclude it's a separate axle, and increment axle count
Return axle count
```

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We found this algorithm to be effective in our initial results, but it must be reviewed to understand its accuracy with different configurations and widths of the Blade sensor.

4.2.4 Classification Algorithm

A classification algorithm makes the final decision on vehicle type based on feature vectors. At the current stage of our research we use a simple classifier based on a decision tree. It is defined as:

```
If number of axles > 2          => commercial truck
Else if wheelbase > 180 inches  => commercial truck
Else wheelbase > 130 inches     => SUV-like vehicles
Else                            => passenger car

Where
commercial truck = panel trucks, buses, tractor-trailers
SUV-like vehicles = pick-ups, SUVs, vans, minivans
```

We selected these values (2 axles, 180 inches and 130 inches) based on the vehicles we observed in the field test. A more refined algorithm would base these thresholds on statistics of expected vehicle types. Another challenge is that some classes of vehicles overlap (some sedans are the same length as small SUVs), so a comprehensive classification algorithm to pre-determined classes must consider additional factors. Another potential area for future research is to consider what classes of vehicles are most relevant for traffic planners and how these map to vehicle sizes. For example, if traffic planners are primarily concerned about road maintenance costs, then vehicle size or weight may be more relevant than traditional classifications.

4.3 Classification Results

As described above, during our experiments we collected vehicle signature data at three different sites inside the USC campus, which resulted in over 1500 vehicle detections. This large amount of information allowed us to capture data from a heterogeneous set of vehicles, including passenger cars, vans, sport-utility vehicles (SUVs), pick-up trucks, and commercial trucks. It is important to mention that we faced several challenges when analyzing our data. First, due to the low-speeds involved in our experiments, we noticed a very high variance in vehicle speed (including vehicles stopping over our sensors). Second, we observed a significant number of vehicles straddling multiple lanes, thus partially triggering our sensors. Third, as is the case with data collected from real deployments, we had to deal with noise and other factors. Based on additional experiments taken following our August data collection, we now believe the sensors in our August deployment showed particularly bad kinds of inter-sensor interference.

4.3.1 Classification Test Data
While we used the algorithms described above to remove noise, segment individual signatures, and extract features from data collected from all three sites, for our

classification algorithms we focused on the data collected at site B. This site enabled us to use our classification algorithms on a dataset comprised of only 48.6% of passenger cars (the remaining being trucks, SUVs, pick-ups, etc).

We focus on the subset of data from Site B/Northbound traffic from 9:15 am to 11:50 am. We discarded data before 9:15 am because we had not yet set up video cameras and so we lack verified ground-truth results. We discarded data after 11:50 am because at that point we began experiments where we intentionally stopped cars over the sensors to simulate "worst case" conditions and we have not yet extended our algorithms to deal with that case. In addition, we temporarily deleted readings between 10:40 am and 11:05 am. Our manual records missed a dozen vehicles at this time and for our preliminary analysis we wanted to be able to verify our results against manual counts. We have since reproduced this missing segment from video; re-analysis with this missing segment is an area of future work. Finally, we also manually deleted 32 records of motorcycles, carts, and bicycles from the dataset. It should not be hard to eliminate these automatically, but our current focus is on the harder problem of distinguishing cars from trucks, not the easier problem of cars from bicycles. Again, as future work we plan to automate this filtering. After filtering we were left with 192 records. Finally, 9 additional records exhibited segmentation problems. Although we do not yet automatically detect these, we believe we can do so relatively easily. We therefore report these values as "not classified", a category that represents failure to classify, but records that are not incorrectly classified.

4.3.2 Results

We started by classifying vehicles in two groups: trucks (including 18-wheelers, cement mixers, and panel-trucks) and non-trucks (includes everything else other than trucks). Results are shown in Table 4,

With just two classes (trucks, type T, vs non-trucks), our classification rates are comparable to current, state-of-the-art published results from Sun et al (2003), and Kwigizile et al (2004). These results were particularly encouraging given that our system was not tuned to specifically deal with the high variability in vehicle speed that we found.

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Table 4:   Classification Results, Trucks vs Non-trucks

	Total Considered	Correctly Classified	Unable to Classify	Incorrectly Classified
Total	183 (100%)	150 (82%)	19 (10%) (9 segmentation errors)	14 (8%)
T	33	25	4	4
Non-T	150	125	15	10

In addition to the two classes of vehicles mentioned above, we expanded our initial classification algorithm to include a third class, S*, comprised of SUVs, pick-up trucks,

vans and minivans. Results are shown in Table 5. Our results were not as good as with only two vehicle classes. Our algorithms depend primarily on vehicle length, but the vehicles in class S* and P overlap in length. *No* classification algorithm based only on length will be able to separate these classes accurately. This can be seen in the data in Table 5 where many "medium-size" vehicles are incorrectly classified as passenger cars (29 out of 61). By comparison, classification of trucks is quite good, with very few trucks being misclassified as S* or P, and very few S* or P types being classified as T.

This preliminary result suggests, first, that our approach is very appropriate if the goal is to classify trucks from non-trucks. For studies about road damage, this level of classification may be sufficient. It also suggests that very fine-grain classification of passenger cars, vans, pickups, SUVs will be quite difficult, given the blending of these vehicle types. One promising approach we may consider in the future is comparison of vehicle signatures against pre-determined vehicle signatures. Such an approach would exploit re-identification algorithms that we're interested in exploring in future research.

Table 5:   Three-way Classification Results

	Total Considered	Correctly Classified	Unable to Classify	Incorrectly Classified			
				Total Incorrect	Incorrect as T	Incorrect as S*	Incorrect as P
Total	183 (100%)	114 (62%)	19 (10%) (9 segmentation errors)	50 (27%)			
T	33	25	4	4	--	2	2
S*	61	21	8	32	6	--	26
P	89	68	7	14	4	10	--

S* = SUV, van, minivan, pickup truck

4.3.3 Comparison with Manual Counts

It is useful to compare the accuracy of our sensor network-based classification system to manual (human) classification described in Section 4.1. The first thing to compare is counting accuracy. Manual classification was 80% accurate. By comparison, our classification system had accuracy rates of 86% for two-way classification and 57% for three-way classification. From this we conclude that our sensor system can actually be better than humans for two-way counts, largely because our system can handle vehicles as rapidly as they occur, while humans can become overloaded and make errors when too many vehicles appear quickly.

We also must state that for three-way classification, humans remain more accurate when compared to our current system. This result is because, even though manual counts miss many vehicles, humans are much better at distinguishing "SUV-like" vehicles (type S*) than our system which uses simple length-based measures. It also suggests several areas for future work: certainly improving our sensor-based approach, possibly using multiple

sensors to validate readings in different ways (for example, to handle cases where a vehicle was only half-way in the lane with the sensor).

Finally, we make one comment about the kinds of errors that manual counting and our automated system make. Our systems errors are typically misclassification, representing a passenger car as an SUV. Manual errors are typically omission---missing a vehicle. This suggests that we can get tighter error bounds and much better vehicle counts with automated systems.

In addition to our quantified results, we have two qualitative observations. First, classification can be successful, even with low-speed vehicles. To our knowledge we are the first group to consider low-speed vehicle classification. Second, preliminary evaluation of vehicle signatures for re-identification suggests that reidentification is possible, but it will require care in sensor calibration.

Our analysis of the dataset is ongoing; we have several directions for additional analysis and algorithm development as outlined in the next section.

CHAPTER FIVE

PLANS AND FUTURE WORK

This report summarizes what we have done in the SURE-SE project. We have several directions outlined for work next year as part of the SURE-FT proposal:

Designing highly robust algorithms. As part of SURE-SE we are currently evaluating a set of classification algorithms. In SURE-FT we plan to investigate the stability of these algorithms across a broader range of vehicles, sensors, and environments. Classification algorithms such as ours have many parameters; an important research direction will be to automate selection of these parameters so that a NOTS can be deployed with as little effort and training as possible.

Complete prototype implementation. As part of SURE-SE we have evaluated specific sensors, computers, and algorithms, each by themselves. In SURE-FT we plan a complete integration of these components to provide a field deployable system.

Validate the algorithms through greater testing. Our current algorithms are based on a specific set of measurement data taken at USC. A major focus of SURE-FT will be validation of the algorithms, configuration, and integrated system through additional controlled experiments and a port-area field test.

Generalize the techniques. To demonstrate a complete and working system, most of our work so far has been focused on building and evaluating a specific system for vehicle classification and observation of vehicle queueing. We plan to focus initially on vehicle classification and move to re-identification as the techniques become more mature.

We anticipate that the techniques that we have developed will also be applicable to related problems, such as measuring transaction times at facilities or monitoring truck traffic on arterials.

BIBLIOGRAPHY

Avery, P.R, C. P. Thomas, Y. Wang, and G. S. Rutherford. (2003) "Development of a length-based vehicle classification system using uncalibrated video cameras,". Presented at *Transportation Research Board 2004 Annual Meeting.* Paper -002848

Banister, D. and J. Berechman (2000) *Transportation Investment and Economic Development.* London: UCL Press.

Benekohal, R.F. and Girianna, M. (2003) "Technologies for Truck Classification and Methodologies for Estimating Truck Vehicle Miles Traveled,". *Transportation Research Record 1855*, pp1-13

Cheu, R. L., Qi, H. and Lee, D-H (2003) "A mobile sensor and sample-based algorithm for freeway incident detection,". *Transportation Research Record 1811*, pp 12-20

Coifman, B (1998) "A Real-Time Computer Vision System for Vehicle Tracking and Traffic Surveillance,". *Transportation Research. Part C: Emerging Technologies,* Volume: 6 Issue: 4, pp 271-288

Gates, T.J., Steven D. Schrock and James A. Bonneson (2003) "Comparison of Portable Speed Measurement Devices,". Presented at *2004 TRB Annual Meeting.* Paper2004-002066.

Gordon, P. and Qisheng Pan (2001) *Assembling and Processing Freight Shipment Data: Developing a GIS-Based Origin-Destination Matrix for Southern California Freight Flows.* Final Report No. 99-25, Metrans, University of Southern California,. Available at www.metrans.org

Gupte, S., Osama Masoud, Robert F. K. Martin, and Nikolaos P. Papanikolopoulos (2002) "Detection and Classification of Vehicles,". *IEEE Transactions on Intelligent Transportation Systems,* Volume3, No. 1

Hansen, M., D. Gillen, A. Dobbins, U, Huang, M, Puvathingal (1993) *The Air Quality Impacts of Urban Highway Expansion: Traffic Generation and Land Use Change.* Final Report UCB-ITS-RR-93-5, Institute of Transportation Studies, University of California., Berkeley

Jain, M. and Benjamin Colifman (2004) "Improved Speed Estimates from Freeway Traffic Detectors,". Presented at *2004 TRB Annual Meeting.* Paper2004-002547

Klein, Lawrence (1999) *Mobile Surveillance and Wireless Communications System Field Operational Test. Final Report UCB-ITS-PRR-99-6. Berkeley, California: California PATH Program.*

Klein, Lawrence (2001) *Sensor Technologies and Data Requirements for ITS.* Norwood: Artech House Publishers

Kwigizile V., Majura Selekwa and Renatus Mussa (2004) *Highway Vehicle Classification by Probabilistic Neural Networks*, (hasn't been published).

Kwon J., Pravin Varaiy and Alexander Skabardonis (2003) "Estimation of Truck Traffic Volume from Single Loop Detector Using Lane-to-Lane Speed Correlation,". *Transportation Research Record 1856*, Paper 03-3294

Lee, Kang (2001) "Wireless Sensing and IEEE 1451", Presented at *Sensor Expo & Conference, Chicago*, IL

Lin, W.H., Joy Dahlgren and Hong Huo (2004) "Enhancement of vehicles speed estimation with single loop detectors,". Presented at *2004 TRB Annual Meeting.* Pape*r*2004-002091.

MacCarley, C.A. et al (1992) "Evaluation of Video Image Processing Systems for Traffic Detection,". *Transportation Research Record 1360,* pp 46-49

Malik, J. and Stuart Russell (1996) *Traffic Surveillance and Detection Technology Development: New Traffic Sensor Technology.* Final Report UCB-ITS-PRR-97-6, Berkeley, California: California PATH Program.

Meyer, M.D. and Miller, E.J. (2001) *Urban Transportation Planning: A Decision-Oriented Approach*, *2nd Edition*. New York: McGraw Hill Press

Middleton, D., Deepak Gopalakrishna, and Mala Raman (2003) *Advances in Traffic Data Collection and Management—White Paper.* Report, Office of Policy, Federal Highway Administration. **No.**BAT-02-006

Miller, E. Kriger, D. and Hunt, J (1999) "Research and development program for integrated urban models,". *Transportation Research Record 1685*, pp 161-170

Mimbela, L. Y. and Lawrence A. Klein (2000) *Summary of Vehicle Detection and Surveillance Technologies Used in Intelligent Transportation Systems*. Report, Federal Highway Administration Intelligent Transportation System Joint Program Office, Available at http://www.fhwa.dot.gov/ohim/tvtw/vdstits.pdf

Moore, Michael R., Stephen F. Smith and Kang Lee (2001) "The Next Step—Wireless IEEE 1451 Smart Sensor Network,". Availabe at http://www.sensorsmag.com/articles/0901/35/pf_main.shtml

Neelisetty S. and Benjamin Colifman (2004) "Improved Single Loop Velocity Estimation in the Presence of Heavy Truck Traffic,". Presented at *2004 TRB Annual Meeting,* Paper 2004-002567

Oh, C., Stephen G. Ritchie and Shin-Ting Jeng (2004) "Vehicle Reidentification using Heterogeneous Detection Systems,". Presented at *2004 TRB Annual Meeting*. Paper2004-002900

Panda, D.P., Craig A. Anderson and Panos G. Michalopoulos (1998) "A new integrated video sensor technology for traffic management applications,". Presented at *Eighth Annual Meeting of ITS America*

Pas, E. (1995) "The urban transportation planning process," in S. Hanson, ed., *The Geography of Urban Transportation, second edition.* New York: Guilford Press.

Ripka, Pavel (1999) "Magnetic sensors for traffic control,". *ISMCR99, Tokyo*, proc. Vol.10, pp. 241-246

Ritchie, Stephen G., Seri Park, Cheol Oh and Carlos Sun (2002). *Field Investigation of Advanced Vehicle Re-identification Techniques and Detector Technologies-Phase1*. Final Report, UCB-ITS-PRR-2002-15 Berkeley, California: California Path Research Program

Shinozuka, M. and John Heidemann (2002) "Pervasive Monitoring and Control of Water Lifeline Systems for Disaster Recovery" Availabe at
http://www.isi.edu/ilense/whumls/index.html

Sivakumar, A. and Bhat, C. (2002) *A Fractional Split Distribution Model for Statewide Commodity Flow Analysis.* Technical Report. Austin, TX: University of Texas, Department of Civil Engineering.

Soulliard, C. J. and Michael C. Soulliard (2002) "Vehicle Detection Goes Wireless,". *IMSA Journal, Jan/Feb 2002*

Sun, Carlos (1999) *An Investigation in the Use of Inductive Loop Signatures for Vehicle Classification,* Final Report, UCB-ITS-PRR-2000-4. Berkeley, California: California Path Research Program

Sun, C., Ritchie, S.G., Tai, W., and R. Jayakrishnan (1999) "Use of Vehicle Signature Analysis and Lexicographic Optimization for Vehicle Reidentification on Freeway," *Transportation Research, Part C,* l7(X), 167-185

Sun, C., Stephen G. Ritchie and Seri Oh (2000*) Inductive Classifying Artificial Network for Vehicle Type Categorization*. Final Reprt, UCI-ITS-WP-00-26, Irvine, California

Transportation Research Board (1995) *Expanding Metropolitan Highways.* Special Report 245. Washington DC: Transportation Research Board, National Research Council.

Transportation Research Board (2002) *Evaluation of the Congestion Mitigation and Air Quality Program*. Special Report 256. Washington DC: Transportation Research Board, National Research Council.

Wang, Yinhai and Nancy L. Nihan (2003) "Can Single-Loop Detectors Do the Work of Dual-Loop detectors?". *Journal of Transportation Engineering,* Vol129, No.2 pp 169-176

Wegener, M. (1994) "Operational urban models: State of the art," *Journal of the American Planning Association* 60(1), 17-29.