University Transportation Research Center - Region 2

Final Report

Vehicle Classification Using Mobile Sensors

Performing Organization: Rensselaer Polytechnic Institute

April 2013

Sponsor:
Research and Innovative Technology Administration (USDOT/RITA)

University Transportation Research Center - Region 2

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

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VEHICLE CLASSIFICATION USING MOBILE SENSORS

Final Report

Prepared for

University of Transportation Research Center, Region 2

Research and Innovative Technology Administration,

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Table of Contents:

List of Figures:

List of Tables:

EXECUTIVE SUMMARY

Real world traffic consists of vehicles ranging from small passenger cars to heavy trucks. Vehicle classification information is a crucial input to transportation planning, facility design and operations. Many techniques have been proposed in the past to perform vehicle classification. The current state-of-the-practice vehicle classification methods however (i) heavily rely on fixed location sensing and detection techniques; and (ii) can only collect data at locations determined by existing traffic monitoring and data collection systems, which can be very expensive to be applied to wide areas.

In this research, the feasibility of using mobile traffic sensors for binary vehicle classification on arterial roads is investigated. Features (e.g. speed related, acceleration/deceleration related, etc.) are extracted from vehicle traces (passenger cars, trucks) collected from real world arterial roads. Machine learning techniques such as support vector machines (SVM) are developed to distinguish passenger cars from trucks using these features. To address privacy concerns, classification is conducted using long vehicle traces and short vehicle traces separately. For classification using long traces, the proportions of accelerations and decelerations larger than 1mpss and the standard deviations of accelerations and decelerations are the most effective features. By classifying general trucks from passenger cars, the average misclassification rate for the best 4-feature SVM model is about 1.6% for the training data, and 4.2% for the testing data. For classification using short traces, it is necessary to define multiple types of traces and analyze them case-by-case. It was found that particularly for the turning movement traces, features such as average speed, standard deviation of speed, maximum acceleration/deceleration and standard deviation of acceleration/deceleration are fairly effective to classify vehicles. The misclassification rate for the best SVM classifier using short traces is about 14.8% for the stop-and-go traffic, and 15.6% for the non-stopped traffic.

Despite many issues and future research questions remaining unsolved in this project, the proposed research does show the feasibility and potential of using mobile data for vehicle classification. It reveals that acceleration/deceleration related features are the most critical for vehicle classification using mobile data. Such acceleration/deceleration based vehicle classification methods using advanced machine learning techniques have the potential to help build a low-cost, wide-area vehicle classification system.

1. INTRODUCTION AND RESEARCH NEED

Real world traffic consists of vehicles ranging from small passenger cars to heavy trucks. Vehicle classification information is a crucial input to transportation planning, facility design and operations. For example, roadway usage by large vehicles is one of the fundamental factors determining the lifespan of highway infrastructure (Coifman and Kim, 2009). Transportation system performance analyses, for instance, Level of Service (LOS) analyses of freeways, highways, and intersections, also require the information of vehicle classifications and counts (Roess et al., 2004). Vehicle classification data are also important to regional demand modeling and emission control. As freight transportation is becoming more and more critical to regional and national economies, freight modeling is now an imperative issue for many transportation management agencies, to which truck classes and volumes are key inputs.

Many techniques have been proposed in the past to perform vehicle classification. On the one hand, the current state-of-the-practice vehicle classification methods rely on fixed location sensors such as pneumatic tubes, inductive loop detectors, piezoelectric sensors, and Weigh-in-motion (WIM) systems, besides manual observation and classification. These approaches can generally be categorized as traffic-intrusive methods since they usually require on-site work that imposes interference with traffic. On the other hand, non-intrusive vehicle classification methods (e.g. radar sensors, infrared sensors, acoustic sensors and computer vision-based sensors) are getting popular due to the avoidance of interference with traffic and the dramatic reduction of operation and maintenance costs. Unsurprisingly, as pointed out by Urazghildiiev et al. (2007), none of these existing classification methods have been proved to be the best for all possible applications. They are either too expensive to be deployed (such as WIM stations) or subject to errors/limitations under specific situations (e.g., pneumatic tubes cannot perform well on high-speed, high-volume road segments; classification using inductive loop detectors does not perform well under congestion; video cameras may be impacted by extreme weather conditions and vehicle occlusions).

Due to the fundamental differences of vehicle classifiers, the existing vehicle classification techniques can also be categorized as axle-based methods, vehicle length (or other vehicle dimensions-based) methods, and methods based on other features (e.g., acoustic signatures, magnetic signatures, spectral signatures). For axle-based methods (e.g., pneumatic tubes and piezoelectric sensors), information of axle configuration (number of axles and axle spacing) needs to be collected first. Such information can then be used to determine the class of vehicles, usually according to the 13 vehicle classes defined by the Federal Highway Administration (FHWA, 1997). For vehicle length or other vehicle dimensions-based classification methods (e.g., radar sensors, inductive loop detectors and computer vision-based sensors), classification relies on the differentiation of vehicle dimensions (e.g. length, width, height and height profile) of different vehicle classes. The third category of methods is similar to the second one, but using features such as acoustic signatures, which can be used to infer vehicle dimension information. The latter two categories of methods may classify vehicles into fewer classes instead of the 13 classes defined by FHWA.

In real traffic applications, however, it is not always necessary to have detailed vehicle classification information with respect to the FWHA's 13-class scheme. As stated in Benekohal and Girianna (2003), some state DOTs regroup vehicles into a smaller number of vehicle types. Due to either the convenience of modeling or data availability concerns, the classification results proposed by some researchers are also for certain regrouped vehicle classes (e.g. Nooralahiyan et al., 1997; Harlow and Peng, 2001; Gupte et al., 2002; Hsieh et al., 2006; Urazghildiiev et al., 2007; Coifman and Kim, 2009).

In this project, we are particularly interested in developing a low-cost method to automatically classify vehicles for large areas using mobile traffic sensors. Mobile sensors (e.g., GPS cellphones, GPS loggers, vehicle equipped GPS devices, smartphones) – those can move with the traffic flow and continuously collect location and speed information – can be used to monitor the movement of individuals or vehicles. Although the collection and sharing of massive mobile traffic data need to overcome institutional (e.g., who should collect the data), policy (e.g., privacy issues), and technical challenges (e.g., bias of the collected samples), they do provide information (e.g. vehicle traces) that promises great advances in many science and engineering fields. Data extracted from mobile traffic sensors can be easily processed to further obtain speeds, accelerations and decelerations. Since different classes of vehicles tend to have different characteristics of speed variations, and acceleration and deceleration rates, this motivates us to use *mobile traffic sensors for automatic vehicle classification*.

The proposed research represents the first step towards this direction by investigating the feasibility of using mobile data for binary vehicle classification on arterials. By "binary", it means that we distinguish trucks from passenger cars. Via mobile traffic sensors, vehicle trace data of passenger cars and trucks are collected separately on arterials. These two datasets are then pre-processed in order to be more compatible. Speed and acceleration/deceleration related features are extracted from the datasets. Machine learning models are developed for feature selection and binary classification.

We first explore the feasibility of classification using long vehicle traces. Since long traces (15-20 minutes) contain more information than short traces, patterns recognized from such datasets should also be more significant. It is found that features related to the variations of accelerations and decelerations (e.g., the proportions of accelerations and decelerations larger than 1 meter per second square (mpss), and the standard deviations of accelerations and decelerations) are the most effective in terms of classification using long traces. In this sense, the proposed method can be categorized as the acceleration/deceleration based vehicle classification method. The results show that by classifying trucks from passenger cars, the average misclassification rate for the best 4-feature learning model is about 1.6% for the training data, and 4.2% for the testing data.

Due to the privacy concerns and data availability issues, long traces may not be always available. Therefore experiments using short vehicle traces are also conducted. Since short traces are more likely to be impacted by specific traffic situation, it is necessary to define multiple types of traces and analyze them case-by-case. It was found that particularly for the turning movement traces, features such as average speed, standard deviation of speed, maximum acceleration/deceleration and standard deviation of acceleration/deceleration are effective to classify vehicles. The misclassification rate for the best SVM classifier is about 14.8% for the stop-and-go traffic, and 15.6% for the non-stopped traffic.

The report is comprised of 6 chapters. Chapter 2 reviews existing literature on vehicle classification. Chapter 3 proposes our research methodology, experiments and classification results in terms of long traces are also presented. Chapter 4 presents the experiment and numerical results using short vehicle traces. Discussions of related issues to the proposed methods are presented in Chapter 5, followed by the concluding remarks and future research directions in Chapter 6.

2. LITERATURE REVIEW

Vehicle classification using data from existing traffic monitoring and data collection system is an extensively studied area. Reviews on this topic were provided by many researchers (e.g., Sun, 2000; Mimbela et al., 2000; Benekohal and Girianna, 2003). Categorizations of these vehicle classification methods could be based on the characteristics during installation (traffic intrusive and non-intrusive) and types of vehicle classifiers (axle configuration, vehicle dimensions, and other features). In general, traffic intrusive vehicle classification methods are inappropriate for freeways, mainly due to the interference with traffic during installation and maintenance; however they may work reasonably well on arterials. Non-intrusive methods, on the other hand, are more appropriate for freeway application; however, they may not be suitable for wide deployment on arterials, due to their incapability in dealing with stop-and-go traffic and their high initial capital costs.

2.1 Intrusive Vehicle Classification Methods

Intrusive vehicle classification methods can be done using tubes, loop detectors, magnetic sensors, and piezoelectric sensors. Originated in 1920s and still being widely used today for short term data collection, pneumatic tubes (Benekohal and Girianna, 2003; Beagan et al., 2007) can detect the number of axles of a vehicle. Although portable and easy to deploy, such sensors are subject to classification errors if multiple vehicles pass by the tube simultaneously. This is particularly a problem for high-volume, high-speed roadway segments.

Inductive loop detectors and magnetic sensors can be used for vehicle classification by detecting vehicle lengths. The classification can be done mainly due to the following equation of traffic flow (Coifman and Kim, 2009):

$$l = v \cdot o \tag{1}$$

Here l is the effective vehicle length, i.e., the summation of the actual vehicle length and the detector length, v is the vehicle speed, and o is the on-time of the vehicle, i.e., the time that the vehicle is on the detector. As the on-time o can be directly measured from the detectors (i.e., from the occupancy), vehicle length can be calculated if the speed is known. Since speeds can be measured directly by dual-loops, equation (1) can be applied straightforwardly for dual-loops. For single-loops however, accurate estimation of vehicle speeds is the key. Estimating average vehicle speeds and volumes of different vehicle classes has been studied in Mikhalkin et al. (1972), Pushkar et al. (1994), Dailey (1999), Wang and Nihan (2000), Sun and Ritchie (2000), Coifman (2001), Wang and Nihan (2003 and 2004), and Kown (2003). Coifman and Ergueta (2003) suggested the use of the median vehicle on-time instead of the mean and found that the results are less sensitive to outliers. More recently, Coifman and Kim (2009) proposed to use the vehicle actuation data to estimate the lengths of individual vehicles, with improved classification performances. However, as Coifman and Kim (2009) reported, the classification performance "degrades during congestion" due to the difficulty of estimating vehicle speeds under congestion. More recently, Cheung et al. (2005) proposed vehicle classification methods using single magnetic wireless sensors. By classifying vehicles to 7 types (passenger car, SUV, Van, Bus, mini-truck, truck, and others), the classification accuracy was shown to be more than 60%.

Piezoelectric sensors (Mimbela et al., 2000; Benekohal and Girianna, 2003) can be used to detect the axle configuration and the weight of a vehicle. Although most frequently used as part of a WIM system, piezoelectric sensors can be deployed alone for vehicle classification purposes. Similar to pneumatic tubes and inductive loop detectors, the major drawback of piezoelectric sensors is the interference with traffic during installation and maintenance. Moreover, such sensors are also known to be sensitive to pavement temperatures and vehicle speeds.

It is also possible to classify vehicles at a WIM station according to the 13 vehicle classes defined by FHWA. The full installation of WIM however requires multiple detection techniques and systems, such as piezoelectric sensors, video cameras, loops, license plate matching, among others (FHWA, 2007). As a result, vehicle classification via WIM is currently limited to dedicated (and sparse) WIM stations.

2.2 Non-Intrusive Vehicle Classification Methods

In recent years, non-intrusive vehicle classification methods (e.g., using radar sensors, infrared sensors, acoustic sensors, and computer vision-based sensors) are getting more and more popular due to the avoidance of interference with traffic and the dramatic reduction of operation and maintenance costs. Microwave radar sensors (Roe and Hobson, 1992; Park et al., 2003; Urazghildiiev et al., 2002) are primarily intended to extract vehicle dimensions (e.g. vehicle length, general vehicle size, height profile, etc.). Urazghildiiev el al. (2007) proposed a classification technique based on down-looking spread-spectrum microwave radar. And the classification accuracy is about 85% for five vehicle classes. Compared with other non-intrusive methods, microwave radar sensors are generally insensitive to inclement weather conditions. However, such technique is not suitable for stop-and-go traffic.

Da Costa Filho et al. (2009) propose vehicle classification methods based on infrared sensors. Vehicle profiles can be measured by the output signals of the infrared light reflected by vehicles. Vehicle classification results can then be obtained by choosing a vehicle template from the databank that best matches the measured vehicle profile. Infrared sensors are however sensitive to environmental conditions, e.g., atmospheric turbulence and inclement weather. Nooralahiyan et al. (1997) use speed-independent acoustic signature of travelling vehicles for classification, and the classification result is about 82.4% for four regrouped vehicle classes. Similar to radar sensors, acoustic sensors are not suitable for stop-and-go traffic. As mentioned in Mimbela et al. (2000), the accuracy acoustic sensor data can be also impacted by cold temperatures.

Compared with other non-intrusive vehicle classification methods, computer vision-based methods (Harlow and Peng, 2000; Gupte et al., 2002; Avery et al., 2004; Hsieh et al., 2006), have generally more accurate classification results. Such classification methods have high initial capital cost and are generally computational expensive. The accuracy of classification is subject to errors due to vehicle occlusion, and extreme weather conditions. Moreover, such methods may not be applied for large-area data collection due to privacy concerns.

Table 1 presents a summary of existing vehicle classification techniques, including the types of vehicle classifiers, and their corresponding advantages and disadvantages.

Table 1: Existing vehicle classification techniques

Technology	Types of vehicle classifiers			Pros & Cons	
	Axle configuration	Vehicle length or other vehicle dimensions	Other features	Advantages	Disadvantages
Manual Observation / videography	x	x		Can obtain detailed classification results	Time & resource consuming; can only be applied for short term data collection and limited area
Pneumatic tubes	x			Relatively inexpensive; automatic classification and short term data collection; portable	Interference with traffic; vulnerable to human errors during installation; durability problem; large errors for high-volume, high speed road segments
Inductive loop detectors		x		Relatively inexpensive; automatic classification;	Interference with traffic; high maintenance cost; over-estimation of truck volumes; Installation is labor intensive and has high failure rate; Performance degrades under congestion

Piezoelectric treadles	x			Relatively inexpensive; automatic classification	Interference with traffic; high maintenance cost; sensitive to temperature and vehicle speed; vulnerable to human errors during installation
Radar sensors		x	x[1]	Non-intrusive; somehow inexpensive; automatic classification; generally insensitive to inclement weather	Not suitable for stop-and-go traffic
Infrared sensors	x			Non-intrusive; automatic vehicle classification	Somehow expensive; sensitive to environmental conditions;
Acoustic sensors			x[2]	Non-intrusive; automatic vehicle classification	Somehow expensive; sensitive to temperatures; not suitable for stop-and-go traffic
Video camera (computer vision-based)		x		Non-intrusive; automatic classification; relatively low operation and maintenance costs;	Sensitive to environmental conditions; high initial capital cost; privacy concerns; computational expensive;
WIM	x	x		Continuous data collection; automatic classification	Full installation is expensive; limited locations

[1]: magnitude and spectrum pattern; [2]: Acoustic signature

2.3 Current vehicle classification practice in New York State

The team were planning to conduct a review of current practice and challenging issues in New York State for vehicle classification. By communicating with Expert and Engineers at the New York State Department of Transportation (NYSDOT), the team was informed that “all classification is done with axle sensors to satisfy the FHWA Scheme F classes of vehicles per HPMS (Highway Performance Monitoring System).” The team then concludes that there is no need to conduct further review on this matter.

2.4 Summary

In summary, existing vehicle classification methods (i) heavily rely on fixed location sensing and detection techniques; and (ii) can only collect data at locations determined by existing traffic monitoring and data collection systems, which can be very expensive to be applied to wide areas (Avery et al., 2005).

Vehicle classification using mobile sensors may overcome some of the drawbacks of existing classification methods, which however will need to face its own challenges. On the one hand, Mobile sensors are flexible with respect to where data collection needs to be done since they do not require the deployment of additional physical monitoring systems or infrastructure (In this sense, the proposed mobile data based classification method in this research is non-intrusive). Mobile traffic data, e.g., 15-20 minutes long vehicle traces as proposed in this research, also contain rich information, such as vehicle speeds and locations, which can be further processed to obtain accelerations/decelerations. This permits sophisticated exploration of such information to derive accurate and robust vehicle classifiers. On the other hand, mobile data usually represent a sample of traffic flow. Although it is shown later in this report it is possible to distinguish passenger cars from trucks based on their distinct mobile data features, it will be challenging to estimate the volume of each vehicle class. Collection of vehicle trace data may also pose privacy concerns which need to be properly addressed. In this research, the feasibility of using short vehicle traces for vehicle classification is also studied. More discussions about the limitations and potential future research directions of the proposed methods are provided in Chapter 5 and Chapter 6.

3. CLASSFICATION USING LONG VEHICLE TRACES

In this chapter, the mobile traffic datasets used in this study are first described. In order to perform vehicle classification, features are extracted from the datasets to characterize different vehicle classes. The classification algorithms are then developed based on the Support Vector Machine (SVM) with quadratic kernel functions.

3.1 Data Description

One of the major challenges for vehicle classification using mobile sensors is the lack of good quality, comparable and large sample size mobile sensor datasets for different classes of vehicles, especially for large trucks. On the one hand, from the experience of other arterial traffic applications, for example real time queue length estimation (Ban et al., 2011) and signal timing estimation (Hao et al., 2011), vehicle traces can be extracted from microscopic traffic simulations. However, this is not an appropriate approach for vehicle classification, due to the fact that vehicle speeds and accelerations/decelerations strictly follow certain pre-defined distributions in micro-simulations, which may not reflect the complexity and randomness of real driving behavior for different vehicle classes. As a result, features extracted from micro-simulation data may lead to erroneous classifications. On the other hand, real world vehicle trace datasets for multi-class vehicles are hard to obtain. Ideally, vehicle traces of different classes of vehicles need to be collected in a perfectly controlled experiment, that is, from different classes of vehicles driving at the same road and during the same time period. Such experiment is difficult to conduct at the current stage.

In this research, vehicle traces of delivery trucks and passenger cars are used for binary classification. Traces of passenger cars were collected from two field experiments (Ban et al., 2011) conducted in the Albany, NY area, which are originally dedicated for performance measures (e.g. queue length estimation, delay estimation) of signalized intersections. The truck trace data were provided by some anonymous logistic companies. We are particularly interested in the vehicle traces on arterials. There are some issues with the truck data: (i) the sampling frequency for truck data is 3 seconds, while the data for passenger cars were collected every second; (ii) information regarding detailed truck classes (e.g., with respect to the FHWA's 13 class scheme) is not available due to privacy agreement, which makes it impossible to classify multiple truck classes; (iii) speed data are biased: when trucks travel at a speed lower than 2 meters per second, the vehicle-equipped mobile sensors tend to be automatically turned off; and (iv) the level of congestion cannot be inferred from the datasets, due to the low penetration rate of mobile data.

In order to make the two datasets comparable, we (i) truncated truck and passenger car traces into samples with similar lengths (15-20 minutes); (ii) reduced the sampling frequency of passenger cars to 3 seconds; (iii) use the mobile data for binary classification only (thus detailed truck classes are not needed); and (iv) speed information is not used at all in this case. In terms of the sample size, there are 52 samples for passenger cars, and 84 samples of trucks. These two datasets were further divided into the training dataset and the testing dataset. In particular, about 50% of passenger cars and 50% of trucks are used for training, and the other 50% of data are used for testing.

These two datasets (for delivery trucks and passenger cars), albeit collected from imperfectly controlled experiments (e.g., the level of congestion and experiment sites are not the same), can still reflect the underlying behavioral characteristics of trucks and passenger cars on arterials, as will be shown later in this report.

3.2 Feature Extraction

Speed related features (e.g., the maximum speed, the average and variance of speeds, etc.) are the most intuitive features that can be obtained from mobile traffic sensors. However, although trucks tend to travel at a lower speed compared with passenger cars, for a relatively long vehicle trace (e.g., 15-20 minutes long, uncongested traffic condition), both passenger car and truck may travel at a speed which is close to the design speed. Thus the maximum speed may not be a salient feature. Moreover, speed related features are very sensitive to the level of congestion: if traffic is very congested, the average and variance of speed tend to be small. Different speed related features are showed in Figure 1 and Figure 2.

In Figure 1 and Figure 2, scatter plots are shown to explore speed related features for passenger cars and trucks. Although it seems that speed related features of the two types of vehicles can be generally separable, it is noticed that the difference of speed related features of passenger cars and trucks contradicts the common sense. For example, Figure 1 shows that trucks have higher maximum or average speeds than passenger cars; Figure 2 shows that trucks have higher standard deviations of speed than passenger cars. The reason for this is that these two datasets were collected at different traffic conditions. As indicated in Ban et al. (2011), traces of passenger cars were collected during peak hours; however, most of the truck data were collected during off-peak hours. Also truck drivers usually choose to use major arterials, which often have higher priority than minor roads. As a result, trucks are less likely to stop due to traffic signals. In addition, such contradictions may be due to the aforementioned bias of the truck speeds: since truck speeds lower than 2 meter per second cannot be collected, the calculated average truck speed will be higher than what it should be. Therefore, speeds are not used for classification in this research. Nonetheless, speed related features may still be useful for classification if data are collected from more controlled experiments (i.e., passenger car and truck data are collected at the same location and during the same time period).

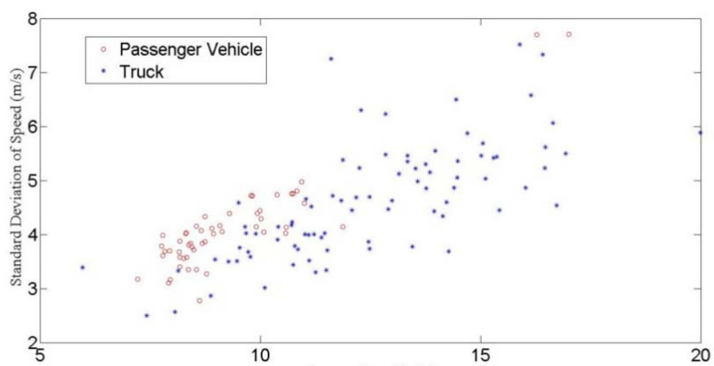

Figure 1: Average speed and standard deviation of speed

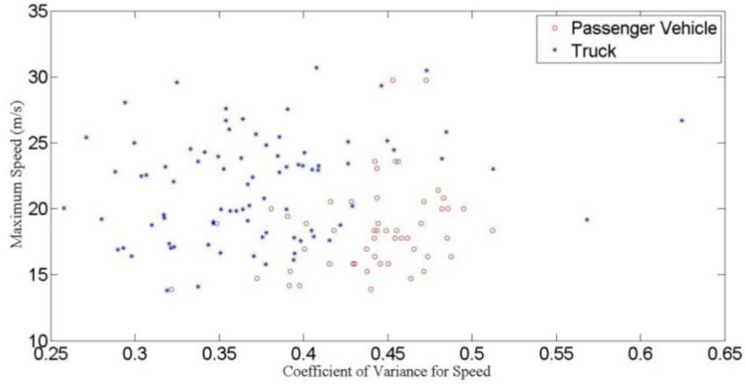

Figure 2: Maximum speed and coefficient of variance for speed

Different from speed related features, acceleration and deceleration characteristics are not very sensitive to the level of congestions. Figure 3 is a scatter plot of the maximum acceleration and deceleration rates for trucks and passenger cars. It is found that passenger cars generally have larger maximum acceleration and deceleration; however, trucks may occasionally have large accelerations and decelerations as well. This is particularly true for a long trace: the longer the trace is, the more likely the largest acceleration and/or deceleration rates may occur.

Since the maximum acceleration and deceleration are not very salient features, we explore the distributions of accelerations and decelerations. The cumulative histograms of accelerations and decelerations of a sample passenger car are depicted in Figure 4, while the counterparts for a sample truck are shown in Figure 5. By comparing Figure 4 with Figure 5, it can be found that passenger cars have a higher probability to exhibit higher acceleration/deceleration rates than trucks. As shown in the two figures, for passenger cars, 35% of accelerations and decelerations are larger than 1 mpss; however, for trucks, these numbers are less than 10%. In this research, four features are extracted to capture the variations of accelerations and decelerations: the proportion of accelerations larger than 1 mpss, the proportion of decelerations larger than 1 mpss, the standard deviation of accelerations, and the standard deviation of decelerations. Scatter plots for these four features are showed in Figure 6 and Figure 7. Notice that the proportion features in Figure 6 are considered to be the most salient features.

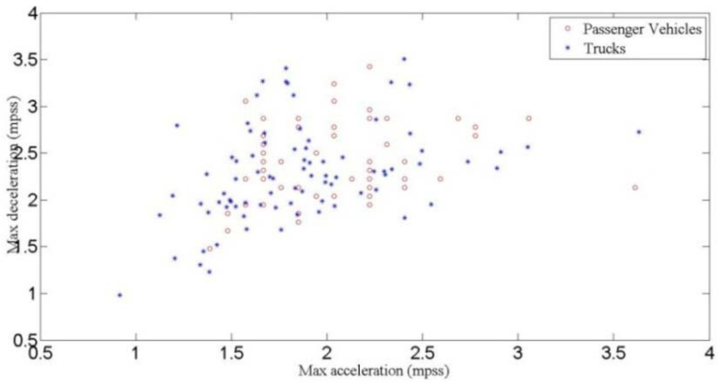

Figure 3: Maximum acceleration and deceleration

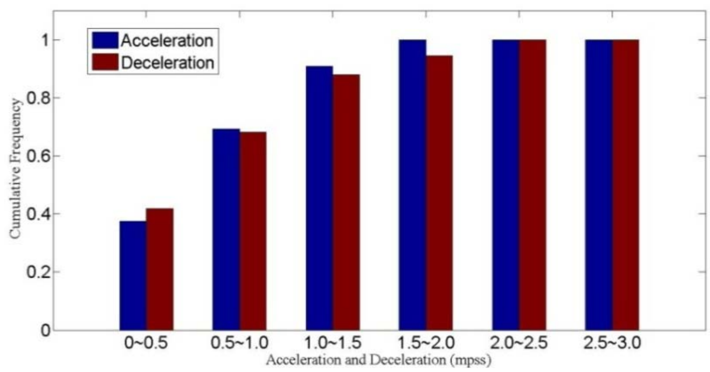

Figure 4: Cumulative histogram of accelerations and decelerations (passenger cars)

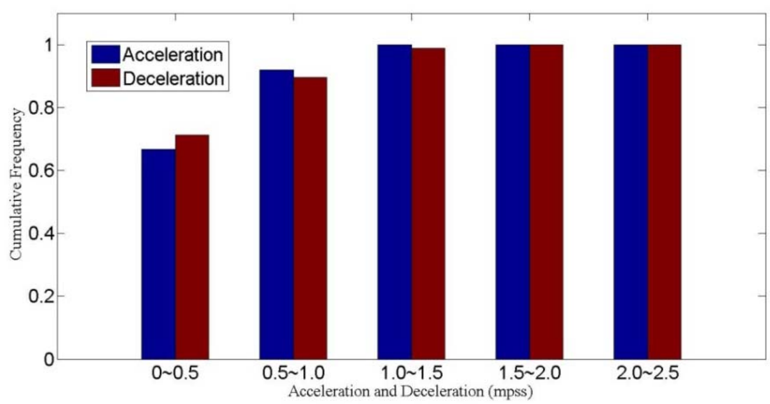

Figure 5: Cumulative histogram of accelerations and decelerations (trucks)

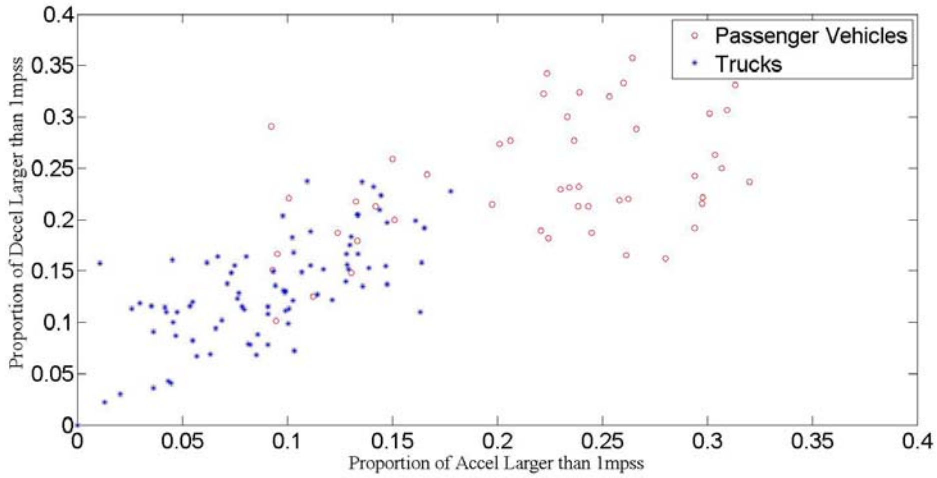

Figure 6: Proportion of accelerations and decelerations larger than 1mpss

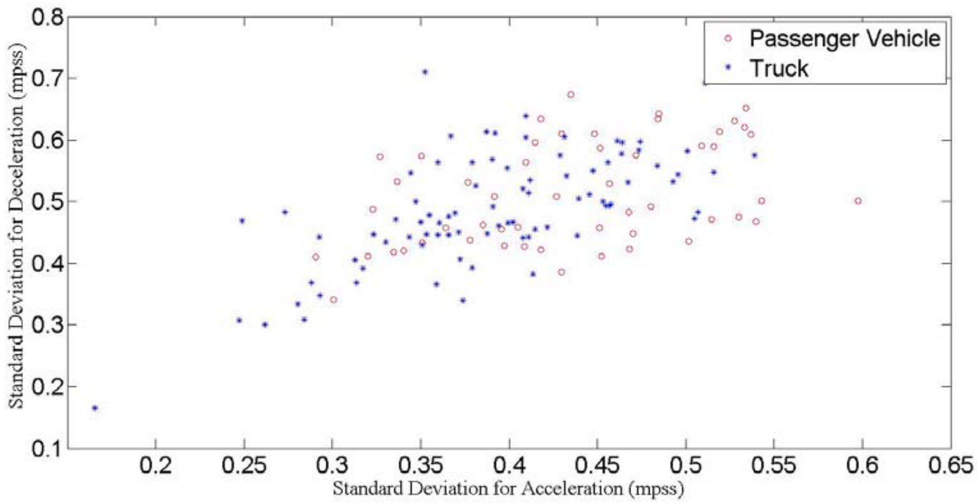

Figure 7: Standard deviation of accelerations and decelerations

3.3 Kernel SVM for Vehicle Classification

With all the features being proposed in Section 3.2, the next step is to find the best combination of the features that can provide the most robust classification results. Here we use SVM with quadratic kernel for binary classification. SVM is a widely used supervised learning technique which can be applied for binary and multi-class classification (Vapnik, 1995). Comprehensive surveys of SVM can be found in Burge (1998) and Cristianini and Shawe-Taylor (2000). Traditional SVM is a linear and binary classifier, which aims to find the model parameters by maximizing the margin, and therefore creating the largest distance between the separating hyperplane and the instances on either side of it.

Considering a training datasets of N samples: $(x_1, t_1), \dots, (x_i, t_i), \dots, (x_N, t_N)$. Here $x_i \epsilon R^d$ is the input (i.e., the vector of extracted features in Section 3.2) of the ith training sample, with

$t_i \epsilon \{1, -1\}$ as the corresponding label, depending on its class. To make things clear, hereafter in this report, we use 1 for trucks and -1 for passenger cars. In a linear form, the decision function can be defined as, where $x = (x_i)_{i=1,\cdots,N}$:

$$y(x) = Sign(w^T \varphi(x) + b)$$

The function determines on which side of the separating hyperplane ($w^T \varphi(x) + b = 0$), the sample x will reside. That is, a vehicle is classified as a truck if $y(x) = w^T \varphi(x) + b \geq 0$ and a passenger car otherwise. Here $w \epsilon R^m$ and $b \epsilon R$ are parameters of the decision function, and $\varphi(x)$ denotes a fixed feature space transformation, which transforms a vector $x \epsilon R^d$ in the original feature space to the transformed feature space in R^m. The reason for this transformation is to deal with classification problems that are not linearly separable (Lauer and Bloch, 2008). In this case, data need to be mapped into a higher dimensional feature space in which the transformed data are linearly separable in the feature space. In SVM, the optimal solution (w^*, b^*) is chosen to be the one that maximizes the margin. For a separable case, a margin is defined as the minimum distance between the points of the two classes, which is measured perpendicularly to the separating hyperplane. And this can be written as a Quadratic Programming (QP) problem (Burge, 1998):

$$Min_{w,b} \frac{w^T w}{2} \qquad (2-1)$$

$$s.t. \qquad t_i(w^T \varphi(x_i) + b) \geq 1, i = 1, \cdots, N \qquad (2-2)$$

Here $w^T w$ is the reciprocal of the margin between the two classes, and the constraints make sure that each training sample x_i is labeled correctly as t_i. To deal with non-separable data, the above problem can be extended by introducing the concept of soft margin that accepts some misclassification of the training samples. To accomplish this, a set of slack variable ξ_i and a control variable C (see equations below) are incorporated to penalize the misclassified data points. Notice that parameter C is used to control the trade-off between the penalization of the errors and the maximization of the margin, which is normally determined using cross validation.

$$Min_{w,b,\xi} \frac{w^T w}{2} + C \sum_{i=1}^{N} \xi_i \qquad (3-1)$$

$$s.t. \qquad t_i(w^T \varphi(x_i) + b) \geq 1 - \xi_i, i = 1, \cdots, N \qquad (3-2)$$

$$\xi_i \geq 0 \qquad (3-3)$$

This problem can be equivalently solved by maximizing the dual lagrangian with respects to the lagrangian multipliers α_i (Burge, 1998):

$$Max\ L(a) = \sum_{i=1}^{N} \alpha_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} \alpha_i \alpha_j t_i t_j\, k(x_i, x_j) \qquad (4-1)$$

$$s.t. \sum_{i=1}^{N} \alpha_i t_i = 0 \qquad (4-2)$$

$$C \geq \alpha_i \geq 0 \qquad (4-3)$$

Here $k(x_i, x_j) = \varphi(x_i) \cdot \varphi(x_j)$ is the so-called the *kernel* function. The use of kernel functions to avoid carrying out $\varphi(.)$ explicitly is known as the "kernel trick" (Cristianini and Shawe-Taylor, 2000). Quadratic kernels are used in this research, namely, $k(x_i, x_j) = (x_i^T x_j + 1)^2$. After solving the above problem, the resulting decision function can then be given as:

$$y(x) = Sign(\sum_{\alpha_i > 0} \alpha_i t_i k(x, x_i) + b)$$

Here x_i corresponds to the support vectors (SVs) - those training data points with non-zero lagrangian multipliers ($\alpha_i > 0$), and *x* is a testing data point. It can be noticed that only a small proportion of training data (i.e., SVs) are retained in the classifier, thus the classification task has been greatly simplified. We also applied other machine learning techniques (K-means, Linear Discriminant Analysis, among others) to our vehicle classification problem, and it was found that SVM out-performs other methods.

3.4 Experiment and Numerical Results

In this chapter, SVMs with quadratic kernels are used for binary classification. Based on the classification results, different combinations of features are evaluated. Firstly, the classifier is trained using the proportions of acceleration and deceleration larger than 1mpss. These two features are considered as the most salient for vehicle classification. Figure 8 to Figure 10 indicate the classification results for both training and testing datasets (circles for training and asterisks for testing), including misclassification rate, false positive and false negative. Notice that the *misclassification rate* is defined as the *ratio* of the number of misclassified samples and the total number of samples, *false positive* is defined as the number of passenger cars being misclassified as trucks, and *false negative* is defined as the number of trucks being misclassified as passenger cars. As previously mentioned, the control variable *C* for soft margin SVM needs to be decided using cross validation. Therefore the classification results are shown for different values of *C*. It turns out that *C* does not impact the classification performance significantly. In this report, the values of *C* that produces the best results for different cases are selected, which are shown in Table 2. Moreover, in order to alleviate the impacts of the sampling scheme of training and testing data, 20 times of random sampling are performed on the original datasets. Since the testing results are more important to us, Figure 8 to Figure 10 show the 20 randomly sampling results for the testing dataset using asterisks. The random plots for training datasets are not showed in this figure, and the average results are depicted using solid curves with circles. It can be observed from the figures that: (i) the average misclassification rate for testing dataset is about 11.4%, which is considered to be relatively high, especially for binary classification; and (ii) the false positive rate is found to be larger than the false negative rate, meaning that passenger cars are more likely to be misclassified as trucks. For a purpose of illustration, the SVM classification results using the proportions of accelerations and decelerations (2 features) are depicted in Figure 11. It is clear that the separating line is nonlinear, which is the optimal solution of the SVM model (3) defined previously.

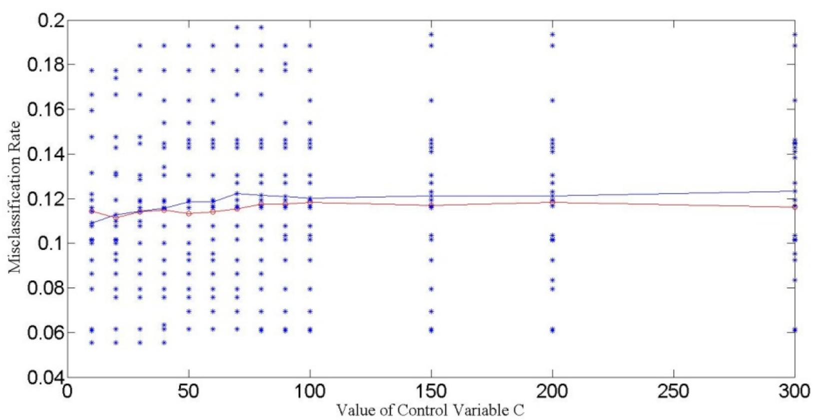

Figure 8: Misclassification rate (proportion of acceleration and deceleration)

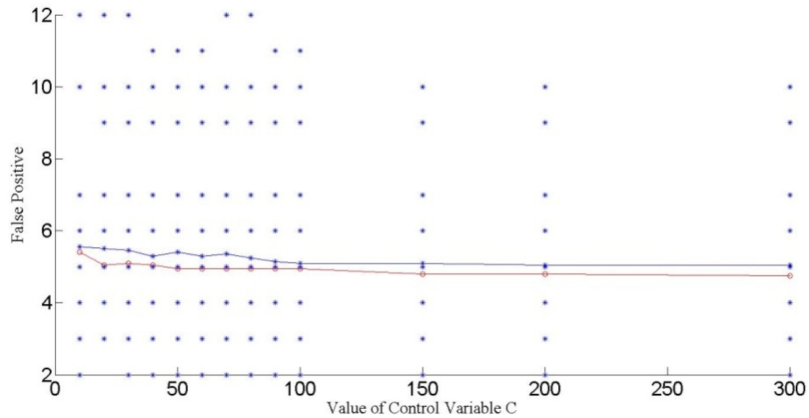

Figure 9: False positive (proportion of acceleration and deceleration)

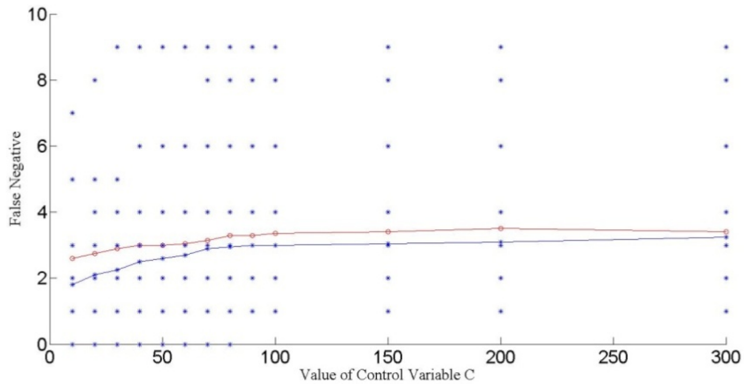

Figure 10: False negative (proportion of acceleration and deceleration)

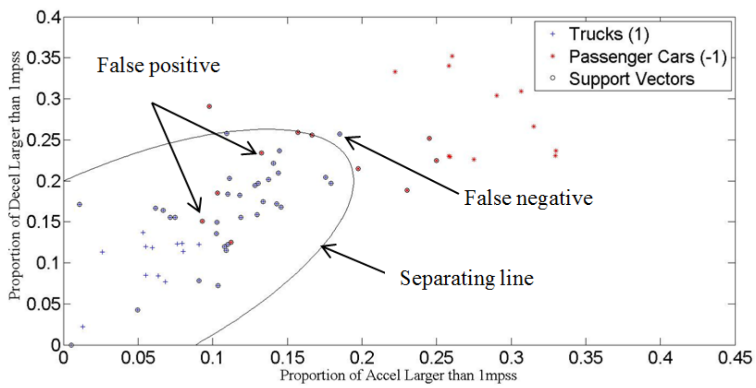

Figure 11: Classification results (proportion of acceleration and deceleration)

More features are then incorporated into the classifier. Figure 12 to Figure 14 depict the classification results for a 4-feature classifier, namely, the proportions of accelerations and decelerations larger than 1mpss, plus the standard deviations for accelerations and decelerations. Similarly, the results for a 6-feature classifier (the 4-feature classifier plus the maximum accelerations and decelerations) are showed in Figure 15 to Figure 17.

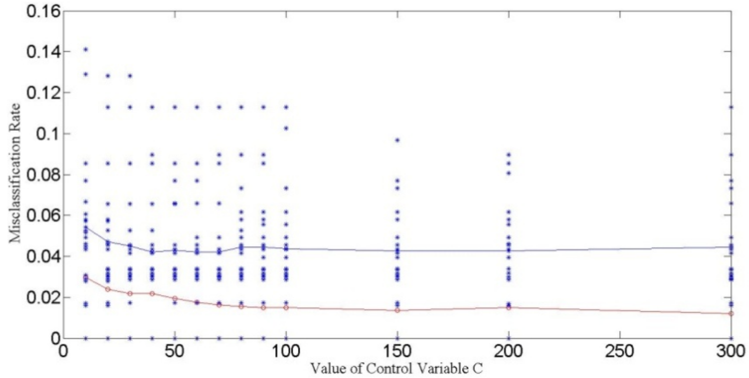

Figure 12: Misclassification rate (proportions and standard deviations)

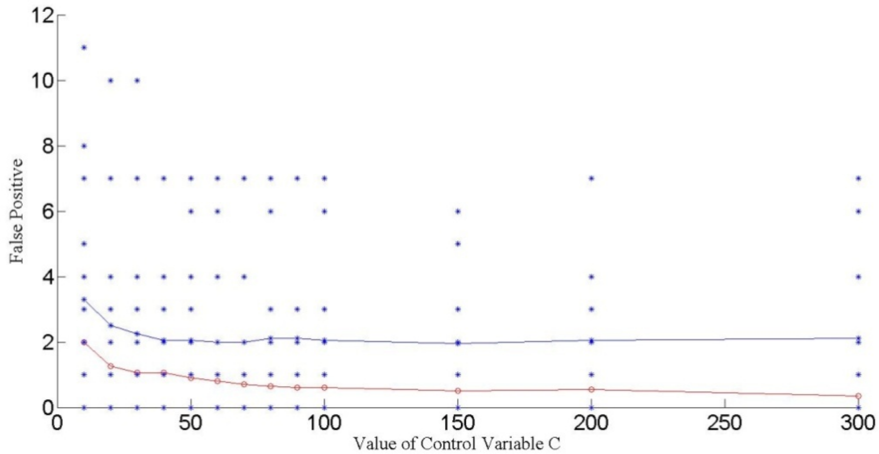

Figure 13: False positive (proportions and standard deviations)

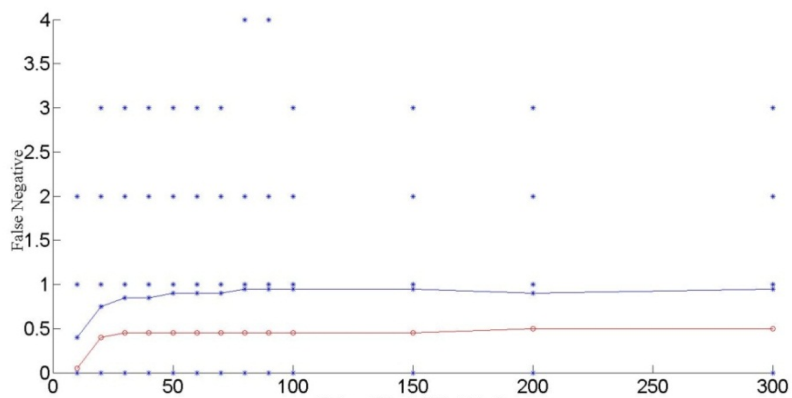

Figure 14: False negative (proportions and standard deviations)

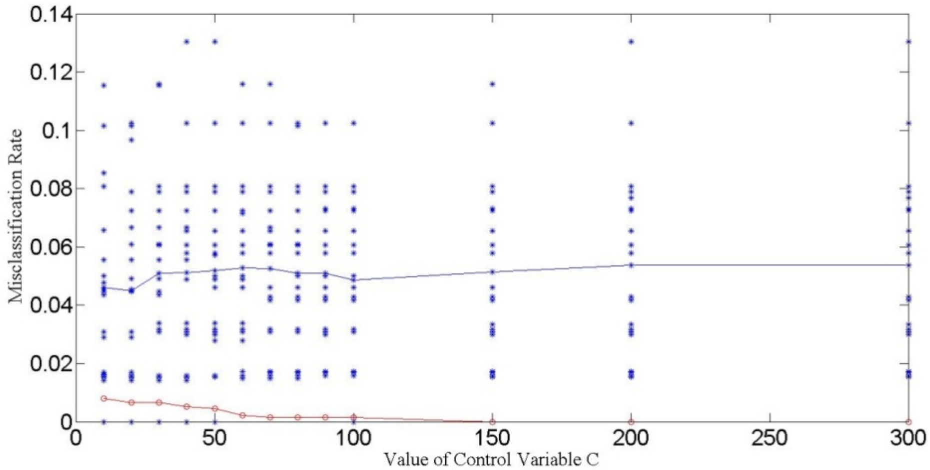

Figure 15: Misclassification rate (6-feature classifier)

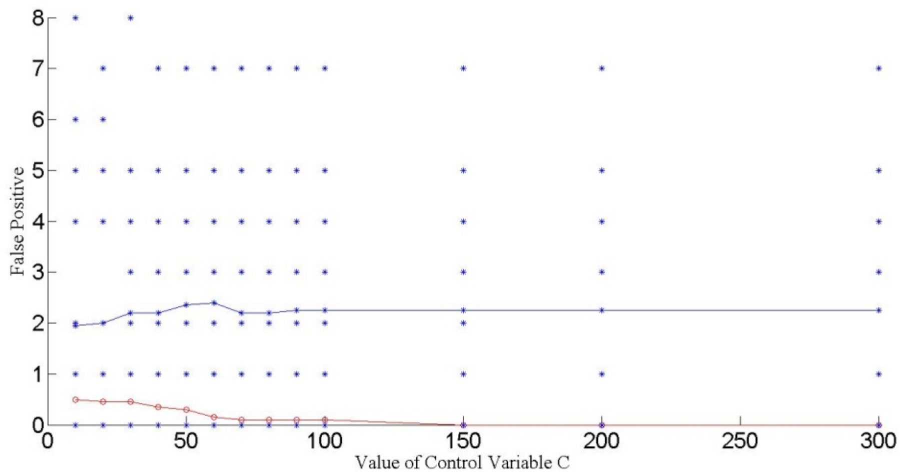

Figure 16: False positive (6-feature classifier)

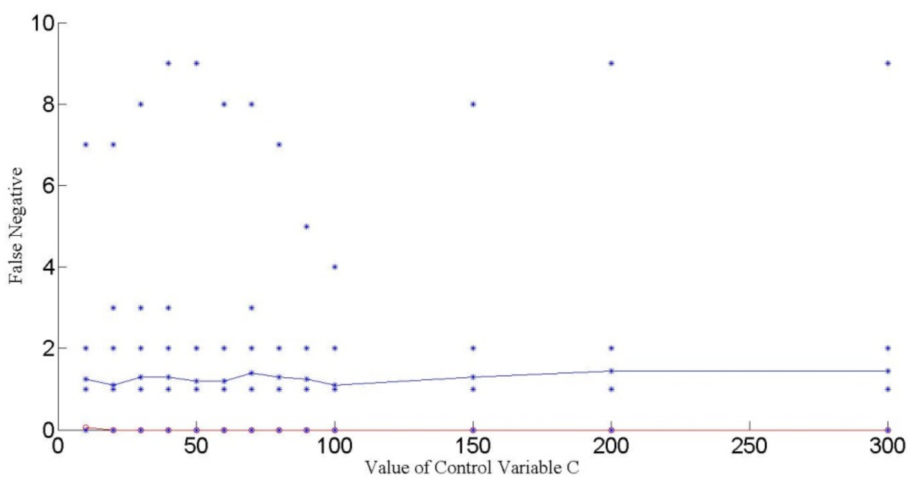

Figure 17: False negative rate (6-feature classifier)

Table 2: Feature selection and classification results (long vehicle traces)

No.	Features	Number of features	Value of $C(C^{+})$	Symmetric penalty cost				Asymmetric penalty cost			
				Misclassification rate (training)	Misclassification rate (testing)	False positive (testing)	False negative (testing)	Misclassification rate (training)	Misclassification rate (testing)	False positive (testing)	False negative (testing)
1	Max ACC/DECEL	2	60	31.31%	43.28%	17.50	13.50	33.57	46.97	16.50	17.00
2	Proportion of ACC/DECEL larger then 1mpss	2	10	11.44%	10.90%	5.55	1.80	11.35%	11.67%	5.20	2.65
3	Standard deviation of ACC/DECEL	2	300	33.34%	37.52%	16.40	8.70	35.13%	37.90%	15.55	9.70
4	Max ACC/ DECEL + proportions	4	10	8.58%	13.06%	5.20	3.60	8.73%	13.42%	5.15	3.90
5	Max ACC/DECEL+ standard deviations	4	60	29.57%	41.06%	16.25	11.20	29.63%	44.32%	14.90	14.70
6	Proportions + standard deviations	4	70	1.62%	4.21%	2.00	0.90	1.43%	4.59%	2.10	1.05
7	All six features	6	20	0.65%	4.49%	2.00	1.10	0.66%	4.86%	2.20	1.15

By incorporating more knowledge into the classifier, the 4-feature and 6-feature SVM models have overall better classification results. The results of all different combinations of features are summarized in Table 2 (for symmetric penalty cost; the asymmetric penalty cost is explained in Chapter 5). Among all different combinations, the 4-feature (case 6) and 6-feature (case 7) classifiers have the best performance. The average misclassification rate of case 6 is about 1.6% for training dataset, and 4.2% for testing dataset. Compared with the results of case 6, the misclassification rate of the 6-feature classifier (case 7) are 0.7% for the training data, and 4.5% for the testing data. This marginal improvement (or even degradation) implies that maximum accelerations and decelerations are not salient features for vehicle classification.

4. CLASSIFICATION USING SHORT VEHICLE TRACES

In real world situation, due to privacy and data availability issues, long vehicle traces may not be always available. In this chapter, we explore the possiblity of using short vehicle traces to characterize vehicle classes. SVM-based models are still applied in this Chapter. However, since short traces contain less information and are subject to specific traffic situations, different data mining strategies should be applied, and therefore different features should be considered.

4.1 Data Description

In terms of classification using short vehicle traces, a major part of the raw data are the same as the datasets described in the previous chapter. However, these datasets are processed to obtain short vehicle traces around intersections. According to Sun et al., (2011; 2012), collecting discrete short vehicle traces within Virtual Trip Line (VTL) zones can help protect privacy, while intersection modeling needs can be simultaneously satisfied. In this chapter, vehicle long traces are truncated to obtain discrete short traces, corresponding to the VTL zone concept. Furthermore, since the two passenger car datasets used in the previous chapter involves mainly turning movements, we take another dataset collected at Wolf Rd., Albany NY to model the through movement traces.

Compared with using long traces, it is relatively hard to perform vehicle classification using short traces. This is because first short traces contain less information. For instance, consider a 3 seconds sampling frequency, a 100-foot long trace may only include several data points. Therefore some aggregated statistics (e.g. proportions of acceleration/deceleration larger than 1mpss) are no longer stable. Secondly, short traces are subject to specific traffic conditions. For example, different traffic states (stop-and-go behavior, level of congestion) and different movement types (turning vs. through movement) may result in significant different patterns. In this regard, it is necessary to define multiple types of traces and analyze them case-by-case. Table 3 summarizes a list of the scenarios that are analyzed. In Table 3, the "stop-and-go" scenario refers to the cases that vehicles stop at the intersection and proceed again. The reason why we categorize the scenarios as stop-and-go traffic and non-stopped traffic is because we want to capture the stop-and-go behavior of the vehicles. A Vehicle trace with stop-and-go behavior is more likely to have lower speed and include major acceleration and deceleration processes. Here one sample corresponds to one short vehicle trace (20-60 seconds long, depending on the specific traffic condition).

Table 3: Types of short vehicle traces

Scenario	Sample size (passenger car/ truck)
A. Stop-and-go, turning movement	104/132
B. Stop-and-go, through movement	143/167
C. Non-stopped, turning movement	57/142
D. Non-stopped, through movement	5/253

As aforementioned, the passenger car datasets and truck datasets are collected from different traffic conditions. To make them more comparable, we (i) truncated truck and passenger car traces into samples with similar lengths (20-60 seconds, corresponds to the VTL zone concept); (ii) reduced the sampling frequency of passengers cars to 3 seconds; (iii) kept speed information but only used the data points within 5m/s-15m/s for feature extraction. This is to rule out the impacts of different control speeds among different datasets and biased truck speed data (as described in Chapter 3). Different from the approach taken in chapter 3, here all the samples are used as the training data, and the target of the SVM-model is to find a classifier that can best explain the training samples. This is partially because the datasets are limited. More datasets need to be collected in the future to construct independent training and testing samples in this regard.

4.2 Feature Extraction

Due to the difference between short and long vehicle traces, the features extracted from short vehicle traces are also different. Below we describe the features we used for vehicle classification using short traces.

(1) Stopped (or not)
(2) Average speed
(3) Standard deviation of speed
(4) Coefficient of variance of speed
(5) Maximum acceleration
(6) Maximum deceleration
(7) Standard deviation of acceleration
(8) Standard deviation of deceleration

Most features are self-explanatory, note that the first feature is mainly used to categorize different types of traces (stop-and-go or non-stopped), which is not an input to the classification model. For passenger cars, the data points with low speed are recorded. Therefore we know exactly if a passenger car stopped or not. For trucks, since the mobile sensor devices will be automatically turned off when the speed is low (less than 2 m/s), we have to infer if the truck stopped or not. First, the data points with low speed (2m/s to 5m/s) were sorted and the data point which have minimum speed can be detected. We then looked at the (time) gaps between this data point and its neighboring data. If any of the gaps are larger than 5 seconds, we define this vehicle as a stopped one. Combinations of features (2) to (8) are the inputs to the SVM model. Here features (2) – (8) were calculated for data points with speeds ranging from 5m/s to 15m/s.

For scenario A (turning movement, stop-and-go), the scatter plots of the features are shown in Figure 18 to Figure 21. It can be observed from these figures that passenger cars tend to have larger average speeds, larger maximum accelerations/decelerations, and larger standard deviations in terms of speeds and accelerations/decelerations. The observations are consistent with our real life experience. Note that compared with the extracted average speed information using long traces (see Figure 1), the speed patterns in Figure 18 are exactly the opposite. One of the reasons is because short vehicle traces only contain the data points around an intersection. The data points at the link segments (usually with higher speed, depends on the actual traffic condition) are not considered. The other reason is that the average speed is calculated for the data points with speeds ranging from 5m/s to 15m/s. Data points with higher speed (caused by larger control speed or less congested traffic condition for the truck dataset) do not contribute to the extracted feature. Although the two vehicle classes cannot be strictly separated using any individual feature, a combination of the features would work as a fairly effective classifier. Classification results regarding this scenario will be provided in chapter 4.3.

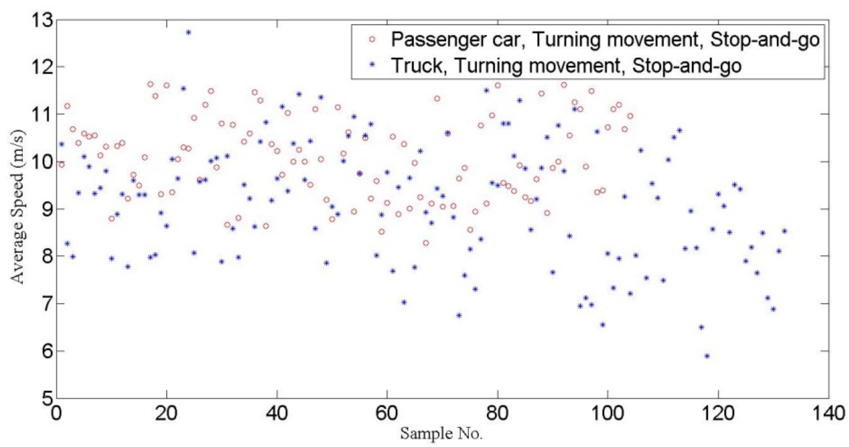

Figure 18: Average speed (turning movement, stop-and-go)

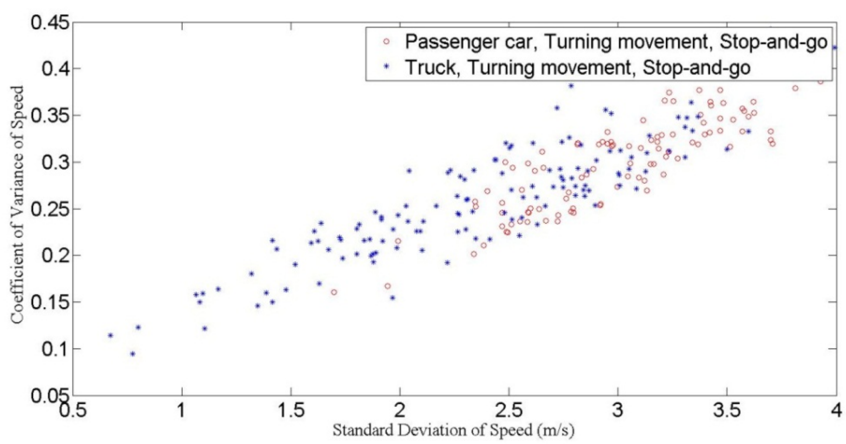

Figure 19: Standard deviation and coefficient of variance of speed (turning movement, stop-and-go)

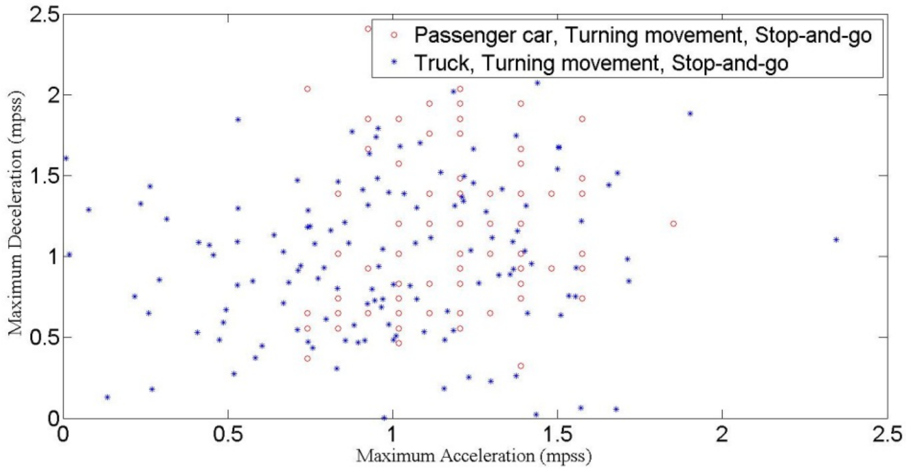

Figure 20: Maximum acceleration/deceleration (turning movement, stop-and-go)

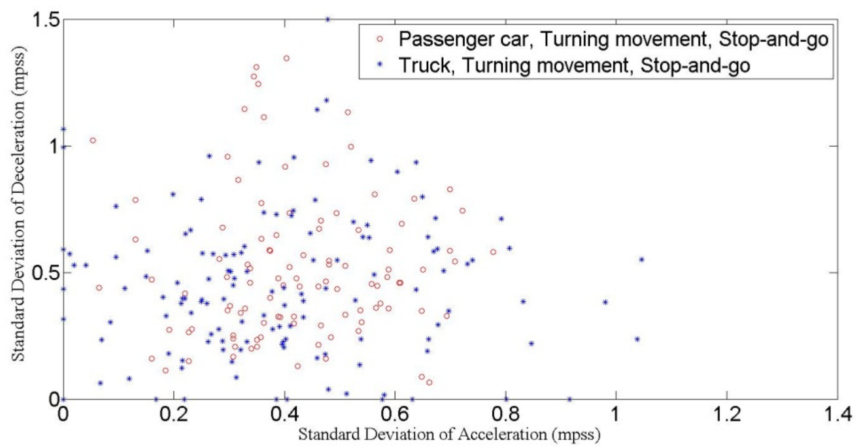

Figure 21: Standard deviation of acceleration/deceleration (turning movement, stop-and-go)

For scenario B (through movement, stop-and-go), the scatter plots of the features are shown in Figure 22 to Figure 25. In this scenario, the extracted features seem to contradict the common sense. For example, the average speed, maximum acceleration/deceleration, deviations of speed for passenger cars are smaller than the counterparts of trucks. This is mainly because the through movement (passenger car) dataset is very congested, the vehicles tend to proceed at a relatively low speed and the driving behavior of passenger cars tend to be homogeneous. Major acceleration/deceleration processes can hardly be revealed in this case. Thus, it can be concluded that it is hard to perform vehicle classification using short traces collected during very congested regime. Since the extracted features do not make much sense, classification techniques are not applied for this scenario. More experiments are needed in the future to justify the feasibility of vehicle classification under this specific scenario.

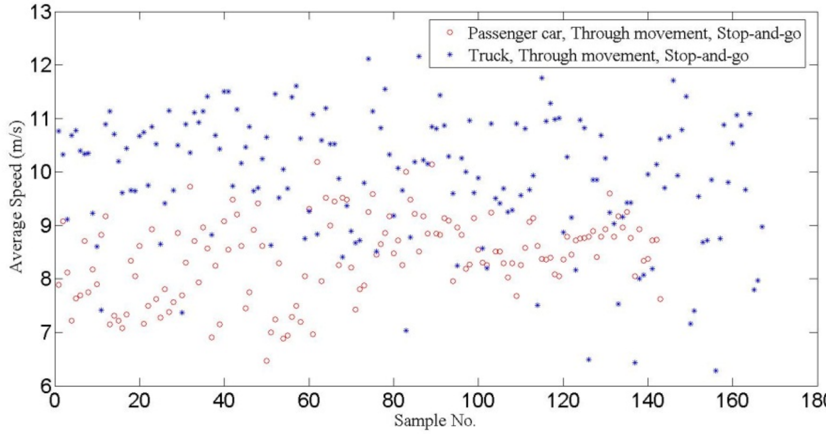

Figure 22: Average speed (through movement, stop-and-go)

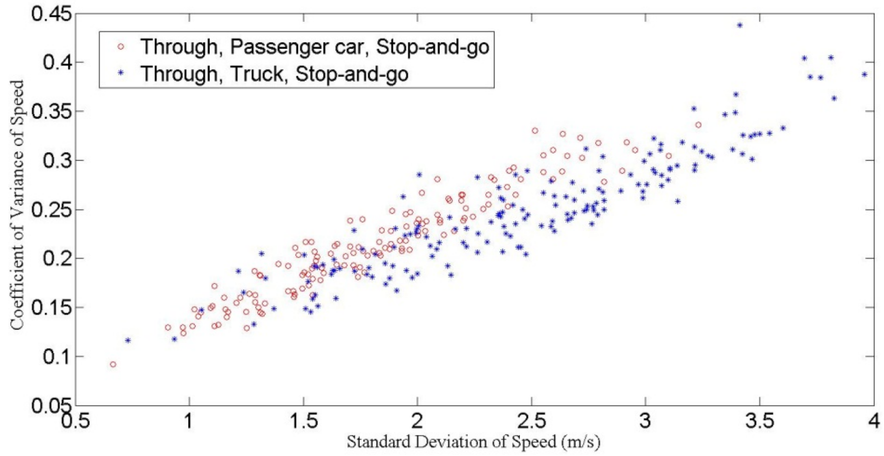

Figure 23: Standard deviation and coefficient of variance of speed (through movement, stop-and-go)

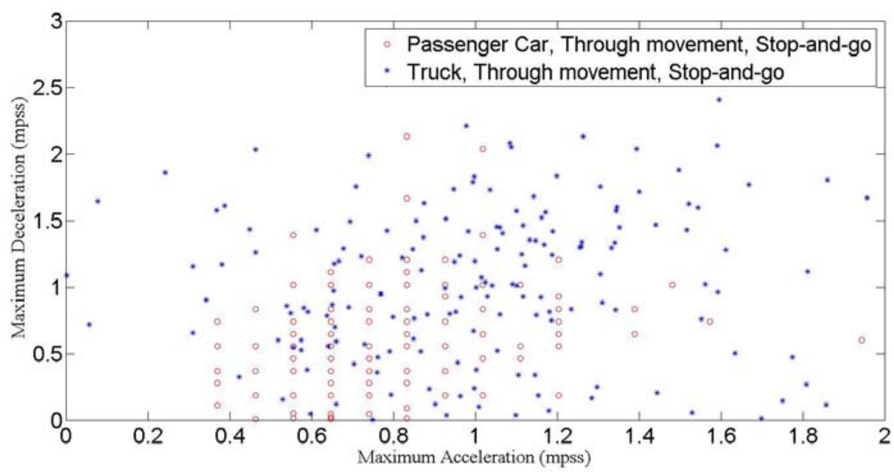

Figure 24: Maximum acceleration/deceleration (through movement, stop-and-go)

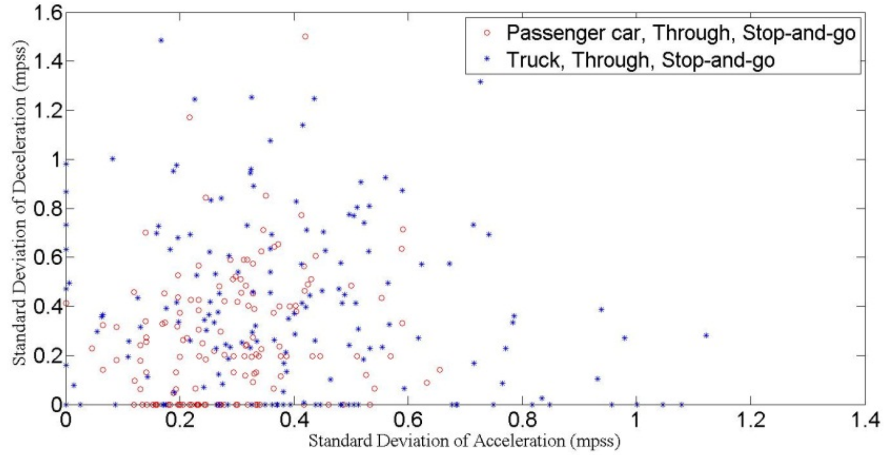

Figure 25: Standard deviation of acceleration/deceleration (through movement, stop-and-go)

The scatter plots of features extracted for scenario C (turning movement, non-stopped) are similar to those of scenario A. As illustrated in Figure 26 to Figure 29, all the features are in general salient. The classification results regarding this scenario are provided in chapter 4.3.

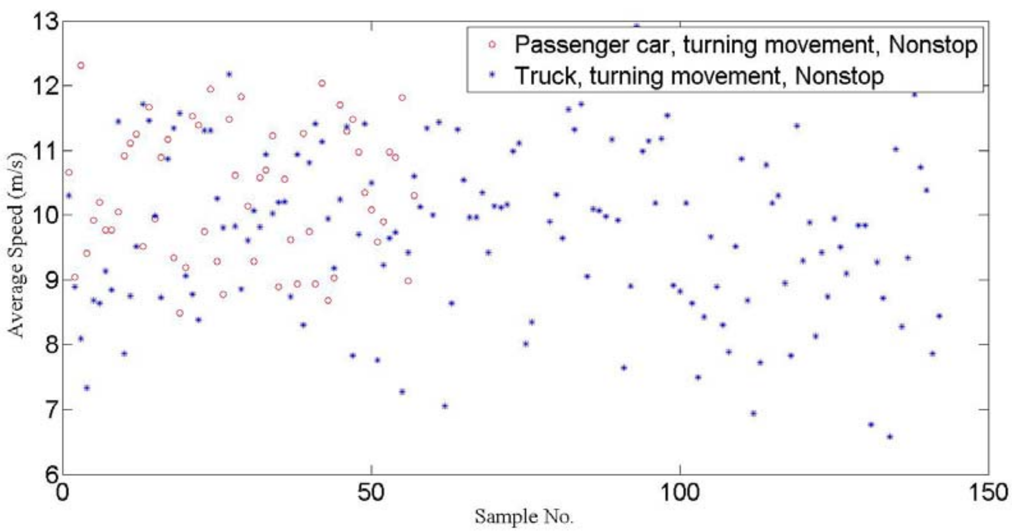

Figure 26: Average speed (turning movement, non-stopped)

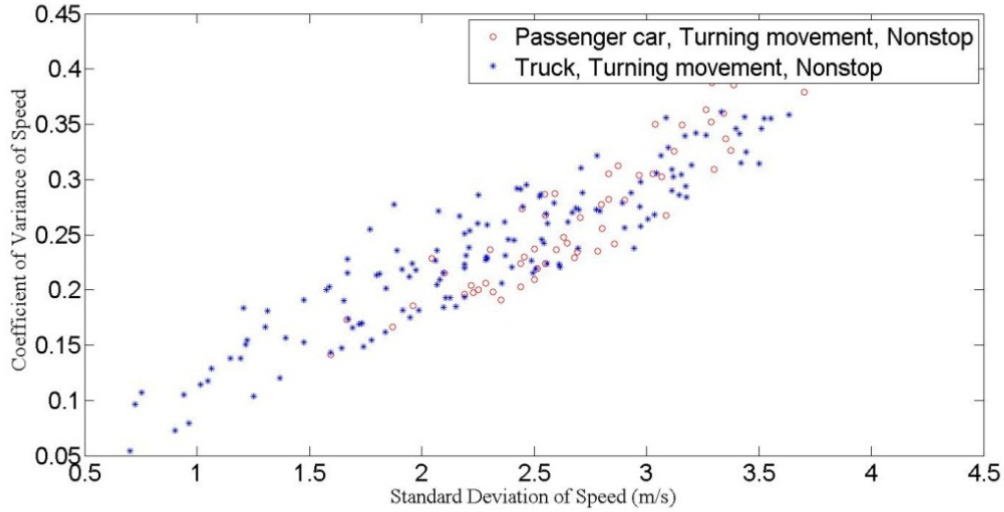

Figure 27: Standard deviation and coefficient of variance of speed (turning movement, non-stopped)

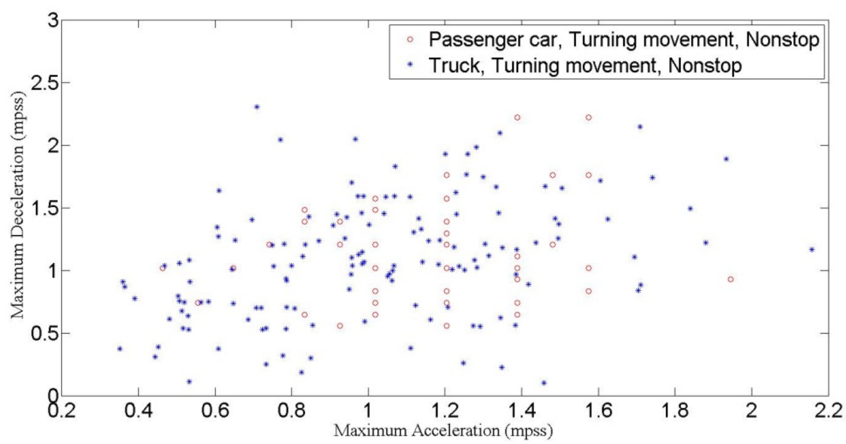

Figure 28: Maximum acceleration/deceleration (turning movement, non-stopped)

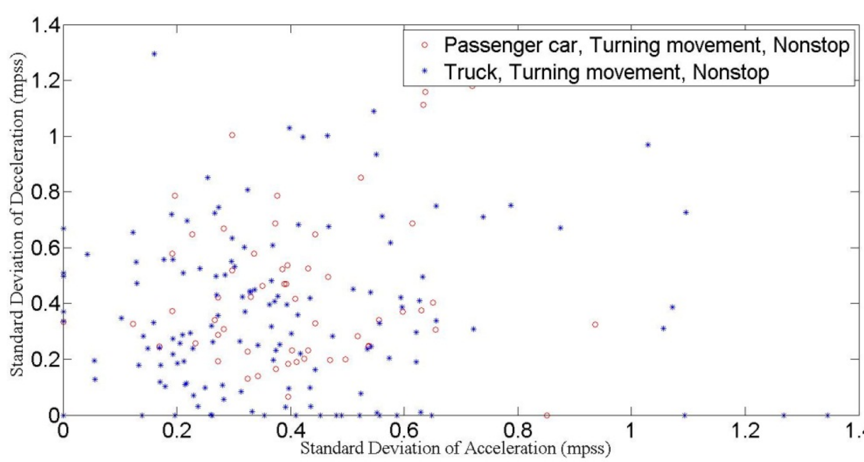

Figure 29: Standard deviation of acceleration/deceleration (turning movement, non-stopped)

For scenario D (through movement, non-stopped), there are not many samples particularly for passenger cars. This is because the through movement dataset of passenger cars are very congested. Most vehicles tend to stop at the intersection due to the traffic signal. It is therefore very hard to perform classification based on such imbalanced and biased datasets. More experiments are needed in the future to justify the feasibility of vehicle classification under this specific scenario.

4.3 Classification Results

SVM with quadratic kernels are applied for binary classification, using short vehicle traces. With respects to different combinations of the features, the classification results for Scenario A and Scenario C are shown in Table 4. Due to the aforementioned issues with the through movement dataset of passenger cars, classification techniques are not applied for Scenario B and Scenario D. Further experiments are needed when appropriate datasets are available.

Table 4: Classification results (short vehicle traces)

Scenario	Features	Value of C	Misclassification Rate
A. Turning, stop-and-go	5:8	40	20.8%
	2, 5:8	500	19.5%
	2:8	50	15.3%
	2:3,5:8	10	14.8%
C. Turning, non-stopped	5:8	20	26.1%
	2, 5:8	500	21.6%
	2:8	200	15.6%
	2:3, 5:8	500	15.6%

For both Scenario A and Scenario C, using only acceleration/deceleration related features (feature 5 to feature 8) provides reasonable classification results. The misclassification rate is 20.76% for stop-and-go traffic and 26.13% for non-stopped traffic, respectively. The reason stop-and-go traffic has a better classification result is because major acceleration/deceleration process are more likely to be revealed in stop-and-go traffic. For non-stopped traffic, passenger cars and trucks may decelerate/accelerate mildly, which cannot fully reflect their corresponding vehicle characteristics. The same conclusion can be reached by comparing the classification results of the two scenarios using other features.

On top of the acceleration/deceleration related features, speed related features (i.e., average speed, standard deviation of speed and coefficient of variance of speed) are incorporated into the classification model. The results indicate that incorporating the average speed and standard deviation of speed can improve the classification results. However, further improvement is not observed by adding the coefficient of variance of speed as another feature.

The classification result for the best combination of the features is 15.25% for Scenario A, and 15.58% for Scenario C. The overall classification results using short vehicle traces are not as good as those obtained using long traces. Classification using (short) through movement traces need to be carefully studied as well in the future. Since trucks need to be maneuvered carefully (e.g. much slower during the course of turning), the research group conjectures that the patterns of through movement traces will be less significant. However, the conjecture is currently hard to be justified due to the lack of appropriate datasets.

5. DISCUSSIONS

In this chapter, some important issues particularly regarding the imbalanced dataset and the privacy concerns related to vehicle classification using mobile sensor are discussed.

5.1 Imbalanced dataset

It should be noticed that in the experiment (e.g. using long vehicle traces), the number of truck samples is larger than the number of passenger car samples. As a result, in Table 2, false positive is usually much larger than false negative, indicating that all these classifiers provide better estimation for trucks than passenger cars (because there are more truck samples for training). This is the so-called class imbalance problem, which has been extensively studied in the machine learning field (e.g., Veropoulos et al., 1999; Wu and Chang, 2003; Akbani et al., 2004; Lauer and Bloch, 2008; Wang and Japkowicz, 2010). Considering a very imbalanced dataset (e.g., for the binary vehicle classification problem, the number of samples for one class can be much larger than the other class), most standard classification method will tend to provide better estimation for the majority class. For classic SVM models, as pointed out by Wu and Chang (2003), the majority class will lie further away from the "ideal" boundary than the minority class. If the misclassification costs are symmetric (i.e., the performance of the classifier is only evaluated using the overall misclassification rate), the imbalanced dataset will not cause any problem. This is because the objective of a classic SVM model (e.g., equation (3)) is simply to optimize for the overall misclassification rate by maximizing the margin of the two classes. However, if the misclassification costs are asymmetric, user may prefer to lower one type of error (such as false positive) over the other type (such as false negative). In this case, a good overall performance, as most classic SVM models would provide, does not necessarily mean the preferred performance (such as to minimize the false positive error) can be satisfactorily achieved.

In real world applications, the collected datasets for different vehicle classes could be very imbalanced (usually there are more passenger cars than trucks, although our collected samples do not reflect this fact) and the costs of misclassification could be asymmetric (e.g., for the revenue generating purpose at a toll booth, it is probably more preferable to lower the error of trucks misclassified as passenger cars than passenger cars misclassified as trucks). Therefore, the class imbalance problem needs to be carefully addressed. As summarized in Akbani et al. (2004), there are two general approaches to deal with this problem. One is to pre-process the training data by either under-sampling the majority class or over-sampling the minority class. The drawbacks for such approach are: (i) data after over-sampling or under-sampling cannot be considered as randomly sampled, therefore cannot represent the true composition of the traffic flow; and (ii) for SVM in particular, removing redundant points (non-support vectors) has no effect to the learned separating hyperplane and removing informational points (support vectors) may impact the accuracy of the model. In this research, therefore, we consider the second approach to address the imbalanced dataset issue by introducing different *penalty costs* for the two classes of instances (called positive and negative instances depending on their signs), as shown below. Two weighing parameters C^+ and C^- are assigned for positive (trucks) and negative (cars) instances respectively. By assigning a larger value to C^- than C^+, the boundary will be pushed closer towards the positive instances, leading to a smaller false positive error.

$$Min_{w,b,\xi} \frac{w^T w}{2} + C^+ \sum_{\{i|t_i=+1\}}^{N^+} \xi_i + C^- \sum_{\{i|t_i=-1\}}^{N^-} \xi_i \qquad (5-1)$$

$$s.t. \qquad t_i(w^T \varphi(x_i) + b) \geq 1 - \xi_i, i = 1, \cdots, N \qquad (5-2)$$

$$\xi_i \geq 0 \qquad (5-3)$$

We implement the above approach (asymmetric penalty cost) in this research to illustrate how the imbalance of false positive and false negative results may be addressed. As shown in Table 2, for the original experiments (symmetric penalty cost), false positive is found to be larger than false negative. If we want to make them more balanced, we can use the original cost as shown in the table for the penalty cost of trucks (i.e., C^+ for positive instances) and pick a larger penalty cost for C^- for passenger cars. In this experiment, we select C^-=2C^+. The results are shown in the "asymmetric penalty cost" columns in the table. We can see that by selecting different penalty costs for the two classes, the overall performance is sacrificed a bit, i.e., the overall misclassification rates increase a little for all cases. However, the false positive errors are reduced while the false negative errors are increased, indicating that the false positive and false negative errors become more balanced. In practice, how to select the best combinations of C^{-} and C^{+} is not a trivial task. However, as shown here, the model (5) is able to address the issue of imbalanced datasets if C^{-} and C^{+} can be properly selected.

5.2 Privacy concerns

The use of mobile traffic data may pose privacy concerns (Dotzer et al., 2005; Hoh and Gruteser, 2007). Consider a second-by-second 15-20 minute long trace on an arterial road, the adversary can easily use the vehicle trace for vehicle re-identification, therefore violating location privacy. Different approaches have been proposed to protect privacy using GPS traces (Rass et al., 2003; Tang et al., 2006; Kargupta et al., 2003; Hoh et al., 2008; Zan et al., 2011; Sun et al., 2011, 2012). Particularly for the data collection process of vehicle classification applications, reduction of sampling frequency (e.g., using 3-second rather than second by second mobile data) and the use of short traces (hundreds-feet-long vehicle traces) can help protect privacy. However, since there is always a trade-off between privacy protection and the data needs for transportation modeling (Ban and Gruteser, 2012; Sun et al., 2012), the performance of the classifiers that are trained using reduced sampling frequency and short traces (as indicated in the classification result session in chapter 4) may also be degraded. This is because major acceleration and deceleration processes are less likely to occur in short traces and accelerations and decelerations tend to be averaged for mobile data with reduced sampling frequency.

The results obtained using long traces in this report provide the “best” case in terms of how one can expect from classifying vehicles using mobile data. The results obtained using short traces on the other hand provide a “second best” case with respects to a privacy-aware vehicle classification method. Further research is needed to investigate “how short” and “how sparse” the vehicle traces should be collected so that a proper trade off can be reached for privacy protection and satisfactory performance of vehicle classification.

6. CONCLUSIONS AND FUTURE RESEARCH

In this research, the feasibility of using mobile traffic sensors for binary vehicle classification on arterial roads is studied. Features (e.g. speed related, acceleration/deceleration related, etc.) were extracted from vehicle traces (passenger cars, trucks) collected from real world arterial roads. These features were then applied for binary classification using the SVM with quadratic kernel functions. For classification using long traces the proportions of accelerations and decelerations larger than 1mpss and the standard deviations of accelerations and decelerations are the most effective features. By classifying general trucks from passenger cars, the average misclassification rate for the best 4-feature SVM model is about 1.6% for the training data, and 4.2% for the testing data. For classification using short traces, it is necessary to define multiple types of traces and analyze them case-by-case. It was found that particularly for the turning movement traces, features such as average speed, standard deviation of speed, maximum acceleration/deceleration and standard deviation of acceleration/deceleration are fairly effective to classify vehicles. The misclassification rate for the best SVM classifier using short traces is about 14.8% for the stop-and-go traffic, and 15.6% for the non-stopped traffic. Issues for the imbalanced datasets and privacy concerns were also discussed.

The proposed research only shows the feasibility of using mobile sensor data for binary vehicle classification. In addition to the issues discussed in Chapter 5, we summarize the possible future research directions as follows:

- The models developed in this research are only tested using limited mobile datasets on arterial streets. More mobile datasets for wide areas need to be collected to further test and validate the models. As long as the traffic is not very congested, we suspect that the proposed methods will not be very sensitive to the traffic volume. Collecting more mobile data will also help us to further verify whether this is true.
- Due to limitations of the collected data, we only showed that it is possible to classify two vehicle classes: passenger cars and trucks. Future research is needed to explore the feasibility of using mobile data for multi-class vehicle classification (e.g., according to the FHWA's 13 classes). Based on our current experience, it does not seem likely that mobile data can be used to distinguish all 13 vehicle classes. Therefore it is interesting to see how many and what groups of vehicle classes can be identified by using mobile data only. The proposed SVM-based classification methods have the potential to be extended for this purpose since they are capable of classifying data into multiple groups (instead of only two).
- The next un-answered question is how to estimate the volume of each vehicle class together with their classification information. A straightforward way to do this, if the

penetration rate for each vehicle class is available, is to infer the total volume for each vehicle class based on its observed volume and the penetration rate. This however can be expected to be coarse, especially when the penetration of mobile data is small and varies significantly over time or location (which is the case today). More sophisticated methods need to be developed to provide better estimation of vehicle volumes for each class.

- As discussed in Section 4, due to data limitations, classification using short through movement traces cannot be conducted in this research. Further research is recommended to collect specific short through movement traces under various traffic conditions and develop classification methods to see if vehicle classes can be distinguished using such short traces.
- Due to privacy concerns, the performance of the vehicle classifiers needs to be tested using different sampling frequency and trace length. The use of "short traces" sounds particularly interesting as this will greatly enhance the privacy of individual vehicles (Sun et al., 2011; Zan et al., 2011). However, this needs to be further justified using other datasets (especially regarding the through movement traces) collected in controlled field experiments.

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