DRIVER AGGRESSIVENESS ANALYSIS USING MULTISENSORY DATA FUSION

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ABSTRACT

DRIVER AGGRESSIVENESS ANALYSIS USING MULTISENSORY DATA FUSION

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Every year a vast number of traffic accidents occur globally. These traffic accidents cause fatalities, severe injuries and huge economical cost. Most of these traffic accidents occur due to aggressive driving behaviour. Therefore, detection of driver aggressiveness could help reducing the number of traffic accidents by warning related authorities to take necessary precautions. Although aggressiveness is a psychological phenomenon, driver aggressiveness can be analysed by monitoring certain driving behaviour such as abrupt lane changes, unsafe following distance and excess acceleration and deceleration. In this thesis work, a method is introduced in order to detect aggressive driving behaviour using a system on vehicle. The proposed method is based on fusion of visual and other sensor information to characterize related driving session and to decide whether the session involves aggressive driving behaviour. Visual information is used to detect road lines and vehicle images; whereas CAN bus information provides certain driving data such as vehicle speed and engine speed. Both information is used to obtain feature vectors which represent a driving session. These feature vectors are obtained by modelling time series data by Gaussian distributions. An SVM classifier is utilized to classify the feature vectors in order for aggressiveness decision. The proposed system is tested by real traffic data and it achieved an aggressive driving detection rate of 94.0%.

Keywords: Driver behavior, driver aggressiveness, road safety, line detection, vehicle detection, CAN bus

ÖZ

ÇOKLU SENSÖR VERİSİ KAYNAŞTIRIMI KULLANARAK SÜRÜCÜ AGRESİFLİĞİ ANALİZİ

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Her yıl dünya çapında büyük sayıda trafik kazası gerçekleşmektedir. Bu trafik kazaları can kayıplarına, ciddi sağlık problemlerine ve büyük ekonomik maliyete yol açmaktadır. Bu trafik kazalarının büyük kısmı agresif sürüş davranışı kaynaklı olarak meydana gelmektedir. Bu nedenle, sürücü agresifliğinin tespit edilip ilgili kurumlar tarafından önlem alınmasının sağlanması trafik kazalarının sayısını önemli ölçüde azaltacaktır. Agresifliğin psikolojik bir olay olmasına karşın, ani şerit değişikilikleri, güvensiz takip mesafesi ve ani ivmelenme gibi sürüş davranışlarının gözlemlenmesi ile analiz edilmesi mümkündür. Bu tez çalışmasında, sürücü agresifliğinin tespit edilmesi için araç üzerinde çalışacak bir sistem sunulmuştur. Sunulan sistem, görsel veri ve sensör verisinin ilgili sürüşü tanımlamak üzere kaynaştırılması ve ilgili sürüşün agresif sürüş davranışı içerip içermediğine karar verilmesine dayanmaktadır. Kameradan alınan veri yol çizgilerinin ve yoldaki araçların tespiti içn kullanılmakta, denetleyici alanı ağ veriyolundan ise araç ve motor hızı bilgisi elde edilmektedir. Elde edilen bu bilgiler, sürüşleri tanımlayan öznitelik vektörlerini elde edilmek için kullanılmaktadır. Bu öznitelik vektörleri zaman serisi şeklindeki verilerin Gaussian dağılımlar olarak modellenmesi ile elde edilmektedir. Bir destek vektör makinesi (SVM) sınıflayıcısı öznitelik vektörlerinin agresiflik içeriği hakkında sınıflandırılması için kullanılmaktadır. Sistem gerçek trafik verisi ile test edilmiş ve %94.0 oranında doğruluk payı ile başarı göstermiştir.

Anahtar Kelimeler: Sürücü davranışı, sürücü agresifliği, yol güvenliği, çizgi tespiti, araç tespiti, CAN bus

In memory of my father Duran Kumtepe,
who was always proud of me

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LIST OF ABBREVIATIONS

ADAS	Advabced Driver Assistance Systems
ANN	Artificial Neural Network
CAN	Controller Area Network
FCWS	Forward Collision Warning Systems
GPS	Global Positioning System
HMM	Hidden Markov Model
HOG	Histogram of Oriented Gradients
kNN	k-Nearest Neighbour
LIDAR	Light Detection and Ranging
MAE	Mean Absolute Error
OBD	On Board Diagnostics
PCA	Principal Component Analysis
RADAR	Radio Detecting and Ranging
RBF	Radial Basis Function
SVM	Support Vector Machine

CHAPTER 1

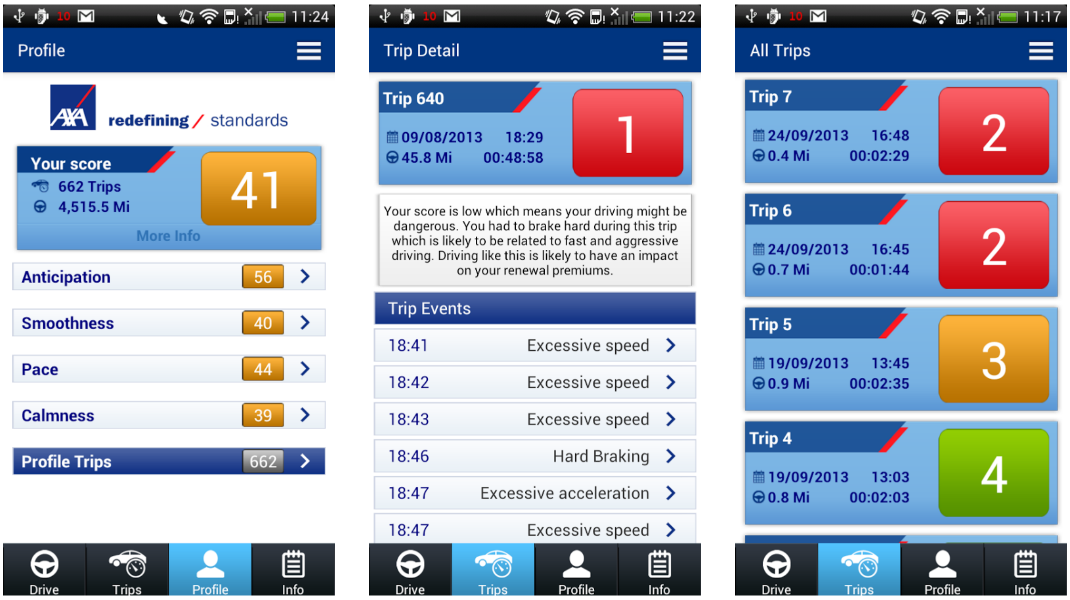
INTRODUCTION

1.1 Motivation

Traffic accidents have become an important problem in the last few decades due to increasing number of vehicles on the roads. Every year 1.24 Million fatalities occur due to traffic accidents globally [88]. Some of these traffic accidents are caused by physical reasons such as road and vehicle conditions. However, human related factors are the main cause of traffic accidents. Among human related factors, aggressive driving behavior constitutes a huge portion of traffic accident reasons. According to a report of American Automobile Association Foundation for Traffic Safety, published in 2009, 56 percent of traffic accidents occur due to aggressive driving behavior [6].

Besides fatalities and injuries, traffic accidents bring about billions of dollars of economical cost for people, governments and companies [88]. Traffic accidents has a cost of USD $518 billion each year globally and the cost per country may reach to 1 - 2% of their annual GDP of an individual country [1]. Losing 1 - 2% portion of a country's GDP means that every year people devoid of a significant amount of governmental services.

Companies and institutions such as rental agencies, insurance companies and public transportation authorities have great interest about driving analysis regarding vital and economical aspects. For instance, one of the biggest insurance companies AXA, provides a discount in the car insurance fees for drivers in some countries. The company rewards the drivers who perform smooth driving behavior during the year with a discount for the next year. Company utilizes AXA Drivesave mobile application which is designed to be used at smart phones. This application collects driving data via the sensors of smartphones and rates the driver according to her driving profile [2]. Different pages of user interface of this application can be seen in Figure 1.1. As can be seen in these figures, different characteristics of driver such as smoothness, pace etc. is rated according to her driving performance.



(a) (b) (c)

Figure 1.1: Snapshots from Axa Drivesave mobile application (a) score page of driver (b) event details of a specific trip (c) list of saved trips

Regarding the presented reasons, reducing the number of traffic accidents is a significant issue to be solved. Considering human related factors, detection of aggressive driving behavior could help reducing the number of traffic accidents by giving necessary warnings to drivers and related authorities.

Aggressive driving behavior is defined as an action "when individuals commit a combination of moving traffic offences so as to endanger other persons or property" by National Highway Traffic Safety Administration (NHTSA). Driver aggressivenss is a psychological concept that does not have a quantitative measure. However, there exist some certain behaviors associated with aggressive driving such as excess and dangerous speed, following the vehicle in front too closely, in other words tailgating, erratic or unsafe lane changes, improperly signalling lane changes, failure to obey traffic control devices (stop signs, yield signs, traffic signals, etc.) [59]. Also, Toledo states that lane changing and acceleration are the characteristic driving behaviors which can be utilized to make inferences about the mood of the driver [82]. Therefore, detecting these behaviors and interpreting related information can yield quantitative information about the driving style of the driver.

Although these behaviors are indication of driver aggressiveness, detection of these behaviors in real time is a challenging task. Existing methods in the literature mostly based on driving simulator data which do not work for real time aggressive driving behavior detection and do not fully reflect the real world conditions. There also exist sensor platform based methods in literature, however, these methods do not consider vehicle following distance and lane following pattern which are very significant for indicating driver aggressiveness. Hence, the proposed system in this thesis work aimed to enable detection of driver aggressiveness in 80 second time periods by considering a wide range of aggressiveness associated driving behaviors.

1.2 Scope of the Thesis

In this thesis work an aggressive driving behaviour analysis system that works in real time is proposed. The system is aimed to perform robust operation with simple and low complexity algorithm in order to be able to work efficiently. The proposed method uses multisensory information in order to extract features that characterize the related driving session. This information is obtained via CAN bus of the vehicle and an on board camera. Then the extracted features are labelled as belonging to an aggressive or a smooth session and they are used to train a classifier which decides on whether the related session involves aggressive driving. The classifier is trained with annotated data so that aggressiveness decision can be modelled regarding the subjective point of view. That is, aggressive driving behavior, which is a subjective and psychological phenomenon, can be modelled quantitatively. The system collects and processes data and creates an aggressiveness decision at the end of a determined period. Length of the period is a design parameter which is discussed in experimental results.

In order to give decision whether a driving session is aggressive or not, road line detection, on road vehicle detection and CAN bus data acquisition are used to extract required information. In the scope of this thesis, different methods in the literature regarding road line detection and on road vehicle detection are studied. Proposed methods for these two modules are described step by step by explaining their advantages over other methods in the literature. Performance results of the proposed methods are presented with the comparison of benchmark methods and datasets in the literature. Modelling and representation of the collected driving information is also introduced with explanation of feature extraction and classification process in order to make aggressiveness classification.

Effectiveness of the overall system is tested with visual and sensor data which is collected with a computer equipped automobile that has a forward camera and CAN bus adapter. During these tests optimum session duration in order to decide aggressiveness is investigated. The effect of accuracy of line detection and vehicle detection modules are examined on aggressiveness decision with conducted experiments. Finally, the proposed system is tested with a publicly available naturalistic driving study data and its effectiveness is confirmed in a different dataset.

1.3 Outline of the Thesis

The organization of this thesis is as follows: Chapter 2 describes the related work about driving behaviour analysis. Different approaches to this problem are studied and existing methods in the literature are presented with their advantages and disadvantages. It is followed by the proposed method description which is based on a multisensory approach. This chapter covers the used computer vision techniques for line detection and vehicle detection modules and their alternatives in literature. Modelling of obtained information and classification process is also presented in this chapter. The chapter ends with test results of the introduced system. Finally, in Chapter 4 concluding remarks on the presented problem and proposed system; and future work are presented.

CHAPTER 2

DRIVING BEHAVIOR ANALYSIS

Driving behaviour analysis has been examined via different approaches in recent years. The ultimate aim of driving behaviour analysis is to improve road safety by assessing different aspects of driving such as aggressiveness, drowsiness, risk factor, driving style and driver performance. As a result of these assessments, providing feedback to drivers or related authorities could provide road safety and more qualified drivers on the road.

Drivers behaviour in traffic is dependent on psychological state of the driver, environmental factors and vehicle capabilities [49]. These characteristics are hard to measure and define quantitatively. Therefore, analysing driver behaviour is more feasible via collecting observable driving signals which are:

- Driving behavioural signals (e.g. pedal pressure, steering angle)
- Vehicle status signals (e.g. velocity, acceleration, engine speed)
- Vehicle position signals (e.g. following distance, lane position)

as presented in [54]. This idea has obtained a big contribution by the development of Advance Driver Assistance Systems (ADAS). These systems are very popular in recent years in order to provide assistance to the driver about the current driving conditions [67]. ADASes are used for collecting data about observable conditions and signals and warning the driver by giving feedback about the individual driving conditions like exceeding the speed limit, departure from road lane or unsafe following distance. However, ADASes do not interpret the driving data to analyse reach a conclusion about driving behaviour.

Over the years different methods to analyse driving behaviour are proposed. These methods varies in terms of cost, practical applicability. In Figure 2.1 cost vs. practical applicability of these methods are presented [34].

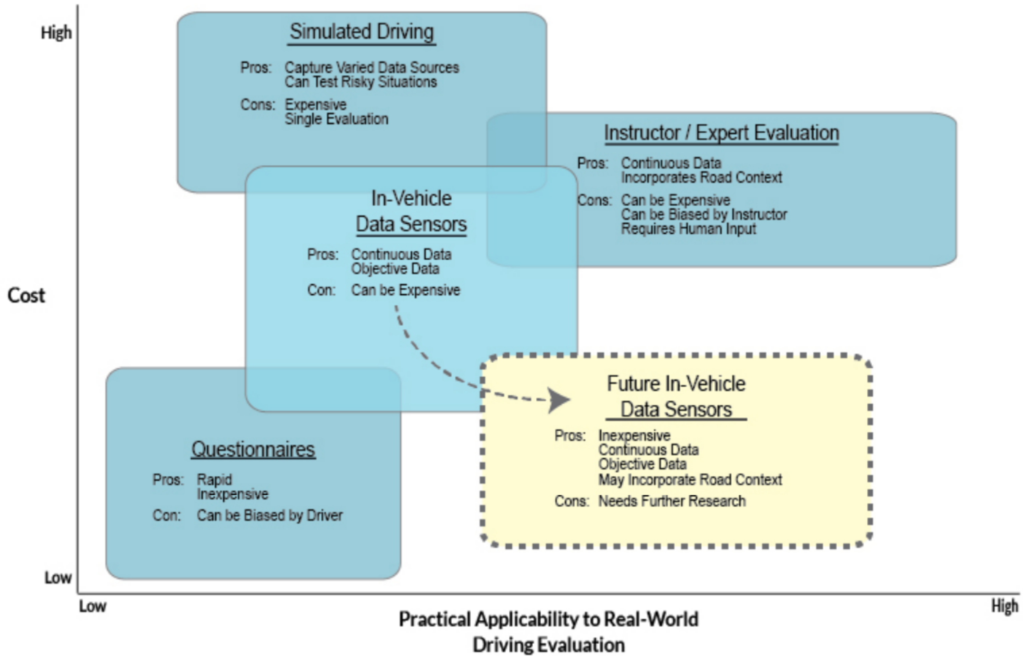


Figure 2.1: Existing assesment methods

The simplest method is to conduct questionnaires about the driving experience [26] or psychological mood which is a subjective and non-effective way regarding contribution to road safety. Conducting questionnaires generally seek to make inferences about relation between psychological variables, behaviours in traffic and accident risk. However, these methods are depends on the past experiences of drivers; therefore, does not contain objective observations.

One other method that highly depends on human interference is instructor/expert evaluation based methods. Similar to conducting questionnaires, the driving experts assesses drivers in terms of performance and other criteria [57]. The effectiveness of this method to correctly evaluate drivers is high since it depends on the expert opinion. However, these method is costly since it requires employment of too much experts.

Following two sub-sections presents the simulator based approaches and in-vehicle systems in a more detailed way since they are in the scope of this thesis study.

2.1 Simulator Based Approaches

For driver behaviour analysis, observing the behaviours of subjects in the simulator environment is a common approach. For this purpose, simulator set-ups are used. An example driving simulator can be seen in Figure 2.2. Simulator environment enables the researchers to collect data about different driving behaviours more easily. Moreover, simulator environment empowers to implement different road scenarios and observe the reaction of drivers in these scenarios.

Figure 2.2: An example of a driving simulator [3]

Simulator based approaches mainly consist of two phases to realize the driving behaviour analysis. In the first phase, driving data to be analysed is obtained through simulator which collected data form different subjects. In the next phase this collected data is analysed using different methods. The methods presented in literature differ from each other in terms of examined data and data analysis [19, 55, 64]. The work presented in [65] is based on collecting data about vehicle position signals such as relative lane position and vehicle status signals such as velocity and acceleration. [19] and [65] uses gas and break pressure signals as a feature to analyse driving behaviour. In [58] eye and head position is detected with a camera and used as a feature.

Different pattern recognition and signal processing techniques are used to analyse simulator data. These methods to decide on aggressiveness, driver style or driving skills can be exemplified as artificial neural networks (ANN) [64], support vector machines (SVM) and k-nearest neighbour (kNN) [19] and hidden markov models (HMM) [24, 31, 65]. Due to the subjective nature of driving analysis, these studies hardly makes any comparison between other studies. The main drawback of these works are that they are using a synthetic environment to measure the driving behaviour. Therefore, they do not fully reflect the real world conditions and reactions that a driver would give in real traffic.

2.2 In Vehicle Multisensory Approaches

In vehicle multisensory approaches are the most recent methods for driving behaviour analysis. The most important advantage of this approach in terms of road safety is that the collected data reflects the real world conditions and in real time applications it enables the creation of necessary warnings to reduce the accident risk. The data acquisition can be done via external sensing devices that are placed on a vehicle [30] or required data can be taken from the controller area network (CAN) bus of a vehicle [71]. Research activities in this field has been boosted with the contribution in computer vision since it enables the extraction of information about vehicle status and environment and provides large amount of information with a simple hardware [73]. In the following sections, studies that performs driving data acquisition from sensors and usage of computer vision in driving behaviour analysis are presented.

2.2.1 Driving Data Acquisition from Sensors

Conducted studies that depend on sensor data acquisition about driving behaviour analysis in literature differ from each other in three aspects. Driving data source, analysed data type and pattern recognition methods to classify the driving or driver are the main differences among existing studies. Although used techniques are similar with simulator based approaches, sensor data acquisition based methods are more efficient in terms of road safety since reflection of real world conditions.

Some of the presented studies in literature performs data collection via external sensors and hardware. With the help of simple sensors such as GPS module to measure velocity and accelerometer that measures lateral and longitudinal acceleration, required data is collected [30, 33, 45]. The main drawback of usage of external sensors is increasing cost and hardware complexity.

One innovative approach to this issue is taking advantage of smart phones. Smart phones are equipped with GPS module, accelerometer working in different dimensions and gyroscope. Data collection is possible using internal sensors of smart phones [34, 36, 53]. As stated in [36] using of smart phones' sensors give noisy measurements due to internal vibration of the vehicle.

A better method which decreases the hardware complexity and gives more clean measurements for data acquisition is to extract data from the CAN bus. CAN bus is a recent technology that the most modern vehicles possess. Since the internal electrical signals of a vehicle pass through CAN bus, it is possible to reach to the vehicle status signals via this interface. Therefore, [17, 44, 68, 71] used CAN bus to obtain these signals for driving behaviour analysis.

Presented methods in the literature shows differences regarding collected data types. Most of the methods in the literature are interested in speed, lateral acceleration and longitudinal acceleration [28, 30] which are the most effectively characterizing indicators of a driving. In [71, 74] gas and break pedal pressure and steering angle is measured an used as a features. In [53] engine speed which is a correlated signal with gas pedal pressure is measured and used for assessment. Other than these driving signals traffic density [73], physical noise in the vehicle [44] and turn signals [33] are exploited as parameters for driving behaviour evaluation.

In all conducted studies in order to give a decision about the driving behaviour, pattern recognition techniques are used. Once the signals are collected via different devices, they either passes through a modelling process(e.g. gaussian mixture model (GMM) [7,30], expressing signals with distribution [73], spectral coefficients [54]) or directly used for classification. For classification purposes, hidden markov model [68, 89], neural network [53], fuzzy logic [89], maximum likelihood classification [55], k-nearest neighbour (kNN) [19] and support vector machine (SVM) [19] are used in existing studies. Since these studies either analyses a different driving behaviour (e.g. aggressiveness or performance) and use different data types or modelling it is not possible to make a qualitative comparison between them.

2.2.2 Exploitation of Computer Vision

Exploitation of computer vision in driver behaviour analysis opened a new dimension in research activities. Because previously mentioned sensors are mostly vital to characterize driving; however, they are limited regarding the data type. In other words, the variety of information to represent driving is constrained with simple sensors. Therefore, using cameras and computer vision techniques, different types of driving information can be obtained and better characterization is possible. Despite this advantage of computer vision methods, the performance of computer vision algorithms is creates a bottleneck for the performance of driver behaviour analysis. Because noisy feature extraction by computer vision tools effects the efficiency of the analysis. Therefore, this situation brings about a trade off.

One important feature that can be obtained by computer vision tools is road lane following behaviour. Discrepancies in lane following could be an indicator of a risky and unsafe driving [70]. In [71, 73, 89] position in the road lane is used. Car following behaviour can also be obtained by camera images as a features that depends on the following distance between the host vehicle and other vehicles. This feature requires the detection of vehicles on the road and distance measurement [7, 92]. Other than these two important features head pose and eye gaze [62] can also be examined through camera images for analysis purposes.

CHAPTER 3

MULTISENSORY DATA FUSION FOR AGGRESSIVENESS ANALYSIS

3.1 Proposed Method

As indicated in section 2, different driving behaviours can be analysed by observable driving signals. By this idea, it is possible to comment on aggressiveness, driving skills or driving style of the driver. In this thesis, driver aggressiveness is analysed using driving signals. Proposed method in order to assess driver aggressiveness follows a multisensory approach since it utilizes different sensing devices to collect real world data on vehicle. In order to characterize the driving in an efficient way, computer vision techniques are also utilized.

As indicated in [59] and [82] aggressive driving is associated with sudden lane changes, tailgating behaviour, excessive speed and abrupt acceleration basically. According to [54], gas and brake pedal pressure are also characterizing features for aggressiveness. Gas pedal pressure is directly correlated with engine speed and brake pedal pressure is directly related with vehicle speed. With the illumination of these information, four different feature types are chosen to represent the related driving session. These features are determined as:

- lane deviation
- collision time
- vehicle speed

- engine speed

Proposed method, extracts lane deviation and forward car distance information from the visual information provided by a camera that is directed to road. For this task computer vision techniques are used which contains road line and vehicle detection. Engine and vehicle speed information is obtained from CAN-bus of the vehicle. These collected information is processed to constitute feature vectors. Obtained feature vectors are classified to detect aggressive driving behaviour. The following sections explains all processes in a detailed way. The overall system flow can be seen in Fig. 3.1.

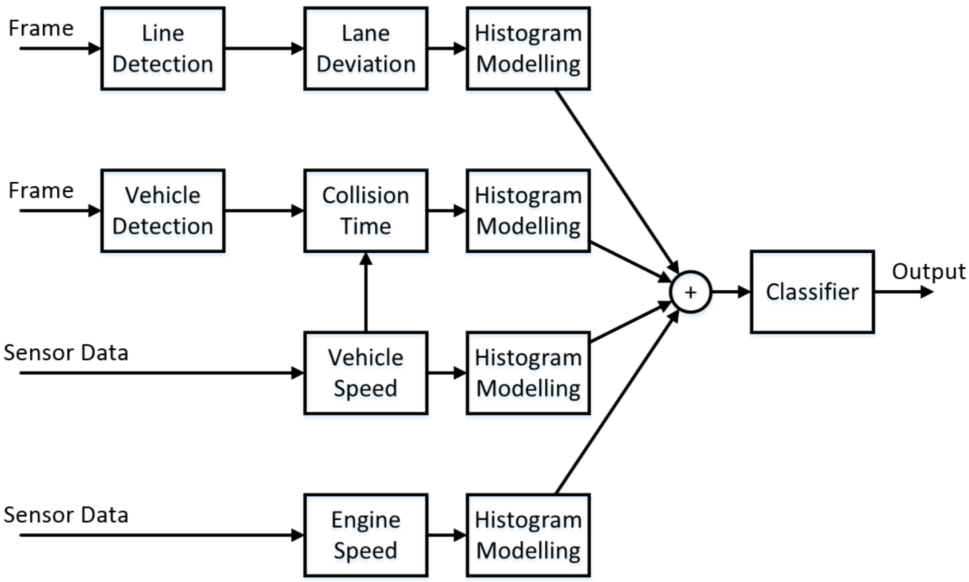


Figure 3.1: Flowchart of the system

3.1.1 Road Line Detection

In order to find the position of the host vehicle, which is the equipped and examined vehicle, inside the road lane, road line detection is required. Drivers who change lanes suddenly and continuously and do not follow the lane properly may involve in aggressive driving attitude. Therefore, detecting the position of the host vehicle inside the lane by detecting the road lines is an important information. For road line detection problem, non-uniformity of road lines is the major challenge [61]. In order to accomplish road line detection task with a robust operation to non-uniformities in road lines, temporal filtering and inverse perspective mapping are used which is a robust, simple and low cost method and proper for the fast operation of the overall system.

3.1.1.1 Related Work

For road line detection, different modalities such as monocular vision, stereo vision, Light Detection and Ranging (lidar), Global Positioning System (GPS) or radar has been used. However, among these modalities monocular vision is the commonly used one since it is the cheapest, most robust and the most compatible method with human visual option. Therefore, most of the work presented in literature use monocular vision. Methods based on monocular vision consist mainly five stages. Not all of the existing methods in the literature passes through these five stages; nevertheless, all algorithms can be mapped to these stages. The basic flow diagram of the road line detection can be seen in Figure 3.2 [11].

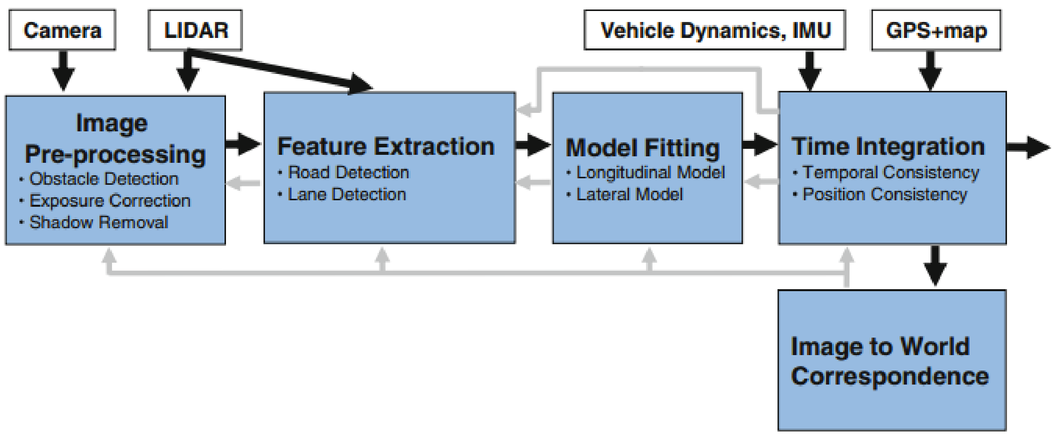


Figure 3.2: Generic flowchart of road line detection [11]

Pre-processing

The main task in pre-processing stage is to reduce the noise in the image and eliminate irrelevant parts that makes the road line detection hard. Illumination effects, shadows on the road, obstacles inside the taken frame and unseen or hardly seen road lines creates noise for the detection process. Colour space transformations can be used to eliminate noise caused by illumination. In [39, 77] uses transformation from RGB colour space to HSV colour space. These transformations are based on the assumption that hue information exist even in the low light conditions. Image filtering techniques are also useful for noise elimination. In [63] gaussian smoothing is used for noise elimination. However, in order to handle different condition more complicated filtering techniques are required. In [61] temporal filtering and intensity based filtering and is used to make the process more robust. In order to eliminate obstacles and unnecessary regions, these regions can be detected and tracked. The main drawback of this approach is unreliability due to high false positive rates [10]. An alternative approach to eliminate unnecessary regions is to define region of interest (ROI) by hand [93] or by segmentation of road inside the image [12].

Feature Extraction

In the feature extraction stage, features that carry information about the road lines are obtained. The main characteristics to be used for feature extraction are that road lines have more intensity and their narrow shape is different than its surroundings. In order to utilize this information gradient based approaches used [61] which is a simple and robust method. In [52] steerable filtering is used which is based on filtering in the predefined directions that is along the road lines. The filtering can be followed by a thresholding operation so as to obtain a binary image and do further operations on this binary image [90]. In [91] image pixels are segmented as blobs and classified as belonging to a road line.

Model Fitting

The objective of this stage is to obtain a high level representation of the road lines by a model using the extracted features. The model fitting can be classified into three methods as parametric, semi-parametric and non-parametric methods [11]. Among the parametric models, the simplest geometric model is straight line. In most of the studies road lines are approximated as straight line which gives a good performance for short range and in highway scenarios [11, 13]. To model curved roads with a long range modelling parabolic curves and generic arcs are preferred [52]. In order to fit the geometric model to the road lines RANSAC [20], hough transform [29, 83] and least squares algorithm [42] are among the existing methods. As semi-parametric methods road lines are modelled with splines and poly-lines. For instance, in [86] road lines are described with b-splines which is a part of active contours depending on the energy optimization. For the non-parametric methods continuous, yet non-smooth boundaries appears [16].

Temporal Integration

Due to the fact that visual information from the camera is taken as image sequences, road line detection output for each image frame is correlated with the preceding or following ones. Therefore, in order to increase the reliability of the detection results most of the existing methods exploit temporal information. Most generally used techniques for temporal integration are kalman filter and particle filter. According to [40] kalman filtering and particle filtering can be used for road line tracking which give the similar performance. However, particle filtering performs slightly better than kalman filtering when the vibration on the vehicle is high which decreases the smoothness of road line positions. Active contours [86] also can be used for temporal integration; however, it brings about a high computational cost compared to kalman or partcile filtering.

Image to World Correspondence

Since the camera is mounted on the car to see the front part, road lines are seen as intersecting lines at a vanishing point in the horizon level. In most of the works in the literature [13, 61, 73], the perspective of the camera is transformed to birds-eye view which allows the road lines to be seen as parallel lines. This operation reduces the resolution in most of the cases; however, provides a practicality and easing to detect road lines. Inverse perspective mapping is performed with a perspective transformation which requires the transformation relation between road plane and camera plane. In [61] this mapping is performed via vanishing point detection while in [38] manually by selecting four destination and four source point and calculating the perspective relation between them since automatic transformation is prone to noisy estimations.

3.1.1.2 Proposed Road Line Detection Method

As presented in Section 3.1.1.1 there exist a huge number of different methods for road line detection in the literature. Quantitatively comparison of these methods is hardly possible since existing studies proposes different combinations of aforementioned road line detection stages in varying complex road scenarios [72]. In [72] some line detection metrics are proposed; however, since this is a recent study existing methods do not report the performance according to these metrics. Therefore, most of the studies presents qualitative results with annotated visuals.

For this study the main concern is to use a robust, simple and low complexity algorithm to detect road lines correctly and fast enough to work in real time. Presented methods in the literature claims to give efficient results qualitatively; however, considering the simplicity and feasibility to work in real time in this study it is decided to use a technique inspired by [61]. Presented technique uses temporal filtering as pre-processing step, gradient based filtering for feature extraction, straight line assumption and horizontal projection for line modelling with the help of inverse perspective mapping and kalman filtering for temporal integration. A flowchart of the line detection module can be seen in Figure 3.3.

One of the most important problems regarding the robustness of the system is non uniformity of road conditions. In order to overcome the problems that are caused by shadows on the road, different light conditions and discontinuities on the road line, a method based on temporal filtering is used [13], [61] which gives robust, fast and simple results.

First, captured image is temporally filtered in order to eliminate dashed lines and discontinuities according to

$$I'_k(x, y) = max\{I_k(x, y), ..., I_{k-K}(x, y)\} \tag{3.1}$$

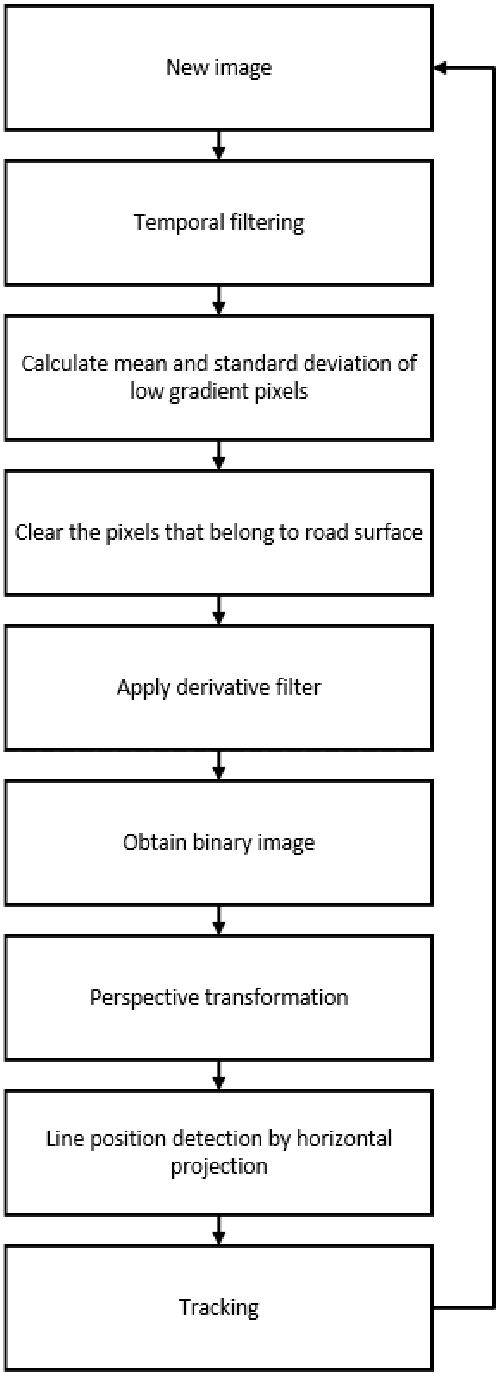


Figure 3.3: Flowchart of proposed road line detection method

where I_k represents the current frame, I_{k-K} represents the K^{th} previous frame and (x, y) are pixel coordinates. K is chosen according to the frame rate and dashed line length so that all road lines can be seen continuous as in Figure 3.4. K is chosen as 10 for the video sequences which contain highway and urban roads and which are captured as 10 frames per second. This operation may result in wrong detections during sudden lane change events; however, tracking detected lines with Kalman filter corrects the possible wrong detections which will be explained at the end of this chapter.

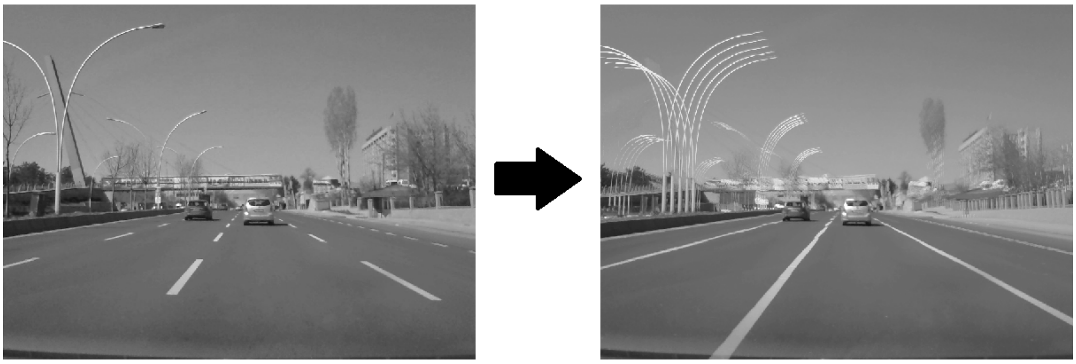


Figure 3.4: Raw image and temporal filtered image

Then the gradient image of $I_k^{'}(x,y)$ is calculated and the high gradient pixels are cleared from $I_k^{'}(x,y)$ to obtain $I_k^{''}(x,y)$. This operation gives the low gradient pixels which represent the road part. Then the mean μ and standard deviation σ values of $I_k^{''}(x,y)$ are calculated so that the mean intensity value of pixels that belong to road part can be found. Once these values are obtained, the pixels that are representing road is eliminated from the image $I_k^{'}(x,y)$ by clearing the pixels that have intensity values less than $\mu+\sigma$. This operation helps to eliminate noise and indicate road lines better. A simple derivative filter F where

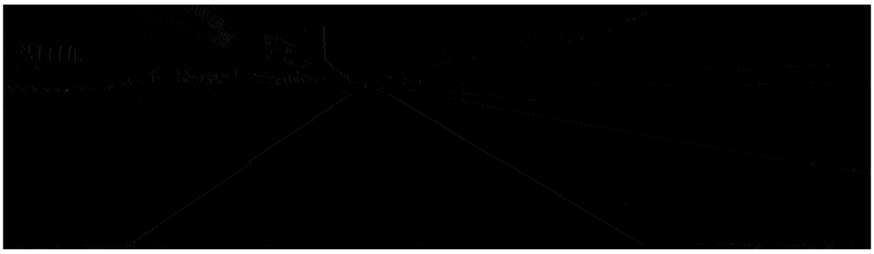
$$F = \begin{bmatrix} -1 & 0 & 1 \end{bmatrix} \tag{3.2}$$

to calculate the gradient is used for indicating the lines. After this operation, binary image is obtained using an adaptive threshold according to Otsu's method [66]. The application results of these steps can be seen in Figure 3.5.

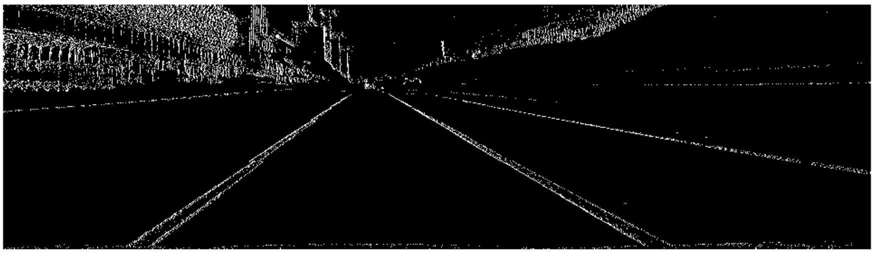
Inverse perspective mapping is an efficient method for road line detection. Camera placed in the front of a vehicle gives the road lines as straight lines intersecting at the horizon level. However, inverse perspective mapping enables the road lines to be seen as parallel lines. Moreover, since monocular vision system is used, inverse perspective mapping will be exploited to measure the distance between vehicles. In order to achieve inverse perspective matching four points

(a)

(b)



(c)



(d)

Figure 3.5: Operations to obtain binary image (a) temporal filtered (b) road pixels cleaned (c) gradient calculated (d)binary

are chosen in the filtered image and they are mapped to four other points in the birds-eye perspective [38] assuming the surfaces are planar. This mapping procedure results in a 3×3 H matrix that contains the transformation parameters. This matrix is calculated before the aggressiveness detection operation and hardcoded to the system. Then during the operation inverse perspective mapping is done by transforming each i^{th} point of the binary image using H matrix as

$$p_k^i = HP_k^i \tag{3.3}$$

At the end of this transformation road lines can be seen as parallel lines from the birds-eye view in the binary image.

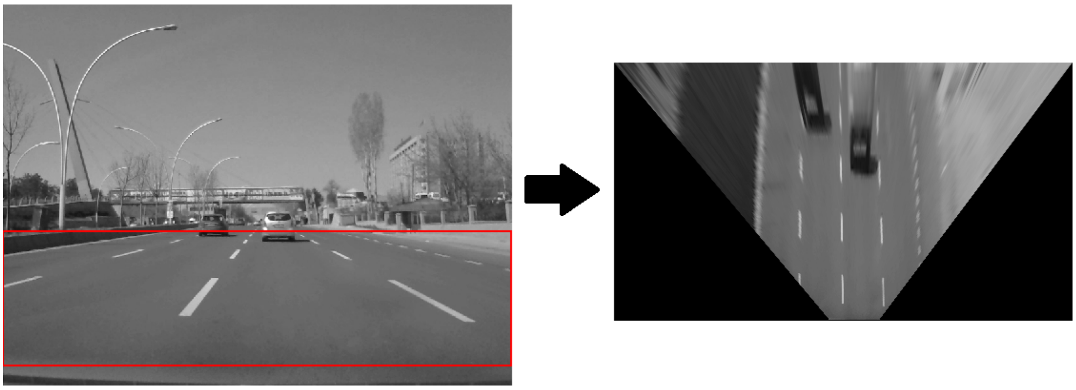


Figure 3.6: Perspective transformation from camera plane to road plane

Since the aim is to find the lateral position of the vehicle inside the road lane, short range line detection is enough for this application. Therefore, road lines are modelled as straight lines. One assumption at this point is that curved roads are seen as straight in the short range. The procedures that are applied in the pre-processing and feature extraction stages perform well enough to indicate the line positions; therefore, a simple procedure is done to locate road lines. Horizontal projection of the image is taken in a limited region so that the line locations appear as peaks in the horizontal projection vector. The region whose horizontal projection taken is chosen to minimize the noise in peak detection as shown as a red box in Figure 3.7. In Figure 3.8 two sample projections are presented. The figures on th left belongs to an image frame during driving in a straight road lane while the figures on the right belongs to an image frame during a lane change event. As can be seen in these figures, horizontal projection vector is distorted due to utilizing last K images in the temporal filter. However, this distortion is so small that certain peaks can still be seen in the projection vector.

Once the horizontal projection of a binary image is obtained, peak locations and their values in this horizontal projection vector is determined according to Algorithm 1.

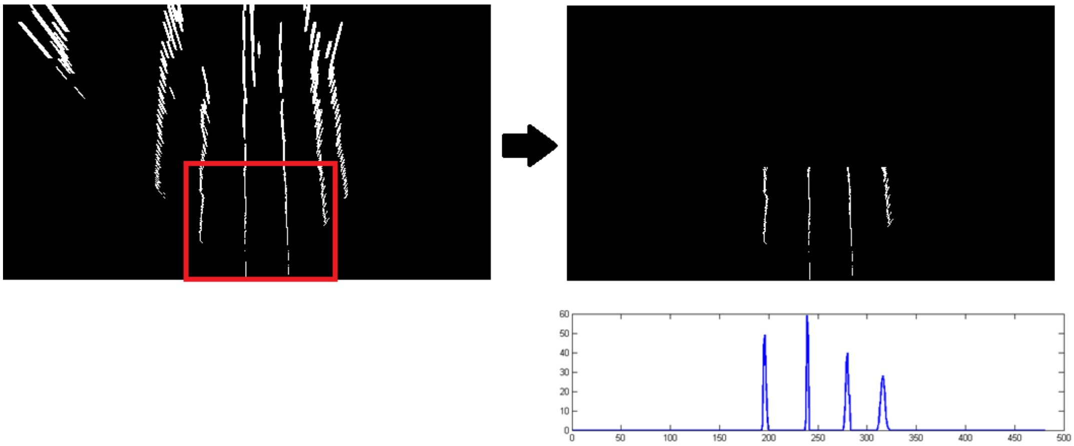


Figure 3.7: Line position detection by horizontal projection The figure on the left top represents the processed and transformed image. The red box represents the limited interest region. The figure on right top is the masked version according to interest region. The graph on right bottom is the horizontal projection of the image

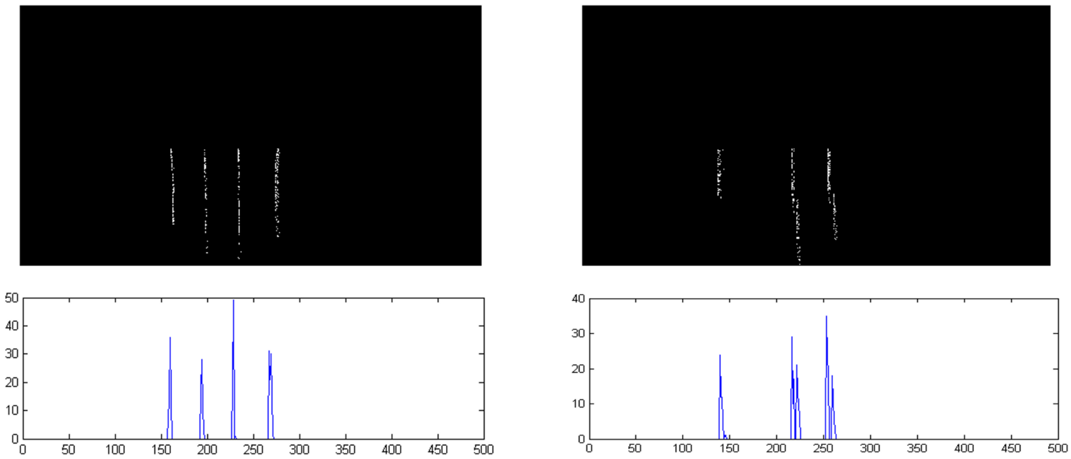


Figure 3.8: Sample binary images and their horizontal projections; figures on the left belong to driving in a straight lane, figures on the right belong to a driving during a lane change

As a result of this process in noisy cases, unnecessary peaks may occur in the

Algorithm 1 Peak Detection Algorithm

$trend \leftarrow increasing$

for $i \leftarrow 1, n$ **do**

  if $trend = increasing$ & $projection(i-1) \leq projection(i)$ **then**

    $continue$

  else if $trend = increasing$ & $projection(i-1) > projection(i)$ **then**

    $trend \leftarrow decreasing$

    $peaks.append \leftarrow projection(i-1)$

    $peakLocations.append \leftarrow (i-1)$

    $continue$

  else if $trend = deccreasing$ & $projection(i-1) \geq projection(i)$ **then**

    $continue$

  else if $trend = decreasing$ & $projection(i-1) < projection(i)$ **then**

    $trend \leftarrow increasing$

    $continue$

  end if

end for

horizontal projection. However, the peaks that indicate a line position generally appears to be the highest ones. In order to eliminate the unnecessary peaks and select the correct ones, a peak selection algorithm is used. The pseudo code of this algorithm is provided as Algorithm 2. As the result of this algorithm example of peak detection can be seen in 3.7.

In Algorithm 2, *minimumPeakDistance* is a value that represents the minimum lane width in pixel values. This value is defined by measuring the lane width in birds-eye view image. However, in order not to miss any proper peaks in projection vector, this value is defined experimentally as 30% less than an average lane width.

One last step that is used to increase the stability and accuracy of line detection is tracking the detected lines which will satisfy the temporal integration of the frames. At this stage, tracking by Kalman filtering is used. As mentioned in Section 3.1.1.1 the two mostly used method for temporal integration of road line detection is Kalman filtering and particle filtering. In literature it is stated that particle filtering performs better than Kalman filtering when the smoothness is low due to high vibration. However, in our case the vibration effect is low since most of the road data is obtained from highways which provides a smooth drive. Therefore, Kalman filtering is used [81] which has a simpler formulation as:

$$\begin{aligned}
\hat{x}_k &= A\hat{x}_{k-1} + Bu_k \\
P_k &= AP_{k-1}A^T + Q \\
K_k &= P_k H^T (HP_k H^T + R) \\
\hat{x}_k &= \hat{x}_k + K_k(z_k - H\hat{x}_k) \\
P_k &= (I - K_k H)P_k
\end{aligned} \tag{3.4}$$

In this formulation x_k is the state of the process and z_k is the measure of the process. P_k represents the covariance matrix, Q represents the process noise covariance, R represents the measurement noise covariance while A, B and H are the coefficient matrices that are relates the current and previous state; state and measurement. States and measurements that are used in these equations

Algorithm 2 Peak Selection Algorithm

$m \leftarrow minimumPeakDistance$

for $i \leftarrow 1, length(peaks)$ **do**

  $maxPeakValue \leftarrow max(peaks)$

  $h \leftarrow location(maxPeakValue)$

  $maxLocation \leftarrow peakLocations(h)$

  $LinePosition.append \leftarrow maxLocation$

  $peaks.remove(h)$

  $peakLocations.remove(h)$

  for $j \leftarrow 1, length(peaks)$ **do**

    if $abs(maxLocations - peakLocations(j) < m)$ **then**

      $peaks.remove(j)$

      $peakLocations.remove(j)$

    end if

  end for

end for

are the 4 dimension vectors that contains x coordinate of both tips of left and right line.

This kalman filter scheme includes smoothing the line detection with kalman filter as well as keeping the visibility counts of lines and recovering missing detections for a specific frame. In other words, detected lines for a specific frame is indicated as lines only if they are consistent and if a line is not consistent for a number of frames it is discarded. Flowchart of this mechanism can be seen in Figure 3.9.

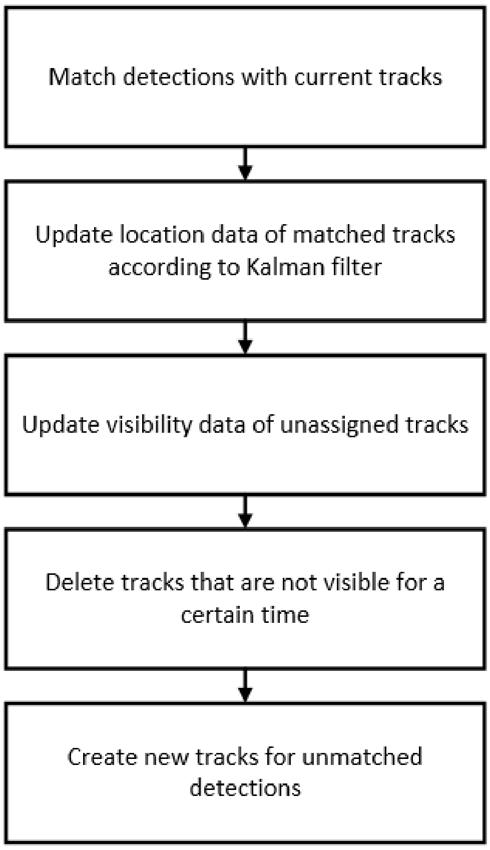


Figure 3.9: Flowchart of Tracking Mechanism with Kalman Filter

According to this algorithm first the found detections are matched with current tracks. The matching process is done by searching each detection among the existing tracks. The track that gives the least error for a detection is chosen as matched track. If the detection is not close to a track less than a specific distance, it is not matched with any tracks. For the matched tracks and detections location parameters of the tracks are updated according to Kalman filter equations and matched detections. For the unmatched tracks, age and visibility counts are updated; tracks that are non-visible for a certain time are cleared and new tracks are defined for the unmatched detections. The visibility and age thresholds are found experimentally and this scheme significantly improves the efficiency of the overall process.

In order to determine the position of the vehicle inside the lane, two closest detected lines from the mid-point, which is defined beforehand as a pixel value according to horizontal positioning of the camera, are chosen as own lane boundaries. Then the horizontal position of the vehicle inside the lane is determined as parameter between -50 and 50 for each frame I_k.

3.1.1.3 Line Detection Results

The presented method is tested with real traffic data which include different environment conditions such as occlusion, shadows, road curve and discontinuities. As can be qualitatively seen in the sample figures (Fig. 3.10) line detection method show robustness to different environment conditions.

In order to test the accuracy and reliability, the presented method is tested with Borkar's dataset [14]. As presented in [14] the available public datasets and benchmark results for line detection is not easy to find. However, Borkar's work is a recent work and in its dataset there exist video sequences containing driving sessions at urban road, metropolitan highway and isolated highway whose ground truth road line positions are provided. Some sample images from Borkar's dataset can be seen in Figure 3.11.

Since the main aim of road line detection module is to extract the position information of the host vehicle inside the lane, these ground truth values are used to determine the ground truth values of lane position. For this task, pixel value of camera center is required since it determines the center of the vehicle inside the lane. In order to find this value, sample video sequences are examined and one frame in which the host vehicle passes on a road line is considered. Due to perspective distortion, all straight road lines in the frames are seen with a

Figure 3.10: Correctly detected lines in different frames

slope different than ∞, that is not vertical, except the ones that the host vehicle is passing on. As can be seen in Figure 3.12 the frame in which the road line is seen as vertical can be used to determine the location of camera center. In Figure 3.12 x-coordinate of the vertical line indicates the camera center value

(a) (b)

(c)

Figure 3.11: Sample images from Borkar's Dataset, (a) urban area, low traffic (b) metro highway, dense traffic (c) isolated highway, moderate traffic

and this is shown with a red line. For this process camera is assumed to be placed in the middle of vehicle.

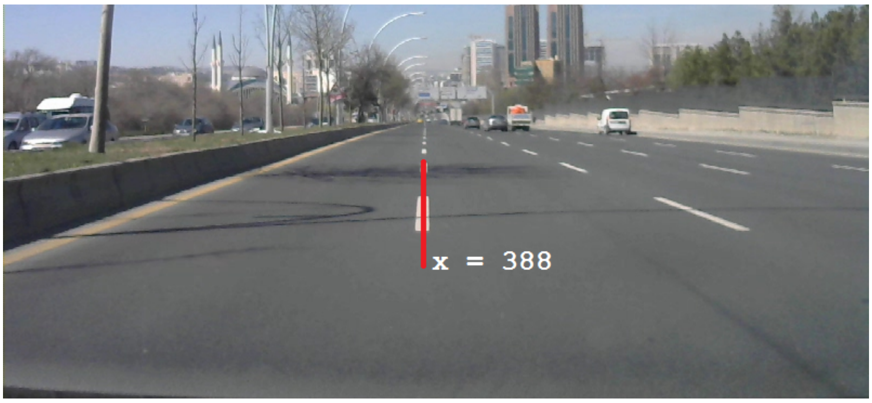


Figure 3.12: Determining camera center by observing the horizontal road line

In Figure 3.13 it can be seen that for different video sequences lane position information is determined accurately. When these figures are examined it can be said that proposed method works better for datasets that contain highway images than datasets that contain urban road images. The main reason of this situation is that in urban roads road lines are not as clear as in highways which makes them difficult to detect. Traffic density also effects the performance of the system since the increasing number of vehicles on road create occlusions and shadows on the road and reduces accuracy. When the metro highway and isolated highway datasets are compared, the effect of traffic density can be seen in the related figures. Another point to mention about the results is that lane change events may create error as can be seen in Figure 3.13 (b). The peaky behaviour of the signal around frame number 350 indicates a very sharp lane change and proposed system fails to detect the lane position correctly at that instant. Due to temporal filter that is used to indicate road lines, very sharp lane changes may create distortion in the filtered image which can be seen as lateral shifts in the road lines. This situation disturbs horizontal projection and creates errors for very sharp lane changes. Adjusting kalman filter parameters for giving more confidence to measurements, that is reducing the covariance of measurements, may work for overcoming this problem. However, the proposed system works well and detects the lane position in lane change events if the lane change does not occur at extreme sharpness. A smooth horizontal movement pattern can be seen in Figure 3.13 (a) between 750^{th} and 900^{th} frames.

In order to quantify the accuracy of the position information over a video sequence, mean absolute error MAE values are calculated. As indicated in [25] MAE can be used for measuring estimation accuracy of driving signals such as speed, orientation etc. Hence for each presented sequence in Figure 3.13 a mean absolute error (MAE) value is calculated as

$$MAE = \sum_{i=1}^{N} \frac{|LaneDeviation_{GT}(i) - LaneDeviation_{measured}(i)|}{N} \tag{3.5}$$

where N represents the total number of frames in a sequence. These values are presented in Table 3.1. MAE values in this table represent the average deviation of measured lane position information from the ground truth value. Among the three different datasets the one which has highest MAE value is urban dataset. The reason of this relatively high value is that in urban region road lines are not

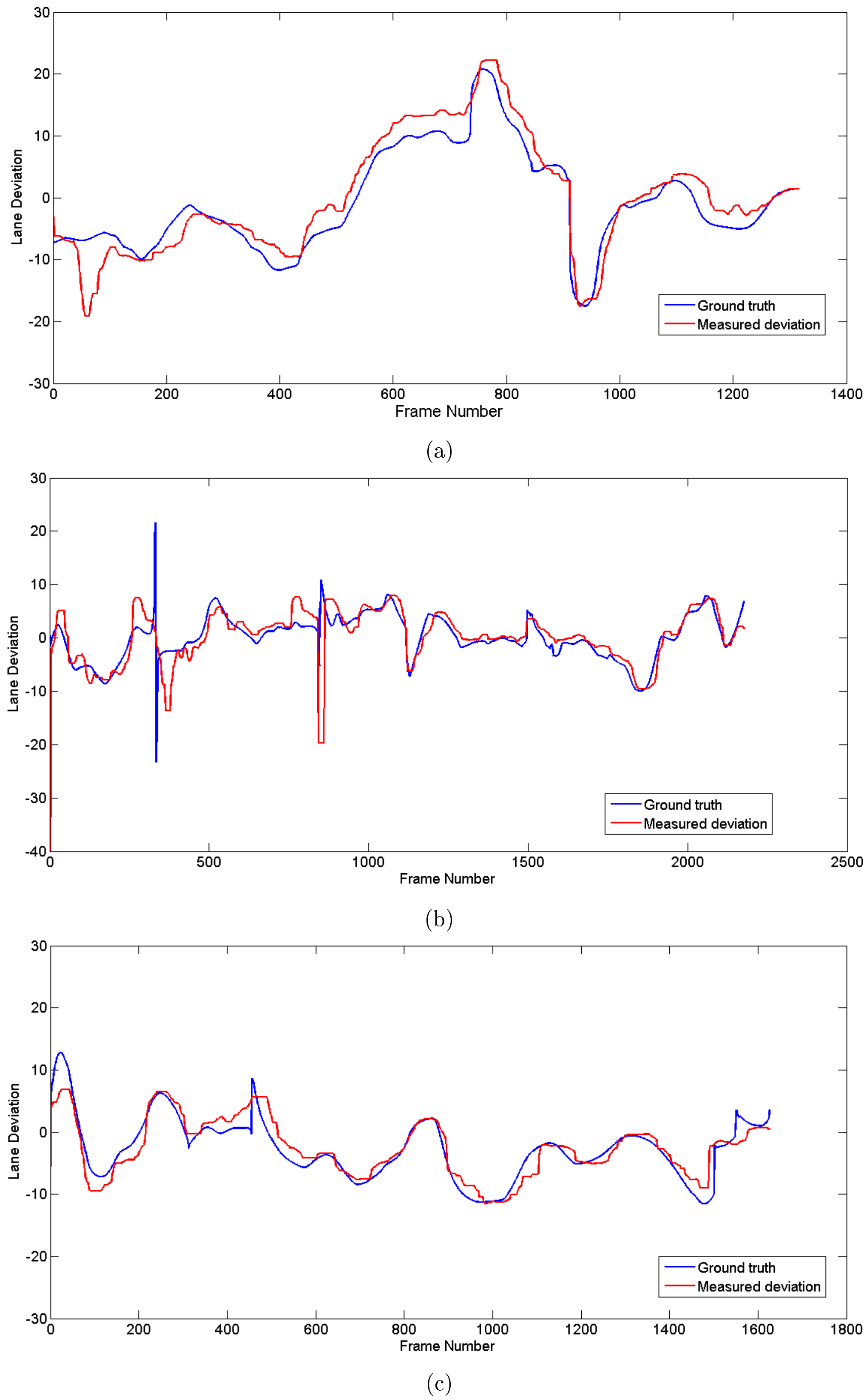


Figure 3.13: Comparison of lane position detection with ground truth values in Borkar's dataset (a) urban area, low traffic (b) metro highway, dense traffic (c) isolated highway, moderate traffic

as obvious as in the highways or main roads. Nevertheless, MAE value of 2.47 in $\{-50 : 50\}$ scale is very low which does not have a significant deteriorating effect on aggressiveness decision. Moreover, the feature extraction method with histogram modelling further eliminates the current error rate by representing time series signal as distribution functions. Regarding the mean absolute error values of the sequences it can be said that for different conditions the presented method performs lane position detection with a reasonable error rate.

Table3.1: Mean absolute error values for different road and traffic conditions

Road Condition	**Mean Absolute Error**
Urban Area, Low Traffic	2.47
Metro Highway, Dense Traffic	1.96
Isolated Highway, Moderate Traffic	1.51

Proposed lane deviation detection method results is compared with other methods in the literature which is tested for Borkar's dataset. As presented in [37], Jung et. al. stated that lane detection rate for their method and Borkar's method are as in Table 3.2. Proposed method is also tested with video sequences from Borkar's dataset containing different conditions and the results are presented in Table 3.2. For this comparison, the measured lane position information is counted as correct if the measured value deviates from the ground truth values less than 4 in $\{-50 : 50\}$ scale. This threshold is determined as 4 since in the Borkar et. al.'s work [14] it is stated that the error is accepted as negligible if it is less than 6 inches. Assuming that the width of a standard road is 3.5 meters, in $\{-50 : 50\}$ discretized scale 6 inches correspond to 4 and correction rate determined according to this threshold.

Proposed method provides similar results with existing methods, performing better for urban dataset which is more critical in terms of aggressiveness detection. Moreover, the lane deviation values over frames will be represented as distributions which is explained in Feature Extraction section. This process will further compensate the deteriorating effect of errors regarding aggressiveness detection.

Table3.2: Correct detection rate of different methods of Borkar's dataset

Category	Borkar	Jung	Proposed
Isolated Highway	98.24%	**98.31%**	93.92%
Metro Highway	98.12%	**98.33%**	95.04%
Urban	87.12%	90.52%	**93.31%**

3.1.2 Vehicle Detection

Vehicle detection process is required in order to find the distances between host vehicle and other vehicles that can be seen from the camera. This distance will be used to build up a feature which characterizes tailgating or unsafe following distance behaviour. Therefore, the process consist of mainly two parts. In the first part, vehicles should be detected in the images and in the second part the distance between the host vehicle and detected vehicles should be found. For vehicle detection task a simple and robust approach is used for the sake of real time operation and HOG features are employed with a cascade classifier. Algorithmic efficiency and accuracy of vehicle detections are also improved by exploiting lane detection results since only the vehicles which are in the same lane with host vehicle are important. This condition enabled running vehicle detection process in a specific region of interest. For the distance estimation part inverse perspective mapping is used since the operation depends on monocular vision.

3.1.2.1 Related Work

Different approaches has been proposed in previous studies about on-road vehicle detection. In most of these studies vehicle detection is associated with forward collision warning systems (FCWS) which is a part of advanced driving assistance systems (ADAS). Existing modalities for on-road vehicle detection mainly include radar, lidar and vision based sensing [76]. RADAR technology uses emission of millimeter wave radio signals to detect vehicles on the road. By analysis of reflecting signals the existence and distance of target vehicles can be determined [50]. Although radar based systems work quite well for narrow field-of-view applications, they provide noisy measurements needing further filtering and de-noising operations. And they fail to discriminate vehicles and different obstacles.

A better alternative to radar sensing is utilization of lidars. Popularity of lidars has rised recently that they are broadly used in autonomous vehicles for obstacle detection [43]. Lidars emit laser beam at invisible wavelengths by scanning the scene and receive the reflected energy to perform object detection. Therefore, lidars provide information about depth and shape of the detected objects. In spite of its efficiency in terms of detection, the main drawback of lidars is the economical cost. The price of the lidar sensors has decreased in the recent years; however, today the cost of lidar systems is the major drawback [76].

Considering efficiency and cost factors together, vision based platforms that exploits image processing techniques are on the top of the list for on-road vehicle detection systems. Vision based systems provide rich data about the environment with low cost. With the help of computer vision and image processing tools this data is analysed and vehicle detection is performed. The main drawback of vision based systems is sensitivity to weather and light conditions compared to previously mentioned methods. Among the proposed systems in the literature, there exist monocular and stereo vehicle detection systems. Both systems use similar methods and algorithms regarding computer vision and image processing techniques; however, as the difference, stereo systems utilize the correlation between the images that are taken by two cameras and extracts depth information. Depth information provides better estimation for distance measurement and better results for occlusion handling [41, 56]. Although stereo based systems provides better results than monocular systems they need more complex hardware and computation power compared to monocular systems.

Monocular vision based on-road vehicle detection systems can be classified into two main categories as motion based or appearance based methods. Appearance based methods detects vehicles inside one image while motion based methods use motion information in image sequences [76]. Although there does not exist a certain performance distinction between appearance and motion based approaches, appearance based methods are more dominant in literature. Appearance based methods provides more direct solution for vehicle detection task while motion based methods first require appearance based cues about objects then extract motion information. Therefore, appearance based methods are more commonly used for vehicle detection [79].

Considering motion based methods for vehicle detection in the literature, optical flow calculation and background subtraction are used as the common tools [76]. Optical flow occur due to the relative motion between camera and scene and can be obtained by calculating the vector field that represent this relative motion [48]. In other words, the location change of a pixel (x, y) between two time instants, represents the optical flow. The vehicles in the scene produce different optical flows according to their velocity and they are also distinguished from the stationary objects [79]. Most of the motion based vehicle detection methods in the literature exploit this idea to detect vehicles on road [8, 51, 69]. Background modelling for vehicle detection is used to model scene which has stable points and to differentiate the moving vehicles in next frame [15]. As explained before, motion based vehicle detection methods do not directly provide solution to vehicle detection problem and need further processes or appearance based information in most of the cases. Therefore, appearance based methods are seen more frequently in the literature.

Appearance based methods basically exploit the distinguishing features of vehicles on road and use techniques to identify regions/pixels that contain these features. For the appearance based methods in the literature, vehicle detection process mainly consist of three steps as:

- Feature extraction
- Feature Classification
- Object tracking

In order to realize an effective description of images a feature extraction procedure is applied. In earlier works, symmtery and edge information is used while in recent works more complex and robust features are used in order to detect vehicles in the scene [79]. Therefore, among the existing different methods in the literature for feature extraction, mostly used ones can be exemplified as HOG [80], Haar-like features [21], SIFT [94], SURF [46] and Gabor features [95]. These features are more efficient for handling challenges illumination changes, pose changes and partical occlusions [79]. According to [76] among these presented features, HOG and Haar-like features constitute the large portion regarding recent vehicle detection works since they provides robust and fast operation.

For feature classification the dominant methods are presented in the literature as artificial neural networks [78], support vector machines [80], cascade classifier [75] and AdaBoost [87]. The common point of these classification methods is that they apply a training process to obtain a decision boundary and classify the samples according to this decision boundary. The presented works in the literature propose the usage of different combination of these classifiers and feature descriptors that are explained in the previous paragraph. For instance in [47] SVM classification is used to classify feature vectors obtained by Haar-like features while in [80] HOG features of images are classified by SVM. Among the classification techniques for vehicle detection, Adaboost and SVM are widely used in recent works since their training process conceive a global optimum over the given training set [76].

Since vehicle detection task is also done over consecutive frames, the utilization of temporal information is done via object tracking. Tracking helps estimation of the vehicle position in the following frame and reduction of false positives. For this task, principal methods in the literature are seen as kalman filtering [32] and particle filtering [18].

One other task to accomplish after vehicle detection is to estimate the distance between the host vehicle and detected target vehicles. With a monocular vision system, distance estimation can be achieved with assumption that the road surface is planar. One approach that is presented in the literature for monocular distance estimation is to utilize the width of the bounding boxes around the detected vehicles. That is the larger width means the closer distance [9].

3.1.2.2 Proposed Vehicle Detection Method

For aggressive driving behaviour analysis application in vehicle detection stage HOG feature extraction is employed. Since HOG is widely used and stated to be a robust approach to identify rear view of vehicles [76]. A cascade classifier detection technique is used in order to detect vehicles inside the images, because cascade classifier is a robust and fast method which can easily be used in real time object detection applications [84]. In order to determine the distances of detected vehicles inverse perspective mapping applied and distances are found from the birds-eye view perspective.

Histogram of Oriented Gradients

In order to describe the vehicle images inside the taken frames, HOG features provides a description based on edge directions since it uses gradients. This corresponds to an effective description because rear view of the vehicles can easily be identified by their characteristic shape. HOG features [23] are calculated according to the flowchart given in Figure 3.14.

As the first step to calculate HOG features x and y derivatives, i.e gradients, (I_x, I_y) are found in order to calculate magnitude G and orientation θ according to:

$$|G| = \sqrt{{I_x}^2 + {I_y}^2} \quad and \quad \theta = tan^{-1}(\frac{I_y}{I_x}) \tag{3.6}$$

Then the image is divided into $N \times N$ cells and a weighted vote is calculated for edge orientation according gradient magnitudes for each pixel in these cells. These votes are utilized to build up a histogram which is quantized into a specific number of bins. In order to increase the effect of gradients which is close to cell center, a Gaussian weighting function is used.

In order to provide a robustness to illumination changes, the cells are normalized.

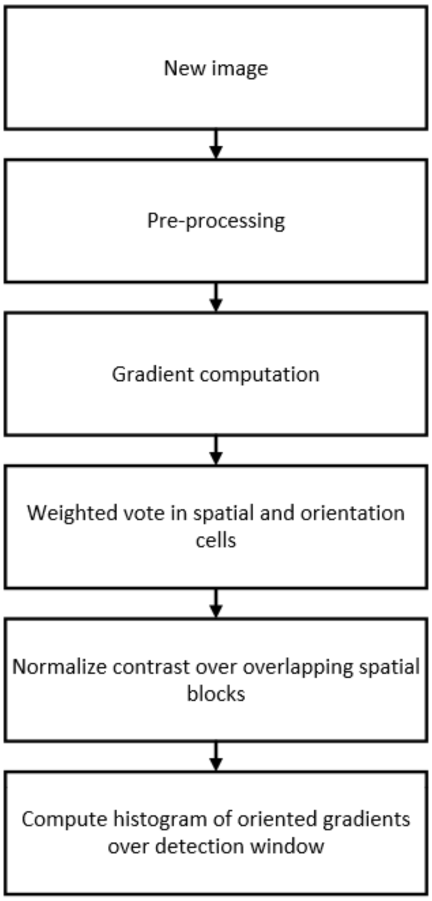


Figure 3.14: Steps to Calculate HOG Features

This process is done over blocks that are constituted by combination of cells 3.15. The normalization process provides the stretching of low contrast regions. Finally the histograms vectors are concatenated to obtain the global feature vector to describe the shape of the image.

For this study number of bins is selected as 9, cell size is chosen as 8×8 and number of cells in a block is chosen as 2×2 as presented in [23]. The presented study in [23] covers an application towards detection of pedestrians; however, the mentioned parameter values provided good results also for vehicle detection task.

Cascade of Classifiers

The HOG features are calculated over a rectangular search window inside the image. For the presented application the smallest search window is determined

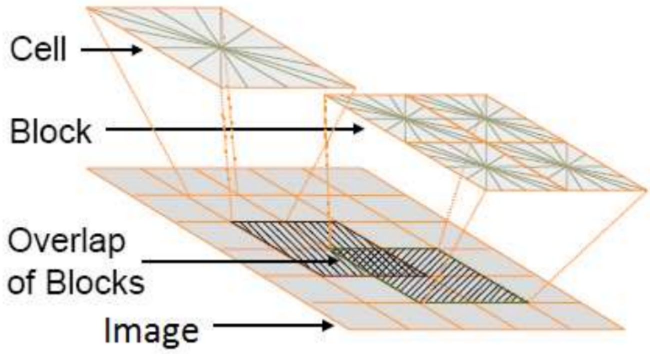


Figure 3.15: Visualization of HOG cells and blocks [27]

as 24×20 in order to represent the shape of vehicle which are very far. And the window size is increased up to 120×100 by keeping the aspect ratio. Once these windows are represented by HOG features as explained in the previous paragraph, classification of these features results in the decision whether there exist a vehicle or not inside the examined search window. For this classification task a cascade of classifiers are used since it increases the detection performance and decreases the computation time [84]. Cascade of classifiers consist of weak classifiers that are combined with different weights to construct a strong classifier. As explained in [76] cascade of classifiers which are trained using AdaBoost performs well for vehicle detection task.

A weak classifier $h_j(x)$ is defined as:

$$h_j(x) = \begin{cases} 1, & p_j f_j(x) < p_j \theta_j \\ 0, & otherwise \end{cases} \tag{3.7}$$

where x is a sub window of the image, f_j is a single feature, θ_j is threshold and p_j is the parity indicating the direction of the inequality sign. Each of these weak classifiers represents a feature. In order to increase the classification performance, a process that is called boosting is applied to these classifiers. Boosting means combining weak classifiers to obtain a strong classifier. As mentioned in [76] vehicle detection studies have moved toward algorithms which converge to a global optimum over training set such as AdaBoost. Therefore, in this work AdaBoost algorithm [5] is used to train weak classifiers which is given in Algorithm 3.

Algorithm 3 AdaBoost Algorithm

$Given(x_{1..i..N}, y_{1..i..N});\ x_i\ a\ sub-window\ and\ y_i \in 0, 1$

$Initialize\ weights\ w_{1,i} = \frac{1}{m}$

for $t \leftarrow 1, T$ **do**

$Normalize\ the\ weights,\ w_{t,i} \leftarrow \frac{w_{t,i}}{\sum\limits_{j=1}^{n} w_{t,j}}$

$Evaluate\ error\ w.r.t\ w_t\ \epsilon_j = \sum_i w_i |h_j(x_i) - y_i|$

$Choose\ h_t\ with\ minimum\ error\ \epsilon_t$

$Choose\ \alpha_t = \frac{1}{2} ln\big(\frac{1-\epsilon_t}{\epsilon_t}\big)$

$Update\ the\ weights\ w_{t+1,i} = w_{t,i} exp(-\alpha_t y_i h_t(x_i))$

end for

As a result of the AdaBoost algorithm a strong classifier $H(x)$ is obtained as shown in Eqn. 3.8.

$$H(x) = \begin{cases} 1, & \sum\limits_{t=1}^{1} \alpha_t h_t(x) \geq \sum\limits_{t=1}^{1} \alpha_t \\ 0, & otherwise \end{cases} \tag{3.8}$$

Cascade of classifiers is based on an approach that uses a decision tree where each stage is a classifier. This cascade structure enables immediate rejection of negative samples in early stages thus increases the detection rate and decreases the computational complexity. Each stage of the cascade classifier is constituted by a boosted classifier which is responsible for any number of features. This structure takes all sub-windows as input, eliminates a portion of negative samples in each stage and passes the positives to the next stage. A schematic description of the cascade of classifiers structure can be seen in Figure 3.16.

For this study a cascade of classifiers is trained using road scene and vehicle rear view images. 1700 empty road scene images are labeled as negative and 820 vehice images are labeled as positive and fed to the classifier for training purpose.

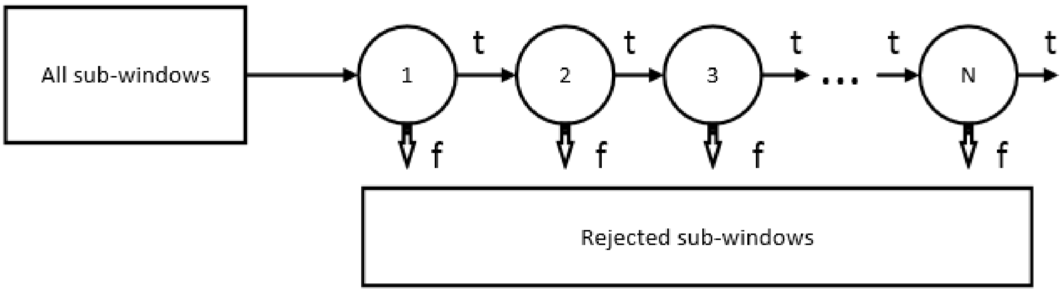


Figure 3.16: Schematic description of the cascade of classifiers structure

Tracking Detected Vehicles with Kalman Filter

Since the vehicle detection task is done over consecutive frames, temporal integration of detection results in different frames increases the detection rate similar to line detection as explained in Section 3.1.1.2. Since the problem is similar to the temporal integration task done for line detection method, the same formulation is applied for this problem too. Therefore, detected vehicle images are tracked by Kalman filter according to Kalman filter equations presented in Equation 3.4 and flowchart presented in Figure 3.9. For this task a constant velocity model is assumed.

Distance Estimation

One last task to be done after the detection of the vehicles is to determine their distances to the host vehicle. In a monocular approach the distance estimation is difficult than the stereo approach since depth information does not exist. However, based on the assumption that the road surface is piecewise planar, perspective transformation of the image to the birds-eye view provides information about the distance of the detected vehicles. On each frame detected vehicles are represented with a bounding box and the midpoint of the bottom edge of this bounding box is used to determine the distance. In other words, the bottom edge is taken as the line where the vehicle touches the road surface and the distance of this edge to the camera is taken as the distance of the vehicle in pixel units as in Figure 3.17. Distance values for the vehicles are determined according to their vertical distance due to this process. However, since the vehicles which are on the same lane are important for the aggressiveness detection, this process provides satisfying results.

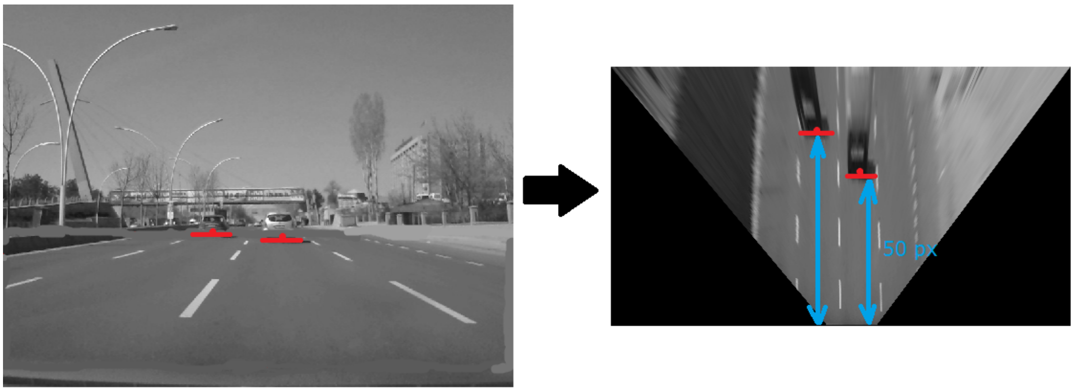


Figure 3.17: Estimation of distance of detected vehicles

As the result of this operation distance of vehicles to host vehicle is determined in pixel units. In order to convert pixel units to metric unit the pixel distance is multiplied by a constant C. This C constant is calculated experimentally according to the experiment set-up before the whole operation starts. This task is achieved by measuring a known distance in pixel values in the same perspective. For instance, the length of a road line in Figure 3.17 is 6 meters and with the given perspective transformation, it corresponds to 20 pixels. Therefore, the constant C is defined as:

$$C = \frac{Distance \quad in \quad metric \quad units}{distance \quad in \quad pixel \quad units} \tag{3.9}$$

3.1.2.3 Vehicle Detection Results

Some examples of vehicle detection are presented in Figure 3.18. In these figures it can be seen that different types of vehicles such as auto mobiles, vans and trucks are detected correctly. These results also shows that proposed system works well for detection of both dark and light coloured vehicles. The vehicles which are at a very far distance from the host vehicle are not detected since they do not have the proper HOG features due to their size. However, this is not a big problem for the overall system since these vehicles which are far from host vehicle do not have significance about driver aggressiveness. When the distance value results are considered qualitatively, it can be concluded that they are reflecting true and coherent results.

Figure 3.18: Correctly detected vehicles and their distances to the host vehicle in different frames

The presented vehicle detection method is a well known and simple scheme and it gives satisfying results regarding our problem definition. So as to assess the performance of the method we utilized LISA-Q Front FOV Dataset [75] which contains 3 different annotated video sequences. Sample snapshots of these datasets can be seen in Figure 3.19. In [75] presented method is tested with LISA dataset and the results are given according to several performance metrics. The details of these metrics can be found in [75].

Since ultimate aim of the method is to find the distance between host vehicle and target vehicle, region of interest in the front view image is reduced according to the results of lane detection. In other words, it is aimed to detect the vehicles

(a)

(b)

(c)

Figure 3.19: Sample images from LISA-Q Front FOV Dataset, (a) Dense (b) Sunny (c) Urban dataset

which are in the same lane with the host vehicle. To accomplish this, other detections which are in different lanes are eliminated but host vehicle's. This approach improved the results significantly for each dataset. In Table 3.3, 3.4 and 3.5 performance results of proposed method with region of interest selection and comparison with Sivaraman's method which is given in [75] can be seen for dense, urban and sunny datasets respectively. For performance comparison purpose, metrics that are given in the work of [75] are utilized. These metrics can be seen in Eqn. 3.10. With TPR, true positive metric, recall and localization of the vehicle detections are measured while FDR, false detection rate, measures the robustness and precision of the system to false positives. Similarly, $FP/Frame$ measures localization using per frame number of false positives while $TP/Frame$ indicates the robustness by per frame number of true positives.

$$
\begin{aligned}
TPR &= \frac{detected\ vehicles}{total\ \#\ of\ vehicles} \\
FDR &= \frac{false\ positives}{detected\ vehicles\ +\ false\ positives} \\
FP/Frame &= \frac{false\ positives}{total\ \#\ of\ frames\ processed} \\
TP/Frame &= \frac{true\ positives}{total\ \#\ of\ frames\ processed}
\end{aligned} \tag{3.10}
$$

Table3.3: Performance Evaluation of Different Methods for Dense Dataset

Method	**TPR**	**FDR**	**FP/Fr.**	**TP/Fr.**
Sivaraman's Method [75]	95.0%	6.4%	0.29	4.20
Our Method w/o Lane Selection	78.4%	43.0%	2.44	3.23
Our Method w/ Lane Selection	89.9%	9.8%	0.09	0.85

Table3.4: Performance Evaluation of Different Methods for Urban Dataset

Method	**TPR**	**FDR**	**FP/Fr.**	**TP/Fr.**
Sivaraman's Method [75]	91.7%	25.5%	0.39	1.14
Our Method w/o Lane Selection	99.0%	36.5%	0.57	0.99
Our Method w/ Lane Selection	99.0%	20.6%	0.25	0.99

Table3.5: Performance Evaluation of Different Methods for Sunny Dataset

Method	**TPR**	**FDR**	**FP/Fr.**	**TP/Fr.**
Sivaraman's Method [75]	99.8%	8.5%	0.28	3.17
Our Method w/o Lane Selection	98.7%	25.9%	1.04	2.97
Our Method w/ Lane Selection	98.7%	4.8%	0.05	0.99

As can be seen in these tables proposed method performs an average accuracy over 95% for different conditions. Combining lane detection results with vehicle detection results significantly improved the performance by increasing true positive rate in dense dataset which includes dense traffic images. Furthermore, it decreased the false positive rate in all cases by outperforming the benchmark results in two datasets.

For the dense dataset due to dense traffic conditions and huge number of vehicles in the scene performance of the proposed system is a little lower than the benchmark method as in Table 3.3. As indicated in [75], active learning process of the benchmark method provides a high detection rate since it constructs a better classifier by training it in an adaptive way. The main reason of this small performance difference is that during lane change events target vehicle is changing and system adapts to new target vehicle after a few frames. Therefore, some false positives and missing detections occur during lane changes. The second reason of the performance difference is that the proposed system is trained using vehicle images taken by a better resolution camera. Hence, the training set contains better image features while the test data does not. This situation also decreases the efficiency of the proposed system.

For Urban and Sunny dataset proposed method provides true positive rate at level of 99% by outperforming the benchmark method at Sunny dataset as presented in Table 3.4 and 3.5. The outperforming result in Urban dataset is due to the fast adaptability of tracking mechanism of the proposed system. For instance, in the Urban dataset when the vehicle is passing on a speed bump, the position of detected vehicle is changing vertically and proposed system can track the vehicle without missing it.

According to main purpose of the overall system which is to detect aggressive driving behaviour, lane selection for vehicle detection increases the performance significantly. This effect can be seen in all types of datasets by high true positive rate and low false positive rate. Lane selection also decreases the computation cost by limiting the search region which is a critical aspect for this application.

3.1.3 CANBUS Data Acquisition

Most of the new cars are equipped with a controller area network (CAN) bus which is enables the communication between different microchips and sensors inside the vehicles. It is one of the protocols of On-Board Diagnostics (OBD) which refers to the self diagnostics and reporting capability of a vehicle. OBD became mandatory in US for the cars that are produced after year 1996 and in Europe after year 2001 [4]. CAN bus has a standardized physical connector and a protocol so that the vehicle data can be obtained using the CAN bus port for analysis and diagnosing purposes.

For the presented system, vehicle status signals such as vehicle speed and engine speed is used as the sensor based information since these information is associated with driving behaviour. As indicated in [59] abrupt acceleration and deceleration can be an indication of aggressive driving. Moreover, the gas pedal pressure is also a characteristic signal regarding aggressiveness [74] which results in the change of engine speed. Therefore, vehicle and engine speed values are used as features. In order to collect these data external sensors can be used [30]. However, instead of using external sensors, CAN bus system of the host vehicle can provide this information with a proper adapter as shown in Fig.3.20. This adapter converts CAN bus signals to be readable through a universal serial bus (USB). As used in [44, 73] collecting the vehicle status signals from CAN bus reduces the hardware complexity.

Figure 3.20: CAN bus adapter

In order to read vehicle and engine speed data from the CAN bus of the vehicle, a proper adapter is used and related data is obtained with timestamps during driving in order to synchronize the CAN bus data with visual data. Vehicle and engine speed data are collected with a period of one second. Therefore, in order to use this data combined with a higher frequency visual data (i.e 10fps frame rate), it is up-sampled by a factor of 10.

Engine speed is a characteristic that depends on the engine and transmission type of the vehicle. Therefore, for the reliable operation of the system the engine speed values that are collected for aggressiveness decision should either be normalized or the same type of vehicle be used for data collection. During the experiments of this study, which is described in Section 3.2, the data collection is done by the same car which does not allow the problems that may occur due to different vehicle types.

3.1.4 Data Fusion

Aforementioned stages are performed to collect information about the behaviour of the driver in the traffic. These collected information is utilized by a feature extraction and classification stage in order to determine whether the related driving session is aggressive or not. For the characterization of the driving session, four different features are chosen considering the aggressive driving indicating behaviours as explained in Section 3.1. These features are as follows:

- Lane Deviation
- Collision Time
- Vehicle Speed
- Engine Speed

The line detection results and lane position determination is used to construct lane deviation feature which characterizes the abrupt lane changing and not following the lane properly. The information obtained from the CAN bus, vehicle and engine speed, is directly used as the features since drivers who show aggressive driving behaviour tend to drive with high and varying speed; therefore, changing engine speed abruptly. The last feature which characterizes the tailgating and unsafe following distance behaviours is the collision time. Collision time feature defines the duration to collision if the vehicle in front would stop suddenly. Therefore, this feature utilizes both speed and target vehicle distance information. Collision time is calculated with a unit of seconds according to 3.11 where d_k is the distance of the target vehicle in meters and v'_k is the vehicle speed in m/s at that instant.

$$CollisionTime(k) = \frac{d_k}{v'_k} \tag{3.11}$$

Histogram Modelling of Features

Considering all features that characterize the driving session, their variation pattern in a certain amount of time is more informative for us rather than the time series signal itself in terms of driver aggressiveness. For instance, the frequency that a driver changes lanes is a more important information than the lane position value at a specific time frame. Therefore, we represented time series signals as density functions and modelled them using Gaussian mixture model (GMM) which is a powerful technique for density representation [85]. Since we are handling the collected data by batch process, Gaussian modelling provides an effective representation of driving data. The works presented in [30] and [85] use Gaussian modelling of driving signals for making inferences about driving profiles and present effective results in terms of accuracy.

For our application, each feature is transformed into density functions (i.e histograms). These histograms are filtered with a median filter in order to eliminate noisy data. Then they are normalized so that all histograms represent the frequency of the data in the same base. A sample representation of an aggressive and smooth data can be seen in Fig. 3.21. As can be seen in Fig. 3.21 (a) and (b), for a smooth driving vehicle speed and engine speed histograms are seen as closer to impulse shape which shows that the variation is low during the driving session. Another observation about vehicle and engine speed is that for aggressive session their mean values are more than the smooth session. Similarly, for the lane deviation histogram in Fig. 3.21 (c) smooth driving session is seen to have less variance than the aggressive one which means that in aggressive session the vehicle did more lateral movements compared to smooth session. In Fig. 3.21 (d) collision time comparison of smooth and aggressive sessions are presented and for aggressive session, mean of collision time is clearly less than the mean of smooth session which shows that the aggressive vehicle followed the vehicles in front with a closer distance.

An aggressive or a smooth session does not necessarily contain all of the mentioned driving behaviours. For instance, lane deviation, vehicle and engine speed features of a driving session may indicate the aggressive behaviour of the related session while the car following pattern of the same session does not indicate any clue for aggressiveness. Hence, fusion of different driving data provides a better representation of the aggressiveness of a driving session since it considers different indicators.

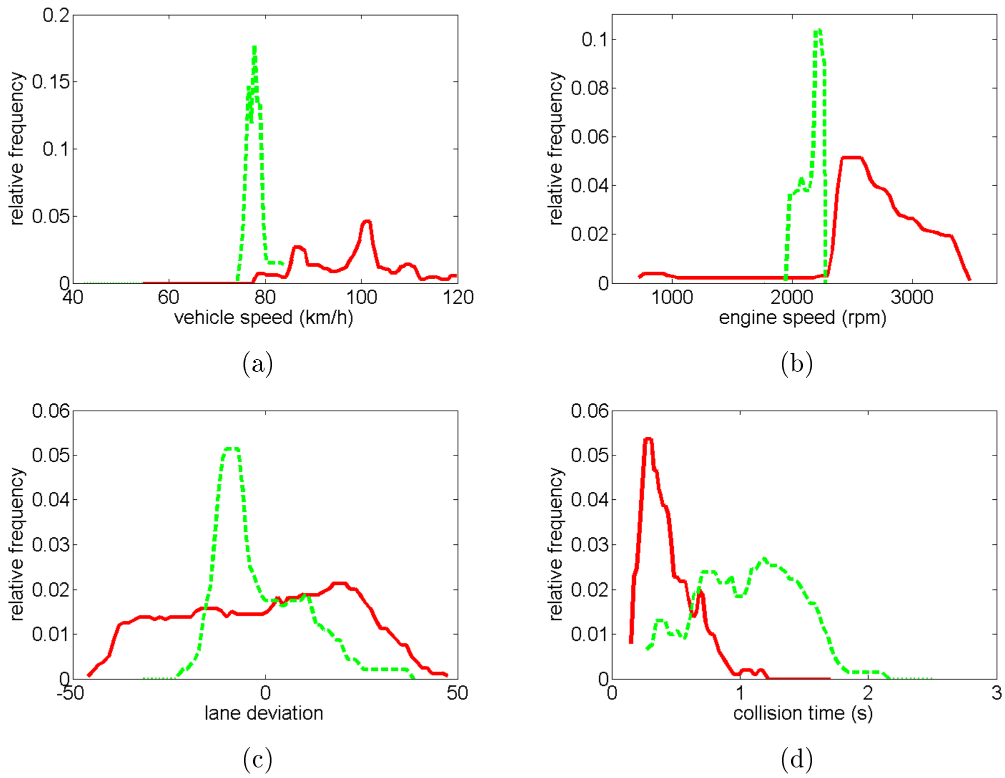


Figure 3.21: Examples of histogram comparison of aggressive and smooth driving sessions for different features; Red solid lines represent an aggressive driving session while green dashed lines represent a smooth driving session in each graph. Figure at (a) presents the vehicle speed distributions, figure at (b) presents the engine speed distributions, figure at (c) presents the lane deviation value distributions and (d) presents the collision time distributions

In order to model the obtained data effectively, the number of GMM components are critical. In order to determine the optimal number of GMM components, sample driving data is modelled using different number of GMM components. In Figure 3.22 GMM modelling of a sample data can be seen which is modelled with 2 components and 4 components. 4 component GMM models vehicle speed data more accurately; however, 2 component GMM data provides a better representation since it gives the general characteristics of the density function with less number of Gaussians. Other obtained driving data also presents similar characteristics as presented in Figure 3.22.

During the experiments it is also observed that density functions of driving signals have one dominant Gaussian component. Hence, histograms are modelled using one GMM component which is denoted by a mean μ and a standard deviation σ value which are enough for representing a Gaussian distribution. GMM components of density function are estimated using expectation maximization algorithm. Each driving feature provided one μ and one σ value. Then these four mean and four standard deviation values are utilized to construct a feature vector consisting eight dimensions. An SVM classifier is employed [22] in order to classify the feature vectors to determine whether a driving session involves aggressive driving behaviour.

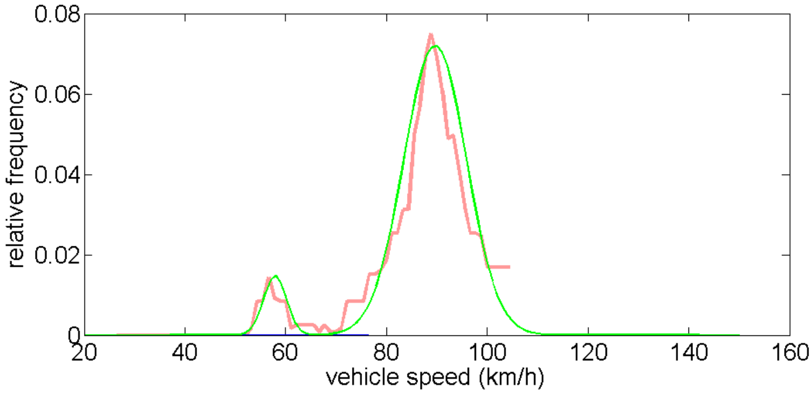
Support Vector Machines

Support Vector Machines [22] are one of the supervised classification tools that separate data points into two classes by a decision boundary. The objective of SVM is to maximize the margin between samples of different classes. The general form of the decision boundary, which is a hyperplane, has the equation:

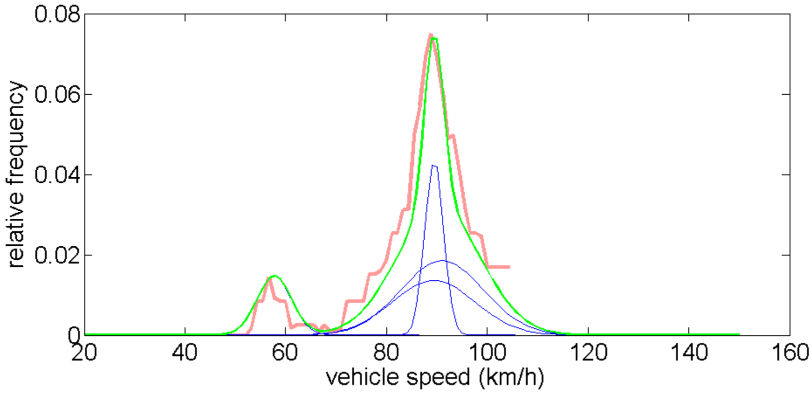
$$f(x) = w^T x + b = 0 \tag{3.12}$$

In this equation x represents the training set of points, in other words vectors which have a dimension of d; while w is a d dimension weight vector and b is a real number. Each vector x_i has a class category denoted by $y_i = \pm 1$. Training procedure of a support vector machine is to find the weight vector w and b that are minimizing $||w||$ subject to the constraint:

$$y_i f(x_i) = 1 \tag{3.13}$$



(a)



(b)

Figure 3.22: Histogram modelling of sample vehicle speed data; The figure presented in (a) represents modelling with 2 Gaussian components, and the figure presented in (b) represents modelling with 4 Gaussian components; The red lines belong to the original data and green lines belong to the aggregation of Gaussian components while blue lines represent the individual Gaussian components

This problem is valid for the case when the data is linearly separable. If the dataset is not linearly separable the optimization process becomes:

$$min(||w||^2 + C\sum_i \xi_i) \tag{3.14}$$

subject to the constraint:

$$y_i f(x_i) \geq 1 - \xi_i \tag{3.15}$$

where ξ_i is used to compensate the effect of misclassified samples due to being linearly non-separable.

In some binary classification problems a hyperplane may not be a proper separating plane. These problems can be overcome by the help of a transformation process which projects the feature vectors to a higher dimensional feature space. By the help of this procedure non-linear classification problems can be handled by support vector machines.

For the driver aggressiveness classification of feature vectors, an SVM classifier with a radial basis function kernel is employed. The reason why radial basis function kernel is chosen is that there exist a non-linear relation between the aggressiveness and related features. For instance, following a vehicle with a close distance is expected to be an indication of driver aggressiveness. However, a driver does not necessarily follow a vehicle in a very close distance in order to be classified as aggressive. Only speed and lane following performance of a driver can indicate its aggressiveness independent from its vehicle following performance. Therefore, the problem shows a non-linear nature. According to Hsu et al. [35], although there does not exist a certain scheme about kernel selection, radial basis function kernel works when the problem is non-linear and the number of features are small.

SVM classification for aggressiveness decision performed well in terms of application reliability and quantitative results of the obtained features for different test cases are presented in Section 3.2.

3.2 Experimental Results

For the test purposes, a mobile set up is constructed in order to collect visual and CAN bus data by vehicle. For visual data collection a 1.2 Ghz portable mini computer (Figure 3.24) and a CCD camera (Figure 3.23) is used. By this platform, video frames are captured at 10 fps with a resolution of 800x600 pixels. For CAN bus data collection the adapter in Figure 3.20 connected to CAN bus port of the vehicle and data acquired through the serial port of the mini computer. The data collected from CAN bus is obtained at each second.

Therefore, data is interpolated so that the sensor data exist for each frame. So as to synchronize the visual and CAN bus data, all of the data is timestamped.

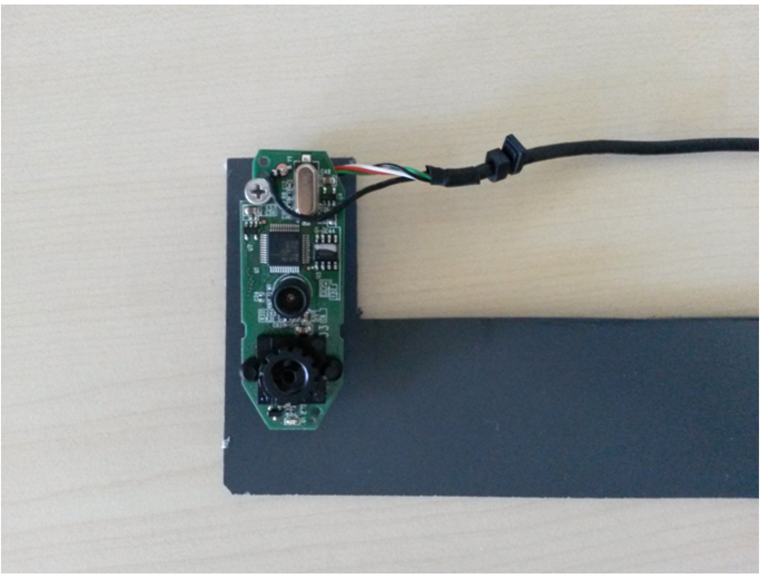


Figure 3.23: Camera to capture visual information

Figure 3.24: Mini computer used in data collection

Utilizing this set up, real traffic data is collected in different time of the day so that different traffic conditions and environment conditions are included in the dataset. The data set also includes different road conditions with occlusions, shadows and different illumination. Whole dataset contains driving sessions of 6 different drivers. During driving, 3 different observers annotated the last 40 seconds as aggressive or smooth. The majority voting of the observers are recorded as the ground truth of the related driving session. These three observers was chosen from a pool of 15 people for different so that a homogeneous aggressiveness annotation can be obtained for the whole dataset.

Test 1: Detection Rate for Different Driving Session Durations

One important parameter that effects the performance of the proposed method is the duration of the driving session. In other words, how long multisensory data is required in order to determine efficiently whether that driving session is aggressive? In order to answer this question the collected data is tested with driving sessions with lengths 40, 80 and 120 seconds. In the work of Gonzalez et al. [30], the driving sessions to evaluate the aggressiveness are determined according to the route length. In other words, driving data of completion of a specific route is utilized for the experiments. The route was 2.5 km's which contains 5×500 meters. Since the speed limit at that route is 50 km/h data duration of a segment corresponds to 36 seconds. Therefore, in this thesis study the aggressiveness annotation is done for each 40 seconds and experiments are conducted for 40, 80 and 120 seconds. From the whole collected data set, total 83 driving sessions including 41 aggressive and 42 smooth sessions having a duration of 40 seconds; 51 driving sessions including 22 aggressive 29 smooth sessions having a duration of 80 seconds; 22 driving sessions including 11 aggressive 11 smooth sessions having a duration of 120 seconds are tested according to proposed algorithm.

Due to limited amount of data, k-fold cross validation technique is used for performance assessment. According to this technique test samples are chosen randomly among the samples, remaining samples are used for training the SVM classifier. This process is performed 10 times and at each run the classifier results are compared with the ground truth. For the 40 seconds long samples, 20 of them; for 80 seconds long samples, 15 of them and for 120 seconds long samples, 9 of them are chosen randomly as test samples. In Table 3.7, 3.8 and 3.9 the related confusion matrices of the test results are given for 40, 80 and 120 seconds long samples respectively.

According to the test results it is observed that the proposed method achieved 91.0% , 94.0% and 82.2% detection rate for 40, 80 and 120 seconds long samples which are presented in Table 3.6. As can be inferred from these results 80 seconds long driving sessions are more efficiently represent the driving characteristics while 40 seconds samples may not allocate enough data or 120 seconds samples may contain confusing data. Although there does not exist so many driving aggressiveness focused study in the literature, the 94.0% detection rate is a successful rate when compared to the result presented in [30] as 92.0%.

In order to train and test the aggressiveness classifier, the driving data is collected and annotated for a specific duration. In other words, during driving data collection, aggressiveness of related samples are determined after a specific number of driving data is obtained. For training and test purposes this periodic operation is utilized; however, for practical operation, once the classifier is trained, the collected samples can be utilized like a sliding window process by utilizing and updating the used driving data. Therefore, a continuous aggressiveness detection can also be possible by this system.

Table3.6: Driver aggressiveness detection rate for different driving session durations

Session Duration	**Detection Rate**
40 seconds	91.0%
80 seconds	94.0%
120 seconds	82.2%

Table3.7: Confusion matrix of aggressiveness classification for 40 seconds long data

		Predicted Class	
		Aggressive	Smooth
Real Class	Aggressive	90	3
	Smooth	15	92

Table3.8: Confusion matrix of aggressiveness classification for 80 seconds long data

		Predicted Class	
		Aggressive	Smooth
Real Class	Aggressive	67	5
	Smooth	4	74

Table3.9: Confusion matrix of aggressiveness classification for 120 seconds long data

		Predicted Class	
		Aggressive	Smooth
Real Class	Aggressive	33	7
	Smooth	9	41

Test 2: Data Fusion by Dimension Reduction

In this test procedure, aggressiveness classification of driving sessions is done using the time series data. In other words, driving data is directly used for classification without applying histogram modelling. For this operation, 80 seconds long driving data is chosen since it presents the best results in the first test procedure. 4 different driving data is concatenated to build up a 3200 dimension feature vector for each of the driving sessions. Since these vectors have a big dimension, principle component analysis (PCA) is applied to these feature vectors before classification. Similar to the procedure in Test 1, 15 samples are chosen randomly among 51 different driving data in order to apply k-fold cross validation technique. Since the reduced dimension after PCA is an important parameter, test is conducted for different feature vector dimensions. These results can be seen in Table 3.10. As can be seen in these results, the system can reach to an aggressiveness detection rate up to 88.2% for feature vectors which have dimension of 15. However, when these results are compared to the results of histogram modelling, histogram modelling of time series data provides a better detection rate.

Test 3: Aggressiveness Detection by Less Number of Features

Table3.10: Aggressiveness detection rate for time series data representation of driving sessions for feature vectors of different dimensions

Dimensions after PCA	**Detection Rate**
5	83.5%
10	85.8%
15	**88.2%**
20	82.9%
25	78.8%
30	78.2%
35	57.6%
40	52.3%
45	47.0%
50	45.3%

Table3.11: Aggressiveness detection rate for absence of one feature

Absent Feature	**Detection Rate**
Lane Deviation	88.8%
Collision Time	92.3%
Vehicle Speed	84.2%
Engine Speed	91.1%

By this test the importance and weight of the different features are investigated in terms of aggressiveness detection. For this purpose, feature vectors of 80 seconds long driving data is utilized by choosing 3 of the different features. In other words, 6 dimension feature vectors are used by eliminating each feature for each run. The k-fold cross validation procedure is applied as described in Test 1. According to this test, aggressiveness detection results in the absence of any feature are presented in Table 3.11.

As can be seen in Table 3.11, absence of vehicle speed feature significantly decreases the detection rate. Similarly, lane deviation feature also has more effect on aggressiveness decision compared to other features. Engine speed has a little effect on driver aggressiveness decision while slightly decreasing the detection rate by the overall result. Th least effective feature is seen as collision time according to these results. Although in the literature vehicle following pattern is presented to be a good indicator of aggressiveness, during practical implementation it is not as effective as other features. The main reason of this situation

Table3.12: Aggressiveness detection by selected two features

Utilized Features	Detection Rate
Lane Deviation & Vehicle Speed	92.1%
Collision Time & Engine Speed	83.5%

is that the collision time parameter depends on the vehicle detection. When there does not exist a vehicle in the scene, efficiency of collision time parameter decreases. Since the used dataset has some video sequences which contain the absence of vehicles, collision time parameter provides the less effective results.

The classifier is run by choosing two most effective and two least effective features in order to observe the effect of fusing different features. Therefore, only 4 dimension feature vectors are used for test purposes. For the first run only lane deviation and vehicle speed is used while for the second run collision time and engine speed is used. The results can be seen in Table 3.12.

For the run that vehicle speed and lane deviation is used, detection performance is found as 92.1% which is almost same as the case where only collision time is discarded. This shows that all the features does not have a cumulative effect. The positive effect of less important features saturates when the number of features are increased. For the case where only engine speed and collision time is used the system achieves a detection rate of 83.5% which means that they are effective for indicating aggressiveness but they are not enough for an good representation.

Test 4: Data Fusion Results on Ground Truth Features

Although the presented feature extraction methods are proven to be reliable and comparable with the methods in the literature, the performance of lane deviation detection and collision time estimation modules will effect the result of the aggressiveness classification. Nevertheless, the histogram representation of the features provides robustness to the process and reduces the deteriorating effect of missing detections in line detection and vehicle detection stages. In Figure

3.25 histogram representation of lane deviation and collision time values of an aggressive and a smooth driving session. Mean and standard deviation values of these histograms are presented in Table 3.13 and 3.14 with mean absolute error values between ground truth and measured time series signals. The data presented in Table 3.13 belong to the sample aggressive session whose histogram is given in Figure 3.25 while the data presented in Table 3.14 belong to the smooth session. As can be seen in these tables the effect of errors in the detection stage can be eliminated significantly utilizing the histogram representation.

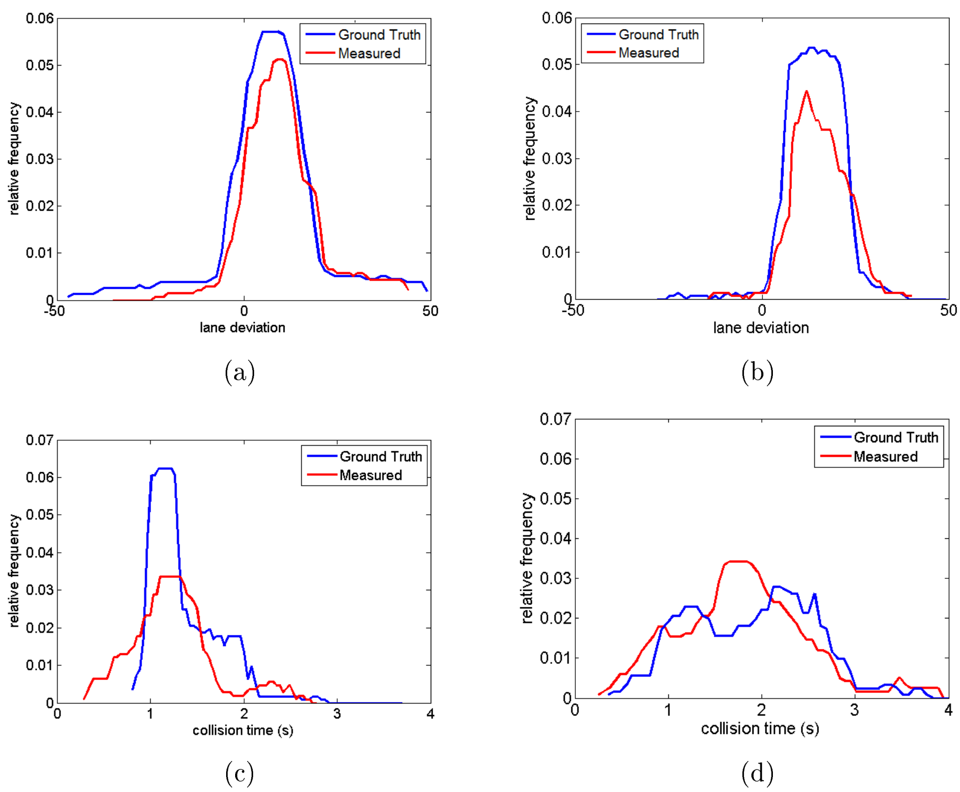


Figure 3.25: Comparison of histograms obtained by ground truth values and measured values, The figure (a) belongs to lane deviation values of an aggressive session, the figure (b) presents the histograms of lane deviation of a smooth driving session; the figure (c) belongs to collision time distribution of an aggressive driving session and the figure (d) presents the histograms of collision time of a smooth driving

Table3.13: Comparison of ground truth and measured features of the sample aggressive driving session

	μ_{lane}	σ_{lane}	$\mu_{collision}$	$\sigma_{collision}$	MAE_{lane}	$MAE_{collision}$
Measured	14.88	7.57	2.01	0.81	3.23	0.58
Ground Truth	14.07	8.01	1.93	0.89		

Table3.14: Comparison of ground truth and measured features of the sample smooth driving session

	μ_{lane}	σ_{lane}	$\mu_{collision}$	$\sigma_{collision}$	MAE_{lane}	$MAE_{collision}$
Measured	9.64	10.73	1.47	0.52	6.78	0.46
Ground Truth	6.70	14.38	1.41	0.48		

Test 5: Aggressiveness detection on 100Car [60] Dataset Proposed aggressiveness detection method also tested with real world data from 100 Car dataset [60]. This dataset is the output of a naturalistic driving study and collected via instrumented vehicles in a large scale. In the publicly available part of this dataset, some driving sessions which are approximately 30 seconds long an they are given with narratives which explain the driving events during this driving session. We investigated these narratives and selected the ones which can be interpreted as an aggressiveness involvement and which can not. For instance, some driving samples are chosen as aggressive which contains events such as sharp lane changes, sudden brakes etc. According to narratives, the ones which include aggressive and sharp actions are annotated as "aggressive" and the ones which includes stable actions as "smooth". We selected total 76 driving sessions according to narratives, tagged 40 of them as aggressive and 53 of them as smooth. In Table 3.16 some sample narratives of 100car data and their interpretation is presented.

Table3.15: Confusion matrix of aggressiveness classification for 100 Car data

		Predicted Class	
		Aggressive	Smooth
Real Class	Aggressive	118	12
	Smooth	8	152

Table3.16: Sample driving sessions with their narratives and aggressiveness interpretation

Sample Number	Narrative of the Session	Aggressiveness
8354	Subject vehicle is driving relatively fast in the left lane as traffic is merging into right lane. Lead vehicle is decelerating withright turn signal on, preparing to merge into right lane, and subject vehicle must brake to avoid hitting lead vehicle in the rear. Subject vehicle is trying to get ahead of right lane traffic before merging.	Aggressive
8392	Subject vehicle is travelling in the rain and almost misses the intended exit. Subject vehicle enters the exit ramp at the last minute, nearly side swiping a vehicle already on the ramp beside it. Subject driver steered slightly left to avoid the crash and other vehicle went ahead on the exit ramp.	Aggressive
8420	Subject vehicle is preparing to merge onto an exit ramp and a vehicle from the adjacent left lane realizes that they need to get onto the exit ramp also and the lead vehicle suddenly crosses the subject vehicle's left lane line into the subject vehicle's lane.Subject brakes hard to avoid hitting the lead vehicle in the rear.	Aggressive
8374	Subject driver is talking/singing to herself and stops behind a line of cars at a light. A following vehicle approaches rapidly and almost hits subject vehicle in the rear.	Smooth
8471	There are two left turn lanes with the subject driver in the far left lane. Vehicle 2 in the left turn lane to the right of the subject's vehicle starts to turn left and cuts the subject driver off.	Smooth
9059	Both the subject driver and lead vehicle are decelerating when the subject driver glances out his right side window. When the subject driver glances, the lead vehicle comes to a stop in front of him.	Smooth

The vehicle speed, lane deviation and collision time data is directly present at 100 Car dataset. However, instead of engine speed gas pedal position data is used due to the direct correlation between them. Using these information, aforementioned feature extraction procedure is applied to the data. In order to validate the reliability of the 100 Car data k-fold cross validation technique is utilized. In each run 29 of the 93 driving session samples are chosen randomly to train an SVM classifier and this procedure is repeated 10 times. Classifier achieved a correct detection at an average rate of 93.1%. Confusion matrix of this process can be seen in Table 3.15.

CHAPTER 4

CONCLUSION AND FUTURE WORK

4.1 Summary

In this thesis work a driver aggressiveness detection system which is creating decision in short time quanta is presented. The proposed system utilizes multi-sensory information to conceive feature vectors and using these feature vectors classifies the driving session as aggressive or smooth. In order to collect driving information, visual and sensor data are obtained and these data are processed using certain computer vision techniques in order to detect road lines an vehicles. Before aggressiveness classification, processed data is modelled and converted to feature vectors in order to represent the aggressiveness of the related driving session. The aggressiveness classifier is trained utilizing the feature vectors and trained classifier decides new driving session whether involves aggressive driving or not.

Available methods in the literature for aggressive driving detection is presented in this thesis work as well as the alternative methods for road line detection and vehicle detection. Modelling of the driving data is also presented as a sub section. For all sub modules and overall system some experiments are conducted to verify the reliability of the modules individually and the system as a whole. According to the overall system experiments, the proposed system achieved a high rate of driver aggressiveness detection.

4.2 Conclusion

The overall system tests showed that the presented multisensory approach is an effective solution for aggressive driving behaviour detection. The presented method satisfies the real time working capability criteria with all its modules by performing 94.0% driver aggressiveness detection rate for 80 seconds driving data. The system takes different driving behaviours, which are associated with aggressiveness, into account utilizing both visual and sensor data while other presented methods depend on a few modalities as presented in Section 2. Using various features and modalities results in high rate of detection performance.

Duration of the driving sessions are examined during the experiments. When the duration of the driving session is less than the optimum, enough number of samples may not be accumulated to build up histograms. Similarly, when the duration of the driving session is too long, driving session may contain both aggressive and smooth patterns in the same time. Therefore, a longer driving session may also be ineffective for determining aggressiveness. According to the experimental results, it is observed that 80 second samples performed better for aggressiveness detection compared to 40 and 120 second samples.

During the experiments each module is tested and their reliability is verified for this application. They are designed and utilized to provide robust and fast solutions. The individual modules performed good results compared to benchmark methods in the literature. The little amount of error in different modules are compensated by histogram representation and Gaussian modelling since the effect of few erroneous samples is low for the overall modelling. This effect is verified by testing the system with ground truth measurements and comparing the error rate of histograms. As the result of these tests histogram characteristics do not change significantly which shows that the error during the detection modules is compensated.

4.3 Future Work

As future work, the proposed system will be tested with more data to observe its performance with different classifiers. The system will be improved in order to provide a rate for driver aggressiveness in a granular approach. In other words, the measurement of aggressiveness level will be provided quantitatively. Another future work that will be considered is that different data modelling approaches will be questioned. For instance, GMM weights of dominant Gaussians in the data modelling stage will be utilized to obtain the aggressiveness result. Moreover, the system will be improved with exploiting a wider range of different features. Combining available features with features from sensor platforms and some data such as session duration, may improve the modelling of the driver behaviour more accurately.

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