DRIVER AGGRESSIVENESS DETECTION USING VISUAL INFORMATION FROM FORWARD CAMERA

Omurcan Kumtepe, Gozde Bozdagi Akar

Middle East Technical University
Department of Electrical & Electronics Engineering
Ankara, Turkey

Enes Yuncu

ISSD Electronics Inc.
METU Technopolis
Ankara, Turkey

ABSTRACT

Among the human related factors, aggressive driving behavior is one of the major causes of traffic accidents. On the other hand, detection and characterization of driver aggressiveness is a challenging task since there exist different psychological causes behind it. However, information about the driver behavior could be extracted from the data that is collected via different sensing devices. This paper presents a method to detect driver aggressiveness using the visual information provided by forward camera. The proposed method is based on detection of the road lines and the vehicles on the road and extracts information related with road lane departure rate, speed of the vehicle and possible forward collision time. Using these extracted features, a classifier is utilized in order to detect if driver shows an aggressive driving behavior. The proposed method is tested by a subjective testing method using 25 different driving sessions and achieved 91.3% success.

***Index Terms*—** Driver aggressiveness, road safety, driving behavior, lane detection, collision detection, intelligent transportation systems.

1. INTRODUCTION

According to World Health Organization, every year 1.24 million fatalities occur due to traffic accidents globally. Currently, traffic accidents are ranked as eight among the other causes of fatalities; and the trends state that by 2030 traffic accidents will be placed in the fifth row of the list. Moreover, economical cost of these traffic accidents is at the level of billions of dollars [1].

Among several factors that causes traffic accidents, the most important one is the human factor. Considering human factors, driver behavior has a stronger effect on road safety than the performance of the driver [2]. Especially, aggressive driving has a significant impact in terms of accidental risk. A study by American Automobile Association Foundation for Traffic Safety stated that 56 percent of deadly vehicle accidents involve aggressive driving behavior [3]. In order to reduce the risk of traffic accidents caused by driver aggressiveness, driver behavior can be monitored and proper warnings can be performed to inform driver and related authorities. Besides reducing the risk of traffic accidents, detecting aggressive driving behavior is important for companies and institutions regarding economical purposes. These can be exemplified as rental agencies, insurance companies and public transportation authorities. 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 performs smooth driving behavior with discount via the AXA Drivesave mobile application which measures and records driving data [4].

In literature, there exist several approaches to measure driver aggressiveness. [5] defines certain variables that may be associated with aggressiveness and verifies them by observing intersections to collect data about the environment and drivers' reactions. In [6] driving simulator is used with different traffic scenarios to collect data and assess driver aggressiveness based on biomedical measurements. [7] discusses frustrating events in driving environment which stimulate the aggressive behaviors in traffic and test these behaviors in simulator setting. [8] proposes a semisupervised learning method to utilize driving data collected by a simulator.

Other than observation dependent analysis, there exist methods in the literature that measure aggressiveness based on sensor data obtained from built in platforms to vehicles. In [9] features such as lateral and longitudinal accelerations and speed are monitored and driver aggressiveness is modeled as a linear filter operating on these signals. The system that is described in [10] exploits the similar features collected by a smartphone in order to recognize the driving style. The work in [11] presents a similar work by proposing a driver monitor system including sensors and cameras by focusing on driver performance. However, there is no study about driver aggressiveness which solely depends on visual signals.

In this paper a camera based approach is presented for driver aggressiveness detection. This approach does not require any external sensors to record driving data. Moreover, it enables the driver aggressiveness analysis to be preformed in real world conditions. The system is based on extracting features from forward camera sequence such as lane departure

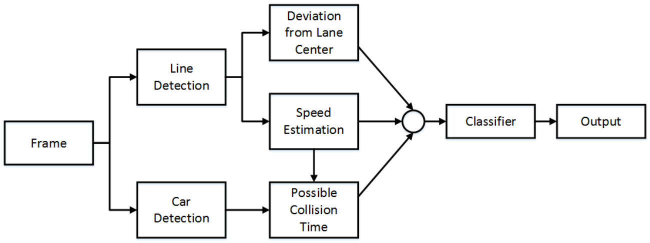


Fig. 1: Flowchart of the proposed method

rate, speed and possible collision time and evaluates them via a classifier to decide if the driver performs an aggressive behaviour. The system assesses video sequences in 90 seconds periods and produces output in near real time.

The organization of this paper is as follows. In Section 2, a driving behavior analysis method is introduced. In Section 3 experimental results of the proposed method are presented, Finally, conclusions and future work is stated in Section 4.

2. PROPOSED METHOD

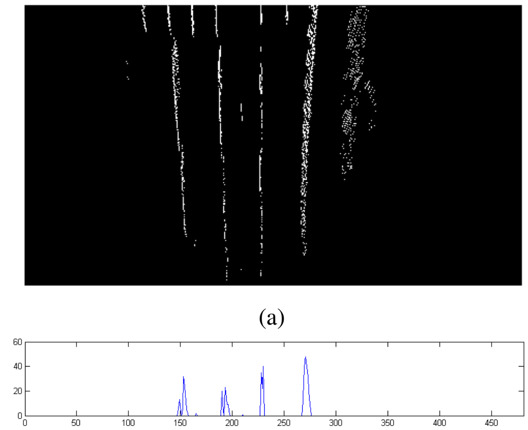
Since aggressive driving behavior is not a clear-cut phenomenon that can be directly measured and assessed, it generally involves some indications [5]. In literature driver aggressiveness is associated with manifestations such as speed, abrupt acceleration and deceleration, sudden lane changes, unsafe gaps between vehicle in front, tailgating etc. [7], [5]. In this study, we use lane departure rate (LDR), speed and possible collision time (PCT) as indicators of aggressiveness and extract these features from visual data (see Fig. 1). In the following sub sections extraction of each of these features from visual data and modeling of aggressiveness decision is described respectively.

2.1. Lane Departure Rate (LDR)

In order to find the lane departure rate, road lines in the video frames are detected as the first step. Shadows on the road, different light conditions and discontinuities on the road line are the major challenges in finding road lines. In order to overcome these problems a feature extraction technique based on exploiting temporal filtering [12] is used to make the process robust. In this technique, the temporally filtered image, $I_k^{'}(x,y)$ is obtained as follows:

$$I_k^{'}(x,y) = max\{I_k(x,y), ..., I_{k-K}(x,y)\} \tag{1}$$

I_k represents the current frame, I_{k-K} represents the K^{th} previous frame and (x,y) are pixel coordinates. Once the image $I_k^{'}(x,y)$ is obtained, its pixels which have low image gradient value are cleared and image is filtered with a derivative filter. Then it is binarized using an adaptive threshold [12].



(a)

(b)

Fig. 2: (a) Perspective transformation applied binary road image; (b) horizontal projection of the image

Road lines can be shown as intersecting lines at the vanishing point inside images captured by forward camera. However, when the perspective of the image is changed to birds-eye view, road lines can be seen as parallel lines which enables them to be located easily. Therefore, a homography matrix H which defines the transformation between image and road plane is utilized to obtain the birds-eye view of the image. The method presented in [12] is based on estimating homography. However as stated in [13], this method is prone to noisy estimations. Therefore, instead of estimating, homography matrix is calculated by [14]:

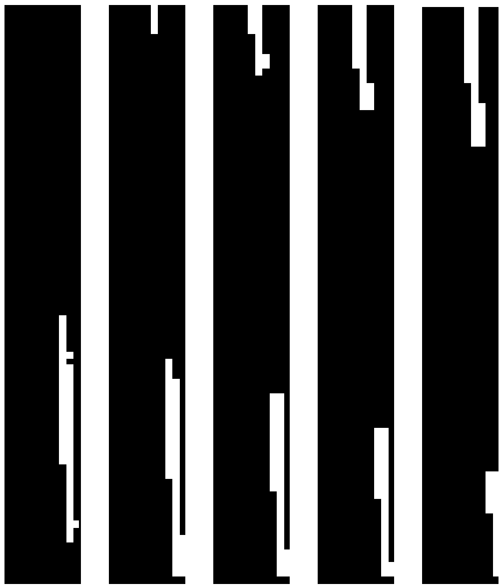
$$H = KRK^{-1} \tag{2}$$

where K is a 3×3 matrix containing the camera calibration parameters and R is the 3×4 matrix that includes the rotation and translation parameters. The transformation between points in different planes is calculated for each point by:

$$p_k^i = HP_k^i \tag{3}$$

An example of transformed binary image can be seen in (2a). While curve fitting is done in [12], in our work horizontal projection of this image is taken by the column-wise summation of pixel values. This process is done on a certain region of the image so that unnecessary details cannot create noise to locate road lines. (2b). Since a limited region from the host vehicle is considered, road lines on the curves can also be seen as straight lines.

Once the horizontal projection of the image is obtained, certain peaks, occurred in this one dimensional projection vector are considered to indicate line positions. Detected lines are smoothed with a kalman filter [15] in order to eliminate noise due to abrupt changes. The lane which is bounded by the closest lines on the left and right of the mid point of the vehicle center is marked as the current lane. The position of the



(a) (b) (c) (d) (e)

Fig. 3: (a-e) Dashed road lines from consecutive frames

vehicle in the current lane is extracted as the LDR parameter between the range of -50 & 50.

2.2. Speed Estimation

Speed estimation is performed by exploiting information retrieved from detected road lines. Since features will be modeled as histograms, an accurate speed estimation is not required. In each frame of the video sequence, the regions that contain the road lines belonging to current lane is masked. In other words, line containing regions in original frames are obtained by using the line information retrieved from temporally filtered image. These masked regions contains dashed road lines.

When this process is utilized on birds-eye view images, dashed lines in consecutive frames show a moving pattern which enables us to calculate horizontal difference of dashed lines between each sequence (see Fig. 3). The difference is defined by two chosen tip points x_k and x_{k-1} of dashed lines. With a moderate level frame rate camera, this difference between each consecutive frames can easily be detected in terms of pixel values. Then these difference values in pixel units are converted to metric units with a constant C. The speed value in terms of km/h is calculated as:

$$v(k) = |x_k - x_{k-1}| \times C \times F \tag{4}$$

where F is the frame rate of camera in terms of frames per second.

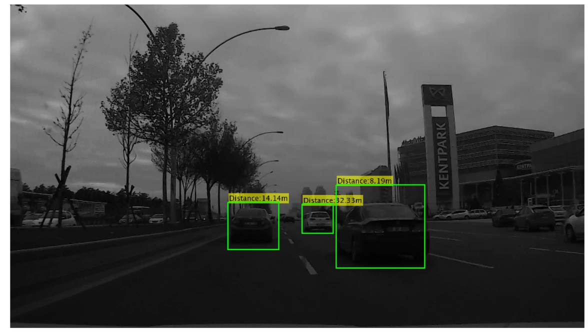


Fig. 4: Detected car images and their distance values

2.3. Possible Collision Time (PCT)

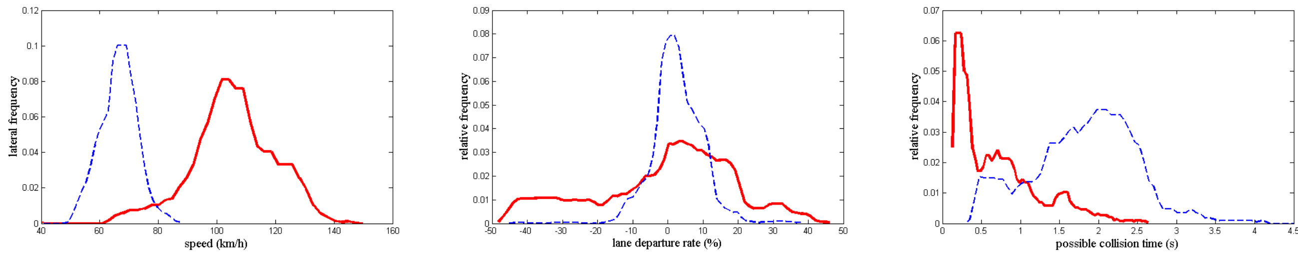
Possible collision time (PCT) parameter is defined to distinguish drivers who exhibit tailgating or unsafe distance between the cars in front. First step to achieve that is to detect vehicles in the scene. In order to detect cars inside the image, Viola-Jones object detection framework is used. This framework is chosen since it is robust and computationally efficient [16].

Car images from real traffic data is used to train a cascade classifier. For training purposes, 470 image patches which include images of backside of cars are used as positive and 970 images which contain empty road figures are used as negative samples. The trained classifier is run on each frame captured by camera. So as to eliminate false positives which occurred as a result of detection process, a kalman tracking algorithm is employed [15].

As the second step to calculate PCT, distances of the detected cars from host car are determined. Using perspective transformation matrix H, the middle point of lower edge of detected car image is transformed to birds-eye view image plane as explained in Section 2.1. This transformation provides the coordinates in order to calculate the distance between the host car and the cars in the scene in pixel units. Then the pixel unit distance values are converted to metric unit using the constant C. An example detection with distance information can be seen in Fig.4.

Finally, the cars which have an overlapping region with current lane are chosen as target cars and their distances to host car are calculated and denoted by d_i. Mostly there exist at most two such cars. PCT value, which defines the elapsed collision time in case the target car suddenly stops, associated with the frame is calculated as:

$$PCT(k) = \frac{min\{d_i\}}{v_k} \tag{5}$$



(a) Speed histogram (b) LDR histogram (c) PCT histogram

Fig. 5: Example histogram representations of extracted features (a-c); solid red lines indicate an aggressive session, dashed blue lines indicate a smooth driving session

2.4. Interpretation of Extracted Features

Three different features are collected for a certain time period in order to characterize the driving behavior. To represent the information efficiently that the features imply, histogram of each feature is calculated. Number of bins of histograms are chosen in order to express the histogram data smoothly. That is, to have a smooth histogram, number of histogram bins kept limited. Noise elimination is done on these histograms using a median filter and histograms are normalized (see Fig. **??**).

Once the histogram of each feature is obtained, it is observed that histograms can be modeled with normal distribution due to the nature of considered features. Therefore, they are modeled by a normal distribution using a maximum likelihood estimation. This estimation provides a mean μ and standard deviation σ of each feature.

During the experiments it is observed that for each type of feature, either mean or standard deviation values are dominant to characterize the driving session. Therefore, σ value of LDR and speed; and μ value of PCT are combined to constitute a 3 dimensional feature vector. These feature vectors are used to train an SVM classifier [17] to detect aggressive driving behavior.

3. EXPERIMENTAL RESULTS

For test purposes several video sequences are taken in real traffic which contains different road conditions such as curves, occlusions and different illumination; and different traffic densities. Video sequences include driving sessions that are performed by 5 different drivers and tagged as aggressive or smooth by majority voting of 3 different observers. Total 25 different driving sessions each having a duration of 90 seconds are analysed. The sessions are chosen as 90 seconds long in order to represent the driving behaviour efficiently. That is, shorter sessions may not contain enough data to decide on aggressiveness. Similarly, longer sessions may reflect both aggressive and smooth behaviours which may lead to wrong decisions. Experiments are performed with 12 aggressive and 13 smooth sessions.

Table 1: Confusion matrix of aggressiveness classification

		Predicted Class	
		Aggressive	Smooth
Actual Class	Aggressive	27	6
	Smooth	1	46

Since the amount of available data is limited, cross validation technique is utilized to evaluate the performance of the proposed system. In each run of the classifier, 17 samples are chosen randomly and used for training purposes and other 8 samples are used for test purposes. This process is repeated 10 times. In each run, results of SVM classifier is compared with ground truth labels and results obtained by all runs are shown with a confusion matrix in Table 1 and the method achieved an average of 91.3% correct detection rate.

According to these results, 27 of 33 aggressive sessions and 45 of 46 smooth sessions are detected correctly. The misclassified sessions are observed to involve incorrect detections during feature extraction phase. Therefore, the detection rate of driver aggressiveness can be increased by implementing better feature extraction methods.

4. CONCLUSION AND FUTURE WORK

In this paper a driver aggressiveness detection method is presented. The proposed method utilizes visual information to conceive feature vectors and using these feature vectors classifies the driving session as aggressive or smooth. Detection rate of the method is competitive with similar works. The flaw in the detection rate is planned to be resolved by improving the feature extraction algorithms. As a future work, the proposed system will be tested with more data to observe its performance with different classifiers. Moreover, the system will be improved with exploiting more features. Combining available features with features from sensor platforms and some data such as session duration, may improve the modeling of the driver behavior more accurately.

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