Characterizing driving behavior using automatic visual analysis

Mrinal Haloi
IIT Guwahati
h.mrinal@iitg.ernet.in

Dinesh Babu Jayagopi
IIIT Bangalore
jdinesh@iiitb.ac.in

ABSTRACT

In this work, we present the problem of rash driving detection algorithm using a single wide angle camera sensor, particularly useful in the Indian context. To our knowledge this rash driving problem has not been addressed using Image processing techniques (existing works use other sensors such as accelerometer). Car Image processing literature, though rich and mature, does not address the rash driving problem. In this work-in-progress paper, we present the need to address this problem, our approach and our future plans to build a rash driving detector.

Categories and Subject Descriptors
H.4.3 [Information Systems Applications]: [Communications Applications]

General Terms
ADAS, Camera sensor, Image analysis

Keywords
Rash Driving detection, Autonomous Driving

1. INTRODUCTION

India is one of the most accident prone country, where according to the NCRB report 135,000 died in 2013 and property damage of worth $ 20 billion[1]. Many a times, accidents and unusual traffic congestion take place due to careless and impatient nature of drivers. In most cases drivers don’t follow lane rules, traffic rules leading to traffic congestion and accidents. Taking effective measure on traffic situation[2] and driver behaviour[15] can prevent accidents and congestion.

A developing country like India needs an effective traffic monitoring and management system. Towards this we propose a visual-analysis-based driving behaviour monitoring system. The visual analysis includes the acceleration, lane-changing, and distance-maintaining behaviour (both from a near-by car and pedestrians). To enhance traffic safety, making road accident and congestion free, cab companies including government and private can adapt our system. Public transportation department can install this system in buses and other vehicles and in traffic junction for monitoring.

In developed countries like U.S.A, with the gradual emergence of autonomous driving research, efforts are on to build a smart driving system that can drive more safely without any fatigue, as compared to humans can be programmed to follow traffic rules. Even for these automatic cars, modelling self-driving behavior by considering distances of surrounding cars and detecting pedestrians is very relevant.

In this work, we use a single wide angle camera sensor for capturing surrounding environment for visual analysis of other drivers behaviour and detecting nearby obstacles. From this data, informative features namely fast side-ways and forward acceleration, wrong direction driving, frequent lane changing, getting-close-to-other-cars-and-pedestrians behavior are computed by using visual analysis techniques. From this collection of features, rash driving behavior can be detected. In Figure 1 we have depicted different possible scenarios for rash driving detection using camera on different infrastructures.

Figure 1: Rash driving Scenarios

The solution to the problem of rash-driving detection using visual analysis is a novel contribution (as compared to[7]). Also, it is a socially-relevant problem in the Indian context. So far, we have defined and extracted the relevant visual features on publicly available datasets. We have collected a small sample of data in the city of Bangalore for
2. RELATED WORK

The related literature can be classified into three categories. First, the works on Image Processing and Computer Vision using single or multiple camera facing the road. Second, driver behaviour understanding using a camera facing the driver. Finally, a limited literature on rash-driving, albeit not using Image Processing.

In the first category, we have works on advanced driver assistance system, traffic safety, autonomous vehicle navigation and driver behaviour modelling using multiple cameras, LIDAR, RADAR sensor etc. These works focus on using image processing and learning based method for lane detection, road segmentation, traffic signs detection and recognition, 3D modelling of road environment (e.g. [5, 11, 12]) Parallax flow computation was used by Baehring et al. for detecting overtaking and close cutting vehicles [2]. For detecting and avoiding collision, Hong et al. had used Radar, LIDAR, camera and omnidirectional camera respectively [6]. They focused on detecting using LIDAR sensor data classifying object as static and dynamic and tracking using extended Kalman filter and for getting a wide view of surrounding situation. For detection of forward collision Srinivasa et al. have used forward looking camera and radar data [7].

Regarding the second and third category, the literature is fairly limited. In some works driver inattentiveness was modelled using fatigue detection, drowsiness, eye tracking, cell phone usage etc. Ji et al. [3] presented tracking method for eye, gaze and face pose and Hu et al. [12] used SVM based method for driver drowsiness detection. Trivedi et al. modelled driver behavior using head movements for detecting driver gaze and distraction, targetting advanced driver safety [19, 20] Using accelerometer and orientation sensor data [7], a rash driving warning system was developed as a mobile application.

3. CHARACTERIZING RASH DRIVING

Rash drivers generally tend to accelerate quickly side-ways and in forward direction. They change lanes frequently and get dangerously close to others vehicles and people. In this section we describe our rash driving estimation algorithm, as visualized in Fig. [2]. From video we take two consecutive frames for extracting features. This features will acts as a input for rash driving algorithm which will be based on thresholding of features values. If rash driving detected we will extract number plate of the car, otherwise will run this algorithm for next consecutive frames.

3.1 Fast side-ways and forward Acceleration

Rapid acceleration also contributes to rash driving. By computing optical flow we can estimate horizontal and vertical flow change of road environment. Frequent change in horizontal flow in the regions of detected cars result of rash lane changing and vertical flow change can give knowledge about relative velocity change of test car with respect to surrounding cars. From optical flow of surrounding region we predict the rash behaviour of other cars. The exact pro-

3.2 Wrong direction driving

In Indian conditions, vehicles coming in wrong direction is also another frequent case of rash driving or rather nuisance. Wrong direction driving is easily estimated by observing anomalies in optical flow in lanes.

3.3 Frequent lane change detection

Another characteristic of rash drivers is frequent lane changing. We have used a robust illuminant invariant lane detection system in our work using inverse perspective projection [3] and cubic interpolation with RANSAC curve fitting [10]. We have assumed a parabolic road model. From road lane fitting, relative position of other vehicles with respect to lanes can be estimated. Also from our lane detection algorithm, departure angle of test car from current lane can be computed.

We have used Lab color space for seperating color and illuminant part of images for better detection of lane lines using 2nd adn 4th order steerable filters. In Fig.[4] we presented camera setup and assumed road model.

3.4 Driving-close-to-vehicles and people-in-front behaviour

Figure 2: Our rash driving detection algorithm

### Equation 1

\[
E(u, v) = \sum_{i,j} \rho_D(I_1(i,j)) - I_2(i + u_{i,j}, j + v_{i,j}) + \lambda [\rho_s(u_{i,j} - u_{i+1,j}) + \rho_s(u_{i,j} - u_{i,j+1}) + \rho_s(v_{i,j} - v_{i+1,j}) + \rho_s(v_{i,j} - v_{i,j+1})]
\]
used HOG feature based deformable part model for detecting and locating other cars and pedestrians with respect to lane lines. For detecting and locating objects in image we will use pyramid based template matching method, where we train car and person model using deformable part model \[9, 8\] based on HOG \[9\] feature. This method can detect car and people very efficiently under occlusion also. Latent SVM trained model is shown in Fig.[6]; and detected car and people is shown in Fig.[7] (Reference for the images [11]).

### 3.4.1 Pinhole Camera Model

For determining distance of obstacle from test car we will use pinhole camera model, this model can give good accuracy for object in front of test car. From error analysis we set different offset for approximately measuring distance.

If a 3D point \(P = (u, v, w)^T\) and its pinhole projected point is \(I_p = (x, y)^T\), then relation \[16\] is given by following equation

\[
x = \frac{\phi_x (\omega_{11} u + \omega_{12} v + \omega_{13} w + \tau_x) + \lambda (\omega_{21} u + \omega_{22} v + \omega_{23} w + \tau_y)}{\omega_{31} u + \omega_{32} v + \omega_{33} w + \tau_z} + \delta_x
\]
where intrinsic matrix $\Lambda$ is given by

$$\Lambda = \begin{bmatrix}
\phi_x & \lambda & \delta_x \\
0 & \phi_y & \delta_y \\
0 & 0 & 1
\end{bmatrix}$$

Rotation matrix of camera can be given by

$$\Omega = \begin{bmatrix}
\omega_{11} & \omega_{12} & \omega_{13} \\
\omega_{21} & \omega_{22} & \omega_{23} \\
\omega_{31} & \omega_{32} & \omega_{33}
\end{bmatrix}$$

Translation matrix as

$$\tau = \begin{bmatrix}
\tau_x \\
\tau_y \\
\tau_z
\end{bmatrix}$$

Finally, employing all the features described, we make a estimate of rash-driving. For now, our proposed system is rule-based. In the future, we will collect samples with and without rash driving, using professional drivers. Using a generative machine learning approach, we can build a probabilistic model to predict rash-driving. We are also considering recording data with naive volunteers, and manually annotating parts of the data where rash-driving tendencies are seen, so as to validate the model.

4. CONCLUSIONS

In this paper we have described a visual analysis method to characterize driving behavior, with a specific focus on rash-driving. Our algorithm is based on calibrated single camera images. The methods are general enough to work on cameras placed on cars as well as on infrastructure. In the future, we plan to integrate this module with the automatic number plate detection and recognition module (as in [14]) for a traffic monitoring application. Though our work is ongoing and preliminary, we believe such a system can have a good societal impact. As described in Section 1 Introduction, we will record a rash-driving dataset in Indian conditions, and test our methods. We will also make a requirements study with government agencies.

5. REFERENCES

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