# Incrementally perceiving hazards in driving 

Yuan Yuan ${ }^{\text {a }}$, Jianwu Fang ${ }^{\text {b,c }, ~ Q i ~ W a n g ~}{ }^{\text {d,* }}$<br>${ }^{\text {a }}$ Center for OPTical IMagery Analysis and Learning and School of Computer Science, Northwestern Polytechnical University, Xi'an 710072, China<br>${ }^{\mathrm{b}}$ Institute of Artificial Intelligence and Robotics, Xi'an Jiaotong University, Xi'an, China<br>' School of Electronic \& Control Engineering, Chang'an University, Xi'an 710064, China<br>${ }^{\mathrm{d}}$ School of Computer Science, and Center for OPTical IMagery Analysis and Learning, and Unmanned System Research Institute, Northwestern Polytechnical University, Xi'an 710072, China

## A R T I C L E I N F O

## Article history:

Received 8 February 2017
Revised 14 September 2017
Accepted 7 December 2017
Available online xxx
Communicated by Marco Cristani

## Keywords:

Computer vision
Hazards detection
Motion analysis
Saliency evaluation
Bayesian integration


#### Abstract

Perceiving hazards on road is significantly important because hazards have large tendency to cause vehicle crash. For this purpose, the feedbacks of more than one hundred drivers with different experience for safe driving are gathered. The obtained feedbacks indicate that the irregular motion behaviour, such as crossing or overtaking of traffic participants, and low illumination condition are highly threatening to drivers. Motivated by that, this paper fulfills the hazards detection by involving motion, color, near-infrared, and depth clues of traffic scene. Specifically, an incremental motion consistency measurement model is firstly built to infer the irregular motion behaviours, which is achieved by incremental graph regularized least soft-threshold squares (GRLSS) incorporating the better Laplacian distribution of the noise estimation in optical flow into the motion modeling. Second, multi-source cues are adaptively weighted and fused by a saliency based Bayesian integrated model for arousing driver's attention when potential hazards appears, which can better reflect the video content and select the better band(s) for hazards prediction in different illumination conditions. Finally, the superiority of the proposed method relating to other competitors is verified by testing on twelve difficult video clips captured by ourselves, which contain color, near-infrared and recovered depth simultaneously and no registration or frame alignment is needed.


© 2017 Elsevier B.V. All rights reserved.

## 1. Introduction

The main goal of this work aims to implement the hazardous object detection in driving in an incremental manner, which only needs a small portion of training frames at the beginning of each video clip. By that we want to exploit the ability for detecting hazards in a certain video by exploiting itself. It is promising when there is no available well labeled training data for the valuable applications existing ambiguous definition [1], such as hazards. From the "Global status report on road safety 2015" launched by World Health Organization (WHO), about 1.25 million [2] people die each year owing to the numerous road traffic crashes, and half of these dying are "vulnerable road users" [2]: pedestrians, cyclists, motorcyclists and other moving objects. Fig. 1 demonstrates some typical examples having potential hazards. Analyzing the reason for this phenomenon [3], auto drivers are believed to be responsible for the fatal crash in about $92 \%$ traffic deaths. Major crash causing

[^0]factors are speeding, careless driving, driving in the wrong lane, and driving after drinking alcohol.

Over the past decades, many researchers have dedicated significant efforts to the development of the Advanced Driver Assistance Systems (ADAS) and autonomous driving [4-6]. However, these techniques are still insufficient to achieve a fully non-human driving system [7]. The challenges are mainly caused by the dynamic, unpredictable traffic scenes being rich of uncertainty .

### 1.1. Motivations

Facing the hazards prediction, we start a questionnaire investigation for safe driving, by which we want to derive the most hazardous behavior that drivers want to avoid in driving. To be specific, we prepared four questions: (1) "Which options of behaviour are dangerous when you are driving on highway?" (2) "Which options of behaviour are dangerous when you are driving on urban road?" (3) "Which options of the information are useful for you in driving?" and (4) "Which options of behaviour should be considered firstly in driver assistance systems?". The answer options for these questions are selected by common consensus. In order to gather more feedbacks,


Fig. 1. Typical hazardous scenarios. (a) Pedestrian crossing; (b) Cyclist crossing; (c) Vehicle overtaking and (d) sudden appearance of animals.
we propagate the questions through instant-messaging apps. Fortunately, 145 participants took part in the investigation ( 99 men and 46 women, mean age of 33.3 years old ranging from 21 to 55 ). All drivers have a valid driving license, and averagely have 5 years driving experience, ranging from 0.5 to 20 years. The average driving mileage of participants is 114523.87 km .

The questionnaire investigation analysis for drivers is demonstrated in Fig. 2. From the results, we can discover that the irregular motion behaviour of frontal objects is highly threatening for drivers, such as overtaking from right side, pedestrian/vehicle crossing. In addition, the illumination and the spacing between vehicles are also important factors in safe driving. In order to confirm the observation, we investigate the latest reports of traffic fatalities ${ }^{1,2}$ released by National Highway Traffic Safety Administration (NHTSA). These reports show that: (1) About $90.4 \%$ percent of pedestrian fatalities occurred when the pedestrian locates in front of the ego-vehicle and is with a crossing behaviour; (2) About 70\% percent of pedestrian fatalities appeared in the nighttime condition; (3) Speeding, such as overtaking, changing lanes contributes the $27 \%$ percent of all fatal crashes, which is second only to drink driving, i.e., $29 \%$ percent. From these discoveries, this work will perceive the hazards that the object crosses or overtakes the egodriving car, as well as a consideration for low illumination condition.

### 1.2. The way to success

Based on the above investigation, this work first contributes an incremental motion consistency measurement to distinguish the hazardous and normal situations. Consistently with the anomaly detection $[8,9]$, motion consistency is the most efficient and straightforward cue for involving the irregular motion behaviour. In this procedure, optical flow is the most promising feature. Considering the infrequent occurrence of hazards, this work tackles the motion consistency measurement with a sparse representation paradigm. Different from the existing sparsity-based anomaly detection methods which usually model the motion noise with a Gaussian distribution, this work formulates the motion noise with

[^1]a Gaussian-Laplacian distribution. It is inspired by that (1) Gaussian distribution is easy to be solved, such as the ordinary least squares (OLS) solution; (2) Laplacian is more adequate to model the noise of optical flow [10] while the Laplacian noise modeling is difficult to solve. ${ }^{3}$ Although this strategy is coincident with the least soft-threshold squares (LSS) [11], our Gaussian-Laplacian distribution has more intrinsic physical meaning. Besides, LSS does not consider the spatial-correlations between different elements (i.e., superpixel ${ }^{4}$ based image representation in this work). However, spatial-correlation exploitation is important to hazards prediction because a more reasonable hazards map should demonstrate consistent hazardous degree for different parts of the same object. It is in coincident with the relevance preservation of visual instances by graph-embedding ranking [12]. Motivated by that, we further introduce a graph-regularizer to infer the geometrical manifold of the motion feature in different image regions, which constitutes a new graph regularized least soft-threshold squares (GRLSS). Furthermore, different from LSS, we solve the objective function with a more efficient joint optimization.

To further boost the performance of hazards prediction, we not only consider the motion consistency principle, but also explore other visual cues. For one reason, motion sometimes cannot distinguish the hazardous target and background very clearly; for another, other cues such as appearance and location are also informative, as demonstrated in Fig. 2(c). Therefore, this work also provides the visual color, near-infrared spectral and visual depth bands to reflect the characteristics from aspects of color, physical material and position of front objects. To this end, we have to design a strategy for fusing them.

Traditional methods of tackling this fusion problem have two choices, feature level and decision level. In this work, we start from the feature level but with a more novel and efficient strategy: saliency evaluation. That is motivated by that (1) the occurrence of accident is always caused by the drivers' inattention and saliency can serve as an effective reminder; (2) saliency is the most successful simulation of human attention mechanism [13-15] and

[^2]
# https://daneshyari.com/en/article/6864605 

Download Persian Version:

## https://daneshyari.com/article/6864605

## Daneshyari.com


[^0]:    * Corresponding author.

    E-mail address: crabwq@gmail.com (Q. Wang).

[^1]:    ${ }^{1}$ https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/811888.
    ${ }^{2}$ https://www.nhtsa.gov/risky-driving/speeding.

[^2]:    3 "Due to illumination or occlusion effects, in optical flow estimation, matching the color or gray value is not always reliable, and the matching noise corresponds to a Laplace distribution which has longer tails than the Gaussian distribution [10]".
    ${ }^{4}$ A superpixel is a local image region grouping pixels with similar characteristics together, and its boundary is almost adhere to image boundaries.

