Simultaneous Analysis of Driver Behaviour and Road Condition for Driver Distraction Detection

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Abstract. The design of intelligent driver assistance systems is of increasing importance for the vehicle-producing industry and road-safety solutions. The article starts with a review of road-situation monitoring and driver's behaviour analysis. The paper also discusses lane tracking using vision (or other) sensors, and the strength or weakness of driver behaviour analysis (e.g. iris or pupil status monitoring, and EEG spectrum analysis). The paper focuses then on image analysis techniques and develops a multi-faceted approach in order to analyse driver distraction via implementing a real-time AdaBoost cascade classifier with Haar-like features. The proposed method is tested in a research vehicle for driver distraction detection using a binocular camera. The developed algorithm is robust in detecting different types of driver distraction such as drowsiness, fatigue, drunk driving, or the performance of secondary tasks.

Keywords: driver assistance systems, driver distraction detection, Haar-like features, cascaded classifier, face and eye detection.

1 Introduction

Preventing road crash fatalities is not only important for individual people or families, but also for governments, insurance companies and automotive industries with respect to social costs, investment criteria, or competitive technology. Among all types of driving behaviour, distracted or drowsy driving is one of the leading sources of traffic accidents. Such behaviour causes the worst and most catastrophic type of road crashes since there is no deceleration at all, no attempt to avoid objects, and no warning. Although automotive companies offer new vehicles equipped with traditional (e.g. air bag, seat belt, automatic cruise control) or modern safety systems (e.g. car parking sensor, night vision, or improved breaking systems), there are remaining threats that need to be resolved by further safety components.

According to the latest report of the World Health Organisation (WHO) on road safety in 2010, more than 1·2 million people died on roads and about 50 million people have been seriously injured (WHO 2010). The WHO also

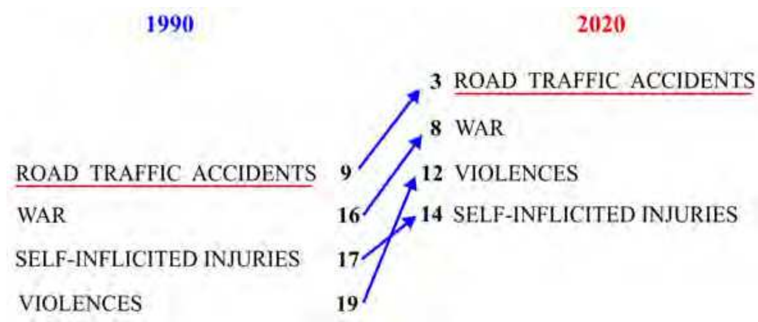


Fig. 1. WHO's anticipation for leading factors of injuries and diseases (the current four uptrend causes).

anticipated that among the current four uptrend causes of disease or injuries, road traffic accidents will rank 3rd by the year 2020 (see Figure 1).

A conservative estimation by National Highway Traffic Safety Administration declares more than 100,000 world traffic deaths annually just because of fatigue driving (NHTSA 2009). Ontario statistics reveals that fatigue and distraction is a factor in 35% of all collisions (Ontario 2010). All these signs signal that today's drivers are becoming more distracted, may be due to a variety of social, and behavioural disorders. On the other hand, driver assistance systems are still in their infancy, and Advanced Driver Assistance Systems (ADAS) are a current major research task that emphasizes on driver's vigilance detection.

Together with current research on *out-vehicle monitoring* (i.e., controlling the traffic environment around the *ego-vehicle*, which is the car the system is operating in), ADAS must be able to monitor driver's attitude, behaviour, and level of consciousness inside the car, for example, to prevent speeding in case of any fatal and dangerous situations.

This paper is structured as follows: Section 2 reviews related work, such as out-vehicle monitoring, and in-vehicle monitoring (i.e. driver consciousness analysis via a non-contact vision sensor). Section 3 prepares then at first for the presentation of our new method by providing required fundamentals, and presents then the method itself. Sections 4, 5, and 6 discuss on appropriate sensors for out-vehicle monitoring, knowledge bases, and fuzzy data fusion, respectively. The proposed method has been analysed with respect to different traffic-related aspects such as weather conditions and lane keeping, and results are also mentioned in those three sections. Section 7 concludes.

2 Related Work

The first active car safety systems on the market intended to increase the driver's comfort, starting with park assistant systems, cruise control and automatic cruise control (ACC). Recent research aims increasingly also on safety for the driver, passengers or pedestrians (Bishop 2005). In this regard, a diversity of work has been done, but a very limited number of work considers synchronously both road situations and driver's vigilance. In the sequel, first we discuss different aspects, techniques and related studies that have been done before either for driver distraction analysis (face monitoring) or out-vehicle monitoring using single sensors (e.g. CCD, stereo vision, short and long range radars, LIDAR, or ultrasound). Then, we will present our method in detail.

2.1 Driver's Vigilance Detection

Wang et al. proposed a mouth movement tracking method using a dashboard-mounted CCD camera to allocate and then record the yawning frequency of a driver (Rongben et al. 2004). Their method determines the interest area for the mouth using a Fisher classifier, back propagation artificial neural network, and Kalman filtering. However, they had not considered the eye status as some drivers fall asleep without yawning.

The influential paper (Bergasa et al. 2006) uses an infrared vision system to track a driver's face via analysing six parameters: Percentage of eye closure, closure duration, blink frequency, nodding frequency, face position, and fixed gaze. Their method is robust for night driving but the performance decreases dramatically in daylight, especially on sunny days. Moreover, the system does not answer issues such as covering sunglasses, and it does not consider other signs of distractions than eye features.

M. H. Sigari provided a hypo-vigilance detection system based on eyelid behaviour and eye-region processing (Sigari 2009). He used a combined method to measure eye-lid distance and eye-closure rate. This method suffers from a high degree of computational complexity and needs to be improved.

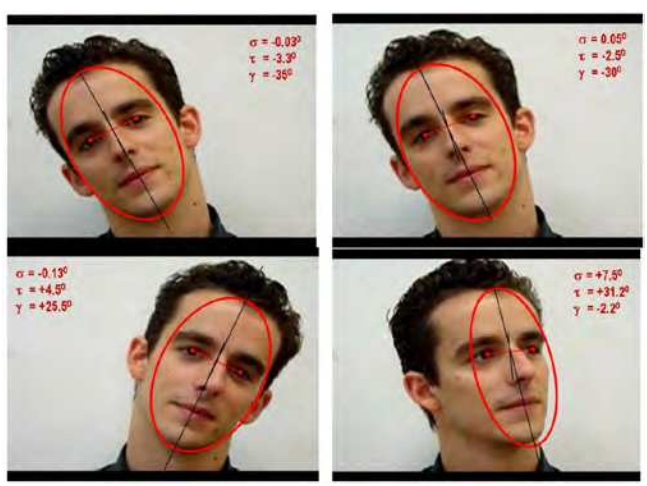


Fig. 2. Elliptical face detection (Batista 2007).

J. Batista offers a framework that combines facial feature locations with statistical elliptical face modelling to determine the gaze of a driver (Batista 2007), but it is not clear how effectively it works for different sex and face types from different nationalities (see Figure 2).

M. Miyaji et al. provided a means to detect eye and head movement (Miyaji et al. 2008). These movements were tracked via standard deviation and categorized features for pattern recognition; however, this method is applied in a simulation only and the results for real world experiments are not available.

(Doshi and Trivedi 2009) worked on contextual information by studying head and gaze data dynamics and body language analysis. They tried to use driver behavioural cues to manifest some useful information to predict future events. The method is nicely evaluated; however, it is still far from being implemented practically.

Recently (Miyaji et al. 2010) introduced a mixed method by applying a Support Vector Machine (SVM) and an AdaBoost learner for three parameters of heart rate (pulse rate index), visual information, and pupil diameter measurement to assess the level of driver's vigilance. The main problem for this approach is data normalization and time alignment because there is a huge difference both for data type and computation time of visual measurement when comparing with heart rate analysis.

(Peiris et al. 2006, Portouli et al. 2007, Furman et al. 2008) tried to measure distraction by considering some sort of biological and psychological phenomena such as EEG, ECG, skin voltage, heart rate change and respiration. The results are supposed to be more accurate than vision-based techniques but it is not applicable in real-world driving situations because of the use a lot of wires and head mounted sensors. These bring some serious distractions even for normally aware drivers (see Figure 3).

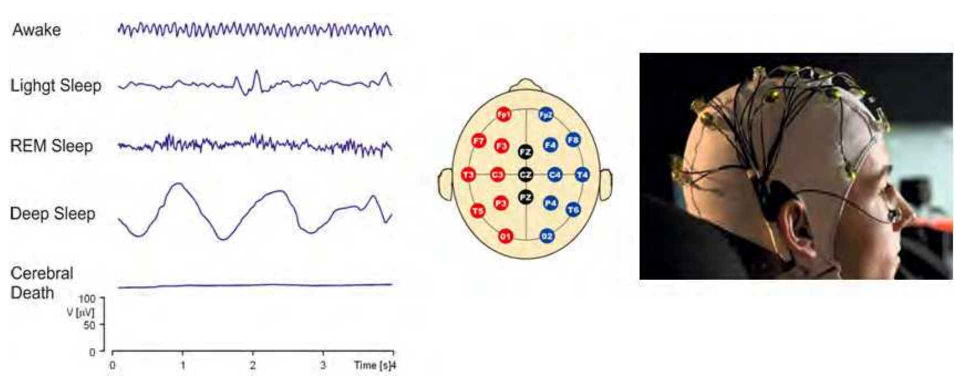


Fig. 3. Driver vigilance analysis via EEG signals (Malmivuo and Plonsey, 1995).

2.2 Out-vehicle Monitoring

Out-vehicle monitoring is opposed to *in-vehicle monitoring* that observes the driver. For typical driving, there are different situations (e.g. driving straight ahead, turning, overtaking, or avoiding obstacle/pedestrians) where those define different kinds of challenges (Klette et al. 2010) for ADAS for detecting environment-related information.

(Gandhi and Trivedi 2006) developed a new approach to evaluate the ego-vehicle surrounding using an omni-directional camera which looks promising but the computational time would be rather high due to real-time monitoring.

(Wijesoma et al. 2004) tried to detect road curbs using LIDAR in comparison to millimetre wave radar. They applied an extended Kalman filter to speed up curb tracking. The method is fast enough and does not suffer from video limitations; but their method requires that the curb is at least 25 mm of height, and it is not so accurate for non-standard roads, curb-less roads, damaged roads, or roads with ramps.

(Danescu and Nedevschi 2009) offered a probabilistic lane tracking system using a stereo vision and grey scale image processing system. Using a particle filter, their method seems robust; however, various weather conditions and poor illuminations cause some limited views leading to limited accuracy.

Wen Wu et al. proposed a detection method for text and road signs (Wu et al. 2005) by integrating 2D image features with 3D geometric structures extracted from video sequences. The detection rate is 88.9% with a 9.2% false hit rate; that is 81% in overall which is not good enough for real-world applications.

S. Velupillai and L. Güvenç used a laser scanner to detect obstacles, pedestrians and other vehicles (Velupillai and Güvenç 2009). They assumed that laser scanners provide promising performance due to their high accuracy, fine resolution, and the ability to work in adverse weather conditions such as snow or rain. Laser emitters are range limited and noise sensitive, and these issues need to be taken into consideration.

3 Methodology and System Design

The above mentioned proposals have their individual benefits and may be considered as possibilities. The main limitation for most of the research provided so far in the field of driver distraction is a focus on the driver only, not accompanied by out-vehicle monitoring. In consequence, the definition for distraction is limited to what can be assessed from a driver's face, especially the eyes. Outside conditions cannot be considered this way for distraction assessments. All research that is mentioned in Section 2.2 is some kind of a driver assistant system, but not on driver distraction research. We are going to define a versatile driver distraction system that allows us that measuring parameters can be changed in dependence of the driving environment, in a dynamic manner over time.

There is no universal definition for driver distraction; we consider more than ten states of distraction in the following two main categories:

1. Drowsiness, conversing with passengers, gazing around, mobile texting, eating, drinking, smoking, talking on the phone, retrieving objects from the car, or comfort setting.
2. Drunken state, day dreaming, high mental work load, or mental fatigue.

We name the first category as *"Visual Distraction"* and the second one as *"Cognitive Distraction"*. In the following, we try to complement our method with other's work to develop a novel hybrid model. The research focuses on providing a warning and steering system in three coherent steps:

Firstly, detect a driver's level of alertness via head, eye and mouth monitoring; secondly (but concurrent to the first step), recognize the driver's ability to precisely keep the lane with a reasonable reaction time; thirdly, design a data fusion system for decision making, warning, and even performing interfering actions such as emergency braking and steer angle correction in nearly inevitable crash anticipations.

3.1 Preliminaries

As mentioned before, contact-based sensors and biological measurements such as EEG are not expected to become a common feature in cars. We are going to continue with non-contact vision sensors. In this section a detailed description of hardware, software and the image analysis techniques are discussed as applied in our research.

Considering the eye anatomy (see Figure 4), the parameters such as eye closure rate, pupil shape and vertical or horizontal size of the iris are promising ways to determine a driver's level of vigilance and drowsiness (Rezaei et al. 2010); however, the pupil is a very "tiny part" of the head and in real-world tests we found that these measurements will be quite challenging and unreliable especially due to asymmetric lightning conditions inside the car, and when sun exposure varies over time. Thus, in this research we consider the head direction and overall eye status as a whole.

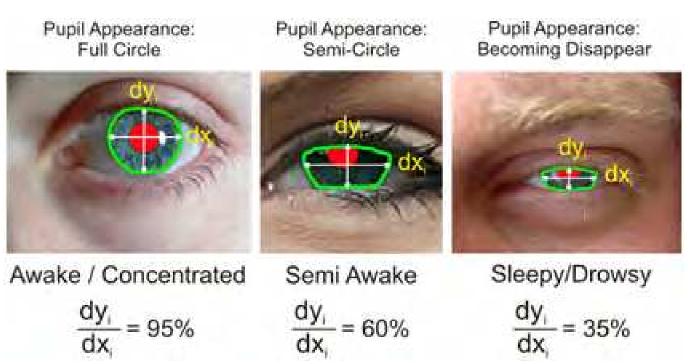


Fig. 4. Distraction evaluation by measuring the vertical and horizontal size of the iris.

Fig. 5. Binocular camera assembly (left) in the research vehicle HAKA1 (right).

Summarising the major research done during the past 20 years in the field, most of them can be assigned into one of the following four categories:

- knowledge-based methods, that include some predefined rules to detect faces based on human knowledge,
- feature-invariant approaches, that are based on face-structure features and are relatively robust to pose and lightning,
- template-matching methods, that judge a state of a face based on pre-stored templates, and
- appearance-based methods, that learn different face models from a dataset of training face images.

The proposed research utilizes a method that is in the fourth category, and details are given below.

We use a 'bumblebee' stereo camera mounted in front of the driver, on the dashboard of a Mercedes Benz A-Class research vehicle called HAKA1. The camera has the possibility of recording both in mono or stereo mode with a focal length of 3·8 mm and a 66° horizontal field of view (see Figure 5).

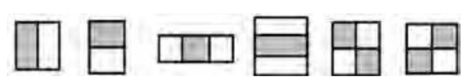


Fig. 6. Samples of Haar-like rectangular features.

Recorded sequences are 30 fps, 640 × 480, and the entire processing is in real time. Inspired from (Viola and Jones 2001) we implemented two individual cascade classifiers, one for the head and one for the eye pair based on Haar-like features. 'Haar-like features' are a term in image processing that refers to some adjacent dark and light features- usually called rectangular features (see Figure 6). This term originally comes from Haar square wavelets shown in Figure 7.

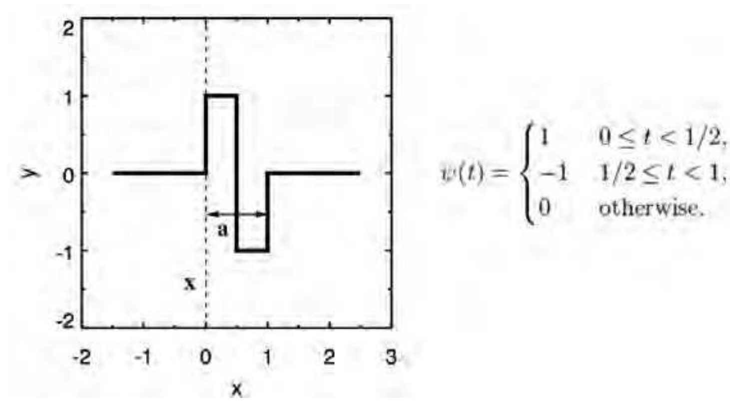


Fig. 7. Haar wavelet.

In 2D space, a square wave is a pair of adjacent rectangles - one bright and one dark.

Features make use of this fact that specific objects (e.g. a face), often have some *general properties*. For example, looking at Figure 8, for all faces there are two important features:

- darker region of eyes compared to cheeks, and
- darker region of eyes compared to bridge of nose.

Following (Viola and Jones 2001), the *integral pixel value*

$$I_{\text{int}}(x, y) = \sum_{0 \le x' \le x \,\wedge\, 0 \le y' \le y} I(x', y')$$

at pixel (x, y) in a scalar image I_{int} is the sum of all pixel values above and left of (x, y) in the original image I. It follows that the integral pixel value for a rectangle ABCD equals

$$\sum_{(x,y) \in ABCD} I(x, y) = I_{\text{int}}(D) + I_{\text{int}}(A) - I_{\text{int}}(B) - I_{\text{int}}(C)$$

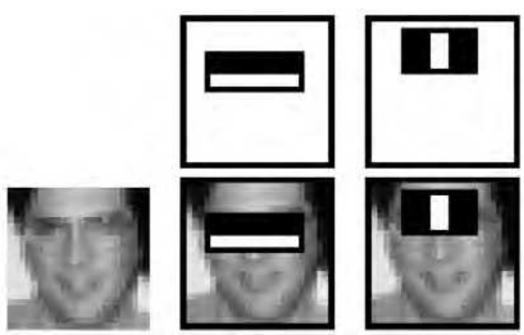


Fig. 8. Two fundamental features exist in all faces.

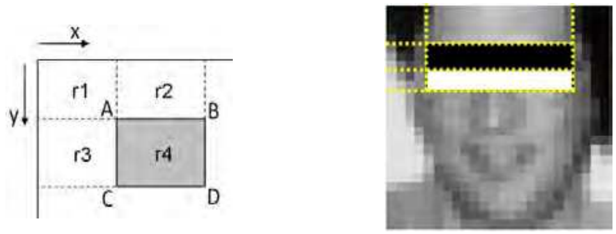


Fig. 9. Left: Calculating integral value for the rectangle ABCD. Right: a sub-window of 24 × 24 pixels with a Haar-like feature bar.

For verifying this formula, see the rectangle ABCD on the left in Figure 9. We have $I_{\text{int}}(D) = r_1 + r_2 + r_3 + r_4$, $I_{\text{int}}(B) = r_1 + r_2$, $I_{\text{int}}(C) = r_1 + r_3$, and $I_{\text{int}}(A) = r_1$.

In order to evaluate the presence or absence of a rectangular feature in an image, simply the integral pixel values in the region of the bright rectangle should be deducted from the integral pixel values in the region of the dark rectangle. So, if the result, called *feature value*, is greater or equal to a threshold then the feature is set to be present.

Figure 9, right, shows a 24 × 24 sample sub-window from a big image of 640 × 480 pixels. Actually in a 640 × 480 image there are more than 530 sub-windows with the size of 24 × 24, and we have to analyse them one by one to detect the query object (e.g. defining the face).

Testing the existence of the two above-mentioned rectangular features, statistically about 50% of all images will be rejected as being non-face sub-windows. Furthermore, almost 100% of clear faces will be detected but the negative point is that we will detect about 40% of false positive images (sub-windows that are not

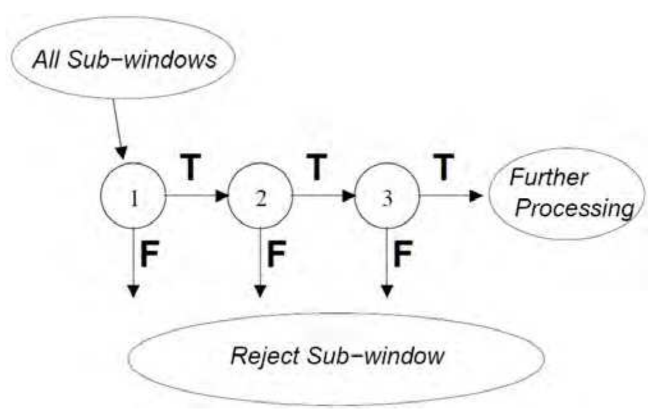


Fig. 10. The structure of the Viola-Jones cascade classifier.

faces but they are detected as face by miscalculation). The computation time in this step is just 60 CPU instruction cycle what is fully satisfactory for real-time applications. In order to cope with the *false positive images* and after passing two of the top mentioned rectangular features in Step 1, then a sequential cascade classifier is applied to test and matches some more rectangular features to detect the faces more accurately with less false-positive results (see Figure 10). If all the features pass the sequential cascades then we consider the sub-window as containing a face inside, otherwise the sub-window will be rejected as "no face".

There are more than 18,000 Haar-like rectangle features that could be checked in a 24×24 sub-window. But certainly it does not need to be checked for all the features as just a few of them are appropriate for face detection. The question is: how to find appropriate Haar-like features for face detection? This is a challenging issue.

3.2 Driver Consciousness Analysis via a Non-contact Vision Sensor

The selection process of Haar-like features is done by an AdaBoost machine-learning algorithm based on a collective dataset of more than 5,000 faces. An AdaBoost learning algorithm is an effective approach to select and arrange appropriate Haar-like features for each step as its error approaches zero exponentially when the number of iterations increases (Freund and Schapire 1999).

In our test, first we applied a Canny edge operator on input images, followed by common pruning, and then the method was tested with a built-in cascade classifier in the OpenCV 2.1 programming environment. Since the driver should

Fig. 11. Face detection results for different ages, sex, and races.

look forward during driving, we used the frontal face detection classifier but we allowed a freedom of face rotation up to $\pm 45°$ to look towards left and right mirrors.

The accuracy of face detection in good lightning conditions with or without covering glasses, was near 100% (just one of the faces that was covered with a very big hat and big sunglasses was not detected). Figure 11 shows the result of forward face detection applied on some photos for different ages, sex, and nationalities.

The next step of the method is eye detection. This step was more difficult than face detection. We trained our designed classifier with more than 9,000 negative and 3,600 positive JPEG images of different size, colour-depth and resolution. The data set also includes more than 6,000,000 sub-windows. We selected different types of open or closed eyes from different people of different countries with different lightning conditions, different eye states and different face poses. The image data set was mainly gathered from two common face data sets, the *Facial Recognition Technology Database* (FERET 2010) and the *Yale University face database* (YALE 2010), and also from a newly emerged web site called *Face of Tomorrow* (FOT 2011).

The best trade-off we experienced for the number of stages in our cascade classifier was at 15-17 stages. The cascade classifier and a machine learning algorithm was implemented on an Intel Core i7 CPU (Quad core) and 4GB of RAM. Performing a smaller number of stages lead to some false-positive eye detections, and utilizing more than 17 stages sometimes caused wrong detections of open eyes as being closed.

In a practical test inside the vehicle we defined three main states for the driver's level of awareness (see Figure 12):

1. *Normal driving condition:* when a frontal face and a pair of open eyes is detectable. See Figure 12 (a).
2. *Sleepiness:* when the frontal face is present, but none of the eyes are detectable for a long period of times such as more than 330 ms (10 frames). That is, if the system is not able to detect eyes for more than 10 continuous frames, so this time is much more than normal blinking and then we consider this as a sign of drowsiness. See Figure 12 (b).

(a) Frontal face, frontal eyes (b) Frontal face, closed eyes (c) No frontal face, no eyes

Fig. 12. Real-time face and eye detection in three different gestures.

3. *Performing of secondary tasks:* when neither frontal face nor eyes are detectable, we consider this state as *performing secondary tasks*, e.g. texting, adjusting radio, or face to face talking to passengers. See Figure 12 (c),

Using a typical PC with a Core 2 Duo CPU of 2·00 GHz and 4 GB of RAM, the system is capable of processing in real time at 30 fps, 640×480. Overall, the system is capable of detecting and tracking the driver's face, eyes (each eye separately), with or without eyeglasses. But the system is trained to consider frontal faces (from $0°$ rotation to $\pm 45°$) as positive faces, so for all face gestures with rotation of more than $45°$ the system neither considers the face nor the eyes, similar to Figure 12 (c).

As the next step, we consider the eye closure rate. The overall time of missing a head (due to rotation) and missing eyes (due to blinking, drowsiness or head rotation) is continually monitored while we keep into account the current speed of the vehicle. For example, in a straight-ahead driving situation, if the current speed is 100 km/h, any occurrences like Figures 12 (b) or (c) that take more than 30 continuous frames (i.e. one second) are considered as serious distraction, while for lower speeds, this time segment may increase to a maximum of 2·5 seconds (for 10 km/h).

3.3 Lane Index and Lateral Position Monitoring

As mentioned before, sometimes the face and eyes of the driver are towards the road, but because of mental fatigue/workload the process of driving is not as regular as expected. The aim of this section is to introduce a model to determine *cognitive distractions* via continuous measurement of vehicle's lateral position and a lane index error (i.e. deviation) from centre of current cruising lane, Figure 13. In addition, this step is a complementary approach for Section 3.2, especially when the driver has covering sunglasses and eye monitoring is not feasible. Previous pilot experimental studies (checked from video recordings) showed that when the subject is drowsy, the zigzag deviation error increases and vice versa (Lin et al. 2005). Similarly, in cognitive distraction or in a drunken state, four common consequences may appear while driving:

1. difficulty in keeping the car within a lane,
2. drifting off the road,
3. more frequent and unnecessary changes in speed, and
4. late reaction time to avoid a dangerous situation.

Computer vision provides methods implementing lane keeping systems with satisfactory results, as described in (Zhou et al. 2006, Jiang et al. 2009). Vision-based lane detection provides lane boundaries ahead of the ego-vehicle, and the vehicle position within the current lane is important for determining the driver's level of vigilance. Using a monocular camera and then applying a dynamic Canny edge detector, Figure 14 shows a good representation of lane boundaries. Afterwards, starting from the left bottom-most pixel and the right bottom-most pixel

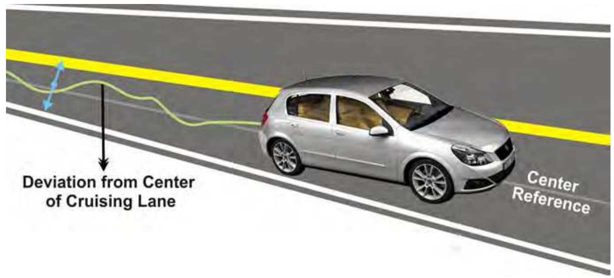


Fig. 13. Lateral position and lane index error from centre of current cruising lane.

of an image, and continuing towards the middle of the image, a continuous parallel lane can be determined (Kol et al. 2006).

After lane detection, the lateral position (and an error index) of the ego-vehicle in relation to the centre of the lane is measurable such that the level of driver distraction/vigilance is measurable as well. However, these vision-based systems are sensitive to street and weather condition; thus, some supplementary sensors need to be added to cover vision sensor drawbacks. In (Weigel et al. 2009), a LIDAR sensor and in (Clanton et al. 2009) GSM is proposed to support the vision-based system.

With respect to various driving situations, some other types of the sensors should be capable of evaluating driver's commands (e.g. steering angle, backing, lane changing, turning a corner and overtaking a vehicle), relative vehicle's velocity, and traffic flow (low or dense). The combination of these parameters will be used to reflect a proper diving situation encountered by the driver. So we need an optimal selection of some appropriate sensors to monitor all these three factors (Kaempchen and Dietmayer 2003). But, which sensor (sensors) is (are) better and optimal? A full discussion on this topic is out of scope of this paper; however we provide a brief review.

Image sensors have some drawbacks, such as low ability of sensing depth but the advantage of higher ability of discrimination than LIDAR and radar. In vision systems, given a two-dimensional view of a 3D world, there is no unique or definitive way to reconstruct the 3D signals. Besides, the data may be corrupted by noise and distortions. Such corruptions come from variations such as weather, shading and lighting, magnetic fields and electrical noise in the sensor, reflections,

Fig. 14. Lane extraction.

movements, imperfections in the lens, mal-calibrations, finite integration time on the sensor (motion blur), or compression artefacts after image capture. Given these daunting challenges, we need to utilize some supplementary sensors to obtain additional contextual knowledge to cope with limitations imposed on visual sensors. A *radar sensor* provides limited lateral spatial information (i.e. the field of view is narrow), and the resolution is very limited at large distances. *LIDAR* has a wider field of view that solves part of the previous problems; however, there are other problems such as low ability of discrimination, clustering errors, or recognition latency, and difficulties in understanding movements in the scene.

Regarding sensor fusion, to implement an optimum sensor deployment is a challenging concern. Besides, the decision on selecting a proper set of object-detecting sensors should be made based on the capability of available sensors and real-time driving condition (Rezaei and Sabzevari 2009, Rezaei and Fasih 2007).

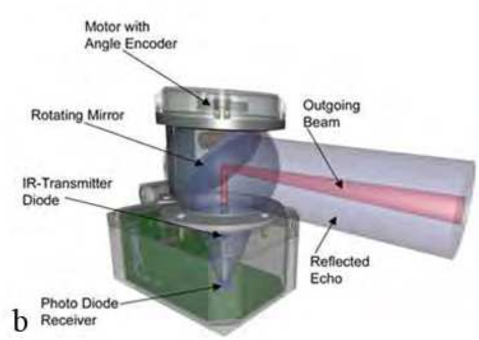
4 Out-vehicle Monitoring Sensors

This section introduces some sensors in more detail that were only mentioned beforehand.

Steering angle sensor: Bosch GmbH provides a vehicle dynamic sensor that measures the steering angle using an integrated calibration system and a special self-diagnosis function; this steering wheel-angle sensor is highly suitable for safety application in intelligent transportation systems.

Yaw rate sensor: Bosch GmbH also developed an accurate gyrometer. The sensor function is a registration of the rotational movement of the vehicle around its vertical axis and is designed to measure the physical effects of yawing and lateral acceleration. In order to achieve this, the sensor features a measuring element both for yaw rate and acceleration. A rotation around the third orthogonal axis, a yaw rate, creates a Carioles' force on the accelerometers, which is detected by the element. Apart from the measuring element for yaw rate, a pure surface micro machined measuring element for acceleration is utilized to measure the vehicles lateral acceleration. This enables a very precise application.


a



b

Fig. 15. (a) Bosch 2^{nd} generation long range radar (b) Alasca XT laser scanner.

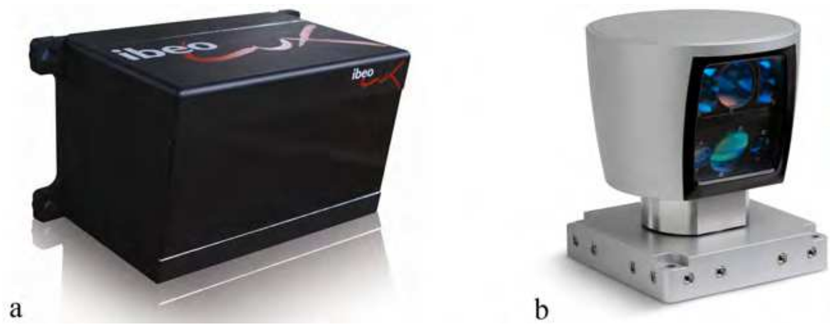


Fig. 16. (a) IBEO LIDAR sensor. (b) Velodyne HDL-64E 360° LIDAR.

Radar, and laser or LIDAR: These sensors are ideal to measure distance from moving or static objects around the vehicle. The radar sensors (Figure 15(a)) are available in two types according to their frequency (long range or short range radar). The other sensor, a laser scanner, is in general more expensive and has a wider viewing angle (Figure 15(b))-(Ibeo 2010). In contrast, laser sensor is highly degraded by weather conditions such as dirt, snow or mud on the back of the target vehicle. LIDAR sensors can be used to obtain a 2-dimensional field of distance measurements. IBEO LUX LIDAR (Figure 16(a)) is capable of detecting distances from 30 cm up to 200 m with a very good viewing angle (240°). The time-of-flight LIDARs, or simply a laser range scanner, are very popular in robotics; because they provide accurate distances to obstacles with higher robustness and less complexity than alternatives such as stereo vision. Velodyne HDL-64E LIDAR (Figure 16(b)), see (Velodyne 2011), is one of the best available ones. Its durability, 360° field of view and very high data rate of 1·3 Mega points per second makes this sensor ideal for demanding perception applications as well as 3D mobile data collection (Table 1).

Weather sensors: In order to add some more realistic factors in driving behaviour analysis in poor weather conditions (e.g. foggy or raining), two kinds of weather sensors are useful (Bahram et al. 2009). *Car rain sensor* (e.g. one that developed by LF Automobile Accessory Company) are appropriate to sense

Table 1. Radar and LIDAR: typical technical features.

	Radar	***Laser* & *LIDAR***
Frequency	76–77 GHz	12·5–25 Ghz
Range	1–150 m	30 cm to 200 m
Search area/Field of view	12°	240° to 360°
Measurement speed	0·2 km/h	1·33 Mpoints/sec.
Laser class	—	Class 1 - eye safe
Precision	0·3°	$\pm 5cm$

the rain and its intensity. The sensor is capable of recognizing raindrops and snowflakes on the windshield and its speed. GLOBALW WE600 *humidity sensor* is another sample sensor in order for road wetness and measuring percentage of humidity. Humidity sensors are normally composed of a solid state capacitative element with a linear amplifier.

5 Hybrid Steering via Contextual Knowledge

A *hybrid steering system* (HSS) is used as a decision layer. Actually, the driver's brain issues a set of driving commands based of human senses fusion. Similarly HSS performs a data fusion based on the raw data from out-vehicle physical sensor fusion. Besides, driver vigilance via in-vehicle sensor(s) is considered as an importance factor for decision layer.

As an example, if the driver forces the acceleration pedal to increase the speed of vehicle according to his/her brain decision; the HSS checks the driver's command with auxiliary mounted sensors data in order to have a safe action. It means, if the sensors report a dangerous dense traffic or the in-vehicle sensors reports the driver "distracted", so the HSS will intervene actuators and the output commands might be something different to the recent driver's command.

All these should be done through a fusion methodology. In order to reduce CPU usage and relevant complexities, we strongly recommend doing the same method that a human do, that is something similar fuzzy fusion method. In this method everything is interpreted as some linguistic membership function plus some basic arithmetic-logical concepts. For a better illustration, here are two sample conceptual membership functions:

IF the driver command is *'overtaking'* AND
The driver is *'fully aware'* AND
The distance to the around vehicle is *'safe'* THEN
Keep left and overtake

IF the distance is *'low'* AND
The driver is *'not aware'* AND
The speed is *'increasing'* THEN
Perform Emergency Breaking and keep right

These linguistic variables (low, high, aware, semi-aware) are not fixed value or terms and can change over the time depending on the overall state of the system. For example if the vehicle speed is too slow then the distance of 10 m is considered as a long but when the vehicle is running in a high-speed motorway the distance of 10 m is considered as being short. In such cases utilizing fuzzy-logic would be efficient (Rezaei and Sabzevari 2009).

6 Lane Keeping with a Fuzzy Fusion Approach

As discussed in Section 4, safe and precise lane keeping is an ideal goal of advanced driver assistance systems when the driver is distracted. Utilizing MAT-

Table 2. Applied sensors and their area of application.

Sensors	***Application***
In-vehicle vision sensor	Driver distraction detection
Out-vehicle vision sensor	Lane detection
Rain & humidity sensor	Weather condition

LAB fuzzy toolbox, the simulation determines an appropriate steer angle correction based on three parameter of:

Current position of vehicle in the lane
Drivers level of awareness
Weather condition (Humidity and Fogginess)

Ideally this simulation tries to figure out a continues steer angle correction to keep the vehicle along the middle of current travelling lane in case of zigzag moving or malfunctioning due to driver distraction or limited view from windshield (foggy weather), or even in both simultaneous situations (bad weather and distracted driver). Considering technical specification of previously mentioned sensors, the arrangements as listed in Table 2 have been considered.

Table 3 shows the important factors for the sensors such as their working range and relevant linguistic variables that are assigned for fuzzy fusion approach. Then a Mamdani fuzzy fusion framework was designed in MATLAB R2009 and Fuzzytech based on above knowledge base (Figure 17).

The inputs are *driver's level of vigilance* which are real data from the camera mounted inside the car to determine driver's distraction, and *weather condition*, *vehicle deviation index* based on current cruising lane and other sensors in Table 2 which are simulated data but are in consistency with technical features of each sensor, and finally the output that is the *correction steer angle*. We used fuzzification as it is able to normalize different value-ranges of data from different types of sensors into some easy to handle linguistic values.

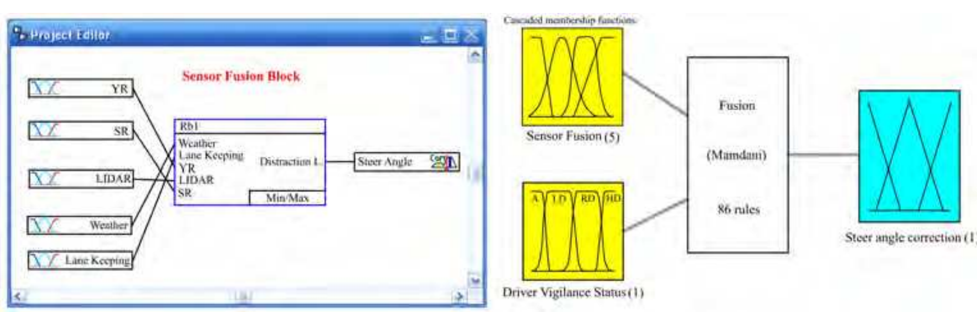


Fig. 17. Structure of fuzzy fusion of sensory data(simulated data) and driver monitoring (real-world data)

Table 3. System sensors, working range and fuzzy linguistic variables.

Sensor type	***Symbol***	***Working range***	***Fuzzy linguistic variable***
Yaw rate sensor	$\Omega : Yaw\ rate$ $-100 < \Omega < 100$	$-100 < \Omega \leq 100$	Low
		$-35 \leq \Omega < 30$	Medium
		$30 \leq \Omega < 100$	High
Steering angle sensor	$\alpha : Steering\ angle$ $-780 < \alpha < 780$	$-780 < \alpha \leq -260$	Low
		$-260 \leq \alpha < 260$	Medium
		$260 \leq \alpha < 780$	High
LIDAR	**FD**: distance from front vehicle (meter)	$0 < FD \leq 5$	Near
		$5 \leq FD < 15$	Far
		$15 \leq FD < 200$	Very far
Weather condition	**H:** humidity (0 to 100 RH)	$0 < H \leq 40$	Normal
		$40 < H \leq 65$	Humid
		$65 \leq H < 80$	Rainy - drizzle
		$80 \leq H < 100$	Rainy and foggy
		$70 \leq H < 90$	Snowy
		$80 \leq H < 95$	Snowy - foggy
Lane keeping	**L**: Lane deviation Index to the centre of lane (meter)	$L < -1{\cdot}5$	Large left deviation
		$-1{\cdot}5 < L < -0{\cdot}5$	Left deviation
		$-0{\cdot}5 < L < +0{\cdot}5$	On the way
		$0{\cdot}5 < L < +1{\cdot}5$	Right deviation
		$L > 1{\cdot}5$	Large right deviation
Distraction detection	**V**: distracted times in second (per minute)	$\mathrm{V} = 0$	Awake
		$1 \leq V < 3$	Lightly distracted
		$3 \leq V < 5$	Remarkably distracted
		$5 \geq V$	Highly distracted

Finally, if the driver is aware or semi-aware, the system output (steer angle correction) could be informed just via a visual or haptic signal; but if the driver is distracted, then the output should interfere on mechanical actuators directly.

Despite of two different types of real world or simulated data, we fuzzify all the data in accordance with the defined linguistic variables based on Table 3, then applying a combination of Gaussian, sigmoid, s-shaped and triangular membership functions for parameters Ω, α, FD, H, L, V along with more than 86 fuzzy rules, Figure 18 obtained. As illustrated, there are three inputs and one output. Horizontal coordinate axes show two of input variables:

Weather condition: 1 indicates sunny and good condition and 6 indicates the worst conditions (rainy, wet, foggy).
Deviation from centre of lane. (Measured in meter).
Driver awareness is the third input that is not showed in the graph but is considered in parallel.

The vertical axis shows the output:

Correction angle: the correction angle to be applied on the role to bring back the vehicle within the centre of the lane.

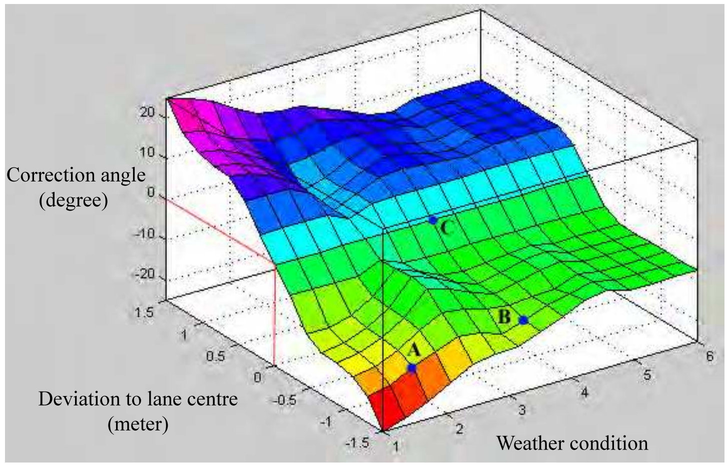


Fig. 18. Steering angle correction based on lane deviation index and weather condition.

According to the reasoning in Section 3.2, if the driver is aware, just a warning appears but if the driver is detected as being distracted then both warning and steer angle correction applies (Figure 18). Steer angle adjustment aims to maintain the vehicle inside the lane. Generally, the output value should be applied either by the driver or by an autonomous system that directly interposes the vehicle actuators (Rezaei et al. 2009).

Paying attention to points A, B and C in Figure 18, it can be concluded that whenever the deviation index become greater and/or weather condition become worse, so the correction angle follows a soft and cautiously trend. For example for point B although the deviation is relatively high (-1 m), however due to bad weather condition (rainy, foggy, slippery) the steer angle could not be changed immediately and significantly (only about 5°). In contrast, whenever the weather is good even for large deviations (e.g. point A) the steer angle could be adjusted with rather high values and more faster (a correction of 25° applies).

Looking at points similar to C, it can be realized that if the lane deviation is small (near zero), so no steering angle correction is needed; no matter what the weather conditions are or the driver's level of consciousness. This indicates that the fuzzy-fusion expert system and the defined rules are performing in a rational manner.

7 Conclusion and Future Work

This article provides a structured review on current technologies for advanced driver assistance systems. A diversity of real world sensors, their advantages and drawbacks has been discussed as contribution to the reviewing part.

The article also proposes a method for concurrent assessment of driver's vigilance focusing on in-vehicle monitoring (head orientation and eye state) plus road situation monitoring (vehicle position and weather state). We derived a feasible and logical methodology towards designing a next generation of driver assistance systems that takes also driver monitoring into account.

The proposed solution combines a sensor array (as input), a perception layer and a decision making layer (as a steering support system), and an action layer (as output). We have tested the first part of the system (face and eye detection) in our research vehicle in real-time and in daylight conditions. Applying the extended Haar training method and recording of 4,000 image sequences while driving, we gained a hit rate of 97·2% for eye detection and a false alarm of 4·6% which are fairly good results for such an application. The second part of the system (vehicle maneuver monitoring) was evaluated in a MATLAB simulation environment but with real sensor parameters. Thus there is still potential for applying real sensors in future work.

The system is real-time with respect to the reported real-world data acquisition. Our current work focuses on a further, more detailed run time and performance analysis, also taking various driving situations into account (say, *benchmarking* for the discussed application). For example, this should also evaluate eye gaze detection and assessing the driver's eye correlation towards moving objects in traffic scenes.

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