Abstract: Driver drowsiness is a major cause of traffic crashes all over the world. The real time detection and assessment of driver impairment through non-intrusive driver drowsiness detection system is a real challenge. Within this paper a quick overview of former development related with driver monitoring system is given. Then latest developments and results concerning sensing capabilities and diagnostic are presented. Finally some promising results are presented.

Keywords: ADAS, Driver vigilance, diagnostic, image processing

1. INTRODUCTION
Over the last decade, the automobile became a very significant market for the electronic industry, accounting for more than 10 percent of the overall turnover. The electronic functions initially applied to the management of the engine have progressively encroached upon safety areas: ABS, air-bag, obstacle detection, etc. security areas: access control, immobilizer and comfort areas: air conditioning and of course driving aids.
To cope with these challenges, car manufacturers, car suppliers and research establishments have pooled their efforts within numerous domestic and international programs. DREAM (Driver Related Evaluation and Monitoring), DETER (Detection Enforcement and Tutoring for Error Reduction), PROCHIP/PROMETHEUS and SAVE (System for effective Assessment of the driver state and Vehicle control in Emergency situations) are some examples associating European partners between 1988 and 1998 with three major objectives:
- Active Driver Safety,
- Vehicle/road communications,
- Car Automatic Control.

Improvement of safety in road traffic corresponds to an increasing demand from a majority of users as well as to a social and economical necessity. Among the problems that impact on traffic safety, the driver’s physical and psychological state and more specifically driver impairment plays an important role. The assessment of the driver Vigilance State has attracted wide interest both in basic research and in solution to the development of monitoring systems. The term “driver impairment” encompasses all the situations in which the driver’s alertness is diminished, and therefore when the driving task cannot be maintained at an adequate level of performance. It is a consequence of stress, fatigue, alcohol abuse, medication, inattention, effects of various diseases.
The major concerns of this paper are to present an overview of the driver monitoring system and the latest achievements. Section 2 is dedicated to a general analysis of the vehicle Safety problems and tries to set down the drowsiness problem and a non-exhaustive state of the art. Section 3 presents a general overview of the driver monitoring system. Section 4 and 5 give some details about the sensors and diagnosis units. At last section 6 presents the latest results.
2. THE VEHICLE SAFETY- AND DROWSINESS PROBLEM

Traffic crashes constitute one of the largest public health problems in industrialised countries. For example, in Europe around 50,000 people are killed and over 1,500,000 are injured each year.

A major focus of research over the last few years has been “driver drowsiness” as a cause of road accidents. National Transportation and Safety Board of US has during the 1990s paid attention to driver fatigue as one of the most important causes of road accidents [National Transportation and Safety Board of US, 1999]. 10-20\% of all accidents is related to driver fatigue [Horne et al, 1999]. More precisely:

- [Bousague, 1995] found that fatigue and/or drowsiness of the driver caused around 30\% of accidents in French highways in the period 1979-1994, whereas about 40\% of fatal accidents on US highways are sleep-related [Garder, 1998].
- 1\% to 10\% of all accidents in the U.S.A. seem to be directly related to sleepiness [Cerrelli, 1996].
- Regarding heavy vehicles crashes [FHWA, 1998] estimated that in the USA fatigue-related crashes constitute 0.71\%-2.7\% of all crashes involving trucks and 15\% to 36\% of all crashes fatal to the truck driver. [Garder, 1998] estimates that fatigue is a factor affecting 30-40\% of heavy truck crashes in US.
- [Knipling et al,1997] establishes that a good detection of fatigue alone could concern between 40\% and 60\% of the crashes with one vehicle and 37\% of truck drivers fatalities [Rau, 1998].
- Expected involvement in such accidents of trucks is 4.5 times greater than for passenger vehicles due to exposure, operational life and night driving [Knipling et al,1997].

Regarding these different statistics, they look sometimes difficult to analyse and interpret. Nevertheless, the influence of driver loss of vigilance and fatigue on vehicle crashes is obvious. Thus the implementation on vehicles of systems able to monitor the Driver State and to assess in real time that a driver impairment is imminent makes sense.

Until now various prototypes and systems for monitoring driver impairment have been developed without any outstanding market success. Most of them base their detection on single driver characteristics for example:

- The Nissan anti-drowsiness system that monitors eyelid movement, the Mitsubishi Driver’s View Detector that analyses the eyes position and blinking, the MICRODAS system based on ocular measurements, the Dozer’s alarm from Australia that measures the inclination angle of driver’s head.
- Other systems are based on physiological measurements of the driver (such as EEG, EOG, ECG, muscle activity) for example the Toyota anti-drowsiness system that detects driver drowsiness through a wrist device. More recent is the SafeTRAC system from USA that is based on lane tracking detection.
- Some systems integrate multi-sensors behavioural characteristics (such as vehicle speed, lane position, etc.), for example in the DETER-EU project [Brookhuis, 1995] or in the PROCHIP PROMETHEUS program [Estève et al, 1995].

The first integrated approach known so far has been the one followed by SAVE project (TR 1047) (1995-1998) [SAVE 1996-1998]; this project had three major goals:

- To diagnose in real time the driver state,
- To inform the driver, about his driving performance, the environment if the pilot has problems and a specialised centre if an accident has occurred,
- To take the control of the car, if the pilot has problems.

To reduce the risk of false alarm a multi-sensors approach has been promoted. It is based on vehicle behaviour analysis (deviation from the lane, obstacle detection, . . .), driver’s action analysis (steering wheel movement, pedal position, . . .) and also driver’s behaviour profile identification and recognition of serious deviations from it (eyelid pattern, head position, . . .). Final results have been reported in [Bekiaris, 1999]. Nevertheless, the system was proven difficult to expand beyond simple road cases (i.e. straight road, with well-defined lanes, etc.), without modules providing strong personalization to the driver’s characteristics and sensors/algorithm improvements.

Since March 2000 the activities of SAVE project have been followed in the context of a French founded project*. Taking into account the lessons and learning of the previous programs, the objectives of this project are:

- To select and confirm the usefulness of pertinent parameters for driver drowsiness monitoring that have been selected in the previous works.
- To further develop and adapt existing sensors to measure the selected parameters.
- To develop and improve processing and diagnosis techniques.

These different steps have been supported by intensive experimental developments based on:

- A Driving simulator located in CEPA-CNRS in Strasbourg
- An experimental vehicle (COPITech vehicle from LAAS-CNRS) equipped with various

* This program is supported by the French ministry of research in the context of the PREDIT program. This project gathers 8 partners; 4 research laboratories: LAAS/ CNRS- CEPA/CNRS, CHU, ONERA; 3 industrial partners: SIEMENS VDO Automotive SAS, ACTIA and THOMSON Texen and one Institute: IERSET.
sensors (eyelid sensor, lane tracking, steering wheel position, pedal movements, . . .)

3. THE DRIVER MONITORING SYSTEM - GENERAL OVERVIEW

The driver monitoring system includes several levels (see Fig 1):

- The sensing/ information processing including various sensors and their associate processing units, (i.e. image processing, . . .).
- The Data pre-processing: that extracts pertinent and discriminate information from the various measurements provided by the sensing level,. .
- The diagnosis unit, which can be considered as the core of the system. It estimates the evolution of the driver state
- And the final decision that provides information to the driver through an adapted HMI.

![Driver monitoring system principle](image)

Figure 1 Driver monitoring system principle

4. SENSING LEVEL AND INFORMATION PROCESSING

As it has been demonstrated in the former projects, to achieve a reliable diagnosis about the Driver State of vigilance, it is necessary to combine different information provided by different sensors. The first purpose of this study was to select the most appropriate information

In order to make this selection several test campaign have been set up both on simulator and experimental vehicle. Tests were operated under medical and physiological expertise (EEG, EOG, ECG, . . .).

At last four information were selected:

- The vehicle speed (provided by the engine control unit)
- The steering wheel movement (resistive or electromagnetic sensor)

The two last information are based on video processing and are concerned with specific developments:

- Eyelid sensor
- Vehicle lateral position.

In addition these experiments gave the following indications:

- The driving behaviour is personalised (Drivers have different driving characteristics in normal and abnormal ways). The driver behaviour could change in the time
- The pertinent parameters for the diagnosis depend on the road situation. This means in practice that most probably we’ll have to distinguish between different road environments (figures 2 and 3)

![Figure 2: Evolution of the lateral distance for 2 subjects: solid: s.d., hatching: average](image)

Figure 2: Evolution of the lateral distance for 2 subjects: solid: s.d., hatching: average

4.1 Eyelid Sensor (ELS) principles

Increase of eyes blink duration appears to be one of the most relevant symptoms for detecting driver’s drowsiness. [Wierville, 1994] uses the measure of the proportion of time that the driver eyes are 80 to 100 % closed to assess drowsiness.

The Eyelid Sensor developed by Siemens is a non-intrusive system based on a distant onboard video sensor and image processing technique [Boverie, 1998; Giralt et al., 1998]

The image is provided by one monochromatic image sensor placed on the bottom of the dashboard. Two lighting units placed on the top of the dashboard at each side of the steering wheel enlighten the driver’s face with near Infrared light. It’s a non-invasive system that doesn’t require any other input and no specific hardware adaptation to the driver.

![Figure 4: Eyelid sensor overview](image)

Figure 4 Eyelid sensor overview

The algorithm is based on a two steps real time approach (50Hz) implemented on a PC:

A first step processes the global scene for robust eye localisation adapted to driver situations and morphologies and to beat whenever is relevant in a bounded sub-image (centred on the eyes).
The second step tracks the pupil position within the sub-image and measures the eyelid aperture and blink duration. The algorithms here yield to locate accurately the eye/pupils for measurement of the eye opening degree, the result are validated by the first step. This two steps interplay aims to achieve a real time eye opening measurement at a limited processing power. It’s well adapted for slow head movements (normal driving configurations). The Eyelid sensor has been tested in various conditions (night, day, ..) for many different drivers and on different vehicles. The results obtained are quite different depending on conditions of the experimentation. Globally, main reasons for low detection rate are bright incident illumination by daytime driving (sundown, ..), glasses, fast head movement, driver specific behaviour (hand on face, inclination of the head, fast head movements ..).

4.2 Lateral position sensor

Vehicle lateral position is also considered as one of the most relevant information for detecting driver’s driving ability in case of driver’s drowsiness. Vehicle lateral position can be estimated by measuring the distance between the vehicle and the lateral white lines. Based on the development achieved in former programs like PROMETHEUS we have developed a specific sensor that fits with our requirements in terms of robustness, accuracy and calculation time (see Figure 5).

Figure 5 Line tracker camera (a) -Line tracker processing overview (b) initial image (c) contour reconstruction, (d) line detection

This sensor includes a video camera, located on the right side of the vehicle looking backward, associated with a processing unit currently implemented onto a PC. The algorithms are based on a two step approach:

- A first step processes the global scene recorded by the camera and extracts, among the various lines the right one. This processing is performed thanks to conventional image processing techniques like contour detection.
- In a second step the distance between the selected line and the vehicle is estimated by the way of 3D geometrical reconstruction.

The sensor is able to process 10 images per seconds (one image each 3m for a vehicle speed around 120Km/h). That looks enough for the application purpose that is currently the motorway. The measurement accuracy is better than 10 cm for a car to line distance lower than 3 meters.

The system is able to reconstruct the missing lines portions (discontinuous line) and able to manage line changes and over passing.

5. DIAGNOSIS PRINCIPLES : ADAPTED PATTERN RECOGNITION APPROACH

5.1 Theoretical background : classical approach

Pattern recognition approach for complex system diagnosis has been firstly investigated in the eighties. This framework constitutes a non-symbolic external approach. Indeed, only numerical observations of the system are taken into account to build up a diagnosis module. Conventional pattern recognition diagnosis can be briefly defined as follow. Firstly, one has to determine a set of “features” (which may be pure observation or composite signals) containing a sufficient amount of information to discriminate normal functioning from abnormal states. Secondly a decision space is defined, corresponding to the symbolic state of the system, i.e. diagnosis: normal behaviour, defect 1, defect 2 … Pattern recognition can also be formally defined as a mapping from observation space into the decision space, and therefore represents a classification problem. To do this one has to determine the best features and the learning method for the classification problem. Several learning processes may be used, leading to different classification modules: e.g. Neural Networks, Bayesian Learning, Statistical Learning…

5.2 Data processing and composite signals

This part of the pattern recognition diagnosis approach, commonly referred to as “feature extraction”, is really fundamental. Because loosely informed composite signals would definitely lead to a bad diagnostic whatever the discrimination module one can use. Feature extraction is usually not easy. Various things, but mainly intuition may guide it: where and how could we find the discrimination information? The classical process to achieve this task is first to start with a well representative database (with a sufficient quantity of observations from the different classes). Secondly, various treatments may be applied on these data also based on intuitive and/or logical ideas: classical statistic, signal processing, frequency analysis, energy distribution, time-frequency analysis, high-order statistic, PCA (Principal Component Analysis, used
very often), ICA (Independent Component Analysis) and so on.

5.3 Our constraints and consequences

In the framework of diagnosis one can distinguish two cases. The first one concerns processes, where abnormal behaviours are all well known. For the second class of systems one can consider that normal behaviour is quite well defined, but abnormal behaviours modes are difficult to be exhibited and classified.

The “driver impairment” detection is certainly one of the most difficult problem in the second category. Indeed, it is not possible to ask an user of the system to drive in impaired condition in order to learn his behaviour. Thus it is clear that using a multiple classes method for diagnosis is definitely doomed to failure. The following is the main rationale behind the method proposed for the “driver impairment” detection: one assume that we can at least quite well define the normal behaviour of the driver and that the states outside this subspace could be considered as abnormal behaviour. This is clearly: one-class pattern recognition detection. A few implementations have been proposed to deal with one class classification problem [Poulard et al, 1997]. All these experiments have shown that the most robust is clearly the statistical one. In few words, it consists of making a statistical modelling of ONLY the normal behaviour data (usually the Probability Density Function) for several feature spaces (as explained before). Finally the result is obtained while combining these statistics outcomes using different approaches: e.g. simply the product, voting method, LMS (Least Mean Square), etc.

From the data processing several feature spaces can be extracted. Figure 7 shows an example of data distribution between vigilant (circles) and non-vigilant (crosses) classes for a selected feature space and for a given driver. These data are processed from lateral deviation and steering wheel movement. They have been recorded during one hour and half, driving on a highway. The figure shows a good separation between the two classes with a concentrated vigilant class and a spread non-vigilant class.

Figure 7 Data distribution

Figure 8 Probability Density Estimation for vigilant period

For the same feature space, Figure 8 gives the Probability Density Function (PDF) representation of the associated vigilant model. It has been learned by the system during the first half an hour driving that has been expertise as a vigilant period.

At last different vigilant models corresponding to different feature spaces are built and aggregated to provide a diagnosis on the overall driving period. Figure 9 and 10 present two examples of the final diagnosis for two different drivers using the same feature spaces compared to a reference three levels expertise of the driver (vigilant, unclear, hypovigilant). Figure 9 represents around 2 hours of driving while Figure 10 represents around 8 hours on two different days.

On these figures, one can see that during all the vigilant phases, the system output is high enough for not firing any alarm (one false alarm). Even if some of the hypovigilant phases are not detected by the

6. EXPERIMENTATION AND RESULTS

Specific experimentation has been achieved on simulator and with the experimental vehicle on the motorway. Their objectives were to record data for training, testing and validate the processing and diagnosis units. Some preliminary and partial results are presented in the following section.
system, it would raise more than ten alarms that would be justified.

Figure 9: diagnostic compared to a 3 levels expertise

Figure 10: diagnostic compared to a 3 levels expertise

7. CONCLUSION

To monitor driver vigilance is a complex problem that requires an user accepted system able to measure and interpret the symptoms independently of driver’s characteristics, way of driving environment and then to warn the driver about the current situation. Since more then ten years, all over the world several teams have tried to propose solutions. Unfortunately, up to now, no efficient and reliable system could reach to the market. The current project explores new directions in order to bring solutions the former problems. Following the previous studies, we have promoted a multisensorial approach. Then specific sensors have been developed and improved with respect to our specific needs. Nevertheless, some work remains to be done specifically on eyelid sensor. Previous projects as for example SAVE were assuming that it was possible to identify in addition to the normal behaviour several classes of impairment: drunk, sleepy. Although this approach looks interesting in a research context but this is not realistic in an applicative one (it is not possible to ask a driver to drive in impaired conditions in order to learn its behaviour). Thus we have promoted a one-class pattern recognition (normal behaviour) approach based on statistical classification that looks much more adapted to our problem. At last specific developments have been achieved in order to identify discriminatory parameters to provide the diagnosis unit. Current results and orientation look promising. Nevertheless they must be confirmed in a near future by intensive tests.

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