A Noninvasive System for Evaluating Driver Vigilance Level Examining Both Physiological and Mechanical Data

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Abstract—**This paper describes a method for designing an intelligent system to improve driver safety. A prototype of the system, which was designed by following this method, is presented. Driver physiological data acquired from sensors on the steering wheel are correlated, using statistical multivariate analysis, to the driver's vigilance level, which was evaluated using polysomnography. A driving simulation was conducted with a mechanical platform, whose data were also acquired and studied the same way. The parameters chosen for the evaluation of driver vigilance are used for the first time in such a system. Data are analyzed offline to set up a real-time driver vigilance controller. The data analysis results in one vigilance-level index for the current driver and situation.**

Index Terms—**Evaluating driver vigilance, mechanical data, noninvasive system, physiological data.**

I. Introduction

Many PROJECTS in European Union (EU) programs are devoted to increasing automobile safety to reduce deaths and accidents by 50% over the next few years [1]. Among these projects is Project Psycho-Physiological Car (PSYCAR), which was funded by the EU and is the result of the cooperation between the "Politecnico di Milano," Milan, Italy, and the Linz Kepler University, Linz, Austria.

Apart from the EU programs, almost all automobile industries are studying new methods to improve active safety. Most of these methods are based on examining engine mechanics and car dynamics or on camera vision systems that continuously monitor the driver [2], [3]. Nevertheless, the greatest disadvantage of such systems lies on the fact that a possible head turning or lowering of the driver can be a significant problem for camera vision, putting the whole system out of order. In addition, vision software complexity can add financial and technical difficulties to the system. Such systems have been proposed by BMW and SEAT. Mercedes-Benz is also studying a similar system [4], whereas Toyota's approach to the problem is also camera based [5]. An interesting project [6] has been presented by the University of Tokyo, Tokyo, Japan; Oita University, Oita, Japan; Shimane Institute of Health Science, Shimane, Japan; and Delta Tooling, which is an industrial equipment manufacturer. Researchers have developed a prototype smart car seat that is capable of detecting when its occupant is on the verge of falling asleep. The seat is equipped with a pair of pulse-monitoring pressure sensors placed at the back and a set of respiration-monitoring sensors placed underneath. This system is obviously noninvasive but focuses only on the detection of sleepiness and does not take into consideration the possibility of a sleep attack, which can occur even without the presence of symptoms of sleepiness [7]. In addition, there has been little information published on this prototype, making it difficult to estimate its performance and compare it with the actual state of the art.

In [8], a system called FaceLAB, which was developed by Seeing Machines, is presented. The 3-D pose of the head and the eye-gaze direction are calculated in an exact way. The system also monitors the driver's eyelids to determine eye opening and blink rates. Using this information, the system estimates the driver's fatigue level. The system can operate both day and night, but at night, its performance decreases. In addition, FaceLAB does not work with some types of eyeglasses and relies on manual initialization of the feature points. The system appears to be robust, but manual initialization is a limitation, although it makes the whole problem of tracking and pose estimation trivial. Another interesting head/eye monitoring and tracking system that can detect driver drowsiness using a camera and color predicates is presented in [9]. However, this system is based on passive vision techniques, and its functionality can be problematic under poor or very bright lighting conditions. Moreover, it does not work at night, when the possibility of sleepiness or microsleep (sleep attack) increases. Other systems [10], [11] use light-emitting-diode illumination to overcome the poor lighting problem. Nevertheless, night vision is still an important obstacle for such systems, and most of them are tested only in simulated environments, without taking into consideration the challenges posed by a real car to the image analysis software, including vibrations and moving background.

The methodology and system presented in this paper are innovative in the field of automobile safety. The innovation lies within the fact that the driver's physiological parameters are acquired using sensors on the steering wheel, which is continuously in contact with the driver's body, and that these data are combined with the car's mechanical data to identify sleepiness and sleep attacks. The driver does not have to do

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anything in particular or, in any case, different from what he is used to doing when entering and driving the vehicle, as in other safety systems [12], [13]. Sensor positioning is fundamental. A possible loss of contact with the driver's body is safety-decrease information because this can only mean that the driver has taken his hands off the steering wheel. Several car dynamic and mechanical parameters are also acquired and evaluated. This combination of the car's behavior and the driver's physiological state is another innovation presented in this paper. The system stores all the data acquired to self-improve with time using neural network techniques, which will be implemented in the next phase of this work. The output of the proposed system is a vigilance level index, which can easily be interpreted by the driver [14].

The proposed system is totally independent of the lighting conditions. This is an important advantage with respect to all camera-based systems. The sensors used permit the acquisition of the necessary data for the estimation of sleepiness level, even in total darkness, when it is most crucial. Obviously, there is no limitation on the type of contact lenses or glasses used by the driver. In addition, there is no need for manual initialization of the feature points, unlike in most of the systems discussed in this section. The proposed system will be able to self-improve and auto-adapt to driver-specific characteristics with the addition of a learning feature, which will be implemented in the next phase of this work. The calculations needed under real-time conditions are also minimal with respect to several camera-based systems that require important calculus power.

II. Selection of the Monitored Physical Parameters

Large-scale research has been done by numerous universities and research teams to define physiological parameters that are able to determine a possible vigilance drop [15], [16]. Using the results of these studies, the necessary sensors for the proposed system are selected. This way, blood pressure, cardiac and respiratory frequencies, hand trembling, galvanic skin resistance (GSR), heart rate variability (HRV), body temperature (THE), blood alcohol and oxygen concentration, and cerebral waves are physiological parameters that can possibly determine the subject's neurophysiologic state [17].

Two different sets of parameters are monitored. This division is made, because some parameters are measured only for determining the driver's attention level (first set of parameters), and some are used only during the research phase as an index to which the second set of parameters is correlated. The second set consists of the noninvasive parameters that will still be used on the real vehicle.

The first set consists of the polysomnography parameters, along with the driver's reaction time. A medical team assisted the Robotics Laboratory Team of the Politecnico di Milano in the acquisition and interpretation of these parameters. The polysomnography parameters acquired were used as an index for driver attention, to which all other acquired parameters are correlated. These polysomnography parameters are the electrocardiograph (EKG), electroencephalograph (EEG), electrooculograph (EOG), chin electromyograph (EMG), peripheral THE, nasal pressure, blood oxygen concentration, and respiratory frequencies. The second set of measured parameters consists of the GSR, HRV, and THE, which are measured using the sensors on the steering wheel.

III. Signal Acquisition and Conditioning

To acquire the GSR, THE, and HRV signals from the steering wheel, a portable device has been developed on demand by ELEMAYA. GSR is measured using two silver plates, whereas, for HRV, a photoplethysmographic sensor is used. THE is measured using a thermocouple. These signals are filtered and amplified by the same ELEMAYA device. The analog-to-digital converter used is a National Instruments DAQ-card 6062E. All electronic board aspects were studied [18]–[21], whereas the signals are sampled at 200 Hz, following the Nyquist criteria.

Mechanical platform data are acquired using a personal computer and a C program. The same program also simulates road and car movement. The sampling rate is set at 65 Hz. Data analysis focuses on the straight parts of the road since driving on a curve highly depends on the driving skills, and in addition, it is highly unlikely for someone to fall asleep while making a curve. The data acquired during the driver's attempt to avoid appearing obstacles are neglected.

The ideal position that the driver should follow is the right lane of the circuit. Based on this, the error is calculated as the distance from the ideal position. The error data are separately normalized for each driver to eliminate the interference of individual driving skills.

The polysomnographical hardware used consists of a portable medical apparatus that is capable of acquiring all the necessary signals. The analysis of these signals determines driver status. For this polysomnographical acquisition, Madcare's Somnological Studio is used. The EEG electrodes are positioned according to the International 10–20 System. Recordings are obtained from the following leads: A1, A2, C3, C4, O1, and O2. For the EEG analyses, the C3 lead is used. The EEG signals are sampled at 200 Hz and filtered with a digital filter (with a cutoff frequency of 64 Hz).

IV. Simulation Protocol and Experiment Details

Simulations are made under two different driver conditions. In the first part, the driver has slept during the previous night, whereas, in the second part, he has been awake for 24 h. In the first state, the driver's nominal condition is evaluated, whereas in the second state, the altered condition is used.

It is important to make accurate measurements of the nominal state for every subject. During the night before measuring nominal conditions, the drivers should have slept for 8 h . Each driver also fills out a questionnaire. The aim of the questionnaire is to determine whether the person is undergoing a situation that could influence his physiological data. Such situations can be stress, anger, fatigue, or lack of willingness to participate in the simulation. If the person declares that he is under such a condition, he is excluded from the simulations.

During the simulations performed with sleep-deprived subjects, when sleep is detected, the driver is woken up. This way,

TABLE I
CATEGORIES OF DATA

Physiological data from the steering wheel	Mechanical data from the simulation platform	Reference data
HRV	Steering wheel position	Polysomnographical signals
GSR	Accelerator pedal position	Reaction time
THE	Brake pedal position	
	Vehicle road position	
	Vehicle speed	

The categories in which the acquired data have been divided. Reference data are used only in the research phase, while from the mechanical data only steering wheel position has been proved to be useful for detecting sleep attacks.

the transition phases are better examined. Simulations always take place in a dark and noiseless environment so that the subject will have a higher chance of falling asleep. The screen used for the projection of the simulation is 100 in wide and is positioned in front of the driver at a distance of about 4 m.

Before data acquisition, the person responsible for the simulation fills out a form with the date, time, and environmental conditions. At the beginning of every simulation session, the car is positioned at the same point in the virtual circuit. Before driving for the first time, each subject is trained on the simulator and learns to follow the predefined route. After these initial procedures, simulation and data acquisition are initialized. During the procedure and in predefined times not known to the subject, an obstacle appears on the screen, and the driver has to apply the brake. This way, his reaction time is measured and stored, along with all the other parameters acquired. This reaction time, along with the polysomnography data [22], [23], determines his attention level.

A total of 19 individuals took part in the tests, 15 of which were men and four of which were women. Nevertheless, four of the subjects (three men and a woman) took tests on an almost-daily basis for further system development. The driving sessions were 30 min long. The hardware used for all sessions is mentioned in the succeeding sections.

V. OFFLINE ANALYSIS AND STATISTICS OF THE ACQUIRED DATA

At the end of every simulation session, data are divided into three categories, as shown in Table I. The first group includes driver physiological parameters, the second group includes platform mechanical parameters, and the third group includes independent parameters used as a reference.

The purpose of the statistical analysis is to correlate the measured parameters with the driver's decrease in vigilance. The driver vigilance index is computed by studying the EEG signals, together with all the other polysomnographical signals and the reaction time of the driver to appearing obstacles. The vigilance index is an analysis-independent variable. These analyses focus on two different purposes: 1) the general behavior of the signals as the driver moves toward sleepiness and 2) the behavior of the same signals at exactly a minute before a sleep attack. The exact sleep-attack moment is determined using EEG power spectral density (PSD) analysis and medical experience.

For the EEG PSD analysis, after studying all the possible solutions, the $\alpha + \beta$ [24] cerebral wave method is chosen as the most appropriate. This method takes into consideration the power that is present in the α and β bands of the cerebral waves. [The cerebral wave frequency bands are defined as δ (0.75–3.75 Hz), θ (4.00–7.75 Hz), α (8.00–12.75 Hz), and β (13.00–20.25 Hz).] For the spectral analysis, the fast Fourier transform was calculated on 4-s mini-epochs with a resolution of 0.25 Hz. The absolute power in each of these bands was then calculated in square microvolts.

In addition to the EEG PSD analysis, the polysomnographical signals are also examined by the medical team. Three different persons, one of whom is completely foreign to the project and its scopes, analyzed the signals to determine the exact sleep-attack moment. This procedure is necessary to avoid defining some cerebral-wave frequency changes that occur due to eye closure or mechanical platform movement as sleep attacks. For this purpose, the medical team studied not only the EEG but all the other polysomnographical signals (mainly, the EOG) as well.

After determining the exact sleep-attack moment, all data from the minute before the sleep attack are divided into 10-s intervals. This procedure is necessary to study the exact time interval before a sleep attack, during which some interesting phenomena occur.

The stored data (physiological and mechanical) are studied using Matlab (version 7, revision 14). The observed phenomenon is nonlinear; thus, a standard linear analysis is not enough. Multivariate analysis is used to identify the categories of the input that are related to a certain output index. Different analysis types are followed. First, an analysis is made based on the mean value and variation observation for every signal acquired under every different driver condition. In addition, correlation and cross-correlation matrices are calculated not only to determine the possible correlation of an acquired parameter with another but also to correlate the acquired parameters with the driver sleepiness index derived from the polysomnographical data.

Principal component analysis (PCA) is used to study the correlation between the measured parameters. This method permits data reduction, based on the amount of information contained. It is important to project data on a plane, because this way, data can be represented as a point cloud in the R^p space, where p is the number of principal components. The PCA of the normalized data is practically based on the calculation of the eigenvalues and eigenvectors of the correlation matrix. Another significant parameter for the PCA is represented by the percent variance explained for every principal component, which is an index for the projection quality. In this case, the PCA leads to data reduction since the car speed, gas pedal, and brake pedal position were proven to be totally independent from the driver sleepiness status, presenting very low percent variance explained values.

Furthermore, cluster analysis is made on the data to simultaneously investigate possible data group formations over a variety of scales by creating a cluster tree that is not a single set of clusters but rather a multilevel hierarchy, where the clusters at one level are combined with the clusters at the next higher level. This allows for a decision as to which level or scale of clustering is appropriate for the application. The cluster analysis in this case is useful to study the possibility of separating the two groups of data, which are the data acquired from sleep-deprived subjects and the data acquired from the same subjects under normal conditions.

Discriminant analysis (DA), which is also used and applied on the data, determines one or more parameters that better discriminate two populations. For the DA, the training set was chosen, keeping in mind that the scope is to distinguish the sleep deprived from the nonsleepy subjects. The details of all the statistical analyses followed exceed the scope of this paper but are available in [25]. The results of these analyses are presented in Section VII.

VI. Real-Time Procedure

The offline analysis results are used to set up a real-time system prototype. In this prototype, the only parameters acquired are the noninvasive parameters (i.e., GSR, THE, and HRV) using the sensors on the steering wheel, along with the mechanical platform data. Driver identification (ID) is also stored. This way, the system becomes personalized and will be, in a future phase, trained based on driver-specific characteristics. The driver ID is obtained using his key to a real car or a password for the simulator. The saved data are also used to calculate the mean number of heartbeats and the steering-wheel standard deviation value, which are needed for data normalization.

All the parameters enter a fuzzy logic classifier that, based on the offline statistical results, determines whether the driver has a high possibility of being sleepy. Practically, the classifier continuously monitors the data to detect a possible decrease in driver vigilance. If the driver is found to be sleepy, then the system is put on alert to focus on detecting a possible sleep attack and to alert the driver. The driver is, in any case, alerted in the case of high sleepiness probability, even without the occurrence of a sleep attack.

The rules for the fuzzy logic classifier and the fuzzy set values are defined offline. The rules are based on the statistical analyses and medical experience. An important reason a fuzzy logic classifier, instead of other techniques, has been used is that fuzzy logic rules are close to natural language; thus, medical experience could be integrated in the system in the form of fuzzy logic rules.

The simulator system uses a Matlab function to call the fuzzy classifier, calculate the safety index, and retrieve important parameters for every signal. As shown in Fig. 1, if the classifier detects high sleepiness possibility, the system stays alert while monitoring variations in the number of heartbeats and the steering-wheel position. If high standard deviation values are detected in the heartbeat signal or very low standard deviation values are detected in the steering-wheel position signal, the system alerts the driver with a sound. The thresholds were chosen to be seven beats for the number of heartbeats and 0.5 for the normalized steering-wheel position standard deviation.

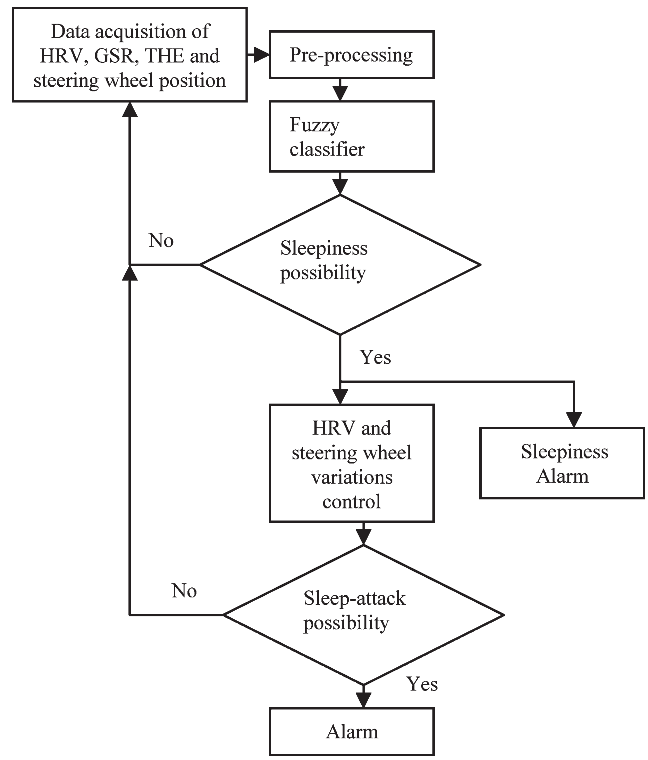

Fig. 1. Real-time procedure flow diagram.

This procedure was chosen according to the results reported in Section VII.

It should be stated clearly once again that sleepiness and sleep attack are different phenomena. However, it is more possible to have a sleep attack when the sleepiness level is high. The fuzzy logic classifier is used to detect sleepiness and put the system on alert in the event of a sleep attack. Sleep attack, however, is detected not by the fuzzy classifier but by a second controller that monitors the heartbeat rate and the steering-wheel movement variations.

The system discussed and analyzed here aims at the detection of both sleepiness and sleep attacks. The idea of a fuzzy logic classifier is not new in the field of automobile active safety systems [26]. Nevertheless, the classification parameters used by the classifier presented here are utilized for the first time in such a system and are not totally invasive, as in the case of EEG-based systems. In [27], a fuzzy controller is used for sleepiness detection, but the input parameters are acquired using image processing techniques. In addition, sleep-attack detection is a problem that is hardly tackled by most of the systems presented in the literature or available on the market. The possibility of identifying both phenomena and alerting the driver on time is the innovation of the proposed system.

VII. Result

By observing the data acquired from the simulations made with the individuals who did sleep during the night before the test, some interesting facts on their mean GSR value can be noticed. The more difficult the driving conditions, the lower the GSR values. The GSR is inversely proportional to perspiration, meaning that drivers perspire more when the driving conditions

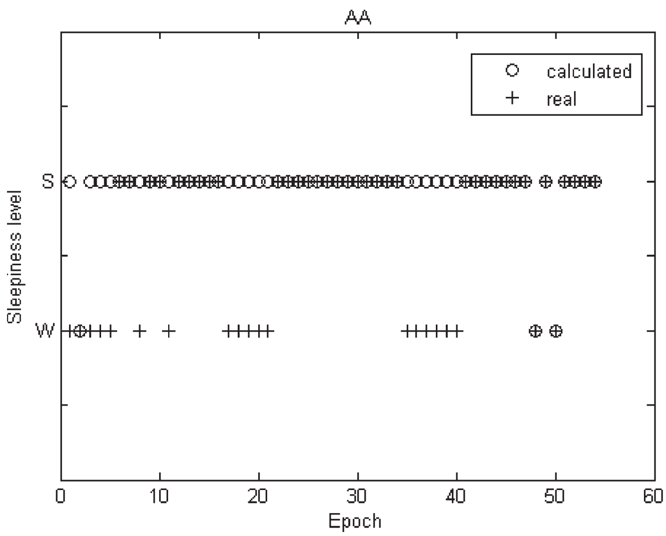

Fig. 2. Confrontation between the calculated and real sleepiness levels for 52 epochs with two sleepiness levels. (+) Real and (○) calculated sleepiness levels for every epoch. In the plot, for every epoch, when + and ○ coincide, the result is considered successful. An epoch is 30 s long, according to sleep medicine standards.

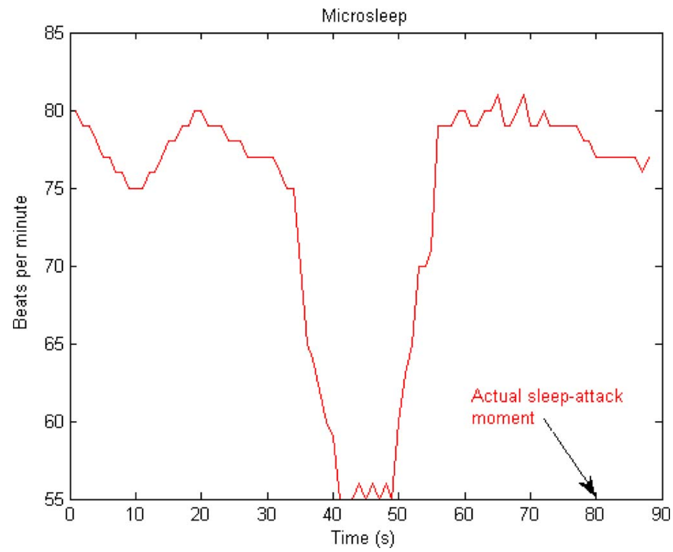

Fig. 3. High variations in the number of heartbeats 40 s before a sleep attack. The number of beats per minute varies from 55 to 80. The phenomenon of high variations is present in many cases and used in the proposed system detect sleep attacks.

TABLE II
PHYSIOLOGICAL PARAMETER VARIATION

Normal condition

	GSR (Ω)	THE (°C)	Heartbeats (bmp)
Subject AA	$3.97 \cdot 10^5$	32.84	77
Subject AG	$2.6 \cdot 10^5$	33.21	84

Altered condition

	GSR (Ω)	THE (°C)	Heartbeats (bmp)
Subject AA	$5.32 \cdot 10^5$	32.14	68
Subject AG	$1 \cdot 10^6$	33.02	72

The table presents the variations in the GSR, THE and Heartbeats signals for two subjects in the normal and altered conditions.

TABLE III
LOW NORMALIZED STANDARD DEVIATION VALUE BEFORE A MICROSLEEP

Steering wheel	1	2	3	4	5	6
Mean	2.9958	1.1638	1.1764	0.9943	1.0264	1.1572
Std_var	2.8497	0.2137	**0.0908**	**0.0822**	0.2035	0.1555

Car position	1	2	3	4	5	6
Mean	0.8156	0.8497	1.0782	1.1075	1.0500	1.1362
Std_var	0.6232	0.1534	**0.0909**	**0.1455**	0.1334	0.4459

A subject presenting very low standard deviation values in steering wheel movement, with respect to his usual value. The six cells correspond to the six 10-s intervals before a sleep-attack. The sixth interval is the final 10-s before the sleep attack. Values are normalized. Especially in the third and fourth interval, the phenomenon is very intense (extremely low movement of t he steering wheel).

are difficult (curved circuit with fast speed). This also means that the driver is more vigilant when the simulation conditions are difficult, because perspiration is inversely proportional to relaxation [28]. Examined from another point of view, the lower the GSR value, the more vigilant the driver. The GSR value can even be ten times higher than the normal value for every person, in the case of a decrease in vigilance.

In addition, as the driver status moves toward sleepiness, the number of heartbeats decreases. Finally, the THE value tends to slowly drop as the subject becomes less vigilant. Using this information, the fuzzy logic classifier was designed and trained. Afterward, driving simulations were made, and the classifier output was compared with the actual driver vigilance level defined by medical analyses. The results present a success value in the range of 60.68%–79.61% and are shown in Fig. 2.

From Table II, it can be noticed how the GSR, THE, and number of heartbeats change for two subjects, with respect to their normal conditions. The data for both subjects in both situations were acquired using the proposed system. The general behavior of the signals is similar for most subjects. Nevertheless, particularly for THE, variations can really be small and difficult to detect.

Apart from these observations concerning the general behavior of the chosen parameters toward sleepiness, the most important results concern data analysis during the minute before a sleep attack. In these analyses, the number of heartbeats and the steering-wheel position signals presented interesting behavior. The heart rate generally tends to drop, but the most important thing noticed is that some significant variations from 20 to 30 s are presented before a microsleep (see Fig. 3). In at least 76% of the cases, these variations were present. The percentage can be increased using a lower threshold value.

Finally, very small standard deviation values were observed in the car position error (see Table III) and the steering-wheel position. The error that the driver made was calculated as the difference between the actual and the ideal car position. Each driver has his own driving style and, thus, his own mean error values. The data were normalized using these values. For every 10-s interval before the microsleep, the mean and standard deviation values of the normalized error were calculated, as shown in Fig. 4. Notice that, during the minute before the

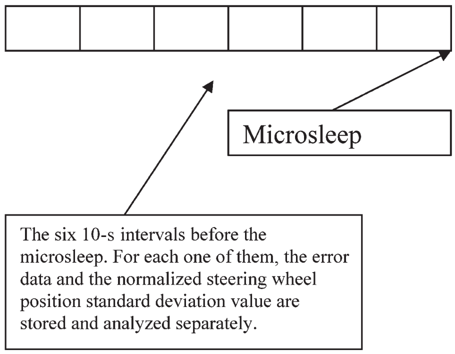

Fig. 4. Analysis was made using the last six 10-s intervals before the sleep attack.

TABLE IV
OCCURRENCE OF THE LOW STANDARD DEVIATION IN THE SIX INTERVALS

	Interval					
Standard deviation	**1**	**2**	**3**	**4**	**5**	**6**
Extremely Low	4/24	5/24	8/24	9/24	9/24	8/24
Very Low	4/24	4/24	6/24	8/24	4/24	5/24
Low	10/24	10/24	8/24	4/24	9/24	8/24
Total	18/24	19/24	22/24	21/24	22/24	21/24

The table presents the number of times in which the phenomenon of low standard deviation is present in each 10-s interval for a total of 24 sleep-attack episodes and the intensity of it. In the third interval, the phenomenon is present in 22 out of 24 cases, and it also very intense (extremely low or very) low values of standard deviation in 14 of them.

microsleep, the standard deviation value of the error made is much lower than usual, and so is the standard deviation value of the steering-wheel position. This implies that, even if the driver is driving far from the ideal position, he is not moving the steering wheel as he usually does. This phenomenon was observed in 87.5% of the cases and can be augmented by lowering the threshold value by only a little.

Analytically, from Table IV, it is evident that the phenomenon of low normalized standard deviation gradually becomes more intense, has a peak at about 20–30 s before the microsleep, and slowly degrades. The total number of times that the phenomenon is present gradually increases but remains almost constant from about 40 s before the sleep attack until the actual time of the sleep attack. The important thing here is that, even though the number of phenomena remains constant, the intensity of such phenomena increases. (There are more extremely low and very low normalized standard deviation values.) Practically, at about 20–30 s before the sleep attack, the phenomenon is at least *very intense* in 70.8% of the cases and at least *present* in 87.5% of the cases.

The sleep-attack identification results were used both separately and in combination to better understand how each of the two phenomena (high heartbeat variations and low normalized steering-wheel movement) can predict a sleep attack. Practically, two controllers, i.e., one that examines heartbeat variations and one that examines steering-wheel movement, were designed. The first and second controllers are, hereinafter, called Controller No. 1 (HRV) and Controller No. 2 (steering wheel), respectively.

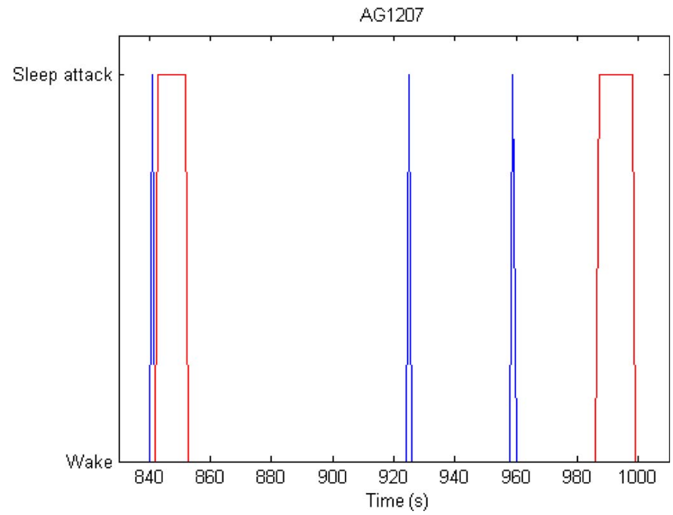

Fig. 5. Results of the use of Controller No. 2 for detecting sleep attacks. (Red line) Real driver condition. (Blue line) Controller's output. The controller detects the sleep attacks before they arrive. The second sleep attack (at about second 990) is twice detected by the controller, i.e., 30 and 60 s before it actually arrives.

From the simulations, some interesting conclusions can be drawn. The average success, in terms of time, for Controller No. 1 was 94.38%, whereas that for Controller No. 2 was 92.80%. This means that both controllers, for the majority of the simulation, provide the right output. The acquisitions were 30 min long for a total of 13 subjects, which leads to a total of 390 min of driving sessions.

About the errors made by the controllers, it is fundamental to know their nature. The positive and negative errors [29] are calculated in terms of the sleep attacks identified. Positive errors can be annoying for the driver but not dangerous. In addition, this kind of errors can be diminished by increasing the critical value for alarm activation. Negative errors, on the other hand, can be dangerous for the driver and can be diminished by lowering the critical value for alarm activation. It is obvious that extreme lowering can lead to an extremely annoying and useless system.

The critical values used during this simulation were chosen after the offline analyses (the critical thresholds are mentioned in Section VI) and generated a total of 83 positive errors for Controller No. 1 and 97 positive errors for Controller No. 2. Most of these errors generated an alarm of an extremely short duration (less than 1 s) and can be avoided by increasing the critical value. A small increase can lead to a decrease in positive errors by leaving the negative errors intact. The important errors are the negative errors. With Controller No. 1, a total of nine negative errors were made, leading to a success value of 66.66%. (Eighteen out of 27 sleep attacks were detected.) With Controller No. 2, the total number of negative errors was six, leading to a success value of 77.78%. (Twenty-one out of 27 sleep attacks were detected). Fig. 5 shows two sleep attack detections by the system (Controller No. 2).

The two systems were then combined to understand the success of the complete system. Combination of the two systems is possible and will minimize the negative errors to only two. This leads to a total success value of 92.59% in terms of success for sleep-attack detection. This combination leads to more positive errors. A tradeoff should be made between the positive errors and the system accuracy.

VIII. Conclusion and Future Development

The research results that have been discussed are promising. A control strategy based on fuzzy classification and a controller that monitors the number of heartbeats and the steering-wheel position can be used to determine a high sleep-attack risk and alert the driver.

The number of heartbeats and the peripheral THE decrease, as well as the increase in the GSR value, are sleepiness indicators that can set the system into a general alert status. These phenomena progress quite slowly and can only be used as precursors of sleepiness and not of an actual sleep attack, which is a fast phenomenon (3–15 s). On the other hand, the standard deviations of the steering-wheel position and the number of heartbeats occur very fast but permit early notification of the driver since the phenomenon usually occurs 20–30 s before a sleep attack. The standard deviation value of the error in the car position is difficult to apply to an actual car, as the ideal position is difficult to recover; however, it is a useful parameter in simulated driving sessions (e.g., in driving license exams).

The simulations made for testing sleep-attack detection controllers are also interesting. The number of negative errors is quite low, but a tradeoff has to be made to ensure a reasonable number of positive errors (false alarms). The authors are studying the possibility of optimizing threshold values.

A study on the applicability of neural networks to the proposed system is also in progress at the Laboratory of Robotics, Politecnico di Milano. The idea is to use the data acquired during a driving session, along with the current driver identity, to adapt the system to each particular driver. This will be made at the end of every driving session, when the engine stops, to ensure that the system real-time speed is not affected by this procedure. The neural network shall be used to retrain the fuzzy logic controller and ameliorate the system with time.

The methodology discussed and proposed in this paper, along with the constructed simulation prototype, is innovative in the field of automobile safety and is used on a daily basis to acquire more data for the statistical analysis and the fuzzy controller setup, with the aim of global automobile transportation safety [30]. The authors are aware that, even if the results are interesting in a simulated environment, real driving conditions can be quite different. The use of another instrument for temperature measurements, instead of a thermocouple, is also being considered to overcome the need for a cold junction. The use of a thermistor can be a solution to measure temperature without the need for a cold junction while keeping the cost low.

It is difficult to test the system under real driving conditions, because not only can it be dangerous to use sleep-deprived subjects for real driving, but EEG measurements are also extremely difficult to perform in a moving car. Some very accurate simulators, however, are available in major automobile companies, and as a next step in this work, the authors are trying to gain access to them for further system testing. Nevertheless, some test sessions in a real car are scheduled to use the proposed system, without the use of EEG and with the subjects under nominal conditions to test the positive errors made by the system. The possibility of combining the proposed system with other sleepiness detection systems will also be examined.

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References

[1] ISTAT, *Internet Published Report on Road Accidents*. [Online]. Available: http://www.istat.it/salastampa/comunicati/non_calendario/20051013_00/novita_editoriale_incidenti_stradali_2004.pdf
[2] Citroen, *Internet Published Article*. [Online]. Available: http://www.citroen.com/CWW/en-US/TECHNOLOGIES/SECURITY/AFIL/
[3] SEAT, *Internet Published Article*. [Online]. Available: http://media.seat.com/view_manager.html?root=35,40
[4] OmniAuto, . no. 510, 15.12.2003, Edimotive S.r.l. [Online]. Available: http://www.OmniAuto.it
[5] Fareastgizmos, *Internet Published Article*, 2008. [Online]. Available: http://www.fareastgizmos.com/transport/worlds_first_precrash_safety_system_from_toyota_determines_whether_drivers_eyes_are_properly_open.php
[6] Pinktentacle, *Internet Published Article*, 2007. [Online]. Available: http://www.pinktentacle.com/2007/03/smart-car-seat-detects-drowsy-drivers/
[7] A. J. Blaivas, R. Patel, D. Hom, K. Antigua, and H. Ashtyani, "Quantifying microsleep to help assess subjective sleepiness," *Sleep Med.*, vol. 8, no. 2, pp. 156–159, Mar. 2007.
[8] Facelab Transport, *Seeing Machines*, Aug. 2004. [Online]. Available: http://www.seeingmachines.com/transport.htm
[9] P. Smith, M. Shah, and N. D. V. Lobo, "Determining driver visual attention with one camera," *IEEE Trans. Intell. Transp. Syst.*, vol. 4, no. 4, pp. 205–218, Dec. 2003.
[10] Q. Ji and X. Yang, "Real-time eye, gaze, and face pose tracking for monitoring driver vigilance," *Real-Time Imag.*, vol. 8, no. 5, pp. 357–377, Oct. 2002.
[11] R. Grace, "Drowsy driver monitor and warning system," in *Proc. Int. Driving Symp. Hum. Factors Driver Assessment, Training Veh. Des.*, Aspen, CO, Aug. 2001, pp. 64–69.
[12] SAAB, *Internet Published Article*. [Online]. Available: http://www.saabvideos.com/2006/10/11/saab-alcokey-helps-drivers-steerclear-of-drinking-and-driving/
[13] Gizmag, *Internet Published Article*. [Online]. Available: http://www.gizmag.com/go/4448/
[14] A. Rovetta and F. Cosmi, "Teleoperator response in a touch task with different display conditions," *IEEE Trans. Syst., Man, Cybern.*, vol. 25, no. 5, pp. 878–881, May 1995.
[15] A. Rovettain "Report and tables with sensors and characters by Internet," Dept. Mech., Politecnico di Milano, Milan, Italy, 2005. Intern. Rep. [Online]. Available: ftp://robo55.mecc.polimi.it id psycar pw psycar folder PSYCAR
[16] A. Rovettain "Report on parameters to be identified in automotive environment," Dept. Mech., Politecnico di Milano, Milan, Italy, 2005. Intern. Rep. [Online]. Available: ftp://robo55.mecc.polimi.it id psycar pw psycar folder PSYCAR
[17] A. Rovetta, "Biorobotics: An instrument for an improved quality of life. An application for the analysis of neuromotor diseases," in *Proc. ICRA*, Seoul, Korea, May 21–26, 2001, pp. 1575–1578.
[18] K. B. Klaassen, *Electronic Measurement and Instrumentation*. Cambridge, U.K.: Cambridge Univ. Press, 1996.
[19] T. H. O'Dell, *Circuits for Electronic Instrumentation*. Cambridge, U.K.: Cambridge Univ. Press, 1991.
[20] S. J. Sangwine, *Electronic Components and Technology*. Boca Raton, FL: CRC, 1994.

[21] E. Doebelin, *Measurement Systems: Applications and Design*. New York: McGraw-Hill, 2004.
[22] A. Rovetta, M. Canina, R. Pegoraro, and M. E. Garavaldi, "Detection and multimodal analysis of brain weak signals to study brain function and disease," in *Proc. Eur. Union Workshop*, Milan, Italy, Nov. 28–29, 1997. Lab. Robotics, Politecnico di Milano, under European Union Commission for ScienceWorkshop.
[23] P. Pinelli, L. Baroni, D. Zara, and S. Battaglia, "Impairment of delay verbal reactions in dementia," *Adv. Occup. Med. Rehabil.*, vol. 4, no. 3, pp. 87–93, 1998.
[24] H. J. Eoh, M. K. Chung, and S. H. Kim, "Electroencephalographic study of drowsiness in simulated driving with sleep deprivation," *Int. J. Ind. Ergon.*, vol. 35, no. 4, pp. 307–320, Apr. 2005.
[25] C. Zocchi, A. Rovetta, and F. Fanfulla, "Physiological parameters variation during driving simulations," in *Proc. IEEE/ASME Int. Conf. Adv. Intell. Mechatron.*, Zürich, Switzerland, Sep. 4–7, 2007, pp. 1–6.
[26] C.-T. Lin, I.-F. Chung, L.-W. Ko, Y.-C. Chen, S.-F. Liang, and J.-R. Duann, "EEG-based assessment of driver cognitive responses in a dynamic virtual-reality driving environment," *IEEE Trans. Biomed. Eng.*, vol. 54, no. 7, pp. 1349–1352, Jul. 2007.
[27] L. Bargasa, J. Nuevo, M. Sotelo, R. Barea, and M. Lopez, "Real-time system for monitoring driver vigilance," *IEEE Trans. Intell. Transp. Syst.*, vol. 7, no. 1, pp. 63–77, Mar. 2006.
[28] P. A. Hancock and R. Parasuraman, "Driver-centred issues in advanced automation for motor vehicles," in *Automation and Human Performance: Theory and Applications*. Mahwah, NJ: Lawrence Erlbaum, 1996, pp. 337–364.
[29] D. Allchi, "Error types," *Perspectives Sci.*, vol. 9, no. 1, pp. 1–37, 2001.
[30] *Quality Standards : ISO 9000ff; VDA Band 3.1 und 4.ff; DIN EN 60300-2 (Reliability Management); VDI 4001-10: Technical Reliability. Safety Standards: IEC 61508 (Meta-Standard).*

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