Physiological parameters variation during driving simulations

PhD. Student C. Zocchi, Prof. Eng. A. Rovetta, Dr. F. Fanfulla

Abstract— **This paper deals with the methodology of using biorobotics principles for creating a new intelligent system, to improve safety in an automobile transportation. Many projects in European Union programs are devoted to the increase of safety in automotive, in order to reduce deaths and accidents down to 50% in the next few years. The project here presented, named PSYCAR (feasibility analysis on a car control system by psychic-physical parameters), aims at a new driving system, where the steering wheel is inserted in an architecture of intelligent sensors, able to monitor the psychophysical state of the driver, in order to avoid accidents due to sleep attacks and microsleeps. All the indications will come from the steering wheel, where the hands and the finger actuate a great part of the car control. Main goal of the research is to define the right parameters for driver's psycho-physical status monitoring during simulated tests. The heart of this paper is the application of multivariate statistics methods for evaluating the correlations between the physiological parameters acquired (EEG, galvanic skin response or resistance, peripheral temperature and heart rate variability).**

I. INTRODUCTION

SYCAR project, funded by European Union (EU) in a PRegional plan, starting from Lombardy Italian Region and Austrian Region, is one of the projects aiming to the determination of the correct psycho-physical parameters to be monitored in the driver and car system to increase safety.

The methodology presented in this paper is innovative for the field of automotive safety, because all the driver's physiological parameters are acquired using sensors on the steering wheel and on the safety belt, which are continuously in contact with the driver's body. The driver does not have to do anything in particular or, in any mode, different from what he is used to do when entering and driving his/her vehicle.

Drivers' fatigue has been implicated as one of the causal factor in many accidents because of the marked decline in the drivers' abilities of perception, recognition and vehicle control abilities while sleepy [1-5]. Driving under the influences of

drowsiness will cause: 1) longer reaction time, which may lead to higher risk of crash, particularly at high speeds; 2) vigilance reduction including non-responses or delaying responding where performance on attention-demanding tasks declines with drowsiness; 3) deficits in information processing, which may reduce the accuracy and correctness in decision-making. Many factors can cause drowsiness or fatigue in driving including lack of sleep, long driving hours, use of sedating medications, consumption of alcohol and some driving patterns such as driving at midnight, early morning, midafternoon hours, and especially in a monotonous driving environment [6]. Accurate and non intrusive real-time monitoring of driver's drowsiness would be highly desirable, particularly if this measure could be further used to predict changes in driver's performance capacity.

Two major categories of methods have been proposed to detect drowsiness in the past few years: one focuses on detecting physical changes during drowsiness by image processing techniques, such as average of eye-closure speed, percentage of eye-closure over time, eye tracking as quantization of drowsiness level and driver's head movements. These image-processing based methods use optical sensors or video cameras to detect eye-activity changes in drowsiness and can achieve a satisfactory recognition rate (i.e. Mecedes-Benz studies [7]). The other methods, followed in the PSYCAR project, are about the measure of driver's physiological changes, such as Heart-Rate Variability (HRV), Galvanic Skin Response (GSR), peripheral Temperature (THE) and electroencephalogram (EEG), as a means of detecting the human cognitive states [8-11].

II. SIMULATOR SYSTEM

A simulator system has been developed at the Robotics Laboratory of the Politecnico of Milan. The system consists of 1) a computer games steering wheel (Logitech Momo) with pedals and brake, 2) a simulated highway projected in front of the driver, giving him the impression of actually driving, 3) the driving cabin simulator mounted on a 6-DOF dynamic Stewart motion platform (developed at "Keplero University of Linz") and 4) the EEG measurement system (Fig. 1). On the right hand, GSR, HRV and THE sensors are placed in order to measure these driver's parameters and to reduce movement artefacts.

Fig. 1. Simulator System.

Manuscript received Jenuary 15, 2007.

C. Zocchi is with Politecnico of Milano, Mechanical Department, Robotics Laboratory, Italy, (phone: +39-02-2399-4847; fax: +39-02-7063-8377; e-mail: chiara.zocchi@ polimi.it).

A. Rovetta, is with Politecnico of Milano, Mechanical Department, Robotics Laboratory, Italy. (e-mail: alberto.rovetta@polimi.it).

F. Fanfulla is with Sleep Centre, Rehabilitation Institute of Montescano, IRCCS, S. Maugeri Foundation, Pavia, Italy (e-mail: ffanfulla@fsm.it).

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A. GSR, HRV and THE sensors

According to previous study [12], GSR was measured using 30mm² non polarizable Ag/AgCl electrodes placed on the median and the ring finger of the right hand with adhesive tape. Typical GSR values fell in the range [150; 300]$10^3\Omega$. For the HRV measure a photoplethysmographic sensor was placed on the forefinger (fig. 2). From the HRV measured, the R-R form and the beats per minutes (BTS) are calculated.

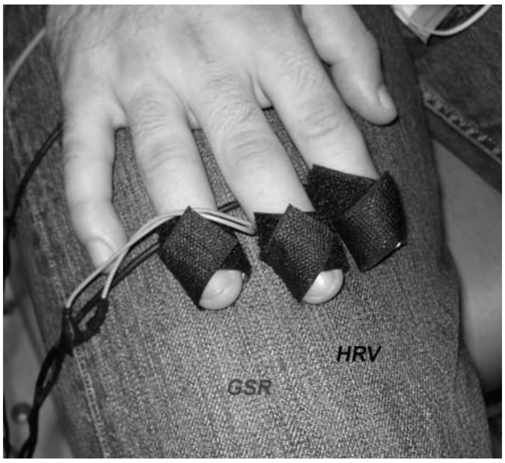

Fig. 2. GSR and HRV placement on the right hand.

B. EEG recording

EEG recording (Embla S7000 and Somnologica Software – Embla - Broomfield, CO - USA) was performed using standard procedures and scored manually in a 30-seconds epoch according to Rechtschaffen and Kales' criteria [13]. The equipment provided simultaneous measurements of EEG_s (C_3-A_2; C_4-A_1; O_1-A_2; O_2-A_1), EOG_s, submental EMG, EKG, airflow by nasal cannula, thoracic and abdominal respirogram by means of a plethysmographic method (X-trace, Embla - Broomfield, CO - USA), SaO_2 by means of a pulse-oximeter.

Microsleeps (MS) were scored as follows [14]: a period of at least 3s with a ϑ (4–7 Hz) rhythm replacing a α rhythm or appearing on a background of desynchronized EEG on all four EEG channels, and without eye-blinking artefacts. Slow eye movements were accepted [15]. The presence of α rhythm was considered as wakefulness, and thus excluded microsleep. No maximal length was defined for microsleep, so that it could evolve into established sleep if it lasted long enough.

All the recordings were separately analyzed by two expert technicians individually and independently, and finally reviewed by the physician.

C. TestProtocol

All subjects executed one or more 30min driving simulation. Before starting the data acquisition, a psychological questionnaire about general sleep/wake habits is completed, on which also date, time and environmental conditions are written. The car at the start of every simulation session is always positioned at the same point of the virtual highway. Each subject, before driving for the first time is also trained to use the simulator and to always follow the same pre-defined route for 5min. At the same time all sensors are calibrated.

After these initial procedures, the driver starts the simulation and the data acquisition is also initialized. During the procedure and in pre-defined times, that the subject does not know, an obstacle appears on the screen and the driver has to brake immediately. In this way, his/her reaction time is measured and stored among all the other parameters acquired (these data will be used in next studies). This response time along with the data from the polysomnography signals [16, 17] will determine driver attention level. The simulations are always made in dark and noiseless conditions in order for the person to have much more possibilities to fall asleep.

D. Subjects

Up to now only 25 subjects (22 men and 3 woman; age range, 24 to 47; mean age 35[±5] years), without particular pathologies, were studied during the execution of one or more 30min driving simulation.

These healthy subjects had no clinical evidence of snoring or sleep apnoeas and no complaint of excessive daytime sleepiness (EDS). They were recruited between students of the Robotics Course (Politecnico of Milan) and the medical team of the Sleep Room (Fondazione Maugeri of Montescano (PV)). Informed consent and a preliminary psychological questionnaire were obtained from all subjects, and the study was also approved by the hospital ethics committee. For the statistical study subjects were divided into 2 groups: one containing subjects who had MS during the driving simulation and the other group the subjects without MS appearance. MS appearance was determined from the EEG.

III. MULTIVARIATE STATISTICS

The purpose of the statistical analysis is to find a relation between all the measured parameters and the driver's attention and vigilance decrease. The index of the driver's attention is measured by studying the EEG signals and microsleeps. In addition to these, another very important parameter that determines driver attention is the reaction time to the appearing obstacles (study not reported in this paper).

The stored data are statistically analyzed using MATLAB (version 7, revision 14): the observed phenomena are not linear and so a standard linear analysis is not adequate. So multivariate analysis is used in order to identify categories of input variable related to a certain controllable output index. Different analysis methods are used to determine all the necessary statistical parameters: the first analysis is based on simple mean value and standard deviation for each signal acquired and for each group. In addition, covariance and cross-correlation matrixes are calculated to determine a possible correlation of one acquired parameter to another, but also to correlate all the acquired parameters with the driver's safety index, derived from the polysomnographical data. Furthermore, a cluster analysis is made, following the hierarchical and the K-means methods, in order to investigate grouping in the data.

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Studying the results of all the above statistical multivariate analysis methods, the upgrade of the already existing fuzzy logic controller may be possible in further works.

A. Mean and standard deviation

The simulator system proposed and discussed in this paper is used in a daily basis in order to acquire enough data to adequately support the statistical analysis. Some preliminary observations can already be done. By observing the data acquired during simulations made with persons that slept during the night before as usual, some interesting facts on the GSR parameter can be noticed [18]: the more difficult the driving conditions, the lower the GSR values. The GSR is inversely proportional to the perspiration and so this result means that the driver skin's perspiration is higher when the driving conditions are difficult (curved circuit, fast car speed).

This also means that the driver is more vigilant when the simulation conditions are difficult, because of the fact that the skin's perspiration is inversely proportional to the person's relaxation. Examined from another point of view, the lower the GSR value, and the more vigilant the driver is.

However considering subjects divided into MS/no MS groups (13/12), GSR and HRV (also RR and BTS) seem to not vary very much as shown in table 1, 2 and fig. 3, 4.

TABLE I

GSR	mean [Ω x10^5]	standard deviation [Ω x10^5]
MS	2,31	0,85
No MS	2,33	0,49

Mean and SD of GSR values.

TABLE II

HRV	Mean [ms]	standard deviation [ms]
Mi	1,48	0,24
No MS	1,47	0,17

Mean and SD of HRV values

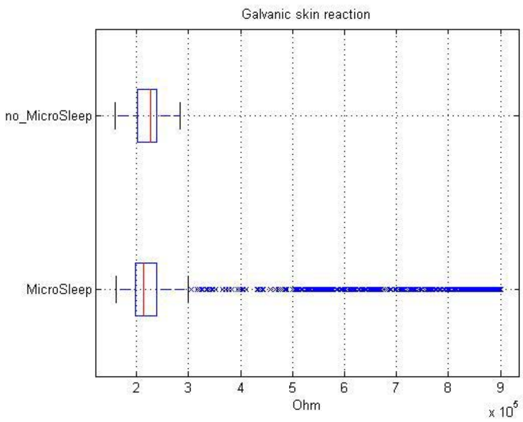

Fig. 3. GSR boxplots.

The boxplots have lines at the lower quartile, median, and upper quartile values. The whiskers are lines extending from each end of the boxes to show the extent of the rest of the data. Outliers are data with values beyond the ends of the whiskers.

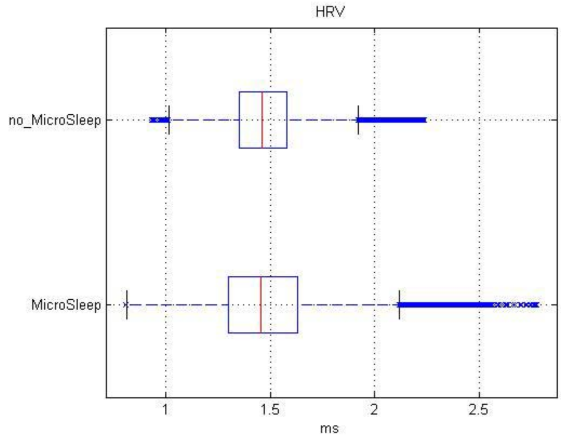

Fig. 4.HRV boxplots.

An important observation is that the mean value of the driver's THE is generally higher when he/she has MS during the simulation (Table 3, fig. 5): the lower THE indicates that no MS subjects are more vigilant and reactive, due maybe also a greater vasoconstriction.

TABLE III

THE	Mean [°C]	standard deviation [°C]
Mi	40,66	0,16
No MS	38,15	0,34

Mean and SD of THE values

The previous analysis is not good enough to understand the correlations between the variables acquired during the simulations.

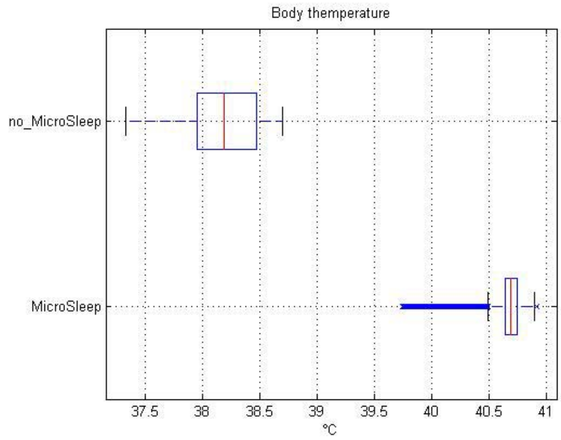

Fig. 5.THE boxplots

B. Correlation between parameters

The hypostasis about the parameters correlation brings to the Multivariate Analysis. In easy situations, in which data are about one parameter for each person of the champion chest, mean and variance give simple information on the gravity centre and the dispersion of the observed values [19]. When there are 2 parameters, supplementary information is given by the covariance or the correlation coefficient that measures the parameters dependence. There are also complex situations, like this case, in which more than 2 parameters have to be considered for each subject: it's difficult find the dependences between parameters and plot data. The covariance matrix of the variables $X_{(1)}$, . . .

,$X_{(P)}$ is the pxp matrix with the variance of the single variables on the diagonal and the covariance between the variables $X_{(i)}$ and $X_{(j)}$ for i≠j. In the same way the correlation matrix (table 4) has the correlation coefficient between the variables $X_{(i)}$ and $X_{(j)}$ for i≠j outside the diagonal. If the unit of one variable changes, its weight in the final results will be modified: in order to avoid the scale effects, it's better to analyse data normalised (centred and reduced). In particular if x_i is the mean of the i variable and σ_i^2 is the variance, then the new variable is (1):

$$y_{hi} = \frac{x_{hi} - \overline{x_i}}{\sigma_i} \qquad (1)$$

The correlation matrixes for each group are here reported (table 4 and 5):

TABLE IV

	BTS	GSR	HRV	RR	THE
BTS	1	-0,20	-0,00	-0,27	0,40
GSR	-0,20	1	-0,01	0,66	-0,80
HRV	-0,00	-0,01	1	0,00	-0,00
RR	-0,27	0,66	0,00	1	-0,62
THE	0,40	-0,80	-0,00	-0,62	1

Correlation matrix for the MS group.

From tables 4 and 5 we can notice that there is a high negative correlation between GSR and THE (about 80%) for the no MS group: this indicates a strong inverse relationship between these parameters. BTS and THE are directly correlated in the MS group (about 40%), while are inversely correlated in the other (about 67%). This information will be very useful for the fuzzy logic controller activation. The GSR and RR are positive correlated for each group. Besides HRV seems not to be correlated with other parameters.

TABLE V

	BTS	GSR	HRV	RR	THE
BTS	1	-0,13	0,00	-0,14	-0,67
GSR	-0,13	1	-0,00	0,48	0,01
HRV	0,00	-0,01	1	-0,00	-0,00
RR	-0,14	0,48	-0,00	1	-0,06
THE	-0,67	0,01	-0,00	-0,06	1

Correlation matrix for the no MS group

From tables 4 and 5 we can notice that there is a high negative correlation between GSR and THE (about 80%) for the no MS group: this indicates a strong inverse relationship between these parameters. BTS and THE are directly correlated in the MS group (about 40%), while are inversely correlated in the other (about 67%). This information will be very useful for the fuzzy logic controller activation. The GSR and RR are positive correlated for each group. Besides HRV seems not to be correlated with other parameters.

Using this information with the others from previous studies [18], the rules for an upgrade of the already existent fuzzy logic controller can be written. The new version of the controller will use also learning features to adapt itself to the driver under monitoring, seen as individual.

C. *Principal Components Analysis (PCA)*

PCA was then used in order to reduce data complexity: the data projection is good when the dispersion of the points, is the greatest [20] that is when the variance of the points belonging to the real champion chest is the greatest. From the observation of the variance explained, it's assumed that more than 90% of information belongs to the III principal components and so, for further analysis, only 3 components are considered. In this way the redundancy are eliminated and the complexity is reduced.

2 different clustering methods, Hierarchical and K-Means methods are then applied to data from PCA, in order to find grouping in all subjects data related to MS appearance.

D. *Hierarchical clustering*

Hierarchical clustering is a way to investigate grouping in the subjects' data, simultaneously over a variety of scales, by creating a cluster tree (fig. 6) that is not a single set of clusters, but rather a multi-level hierarchy, where clusters at one level are joined as clusters at the next higher level. This allows deciding what level or scale of clustering is most appropriate in the application. In order to have a better tree, the distances between the links are calculated minimizing the distance typology "correlation". It's possible to verify it using the Cophenet index: the better the approximation, the greater the index is: in this case c=0,9646. The Hierarchical method found 2 clusters where subjects are divided according to the MS appearance with about 67% of goodness.

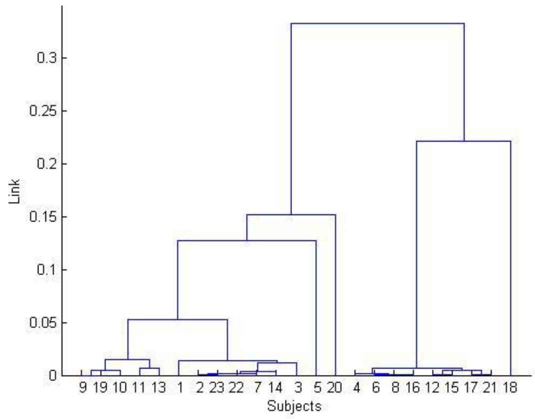

Fig. 6.The numbers along the horizontal axis represent the subjects in the original data set. The links between objects are represented as upside down U-shaped lines: the height of the U indicates the distance between the objects

E. *K-means clustering*

K-means clustering can best be described as a partitioning method. That is the function k-means partitions the observations in the data into K mutually exclusive clusters and returns an indices vector, indicating to which of the k clusters it has assigned each observation. Unlike the hierarchical clustering method, k-means does not create a tree structure to describe the groupings in the data, but rather creates a single level of clusters. Another difference is that K-means clustering uses the actual observations of objects or individuals in the data and not just their proximities.

These differences often mean that k-means is more suitable for clustering large amounts of data. k-means treats each observation in the data as an object having a location in space and it finds a partition in which objects within each cluster are as close to each other as possible, and as far from objects in other clusters as possible. Each cluster in the partition is defined by its member objects and by its centroid, or center, the point to which the sum of distances from all objects in that cluster is minimized (fig. 7).

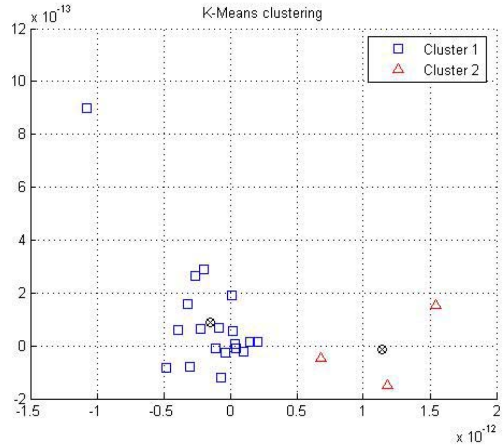

Fig. 7. K-Means clustering

K-means computes cluster centroids differently for each distance measure, to minimize the sum with respect to the measure specified.

From fig. 7 we can immediately observe that in 1 cluster there are only 3 subjects. Maybe this result is due to the small champion chest considered in this study and so the results of the Hierarchical clustering are the only considerate in further analysis.

F. Hierarchical classification results

Classification results can be summarized in the confusion matrix. In this matrix the rows represent the real classes, i.e. classes with data of the training set, while the columns are the classes assigned to the objects after the application of the classification technique (i. e. hierarchical clustering, see table 6).So the numbers outside the diagonal are objects that, as well they belong to a class, are erroneously assigned to another.

TABLE VI

FITTING

CLASS	MS'	No MS'	Total
M	6	3	9
n	8	6	14
Total	14	9	23

Confusion matrix.

The parameter that simply summarizes the result of a classification is the error rate, ER% [20] defined as (2):

$$ER\% = 1 - \frac{\sum_{g} c_{gg}}{n} 100 \quad (2)$$

where c_{gg} are the elements on the confusion matrix diagonal.

The sensibility of a class is the percent ratio between the objects assigned to that class c_{gg} and the total number of objects belonging to the same class n_g (3):

$$Sn_g = \frac{c_{gg}}{n_g} \cdot 100 \quad (3)$$

The sensibility defines the ability of a class of representing the objects of that class. The specificity of a class is the percent ratio between the object of the considered class assigned to the class g' and the total objects assigned to that class $n_{g'}$ (4):

$$Sp_g = \frac{c_{gg}}{n_{g'}} \cdot 100 \quad (4)$$

It defines the ability of a class to isolate objects of that class from the other classes, (i.e. the degree of purity). Another index of diversity is the Gini's one, defined like this (5):

$$G.I. = \sum_{k \neq k'} p_k \cdot p_{k'} \quad (5)$$

where p_k is the probability of the k event and the summation runs on the products between couple of different events. This index gives the impurity quantity of a group.

All these parameters are collected for evaluating the fitting goodness (table 7):

TABLE VII

Gini index$_{real}$	ER$_{fitt}$	Sn$_{fitt}$	Sp$_{fitt}$	Gini index$_{fitt}$
23,82%	66,67%	47,83%	42,86%	90,70%

.Parameters for the classification.

The Sn_{fitt} indicates a better class representation than the specificity Sp_{fitt}. The Gini's index related to the initial value, gives the following decrease of impurity.

These parameters show that the Hierarchical method can be used as a classifier in our work with about a 40% of goodness.

IV. Conclusion

The already developed simulation system along with the well defined protocol also presented earlier in this paper is being used to acquire data for the statistical analysis and the fuzzy controller set-up. The final results of the research will be presented after the validation of the system and tests on a major number of drivers, in order to add more significance to the statistics.

The methodology discussed and proposed is innovative for the field of safety in automotive, because it aims to acquire and use the information derived from a set of non wearable sensor in contact with he driver. Nevertheless, the experience acquired by these simulation procedures will be used to set up the final simulator system.

Further studies will be about the spectral EEG and EKG analysis, the reaction times and the circadian rhythms influence.

ACKNOWLEDGMENT

Thanks to the "Keplero University of Linz", partner in the PSYCAR project and to all who collaborated.

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