Emotional Response Analysis Using Electrodermal Activity, Electrocardiogram and Eye Tracking Signals in Drivers With Various Car Setups

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***Abstract*—In the automotive industry, it is important to evaluate different car setups in order to match a professional driver's preference or to match the most acceptable setup for most drivers. Therefore, it is of great significance to devise objective and automatic procedures to assess a driver's response to different car settings. In this work, we analyze different physiological signals in order to evaluate how a particular car setup can be more or less stressful than others. In detail, we record an endosomatic Electrodermal Activity (EDA) signal, called Skin Potential Response (SPR), the Electrocardiogram (ECG) signal, and eye tracking coordinates. We eliminate motion artifacts by processing two SPR signals, one from each hand of the driver. Tests are carried out in a company that designs driving simulators, where the tested individuals had to drive along a straight highway with several lane changes. Three different car setups have been tested (neutral, understeering, and oversteering). We apply a statistical test to the data extracted from the cleaned SPR signal, and we then compare the results with the ones obtained using a Machine Learning algorithm. We show that we are able to discriminate the drivers' response to each setup, and, in particular, that the base car setup generates the least intense emotional response when compared to the understeering and the oversteering car setups.**

***Index Terms*—Skin Potential Response, Electrocardiogram, Eye Tracking, Supervised Machine Learning Algorithm, Stress Detection**

I. Introduction

The emotional stress in car drivers can be harmful to their health, causing mental disorders and physical pain [1], [2]. Furthermore, drivers who experience emotional stress are prone to abnormal behaviour such as discourtesy and aggressiveness [3], [4]. More dangerous effects can arise when stress influences the driver's driving performance leading to risky driving styles [5], [6] and causing accidents [7]. A survey in [8] reviews the emerging sensor technologies for acquiring drivers' physiological signals, also monitoring their behaviour, the vehicle, and other environmental data.

A large part of emotion detection methods rely on physiological measurements [9]–[11], and their applications concern the analysis of how the drivers' stress is influenced by traffic, road type or driving tasks [12]–[14].

Physiological signals are often used with Machine Learning techniques. Authors in [15] present a method to identify driving-induced stress patterns in Electroencephalograms (EEG) through the use of a Support Vector Machine (SVM), a Neural Network (NN), and a Random Forest (RF). The preprocessing of data in systems which use Machine Learning techniques is crucial as well. For example, authors in [16] develop a preprocessing algorithm to correct the artifacts that cause troubles when detecting peaks in Electrocardiogram (ECG) and Photoplethysmography (PPG) data, and the subsequent classification has been carried out using Linear Discriminant Analysis (LDA), Decision Tree (DT), and k-Nearest Neighbours (kNN) classifiers. In [16] the machine learning classification is preceded by a data mining algorithm in order to avoid oversampling and improve the performance of the classifiers. The system proposed in [17] combines Heart Rate (HR) and vehicle and environmental information with the aim to develop a feature learning system based on Convolutional Neural Networks, and followed by an LSTM Recurrent Neural Network classifier. A comparison is carried out between the proposed method and a system which relies on manually selected features.

In this contribution, we propose a system to estimate the responses and the emotional states of individuals in a simulated driving scenario. We analyze different signals, such as the Skin Potential Response (SPR), the ECG, and the eye tracking coordinates, which allow deriving some characteristics of the emotional response of a car driver. In particular, our main goal is to discriminate the driver's response to different car setups, in order to identify the one which is more comfortable and less stressful. We consider the SPR signal instead of the more commonly used Skin Conductance Response (SCR) since it can be recorded more easily, and no current has to be applied to the skin. Moreover, the electrode impedance and possible skin impedance changes have a smaller influence on this signal [18], [19].

While driving, motion artifacts can appear on the SPR signals recorded from the hands of the driver, due to hand

pressure and movements on the steering wheel [20]–[22]. Thus, we use an algorithm that takes as input the SPR signals, taken from both hands, and generates a cleaner SPR signal. The experiments are carried out in a company using a professional dynamic car driving simulator that reproduces a realistic car behaviour (see Fig. 1). The subjects had to drive along a highway, while having to perform a series of lane change tasks defined by cones positioned along the track. We analyze the signals recorded when the subjects drove with a particular car setup (neutral or "base", understeering or US, oversteering or OS). We show that the base car setup is perceived as less emotionally intense when compared to the other car setups. The ability to discriminate the driver's emotional state with different car setups is of paramount importance for the automotive industry, e.g., when designing and testing new car prototypes.

Fig. 1. The VI-grade professional dynamic simulator.

II. The proposed system

The scheme of the proposed system is shown in Fig. 2. As mentioned before, for each test subject, we collect two SPR signals, one from each hand, the ECG from the chest, and a recording of the eyes movements during the drive, using an eye tracking device. The two SPR signals are processed to remove the motion artifacts, and the output is one cleaned SPR signal. Using all of these signals, we then estimate the emotional state of the driver using the aforementioned car setups. In particular, the simulated vehicle was designed with three different setups, modeling different values of mass distribution, suspension hardness, aerodynamic coefficients, and other parameters. More in detail, the OS setup was designed to emphasize vehicle oversteering (i.e., with a heavier front and a lighter rear), the US one to emphasize understeering (lighter front and heavier rear), while the Base setup was neutral, in order to mimic a daily use vehicle.

The sensor used for SPR and ECG recordings is similar to the one we describe in [23], [24], and is the core of the VI-BioTelemetry system developed by VI-grade [25]. The SPR signals are acquired from the palm and the back of each

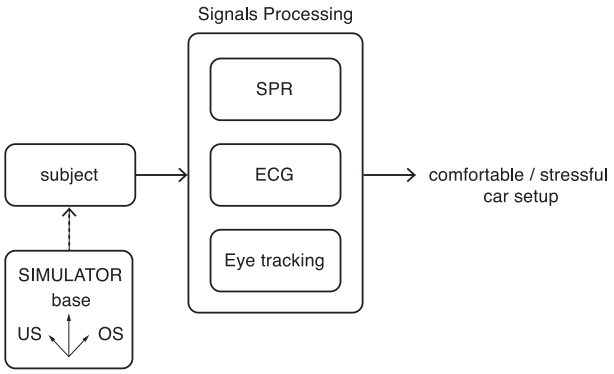


Fig. 2. Scheme of the proposed system.

hand, while the ECG channels are extracted from the subjects' chest, wearing a commercial vest with wet electrodes. An analog front end deals with SPR and ECG signal conditioning. Moreover, the Smart Eye Aurora eye tracking sensor [26] is positioned in the car to record the eye movements of the subjects.

The Motion Artifact (MA) removal algorithm, which we already described in [27], is rooted on the two assumptions that the motion artifact enhances the local energy of the SPR signal, and that the motion artifacts rarely appear simultaneously in the two SPR signals. The output of this algorithm is a new clean signal that follows the smoother SPR signal.

Finally, the acquired signals are processed and analyzed, as we will explain below.

III. Experimental setup

The experiments are carried out using the professional dynamic driving simulator DiM150, with 9-degree of freedom, developed by VI-grade. Four male subjects were tested. They gave consent for the recording of their physiological parameters. The tests were also run in accordance with the principles of the Declaration of Helsinki.

The subjects were asked to drive on a 15 km long straight highway, with ten consecutive double lane changes, one every 1500 m (see Fig. 3). The double lane change maneuver is a road path delimited by cones, and it consists of an entry lane with a length of 30 meters, a 25 meters long side lane and a 60 meters long exit lane. The width of the entry lane is 3 meters, while side and exit lanes are 3.2 meters wide. The lateral and longitudinal offsets between entry and side lane are respectively 0.8 and 30 meters. Side and exit lane have the same lateral offset and 85 meters longitudinal offset. The whole maneuver takes 170 meters. Each maneuver is preceded by two road signs placed at -100 and -200 meters to prepare the pilot. They had to perform the lane changes trying to avoid the cones. Each individual had to repeat the whole 15 km long driving session three times, one for each different car setup.

Fig. 3. The cones placed along the track that mark the lane changes.

IV. Experimental results

A. SPR signal analysis

We first analyze the SPR signal at the output of the MA removal block. The SPR is substantially a short-term estimator of the energy of the sympathetic nervous pulses sent to the sweat glands on the hands, and it can be a good indicator of the driver's stress level.

Since the drivers had to repeat the same double lane change task ten times during the single test with each car setup, we divide the track into ten sections, with every task positioned in the middle of them. The distance between the tasks is uniform, i.e., $d_i = 1500i$ m, $i = 1, 2, \ldots, 10$. We analyze the SPR data in the intervals $[d_i - 750, d_i + 750]$ m. For each of these intervals, we compute the RMS value of the SPR signal, which gives us an indication of the average sympathetic activity for each driver and each car setup. We report in Table I the $mean \pm SD$ (in mV) of the collected ten values, again for each subject and each car setup. We also provide in Fig. 4 a graphical view of the results.

TABLE I
SPR mean ± SD (in mV) for each subject and each car setup

Subject	Base (mV)	OS (mV)	US (mV)
1	0.76 ± 0.22	1.61 ± 0.7	1.56 ± 0.55
2	0.56 ± 0.12	0.87 ± 0.23	0.78 ± 0.25
3	0.37 ± 0.1	0.46 ± 0.06	0.5 ± 0.08
4	0.43 ± 0.09	0.55 ± 0.14	0.34 ± 0.09

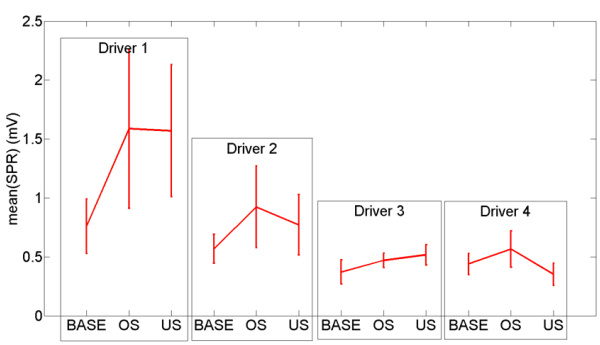


Fig. 4. SPR mean and standard deviation, for each driver and each car setup.

Table II shows the p-value of the paired t-test. We highlight the cases of $p \leq 0.05$, indicating a statistically significant difference between the RMS values in the two setups. From Fig. 4 and Table II, we notice that for subjects 1, 2, and 3 the Base car setup is perceived as less stressful than the OS setup with good significance. For subject 4, the Base car setup is also perceived as less stressful than the OS setup, but less significantly ($p = 0.08$). For subjects 1 and 3 the Base car setup is perceived as less stressful than the US setup with good significance. For subject 2 the Base car setup is perceived as less stressful than the US setup as well, even if slightly less significantly ($p = 0.06$), while for subject 4 the Base car setup results to be more stressful than US. The OS setup appears to be slightly more stressful than US for all the drivers, except for subject 3. However, the statistical significance of the paired t-test is limited for three subjects out of four.

TABLE II
Paired t-test probability p considering Base and OS car setups, Base and US, US and OS, for each subject

Subject	Base vs. OS	Base vs. US	OS vs. US
1	**0.01**	**0.03**	0.62
2	**0.01**	0.06	0.23
3	**0.05**	**0.03**	0.25
4	0.08	**0.02**	**0.004**

When we consider the sympathetic nervous system activity analyzed through the recorded SPR signals, we conclude that, for each driver, there is at least one setup that is perceived differently from the others. More specifically, we can see that the Base setup is significantly less stressful for the majority of the subjects (except for subject 4), while the OS setup seems to be the most demanding.

Another interesting observation concerns the high variability of the SPR values for subject 1. This is due to an increasing engagement of this driver to the task. Fig. 5 shows the SPR signal of subject 1 during the 15 km drive. We observe an increase in the SPR RMS values starting from the fifth lane change. Note that the vertical lines indicate the starting point of the double lane change tasks.

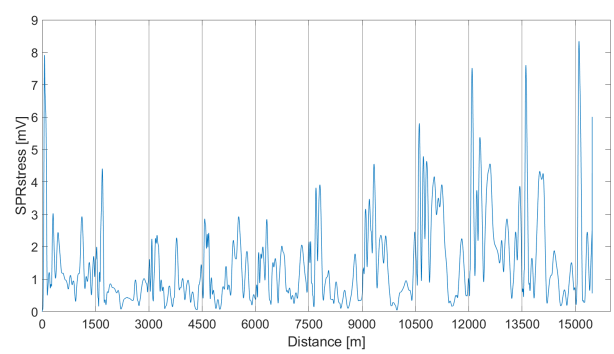


Fig. 5. SPR signal for one test subject (local RMS value).

To further analyze the SPR signal, and evaluate if a given car setup is perceived by the subjects as more or less stressful than others, we use a Machine Learning classification algorithm. In particular, we use an optimized model of a Support Vector

Machine, already trained on a larger set of data, coming from a previous experiment carried out in the same company using the same simulator. In this previous experiment, 18 individuals were considered. They were instructed to drive manually on a 67 km long highway and to complete 12 distinct tasks, located at different positions, meant to induce stress reactions in them. The time to complete all of the tasks was about 40 minutes, and the 12 tasks were: Double lane change (right to left or left to right), Tire labyrinth, Sponsor block (from left or from right), Slalom (from left or from right), Lateral Wind (from left or from right), Jersey LR, Tire trap, Stop. Some specific statistical features were extracted from the cleaned SPR signal (the output of the MA removal algorithm). Regarding the SPR signal, we computed the block variance, the energy, the mean absolute value, the mean absolute derivative, and the maximum absolute derivative. All of these SPR features were calculated from 15 s long blocks at a time, and were given as input to the SVM classifier. We then took into consideration a new block every 5 seconds, so that each interval overlapped the previous one by 10 seconds. We applied a normalizing procedure to the SPR signals to make them consistent when dealing with different individuals. Since we knew when the tasks were located on the track, we could establish when the individuals were supposed to be stressed. In particular, if a 15 s long time interval occurred outside of the stress tasks we associated a label "0" to it, meaning that it was a non-stress interval, while if a time interval occurred inside or intersected the stress tasks, we associated a label "1" to it, meaning that it was a stress interval. The SVM classifier was developed in Matlab 2017.a using a Radial Basis Function (RBF) kernel. The Bayesian optimization procedure was also utilized during the training procedure. We used the leave-one-subject-out procedure (training considering all of the subjects, and excluding the one on which the classifier is then tested). A method to remove isolated "1" labels is applied to the classifier's output, as explained in [28]. To calculate the final performance, we averaged the test results for all individuals. We obtained an Accuracy of 73%, which proved the effectiveness of the SVM.

This trained and optimized SVM model, which can identify stress time intervals with good performance, is then used to analyze the new SPR signals of the four drivers in the different car setups. We collect all of the 15 seconds long time intervals related to the SPR signal, we normalize them similarly to what we do for the training data, and we extract the same five features. We then run the SVM as a test on these time intervals, and we count the output labels equal to "1" or "0", i.e., stress or non-stress, for each driver and each car setup. This gives us a general indication of the stress reactions of each subject during the overall track. Fig. 6 shows the percentage of "stress" labels, i.e., the ratio between the number of stress labels and the total labels for all the track for that particular car setup. This confirms the results we obtained before, and in fact, the label count for the base car setup is generally lower than the US and OS ones, thus indicating that it is being perceived as the least stressful.

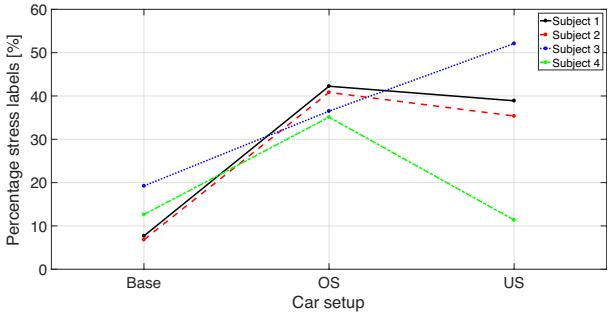


Fig. 6. Percentage of stress labels for the four subjects in the different car setups.

B. ECG signal analysis

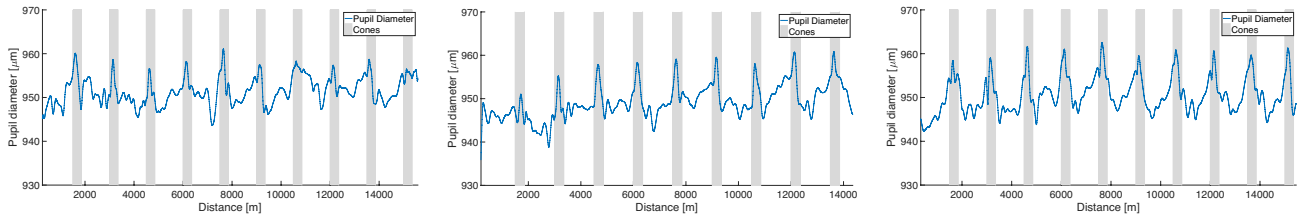
As already introduced in Section II, we also recorded the ECG signal from each subject's chest. We analyzed the characteristics of the instantaneous Heart Rate of a subject among all the three different car setups. The recorded data did not reveal a meaningful difference of the mean HR for the subjects in different car setups. In particular, the mean HR of the four subjects was similar in the three setups, with average value 83.20 bpm, 98.65 bpm, 80.45 bpm, 96.67 bpm, for subjects 1, 2, 3, and 4, respectively.

C. Eye tracking signal analysis

An eye tracking device (Smart Eye Aurora) has been used to provide a real-time data stream of signals related to eye movements. More specifically, we focused on the pupil diameter. We noticed that, independently of the car setup, drivers increase the pupil diameter when approaching the cones. Considering for example subject 1, Fig. 7 shows this behaviour in the Base, OS, and US car setups, respectively. Similarly to what happens to the other subjects, there is not an evident different eye reaction when considering different car setups. So we can say that the drivers become aware when about to perform the tasks, but with no particular difference in the three setups.

V. Conclusion

In this paper, we proposed a system that analyzes some physiological signals from drivers, with the aim of evaluating their emotional responses when driving in a simulated scenario with different car setups. Even if the number of cases we analyzed is limited, we can conclude that the SPR signal can be useful to discriminate the emotional state of the driver in different setups. This can be important for an objective and automatic assessment of the driver's response to different car settings. In this respect, the ECG and eye coordinate signals do not seem to provide significant additional information. As a result of our experiments, we conclude that the Base car setup clearly induces the lowest SPR activity in the majority of the drivers. This consideration is confirmed by both the t-test statistical method and the SVM classification algorithm. As regards the SPR response, the OS and US setups can be considered equivalent.



(a) (b) (c)

Fig. 7. Pupil diameter variations for subject 1 during the drive, with Base (a), OS (b), and US (c) car setups, respectively. Grey rectangles represent the double lane changes.

VI. Acknowledgment

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