Reducing Stress and Fuel Consumption Providing Road Information

Víctor CORCOBA MAGAÑA; Mario MUÑOZ ORGANERO[a]

vcorcoba@it.uc3m.es, munozm@it.uc3m.es

[a] Telematics Department. Carlos III University Madrid Leganés, Madrid, Spain

KEYWORD

Intelligent Transport System; Fuel Consumption Optimization; Data Envelopment Analysis (DEA); Driving Assistant; Android; Applications; Mobile Computing

ABSTRACT

In this paper, we propose a solution to reduce the stress level of the driver, minimize fuel consumption and improve safety. The system analyzes the driving style and the driver's workload during the trip while driving. If it discovers an area where the stress increases and the driving style is not appropriate from the point of view of energy efficiency and safety for a particular driver, the location of this area is saved in a shared database. On the other hand, the implemented solution warns a particular user when approaching a region where the driving is difficult (high fuel consumption and stress) using the shared database based on previous recorded knowledge of similar drivers in that area. In this case, the proposal provides an optimal deceleration profile if the vehicle speed is not adequate. Therefore, he or she may adjust the vehicle speed with both a positive impact on the driver workload and fuel consumption. The Data Envelopment Analysis algorithm is used to estimate the efficiency of driving and the driver's workload in in each area. We employ this method because there is no preconceived form on the data in order to calculate the efficiency and stress level. A validation experiment has been conducted using both a driving simulator and a real environment with 12 participants who made 168 driving tests. The system reduced the slowdowns (38%), heart rate (4.70%), and fuel consumption (12.41%) in the real environment. The proposed solution is implemented on Android mobile devices and does not require the installation of infrastructure on the road. It can be installed on any model of vehicle.

1. Introduction

Many traffic accidents are due to distractions. In [Transportation, 2008] risk factors of traffic accidents are categorized as follows: human factors (92%), vehicle factors (2.6%), road/environmental factors (2.6%), and others (2.8%). Among these, drivers' human factors consist of cognitive errors (40.6%), judgment errors (34.1%), execution errors (10.3%), and others (15%).

To reduce traffic accidents due to dangerous behaviors of drivers, it is necessary to investigate, measure, and quantify the drivers' workload. The term "load" in this context indicates the portion of capacity that is needed to drive. This capacity is limited. Therefore, if the task requires a lot of ability is likely that the driver makes mistakes. The level of workload is affected by several factors such as: road type, traffic conditions, driving experience, and gender. Stress can be defined as a change from a calm state to an excitation state in order to preserve the integrity of the person. Most stressors are intellectual, emotional, and perceptual. There are two types of stress: eustress and distress. Eustress is a good stress that improves performance and motivates. The stress is also classified as “eustress” when it leads us to a favorable state. In opposition, if the stress is negative and causes a degradation of performance, it is called "distress". This type of stress is due to an increase in the workload. This increase may be due to multiple causes as: deceleration lane, a call, traffic density, etc.

There are many works on measuring and quantifying the driver workload. In [Changxu, 2007], Wu and Liu described a queuing network modeling approach to model the subjective mental workload and the multitask performance. They propose to use this model to automatically adapt the interface of driving assistant according to the workload. In [Itoh, 2010], Itoh et al. measured electrocardiogram (ECG) signals as well as head rotational angles, pupil diameters, and eye blinking with a faceLAB device installed in a driving simulator to calculate driving workload. In [Teh, Jamson, 2012], the driver workload from lane changing were measured through simulation test driving. In [Sega, 2011], a multiple linear regression equation to estimate the driving workload was proposed. The model employs variables such as: speed, steering angle, turn signal, and acceleration. [Ji, Zhu, 2004] presented a probabilistic model for detecting fatigue based on visual characterize such as eyelid movement, gaze movement, head movement, and facial expression. This method was extended to detect “Nervous” and “Confused” affective states. This work demonstrates the suitability of Bayesian Network for information fusion and estimation of the stress level.

On the other hand, the impact of the cognitive load on the driver behavior has been studied on many papers. In [Kim, 2011] analyzed the relationship between drivers’ distraction and the cognitive load. It was discovered that heart rate, skin conductance, and left-pupil size were effective measurement variables for observing a driver’s distraction. Reference [Engströma, 2005] showed that the visual demand causes a reduction in the speed and increased variation in maintenance lane. However, the cognitive load does not affect speed. In this work the authors highlight that detection of events is very important in order to capture the main safety related effects of cognitive load and visual tasks. In [Zhang, 2008], the authors propose to use a set of variables (vehicle speed, steering angle, acceleration, and gaze information) to predict the workload driver. The authors achieved an accuracy of 81% with this method. Other studies [Adell, 2011] propose to use the movement of the steering wheel as an indicator of driver workload.

In conclusion, there are a limited number of works where the workload is analyzed in a real environment driving. Furthermore, there are not applications. The main contribution of this paper is the proposal of an assistant that employs this information about the driver stress and his driving style to build a database which contains the road sections where driving is difficult for the drivers (high workload and fuel consumption). The objective is to provide knowledge about these places in advance in order to avoid inefficient actions and improve safety.

2. Discovering areas where driving required a high workload

The first step of the proposed algorithm is to find out in which regions the driver is driving inefficiently and stress increases (difficult areas). Data Envelopment Analysis [Charnes A, 1985)] is used to estimate the efficiency of driving and the stress level in each area. Data envelopment analysis (DEA) is a linear programming methodology to estimate the efficiency of multiple decision making units (DMUs) when the production process presents a structure of multiple inputs and outputs. This method was proposed by Charnes, Cooper, and Rhodes [Charnes, 1978].

In our proposal, each DMU represents a different road section. The algorithm compares the driving behavior in different sections in which the route has been divided. The aim is to detect the road points where the driver workload is high and fuel consumption increases. The output of the algorithm is a number between 0 and 1(efficiency). The best regions from the point of view of energy consumption and safety will have an efficiency of 1. Stress regions will have a low value close to 0 as efficiency. If we consider a set of road sections “n” (DMU_n), each of them with an I number if inputs and O number of outputs, the efficiency measure E_k for DMU_k is calculated by solving the following linear programming model.

Maximize:

$$E_k = \sum_{o=1}^{O} q_{o,k} \times y_{o,k} \tag{1}$$

Subject to:

$$\sum_{o=1}^{O} q_{o,k} \times y_{o,n} - \sum_{i=1}^{I} p_{i,k} \times x_{i,n} \leq 0;\ \forall\, n \quad (2)$$

$$\sum_{i=1}^{I} p_{i,k} \times x_{i,k} = 1 \quad (3)$$

$$p_{i,k}, q_{o,k} \geq 0;\ \forall o, \forall i \quad (4)$$

where $p_{i,k}$ and $q_{o,k}$ are the weight factors for each and are determined to DMU. Therefore, we have to solve the linear programming model "n" times, once for each driver. The region is considered as difficult when E_k is less than 1 and close to 1.

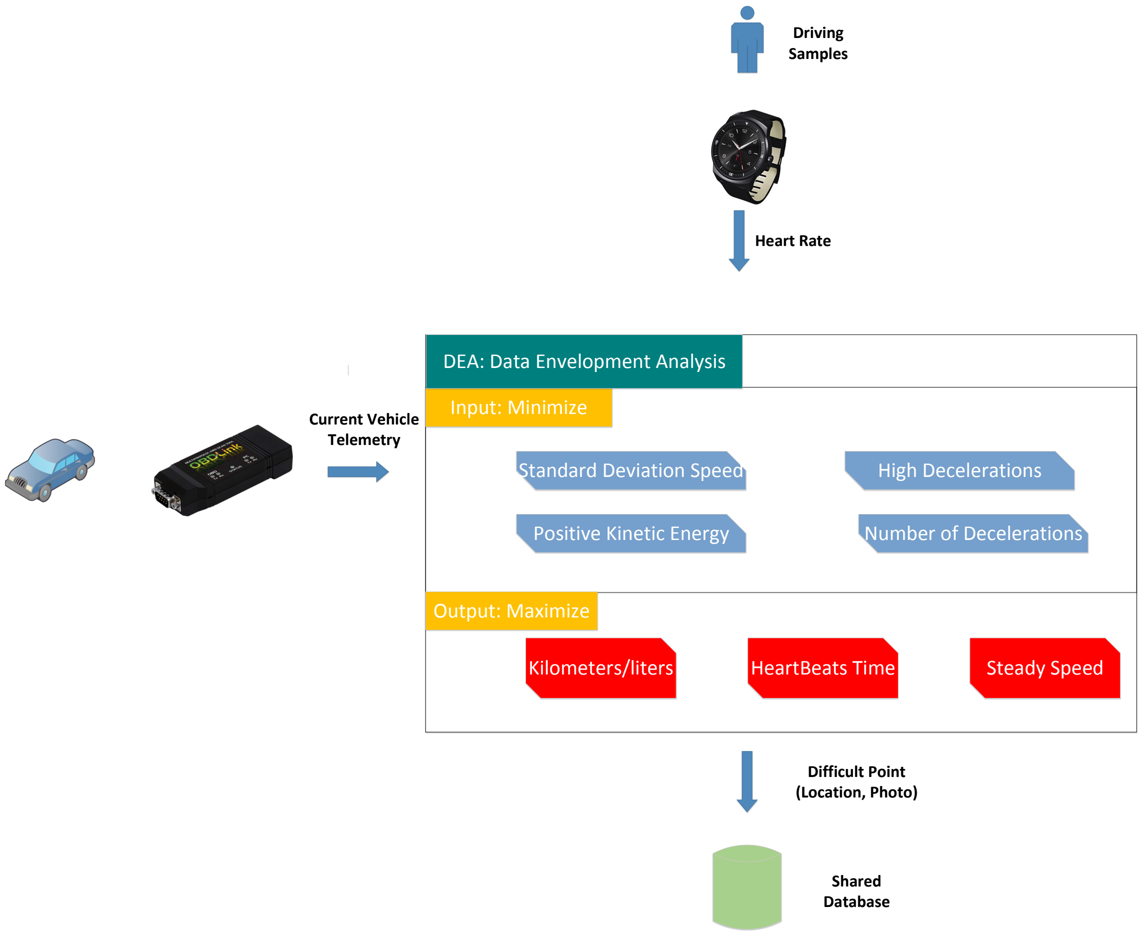

Fig. 1. Schema of the solution

We propose to employ this method because there is no preconceived form on the data in order to calculate the efficiency and stress level. DEA estimates the inefficiency in a particular DMU by comparing it to similarly DMUs considered as efficient. Other solutions estimate the efficiency associating the values of the entity with statistical averages that may not be applicable to that context. We have to take into account that each driver has particular characteristics, e.g.: the usual value of average acceleration is - 1.5 m/s_2 for driver A while that for another is - 1 m/s_2 (driver B). In this case, when the acceleration is higher than - 1.5 m/s_2 could mean that the user is approaching a curve for driver B, and while in case A is a normal value and does not provide information.

In this type of algorithms is very important the election of input and output parameters because they directly affect the accuracy of the results. We have to identify which variables affect fuel consumption and level of stress. The selection is based on the longitudinal dynamics of the vehicle [Ben Dhaou, 2011] and the observation of real driving samples. On the other hand, we have to decide what we want to maximize and minimize. In our case the input variables are minimized and the output variables are maximized.

Input parameters (Minimize):

- Standard Deviation of speed (km/h): If the driver has to be varying the speed constantly, the probability of making driving mistakes increases as well as the stress level. Furthermore, the driver could cause an accident chain. The fuel consumption is reduced because there is no acceleration resistance force if the driver is only keeping the vehicle speed. Therefore, the tractive force required to move the vehicle will be less.
- Percentage of high decelerations (higher than 2.5 m/s^2): The intensity of decelerations is an important parameter that affects both safety and fuel consumption. Sudden decelerations increase the stress of the driver and occupants. At the same time, they can cause pileup when the vehicle from behind cannot brake in good time. On the other hand, these slowdown are performed using the brake. In this case, the power generated by the engine previously is wasted. It is best to use the engine brake, softening the deceleration profile.
- Number of decelerations: The decelerations increase the driver workload and cause stress. On urban roads, it is frequent that the number of stress regions is greater than in highway due to traffic signs.
- PKE (Positive Kinetic Energy, m/s^2): It measures the aggressiveness of driving and depends on the frequency and intensity of positive accelerations [Nesamani, 2011]. A low value means that the driver is not stressed and drives smoothly. An unusual high value may indicate that driver are driving in an area that requires special attention such as acceleration lanes or roundabouts. It is calculated using the following equation:

$$PKE = \frac{\sum(v_i - v_{i-1})^2}{d} \tag{5}$$

where v is the vehicle speed (m/s) and d is the trip distance (meters) between v_i and v_{i-1}.

Output parameters:

- Heartbeats Time (milliseconds): Stress, fatigue and sleepiness has a great impact on the automatic nervous system. Furthermore, there is a strong relationship between heartrate and nervous system. When the driver is stressed, the time between heartbeat and heartbeat decreases. On the contrary. if the driver is relaxed, the time increases.
- Fuel Consumption (km/l): If driver softens the deceleration profile, he or she will take advantage of the power generated by the engine will, and therefore the fuel consumption will be reduced. Safety and fuel consumption are linked. An aggressive driver is more likely to have traffic accidents and the fuel consumption is higher in comparison with an efficient driver.
- Driving time at steady speed (seconds): Driving at a constant speed is one of the classical advices from eco-driving assistants. Every time a driver uses the brakes, forward-movement energy is converted to heat by the brake pads and is lost. On the other hand, when driver speeds up, it requires extra energy to increase speed due to the acceleration resistance.

The system saves the road section location on a shared database when it detects that it is difficult driving area where the stress increases and the driving style is less efficient. The solution employs this database in order to warn the driver when he or she is approaching to a difficult area. Therefore, he will know that is coming to a region where it should take precautions. The solution provides a deceleration profile. The objective is to prevent sudden downturns in the stress area. To calculate the optimum speed of entry into the region's stress, we take into account the rest of driving samples taken by the drivers and select the one which is associated with less stress (the lowest value of heartbeats time).

The solution requires an Android mobile device, a heart rate monitor and an OBD/Bluetooth device. The data acquisition system is described further in the section 3. The communication interface from the driving assistant is very important. Distractions due to the manipulation of devices such as GPS receivers or mobile phones are the cause of a large number of accidents [Dong, Hu, Uchimura, & Murayana, 2011]. When designing an in-vehicle information system it is important to ensure that the recommendations and the method to convey these tips do not negatively affect cognitive processing and driving performance [Peissner, 2011]. The mobile phone is fixed on the windshield, where the driver can easily see the screen without taking the eyes off the road. In addition, we may reduce distractions using proposals such as Google Glass or Garmin HUB [Google, 2015] [Garmin, 2015]. These devices allow the user to receive visual information and to pay attention on the road. The proposal uses the speaker [Young, 2007] to warn the user when must release the accelerator pedal or slow down because he or she is approaching the stress region.

3. Data Acquisition System.

The proposal employs the following devices to model the driving behavior on each road section:

Android SmartPhone; Such devices are ideal due to their multiple connections (3G, Bluetooth, and WIFI) and sensors (GPS, accelerometer, and gyroscope) that allow us to model the behavior of the driver and the environment. In our solution, GPS is used to obtain the vehicle location. This allows us to find out where are the regions where the workload is greater. The vehicle telemetry and the stress are obtained by external devices. These devices are connected to the smartphone using Bluetooth. It is necessary that the smartphone supports Bluetooth 4.0 (Low Energy).

Heart Rate Monitor: This device allows us to get the heartbeats time. In this paper, we have used an Android Wear smartwatch with optical heart rate monitor. However, the solution is compatible with any heart rate monitor which includes Bluetooth 4.0.

OBD Bluetooth Adapter: The current vehicles have a large number of sensors. These sensors send data to the Engine Control Unit (ECU) of the vehicle through buses such as: CAN, MOST, LIN and FlexRay. These data can be monitored using the OBD port [Godavarty, 2000]. OBD is a port that allows us to evaluate the emission of greenhouse gases and do in-depth diagnostic about the operation of vehicle. In our case, we requires the vehicle speed and the mass air flow. Vehicle speed is employed to analyze the driving behavior. Mass air flow allow us to estimate the fuel consumption.

To obtain the vehicle diagnostic values, we connected a Bluetooth adapter [OBDLink, 2015] to the OBDII port. The mobile device sends a PID to Bluetooth adapter. PID is an identifier. For example, vehicle speed is PID “0D”. The Bluetooth adapter sends the PID to the vehicle's bus. Then, a device on the bus recognizes the PID and sends the value for that PID to bus. Finally, the Bluetooth adapter reads the response, and sends it to mobile device.

3.1. Estimation of fuel consumption

In order to assess the impact of the use of the driving assistant on energy saving and to detect inefficient regions, a mechanism to estimate fuel consumption levels is required. Some vehicles provide an indicator for the engine fuel rate (PID 5E; liters/hour) through the OBD2 port, but fuel flow sensor information is not always available through the OBD2 port.

However, we can calculate the fuel consumption from other sources such as the mass air flow (MAF) sensor, the air/fuel ratio, RPM, effective pressure (MEP), and the fuel consumption map of the specific car. We can find in-depth information about how to estimate fuel consumption/CO2 emission from OBD sensor data and what are the potential problems in [Riener, 2010].

In our case, we estimate the fuel consumption using the speed and the MAF (mass air flow) sensors. Fuel consumptions is calculated using the following equation:

$$mph= (AF *fuelDensity*454*VSS*0.621371)/(36*MAF) \quad (6)$$

where:

- *AF:* It is the air / fuel ratio. This value is ideally set to 14.7 grams of air per gram of fuel.
- *fuelDensity:* The value is 6.17 pounds per gallon for gasoline and 7.13 pounds per gallon for diesel. These are average values since they depend on the type of fuel.
- *VSS:* This variable is the vehicle speed in km/h.

MAF (mass air flow): this variable corresponds with the mass air flow measured in grams per second and obtained through the MAF sensor. In vehicles without this sensor, the MAF is estimated from engine speed, manifold absolute pressure and intake air temperature using the Ideal Gas Law

3.2. Calculating the deceleration profile

The objective is that the vehicle speed is the same as the speed of the best driving sample (from the point of view of energy and stress) located in the stress region without using the brake pedal. In order to estimate the distance required to slowdown smoothly a vehicle driving at a certain speed "x" at a particular location "z", without using the brake pedal, and the final vehicle speed must be "y", the following equation can be used:

$$M\frac{dx(t)}{dt} = F_T(t) - F_R(t) \quad (7)$$

where $M, F_T(t)\ and\ F_R(t)$ are the equivalent mass of the vehicle and its rotating part, the traction force, and the sum of all motion resistance forces, respectively. In order to estimate the distance required to decelerate the vehicle, $F_T(t)$ could be considered as 0. We are assuming that the gear is set to neutral. In this case, we can cover more distance than when we use the engine brake (gear engaged). Therefore, the minimum resistance force (without braking) could be calculated as:

$$F_R(t) = \frac{1}{2}C_D\rho_a A_V x^2 + \mu Mg\cos\theta(z) + Mg\sin\theta(z) \quad (8)$$

where $C_D, \rho_a, A_V, \mu\ and\ \theta(z)$ are the drag coefficient, the air density, the frontal area of the vehicle, the rolling resistance coefficient, and the road slope angle as a function of location z, respectively. Drag force is not significant because time driving at a high speed is very low (the aim is to decelerate). Therefore, the first part of the equation can be ignored and the resistance force is approximated by:

$$\mathrm{F_R(t)} = \mu\mathrm{Mg}\cos\theta(z) + \mathrm{Mg}\sin\theta(z) \quad (9)$$

The rolling resistance coefficient (μ) is dependent on a great number of parameters such as: the surface, the radius of the tire, the weight, the tire pressure, the temperature and the speed. However, we can estimate the coefficient using the following equation:

$$\mu = 0.008 * \left[5.1 + \frac{5.5+9p}{pn} + \frac{8.5+3p}{pn} * \left(\frac{x}{100}\right)^2\right] \quad (10)$$

where p is the weight per tire (t), pn is the tire pressure (Kg/cm^2) and x is the vehicle speed (Km/h).

The road slope angle can be estimated from the mobile device embedded sensors (GPS and Barometer). GPS is less accurate than barometer but it is included on all smartphones. On the other hand, the values obtained from the barometer are influenced by the air density and temperature. Therefore, it also shows an approximation. Other more precise methods require additional hardware such as Lidar. The estimated distance to slowdown the vehicle when travelling at a certain speed "x" can therefore be calculated as:

$$d_S \approx \frac{x^2 - y^2}{2(\mu g \cos\theta(z) + g \sin\theta(z))} \tag{11}$$

It is possible that the estimated distance to slowdown the vehicle without using the brake pedal could be greater than the current distance between vehicle and stress region. In this case, the driver has to use the brake pedal to be able to decelerate the vehicle on time. The intensity of braking required is estimated using the following equation:

$$DE = \frac{y^2 - x^2}{2d} \tag{12}$$

where *DE* is the deceleration value, *y* is the initial speed from the best driving sample when driver was in the stress region, *x* is the current speed and *d* is the distance between the vehicle and the stress area.

4. Validation of the proposal

4.1. Results using a driving simulator

In order to evaluate the energy savings achieved when using the proposed solution, 120 test drives have been performed using OpenDS driving simulator [OpenDS Simulator, 2015], by 6 different drivers. Each driver followed the route 20 times, half of the times using the advices provided by the eco-driving assistant, half of them without using the assistant. In order to define a counter-balanced experiment, three drivers used the driving assistant on the first 10 laps (and drove without it on the remaining). The order of utilization of the assistant was inverted for others drivers. The route has a length of 2.9 Km. The road is a motorway. However, there are several regions where stress is greater due to the dense traffic and traffic signs that require slowing down sharply. Figure 2 shows a driver using the driving simulator.

Fig. 2. Driver using OpenDS simulator

The table captures the average value of efficiency obtained by the algorithm in the stress regions. The output is a value between 0 and 1. A high value means that there is no stress in the region. To obtain the inefficient areas, the algorithm compares the driver behavior in each region. The solution assigns 1 as efficiency value when it is the place where the drive drove better from the viewpoint of efficiency and safety. In the table 1, we can observe how the efficiency value is low in all areas where driving is difficult. Therefore, we can affirm that solution allows to find out accurately which are the most difficult regions for the driver.

Stress Region	Driver A	Driver B	Driver C	Driver D	Driver E	Driver F

1	0,3390	0,0490	0,1854	0,2432	0,2336	0,1784
2	0,2470	0,1465	0,1870	0,3776	0,2462	0,1438
3	0,1980	0,1262	0,3954	0,1951	0,1607	0,2229
4	0,3220	0,1364	0,2359	0,1655	0,3070	0,2074

Table 1. Efficient value calculated by DEA in the stress regions.

Figure 3 shows the heartbeat time intervals (i.e. interval between 2 consecutive heatbeats). This variable is improved by 4.89% on average when drivers used the driving assistant. The heartbeats time interval is influenced by the sympathetic nervous system and parasympathetic nervous system. A high value means that the driver is not stressed. On the other hand, stress depends on many independent factors of the driving such as the physical activity, the fatigue, working time, etc. In order to avoid inaccurate results, all driving tests have been made in the morning before work and when the driver was relaxed and he or she had slept 8 hours at least.

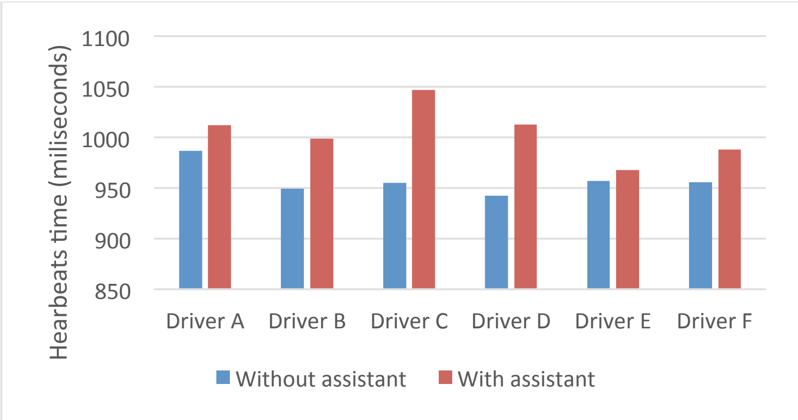

Fig. 3. Heartbeats time with and without the solution

Figure 4 captures the standard deviation of vehicle speed. This variable is improved by 13.19% on average when drivers used the driving assistant. Changes in vehicle speed increases fuel consumption and stress level of the driver. If the user accelerates and brakes frequently, the likelihood of making driving mistakes will be greater. Furthermore, the driver could cause an accident chain because the car behind might not have enough time to stop.

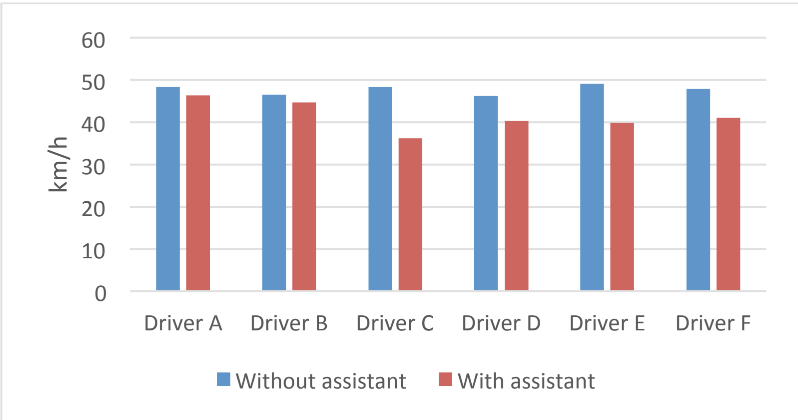

Fig. 4. Standard Deviation of Speed with and without the solution

Figure 5 captures the number of sudden decelerations (higher than -2.5 m/s^2). In order to improve fuel consumption and safety, the implementation of the system should minimize the number of times in which the use of the brakes is required (making decelerations as smooth as possible by releasing the accelerator pedal on time). This variable was reduced by 59% on average when drivers employed the solution.

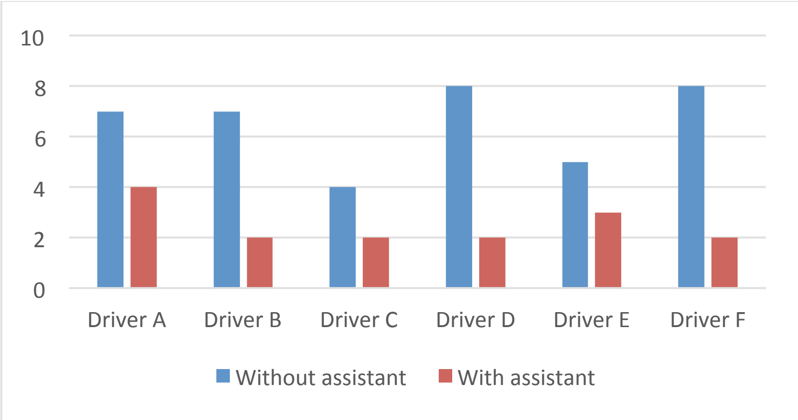

Fig. 5. Number of sudden decelerations with and without the solution

The major difference introduced by the use of the driving assistant is appreciated when driver is driving in the stress area. The results of magnifying the deceleration pattern one of the times that the driver has to deaccelerate with and without the assistant is presented in Figure 6. This figure shows the speed profile when he is close to a stress region. A speed limit sign is the cause. The vehicle speed is too high when the driving assistant is disabled and the driver has to brake sharply, wasting the energy previously produced. On the other hand, this maneuver may cause a traffic chain accident and increases the stress level because driver has to take a decision quickly. However, when the assistant is enabled, the driver adjusts the speed and prevents the sudden slowdown. In this case, the demand for attention is lower and the stress level of driver is improved. Furthermore, fuel consumption is reduced. Providing an alert to the driver when vehicle is close to the stress area in order to release the accelerator is positively correlated with fuel consumption savings and the safety. However, the degree of improvement depends on the skill of the driver and his or her response when receiving the recommendations. The average fuel consumption was 3.55 l/100 km without the solution and 0.22 l/100 km with the driving assistant. In the second case, energy consumption was so low because the driver uses the engine brake most of the time. Figure 7 captures the heartbeats time. We can observe that when the driver employs the proposal, the heartbeats time remains constant and its value is high (low stress). However, the stress increases (low heartbeats time) when the solution is disabled and the user has to brake abruptly. If the trip has many stress areas, we will obtain a significant improvement.

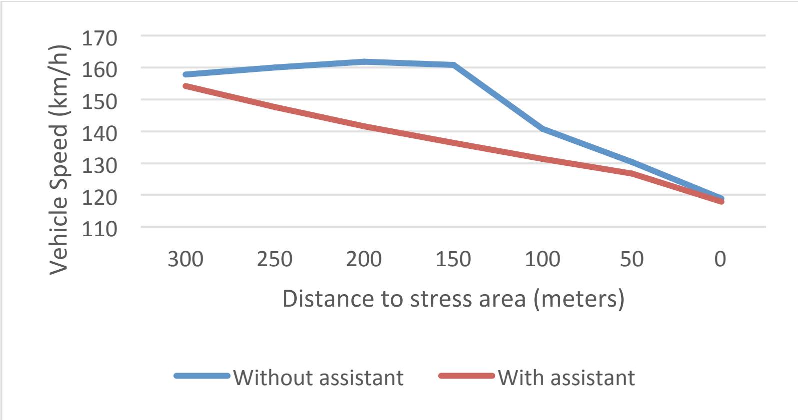

Fig. 6. Deceleration profile close to a stress region with and without the solution

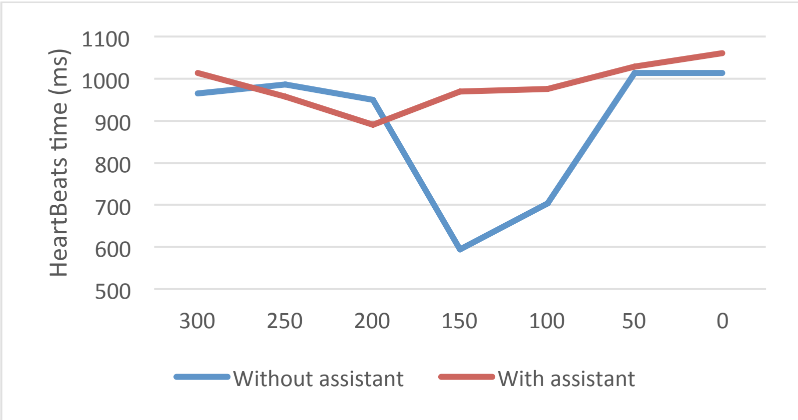

Fig. 7. Evolution of heartbeats time close to a stress region with and without the solution

4.2. Results in a real environment

The solution was deployed on a LG G3. This device is equipped with a Quad-Core Qualcomm Snapdragon 801 at 2.5 GHz, Bluetooth LE, and 3 GB of RAM. The OBDLink OBD Interface Unit from ScanTool.Net [OBDLink, 2015] was used to get the relevant data (vehicle speed, fuel consumption, and acceleration) from the internal vehicle's CAN bus. The OBDLink OBD Interface Unit contains the STN1110 chip that provides an acceptable sample frequency for the system. In our tests, we obtain two samples per second. Heart rate was got through LG GWatch-R. This smartwatch run Android Wear and consists of a 1.2 GHz Quad-Core Qualcomm Snapdragon 400 processor, 4GB internal storage and 512MB RAM. In addition, it has Bluetooth LE connectivity, barometer, accelerometer, gyroscope, and heart rate monitor (HRM).

In order to evaluate the proposed system, 48 test drives have been performed with 6 different drivers. The tests were performed in Madrid between the months of November 2014 to January 2015. The selected routes (A and B) has both parts of urban road and a highway. All tests were made under similar conditions (time, traffic, and weather). The vehicles employed were all Citroen Xsara Picasso 2.0 HDI.

Drivers were divided into two groups: X and Y. Each group completed a different route (A, B). The experiment consisted of two phases. In the first phase, drivers completed the route 4 times without the use of shared database. At this stage the aim was only to discover areas where stress and fuel consumption is high. Group X drove in route A and group Y drove in route B. In the second stage, the drivers had to drive 4 times in a route different from the first stage. Therefore, group X drove in route B and group Y drove in route A. The objective was that drivers did not know the route. In this case, the solution was activated. The drivers received warnings (and the optimal deceleration profile) when they were near a difficult area.

Table 2 shows the results obtained in the first phase of the experiment, when the solution was disabled. The objective of this test was only to build the shared database with areas where driving is difficult.

Table 3 captures the results of the second phase. In this case, the system was activated and provided information (deceleration profile) to the user when he was approaching a difficult region. As mentioned in the previous section, the drivers drove on different routes from the first phase. Therefore, they did not know the road environment. We can see that the fuel consumption is improved by 12.41% and the heart ratio is reduced by 4.70% when the proposal is enabled. In addition, we should highlight that driving is softer (PKE value is lower than in the first phase of the experiment). The reason is that the user can observe the environment in advance and adjust the vehicle speed.

	Route	Average HeartRate (b.p.m)	Std. HeartRate (b.p.m)	Fuel Consumption (l/100 km)	PKE (m/s2)
Driver X1	A	82.36	8.96	6.93	0.3081
Driver X2	A	75.34	4.20	6.52	0.2995
Driver X3	A	76.10	10.11	6.83	0.3049
Driver Y1	B	76.10	10.07	6.95	0.3052
Driver Y2	B	75.50	4.55	6.51	0.2979
Driver Y3	B	75.13	5.43	6.41	0.2831

Table 2. Results without using the solution (First Phase).

	Route	Average HeartRate (b.p.m)	Std. HeartRate (b.p.m)	Fuel Consumption (l/100 km)	PKE (m/s2)
Driver Y1	A	73.64	3.13	5.85	0.2636
Driver Y2	A	73.60	2.76	5.80	0.2576
Driver Y3	A	73.62	3.89	5.90	0.2599
Driver X1	B	72.60	2.59	5.81	0.2497
Driver X1	B	72.11	2.35	5.86	0.2422
Driver X3	B	73.27	3.03	5.93	0.2562

Table 3. Results using the solution (Second Phase).

Figure 8 captures the deceleration profile with and without the driving assistant close to a stress region Graphically, the deceleration rate when using the solution results in a more gradual deceleration pattern. The user has to brake abruptly when he does not receive information about the environment in advance. This causes increased stress and more likely to have a traffic accident.

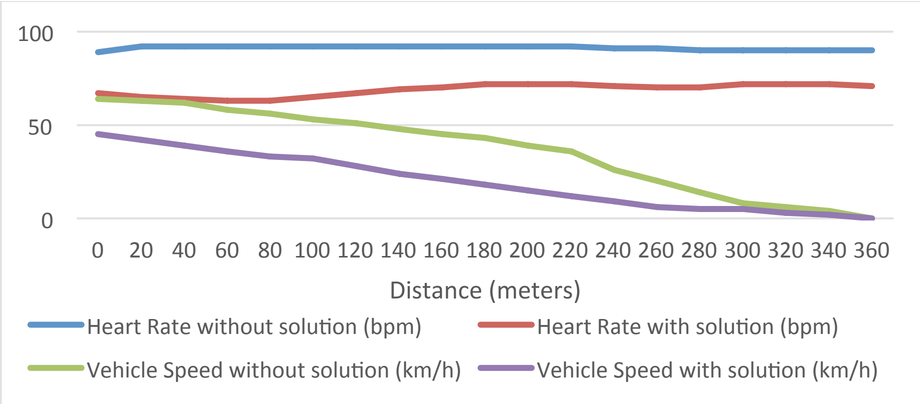

Fig. 8. Deceleration pattern comparison at one difficult area (high fuel consumption and stress) with and without using the solution

5. Conclusions

In this paper, we proposed a method for reducing stress and fuel consumption. The solution builds a shared database with the areas where driving is more difficult based on the driving style and the driver's workload. Data Envelopment Analysis is used to discover these areas. This method takes into account the particular characteristics of each user. The shared database is used to provide information in advance about the road environment so that driver can adopt appropriate measures (e.g. deceleration profile if the vehicle speed is not suitable). The objective is that the user drives in the stress region at a speed that minimizes stress and fuel consumption. The results show a significant improvement in fuel consumption and a reduction in the driver stress. Driving is smoother. In the literature, we found a large number of papers about how to measure the driver workload. However, they do not propose any methods to reduce it and tests are conducted in simulators. The main contribution of this work is an application to improve safety and fuel consumption using the information of the level of driver stress and his driving.

As future work, we want to apply a filtering algorithm in the shared database which contains the inefficient regions in order to select those that were detected by users with a similar driving profile. This would allow us to issue more precise recommendations and to avoid false positives. Furthermore, we want to employ other sensors to assess the driver stress as galvanic sensors or camera but always keeping in mind that they should not be intrusive.

6. Acknowledgments

The research leading to these results has received funding from the "HERMES-SMART DRIVER" project TIN2013-46801-C4-2-R within the Spanish "Plan Nacional de I+D+I" under the Spanish Ministerio de Economía y Competitividad and from the Spanish Ministerio de Economía y Com-petitividad funded projects (co-financed by the Fondo Europeo de Desarrollo Regional (FEDER)) IRENE (PT-2012-1036-370000), COMINN (IPT-2012-0883-430000) and REMEDISS (IPT-2012-0882-430000) within the INNPACTO program.

7. References

Adell, E., Varhelyi, A., & Fontana, M. (2011). The effects of a driver assistance system for safe speed and safe distance: A real-life field study. *Transportation Research Part C: Emerging Technologies, 19*(1), 145–155. doi:10.1016/j.trc.2010.04.006

Ben Dhaou, I. (2011). Fuel estimation model for Eco-Driving and Eco-Routing. *IEEE Intelligent Vehicles Symposium IV*, 37-42. doi:10.1109/IVS.2011.5940399

Changxu, W., & Yili, L. (2007). Queuing network modeling of driver workload and performance. *IEEE Transactions On Intelligent Transportation Systems, 8*(3), 528-537. doi:10.1109/TITS.2007.903443

Charnes, A., Cooper, W., & Rhodes, E. (1978). Measuring the Efficiency of Decision Making Units. *European Journal of Operational Research, 2*(6), 429-444. doi:10.1016/0377-2217(78)90138-8

Charnes, A., Cooper, W., Golany, B., & Seiford, L. (1985). Foundations of data envelopment analysis for Pareto-Koopmans efficient empirical production functions. *Journal of Econometrics, 30*(1-2), 91-107. doi:10.1016/0304-4076(85)90133-2

Dong, Y., Hu, Z., Uchimura, K., & Murayana, N. (2011). Driver inattention monitoring system for intelligent vehicles: A review. *IEEE Transactions on Intelligent Transportation Systems, 12*(2), 596–614. doi:10.1109/TITS.2010.2092770

Engströma, J., Johanssona, E., & Östlundb, J. (2005). Effects of visual and cognitive load in real and simulated motorway driving. *Transportation Research Part F: Traffic Psychology and Behaviour, 8*(2), 97–120. doi:10.1016/j.trf.2005.04.012

Frith, W., & Cenek, P. (2012). *AA Research: Standard Metrics for Transport and Driver Safety and Fuel Economy*. Opus International Consultants Central Laboratories.

Garmin. (9 de 1 de 2015). *Garmin HUB*. Obtenido de https://buy.garmin.com/en-US/US/prod155059.html

Godavarty, S., Broyles, S., & Parten, M. (2000). Interfacing to the on-board diagnostic system. *IEEE-VTS Fall VTC 2000*, *4*, págs. 2000-2004. doi:10.1109/VETECF.2000.886162

Google. (9 de 01 de 2015). *Google Glass*. Obtenido de http://www.google.com/glass/start

Itoh, M., Kawakita, E., & Oguri, K. (2010). "National motor vehicle crash causation survey," Washington, DC, USA, Tech. Rep. DOT HS 811 059, Jul.]. *17th ITS World Congress*, (págs. 1-11). Busan, South Korea.

Ji, Q., Zhu, Z., & Lan, P. (2004). Real-time non-intrusive monitoring and prediction of driver fatigue. *53*(4), 1052–1068. doi:10.1109/TVT.2004.830974

Kim, J. H., Kim, Y. S., & Lee, W. S. (2011). Real-time monitoring of driver's cognitive distraction. *Spring Conf. Korean Soc. Autom. Eng.*, (págs. 1197–1202).

Nesamani, K., & Subramanian, K. (2011). Development of a driving cycle for intra-city buses in Chennai. *Atmospheric Environment, 45*(31), 5469–5476. doi:10.1016/j.atmosenv.2011.06.067

OBDLink. (9 de 1 de 2015). *OBDLink ScanTool*. Obtenido de http://www.scantool.net

Peissner, M., Doebler, V., & Metze, F. (2011). *Can voice interaction help reducing the level of distraction and prevent accidents? Meta-Study on Driver Distraction and Voice Interaction*. White Paper.

Riener, A., Ferscha, A., Frech, P., Hackl, M., & Kaltenberger, M. (2010). Subliminal vibro-tactile based notification of CO2 economy while driving. *2nd International Conference on Automotive User Interfaces and Interactive Vehicular Applications AutomotiveUI*, (págs. 92-101). Pittsburgh, Pennsylvania, USA.

Sega, S., Iwasaki, H., Hiraishi, H., & Mizoguchi, F. (2011). Verification of Driving Workload Using Vehicle Signal Data for Distraction-Minimized Systems on ITS. *18th ITS World Congress*, (págs. 1-12). Orlando Florida.

Simulator, O. D. (25 de 9 de 2015). *OpenDS Driving Simulator*. Obtenido de http://www.opends.de

Teh, E. T., Jamson, S., & Carsten, O. (2012). How does a lane change performed by a neigh-boring vehicle affect driver workload? *19th ITS World Congress*, (págs. 1-8). Vienna , Austria.

Transportation, U. D. (2008). *National motor vehicle crash causation survey*.

Young, K., & Regan, M. (2007). *Driver distraction: A review of the literature*. NSW: Australasian College of Road Safety.

Zhang, Y., Owechko, Y., & Zhang, J. (2008). Learning-Based Driver Workload Estimation. En *Computational Intelligence in Automotive Applications* (págs. 1-17). doi:10.1007/978-3-540-79257-4_1