This is a postprint version of the following published document:

Corcoba Magaña, Víctor; Muñoz Organero, Mario (2015) "Reducing Stress and Fuel Consumption Providing Road Information", in Ambient Intelligence - Software and Applications, Advances in *Intelligent Systems and Computing, : 6th International Symposium on Ambient Intelligence (ISAmI 2015),* Volume: 376, pp. 23-71.
DOI: 10.1007/978-3-319-19695-4_3

# Reducing Stress and Fuel Consumption Providing Road Information

**Víctor Corcoba Magaña and Mario Muñoz Organero**

**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 and driver workload during the trip. If it discovers an area where the stress increases and the driving style is worse from the point of view of energy efficiency, a photo is taken and is saved along with its location in a shared database. On the other hand, the solution warns the user when is approaching a region where the driving is difficult (high fuel consumption and stress) using the shared database. In this case, the proposal shows on the screen of the mobile device the image captured previously of the area. The aim is that driver knows in advance the driving environment. Therefore, he or she may adjust the vehicle speed and the driver workload decreases. Data Envelopment Analysis is used to estimate the efficiency of driving and driver workload 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 with 6 participants who made 96 driving tests in Spain. The system reduces the slowdowns (38 %), heart rate (4.70 %), and fuel consumption (12.41 %). 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.

**Keywords** Intelligent transport system, Fuel consumption optimization, Data envelopment analysis (DEA), Driving assistant, Android, Android wear, Applications, Mobile computing.

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# 1 Introduction

Many traffic accidents are due to distractions. In [1] 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.

There are many works on measuring and quantifying the driver workload. In [2], 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 [3], 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 [4], the driver workload from lane changing were measured through simulation test driving. In [5], 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.

On the other hand, the impact of the cognitive load on the driver behavior has been studied on many papers. In [6], Kim et al. 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. [7] 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. [8], 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 [9] 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 shared database which contains the places where driving is difficult (high workload and fuel consumption). The objective is to provide knowledge about these places in advance 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 [10] 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 pro-duction process presents a structure of multiple inputs and outputs. This method was proposed by Charnes, Cooper, and Rhodes [11] (Fig. 1).

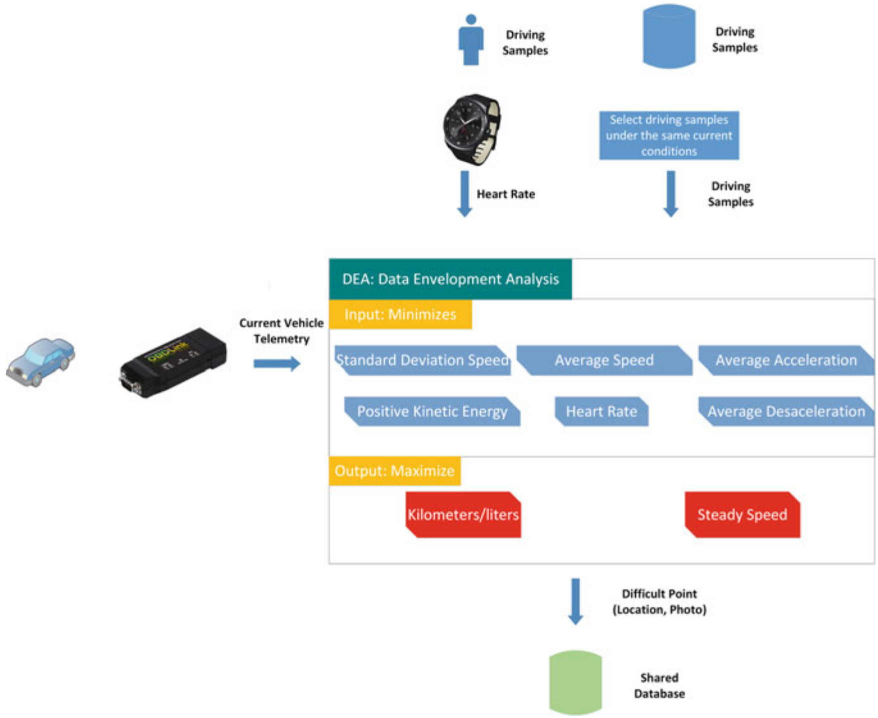


**Fig. 1** Schema of the solution

In our proposal, each DMU represents a different driving samples obtained under similar conditions (weather, traffic and road type) by the same driver. The aim is to detect the road points where the driver workload is high and fuel consumption increases. If we consider a set of drivers 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:

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

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

$$p_{i,k}, q_{o,k} \geq 0; \forall o, \forall i \tag{4}$$

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.

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 [12] 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:

- Heart rate: Average Speed
- Standard Deviation of speed
- Average Deceleration
- PKE (Positive Kinetic Energy):

Output parameters:

- Fuel Consumption (km/l)
- Driving time at steady speed

Positive Kinetic Energy (PKE) measures the aggressiveness of driving and depends on the frequency and intensity of positive accelerations [13]. 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 $v_{i-1}$.

The system takes a photo when it detects that it is difficult driving area where the stress increases and the driving style is less efficient. Photo and location (latitude and longitude) are stored in a shared database. On the other hand, the solution used the shared 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 and the causes of this warning. The device 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 [14, 15]. These devices allow the user to receive visual information and to pay attention on the road.

# 3 Evaluation of Proposal

## *3.1 Experimental Design*

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 [16] was used to get the relevant data (vehicle speed, fuel consumption, and acceleration) from the internal vehicle's CAN bus [17]. 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, 4 GB internal storage and 512 MB RAM. In addition, it has Bluetooth LE connectivity, barometer, accelerometer, gyroscope, and heart rate monitor (HRM).

In order to evaluate the proposed system, 96 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 (photos on the device screen) when they were near a difficult area.

# 4 Results

Table 1 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 2 captures the results of the second phase. In this case, the system was activated and provided information (photos) 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.

**Table 1** Results without using the solution (First Phase)

| | Route | Average heart rate (b.p.m) | Std. heart rate (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 using the solution (Second Phase)

| | Route | Average heart rate (b.p.m) | Std. heart rate (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 |

The major difference introduced by the use of the driving assistant is appreciated in the presence of difficult areas where drive has to adjust the vehicle speed. The results of magnifying the deceleration pattern and heart rate in one of the occasions that the drivers has to slow down is presented in Fig. 2. 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. Providing information to the driver is positively correlated with obtaining smooth deceleration patterns in general. The degree of improvement depends on the skill of the driver and his or her response when receiving the warning. Furthermore, smooth deceleration pattern has a positive impact on fuel consumption. In this case, the vehicle takes advantage of the kinetic energy to move until the point where the vehicle should stop or reduce the speed and is not wasted.

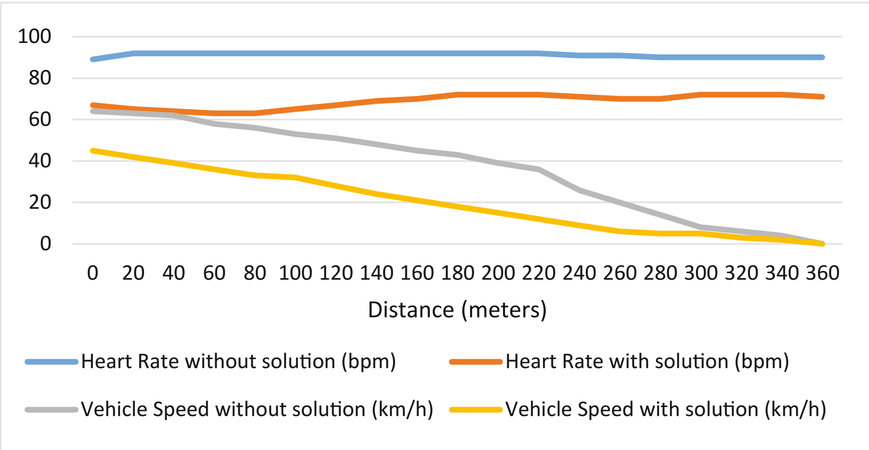


**Fig. 2** Deceleration pattern comparison at one difficult area (high fuel consumption and stress) with and without using the solution

## 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 and the driver 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. The results show a significant improvement in fuel consumption and a reduction in the driver stress. 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 remove the causes that the region is difficult to drive using the captured image, e.g.: detecting that there is a very pronounced curve in the region. This would allow us to issue more precise recommendations and reduce possible distractions caused by the wizard. We also employ other measures to assess the stress of the user as galvanic sensors or camera but always keeping in mind that they should not be intrusive.

**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 Competitividad 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.

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