

Estimating the Stress for Drivers and Passengers Using Deep Learning

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Abstract

The number of vehicles in circulation has become a problem both for safety and for the citizens health. Public transport is a solution to reduce its impact on the environment. One of the keys to encourage users to use it is to improve comfort. On the other hand, numerous studies highlight that drivers are more likely to suffer physical and psychological illnesses due to the sedentary nature of this work and workload. In this paper, we propose a model to predict the stress level on drivers and passengers. The solution is based on deep learning algorithms. The proposal employs the Heart Rate Variability (HRV) and telemetry from the vehicle in order to anticipate the incoming stress. It has been validated in a real environment on distinct routes. The results show that it predicts the stress by 86 % on drivers and 92% on passengers. This algorithm could be used to develop driving assistants that recommend actions to smooth driving, reducing the workload and the passenger stress.

1. Introduction

Cognitive errors appear in highly cognitive demanding situations in which the cognitive load as perceived by the driver is high and the actions taken by the driver to handle those situations are in many occasions not appropriate. The data presented in [U.S. Department of Transportation, 2008] categorizes the major risk factors responsible for traffic accidents as follows (according to their impact): 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%).

There are many proposals on measuring and quantifying the driver's cognitive load and stress levels. In [Gao et al., 2014] the authors propose a method for detecting stress based on facial expressions. They employed a near-infrared (NIR) camera to capture the near frontal view of the driver's face. Tracking face is made using a supervised descent method (SDM) [Xiong and Torre, 2013].

In [Eilebrecht, 2012], the research analyzed the suitability of the heart rate variability (HRV) to measure the driving workload. The results conclude that the HRV could be used as a good workload indicator, although it is also affected by many other factors that may have an influence on it. To solve this problem, the author suggested using other parameters such as: skin conductivity, gripping pressure on the steering wheel, respiration or blood pressure. In the paper [Rodrigues et al., 2015], the authors also observed that variability is not enough to detect the stress. They also mentioned the meaning of previous driver experience. Novice drivers are more likely to get stressed driving in difficult situations.

Currently, the vehicle has become an essential element, both for the freight transport and the city residents. In Japan [Elbanhawi et al, 2015] statistics show that each person travels 7500 Km on average per year. On the other hand, many of these trips are made by bus or rail. In the United States [Innamaa and Penttinen, 2014], commuters travel more than 20 billion miles by bus and 9 billion miles by commuter rail. In the literature there are many methods for evaluating the comfort of the passenger. The author in [da Silva, 2002] proposes various measures based on vibrations, noise, temperature and air quality for this. He also mentioned that actions such as accelerating, braking, or engaging the clutch impact on the level of comfort in the driver. The road geometry is another factor to consider.

[Hoerock, 1977] studies the relationship between the passenger comfort and the longitudinal motion. He estimated nominal acceleration values in the range of 0.11 g to 0.15 g and a maximum jerk region of 0.30 g/sec in the longitudinal direction to maintain a good comfort level. For safe emergency response, maximum acceleration of 0.52 g is estimated to prevent

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dislodgment. The author also noted that these results are affected by passenger type. In addition, he concluded that there are few studies analyzing the over short distances. In this scenario, the start-stop movements are very frequent, disturbing the passengers.

The authors in [Wang et al., 2001] propose a driving assistant that estimates the discomfort in real time. This solution is based on the analysis of the accelerations. The objective of this study is that the driver change his driving style in order to reduce the passenger ride discomfort and provide passenger-friendly maneuvers.

The authors in [Innamaa and Penttinen, 2014] made a study about the impact of Green-driving applications on fuel consumption, speeding and passenger comfort. The results demonstrated that the driving assistant improved the decelerations and the driver's service attitude in peak traffic significantly. This was also experienced as more pleasant by passengers. All these works is based on questionnaires whose responses are subjective. The consequence is a large variation among the different results.

In conclusion, there are many proposals to detect the driver stress and measure the comfort of the passengers. However, there are no solutions to predict a worsening for the tension on drivers and passengers in real scenarios. In this paper, we propose a model that allows us to estimate if the driver or passenger will experience an increase in the stress level.

The aim is that assistive tools to prevent the stress or avoid it could be developed in the future based on our proposed algorithm. This algorithm could be used to build a driving assistant that recommends an optimal vehicle speed in order to maximize comfort while driving. This recommended speed will minimize the driving workload and the speed fluctuations. The reduction in the number and intensity of the accelerations will improve the comfort of the drivers and passengers.

Proposal for the estimation of stress level on drivers and passengers

2.1 Objective

Our goal is to predict the stress, both for drivers and passengers, based on the current measurements of stress level and vehicle telemetry.

2.2 Input variables

In this work, the input variables can be classified into two groups: variables related to the stress level and variables associated with the vehicle telemetry.

Measurements of stress level

Heart Rate signals are employed as an indicator for the Autonomic Nervous System (ANS) neuropathy for normal, fatigued and drowsy states because the ANS is influenced by the sympathetic nervous system and parasympathetic nervous systems. This indicator is not intrusive. A high heart rate correlates with the driver experiencing stress.

Among the different variables previously described as presented in the existing literature we have used the Heart Rate Variability (HRV) since it has been assessed as one having a higher correlation with stress levels together with Skin Conductivity (SC).

One major limitation of the HRV signal in order to estimate the level of stress and cognitive load is that there are other factors such as the physical exercise that also impact the measured values. As described in the previous section, the experiment has been designed to minimize the impact that factors outside the study have on the measurements. In this way, only data from drivers driving alone to work and back home in similar situations each day (same hour, same traffic conditions, with moderated previous walking to get into the car and a relaxation period of 30 seconds before driving, with the mobile phone muted, with the radio switched off and without using any navigation system) have been taken. The same methodology was applied to passengers.

In addition, we analyze the driving behavior. The combination of these two groups of variables allows us to build a model to predict the stress on drivers and passengers accurately.

We can consider Heart Rate Variability (HRV) from two different domains: Time and Frequency. Time domain analysis of HRV implicates quantifying the mean or standard deviation of RR intervals. Frequency domain analysis means calculating the power of the respiratory-dependent high frequency and low frequency components of HRV. In our case, we are going to use measures on the time domain. There are many HRV that can be defined on this domain such as: mean RR interval (mRR), mean heart rate (mHR), standard deviation of RR interval (SDRR) or standard deviation of heart rate (SDHR).

We have chosen the following variables based on real tests:

- Average HeartRate (b.p.m): This variables has a high value when the driver or passenger experiences high levels of stress.
- Average RR (ms): It measures the time between beat-beat (consecutive heartbeats). Its value decreases when there is an event that causes stress on the driver. On the contrary, a high value means that the driver is relaxed.
- Standard deviation of RR intervals (ms): the variation between beat and beat (inter-beat period) increases when the driving workload is high.
- RR50: It is the number of pairs of successive RRs that differ by more than 50 ms. A high number allows us to detect stress situations.
- Average acceleration (positive and negative): Frequently, these actions cause stress. For example, if the car in front braked suddenly, the driver from behind will have to react quickly. This situation increases the tension, both for drivers and for passengers and demands attention.

Driving behavior

Figure 1 captures the driving speed profile and the result of the difference between the current RR and the previous RR. We can observe that the driver's perceived tension increases between seconds 2 and 4, when the driver is accelerating. In addition, the stress level also worsens in the interval between 15 and 23 seconds. During this period, the driver was accelerating and braking frequently.

- Positive Kinetic Energy (PKE): This variable measures the aggressiveness of driving. Its value depends on the intensity and frequency of the accelerations. If it is high means that the driver accelerated sharply and frequently. This driving style has a negative impact on the stress level, both for drivers and passengers. In the case of the driver it implies that he or she has to make faster decisions in order to avoid accidents.
- The intensity of turning: We detected during testing that the tension increased in the majority of the drivers when there were curves on the road. The degree of impact depends on the road angle (intensity of turning required).

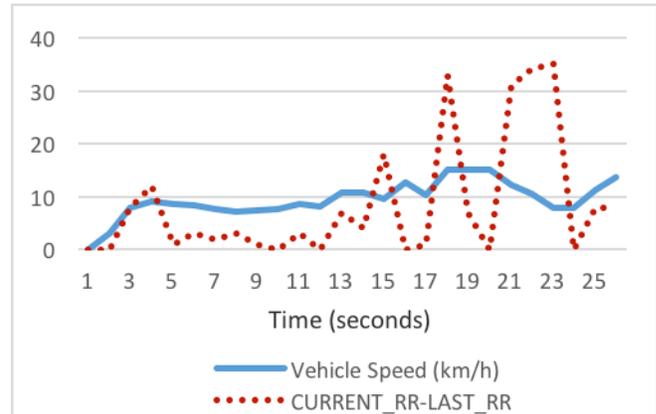


Fig. 1. Schema of the driving assistant.

In order to minimize the random errors introduced by the sensors in each sample, values are averaged each 5 seconds. The measured values in the last 5 seconds of driving are then used to estimate the upcoming stress level for the next 5 seconds of driving. Therefore, a 10 second window is selected for the computations and validation.

2.3 Method

In order to validate results we consider two cases. The first scenario is to predict the drivers stress. The second case is to estimate the incoming stress for the passengers.

In the first case, 6 different users using 2 different cars in 2 different regions have been selected. The regions were Sheffield in the UK and Madrid in Spain. The vehicle models were an Opel Zafira Tourer and a Citroen Xsara Picasso. In total, we have obtained 100 test drives with around 2000 minutes of driving. Each test drive comprised both urban and inter-urban (rural and highway) sections.

One major limitation of the HRV signal in order to estimate the level of stress and cognitive load is that there are other factors such as the physical exercise that also impact the measured values. The experiment has been designed to minimize the impact that factors outside the study have on the measurements. In this way, only data from drivers driving alone to work and back home in similar situations each day (same hour, same traffic conditions, with moderated previous walking to get into the car and a relaxation period of at

least 30 seconds before driving, with the mobile phone muted, with the radio switched off and without using any navigation system) have been taken.

In the second case, 6 different bus drivers and 6 passengers have participated. The regions were near Sheffield in the UK. In total, we have obtained 30 test drives with around 1200 minutes of driving. Each test drive comprised both urban and inter-urban sections. As in the first case, the experiments were conducted under similar conditions in order to get accurate results.

A Polar H7 band was used to record the HRV signal. The band was paired with a Nexus 6 Android Mobile device running an application implemented for the experiment which recorded the HRV together with GPS data and telemetry data such as the driving speed.

In order to predict the stress level, we only use a heart rate strap because this device is not intrusive and the cost is low. These features allow us to make tests with a broad population. The aim is to maximize the acceptability. The user only has to buy a heart rate strap that costs about 50\$. There are many solutions [Mohan et al., 2016] which demonstrate that only with this variable, you can get a good stress estimate.

The current acceleration of the vehicle is calculated based on the measured speed as follows:

$$a_i = \frac{v_i - v_{i-1}}{t_i - t_{i-1}}$$

In which v_i represents the speed at the sample number i , a_i the estimated acceleration at that sample and the derivative of the speed is estimated by dividing the increment in speed by the time elapsed between the consecutive samples $i-1$ and i .

The positive kinetic energy (PKE) is estimated over a period of time as follows:

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

Where v_i is the speed (meters/seconds) and d is the trip distance (meters).

The intensity of turning is estimated using the following formula:

$$TI_i = \cos^{-1} \frac{\overline{l_i} \cdot \overline{l_{i-1}}}{\|\overline{l_i}\| \|\overline{l_{i-1}}\|}; v_i > th$$

Where the numerator represents the dot product between the average direction vectors in the last 5 seconds and the average direction vectors in the next 5 seconds and the denominator captures the norm of such averaged vectors. The direction vectors are calculated from the GPS coordinates. The average over a period of 5 seconds is used to minimize the impact of random errors in the GPS signal. In order to eliminate the errors introduced at low speeds, a threshold in the speed is used. This threshold has been empirically evaluated and a value of 1 m/s has been found to perform well and therefore selected for the experiment.

3 Validation of the proposal

We capture the results for drivers and passengers in two different sub-sections.

3.1 Prediction of driver stress

This section captures the results of training the algorithms leaving out one particular driver and using the trained algorithms with the data coming from the other drivers (5 drivers) to predict the stress levels. To validate results, we have used 5 different algorithms to capture different families of machine learning techniques: Support Vector Machines (SVM), Multi-Layer Perceptron (MLP), Naïve Bayes, C4.5 and Deep Learning. The confusion matrixes are captured in tables 1 to 5.

We can see that the Deep Learning algorithm has obtained the best result both in terms of accuracy and positive hits. This algorithm is able to predict stress situations by 86%. On the other hand, other algorithms predict high driving workload by 52%. In this case, the algorithm which presents the best accuracy is c4.5.

Deep Learning is a method that introduces a new way to train multilayer networks. This technique allows us to discover the complex relationships between variables.

TABLE 1
SVM FOR PREDICTING STRESS (DRIVER)

| Actual/Predicted | Yes | No |
|------------------|-------------|-------------|
| Yes | 0.70 | 0.30 |
| No | 0.35 | 0.65 |

TABLE 2
MLP FOR PREDICTION STRESS (DRIVER)

| Actual/Predicted | Yes | No |
|------------------|-------------|-------------|
| Yes | 0.43 | 0.57 |
| No | 0.26 | 0.74 |

TABLE 3
NAÏVE BAYES FOR PREDICTION STRESS (DRIVER)

| Actual/Predicted | Yes | No |
|------------------|-------------|-------------|
| Yes | 0.35 | 0.65 |
| No | 0.16 | 0.84 |

TABLE 4
C4.5 FOR PREDICTION STRESS (DRIVER)

| Actual/Predicted | Yes | No |
|------------------|-------------|-------------|
| Yes | 0.59 | 0.41 |
| No | 0.32 | 0.68 |

TABLE 5
DEEP LEARNING FOR PREDICTION STRESS (DRIVER)

| Actual/Predicted | Yes | No |
|------------------|-------------|-------------|
| Yes | 0.86 | 0.14 |
| No | 0.17 | 0.83 |

TABLE 6
SVM FOR PREDICTING STRESS (PASSENGER)

| Actual/Predicted | Yes | No |
|------------------|-------------|-------------|
| Yes | 0.64 | 0.36 |
| No | 0.28 | 0.72 |

TABLE 7
MLP FOR PREDICTION STRESS (PASSENGER)

| Actual/Predicted | Yes | No |
|------------------|-------------|-------------|
| Yes | 0.70 | 0.30 |
| No | 0.20 | 0.80 |

TABLE 8
NAÏVE BAYES FOR PREDICTION STRESS (PASSENGER)

| Actual/Predicted | Yes | No |
|------------------|-------------|-------------|
| Yes | 0.85 | 0.15 |
| No | 0.35 | 0.65 |

TABLE 9
C4.5 FOR PREDICTION STRESS (PASSENGER)

| Actual/Predicted | Yes | No |
|------------------|-------------|-------------|
| Yes | 0.75 | 0.25 |
| No | 0.23 | 0.77 |

TABLE 10
DEEP LEARNING FOR PREDICTION STRESS (PASSENGER)

| Actual/Predicted | Yes | No |
|------------------|-------------|-------------|
| Yes | 0.92 | 0.08 |
| No | 0.03 | 0.97 |

3.2 Prediction of passenger stress

This section captures the results of training the algorithms leaving out one particular passenger and using the trained algorithms with the data coming from the other passengers (5 drivers) to predict the stress levels. The confusion matrixes are captured in tables 6 to 10.

In this case we see that the prediction of the passenger stress is more accurate than the first scenario taking into account all the algorithms. We have found during experiments that passengers are always more relaxed than the driver. Stress only increases when there is a high stress event such as high deceleration, high acceleration or jerk. In this case, Deep Learning algorithm is able to predict stress situations by 92%. The remaining algorithms only obtained a hit rate of 74% on average.

3 Conclusions

The results demonstrate the suitability of deep learning algorithms to predict the perceived stress both for drivers and passengers. We have also observed that the prediction of stressful situations is easier for the passengers. Drivers are subjected to more difficult situations. Therefore, it is more complex to anticipate upcoming reactions for drivers than for passengers. In addition, both types of users do not start from the same stress level. Driving is a difficult task because drivers have to do multiple actions at the same time. This causes that the drivers stress levels are higher than the passengers stress levels for the same road conditions.

As future work, we want to add more information in order to increase accuracy in the prediction of the driver stress. The previous activity level, sleeping time,

working time, the upcoming traffic signs, and the driving style from the nearby driver are variables that can be useful to improve the solution. On the other hand, the results of this paper could be employed to develop driving assistants that avoid or reduce the driving workload.

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