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Estimation of the Optimum Speed to Minimize the Driver Stress Based on the Previous Behavior

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Abstract Stress is one of the most important factors in car accidents. When the driver is in this mental state, their skills and abilities are reduced. In this paper, we propose an algorithm to predict stress level on a road. Prediction model is based on deep learning. The stress level estimation considers the previous driver's driving behavior before reaching the road section, the road state (weather and traffic), and the previous driving made by the driver. We employ this algorithm to build a speed assistant. The solution provides an optimum average speed for each road stage that minimizes the stress. Validation experiment has been conducted using five different datasets with 100 samples. The proposal is able to predict the stress level given the average speed by 84.20% on average. The system reduces the heart rate (15.22%) and the aggressiveness of driving. The proposed solution is implemented on Android mobile devices and uses a heart rate chest strap.

Keywords Intelligent transport system · Stress driver · Driving assistant · Deep learning · Particle Swarm Optimization · Android · Mobile computing

1 Introduction

According to many researchers, excessive speed is the cause of a large number of accidents. Therefore, it is one of the most important variables for predicting the risk of accidents and its severity. In [1], the authors of the report pointed out that speeding (speed higher than speed limits) is responsible for 18% of accidents in London during the year 2014, whereas travelling too fast for the road conditions caused 8 per cent of fatal accidents. Reducing average speed, results in a decrease of the number of fatalities [2].

Besides the vehicle speed, there are other related factors that affect safety such as sudden accelerations and decelerations and aggressive driving. 56% of fatal accidents between 2003 and 2007 involved one or more aggressive actions [3], such as: suddenly changing speeds, making an improper turn or erratic lane changing. This behavior is often related to the stress of the driver. Stress can be defined as a change from a calm state to an excitation state in order to preserve the integrity of the person. If the stress is negative, it is called ‘‘distress’’. This type of stress is commonly due to an increase in the workload, such as traffic density, inappropriate vehicle speed, etc. It causes irritability, lower concentration and problem to take decisions and has also physical symptoms such as headache and a fast heartbeat. Stressed drivers are more likely to engage in risky behaviors and having accidents [4].

There are many proposals to detect stress and measure the workload [5]. Most of them are based on physiological features such as electromyogram, electrocardiogram, respiration, and skin conductance. Non-invasive and non-intrusive sensors are particularly interesting for measuring driver stress.

In the literature there are many assistants that help to adapt the speed in order to maximize safety and reduce fuel consumption. These systems are called "Intelligent Speed Adaptation" (ISA). A large number of researchers have evaluated the benefits that these systems provide regarding safety and fuel consumption. ISA has been evaluated estimating a reduction of the accidents between 25% and 30% if all vehicles use ISA system.

2 Our Approach

In this work, we propose a driving assistant that estimates the optimal average speed for the next road section taking into account the driving and the stress level on previous road section. In addition, the algorithm considers the vehicle telemetry obtained by the driver in some of the previous driving under similar driving conditions.

The idea is that the driving assistant proposes an average speed for the road section, which minimizes the driver stress and does not increase the trip time significantly. This speed does not require a sudden change in driving habits because the proposed average speed is based on the driver. The objective is to avoid one of the biggest problems of the driving assistant: frustration and impatience.

2.1 Estimation of the Optimum Speed to Avoid Stress

Particle Swarm Optimization (PSO) [7] and Deep Learning [8] are used to estimate the average speed for each section of the road. Figure 1 shows the flowchart to estimate the optimum speed. The main advantage of PSO algorithm is that it maintains multiple potential solutions at one time. We employed Deep Learning as fitness function because it allows us to represent complex relationships between data. Other algorithms were tested during the test stage as neural networks. However, deep learning obtained the highest hit ratio.

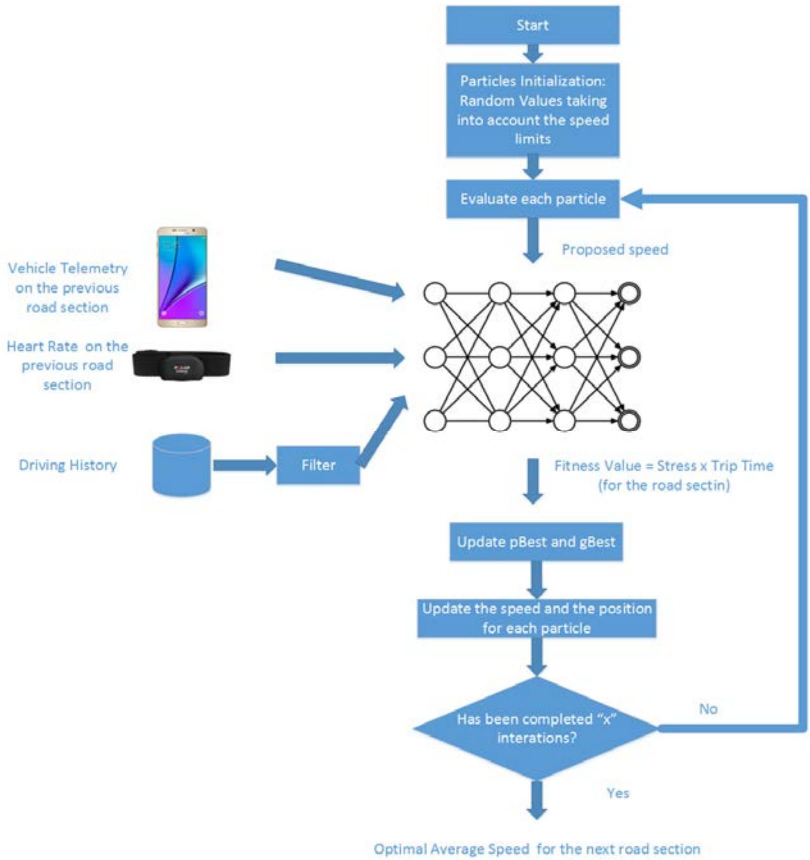

Fig. 1 Flowchart to estimate the optimum speed for reducing stress and fuel consumption

Each solution is represented by a particle in the search space. It has the following elements:

- Position: In our case is the recommended speed for reducing the stress level.
- Pbest: This is the best position on the current particle (speed that minimizes the heart rate and improves the driving style).

- Gbest: It is the best position among all particles.
- Speed: Is calculated using equation 1. It determines which will be the next speed of the particle.

$$v_i(t) = w*v_i(t-1) + c1*r1*(Pbest(t-1) - x_i(t-1)) + c2*r2*(Gbest-x_i(t-1))$$

where $v_i(t)$ is the particle's velocity at time t, w is the inertia weight, $x_i(t)$ is the particle's position at time t, Pbest is the particle's individual best solution as of time t, and gBest(t) is the swarm's best solution as of time t, c1 and c2 are two positive constants, and r1 and r2 are random values in the range [0–1]

The particles "fly" or "swarm" evolve through the search space to find the minimum value. During each iteration of the algorithm, they are evaluated by an objective function to determine its fitness. Next position is calculated by equation 2:

$$x_i(t+1) = x_i(t) + v_i(t+1)$$

where $x_i(t)$ is the current particle's position and $v_i(t + 1)$ is the new velocity.

2.2 Evaluation of the Particles

The fitness function is a deep learning algorithm. This type of algorithms have their origin in neural networks, the main difference is the number of hidden layers and the training process. Deep learning algorithm estimates the stress level given a recommended speed (the particle position) based on:

- The driving and the stress level on the previous road section
- Telemetry samples from the next road section takes by the user other days

In figure 1, we can see that there is a filter applied to the driving history. The algorithm is trained with samples of driving that were obtained under conditions similar to the present ones. We must bear in mind that speed is a variable that depends on a large number of factors such as the traffic state or weekday. In our case, we consider the following elements to filter:

- Weather State: The number of vehicles on the road grows when the weather conditions are bad, increasing the likelihood of traffic incidents. Moreover, the roll coefficient changes. Therefore, the advice have to take into account that factor. In addition, many studies highlight that when it is hot, the fatigue appears before. On the other hand, cognitive capacity of the driver worsens when it is cold.
- Traffic State: When traffic is heavy, the stress level increases. In these cases, the vehicle speed must be adjusted in order to avoid accelerations and decelerations.
- Time: Fuel consumption is increased at rush hours. The driver has to accelerate and slow down more frequently. In addition, the engine is switched on during more time. This situation causes stress, increasing the

accidents risk. On the other hand, night driving maximizes the likelihoods of sleep despite he or she has previously slept. This is due to the sleep cycle. Therefore, we have to take into account the time when we estimate the optimum speed.

- Weekday: The rush hour depends on the day. For instance, it is common that the average speed is higher on weekend because there is less traffic. If the road conditions are good, the system should recommend an average speed high enough to avoid the frustration of the driver.

Deep Belief Network that we have defined in our proposal has the following input variables:

- Recommended average speed (km/h): It is the vehicle speed proposed by the PSO algorithm. If the speed is too high, the stress will increase because driver has less time to make decisions. On the contrary, if the speed is abnormally low, fuel consumption will increase because the engine will be running more time. In addition, it may cause traffic incidents and the stress level from road users would be higher.
- Positive Kinetic Energy (m/s^2): It measures the aggressiveness of driving and depends on the frequency and intensity of positive accelerations [9]. A low value means that the driver is not stressed and drives smoothly. The value is calculated using the following equation:

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

  where v_i is the vehicle speed (m/s) and d is the trip distance (meters) between v_i and v_{i-1}.
- Average Acceleration (m/s^2): The acceleration (positive and negative) may indicate the presence of stress or fatigue. These actions increase the likelihood of traffic accidents and fuel consumption.
- Speed (Km/h): This variable allows us to model the driver behavior. For each section, we consider the following measures statistics: minimum, medium, maximum, average, and standard deviation.
- Average Heart Rate (b.p.m): Heart Rate signals are employed as an indicator of ANS neuropathy for normal, fatigued and drowsy states because the ANS is influenced by the sympathetic nervous system and parasympathetic nervous system. This indicator is not intrusive. A high heart rate means the driver has stress.

The output of the deep learning algorithm will be an estimate of the stress level when the driver drives at “x” km/h on average. The output can take the following values:

Low Stress	Normal Stress	High Stress
0.5	1	1.5

The final value of the fitness function is given by the value of estimated stress and the time required to complete the road section. The goal is to find a velocity that balances stress level and travel time, staying safe on the road.

2.3 Experimental Design

The speed assistant was deployed on Galaxy Note 4. This devices supports Blue-tooth Low Energy. Heart Rate was monitored using GEONAUTE[1]. In order to validate the algorithm, we employed five datasets with 100 driving samples. Table 1 describes the dataset features. Each column captures the number of samples where the driver stress is low, normal and high, respectively. The driving samples were obtained on real tests. Each dataset contains the vehicle telemetry and the heart rate obtained in the current road section and the previous road section. Driving tests were performed in Seville. Trip distance was 23 km. This track has highway, secondary road, and urban road. The route was divided into section of 500 meters. We have chosen this length after making several tests with the datasets. Figure 2 captures the entire route (green line). We chose five road sections to analyze the algorithm. The vehicle was a Seat Ibiza Sport 1.9 TDI (2008). Tests were performed under similar road conditions.

Table 1 Dataset Features employed to validate the algorithm

	Low Stress	Normal Stress	High Stress	Total
Dataset 1	58	30	12	100
Dataset 2	18	53	29	100
Dataset 3	36	28	36	100
Dataset 4	34	21	45	100
Dataset 5	35	43	22	100

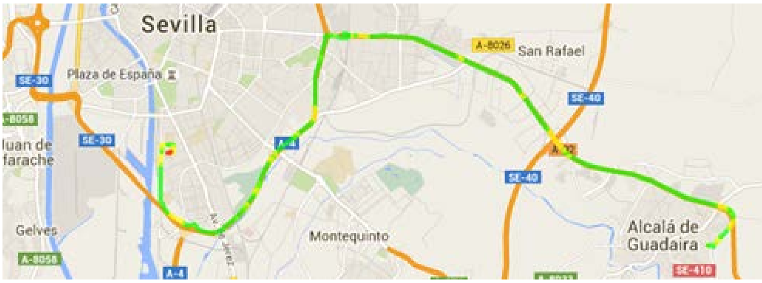

Fig. 2 Route for the driving tests

[1] http://www.geonaute.es/cinturon-cardiofrecuencimetro-bluetooth-smart-40-id_8288269

2.4 Results

Table 2 presents the results (Mean squared error and hit rate) of the algorithm considering the five datasets and using 10 fold cross validation. The proposal is able to predict the stress given the average speed by 84.20 % on average. The deep learning algorithm was run with 3 hidden layers, 200 units per layer and 300 epochs.

Table 2 Results of the 10 fold cross validation using the proposal

	MSE	Hit Rate (%)
Dataset 1	0.156802	84 %
Dataset 2	0.131412	85 %
Dataset 3	0.111304	89 %
Dataset 4	0.071342	92 %
Dataset 5	0.283674	71 %

Figure 3 shows the average heart rate obtained by the driver on different road sections without and with the speed assistant. The heart rate decreases by 15.22 % on average taking into account all driving samples. The heart rate value is influenced by the sympathetic nervous system and parasympathetic nervous system. A low value means that the driver is not stressed.

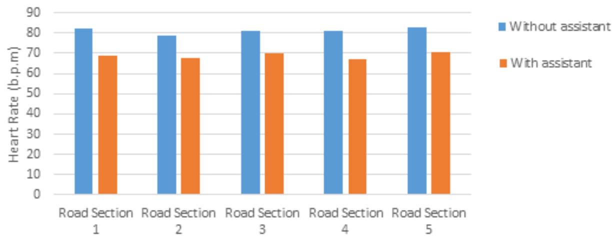

Fig. 3 Average heart rate (b.p m) using the speed assistant

Figure 4 illustrates the positive kinetic energy obtained by the driver when driving with and without the speed assistant. This variable measures the aggressiveness of driving and depends on the frequency and intensity of positive acceleration. A low value means that the driving is not aggressive. The positive kinetic energy decreases by 33.53 % on average when the driver uses the proposal. Moreover, a smoother driving saves more fuel.

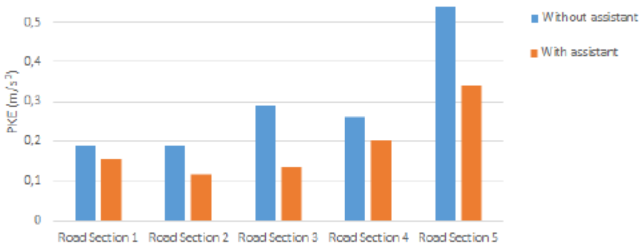

Fig. 4 Positive Kinetic Energy (m/s^2) using the speed assistant

Figure 5 shows the average standard deviation of vehicle speed for each road section. Following the recommended speed provided by the solution, standard deviation is reduced 37.09 % on average.

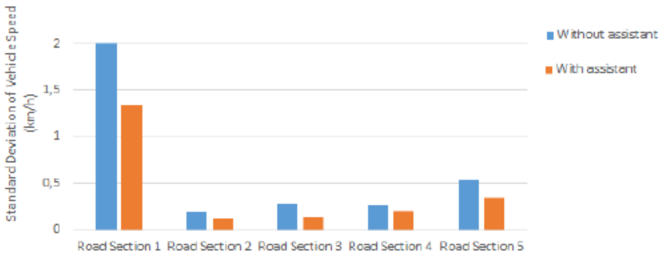

Fig. 5 Standard Deviation of Vehicle Speed (km/h) using the speed assistant

3 Conclusions

In this paper, we have proposed an algorithm to estimate the driver stress given speed and heart rate for a road section. The goal is to prevent stress and dangerous situations, based on current driving context, taking data from road conditions (weather and traffic), time, and previous driving. In this paper, we present a speed assistant that uses driving context, deep learning technics along with Particle Swarm Optimization (PSO) to calculate a speed that minimizes the stress without increasing the trip time. The results show a significant improvement in the driving style and the driver stress.

As future work, we want to validate the algorithm with more users and more routes. It would also be interesting to analyze the effect that the solution has in the stress of the other road users. In addition, we want to introduce new variables to improve the prediction model such as previous stress, working time, sleeping time, and quality of sleep.

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