Physiological Data Recording in VR Simulator for Sleepiness Detection During Driving

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Abstract: Drowsy driving is a major issue in road safety. In this paper, we propose a description of an experimental data collection to develop a drowsiness detection model. The objective of this data collection was mainly to gather physiological data of individuals in simulated driving situations. We designed a realistically annoying scenario to induce fatigue while staying close to real driving conditions. The experiment was run on an augmented reality platform called CAVE. The need for contextualization came early in the design of the experiment. Therefore, in addition to physiological data, we added much more data sources, from driving habits to driving behaviour in addition to self-assessment of fatigue levels and the gold standard (EEG). As a result, this experience helped us create a data set of physiological data completed by elements of context and driving behaviour. Thus allowing us to perform a very rich analysis of these physiological data.

1 INTRODUCTION

Drowsy driving is one of the deadliest causes of accidents (Board, 1999). Yet it is really difficult to estimate the part of drowsiness among other causes of accidents because fatigue isn't easy to measure after an accident. While drug use can be measured in blood, speeding can be evaluated from structure deformation but the equivalent analysis is impossible with drowsiness.

Therefore, industrial (Friedrichs and Yang, 2010) and political (EuropeanCommission, 2021) actors are actively trying to find solutions to detect drowsiness and alert drivers while he is still awake. From a broader perspective, monitoring driver attention on the driving task will be a major challenge for future vehicles. Autonomous driving cars is a very popular topic and major car companies are trying to make this a reality. For the next generation of vehicles to come, the autonomous level will be at 3, which means the driver isn't required to keep his hand on the wheel but should be able to take back control at any time. Therefore drowsiness and attention monitoring will be key, as the car should ensure the driver will be able to take that control back.

Our vehicles are becoming more of computers on wheels. They are full of sensors gathering data on the road, on the driver, or on the weather. Our approach is to replicate the type of information available in a modern car and use the combination of this data to detect drowsiness. In this study, we tried to gather data used in a multitude of systems. We record driving behaviour-related data, video of the face, and physiological signals, thus covering the three main solutions developed to detect drowsy driving.

Doing that we set two important constraints for our experiment. First, it should be immersive for the subject. Being able to offer a driving environment closer to reality will help to record more relevant data as the subject will have close-to-reality reactions. The second, constraint is to limit the invasiveness of sensors. We thought that sensors used in the experiment should be able to be used in real driving situations by everyone. This is why we chose small Bluetooth sensors which didn't interfere with the subject driving actions.

In this paper, we will describe the used hardware and explain how we set up the experimental scenario. We will then go through all the collected data and how we processed them in order to create a clean and rich

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database. We will also give the results of our first analysis.

The experiment took place in France, in order to record data from subjects we have obtained an agreement with the ethical research committee of Sorbonne University (CER-SU) on protocol n°CER-2021-018.

2 RELATED WORK

Many studies have been conducted to develop drowsiness detection systems (Sahayadhas et al., 2012). We can divide them into three major categories.

The first category is the analysis of driving behaviour using vehicle information like steering wheel angle or lane departure detection. Datasets have been recorded by car manufacturers in real driving conditions (Friedrichs and Yang, 2010) but most commonly in simulated conditions like (Chai et al., 2019). Using the first approach you aim to develop a system that can easily be embedded in a vehicle. The latest approach aims to gather the maximum data possible to find out which are the most important signals. Models have been developed to anticipate behaviour that might be dangerous on the road such as (Kim et al., 2017) work. Other models use this information to provide personalised help to the driver (Hori et al., 2016).

The second category uses cameras to analyse driver faces, especially eye closure or blinking like in (McKinley et al., 2011) and (Abe et al., 2011). The latest approaches in this domain use deep learning methods to process images and show good results in both detection and anticipation of drowsy events (de Naurois et al., 2019)

The third approach is based on physiological signal analysis. It may be based on Electroencephalogram (EEG) and Electrooculogram (EOG) but these approaches are tough to use on real driving conditions due to vehicle vibration, static electricity and limited embeddability of devices. Cardiac signals like Electrocardiogram (ECG) and Photoplethysmoraphy (PPG) also seem to carry enough information and are easier to implement in real cars with more consumer-friendly sensors. Additionally, PPG provide an easy set-up and a non-intrusive driving experience compared with EEG and EOG.

Paper Contribution: In this paper, we present a multi-source dataset for drowsiness detection. Our approach aims to bring simulated driving experiments to a new level, not by using cutting-edge technologies but through sensors and signals that can realistically be measured in real driving conditions for direct use in ecological conditions.

3 DATA COLLECTION PROCESS

3.1 Inclusion Phase

According to ethical criteria and constraints related to the study, subjects were exclusively recruited within Université de Technologie de Compiègne (UTC). They were either students, professors, researchers or members of the administration that were contacted thanks to internal weekly communication. Subjects were invited to read the description of the experiment and answer a few questions about themselves. This questionnaire helps us to filter subjects on driving experience, gender and age in order to ensure diversity within our database. We also make sure no subjects were taking any medication or drug which could possibly modify heart rate or heart rate variability.

Lastly, since the experimentation would take place in front of a screen we also asked them about their tendency to feel motion sickness. If selected, subjects were then contacted to schedule an experiment time.

3.2 Participants

97 participants volunteered to participate in our study. 4 were rejected due to inclusion criteria. 33 were selected from the remaining, the other were put on a waiting list.

3.3 Simulation Platform

The experiment took place in a Cave Automatic Virtual Environement (CAVE). CAVEs are augmented reality platforms where a subject is surrounded by glass panels (Cruz-Neira et al., 1993). The virtual environment is projected through these panels thanks to projectors placed outside the cube. Subjects can move freely within the cube while being surrounded by the virtually created environment. In this specific experiment, we placed a seat with a wheel and pedals, thus reproducing the usual driving commands. The projected environment reproduced the point of view from the driver's seat of a car, showing the car structure, infotainment system and the road through the windscreen.

3.4 Sensors

For data collection, we used sensors available on the shelf. Three devices were selected to study their

Figure 1: Subject being installed in the CAVE.

ability to provide a good signal in driving situations. These devices measured three signals: Heart Rate Variability (HRV) with ECG, HRV with PPG and EEG.

EEG is recorded using Dreem headband (Arnal et al., 2019). This headband was developed to analyse sleep quality for daily usage. It is, therefore, a very light and easy-to-wear sensor. It records a 6 channel EEG at 250Hz. The device shape and electrode placement are described in figure 2.

Figure 2: Electrode placement for Dreem EEG sensor.

We used two different techniques to measure HRV. The first sensor is an elastic band with electrodes attached to it with the ability to communicate via Bluetooth. The interval identification technique is based on ECG and consists of the identification of the R peak in QRS complexes, to then measure the time between two peaks. The identification is performed directly on the device. We used Cardiosport TP5 Heart Rate Monitor (Cardiosport, 2022) to perform that measure. This device has an integrated Bluetooth processor that can send data in live conditions. The second technique uses PPG to measure the time between two blood waves by analysing the opacity of the veins (Allen, 2007). We used Garmin Venu SQ (Garmin, 2022) which is a smartwatch made to be used all day long with light and comfortable materials. This device connects to a mobile application to send live HRV data.

3.5 Simulation Scenario

The simulation scenario proposed to all subjects was identical. It consists of a fifty kilometres left-hand loop starting in an urban zone, then going through a forest with varying tree density. Along the road, various left and right turns were created to reduce the feeling of going in circles. Subjects were alone on their side of the road to avoid unwanted collisions with other cars that may force the simulation to stop too early. On the other side of the road, groups of cars were placed to improve the immersion and reduce the emptiness of the environment. Subjects were asked to drive when possible with cruise control activated and set at 100km/h. They had a button on the steering wheel specifically dedicated to that function. Two events were added to the scenario to measure the subject's reaction in drowsy conditions. A previous study proved this approach to be efficient to induce and measure stress (Zontone et al., 2020). The first event was placed after fifteen minutes of driving. We choose this moment as we observed in precedent measures that drivers tend to have their first drowsy event after 15 min on task. The event is composed of a set of trucks and lights, simulating road work on the right side, forcing the driver to change lanes to avoid the collision. The second event is an animal crossing the road. With no lights and no previous indications, this object is harder to anticipate and requires much more attention. It's placed after 45 minutes of experience in the middle of a straight line, which is the most annoying section of the circuit.

For the simulated environment, we choose to simulate clear weather at night just before dusk so that rain doesn't impact the experiment.

3.6 Experimental Protocol

Here is how a standard measure goes:

1. Welcome the subject on the platform.
2. Ask the subject to fill in a questionnaire on his sleeping habits.

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3. Start and install physiological sensors on the subject.
4. Install the subject in the CAVE.
5. Start a training loop until the subject feels at ease with the commands.
6. Last briefing on what is expected from the subject during the experiment.
7. Auto-evaluation formation, explain what is expected from them in order to record KSS.
8. Synchronisation of all signals.
9. Driving can start.
10. After completing the two loops, the driving stops.
11. Subject is invited to leave the CAVE
12. Subject is asked to fill in the last questionnaire on his feeling during the experiment.
13. Sensors are removed.
14. End of the measure.

A simplified and schematic version of the protocol is represented in Figure 3.

For the synchronisation part, we asked subjects to hold their hand in front of the camera, blocking the view, while turning the steering wheel on the right. Meanwhile, the operator was on the computer doing a countdown from 3 to 0. At 0, the subject releases the steering wheel and unblocks the camera view, and the operator presses the starting key at the same time. Software developed for the experiment record the timestamp of the key press.

In order to ensure synchronisation between systems that could have a small variation in clock we used UNIX timestamps from a remote server on every device.

As a result, we have a hand movement on the camera, a common timestamp between the computer and smartphone combined with a peak in simulator signal due to steering at the same time. This is our synchronisation point.

3.7 Personal Context

During the inclusion process and before the experiment, subjects were asked to answer a few questions about themselves. There were two main subjects covered by these questions, the first one being drivings habits and the second one being sleep health.

We selected only people that obtained their driving license at least one year ago and who are driving frequently since. We asked subjects more precise questions about their driving habits regarding long and night trips when drowsiness is more likely to appear. Regarding the sleep health topic, we asked subjects to describe their sleep quality, and how many hours of sleep they had the days before.

These data will help to detect trends amongst the measured population. The first analysis shows that experienced drivers, which often drive for a long time are less affected by the simulation. It's also really useful to analyse the correlation between the sleepiness of a subject and the length of his previous nights.

3.8 Physiological Data

Physiological sensor record two different types of information. Firstly we have EEG signals measured on eight channels with a sample rate of 250Hz. EEG is the gold standard signal in sleep scoring. This signal will be used for data annotation and analysis.

Secondly, we have two sensors gathering heart-related data. More specifically, these sensors measure beat-to-beat intervals.

The frequency of these data is variable as both these sensors send new data every time they detect a new beat. This data will later be used to develop a classification model.

3.9 Driving Behaviour

The simulation software is able to record many signals while the simulation progresses. We choose to filter signals that were relevant to our simulation scenario, as well as signals that proved their importance in the literature.

The set of signals is composed of:

- Position of the Centre Of Gravity (COG) of the vehicle on the map.
- Speed of the COG of the vehicle.
- Acceleration of the COG of the vehicle.
- Wheel angle and rotation speed.
- Pressure on the brake and acceleration pedals.
- Activation state of cruise control.
- Distance between COG centre of the nearest lane.

These signals were recorded with a sampling frequency of 100 Hz.

3.10 Auto-Evaluation

Fatigue is a continuous state which isn't perceived the same by everyone. It is a physiological reality but also a personal feeling. Depending on whether we feel physical fatigue or psychological fatigue, our perception of our fatigue level is quite different and can

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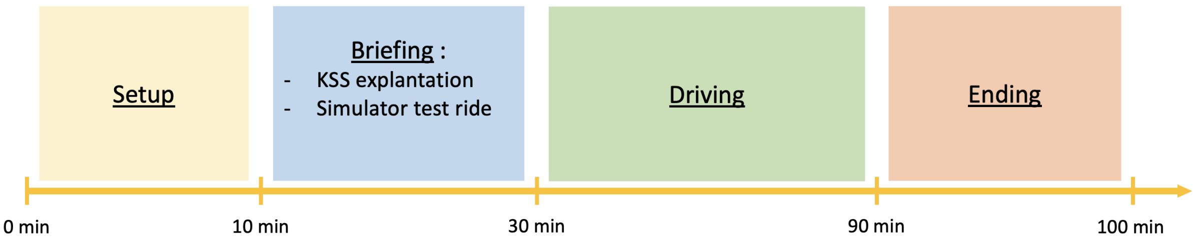

Figure 3: Schematic experimental protocol.

greatly vary. To normalise the definition of drowsiness levels, a scale going from 1 (Very Alert) to 9 (Very sleepy) has been determined and is used in a vast majority of studies (Kaida et al., 2006) and is also the reference scale for European Union (EU).

Therefore we implemented the assessment of this scale in the experiment. As for the technical solutions we chose to ask the participants to press a numerical key on a Numpad every five minutes. This gap was selected according to EU technical requirements on Karolinska Sleepiness Scale (KSS) rating protocol (EuropeanCommission, 2021).

However, note that measuring drowsiness with this scale has many flaws. First of all, it requires the subject to make a cognitive effort in order to answer the question. While the scale is not overly complex it still requires some time to adapt and understand how to correctly rate ourselves. That is why a great part of the briefing is focused on explaining KSS. Secondly, this auto-evaluation is, in essence, subjective. People tend to over and/or under-estimate their drowsiness level all the time. Therefore auto-evaluation has a bad impact on the experiment and we have to take the result with care, taking into account potential bias.

3.11 Labelling Data

Labelling our dataset is a key part of our study since we aim to use it for supervised machine-learning applications. The objective is to develop a system which is able to detect drowsiness states in opposition to awake states. It is a binary classification problem.

We can use three different pieces of information to label data:

1. EEG:

   EEG is a gold standard signal used, in combination with EOG and ECG, for sleep scoring method by sleep specialists. This method consists on the analysis of 30 seconds segments of signal and the association of a tag : sleep or no-sleep. This tagging method requires a qualified set of professional reviewers.

   While being the most precise on sleep detection, this method isn't as efficient to detect rapid drowsy event. That is a major issue, because while driving subject won't fall completely asleep. Their drowsy events will more likely be short moments of absence which aren't easily recognisable on polysomnographic records.

2. KSS:

   KSS gives a subjective assessment of a fatigue level. While this scale has 9 levels we can divide them in two categories: 1 to 7 for awake and 7 to 9 for drowsy. However using this information directly as a training target can have many flaws. As it is a subjective information we can't be sure if the level associated with the situation really corresponds to the true definition of the level. Also, we can't normalise levels among participants as an eight for someone can mean a six for another.

3. Video:

   Lastly, we can use the video of the face and the point of view of the driver to identify drowsy behaviour and driving mistakes caused by drowsiness. The method first consists of the definition and the selection of a list of observable events that may be interesting to annotate. The list has been defined by studying literature and observing subjects in driving simulators. The result is a list of seven events which are: Yawning, Change of position, Long blink, Face/Neck scratch, Loss of Control, Accident and Sleep. The next step is reviewing conjointly both of the videos and selecting tags as they occur during the measure.

   The reviewing process is done by two different people. Then a third one validates every event. This process ensures no events can be missed and no event can be falsely tagged.

3.12 Dataset

The final dataset content is summarised in table 1. It is composed of three synchronised physiological signals as well as nineteen behaviour-related signals, an auto-assessment drowsy scale based on KSS, a video feed of the face of the driver and a video feed of the point of view of the driver, lastly it is composed of personal and driving habits data on the subject.

Each signal can be used for direct interpretation, annotation or classification purposes. Some examples are presented in this table but the possible applications are not limited to this.

4 PRELIMINARY ANALYSIS

In this section, we will perform a preliminary analysis of our data. As our objective was to record drowsiness we should ensure that we have sufficient drowsy drivers and drowsy events. Since we determined different methods of annotation the proportion of drowsy drivers may slightly vary from one to another. The proportions are pictured in figure 4.

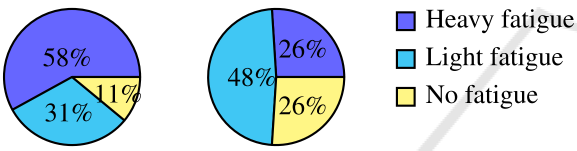

Figure 4: Proportion of trips with drowsy drivers according to KSS (left) and video (right).

In these graphics, Heavy fatigue corresponds to either KSS > 6 or a video tag of clear loss of control. Light fatigue is for $7 >$ KSS > 4 or a video tag of early external signs of fatigue. No fatigue is for $5 >$ KSS and no video tags. From this figure, we can conclude that these methods give significantly different results. Subjects tended to overestimate their fatigue level and were globally able to drive even though they graded their drowsy state as > 6. We can also conclude we have been able to record a significant amount of fatigue events considering subjects were not sleep deprived.

4.1 Driving behaviour

Early analysis of behaviour signals extracted from the simulator show which one will be the most important. We observed three principal features that were particularly affected during drowsy events, namely: Distance to the middle of the road, angle of the wheel, and rotation speed of the wheel. Figure 5 shows an example of these signals.

In this graphic, we can see three seconds where there was no wheel activity while the car was going away from the centre of the lane. Then the driver starts a trajectory correction to replace the vehicle closer to the centre.

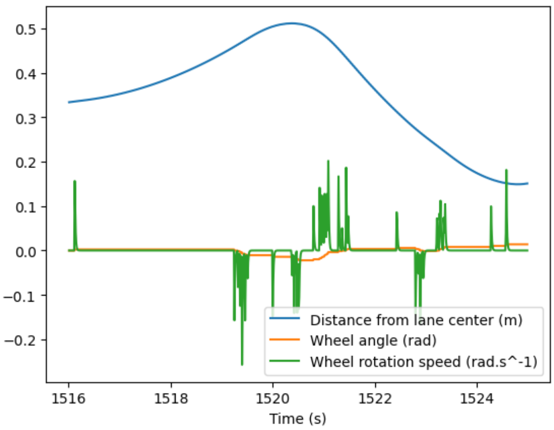

Figure 5: Behaviour signals during drowsy events.

If we look at the maximum values reached during drowsy and standard measures, we can see a drowsy driver going far away from the centre line and having spike activation of the wheel more critical than the average driver (Table 2).

With these features from behavioural signals, we can characterise the difference in behaviour between two populations. The subsequent development would improve these parameters and test their relevance in a machine-learning model.

4.2 Physiological Signal Processing

The first physiological data processing shows a great quality difference between our sensors. For example, with the PPG watch, we have an average recording time of 3646 seconds (standard deviation of 100 s), while the ECG belt has 2927 seconds average with a standard deviation of 1396 s.

We discovered the Bluetooth connection between the belt and the computer failed many times, thus creating very short records for some subjects. Thankfully this behaviour only impacted six people.

5 POTENTIAL LIMITATIONS

During this experiment and while we performed our first analysis, we noted some limitations of our work that should be disclaimed. However, the limitations aren't limited to the ones listed after that.

Even if finding differentiating characteristics to identify events is essential for the analysis, we can't be sure these characteristics can be generalised. Our model should apply to many people and shouldn't be helpful only for one type of driver.

Also, it is difficult to evaluate how different the subject's physiological state would be in actual driv-

Table 1: Dataset content summary.

Type	Data	Use
Personal data	- Gender, Age, … - Driving and sleep habits	*Interpretation*
Subjective	- KSS	*Interpretation* *Labelling*
Physiological	- HRV (with ECG) - HRV (with PPG) - EEG	*Classification* *Interpretation* *Labelling*
Driving behaviour	17 signals : - Position, speed, acceleration and rotation (x/y/z) (12) - Steering wheel actions (2) - Road position (3)	*Classification* *Interpretation* *Labelling*
Video	- Face recording - Point of view recording	*Labelling*

Table 2: Difference between a drowsy and awake driver on some signals.

Signal	Drowsy	Awake
Distance from lane centre (m) (MAX then AVG on population)	6.2	2.5
Wheel rotation speed (rad.s^{-1}) (MAX then AVG on population)	8.8	6.7

ing conditions. Therefore, the principal solution would be to record even more subjects to get the most heterogeneous data set possible, thus covering the most physiological responses imaginable.

Finally, the quantity of data is critical when developing a machine-learning algorithm. While having a lot of drowsy events, this data set remains quite unbalanced between awake and fatigued states. Different techniques can be used to answer that issue, like data augmentation.

6 CONCLUSIONS

In this research, we developed an experimental protocol to record the data from subjects in simulated driving conditions. Considering many previous studies, we added a large variety of sources. The objective was to induce fatigue by gathering the subject's states when they were about to fall asleep.

The experimental protocol has been validated with self-assessment and video annotation, which makes it reliable for machine learning developments. With one-third of people having at least one tired event during their measure, this data set presents enough positive events to be detected. In addition, the population measured is quite diverse in terms of age, gender, driving and sleep habits, making our data set a powerful resource for developing a model.

The data set could be used differently to study the correlation between physiological signals and drowsiness in a mono-modal or multi-modal approach. It could also be used to compare data sources between them, for example, comparing the signal from ECG band and Garmin smartwatch.

From the early analysis, we can find differentiating characteristics for some drowsy events. The following work will determine if a predictive drowsiness model can be developed on this database. This will be possible by finding ways to generalise the characteristics of our population. Developing features and implementing some based on the literature is also an extensively considered approach. Another perspective would be to use this protocol, which has proven to be efficient, on longer measures to gather more drowsy events.

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ETHICS DECLARATIONS

All volunteers gave their informed written consent following approval and in accordance with the CER-SU Review Board.

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