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Driver drowsiness detection using non-intrusive eletrocardiogram and steering wheel angle signals

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Resumo

De acordo com a Administração Nacional de Segurança de Tráfego nas Rodovias dos EUA, alega que um total de 100.000 acidentes de veículos a cada ano é consequência da fadiga do condutor. Deste modo, tendo em conta estes números, embora a automatização dos veículos seja uma realidade emergente e uma grande ajuda na resolução desta questão, é uma realidade que ainda está longe de ser uma tecnologia do dia-a-dia. De facto, atualmente, grande parte da indústria automóvel ainda baseia a sua tecnologia nos níveis 0 e 1 de automação, níveis estes que se caracterizam por serem totalmente dependentes da intervenção humana. Com base nesta informação, é correto concluir que é ainda uma necessidade emergente encontrar soluções rápidas para este problema, mesmo que sejam soluções aparentemente temporárias. Ora, na literatura pode verificar-se a exploração de várias abordagens para detecção de fadiga. Os métodos subjetivos são os mais utilizados apesar de não serem os mais eficazes. Deste modo, métodos baseados no comportamento, baseados em sinais fisiológicos, baseados em características retiradas da utilização do veículo em si ou mesmo métodos multimodais são comumente utilizados na literatura.

Desta forma, numa primeira abordagem, esta dissertação irá apresentar o estado da arte relativamente à utilização das técnicas acima descritas. Para além disso, é apresentada também uma revisão de possíveis ambientes de aquisição de medições para o estudo da fadiga e soluções atuais no mercado.

Assim, esta dissertação teve como objetivo a utilização multimodal de métodos de natureza diferente para a previsão do estado fatigado do condutor, nomeadamente o ângulo associado à manipulação do volante do condutor e o ECG do mesmo. Para o efeito, a base de dados SleepEYE foi utilizada , incluindo as medições dos sinais em estudo de 18 condutores durante o dia e a noite. Uma estrutura típica de um problema de *machine learning* foi utilizada. Assim, de modo a prever o estado de fadiga, utilizando a escala KSS resultado da autoavaliação de cada condutor como base, foram seguidas duas abordagens: avaliação de fadiga com base no valor absoluto da escala e avaliação da fadiga com base na comparação com o estado anterior. Deste modo, 16 e 17 características foram extraídas dos sinais de *ECG* e *steering wheel angle*, respectivamente. A utilização dos dois sinais de forma conjunta foi efetuada concatenando as características dos dois sinais e utilizando combinação de classificadores.

A título de conclusão, verificou-se que a avaliação comparativa ao estado anterior do estado de fadiga demonstrou ser mais eficiente que a avaliação baseada na avaliação absoluta do condutor, verificando-se um aumento de 7% na *accuracy* final: na primeira abordagem verificou-se uma *accuracy* de 82% utilizando SVM, enquando que na segunda abordagem foi obtida uma accuracy de apenas 94% concatenando as características dos dois sinais. Contudo, ao utilizar a técnica de combinação de classificadores conjugando os modelos SVM treinados com o ECG e o SWA previamente treinados em separado, é possível obter uma performance de 94%. Todavia, este resultado não é melhor que os obtidos anteriormente. Deste modo, verificou-se que a utilização da concatenação dos dois sinais foi benéfica apenas na abordagem relativa de previsão de fadiga. Para além disso, a utilização das características do sinal SWA revelou ser mais eficiente na tarefa

de previsão do estado de fadiga quando comparado com o ECG.

Este trabalho está integrado no projeto AUTOMOTIVE (detecção automática de sonolência multiMOdal para veículos inteligentes) e foi proposto pela empresa textit CardioID Technologies e pelo INESC-TEC.

Abstract

This dissertation focused on the non-intrusive multimodal detection of drowsiness on vehicle drivers. In fact, according to the US National HighwayTraffic Safety Administration (NHTSA), a total of 100,000 vehicles crashes each year are a consequence of driver drowsiness. Considering these numbers, although fully automated vehicles will probably be a great help on this issue, this is a reality that is still far from being a day-by-day technology used. Actually, the level 0 and level 1 of automation, which are fully dependent on human intervention, are still the most used by vehicles nowadays. Following this, it is important to find solutions for this problem, even if temporary. There are various approaches for drowsiness detection presented in the literature. Subjective methods are the natural ones used, however, they can not be the most efficient for the purpose. This way, behavior methods, physiological, vehicle-based methods and even multimodal approaches are being explored all around the world.

Regarding this, as a first approach, this dissertation presents a study of the state of art of the drowsiness detection techniques previously mentioned, a review on the possible environments on which drowsiness measurements can be acquired and possible solutions for the problem currently in the market.

Specifically, on this dissertation, vehicle and physiological methods are going to be explored, in particular, ECG and steering wheel angle (SWA). For the effect, SleepEYE database was used and includes the measurements of the two signals in study 18 drivers during day and night. Following this, a typical framework of a machine learning problem was followed. In addition, by making use of the Karolinska Sleepiness Scale, used for self-evaluation by each driver to evaluate the state of drowsiness, two approaches were followed: drowsiness evaluation based on the absolute scale value and drowsiness evaluation based on the comparison with the previous state. This way, 16 and 17 features were extracted from the ECG and SWA signals, respectively. Then, a machine learning model was constructed for drowsiness classification, concatenating the two signals features for multimodal and using classifier combinations.

Finally, regarding the conclusions of this work, it was verified that the relative evaluation of the driver state in comparison to the previous state demonstrated to have a better performance when compared to the absolute evaluation, having an increase of performance of 12%. In fact, the first approach mentioned obtained an accuracy of 82% using SVM and the second approach got an accuracy of 94% with SVM, by concatenating the features of the two signals. Also in this second approach, by classifier combination of the SVMs using ECG and SWA individually obtained a score of 94%, although it was not greater that the scores previously obtained. Thus, one can conclude that the concatenation approach benefits the prediction of the drowsiness state only on the relative approach. On the other hand, SWA obtained a higher overall performance for both of the approaches in study.

This work is integrated on the project AUTOMOTIVE (AUTOmatic multiMOdal drowsiness detection for smart VEhicles) and was proposed by the company *CardioID Technologies* and INESC-TEC.

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Esta dissertação de certo que não poderia chegar a bom porto sem o precioso apoio de muitas pessoas. Queria agradecer aos meus orientadores Professor Dr. Jaime Cardoso, à Professora Ana Rebelo e ao Professor André Lourenço pela disponibilidade e ajuda ao longo de toda a tese.

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Margarida Fernandes

"If you are not failing every now and again, it's a sign you are not doing anything very innovative."

Woody Allen

Contents

List of Figures

List of Tables

Abbreviations and symbols

ADAS	Advanced Driver Assistance Systems
ADS	Automated Driving Systems
AECS	Average Eye Closure Speed
ANN	Artificial Neural Network
ANS	Autonomic Nervous System
ApEn	Aproximated Entropy
AR	Autoregressive Model
BAG	Bagging
BN	Bayesian Network
CGF	Center of Gravity of Frequency
CV	Cross Validation
DT	Decision Tree
DWT	Discrete Wavelet Transform
ECG	Electrocardiogram
EDA	Electrodermal activity
EEG	Electroencephalogram
EMG	Electromyography
EOG	Electrooculography
ESS	Epworth Sleepiness Scale
FEUP	Faculty of Engineering of Oporto University
FFT	Fast Fourier Transform
HF	High Frequency
HOG	Histogram of Oriented Gradients
HRV	Heart Rate Variability
KNN	K-Nearest Neighbour
KFD	Kats Fractal Dimension
KSS	Karolinska Sleepiness Scale
LBP	Local Binary Patterns
LDA	Linear Discriminant Analysis
LF	Low Frequency
LR	Logistic Regression
MOL	Multilevel ordered Logit
MSLT	Multiple Sleep Latency Test
MWT	Maintenance of wakefulness test
NADS	National Advanced Driving Simulator
NHTSA	US National Highway Traffic Safety Administration
NN	Neural Network
ORS	Observer rated sleepiness

PERCLOS	Percentage of eyelid Closure Over the pupil over time
PPG	Photoplethysmography
PSD	Power Spectral Density
Q1	First Quartile
Q2	Second Quartile
Q3	Third Quartile
RBF	Radial basis function kernel
REM	Rapid eye movement
RF	Random Forest
RRI	R-R peaks intervals
SAE	Society of Automotive Engineers
SamEn	Sample Entropy
SCR	Skin Conductance Response
SD1	Short-term variability
SD2	Long-term variability
SDLP	Standard Deviation of Lane Position
ShEn	Shannon Entropy
SMOTE	Synthetic Minority Oversampling Technique
SpEn	Spectral Entropy
SPS	Samn-Perelli Seven-point Fatigue Scale
SR	Sleep-related
SSS	Stanford Sleepiness Scale
SVM	Support Vector Machine
SWA	Steering Wheel Angle
SWM	Steering Wheel Movement
TR	Task-related
VAS	Visual Analogues Scale
VLF	Very Low Frequency
VTI	Swedish National Road and Transport Research Institute
ZCR	Zero Crossing Rate (ZCR)

Chapter 1

Introduction

Nowadays, driving a car is an everyday complex task for many people and requires a lot of physiological and cognitive skills. This way, the development of motorization has a direct impact on the number of driving accidents. Driving accidents can have many causes, such as alcohol drinking, distractions, and others. However, one of the major causes is driver drowsiness due to sleep deprivation and can provoke bad physical injuries and deaths. According to the US National Highway Traffic Safety Administration (NHTSA) [**?**], the statistics show that a total of 100,000 vehicle crashes each year are a consequence of driver drowsiness. Also, the National Sleep Foundation has reported that 60% of adult drivers drive while feeling drowsy and 37% have ever actually fallen asleep during driving. As described, this is a big problem and needs a solution. The development of fully self-driving, with no human intervention, would possibly completely solve this problem, however, it is far from being a day-by-day used technology. There are five automation levels, according to SAE (Society of Automotive Engineers) [7]:

- **Level 0: Fully manual vehicle** - most cars are in this level. They are fully manual vehicles, so the driver controls every aspect of the driving;

- **Level 1: One single automated aspect** - is the first level to be considered as an autonomous car because already has Advanced Driver Assistance Systems, ADAS, including steering, speed, or braking control;

- **Level 2: Automated steering and acceleration capabilities** - the car has some automation capabilities such as stay in lanes and self-parking due to the control of both the steering and acceleration/deceleration ADAS capabilities;

- **Level 3: Environment detection** - the vehicle is able to detect the environment around and make decisions according to it, for example, overtaking slower vehicles (Automated Driving Systems (ADS)). However, still requires human intervention when the car is unable to do or fails a task.

- **Level 4: No human interaction required** - has the same capabilities of level 3, however, the vehicle is able to correct itself in case of error. On this level, human interaction is not required although it has the manual mode if needed.
- **Level 5: fully self-driving automation** - vehicles don't need human intervention just like level 4. However, it is capable of being more responsive and has a better driving quality than manual driving.

Nowadays, normal cars can be inserted in level two, however, level 3 and 4 will slowly be inserted in the market in the next years. On these levels (2,3 and 4) human intervention is still present and so fatigue is still an issue. Also, level 5 is expected to be introduced from 2025 on. This way, it still makes sense to try to solve this problem.

Facing this problem, many researchers (Table 2.1; Table 2.3; Table 2.4) have tried to correlate driver behaviors with drowsiness state with a different machine and deep learning methods in order to predict the driver's state and alert the driver if it is wise to drive.

1.1 Goals

The thesis was proposed by CardioID Technologies, a Portuguese company, that developed *CardioWheel* [8] (Figure 1.1) an Advanced Driver Assistance System that acquires the electrocardiogram (ECG) from the driver's hands to continuously detect drowsiness, cardiac health problems, and biometric identity recognition.

Figure 1.1: Cardio-wheel sensor [1]

The project AUTOMOTIVE, AUTOmatic multiMOdal drowsiness detection for smart VEhicles, initiated in 2018 by INESC-TEC and CardioID Technologies was the starting point for creating a system to detect automatically the driver's fatigue. The objectives of this project is to use ECG-based biometric recognition of the driver's identity to achieve a personalized and more efficient monitoring. Moreover, since it is really difficult to access real data, the project will create an automobile driving simulator and implement transfer learning techniques.

The work of this thesis, as carried out in this project, aims to develop computational models specifically focusing on non-intrusive algorithm's of drowsiness detection, in particular, physiological and vehicle-based methods. More precisely:

- Apply pre-processing techniques that can possibly enhance the final results.
- Identify main features that help differentiating "drowsy" and "alert" state;
- Develop and compare computational model of classification and fatigue prediction;

A database, *SleepEYE* [9], with real-driving conditions (with the controlled environment) will be used.

1.2 Contributions

The thesis presented here is innovative by several reasons:

- Multimodal approach of drowsiness detection, focusing on steering wheel angle (SWA) and ECG signals;
- Using several strategies of machines learning and classifier combination;
- Comparison between drowsiness state detection approaches.

1.3 Structure of Dissertation

Apart from the introduction, this document contains 4 chapters. On chapter 2, the drowsiness fundamentals, state-of-art, are discussed methodologies and experimental-setups related to drowsiness detection. On chapter 3, is described the methodologies that integrate the workflow for drowsiness detection and prediction. The following chapter, Chapter 4 describe the results obtained and respective discussion. Finally, in chapter 5, conclusions regarding the developed work are presented.

Chapter 2

Literature Review

In this chapter, the condition of drowsiness, sleep, and fatigue associated with the driving task will be discussed. Also, the state of art for drowsiness detection will be explored. Moreover, experimental setups and products already in the market will be described.

2.1 Drowsiness on driving task

Sleep is a deterministically evolving, self-limiting, period of reduced activity also characterized by a reduction of consciousness. Sleep is a very important process to restore responsiveness to stimulation, the skill needed for every task on every individual in life. Sleep cycles last 90 minutes and each cycle is divided into two modes: rapid eye movement (REM) sleep and non-REM sleep, which includes three separate stages [3]:

- **Stage I:** transition from awake to asleep;
- **Stage II:** light sleep;
- **Stage III:** deep sleep

Sleep stages and cycles can be distinguished by analyzing changes in physiological signals, such as brain activity (analyzed using EEG), body temperature, respiratory changes and cardiovascular and even muscle activity (analyzed using ECG and EMG, respectively).

The state between being awake and stage I is designed drowsiness. This state can easily evolve to an actual sleep state. It is characterized by a reduction of alertness, decay of the level of attention and environmental sensory response. In addition, sleepiness can be defined as the inability to stay awake and also situations when full attention was required. Although sleepiness and drowsiness are usually used for the same meaning, drowsiness can be described by objective measures in contrast with the term sleepiness, which refers to a more subjective patient state. This way, sleepiness is usually rated qualitatively and quantitatively by scales.

On the context of drowsiness on the driving task, it makes sense to address fatigue. Fatigue is related to a reduction of the capacity to execute task and reduced efficiency of accomplishment, usually accompanied by a feeling of weariness and tiredness. Although a patient can have symptoms of fatigue unrelated to being sleepy or drowsy, the opposite is not true, a person cannot be sleepy/drowsy without being fatigued. So, fatigue detection is a way of detecting drowsiness in this context. There are various causes for fatigue: sleep-related and task-related (Figure 2.1).

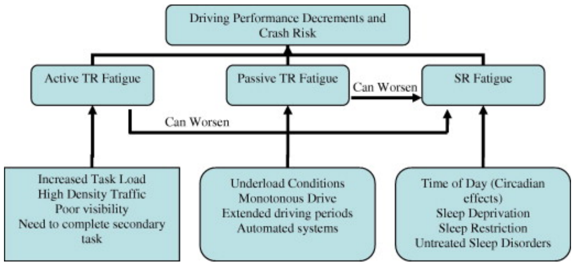

Figure 2.1: Fatigue possible causes. Source: [2]

Sleep-related (SR) fatigue type relates to circadian rhythm, sleep disorders or sleep deprivation. In fact, the body's natural circadian rhythm (24 hour cycle) is responsible for sleep/wake alternation during the day, is characterized by peaks of sleepiness along the day. A lack of attentiveness is common in the early afternoon, for example. Consequently, dysregulation of circadian rhythms results in increased drowsiness states having a direct effect on the driving performance of the person. On another hand, Task-related (TR) fatigue alludes to driving conditions and other demanding activities. This type of fatigue can be distinguished in two types: active and passive. Active TR happens in a situation of high demanding driving, in contrast with passive TR which relates to underload driving conditions, such as monotonous roads [2], [10].

For all causes of fatigue, regardless of the fact of feeling sleepy or not, the effect on the person are always the same. Specifically, in the driving task, drowsiness signs include struggling in focusing, frequent blinking or heavy eyelids. Also, daydreaming, disconnected thoughts are common and trouble remembering events that just occurred or missing exits are also common. Other common behaviors include yawning repeatedly or rubbing the eyes. In terms of vehicle handling, drifting the car from the lane, tailgating distracted driving missing the right way, feeling irritability or aggressively and also with lower reaction time usually occur [11]. Although sleeping and caffeine, for example, is considered the best countermeasures for this issue, because automatically solve the problem, it is important to consider automation as a relevant resolution option [10].

In conclusion, this study will focus on general drowsiness detection without considering causal factors, for the above reasons explained.

2.1.1 Methods of drowsiness detection

Drowsiness can be detected by analyzing changes in the behavior of the driver, affecting biosignals and vehicle handling. This way, there are four main methods of drowsiness detection: subjective, behavior, vehicle-based and physiological [3]. However, a multimodal approach combining several methods is also considered.

2.1.1.1 Subjective detection

Subjective detection is based on the driver's personal estimation and is usually evaluated resorting to scales.

- The most common one used is the Karolinska Sleepiness Scale (KSS), a nine-point scale that has state descriptions for each step, as shown in figure 2.2. When the KSS was used with EEG or EOG, the changes observed in this equipment with drowsiness do not usually appear until KSS scores reach more than seven points [12].

Rating	Verbal descriptions
1	Extremely alert
2	Very alert
3	Alert
4	Fairly alert
5	Neither alert nor sleepy
6	Some signs of sleepiness
7	Sleepy, but no effort to keep alert
8	Sleepy, some effort to keep alert
9	Very sleepy, great effort to keep alert, fighting sleep

Figure 2.2: KSS scale [3]

- Stanford Sleepiness Scale (SSS) also evaluates the level of alertness. The person should choose the best suitable condition at the time from 7 statements. Usually, the purpose of SSS is to study the effects of sleep deprivation, sleep fragmentation and circadian rhythms [12].

- Visual Analogues Scale (VAS) is a horizontal line 100 mm long across a page, anchored by word descriptors at each end. The person should choose and mark in the scale its state along the task. According to [13], VAS is more accurate when compared to SSS [12].

- Epworth Sleepiness Scale (ESS) is used to evaluate the probability of falling asleep during the day. With this scale, the individual must self-evaluate the drowsiness state by answering to an eight-item questionnaire that gives, in the end, an overall score of daytime sleepiness [12].

- Samn-Perelli Seven-point Fatigue Scale (SPS) evaluates in seven levels from 1, fully alert and wide awake to 7, complete exhausted [12].

Apart from scales, there are other subjective methods that can be used, for example, Observer rated sleepiness (ORS). The evaluation is made by trained individuals or experts who rate the condition of the driver by analyzing recorded videos, usually in real-time [14].

Maintenance of Wakefulness Test (MWT) [15] and Multiple Sleep Latency Test (MSLT) [16] are also tests that can be used for drowsiness subjective evaluation.

2.1.1.2 Behaviour Detection

Behavior methods of drowsiness detection involve non-invasive observation of a driver's external state. These methods are based on detecting specific behavioral cues exhibited by a driver while in a drowsy state [17]. This way, by recurring to a video camera for image acquisition, the system is capable of making a decision whether the driver may be drowsy or not, by extracting specific metrics with computer vision and machine learning techniques. A typical approach relies on extracting metrics related to facial expressions, which can be correlated with a drowsy states, such as rapid, constant blinking, nodding of the head, or frequent yawning [18].

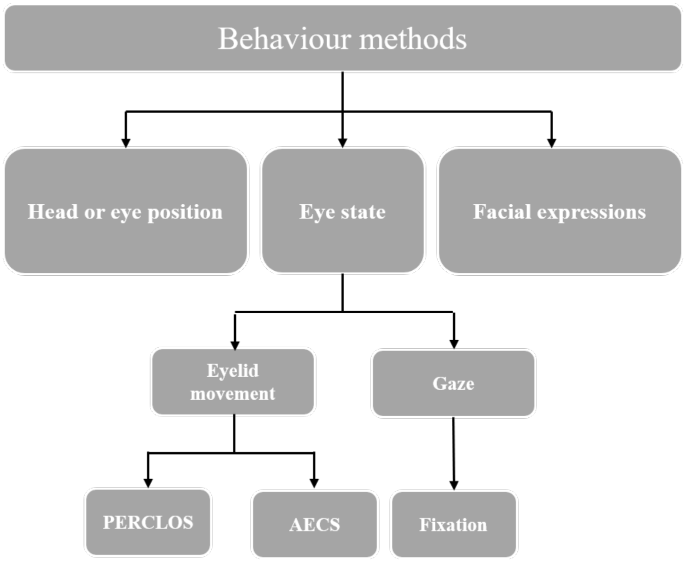

Figure 2.3: Scheme of behavioral measures

Some behavioral methods are presented on Figure 2.3. In fact, in a drowsy state, some of the muscles in the body begin to relax, which can lead to nodding. This way, algorithms aim to detect this movement of the head, eye position, and facial actions, and require stereoscopic vision or 3D vision cameras [17]. Nevertheless, as is known, frequent yawning reflects a more relaxed state which can lead to a drowsy/sleepy state. However, yawning should never be used as stand-alone feature, because it does not always occur before the driver goes into a drowsy-state [17]. A drowsy state can also be easily detected by analyzing the eye state, more specifically eye movement and gaze. Addressing the frequency of blinking, there are two possible measures: PERCLOS (PERcentage of eyelid CLOsure over the pupil over time) and Average Eye Closure Speed (AECS). In fact, a drowsy person blinking will be much slower when compared to an awake/alert person. On another hand, the movement of a person's pupil (gaze) may have the potential to indicate one's intention and mental condition [19]. Usually, while driving, the gaze is mainly in the direction of the road. When drowsy a person tends to look at other directions for a long period of time and also because their visual awareness is reduced, it is difficult to concentrate on one direction.

After extracting the different described metrics, some machine learning techniques are used to find patterns in order to predict the state of the driver of pre-classified data. Some articles of the literature follow these methodologies, as presented on Table 2.1.

2.1.1.3 Vehicle-based detection

Vehicle-based detection is made by making a interrelation between the driver's alertness state and vehicle parameters. The two major measures are the steering wheel movement (SWM) and the standard deviation of lane position (SDLP). These parameters help to identify some driving patterns that are related to many events that lead to accidents.

Many accidents on the road are caused by leaving a designated lane and crossing into a lane of opposing traffic or going off the road. This way, SDLP measurement monitors the car's relative position within its lane with an externally-mounted camera [17]. An experiment conducted by Ingre et al. derived several statistical features based on SDLP, found that when the Karolinska Sleepiness Scale (KSS) ratings increase, SDLP (meters) also increases. However, it does not show consistent results on all subjects. For some subjects, the KSS ratings are very high, while SDLP do not increase accordingly [38].

There are some disadvantages of SDLP-based method: on one hand, its robustness is not satisfactory. Also, sensing of vehicle lateral position is very expensive in terms of hardware requirement and computing, as it requires capturing and processing of road image data. It is highly affected by external factors, such as lane marks, temperature, lighting, etc. In addition, drivers under the influence of alcohol and drugs will show the same SDLP features [38].

SWM consists of measuring the steering wheel movement data, detecting slightest changes on the steering wheel positions, using an angle sensor mounted on the steering column. Actually, a drowsy person tends to do less of small, smooth corrections on the steering wheel when compared to a not-fatigued individual and also when it does occur, it is large and sudden [39]. This micro-corrections can be evaluated by analyzing the steering wheel angle (SWA). In order to eliminate the effect of lane changes, the researchers consider only small steering wheel movements (between 0.5 and 5), which are needed to adjust the lateral position within the lane [19]. Also, some corrections can be mistaken with curves. A potential problem with this approach is the high number of false positives. SWM-based systems can function reliably only in particular environments as it is very reliant on the geometrical features of the road, so the method can only work in certain situations [38].

One possible way to avoid unreliable results, although many algorithms are developed using databases acquired in simulated environments [40] [41] [42], is to use real environment datasets for drowsiness detection algorithms. In fact, only in real driving experience, it is possible to note the non-linearity, time-space variation, and instability of the driving task [38].

One important step on the drowsiness detection with SWA signal is a pre-processing procedure, due to its dependency on road conditions. Usually, pre-processing includes removing the elimination of the road curvature, as it could be mistaken as being a macro-correction on the steering wheel, as it corresponds to a great angle value. It is considered to be a road curvature when

Table 2.1: State-of-art of behavioral methods for drowsiness detection

Source	Year	Drowsiness measure	Feature Extraction	Classification
[20]	2017	PERCLOS	HOG, MaximumLikelihood algorithm Spectral Regression	Threshold based
[21]	2016	Head pose, Yawning	Steerable filters, Histogram of oriented gradients (HOG), Haar features	SVM
[22]	2015	PERCLOS	Local binary pattern (LBP)	SVM
[23]	2013	Pupil, Head pose estimation	Geometric constraints, Lucas–Kanade optical flow method	SVM
[24]	2012	Pupil	Red eye effect, Texture detection method	Ratio of eye-height and eye-width
[25]	2012	PERCLOS, Head pose	Active Appearance Model	Threshold based
[26]	2012	PERCLOS, AECS, Mouth opening	Correlation coefficient template matching	SVM
[27]	2010	Blink duration	Eye Horizontal Symmetry	Threshold based
[28]	2010	PERCLOS	Unscented Kalman filter algorithm	SVM
[29]	2010	Eye State	Condensation algorithm	SVM
[30]	2010	Eye blink	Duration of eyelid closure, No. of continuous blinks, Frequency of eye blink	Region Mark Algorithm
[31]	2009	Multi Scale dynamic features	LBP	Ada boost
[32]	2009	Yawning	Gabor wavelets	LDA
[33]	2007	Facial action	Wavelet Decomposition	SVM
[34]	2007	Eye Closure Duration Freq of eye closure	DWT	Neural Classifier
[35]	2007	Eye closure duration, Frequency of eye closure	DWT	Neural Classifier
[36]	2004	PERCLOS, eye closure duration, blink frequency	Modification of the algebraic distance algorithm for conics Approximation Finite State Machine	Fuzzy Classifier
[37]	2004	PERCLOS, AECS, Gaze, Facial Expression, Head pose	Gabor wavelet Generalized regression neural networks	BN

there are many consecutive SWA value of the same signal. After being detected, road curvatures values are subtracted to SWA signal itself [43] [40].

Features of steering wheel movement can be organized in time, frequency and state space domains. Some of the features are described on the Table 2.2 [41].

Table 2.2: Features of steering wheel movement

Time domain	· Regression descriptors (e.g. regression slope, intercept, maximum of regression error) · Class distribution measures ((e.g. number of values within steering angle bin 0.0-0.1) · Peak amplitudes and distances (e.g. mean distance of peaks; maximum of peak amplitude) · Entropy · Zero crossing distances and slope (e.g. maximum of distance between consecutive zero crossings)
Frequency domain	Power spectral density per frame related metrics
State space features	· Three-dimensional state space: steering wheel position, steering wheel velocity, steering wheel acceleration · Trajectory based descriptor contours ((angle between consecutive trajectory parts, distance to centroid of attractor, length of trajectory leg)

For pattern recognition of the features extracted with SWA signals, machine learning, and deep learning approaches are used. More precisely, Support Vector Machine (SVM), fuzzy classifier, Bayesian Networks (BN), neural classifiers (ANN), Logistic Regression (LR), K-Nearest Neighbour(KNN), Decision Tree (DT) and Random Forest (RF) algorithm are used in the literature, as it can be seen on Table 2.3.

Table 2.3: State-of-art of vehicle-based methods for drowsiness detection

Source	Year	Drowsiness measure	Feature Extraction	Classification	
[44]	2017	SWA	ApEn	Decision tree	
[38]	2017	SWA	Entropy from SWA time series within fixed time windows. ApEn: approximate entropy APLA: adaptive piecewise linear approximation. Warping Distance of Dynamic Time Series	Binary decision model, S stands for the standard linear time series acquired through online unsupervised learning Threshold	
[45]	2015	lateral lane position lane heading, and vehicle heading	Standard deviation using: · absolute value of lateral position · absolute value of lane heading · absolute value of vehicle heading	Deviation of lateral lane position Deviation of vehicle heading difference Wilks' Lambda	
[46]	2012	SWA	Steering angle at each second from 60s before a lane departure (or matched case) to 6s before the lane derandom forest algorithm parture	Random forest algorithm	
[47]	2009	SWA	Time domain Frequency domain State space	SVM (linear kernel) SVM (radial kernel) Nearest neighbour Decision Tree Logistic Regression	
[41]	2009	SWA	time domain features frequency domain features state space features	Ensemble classification (SVM$_l$, SVM$_r$, $DT, 5-NN, LR$)	
[40]	2007	SWA	Sum of vectors on every 15-second interval	Neural Networks	
[43]	2001	SWA	Steering angle data were discretized and coded into an eight-dimensional vector	Neural Networks	89.9 %

2.1.1.4 Physiological detection

Physiologic signals can also be an accurate method for drowsiness detection. In fact, on the early stages of sleepiness, these signals suffer notable changes, which means that is it possible to alert the driver with time in case of dangerous case of fatigue, in order to prevent road accidents. The most used electrophysiological signals for this purpose are ECG (Electrocardiogram), EEG (Electroencephalogram), EOG (Electrooculogram), PPG (photoplethysmography) and EDA (Electrodermal Activity). One advantage of this method is eliminating the number of false positives on drowsiness detection.

- **EOG**: measures the electrical potential difference between the cornea and the retina of a human eye. This difference is correlated with the alertness level of the subject by analyzing the eye behavior. Actually, if the eye movement is slow, chances are that the driver is on a drowsy state. However, this method is really invasive because direct contact with the driver is needed: a disposable electrode is placed on the outer corner of each eye and a third electrode at the center of the forehead for reference. Despite being invasive and not usually a practical method in the real world, it is a very precise way for drowsiness detection [17].

- **EEG**: measures the electrical activity of a human brain. It is actually one of the most used methods in the literature and it is highly accurate. It is proved that changes in sleep condition affect the autonomic nervous system (ANS). This way, by nature, EEG signal is complex and has multiple frequency bands and each one of these frequencies is itself correlated with the state of the drowsiness of an individual [48]:

  - **delta band (0-4 Hz)** : deep sleep and sleep position;
  - **theta band—which (4-7 Hz)** : drowsiness;
  - **alpha band-which (8-13 Hz)** : relaxation state and closed eyes ;
  - **beta band—which (13-30 Hz)**: alertness;

  The problem with EEG drowsiness measurements is that the frequencies used are very prone to errors, are really invasive as it requires direct contact with the individual and demands very specific conditions in order to proper measurement. This way, on a real-world driving situation, it is really difficult to use the EEG measure sensors, as having electrodes attached to the driver's head is not convenient. Also, in this case, it could have the opposite effect of the one proposed: these sensors could disturb the driving task and lead to road accidents [17].

- **ECG**: measures the electrical activity of a human heart. By analyzing the ECG signal, it is possible to detect minute changes on heart rate. Usually, the ECG wave that traduces the heart behavior follows a pattern and it is specific for each individual.

  The heart rate is controlled by the balance between the two branches of the autonomic nervous system (ANS)[49], the sympathetic nervous system and the parasympathetic nervous system: while drowsy or in a relaxed state, an increase in the parasympathetic activity and/or a decrease in sympathetic activity is noted, awake state the opposite happens.

The variability of the heart rate is described using Heart Rate Variability measure (HRV) and can be used to indirectly measure the ANS activity. HRV is based on the analysis of consecutive sinus rhythm R-R intervals 2.4, corresponding to a beat-to-beat changes measure.

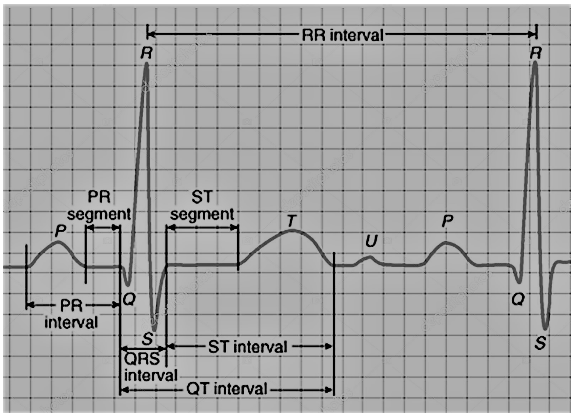

Figure 2.4: Heart-beat representation [4]

An increased HRV indicates a higher parasympathetic activity, as the time interval length between heartbeats variates, indicating more variability [50]. Usually, time and frequency domain methods are used to analyze HRV. Relating time domain features, RRI (R-R intervals) are used. Usually, low heart-rate can induce drowsiness state. In relation to frequency domain features, these ones can be obtained using a power spectral density (PSD) of the RR intervals. These intervals are can be classified in three frequency bands[49]:

- Very low frequency (VLF) (0-0.04 Hz)
- Low frequency (LF) (0.04-0.15 Hz)
- High frequency (HF) (0.15-0.4 Hz)

These bands are correlated with the drowsy/awake state: while awake, the heart rate tends to be much closer to the HF, but when the driver enters on a drowsy state, there is a clear decrease on the heart rate and it tends to LF band. Consequently, there is a decrease in the LF/HF ratio [19].

Before extracting features that will be further used for drowsiness detection, a pre-processing of the ECG signal is needed. For noise and power interference suppression, band-pass filters are used [51]. Next step consists of detecting R-R peaks, which define an ECG frame. Tompkins QRS complex detection and Wavelet transform-based algorithm [52] are two common methods for this purpose with accuracy larger then 99% [51]. This way, time domain features can be extracted. Frequency domain features are usually obtained using a power spectral density (PSD) and it can be calculated by recurring to Fourier analysis or an autoregressive (AR) model [53].

ECG-based methods can be really accurate however when in an intrusive way. On driving-task, ECG values are extracted with non-intrusive sensors, obtaining noiseless signals, which jeopardizes signal processing for feature extraction. However, usually requires a heavy computational load because the sampling rate of ECG is usually more than several hundred Hz, for an accurate R-R interval peak detection [51].

- **PPG**: Photoplethysmography (PPG) is a non-invasive technique that detects changes in peripheral blood circulation. The signal extracted by this technique allows the determination of the Pulse Rate Variability, which is related to the ANS activity. PPG signal is extracted making use of a pulse oximeter which considers low-intensity IR light to be proportional to the quantity of blood flowing through the blood vessels [19][54].
- **EDA** EDA refers to the phenomena where the change in sweat levels of a human directly reflects the mental state of the person. In fact, skin conductance response (SCR) is one of the parameters to identify sudden physiological changes which also influence the mental state of the individual. In this direction, there are various studies in order to correlate drowsiness state with SCR [54] [54].

For pattern recognition of drowsiness with the physiological signals discussed, the most commonly used machine learning and deep learning approaches are NN, LDA, K-means clustering, Fuzzy logic system, SVM, BN, ANN, Linear Regression Model, see Table 2.4, which represents the state-of-art for physiological methods of drowsiness detection.

Table 2.4: State-of-art for Physiological methods of Drowsiness Detection

Source	Year	Pre-Processing	Feature Extraction	Classification
[55]	2018	None	SampEn of RR peaks SampEn of R peaks	ANOVA Tukey test
[56]	2018	None	HRV time and frequency domain features	SVM KNN NB LR
[57]	2017	Notch filter (Band Stop filter)	HRV time and frequency domain features	LR
[58]	2017	None	Frequency domain features: HF, VF, VLF	Threshold based
[51]	2016	linear phase low-pass filter	HRV analysis related features	SVM
[59]	2016	Signal qualification block based on standard deviation of ECG amplitude	Frequency domain HRV features	LDA
[60]	2014	Band-pass filter	DWT	K-means clustering
[61]	2014	None	Frequency domain HRV features (FFT)	BN
[62]	2013	Band-pass filter	FFT	Fuzzy logic system
[53]	2013	Second order, bidirectional, Butterworth, band-pass filter	Time analysis, Wavelet decomposition, Spectral analysis	ANN
[63]	2012	High-pass filter and thresholding	Neighborhood search	SVM
[64]	2011	Band-pass filter	FFT	SVM
[65]	2011	BioSigBrowser	HRV analysis related features	LDA
[66]	2011	Averaging and low-pass filters	PSD for frequency HRV, skin conductivity and respiration features	LDA, Naive Bayes
[67]	2011	Band-pass filter	FFT	Neural Network
[68]	2010	Band-pass filter ans visual inspection	DWT	ANN
[69]	2009	Low-pass filter and visual inspection	DWT	ANN
[70]	2009	None	Mean power frequency EEG features and frequency domain HRV features (PSD) using FFT	Threshold based
[71]	2008	Independent component analysis decomposition	Power Spectrum Analysis using FFT	Self-organizing Neural Fuzzy Inference Network
[72]	2008	Low-pass filter	FFT	Mahalanobis distance
[73]	2008	Band-pass filter	FFT	Linear Regression Model
[74]	2005	Low-pass Butterworth filter, Smoothing filters	PSD using FFT for frequency HRV and respiration features	SVM, Decision Trees, Naive Bayes

2.1.1.5 Hybrid detection

In the previous sections, different approaches for drowsiness detection were presented. In fact, each one has its advantages and disadvantages.

Regarding subjective measures, they are not feasible for real-time monitoring systems, so usually are used as a support to other methods or even ground truth. Moreover, in some articles, PERCLOS is used as ground truth too.

Behavior methods are non-intrusive and have great results. However, as they require specialized hardware and cameras, they can be more expensive and also are constrained by external factors such as illumination or unexpected features on persons face, for example, glasses, which can really difficult eye movement analysis, for example.

About vehicle-based methods, provide satisfactory results and are non-intrusive, however, they tend to be too dependent on the geometric characteristics of the road and less dependent on kinetic characteristics of the vehicle. Besides, differences in vehicle-metrics can be caused by other factors different from drowsiness, for example, distractions or alcohol or drugs influence.

Physiological methods are very reliable methods with great accuracy, however in an intrusive way. Although there are non-intrusive methods, on ECG signal acquisition case, the signal quality is lost. EEG and EOG signal still require intrusive sensors on the scalp and on the eyes.

Analyzing all these strengths and weaknesses of the various methods, one approach for drowsiness detection and prediction with better accuracy is to combine various methods, developing multimodal algorithms. On Table 2.5 are presented some multimodal approaches.

Table 2.5: State-of-art of hybrid methods for drowsiness detection

Source	**Year**	**Metric**	**Feature Extraction**	**Classification**
[75]	2018	EEG	Delta, theta, alpha, beta content of Frontal, Parietal, Occipital and Temporal lobe	RF with 2 classes: Alert versus slightly drowsy RF with 3 classes: Alert versus moderately drowsy or more
		ECG	Mean of RRI, CVRR, LF/HR and HF	
		Eye movement	The number of blinks Duration time of eye closure	
		Seat pressure	Distance of centroid movement x, y coordinate of the centroid	
		Driver behavior	Mean vehicle velocity Mean vehicle acceleration Mean steering wheel acceleration Mean distance from lane center	
[76]	2016	Driving behavior	Vehicle Speed Lateral position and Steering wheel angle related features	MOL
		Eye movement	Blink frequency Blink duration PERCLOS Pupil	
[77]	2013	ECG	LF/HF ratio	LM with 3 classes: not drowsy, a little drowsy and deep drowsy
		EOG	Head location and face tracking Head pose and face tracking Gaze estimation Blink detection	
		SWA	Sterring veloicity Mean of absolute position Low steering percentage Std of position Steering reversals Steering SameSide FFT: LowBand, Mid Band and HighBand	

2.2 Drowsiness detection products on the Market

Some products of drowsiness detection are already in the market. Most of them integrate behavior and vehicle-based methods. However, there are products that also use physiological signals for this purpose.

Some companies sell sensors and cameras to other companies for drowsiness detection purposes. Examples are *Bosch* and *Valeo*:

- ***Bosch*** already sells self-developed steering-angle sensors to car manufacturers such as *Volkswagen* (*Volkswagen's Passat alltrack* [78]). Apart from steering behavior, other vehicle-based metrics are used: 70 signals are received via the vehicle's Controller Area Network (CAN) related to the length of a the trip, use of turn signals, and the time of day, predicting the drowsiness state of the driver [79]. When the individual is considered to be in a drowsy state, an icon such as a coffee cup flashes on the instrument panel to warn him that he need a rest. Besides, *Bosch* already started developing a system with a camera for face feature drowsiness detection, a solution that was presented in Consumer Electronics Show (CES) in 2017 in Las Vegas [80].

- On the same conference, *NVidia* [81] presented the Co-Pilot, that making use of artifitial intellence is able to learn the behaviors of individual drivers and realize when they are not operating according to the rules. Drowsiness detection with integrated alarms is made by analyzing driver' standard posture, head position, eye-blink rate, facial expression and steering style. *NVidia* sends this solution on a chip and already sells for companies like *Audi*, *Mercedes* and *Tesla*.

- ***Valeo*** [82] is also a company that sells cameras for automotive applications that does real-time monitoring of eye movement, eyelid movement, pupil position, head angle, and other key features. Drowsiness detection with integrated alarms is made combining this information with vehicle trajectory and tracking information.

- ***Plessey*** [83] product, *imPulse^{TM}*, uses ECG signal, the signal acquired with a capacitive sensor, WARDEN$^{\text{TM}}$ system that doesn't require skin contact. Drowsiness detection is made by extracting HRV-based features. Also, WARDEN$^{\text{TM}}$ system is easily incorporated inside vehicle seatbacks to access the necessary biometric signals. Alike this last one, *Harken*, a public-private European consortium, created a system of real-time drowsiness monitoring of cardiac and respiratory rhythms using sensors incorporated in the seat cover and safety belt of a car.

The following companies already have products in the market:

- ***Mercedes*** and *Volvo* also self-developed systems of drowsiness detection. *MERCEDES Attention Assist^{TM}* [84] is a solution that integrates 90 indexes related to steering wheel angle and lane deviation and external factors as weather and road surface influences. When the system considers that the individual is fatigued, it will send an audible and visible alert letting the driver know it's time to take a break. *Volvo* developed *DAC*, Driver Alert Control [85], which is a camera-based method that determines ideal road trajectory and compares it to steering wheel movements. When the system determines that the driver is in a drowsy state, it sends an alert. If the driving task is not improved, the alert is repeated.

- ***StopSleep*** [86] is a company from the UK that developed an anti-sleep ring, which uses cutaneous sensors measures electrodermal activity for fatigue detection, with integrated alarms.

- ***Wearvigo*** [87] developed a wearable, a smart headset, that uses over 20 parameters, like blinks related measures, blink rates, blink durations and drooping eyelids for drowsiness detection. Also, uses an accelerometer and gyroscope for movements of the head measurement.

On other hand, other companies already have prototypes, however are still on investigation phase, like *SafeCap* and *CardioID Technologies*:

- ***SafeCap*** [88] is also another system developed by a Brazilian division of Ford, specifically for truck drivers. The metric used for drowsiness detection is head movement detected with accelerometers and gyroscopes on a hat. If the driver is considered to be on a drowsy state, light, sound and vibration alarms are activated.

- ***CardioID Technologies*** is a Portuguese company that developed a system for drowsiness detection by ECG analysis. Cardiowheel [**?**] is an Advanced Driver Assistance System for real-time continuous monitoring that uses sensors embedded in the steering wheel that by hand skin contact acquire the ECG. The steering wheel is customized with a special cover with conductive elements that allow acquisition of electrical impulses generated by the heart. This company also develops algorithms capable of monitoring multiple cardiac pathologies. Driver's identity can also be extracted from the ECG signal.

2.3 Experimental setups

Datasets are a big key point on this kind of studies because the conditions they have acquired in influence the type of data and the reliability of the results. They are four types of experimental setups for acquiring data related to driving task: driving simulators, test tracks, road studies, naturalistic driving studies.

2.3.1 Driving simulators

Driving simulators are systems that with computer generated gives the driver the feeling of sitting in a real car with real driving experience. Driving simulators have as great advantage allowing a safe environment for driving research, enabling a customization of a range of human factors related to driving problems. Furthermore, this simulator, because connected to digital computers, provides an easier way to acquire and storage data. [89].

One of the biggest driving simulator centers is the *Tongji University Advanced Driving behavior and Traffic Safety Research Simulator*. This simulator, currently the most advanced in China, incorporates a fully instrumented Renault Megane III vehicle cab in a dome mounted on an 8 degree-of-freedom motion system [89].

The National Advanced Driving Simulator (NADS) simulation center developed NADS-1, the largest motion envelope of the US and the 2nd in the world in a driving simulation. The NADS-1 utilizes an actual vehicle cab and projects scenery 360 degrees around the driver on the interior walls of the dome that houses the cab. The vehicle cab is mounted on 4 independent actuators that provide vibration associated with driving on varying road surfaces. The entire dome is mounted on a motion base that can independently provide yaw, roll, pitch, turning, lateral and longitudinal cues to the driver. All in all, the NADS-1 has a 13 degree-of-freedom motion base [90].

Sim IV is a driving simulator of the Swedish National Road and Transport Research Institute (VTI). This simulator constitutes a really reliable and realistic simulation which provides a 210-degree forward field of vision driving experience, both longitudinal and lateral acceleration and can simulate a passenger car and truck compartments [91].

CARRS-Q is the other system of driving simulation operational at the Centre for Accident Research and Road Safety – Queensland. It operates with eight computers, three projectors and a six degree of freedom (6DOF) motion platform that can move and twist in three dimensions [92].

Furthermore, CardioID Technologies makes use of a simulator [93] developed by the partners of the present project at ISEL (Instituto Superior de Engenharia de Lisboa) and ULHT (Universidade Lusófona de Humanidades e Tecnologias), this task aims at acquiring such data in an intuitive driving simulation environment, acquiring ECG, EEG and as visual information (video streams of the driver) data type. This simulator, in terms of hardware, includes:

- gamer-type personal computer;
- system with steering wheel, pedals and gearbox;
- wide screen;
- biological signal acquisition system integrated in the steering wheel;
- sensor for capturing and tracking poses and gestures, such as Leap Motion or Intel RealSense;
- camera

Regarding software, it uses Unity3D game engine.

In addition, FEUP also conducted a project, AUTODRIVING, on which was developed a driving simulator. The main goals of the project included studying the driver's activity and behaviour during the autonomous driving, the research of the takeover of vehicle control task under different circumstances and identification of population groups' understanding of the system functioning [94].

2.3.2 Test tracks

Test tracks are made with instrumented vehicles in a controlled environment, allowing the adjustment of various variables, usually closed to public traffic, to guarantee safety.

2.3.3 Road Studies

On-road studies are controlled tests in a pre-determined road in a controlled time, however, the study goes on real-traffic. Also, there may be an experimenter in the car, someone who already knows the way. SleepEYE dataset was acquired on a study of this type. It is a collaborative project between Smart Eye, Volvo Cars and VTI (the Swedish National Road and Transport Research Institute) within the competence center Virtual Prototyping and Assessment by Simulation (ViP) [5], database that will be further described in section 3.2.

2.3.4 Naturalistic driving studies

These ones refer to tests that are made on real driving conditions, in every aspect: normal traffic and there is no experimenter on the car. To get reliable results, these type of study is conducted usually long-term. Also, the test route is not pre-defined, the driver is free to choose the way. This type of study has as an advantage containing a much larger range of situations and unpredictable events.

100-Car Naturalistic Driving Study is one example of a naturalistic driving study. This database contains information of 2,000,000 vehicle miles, almost 43,000 hours of data, 241 primary and secondary drivers, 12 to 13 months of data collection for each vehicle, and data from a highly capable instrumentation system including five channels of video and vehicle kinematics[95].

Another study conducted by Australia Naturalistic Driving Study (ANDS) has the goal of understanding what people do when driving their cars in normal and safety-critical situations. This study was conducted with 360 volunteer drivers (180 from New South Wales and 180 from Victoria) with a private vehicle equipped with a data collection system along 4 months [5].

CardioID Technologies and INESC-TEC also participated on a Naturalistic Driving Research, acquiring ECG signals of one typical trip (350 km), during several typical workdays [9].

2.3.5 Application of experimental setups

The different types of experimental setups also have different applications and are more or less useful depending on the purpose. There are two main characteristics to be analyzed on each experimental setup type: setup validity and degree of control. In fact, in some applications, it is important to consider if the data acquired will be transportable to the real-world conditions, meaning if they can be generalized for more situations rather than the ones from the study. On another hand, on more scientific studies, the degree of control of the study is a key aspect. Controlling the experiment reduces the risk of taking wrong conclusions or confounded results. Knowing all the variables, such as road type and participants, leads to a more reliable study because in this way one knows all the variables on which the results are dependent on. This way, control is needed for reliable repeatability within a reasonable time frame. On another hand, controlled environments reduce the risk of accidents during the study, which is important for ethical reasons.

Setup validity and the high degree of control are two parameters that are really difficult to conciliate. Analyzing the 4 types of experimental setups, simulator studies have a high degree of control however their setup validity is low, due to its controlled environment and selection of variables. In contrast, naturalistic driving studies have high setup validity because they are really close from real driving conditions, but due to its variability and unpredictability, has a low degree of control so it is not so reliable in scientific work when c compared to simulators. Road-studies and Test-tracks are in the middle of the last two, as road-study is made in a controlled environment but in real traffic conditions and test-tracks are controlled environment but in real roads without traffic. Figure 2.5 illustrates the analysis of these two parameters of the four experimental setups referred.

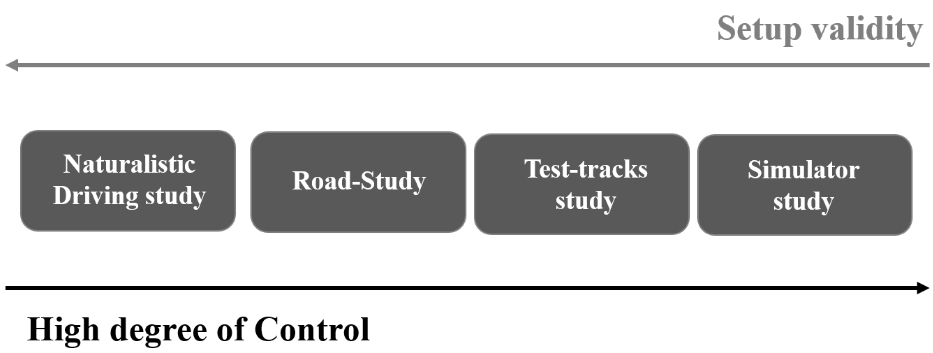

Figure 2.5: Classification of experimental setups in degree of control and setup validity

Chapter 3

A framework for driver drowsiness monitoring

In this chapter a framework used for drowsiness detection will be described, including all the methodologies used and database description. Also, two different approaches of drowsiness prediction will be performed.

3.1 Generalized Framework for Drowsiness Detection

Drowsiness detection and classification problem followed a typical machine learning approach, as described on Figure 3.1. On this dissertation, the main goal was to understand if a multimodal approach, by using signals of different nature such as ECG and SWA, would improve the general efficiency of a model for drowsiness detection on drivers. A conventional machine learning instead of a deep learning approach was chosen as the amount of data available was limited. Following this, the SleepEYE database was used for this work and it will be described on the following section 3.2.

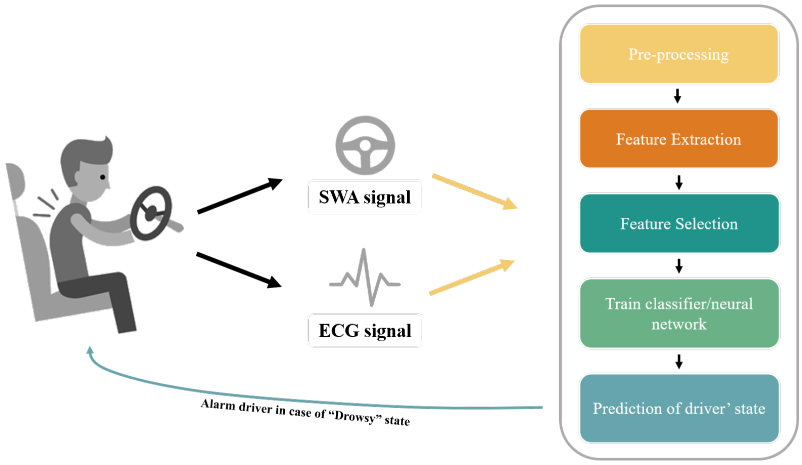

Figure 3.1: Framework of Drowsiness detection based on Vehicle and ECG-based

Table 3.1: Start and end times for the driving sessions

Driving session	Start	End
Participant A alert	15:30	17:15
Participant B alert	17:45	19:30
Participant A sleep deprived	00:15	02:00
Participant B sleep deprived	02:45	04:30

3.2 SleepEye Database description

SleepEYE is a collaborative project between Smart Eye, Volvo Cars and VTI (the Swedish National Road and Transport Research Institute) within the competence center Virtual Prototyping and Assessment by Simulation (ViP). This database was provided by the Swedish National Road and Transport Research Institute [5].

3.2.1 Participants

Twenty drivers (ten women) participated in the study. The participants were recruited based on a random sample from the Swedish register of vehicle owners. The main inclusion criteria were:

- Between 30 and 60 years old
- Healthy
- Normal weight
- No shift workers
- No professional drivers

3.2.2 Procedure

The procedure is described on the Final Project of the SleepEYE project, "Camera-based sleepiness detection" [5], as it will be presented on this subsection. Sleepiness and wakefulness forms were sent to the participants before the experiment to be filled in the three nights and two days immediately prior to the experimental day. The participants were instructed to sleep at least 7 hours per night the three nights prior to the test. Two drivers participated each experimental day. The first participant arrived at 2 p.m. and the second at 4 p.m. When the participants arrived they were given written and oral information about the test and were then asked to fill in an informed consent form and a response form. They also had to show their driving license and to do a breath alcohol test. The test leader then applied electrodes for physiological measurements. Each participant took part in two driving sessions on each test occasion: the first was the alert condition and the second was the sleep-deprived condition, Table 3.1.

Each driving session lasted for about 90 min. The time between the sessions was spent at the laboratory, where the participants could read, watch TV etc. The participants were served dinner after the first driving session and fruits and sandwiches during the night. They were not allowed to eat or drink caffeine from 1 p.m. on an experimental day. The participants were instructed to drive as they would do in "real life". However, while driving they were not allowed to speak, listen to the radio or do anything else that would counteract their sleepiness. During each driving session the participants rated their sleepiness level on the 9-grade **Karolinska Sleepiness Scale (KSS)** every five minute.

During the experiment, a test leader was sitting in the front passenger seat. The car had dual command and there was a small screen in front of the test leader showing the driver's face so that the test leader could see if the participant closed his/her eyes. The test leader was responsible for the safety and was prepared to take control of the vehicle if the driver became too sleepy. However, the intention was not to let the driver fall asleep but to stop the driving session before the driver fell asleep. The test leader was also supposed to stop the driving session if the driver drove in a non-safe way, either because of sleepiness or of other reasons (e.g. exceeded posted speed limit). The participants were explicitly told not to exceed the posted speed limit. They were also told that they were allowed to stop for a break if they felt that it was necessary for their safety. If the driver chose to take a break, it was prescribed that the test leader would abort the current drive. After the sleep-deprived session, the electrodes were removed and the participants were sent home by taxi.

3.2.3 Test Route

Each driving session took 90 minutes on a road with approximately 2 x 79 km, on the E4 motorway from Linköping (exit 111) to Gammelsta (exit 128) and back. A 110 km/h posted speed limit was taxed during the whole route, except for a road section of 750 meters in Norrköping, where the posted speed limit was 90 km/h. 3.2.

Figure 3.2: Teste route: Motorway E4. The test route started at exit 111 in Linköping and the turning point was at exit 128 in Gammelsta. Source: [5]

3.2.4 Data acquisition

SleepEYE database signals were acquired using a Volvo XC70 with an automatic gearbox in the described experiment. During the tests, there was a sign on the rear of the car with the text

"Measurement vehicle". Vehicle data, such as speed and lateral position, was logged with 10 Hz. Physiological data – EEG, EOG, and ECG – was recorded by a Vitaport 3 (TEMEC Instrument B.V., The Netherlands) with 256 (EEG and ECG) or 512 Hz (EOG). All data acquisition systems were connected to each other in order to facilitate synchronization of data.

3.3 Data preparation and Labeling

As previously mentioned, drowsiness state was evaluated by each patient using an quantitative scale, KSS scale, each 5 minutes of driving. In this direction, for drowsiness classification was performed following two different approaches:

- **Absolute evaluation**: Classification of drowsiness' state of the individual considering the absolute value of the KSS scale.

  This way, a binary and multiclass classification was considered, as represented on Figure 3.4.

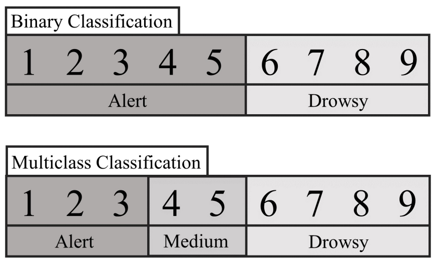

Figure 3.3: Kss-based labeling division

- **Relative evaluation**: Classification of drowsiness' state of the individual considering the changes of the drowsiness self-evaluation using the same scale along the driving session, comparing two consecutive 5 minute frames, aiming to evaluate the evolution of the individual's drowsiness state.

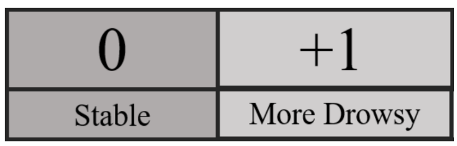

Figure 3.4: Kss-based labeling division

In order to divide the data according to the approaches previously described, as ECG and SWA signals were acquired on different frequency rates, a resampling of the steering wheel angle data, SWA, was necessary.

In order to analyze both ECG and SWA signals and extract features that allow the drowsiness detection, a 5 minute sliding window with an overlap of 1 second was used for the signal of each individual, both day and night acquisitions, on both signals.

3.4 Steering wheel angle - based (SWA)

SWA signal measures the corrections of the steering wheel during the driving task. These values correspond to the deviation, positive or negative, in relation to the axis that indicates the direction of the movement, as represented on Figure 3.5.

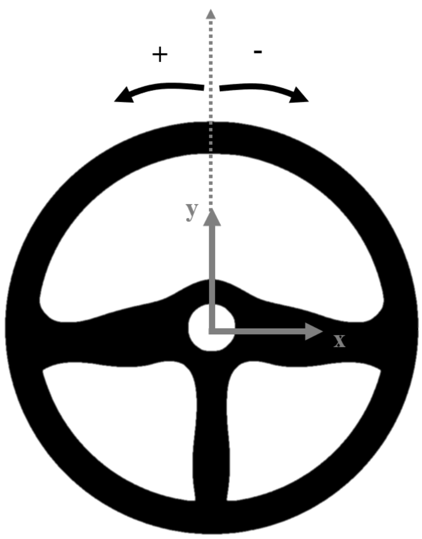

Figure 3.5: SWA signal acquisition representation: y and x represent the referential; the streak line represents the axis that indicates the direction of the movement; "+" and "-" represent the positive and negative angle values

3.4.1 Pre-processing

The SWA signal typically wave is presented in Figure 3.6. In fact, in order to obtain a proper SWA signal for feature extraction, as this signal is influenced by geometric road characteristics, usually a pre-processing procedure is needed.

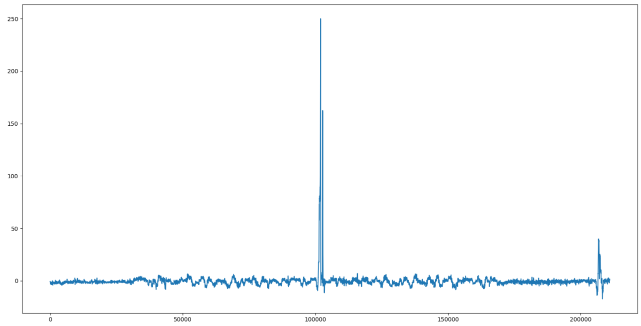

Figure 3.6: Original steering wheel signal wave form

In the literature, it is in fact specified that only angles between 0.5° and 5° are considering as being steering wheel corrections. Apart from this, curves can be mistaken as being macro-corrections, which can really influence final results, present on Figure 3.7. In this direction, the effect of road curvature on steering signal was removed applying a sliding window, using the following equations (3.1, 3.2).

$$M_{\Theta} = \frac{1}{W} \sum_{k=n_l}^{n_l+w+1} \Theta(k) \tag{3.1}$$

$$\Theta * (k) = \Theta(k) - M_{\Theta} \tag{3.2}$$

Where, W corresponds to the length of sliding window, n_l is the first point (left side) of the window and M_{Θ} is the average of steering angle Θ in the sliding window which has been subtracted from raw signal to obtain the $\Theta * (k)$ (the preprocessed signal).

After pre-processing, the resulting signal is presented on figure 3.7.

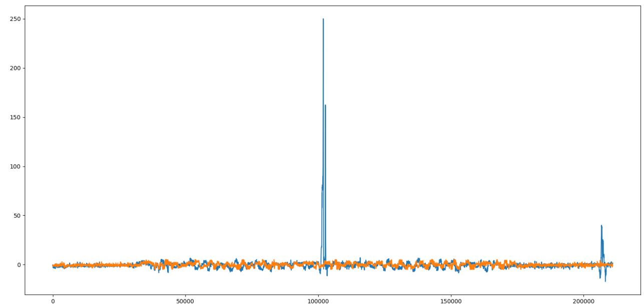

Figure 3.7: Comparison between Steering wheel angle signal before (in blue) and after pre-processing (in orange)

3.4.2 Feature extraction

A proper training of a model which is capable of classifying the drowsiness state involves extracting signal characteristics that define the state of the driver in terms of drowsiness. This way, two types of features were extracted: time domain and frequency domain, presented on Table 3.2.

Table 3.2: Features extracted from steering wheel angle signal

index	**Time domain features**
i1	Range
i2	Standard Deviation
i3	Energy
i4	Zero Crossing Rate (ZCR)
i5	First Quartile
i6	Second Quartile
i7	Third Quartile
i8	Katz Fractal Dimension (KFD)
i9	Skewness
i10	Kurtosis
i11	Sample Entropy (SamEn)
i12	Shannon Entropy (ShEn)

index	**Frequency domain features**
i13	Frequency variability
i14	Spectral Entropy (SpEn)
i15	Spectral Flux
i16	Center of Gravity of Frequency (CGF)
i17	Dominant Frequency
i18	Average Value of PSD

3.4.2.1 Range

Range of the signal corresponds to the difference between minimum and maximum of signal (Equation 3.3).

$$range = max(\Theta) - min(\Theta) \tag{3.3}$$

3.4.2.2 Standard Deviation

Standard Deviation is the dispersion of the data around mean value, as presented by the equation below (Equation 3.4).

$$Standarddeviation(\sigma) = \sqrt{\mu_2} \tag{3.4}$$

3.4.2.3 Energy

The energy of a signal corresponds to the sum of the square of signal magnitude (Equation 3.5).

$$energy = \sum_{n=-\infty}^{\infty} |x(n)|^2 \tag{3.5}$$

3.4.2.4 Zero Crossing Rate

The zero crossing rate describes the number of steering changes per second (Equation 3.6).

$$\sum_{i=0}^{256} \Theta[i] * \Theta[i-1] \tag{3.6}$$

3.4.2.5 First, Second and Third Quartile

In order to calculate the first, second and third quartile of the signal, two parameters must be previously calculated: lower half and upper half. The lower half is defined as being the set of all values that are to the left of the median value when the signal values have been put into increasing order. On the other hand, the upper half corresponds to the set of all values of the signal that are to the right of the median value when the data has been put into increasing order.

In this direction, the first quartile (Q1) is the median of the lower half of the signal, corresponding to more a less 25% of the numbers in the data lie below Q1 and about 75% lie above Q1. The second (Q2) is defined to be the data cut in half. Finally, the third (Q3) is defined as being the median of the upper half of the data set. This means that about 75% of the numbers in the data set lie below Q3 and about 25% lie above Q3.

3.4.2.6 Katz Fractal Dimension (KFD)

In Katz's algorithm, the fractal dimension is calculated directly from the time series and can be defined as $D = \frac{\log_{10}(L))}{\log_{10}(d)}$ where L refers to the total length of the signal's time series and d to the Euclidean distance between the first point in the series and the point that provides the furthest distance with respect to the first point. The final equation of KFD is presented on Equation 3.7, after proper normalization (n refers to the number of steps in the waveform).

$$D = \frac{\log_{10}(n))}{\log_{10}(\frac{d}{L}) + \log_{10}(n)} \tag{3.7}$$

3.4.2.7 Skewness

Skewness corresponds to the degree of distortion of the signal from its normal distribution, measuring the lack of symmetry of the data in the study. This way, a symmetrical distribution has a skewness of value zero. There are two types of Skewness: Positive and Negative. Positive skewness refers to the situation when the tail on the right side of the distribution is longer and, consequently, the mean and median will be greater than the mode. On the contrary, negative skewness is when the tail of the left side of the distribution is longer than the tail on the right side. The mean and median will be less than the mode.

3.4.2.8 Kurtosis

Kurtosis a statistic term that described the tails of a distribution. This metric describes the extreme values in one in comparison to the other tail. Actually, kurtosis measures of outliers present in the distribution. High kurtosis indicated that data has heavy tails or outliers and low kurtosis the opposite. Both these results could indicate unwanted results or wrong data. This way, there are 3 possible good kurtosis values: Mesokurtic (equal to 3), Leptokurtic (greater than 3) and Platykurtic (lower than 3).

3.4.2.9 Shannon Entropy

Entropy is the measurement of the uncertain. Regarding this, Shannon entropy (ShEn) is one of way to determine if and in this particular case will refer to the randomness in a driver's steering control. Shannon entropy (H) of an event X can be determined by Equation 3.8, where n is the number of possible outcomes $p_1, ..., p_n$ are the probability of the event on focus to happen.

$$H(X) = H(p1, ..., pn) = -\sum_{n}^{i=1} p_i log_2 p_i \tag{3.8}$$

3.4.2.10 Frequency Variability

Frequency variability refers to the variability of the frequency of the signal on a defined frequency band. On this context, variability was determined between the 20 to 60 Hz.

3.4.2.11 Spectral Entropy (SpEn)

Spectral entropy calculation is based applying the Shannon function to the normalized power spectrum (Equation 3.9). On this case, all the values in the power spectrum are equally on the calculations, independently of their location on frequency axis. Spectral entropy is useful in order to describe the irregularity of the signal, that is correlated with drowsiness.

$$E = \sum_{f=\frac{-fs}{2}}^{f=\frac{fs}{2}} = PSD_n(f) \log_2 [PSD_n(f)] \tag{3.9}$$

3.4.2.12 Spectral Flux

Spectral flux evaluates the variation of spectrum between two successive frames. On a more simple way, determines how quickly the power spectrum of a signal is changes in comparison to the previous one. It is calculated by squaring the differences between the normalized magnitudes of the spectrum of the two successive short-term windows.

3.4.2.13 Center of Gravity of Frequency (CGF)

Center of Gravity of Frequency is the Spectral centroid of the signal. This way, Spectral Centroid is obtained by evaluating the "center of gravity" using the Fourier transform. For each frame, SC is defined as the average frequency weighted by amplitudes, divided by the sum of the amplitudes, as presented on Equation 3.10, where f(n) is the amplitude corresponding to bin n in DFT spectrum.

$$SC = \frac{\sum_{N1}^{k=0} f(n)x(n)}{\sum_{N1}^{k=0} f(n)} \tag{3.10}$$

3.4.2.14 Dominant Frequency

Dominant frequency is obtained by determining the maximum value of the Power Spectral Density (PSD).

3.4.2.15 Average Value of PSD

Average Value of PSD, as the name indicates, is the mean value of a sliding window of the Power Spectral Density (PSD).

3.5 Eletrocardiogram-based (ECG)

3.5.1 Poincaré plot

The Poincaré plot is a technique taken from nonlinear dynamics, portrays the nature of these fluctuations graphically. It corresponds to a scatter-plot on which the RR intervals are plotted against the next frame. This analysis is an important quantitative-visual technique and it has demonstrated to provide information as well as detailed beat-to-beat information on the behavior of the heart.

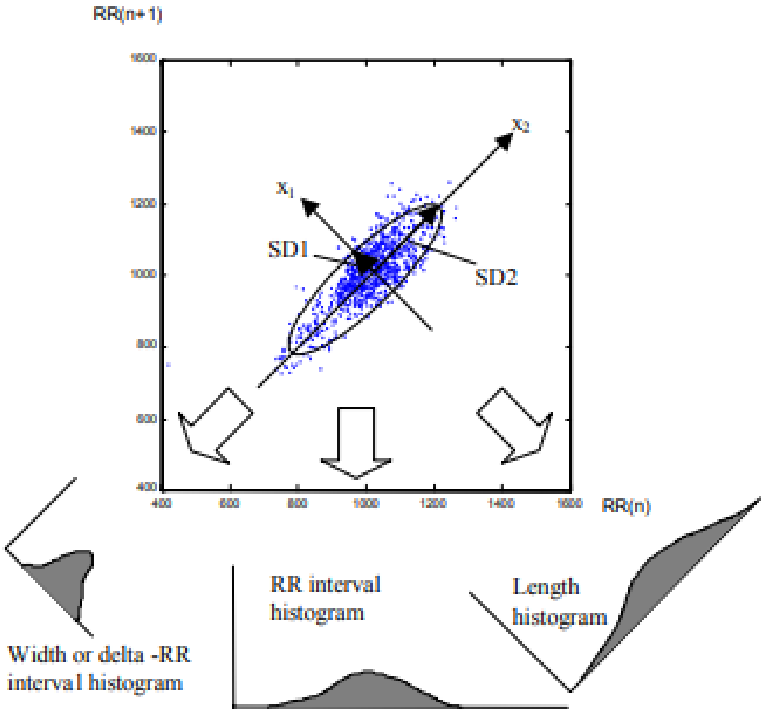

Figure 3.8: An example Poincaré plot, also detailing the ellipse fitting process and the histograms derived from the plot

In particular, the dispersion of points perpendicular to the line-of-identity reflects the level of short-term variability while the dispersion of points along the line-of-identity corresponds to the long-term variability. To determine this parameters, SD1 and SD2, short and long-term variability respectively, it is common to characterize the shape of the plot as being an ellipse. Regarding this, SD1 is determine by the standard deviation of points perpendicular to the axis line-of-identity, while the SD2 is calculated by determining the standard deviation of points along the line-of-identity. This method is described on the paper of Brennan, Michael, Marimuthu Palaniswami, and Peter Kamen [96]. Other feature used was the ratio between SD1 and SD2.

3.5.2 R peaks of ECG detection

For some time domain features' extraction it was demanding to detect the R peaks indexes and its amplitudes and, consequently, calculate the time intervals between them (RRI).

This way, for peak detection, Pan-Tomkins algorithm was implemented [97]. The steps followed for this purpose are described in Figure 3.9. First, the signal was filtered by applying a bandpass filter, in particular, a Butterworth filter (low cut frequency 1 Hz and high cut frequency 100 Hz), in order to remove possible intrinsic noise. Then, for QRS slope information extraction, a first derivative was applied. The following step consisted of squaring the signal to intensify the values received by the derivative. Afterwards, a signal convolution on a defined integration window (15 samples) was applied. Finally, for peak detection on the integrated signal, Janko Slavic

[6] peak detection algorithm was used, obtained the amplitudes and indexes of the R peaks of the ECG signal. This method find peaks within a minimum spacing width to the next peak and with amplitude value greater or equal to the limit defined. On this case, spacing was defined as 1, the minimum, and limit was defined as 0, as it is optional. The resulting peak detection can be observed in Figure 3.10.

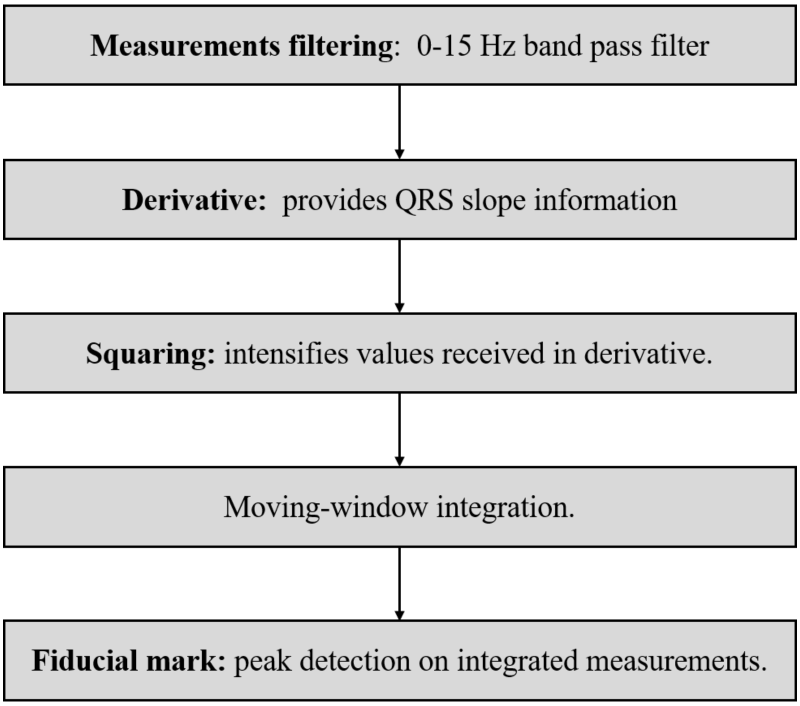

Figure 3.9: R peak detection framework

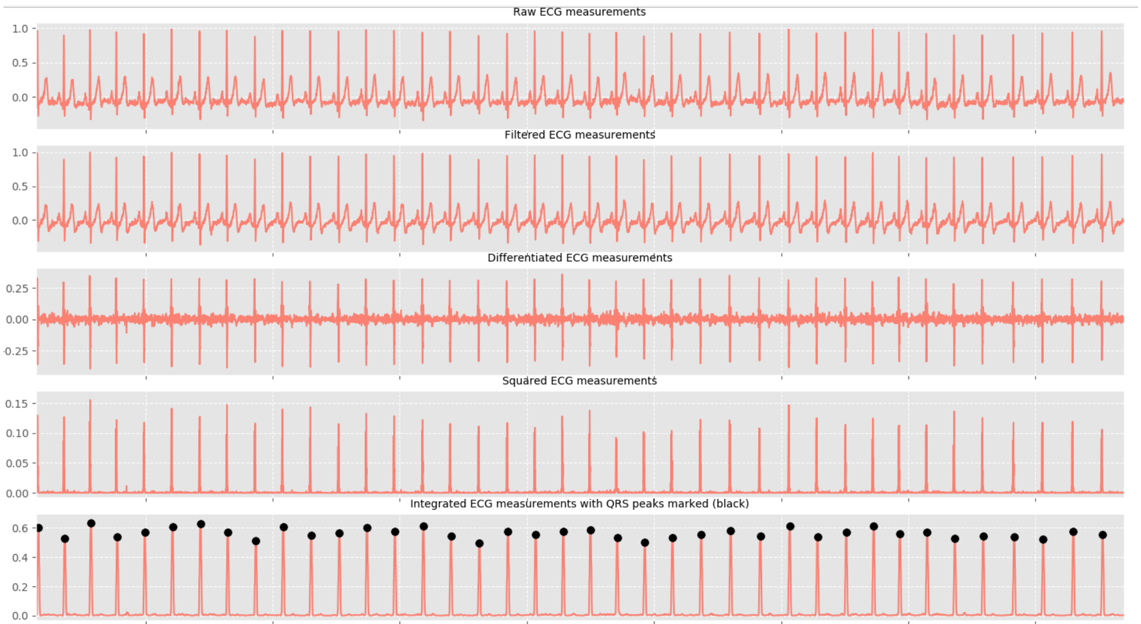

Figure 3.10: R peak detection visualization step by step

3.5.3 Feature Extraction

For drowsiness detection, HRV analysis was used. HRV, which is defined as an RR interval (RRI), corresponds to the fluctuation on an electrocardiogram (ECG) trace. Sixteen time and frequency domain features were extracted (Tables 3.3 and 3.5).

Time domain	Description
MRRI	Mean RR intervals
MHR	Mean heart rate in ms
SDNN	Standard deviation of RR intervals
SDSD	Standard deviation between RR intervals
RMSSD	Root mean square of the differences between consecutive RR intervals
NN50	Frequency of successive differences of RR intervals //that spanned more than 50 ms
pNN50	Percentage value of NN50

Table 3.3: Table of HRV-based feature extraction

Frequency domain	Description
HF	Mean high frequency
LF	Mean low frequency
LF/HF	Ratio between low and high frequencies
HFnu	Normalized HF
LFnu	Normalized LF
TotalPower	sum of HF, LF and VLF

Table 3.4: Table of ECG Frequency domain features

Pointcaré plot domain	Description
SD1	Short-term variability
SD2	Long-term variability
SD2/SD1	Ratio between SD2 and SD1

Table 3.5: Table of ECG Frequency domain features

3.5.4 Feature Selection

Feature Selection step is an important step to filter the features that are not that important or even can affect the final results instead of enhancing them. Actually, it has many advantages such as enabling the machine learning algorithm to train faster, reducing the complexity of a model and, consequently, making it easier to interpret. Nevertheless, it improves the accuracy of a model on the case on which the right subset is chosen. Finally, it reduces overfitting, meaning, prevents a too close or over-adapted algorithm to the set of data used to train the model. Regarding this, a open-source class of feature selection was used, *FeatureSelector* class. This class includes five different methods:

- Features with a high percentage of missing values
- Collinear (highly correlated) features
- Features with zero importance in a tree-based model
- Features with low importance
- Features with a single unique value

3.6 Classification

After feature extraction for both signals, drowsiness classification involves the training of a model. In this direction, the models tested were Support Vector Machine (SVM), k-nearest neighbors (KNN). Moreover, ensemble methods were also trained, such as Bagging Classifier. These classifiers are going to be described on the following subsections.

3.6.1 Supervised methods

Supervised methods are commonly used for classification and regression problems. These methods use ground truth in their training models. So, the model has previous knowledge of what the output values for our samples should be. This way, the main goal of supervised learning is to learn a function that, given a sample of data and desired outputs, best approximates the relationship between input and output observable in the data [98]. Supervised methods are going to be described in the following sections.

3.6.1.1 SVM

Support Vector Machines is an algorithm of machine learning that is frequently used because usually gets really good results in terms of accuracy and also requires less computation power when compared to other methods. The main goal of this algorithm is to find a hyperplane in an N-dimensional space, being N the number of features used, that divides the data points for proper classification. For example, to classify two classes of data points, the hyperplane chose is the one which has the maximum margin, in order to increase the probability of accurate classification of future unknown data.

The loss function that helps maximize the margin is hinge loss, as presented on Equation 3.11.

$$c(x,y,f(x)) = \begin{cases} 0, & if \quad y \times f(x) \geq 1 \\ 1 - y \times f(x), & else \end{cases} \tag{3.11}$$

In this direction, the resulting cost (c) is 0 if the predicted and real value have the same sign. If not, then the loss value is determined. In addition, a regularization parameter is added to the loss function. This parameter balances the margin maximization and loss. The loss function with the regularization parameter is presented on equation 3.12.

$$min_w \lambda \|w\|^2 + \sum_{i=1}^{n} (1 - y_i(x_i, w)) \tag{3.12}$$

After obtaining the loss function, in order to get the gradients, it needs to take partial derivatives with right weights. Then, by using the gradients, it is possible to update the weights (Equations 3.13 and 3.14).

$$\frac{\delta}{\delta w_k} \lambda \|w\|^2 = 2\lambda w_k \tag{3.13}$$

$$\frac{\delta}{\delta w_k}(1 - u_i(x_i, w)) = \begin{cases} 0, & if \quad y_i(x_i, w) \geq 1 \\ -yix_{ik} & else \end{cases} \tag{3.14}$$

In the case of the model not predicting the class correctly (no misclassification), it is necessary to update the gradient from the regularization parameter (Equation 3.15).

$$w = w - \alpha \cdot (2\lambda w) \tag{3.15}$$

In the case of misclassification, the loss function is included with the regularization parameter to perform gradient update (Equation 3.16).

$$w = w - \alpha \cdot (y_i \cdot x_i - 2\lambda w) \tag{3.16}$$

3.6.1.2 Random Forest

Random forest is a supervised learning algorithm. It builds multiple decision trees and combines them to get a more accurate and stable prediction.

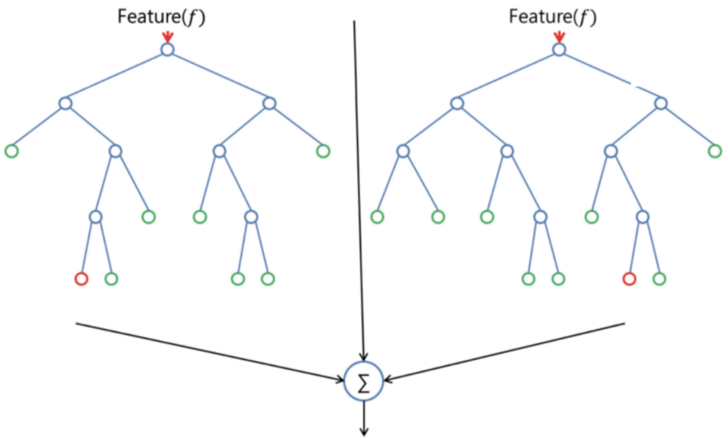

Figure 3.11: Random Forest example

As can be seen in figure 3.11, these trees grow upside down. This classifier, as the name suggests, grows the different trees adding randomness. This is done by searching the best feature among a random subset of features, instead of just selecting the next feature while splitting a node. This way, it is possible to achieve a more robust model. Thus, only a random subset of features is used for the algorithm to split a node. In addition, one can add more randomness to the model by using random thresholds for each feature rather than searching for the best possible threshold [99].

3.6.1.3 K-Nearest Neighbours

K-Nearest neighbors is a non-parametric technique, meaning that does not involve any assumptions on the underlying data distribution. This way, it does not use the training data points to do generalizations, so KNN keeps all the training data on the testing phase. The training phase is almost non-existent. KNN is based on feature similarity, so the classification of the new data point is done depending on how approximated out-of-sample features resemble the training set. Therefore, the data point is classified by the majority vote of its neighbors and it is included to that class [100].

3.6.2 Ensemble Classifiers

3.6.2.1 Bagging Classifier

Bagging is an ensemble classifier that can be used to improve the accuracy of Classification and Regression Trees (CART). Bagging constructs n classification trees using bootstrap sampling of the training data and then combines their predictions to produce a final meta-prediction. Bagging Classifier's primary tuning hyper-parameter is the number and size of each base estimators.

3.6.3 Classifier Combination

One approach that can improve the results is to combine the classifiers. The main goal is to take into consideration the decisions of various classifiers to form the final decision. For the purpose, it is important to have in consideration the level of fusion: fusion before classification/matcher stage, that is, at the sensor and feature levels and fusion after classification/matcher. Fusion levels after classification can be performed at different levels: rank, decision and score levels. Rank level fusion is used when the output of each classifier is a subset of possible measures stored in decreasing order of confidence. On the other hand, on decision/abstract level fusion each classifier makes the decision independently, being then combined. Finally, in a score level fusion, each classifier provides an opinion on the possible decisions, where non-homogeneous metrics can be used. Furthermore, combination strategies should also be considered, according to the execution order of the combination: sequential, parallel and hybrid combination. Regarding sequential combination, the output of one classifier is used as input to another classifier, which means that is the execution order is changed, the final output will also be different. On the contrary, the parallel combination consists of merging the different output results of different classifiers, so the order is not important. Finally, the hybrid combination is itself a fusion of the sequential and parallel combinations.

On the decision level, majority voting is commonly used for its simple theoretical analysis. There are two types of voting: in the case of hard voting, the class label Ŷ is chosen via majority (plurality) voting of each classifier, C, as described on the following equation.

$$\hat{Y} = mode\{C_1(x), C_2(x), ..., C_n(x)\} \tag{3.17}$$

On the other hand, on soft voting, on which wj defined the weight that can be attributed to the classifier j and p_{ij} is the probability of label i computed by classifier j, defined by the following equation:

$$\hat{Y} = argmax \sum_{n}^{j=1} w_i p_{ij} \tag{3.18}$$

3.6.4 Balance of Classes

One important aspect to analyze when developing a machine learning problem is to take in consideration the balance between the classes. Regarding this, as one can see on Figure 3.12, the classes "Alert" and "Drowsy" although they are not very unbalanced, it still makes the difference on the model performance.

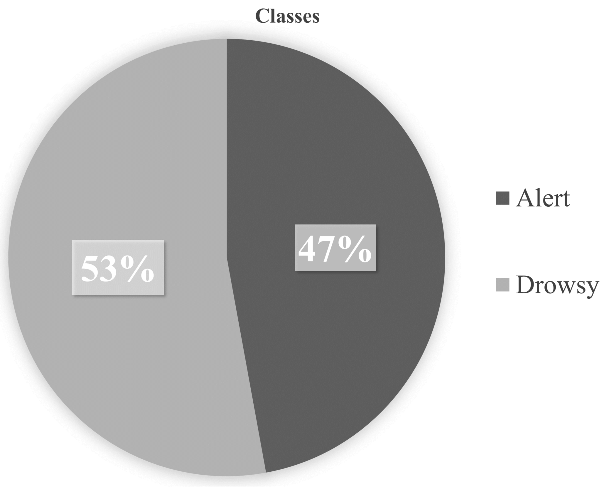

Figure 3.12: Balance between Classes "Alert" and "Drowsy"

Also, by analyzing the Figure 3.13, it is possible to verify that the classes are highly unbalanced.

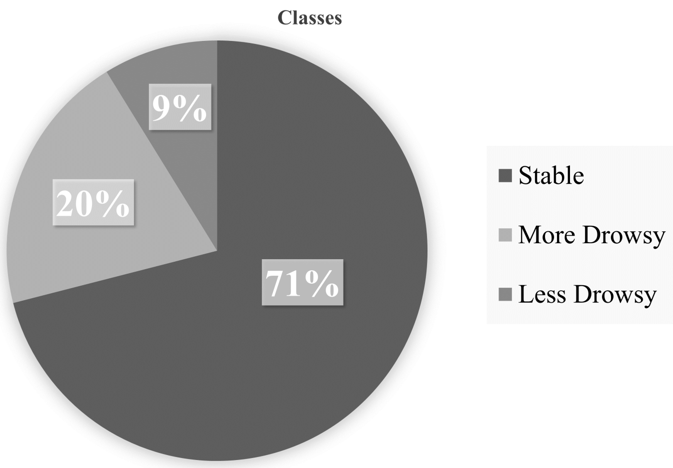

Figure 3.13: Balance between Classes "Stable", "More Drowsy" and "Less Drowsy"

In both cases, this could dramatically affect the performance of any future classifier developed and trained. This way, there are several methods that solve this problem of imbalanced classes. On this case, the option chose was to do an oversampling of the minority class. First of all, it is important to clarify the idea of oversampling and undersampling. Oversampling is needed when it is important to have a balanced dataset and increase the overall amount of data, which means the minority class will suffer an resampling to the size of the majority class. On the other hand, undersampling is exactly the opposite. On this case, an oversampling is needed because it is important to increase the amount of data for model trainning. Following this, SMOTE (Synthetic

Minority Oversampling TEchnique) was used. This technique is similar to a regular resampling with the difference that instead of just adding more examples from the minority class, SMOTE syntheses elements for the minority class, based on those that already exist. This way, randomly points are picked from the minority class and computed using KNN for this point. As following step, the synthetic points are added between the chosen point and its neighbors.

3.6.5 Cross validation strategy

Cross-validation serves as model validation in order to guarantee the model is reliable and how well it will generalize to new data. Furthermore, it helps to make sure that the model has got most of the patterns from the data correct, and it is not picking up too much on the noise, or in other words its low on bias and variance. Regarding this, cross-validation aims to test the model on the training phase, dividing the training dataset into train and validation sets. This method avoids problems of overfitting or underfitting. Overfitting refers to the situation where the model performs too well on the training phase, which means that will not generalize. On the other hand, underfitting is the opposite, meaning the model will perform poorly on finding patterns on the dataset for the class division.

It is important on this particular problem to have in consideration the influence of the biometric traces of each patient on the signals. In fact, while training the model, it important to be careful while splitting the data for train and test phases, because it can cause erroneous results. In this direction, two approaches were made to split the data for cross-validation using *Groupkfold* cross-validation. On the first approach, it is guaranteed that the same individual is not on the train and test sets at the same time. In fact, as demonstrated on the Figure 3.14, it is used a *Groupdkfold* with 18 splits, working like a *LeaveOneOut* cross-validation, meaning that iteratively the test set is composed by one different individual.

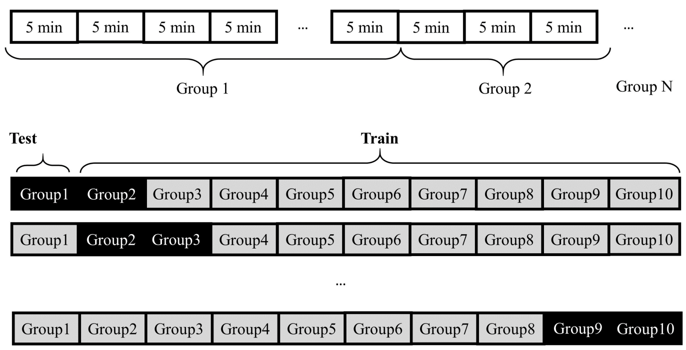

Figure 3.14: GroupKFold CV

The following step included cross-validation with the training dataset in train and validation sets. In order to find the best parameters for training the different models, *GridSearchCV* was used with *StratifiedShuffleKFold*. Because the classes are unbalanced and the dataset is small, it is recommended to use this type of CV. Regarding this, this cross-validation object is a merge of *StratifiedKFold* and *ShuffleSplit*, which returns stratified randomized folds. The folds are made by preserving the percentage of samples for each class.

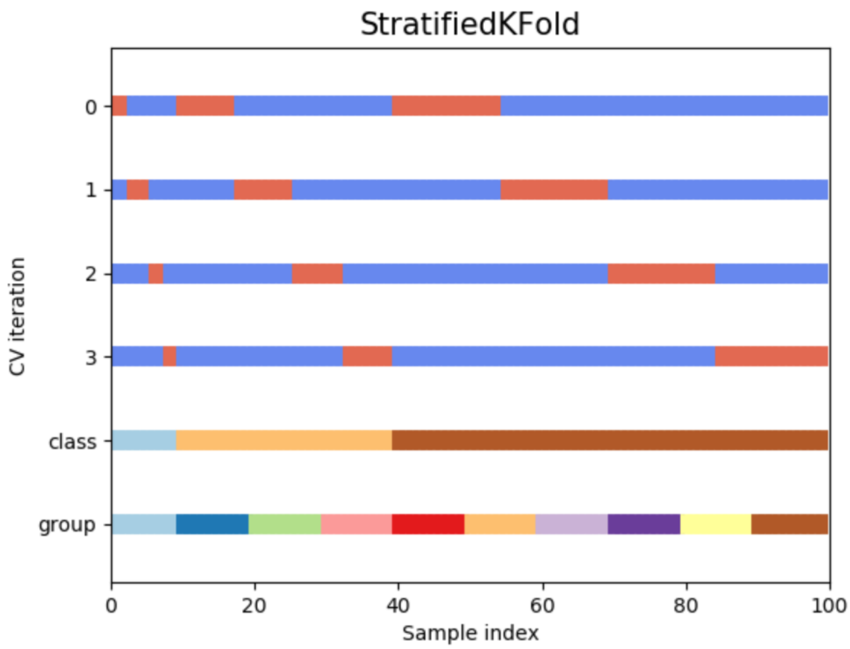

Figure 3.15: StratifiedKFold visual representation [6]

GridSearchCV function is useful to tune the model according to its hyperparameters. While a parameter is an internal characteristic of the model and its value can be estimated from data, the hyperparameter is the opposite, is a characteristic of a model that is external to the model and whose value cannot be estimated from data. In this direction, these methods aim to find the optimal hyperparameters of a model which results in the most "accurate" predictions. For the models in use on this particular problem, the hyperparameters are described in Table 3.6.

Table 3.6: Hyperparameters and defined range for GridSearchCV

Model	Hyperparameter	Description	Range used for GridSearchCV
SVM	Kernel	Selects the type of hyperplane used to separate the data	RBF
	Gamma	Hyperparameter for non linear hyperplanes. The higher the gamma value it tries to exactly fit the training data set.	[1e-4, 1e-3, 0.01, 0.1, 0.2, 0.5, 0.6, 0.9]
	C	Penalty parameter of the error term. It controls the trade off between smooth decision boundary and classifying the training points correctly.	[1, 10, 100, 1000, 10000]
KNN	n_neighbours	Represents the number of neighbors to use for kneighbors queries	[1, 2, 3, 5, 10, 15]
	L_ distance	This is the power parameter for the Minkowski metric.	**l1**, p=1, Manhattan_istance , **l2**, p = 2, Eucliddean_istance **l_**, arbitrary p, Minkowski distance
	Weights	Weight function used in prediction.	**'uniform'** : All points in each neighborhood are weighted equally. **'distance'** : Closer neighbors of a query point will have a greater influence than neighbors which are further away.
RF	n_estimators	number of trees in the foreset	[200, 300,500,1000,4000]
	max_features	max number of features considered for splitting a node	'auto', 'sqrt'
	max_depth	maximum number of levels in each decision tree	[8, 10, 50, 70, 100]
	min_samples_plit	minimum number of data points placed in a node before the node is split	[3,4,5,6,7]
	min_samples_eaf	minimum number of data points allowed in a leaf node	[1,2,3]
	bootstrap	method for sampling data points (with or without replacement)	'True', 'False'
LR	C	Regularization parameter: For small values of C, are created simple models which underfit the data. For big values of C increase it's complexity, and therefore, overfit the data.	np.logspace(-3,3,7)
	Penalty	if a feature occurs only in one class it will be assigned a very high coefficient by the logistic regression algorithm. In this case the model will learn all details about the training set, probably too perfectly. This way, regulation parameters are added to penalize high coefficients.	l1 - norm l2 - square of the norm multiplied by 1/2,

3.6.6 Performance assessment

When training a certain model, it is important to evaluate its performance. Usually, on the test phase involves comparing the predictions made for the test data with the ground truth. This ground-truth correspond to associating a certain label for each data point. For drowsiness detection, usually this ground truth values are based on subjective scales, namely KSS scale, that is the most used. *SleepEYE* database uses this scale. Some works use PERCLOS, time of drive and occurrences of crashes, namely in simulator studies, as ground-truth.

For driver state classification, some works classify sleepy state in two classes, alert/awake or drowsy, but others evaluate driver state in three classes: alert/awake, drowsy and very drowsy.

In this direction, after training the model, on the testing phase, predictions are usually evaluated by calculating the accuracy. Accuracy is defined as being the number of correct predictions (according to ground truth) from all the predictions. So, accuracy, in a binary approach is defined as [101]:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

Where, TP is True Positives (Drivers classified as "drowsy" and were actually "drowsy"), TN is True Negatives (Drivers classified as "alert" and were actually "alert"), FP is False Positives (Drivers classified as "drowsy" when were actually "alert") and FN is False Negatives (Drivers classified as "alert" when were actually "drowsy").

In particular on binary drowsiness detection, confusion matrix is presented on Table 3.7.

Table 3.7: Confusion matrix

		Actual	Values
		Alert	Drowsy
Predicted	Alert	TN	FN
Values	Drowsy	FP	TP

On three classes problem, accuracy is calculated as follows:

$$Accuracy = \frac{\sum_{i=1}^{3} C_{i,j}}{\sum_{i=1}^{3}\sum_{j=1}^{3} C_{i,j}}$$

Where, C represents the confusion matrix $C = C_{i,j3x3}$, being $C_{i,j}$ the number of samples predicted as i with true label j. On the equation, the number 3 on the sum represents the three classes.

Apart from accuracy, there are other metrics to evaluate the performance of a classification model. Precision refers to the proportion between the drivers classified as drowsy and the ones who were actually drowsy and all the drivers classified as drowsy [101].

$$Precision = \frac{TP}{TP+FP}$$

Recall or Sensitivity refers to the proportion between the drivers classified as drowsy and the ones who were actually drowsy and all the drivers that actually are drowsy [101].

$$Recall = \frac{TP}{TP+FN}$$

Specificity refers to the proportion between the driver's classified as "alert" being actually "alert" and all the drivers classified as "alert" [101].

$$Specificity = \frac{TN}{TN + FP}$$

F1 Score represents both precision and recall metrics. It refers to weighted average of the precision and sensitivity [101].

$$F1 \quad Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Finally, mean square error (MSE) refers to the quality of an estimator and measures the average of the squares of the errors (n is the total number of samples and Y_i is the label (predicted or real) of sample i [101].

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (Y_i^{predicted} - Y_i^{real})^2$$

Chapter 4

Results and discussion

4.0.1 Classifiers and Feature Comparison

On the next subsections, results obtained with the framework previously described will be presented and discussed. On a first approach, the hipotesis that the multimodal approach would improve the performance of drowsiness prediction will be discussed. Also, a comparison between the two methods of drowsiness prediction will be described and also discussed, in particular, between the use of the absolute values of the KSS scale and the relative evaluation of the driver' state.

4.0.1.1 KSS scale absolute classification

On this subsection are presented the results obtained following the framework described on the previous sections. Regarding this, on Table 4.1 are presented the accuracy of the model after cross validation obtained using ECG and SWA features in separately and concatenating the features extracted of the two signals (ECG+SWA), for binary approach.

Classifier	ECG (%)	SWA (%)	ECG + SWA (%)
SVM	62 ± 0.112	70 ± 0.124	66 ± 0.132
RF	78 ± 0.0524	76 ± 0.0547	80 ± 0.0085
KNN	72 ± 0.063	66 ± 0.049	71 ± 0.0471
BAG	68 ± 0.055	62 ± 0.069	70 ± 0.036

Table 4.1: Cross Validation accuracy results (average and standard deviation) for different classifiers using ECG, SWA and their combination - KSS scale absolute evaluation

On the results presented, applying the Feature Selection methods was beneficial for the ECG final score. This way, some of the features were identified as collinear, so they were not benefiting the model and inclusively making it have a worst performance. The following Table 4.2 presents the thresholds used for each method and the features identified.

Method	Threshold	Features identified
Missing	0.8	None
Correlation	0.98	LFnu TotalPower SDSD RMSSD pNN50 SD1
Single Unique	-	None
Low importance	-	None
Zero importance	0.99	None

Table 4.2: Features selected for ECG feature matrix after Feature selection methods being applied for KSS absolute scale evaluation

The following Table 4.3 presents the results on the testing phase obtained using ECG and SWA features individually and concatenating the two type of features, for binary approach.

Classifier	ECG (%)	SWA (%)	ECG + SWA (%)
SVM	87	87	82
RF	71	84	71
KNN	61	76	63
BAG	56	74	67

Table 4.3: Testing phase accuracy results (average and standard deviation) for different classifiers using ECG, SWA and their combination - KSS scale absolute evaluation

As additional information, the following Tables present the performance of each model on each class using F1-score metric, on the testing phase.

Support Vector Machines

Classifier	"Alert"	"Drowsy"
ECG	84%	89%
SWA	84 %	89%
ECG+SWA	80%	85%

Table 4.4: Support Vector Machine f1-scores for "Alert" and "Drowsy"

Random Forest

Classifier	"Alert"	"Drowsy"
ECG	75%	68%
SWA	85%	84%
ECG+SWA	75 %	68%

Table 4.5: Random Forest f1-scores for "Alert" and "Drowsy"

K nearest neighbours

Classifier	"Alert"	"Drowsy"
ECG	67%	53%
SWA	78%	74%
ECG+SWA	69%	54%

Table 4.6: K nearest neighbours f1-scores for "Alert" and "Drowsy"

Bagging Classifer

Classifier	"Alert"	"Drowsy"
ECG	60%	52%
SWA	74%	74%
ECG+SWA	71%	63%

Table 4.7: Bagging Classifier f1-scores for "Alert" and "Drowsy"

4.0.1.2 Discussion

By analyzing the test accuracy, SVM got the higher results. Furthermore, apart from SVM, all the others presented considerably higher results by using the SWA. Consequently, the concatenation of the two features didn't seem to improve the drowsiness detection.

In fact, f1 score metric shows that although the classes were balanced to train the models, there is still some difference on the performance of the the two classes, although there is not a pattern of better classification of one class in comparison with the other.

4.0.1.3 KSS scale relative classification

On this subsection are presented the results obtained following the framework described on the previous sections that aims to predict the state of the driver in terms of drowsiness in comparison to the previous state. On this case, the state of drowsiness was classified following an binary approach, "Stable" and "More Drowsy", according to the KSS scale. Actually, a third class, "Less Fatigued", was considered however due to the poor amount of data and consequent bad classification, even applying resampling techniques, it will not be presented on the next tables. Apart from this issue, the classes considered were also unbalanced. This way, an oversampling of the class "More Drowsy" was performed, from 101 samples to 355 samples using a resampling function. SMOTE was also used but it didn't balance the classes properly.

On this approach, as a first step, consecutive frames that presented a difference of drowsiness state using the differences of the KSS scale were detected. After this, features were extracted for each frame and the final matrix of features was constituted by the difference between the features of two consecutive frames. Other strategies were tested, like concatenation of features of the two consecutive frames and ratio, not presenting satisfactory results.

Regarding this, on Table 4.8 are presented the GroupKFold CV results (average and standard deviation) for each classifier used, obtained using ECG and SWA features in separately and concatenating the features extracted of the two signals (ECG+SWA).

Classifier	ECG (%)	SWA (%)	ECG + SWA (%)
SVM	71 ± 0.041	76 ± 0.144	84 ± 0.152
RF	92 ± 0.0158	92 ± 0.015	94 ± 0.015
KNN	77 ± 0.073	75 ± 0.092	75 ± 0.097
BAG	68 ± 79	67 ± 0.0543	70 ± 0.068

Table 4.8: Cross validation accuracy results (average) for different classifiers using ECG, SWA and their combination - KSS scale relative evaluation

After training, the models were tested on unseen data. The results are presented on the following Table 4.9.

Classifier	ECG (%)	SWA (%)	ECG + SWA (%)
SVM	88	92	94
RF	86	89	92
KNN	77	90	91
BAG	79	77	77

Table 4.9: Testing phase accuracy results (average) for different classifiers using ECG, SWA and their combination - KSS relative evaluation

Apart from overall accuracy, it is important to evaluate the performance of each model on each class.

The following Tables 4.10, 4.11, 4.12, 4.13 present the performance of each model on each class, "Stable" and "More Drowsy", using F1-score metric, as it is a function of Precision and Recall and it is useful to evaluate unbalance performance between two classes.

Support Vector Machines

Classifier	"Stable"	"More Drowsy"
ECG	88%	89%
SWA	94%	89%
ECG+SWA	95%	93%

Table 4.10: Support Vector Machine f1-scores for "Stable" and "More Drowsy"

Random Forest

Classifier	"Stable"	"More Drowsy"
ECG	87%	86%
SWA	90%	88%
ECG+SWA	93 %	91%

Table 4.11: Random Forest f1-scores for "Stable" and "More Drowsy"

K nearest neighbours

Classifier	"Stable"	"More Drowsy"
ECG	76%	79%
SWA	92%	89%
ECG+SWA	91%	91%

Table 4.12: K nearest neighbours f1-scores for "Stable" and "More Drowsy"

Bagging Classifier

Classifier	"Stable"	"More Drowsy"
ECG	77%	81%
SWA	77%	78%
ECG+SWA	76%	79%

Table 4.13: Bagging Classifier f1-scores for "Stable" and "More Drowsy"

4.0.1.4 Discussion

The results presented show that SVM obtained the greater results, although RF and KNN achived similar accuracy. In fact, it is notorious that steering wheel angle obtained better results when comparing to ECG on fatigue state prediction. On other hand, the multimodal approach by feature concatenation in fact obtained better results, however, the difference is not significant when comparing to the use of the steering wheel angle itself.

Furthermore, analyzing the performance of each model per class, f1 score metric shows that, on ECG case, "More Drowsy" class obtained greated results than "Stable" class, apart from KNN that presents the opposite case. However, RF and SVM, which obtained better overall results, also presented the greatest balance on classifying the two different classes.

4.0.2 Comparison between KSS scale absolute and relative evaluation

After analyzing the two strategies, it was concluded that evaluating the fatigue state of an individual in comparison to the previous state can be a lot more effective than using the absolute value of the scale. In fact, the results suffered an improvement of 7%. Furthermore, by using the absolute KSS scale the combination of the two signals is was not beneficial for the drowsiness detection, however by evaluation the drowsiness on comparison to the previous state, the concatenation of features presented better results. On the other hand, steering wheel angle presented better results in comparison with the ECG features on both of the approaches.

4.0.3 Classifier Combination

One strategy used on the literature is to combine the final decisions of each classifier. Regarding this, due to similar final results on the case of KSS scale relative evaluation, an attempt of improving final accuracy was performed. Table 4.14 shows the classifier combination between the predictions of classifiers after concatenating of features ECG and SWA. For the purpose, VotingClassifer was the model used with weights definitions, according to the importance of the classifiers. Finally, "soft" and "hard" voting types gave the same results. This way, on the Table 4.14 there are only presented the results obtained with "soft" voting.

Voting	Classifiers	Weights	Accuracy
soft	SVMconcat + RFconcat	4-2	94 %
hard	-	-	
soft	SVMconcat + KNNconcat	4-2	94 %
hard	-	-	
soft	KNNconcat + RFconcat	1-1	90 %
hard	-	-	

Table 4.14: Accuracy on the test phase using the Voting classifier for classifier combination, being SVMconcat, RFconcat and KNNconcat the SVM, RF and KNN classifiers trained with concatenation of ECG and SWA.

On other hand, due to the lack of performance by concatenating the features of the two signals on the KSS scale absolute approach of 4% and because the accuracy of both features individually using SVM is similar, classifier combination was also applied on an attempt of obtaining higher results, as presented on Table 4.15.

Voting	Classifiers	Weights	Accuracy
soft	SVMekg + SVMswa	1-1	87 %
hard	SVMekg + SVMswa	1-1	94 %

Table 4.15: Accuracy on the test phase using the Voting classifier for classifier combination of SVMekg and SVMswa.

4.0.4 Discussion

In fact, the results obtained after classifier combination were not better when compared with the previous ones. Actually, on the first case of KSS scale relative approach, although the final resuls were similar, RF and KNN look like their predictions don't help the final results obtained with SVM. On other hand, KNN and RF combined give worst results in comparison to their performance individually. On the other case, maybe to the fact that both of performances are equally high and good, VotingClassifier was not able to obtain a better result.

Chapter 5

Conclusions and Future Work

5.1 Conclusions

In fact, drowsiness-related road accidents are really an issue. Sleepiness, drowsiness and fatigue are all correlated to this same driving problem. Actually, there are different types of fatigue, defined by the different causes of it, either sleep deprivation or task-related fatigue. Independently of the fatigue type, resulting effects on a person are the same and can really badly influence the driving task. At the same time, as the full automation type cars are possibly a remote reality, the driving task will continue to be very dependent on human intervention. Moreover, drowsiness is in fact of the main causes of road driving accidents. In this direction, as new technology is emerging exponentially and people are getting more open to the use of it in their daily lives, many works are focusing on automatic detection of drowsiness using non-intrusive methods, so it does not affect the driving task itself. In this document, drowsiness detection methods regarding vehicle, physiological, behavior-based techniques, and subjective methods were revised, helping on constructing a general framework for this problem. In this direction, the main goal of this thesis was to use vehicle-based, in particular, steering wheel angle, and ECG-based methods and with machine learning technique develop a framework for drowsiness detection. In conclusion, the concatenation of the two signals showed to improve the overall performance of drowsiness classification just on one of the approaches, in particular the KSS scale relative approach. On the other hand, it was notorious that the evaluation of drowsiness state in comparison with the previous one was way more effective when compared to the use of the absolute value of the KSS scale. However, although by concatenating the features the difference between the scores of the two approaches is around 12%, classifier combination revealed to be obtain a better performance than concatenation on the case of absolute value of the KSS scale, although it is not better than the scores obtained by the signals individually. In addition, the SWA features showed to obtain a better performance on drowsiness prediction when compared to the ECG features on both of the approaches. Despite of this, the lack of data available and the imbalanced between classes and per person interfered on the performance of the models, for both of the approaches.

5.2 Future Work

Regarding this, as future work, it would be important to implement the algorithms described but use a bigger database or to produce augmented data with the database available. In fact, the lack of amount of data damages the training of the models. In addition, in the case of having more data available, deep learning approaches could also be a great improvement on this type of problem. Apart from this, it would be interesting to search for more relevant features and also explore more Machine Learning approaches. Additionally, a fusion between the two approaches, using the absolute value of the scale and the relative scale, would be very interesting, as in a real application it is important to predict the tendency of the driver to be on a drowsy state and the intensity of the fatigue. As an example, the state of passing from "3" to "5" on the KSS scale is very different from passing from "4" to "7", as it is much more dangerous to be highly drowsy than passing from a normal state to a state of a bit more drowsy than the usual. Finally, it would be important to test the algorithms on real data, for example, in the case of ECG, it was important to test on non-intrusive ECG acquisition data, as it will have much noise that will probably make the task more difficult.

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