Enhancing Driver Monitoring Systems using Peripheral Cardiac Signals

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Abstract

Current trends in semi-autonomous driving and Advanced Driver Assistance Systems (ADAS) place the driver's state in a spotlight, giving rise to the field of Advanced Driver Monitoring Assistance Systems (ADMAS). Most implemented systems rely on vehicle parameters such as lane position, lateral acceleration, and steering wheel behavior, addressing situations created by specific states (e.g., inattentiveness or extreme drowsiness). However, they are not typically able to predict events in advance. As a preventive feature, analysis of physiological signals, such as Heart Rate Variability (HRV), can provide the insight needed. On the other hand, standard methods to acquire such signals are too invasive for a comfortable driving environment, as they normally require the use of chest straps.

This work investigates the feasibility of using Peripheral Cardiac Signals as sources of inter-beat intervals (IBIs) for HRV analysis. Specifically, it explores both wrist-based Photoplethysmography (PPG) and off-the-person Electrocardiography (ECG) as non-invasive cardiac sensing methods, as well as the interchangeability of these systems with gold standard chest straps, to create a flexible framework for drowsiness detection.

A driving simulator was prepared to record sessions on a highway setup. Three different types of sensors were used simultaneously: a chest band (Movesense, ECG with sampling frequency of 512Hz), a wristband (PulseOn, PPG at 25Hz), and a steering wheel with conductive surface (Cardiowheel, ECG at 1000Hz). Simulation sessions involved 8 volunteers, each participating in two half-hour drives.

Using the collected data, similarity of HRV features across Peripheral Cardiac Signals was calculated to evaluate their equivalency and potential use of such acquisition devices.

A positive outcome was obtained, as most features showed acceptable levels of similarity (>0.6) and low levels of error (<0.1), and the poorly performing features reflect the effects that time uncertainty and temporary signal loss have in very short-term time domain features.

Keywords: Driver State Monitoring; Advanced Driver Assistance Systems (ADAS); Heart Rate Variability (HRV); Peripheral Cardiac Signals.

1 Introduction

Current trends in semi-autonomous driving and Advanced Driver Assistance Systems (ADAS) place the driver's state in a spotlight, which allows for the adjustment of vehicle performance and behavior, giving rise to the field of Advanced Driver Monitoring Assistance Systems (ADMAS) [1]. Given their easy implementation, and the fact that most necessary sensors are already included in modern vehicles, most systems designed to give insight on driver's state rely on features such as lane position, lateral acceleration, and steering wheel behavior. However, these features only show significant deviations from baseline when driver states like distraction and fatigue have already set in. This limits the benefits that such systems can have, as they can only be used to manage a potentially dangerous driver state instead of preventing it.

Physiological signals, on the other hand, reflect the internal state of the individual and can provide information on changes in their alertness/drowsiness states before external manifestations occur. This difference allows biosignal-based solutions to work on prevention rather than management of potentially dangerous driver situations. Various signals have been proved to carry such information, namely the Electroencephalogram (EEG) and Heart Rate Variability (HRV) [2] [3].

EEG is the signal obtained by measuring the electrical fields produced by action potentials generated by neurons in the brain. Gold-standard devices to acquire it involve a matrix of several electrodes distributed throughout the scalp. Although this signal is strongly correlated with cognitive load, alertness and drowsiness onsets, the apparatus needed to perform an EEG acquisition is too complex and intrusive, besides requiring specialized technical knowledge to properly place the sensors.

HRV is a set of indicators derived from the analysis of the time intervals between heart beats, called Inter-Beat Intervals (IBI)s [3]. These intervals are modulated by the balance between sympathetic and parasympathetic system contributions, and so its variability reflects the dynamics of that same balance [4]. IBIs are commonly obtained by detecting R peaks in an Electrocardiogram (ECG) and measuring the time difference between each consecutive pair. From the sequence of IBIs, different features can be derived, which can be divided into three main categories: time domain, frequency domain, and non-linear domain. This categorization determines the process used to calculate each set of features: statistical description of the interval values, analysis of its frequency components, or chaos related metrics, *i.e.,* self-similarity and complexity of the time series of intervals, respectively.

While traditional methods to obtain ECG are also intrusive and complex, with several electrodes placed across the chest, more user-friendly alternatives can be found, such as chest bands and even off-the-person ECG sensors, of which the Cardiowheel is an example [5]. Additionally, cardiac rhythm can also be obtained from Photoplethysmography (PPG) [6], which uses the optical properties of hemoglobulin to detect the passage of blood on arteries and is increasingly present in consumer electronics products such as smartwatches and fitness wristbands. This enlarges the set of options from which to measure cardiac rhythm using non-intrusive sensors. This set, off-the-person ECG [7] and PPG, is hereinafter referred to as Peripheral Cardiac Signals.

Having a diverse set of devices capable of providing cardiac rhythm information, and thus derive HRV, accelerates the implementation of biosignal-based systems for driver state monitoring, as it provides car manufacturers and drivers with the choice of what better suits their product or their utilization of the vehicle. Furthermore, if all sensors are proven equivalent, development of solutions to interpret these signals can be made to be agnostic to the specific sensor used in each case, and thus be universally distributed.

This work focuses on this last point, addressing the question whether IBIs obtained from different sensors provide equivalent information. To test this, a driving simulator was used to collect data from drivers, performing simultaneous acquisition with three different sensors: a chest strap, an off-the person sensor (both recording ECG) and a wristband (measuring PPG). From these signals, IBI sequences were obtained and HRV features were derived in windows of two minutes. At last, the resulting features were compared to investigate their similarity across devices.

The pursuit of these questions was prompt by the participation on a large-scale naturalistic driving project, the i-DREAMS [8], where the ability to measure driver's state through HRV is a necessity to build its coping capacity dimension, *i.e.,* the modelling of how well a driver can adapt to the task at hands.

2 Methodology

2.1 Experimental Setup

For this work, the experimental sessions were conducted on a driving simulator developed by CardioID under the scope of the AUTOMOTIVE project **[9]**. This simulator, intended to showcase the company's technology and provide an environment for data collection and further development, consists of two urban scenarios and one highway connecting them, where drivers manipulate a vehicle through a steering wheel and a set of pedals (accelerator and brake). The simulated vehicle had an automatic gear shift so that participants did not have to control that variable and could keep both hands on the steering wheel for the duration of the driving session.

By having the highway being parametrized and procedurally generated, it was possible to customize travelled distance and road geometry complexity for this set of measurements. Specifically, the highway was set to have 30km, with very simple road geometry, *i.e.,* curves demanding a maximum of 5 degrees of wheel turn, and cars coexisting in the same road only during the first 5 kilometers, with a speed set to 50km/h. This design was chosen to set an alertness incentive at the beginning of the experiment and, after the first five kilometers, to promote drowsiness through cognitive underload. By asking subjects to maintain a constant speed of 60km/h throughout the session, it was guaranteed that they had initial interactions with the other vehicles and had to overtake them to continue their trip.

Throughout the sessions, subjects were instrumented with three different devices to measure their heart rate and subsequently derive HRV features: the Cardiowheel, installed in the simulator's steering wheel, which directly outputted IBI values; the Movesense, a chest band that measures lead I ECG directly in the chest with a sampling frequency of 512Hz; and the PulseOn OHR, a wristband with a PPG sensor, measuring this signal at 25Hz. Figure 1 shows the three devices and their placement on the test subjects.

Figure 1 Placement of sensors: Cardiowheel (left), Movesense (center), PulseOn (right).

Each driving sessions consisted of 30-minute drives through the highway connecting the two cities in the simulation. Participants were asked to perform two sessions, one in the morning and another later in the day to promote different baseline alertness/drowsiness states. For all sessions, subjects were informed that they should not drink coffee, energetic drinks or consume any type of alcohol. They were also briefed before their first session about the experiment objectives and the data being collected, signing an informed consent form. Finally, they were instructed to drive at a constant speed of 60km/h, keep both hands on the wheel, follow the rightmost lane every time it was possible and follow normal driving rules, *i.e.,* not crossing to the other side of the highway, collide with other vehicles, etc.

2.2 Data Processing and HRV Derivation

While Cardiowheel provided the IBI values, both Movesense and PulseOn returned a signal that needed processing before those values were obtained. The ECG coming from Movesense was already filtered, thus IBI values were obtained by detecting the R-peaks using the Pan-Tompkins method and calculating the time difference between successive peaks. PPG signal obtained with PulseOn was firstly filtered using the filter described in **[10]** and its systolic peaks detected using the adaptive threshold method described in **[10]**. By computing the difference between those peaks, this third set of IBI values is obtained.

Table 1 HRV features evaluated.

Domain	Feature	Description
Time	mHR	Mean of instantaneous heart rates.
	sdNN	Standard deviation of normal beats (heart rates between 30 and 180bpms).
	sdSD	Standard deviation of successive time differences.
	RMSSD	Root mean square of successive time differences.
	NN50	Number of successive beats that differ more than 50ms.
	pNN50	Proportion of successive beats that differ more than 50ms.
	NN20	Number of successive beats that differ more than 20ms.
	pNN20	Proportion of successive beats that differ more than 50ms.
Frequency	HF	High frequency component (0.15 – 0.4Hz).
	TF	Total spectral power.
	nuHF	Normalized high frequency component (0.15 – 0.4Hz).
	nuLF	Normalized low frequency component (0.015 – 0.15Hz).
	L2HF	Ratio between Low and High frequency components.
Non-Linear	SD2	Second component of Pointcaré plot covariance.
	DFAalpha1	α1 component of Detrended Fluctuation Analysis.

To mitigate the effects of faulty peaks, the three sequences of IBIs were corrected using the method described in **[10]**, a conservative approach to IBI correction, which, by assuming a limited range of variation between successive IBIs, can detect and correct both missed peak detections (abnormally long IBIs) and false peak detections (abnormally short IBIs).

Having the sets of corrected IBIs for each session, HRV features were calculated for each 2-minute window with 50% overlapping. Table 1 describes the features evaluated. Based on **[10]**, only the features that showed relevant performance to detect drowsiness within the time frame of 2 minutes were tested in this work.

2.3 Comparison of HRV Features

For each feature, three different pairs of comparison were defined: Movesense–Cardiowheel, Movesense–PulseOn and Cardiowheel–PulseOn. Each pair was evaluated using a set of similarity or error metrics, namely:

Cosine Similarity

$$S(f1, f2) = \frac{\langle f1, f2 \rangle}{\|f1\| \times \|f2\|} \tag{1}$$

Root Mean Squared Error

$$E(f1, f2) = \sqrt{\frac{\sum_{i=1}^{n}(f1_i - f2_i)^2}{n}} \tag{2}$$

Normalized Root Mean Squared Error

$$E(f1, f2) = \frac{\sqrt{\frac{\sum_{i=1}^{n}(f1_i - f2_i)^2}{n}}}{\max(f1) - \min(f1)} \tag{3}$$

Root Mean Square Similarity

$$S(f1, f2) = \sqrt{\frac{\sum_{i=1}^{n}\left(1 - \frac{|f1_i - f2_i|}{|f1_i| + |f2_i|}\right)}{n}} \tag{4}$$

Equations (1-4) define the metrics used, where S and E relate to metrics of Similarity and Error respectively, f1 and f2 correspond to the feature vectors being compared, and their subscripted version corresponds to the i-th entry of that vector.

3 Analysis and Results

In this experiment, 16 sessions were recorded, two for each of 8 subjects (7 males and 1 female). This population was characterized by ages 33.42 +/- 10.90, each participant with more than 4 years of driving experience.

The results of computing the descripted metrics for all features are presented in Tables Table **2**, Table **3**, and Table **4**, which aggregate features from each of the three domains: time, frequency, and non-linear respectively.

Time domain features, Table 2, present overall very high similarity between all sources, except for *sdNN*, *sdSD* and *RMSSD*, which have low cosine similarities and higher normalized RMSE. It is also noteworthy that in these cases, the pairs that perform particularly poorly are the ones involving Cardiowheel, with the normalized RMSE being highest when comparing the Cardiowheel with PulseOn, the two non-intrusive sensors.

Regarding frequency domain features, Table 3, normalized high and low frequency components, as well as the ratio between the two, present RMSS very close to 1.0 and normalized RMSE bellow 0.1 across all pairs. This suggests high levels of proximity between the features produced by different source signals. In these features, cosine similarity also points to some degree of equivalence across signals, however, while the Movesense–PulseOn pair presents values very close to 1.0, the pairs involving Cardiowheel see that metric reduced to around 0.5 in the normalized low frequency component and *L2HF*. High frequency and total spectrum power have lower similarities and higher error than the other frequency domain features. In particular, the Cardiowheel–PulseOn pair has a cosine similarity close to 0.2 in both features, suggesting no relevant similarity, and the pair Movesense–Cardiowheel has a normalized RMSE above 0.5, also indicating a significative difference between these features when obtained from different sources.

Table 2 Results for time domain features.

Feature	Pair	Cosine Similarity	RMSE	Normalized RMSE	RMSSimilarity
mHR	Movesense – Cardiowheel	0,958387	1,066298	0,014459	0,945729
	Movesense – PulseOn	0,978380	0,773849	0,010493	0,960405
	Cardiowheel – PulseOn	0,939877	1,268887	0,018433	0,930115
sdNN	Movesense – Cardiowheel	0,203325	0,016876	0,2672329	0,726198
	Movesense – PulseOn	0,542674	0,009089	0,1439350	0,703759
	Cardiowheel – PulseOn	0,215653	0,016236	0,933386	0,649901
sdSD	Movesense – Cardiowheel	0,289917	0,015607	0,357587	0,675396
	Movesense – PulseOn	0,530272	0,008722	0,199838	0,67017
	Cardiowheel – PulseOn	0,233871	0,015815	1,477078	0,630129
RMSSD	Movesense – Cardiowheel	0,289713	0,015593	0,359581	0,675400
	Movesense – PulseOn	0,530272	0,008704	0,200714	0,670122
	Cardiowheel – PulseOn	0,233364	0,015800	1,552089	0,630512
NN50	Movesense – Cardiowheel	0,749212	1,417968	0,05082	0,63465
	Movesense – PulseOn	0,780969	1,540242	0,055202	0,699453
	Cardiowheel - PulseOn	0,916018	0,994277	0,026706	0,754901
pNN50	Movesense – Cardiowheel	0,467594	0,020196	0,107627	0,648427
	Movesense – PulseOn	0,637097	0,01678	0,089422	0,670803
	Cardiowheel – PulseOn	0,648511	0,018096	0,084206	0,751066
NN20	Movesense – Cardiowheel	0,837069	2,206398	0,03532	0,727669
	Movesense – PulseOn	0,935737	1,672681	0,026777	0,813197
	Cardiowheel – PulseOn	0,923399	1,677352	0,023067	0,828699
pNN20	Movesense – Cardiowheel	0,691023	0,02452	0,056349	0,756558
	Movesense – PulseOn	0,846615	0,018224	0,04188	0,793279
	Cardiowheel – PulseOn	0,802769	0,021226	0,043277	0,872096

At last, referring to non-linear domain features, Table 4, the α_1 component of Detrended Fluctuation Analysis presents values of cosine similarity and similarity close to one and low errors, while the *SD2* component of Pointcaré plot has lower values of cosine similarity, with the pairs that include Cardiowheel reaching values around 0.2 for this metric. In this feature, RMSE is also increased, however, the decrease in RMSS is not as evident as in other cases where cosine similarity and normalized RMSE suggested a significative difference.

Table 3 Results for frequency domain features.

Feature	Pair	Cosine Similarity	RMSE	Normalized RMSE	RMSSimilarity
HF	Movesense – Cardiowheel	0,40654	0,013265	0,527108	0,553828
	Movesense – PulseOn	0,612903	0,006506	0,258531	0,575903
	Cardiowheel – PulseOn	0,275265	0,013898	0,172965	0,48963
TF	Movesense – Cardiowheel	0,403181	0,013297	0,545524	0,554915
	Movesense – PulseOn	0,611312	0,00652	0,267489	0,572869
	Cardiowheel – PulseOn	0,273191	0,013915	0,175973	0,48979
nuHF	Movesense – Cardiowheel	0,81655	0,022791	0,033073	0,940106
	Movesense – PulseOn	0,952292	0,016596	0,016596	0,968696
	Cardiowheel – PulseOn	0,796512	0,039996	0,039996	0,935895
nuLF	Movesense – Cardiowheel	0,510887	0,017098	0,074342	0,897524
	Movesense – PulseOn	0,835513	0,008503	0,03697	0,926742
	Cardiowheel – PulseOn	0,437627	0,017811	0,120265	0,891558
L2HF	Movesense – Cardiowheel	0,587397	0,018956	0,058385	0,875981
	Movesense – PulseOn	0,87113	0,009712	0,029914	0,905664
	Cardiowheel – PulseOn	0,533638	0,019627	0,085455	0,869662

Table 4 Results for non-linear domain features.

Feature	Pair	Cosine Similarity	RMSE	Normalized RMSE	RMSSimilarity
SD2	Movesense – Cardiowheel	0,172544	0,018242	0,208453	0,741036
	Movesense – PulseOn	0,53606	0,010226	0,116857	0,715625
	Cardiowheel – PulseOn	0,226707	0,01711	0,434034	0,658692
DFAalpha1	Movesense – Cardiowheel	0,783841	0,031933	0,035119	0,86737
	Movesense – PulseOn	0,94096	0,016776	0,01838	0,889121
	Cardiowheel – PulseOn	0,76454	0,030981	0,045591	0,863951

4 Discussion

Out of the 15 analyzed features, 9 present similarity values that indicate the feasibility of using any of the three different sources to derive heart rate variability with equivalent results. However, the remaining 6 need further discussion, as the results indicate an obstacle to seamless interchange between sensor devices for a HRV based drowsiness detection system.

For time domain features, the ones with lowest performance were *sdNN*, *sdSD* and *RMSSD*, all of them particularly sensitive to the precision of each measured IBI. This precision is the factor that is most affected when switching devices and we can identify two reasons for this. Firstly, by changing device, sampling frequency of the base physiological signal (ECG or PPG) is changed. This way, having devices with sampling frequencies 1kHz, 512Hz and 25Hz, the uncertainty associated with measuring a given IBI is, respectively 1ms, 2ms and 40ms. Furthermore, the fact that the ECG detected by the Cardiowheel depends on constant and symmetric contact of both hands on the steering wheel makes it the source most likely to have signal loss during sessions. When possible, detected segments with missed signal have IBIs interpolated to try to minimize the impacts of missing beats for such short-term HRV analysis. This reconstruction introduces an error that, depending on the duration of signal loss moments, can greatly surpass the uncertainties described previously.

The points described in the last paragraph also fit as an explanation for the poorer performance of features like high frequency component and *SD2*, that are affected by, respectively, very short-term fluctuations in IBI values, and differences between successive IBIs.

Regarding the results of total spectrum energy, *TF*, it is important to acknowledge the resemblance between this feature's results and the ones from *HF*. This similarity suggests that differences between *TF* estimations from different sources are mainly guided by changes in high frequency components, again adding evidence to the proposition that local uncertainty and reconstruction error are in the origin of this feature's dissimilarity across devices.

Finally, the fact that worst cases are pairs where Cardiowheel is involved leads to the claim that reconstruction error is more relevant than time resolution. This is especially relevant to establish that, even having an uncertainty of 40ms when estimating IBIs, devices measuring PPG at sampling frequencies as low as 25Hz are not to be discarded as alternatives to cardiac rhythm sensors for driver drowsiness detection applications.

5 Conclusions

This work aimed to make a first step into the research of HRV-based driver drowsiness detection systems capable of obtaining data from any source of cardiac rhythm information. To do so, three different devices were used in simulated driving sessions: a chest band and a steering wheel capable of measuring ECG, and a wristband measuring PPG.

By measuring similarity and error between HRV features derived from these sources, a positive outcome was obtained, as most features showed acceptable levels of similarity (>0.6) and low levels of error (<0.1). However, some aspects must be taken into consideration when using this equivalency, namely that features related to very short-term variations, such as ones dealing with successive IBIs and high frequency components, are the most affected by imprecisions in IBI estimation and reconstruction in case of signal loss; and that signal loss is the most powerful source of dissimilarity.

These results show that all three sensors are potentially usable in the context of drowsiness detection, presenting a trade-off between signal quality and convenience of use. While chest straps are without any doubt the sensor type that provides signal with better quality and robustness, it must be voluntarily worn by the drivers each day. As a middle ground, smart watches and wristbands provide a wearable with high population penetration. Yet, these wearables are considered a fashion choice, and some drivers might not adhere to it. The steering-wheel form factor of the CardioWheel guarantees the presence of the sensor in all drives and demands no alteration on drivers daily actions and fashion choices but needs to successfully identify segments of time where incorrect contact with the sensor is made. Overall, the authors see the results of this study as supporting a future where different drivers select the sensor type that better suits their habits, style and needs, but more importantly, where this trade-off between signal quality and convenience of use does not compromise the implementation of drowsiness detection based on HRV analysis in any point of its range.

To solidify the insight gained during this work, future work must be developed. Similar sessions must be conducted on a larger population, one that better equalizes gender distribution and covers a wider age range. Also, an analysis must be conducted to determine a threshold of missing signal proportion from which HRV analysis is blocked, to minimize the errors created by excessive reconstruction. Furthermore, collection of such data would allow the investigation of which HRV features are relevant for drowsiness detection.

A future step that should also be taken is to evaluate the effect of changing the device on drowsiness detection coherence, *i.e.,* to collect HRV data with different devices in driving sessions and have drowsiness levels annotated.
Machine learning models could then be built using the reference data source, i.e., ECG measured directly in the chest, and the collected drowsiness state annotations. The agreement between this model's predictions on reference device data and other devices' data should be measured to determine whether a sensor agnostic drowsiness detection system can exist, and the impacts that the type of sensor has on its performance.

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