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Enhancing Driver Monitoring Systems using Peripheral Cardiac Signals

Lourenço A. Rodrigues, Pedro Costa, Carlos Carreiras, Ana Fred, André Lourenço

cardioid HEARTMETRICS EXPERTS
TÉCNICO LISBOA

Presented By: Carlos Carreiras
CTO, CardioID

Outline

- Introduction

- Methods
  - Data acquisition
  - Experimental setup
  - Comparison metrics

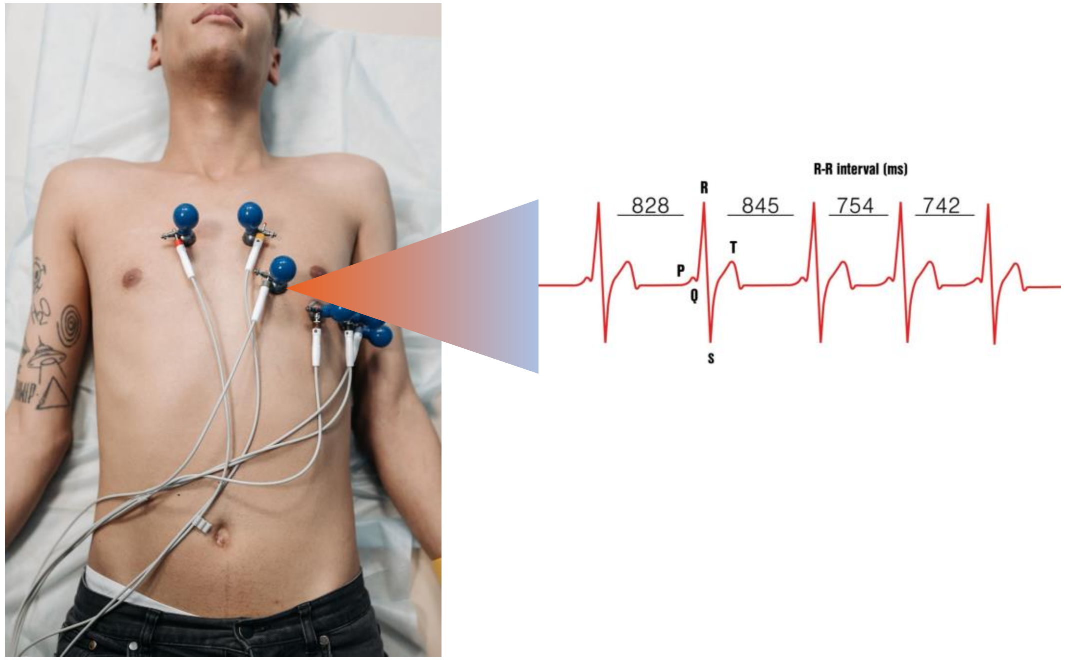
- Results
- Conclusions

Introduction

- The driver is pulled to the spotlight of ADAS, giving rise to Advanced Driver Monitoring Assistance Systems (ADMAS).
- Driver state recognition is crucial for behavior adjustments.
- Most current ADMAS rely on indirect observations, through vehicle sensors.

Photo by JESHOOTS.com: https://www.pexels.com/photo/man-inside-vehicle-13861/ (edited).

Introduction



Electroencephalogram

Balance between α and β waves is a strong indicator of drowsiness onset.

Heart Rate Variability

Dynamics of heart rhythm are modulated by the autonomous nervous system.

Stock photo provided by Instituto de Telecomunicações

Photo by Pavel Danilyuk on Pexels

Introduction

Peripheral Cardiac Signals

Set of biosignals that contain information on cardiac rhythm but are acquired through minimally intrusive sensors.

PCS offer clear advantages in terms of ease of use and adhesion by potential users, but is the HRV analysis derived from these signals equivalent to that of conventional systems?

Methods: Data Acquisition

Movessense Chest Band

Lead I ECG @ 512Hz

CardioWheel

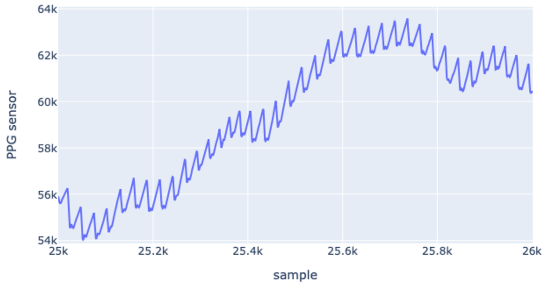
Lead I ECG @ 1000Hz

Pulseon Wrist Band

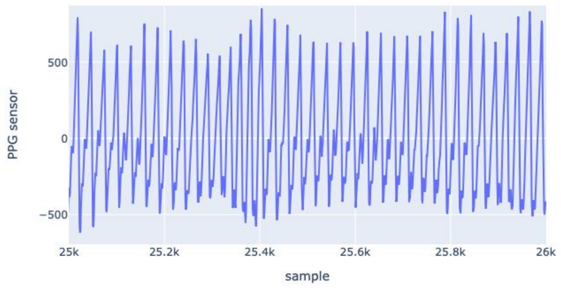
Wrist PPG wave @ 25Hz

Methods: Data Acquisition

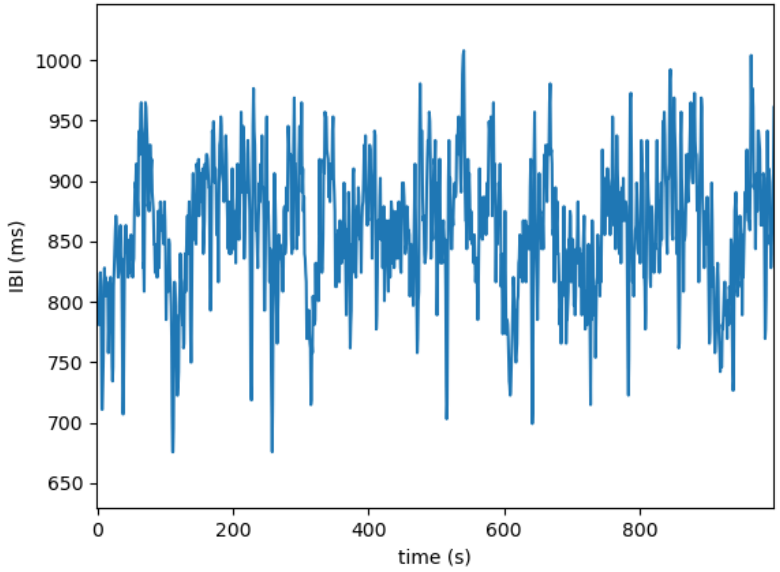
PulseOn



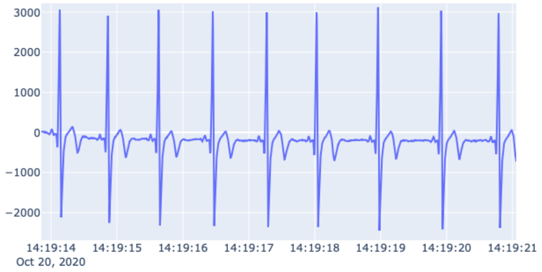
Filtering



Peak detection



Movesense



Directly outputted IBIs

CardioWheel

Methods: Experimental Setup

- 30-minute drive x2 (alert and drowsy sessions)
- Drivers had to follow normal road norms, and maintain an average speed of 60km/h.
- Road was procedurally generated.
- The first 5km had other cars in the road that drivers had to overtake.

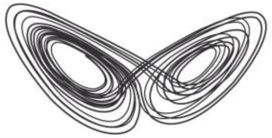
Methods: Comparison Metrics

mHR sdNN sdSD RMSSD

NN50 pNN50 NN20 pNN20

HF nuHF TF

L2HF nuLF



SD2 DFA $\boldsymbol{\alpha_1}$

Cosine Similarity

$$S(f_1, f_2) = \frac{\langle f_1, f_2 \rangle}{\|f_1\| \times \|f_2\|}$$

Root Mean Squared Similarity

$$\mathrm{S}(f_1, f_2) = \sqrt{\frac{\sum_{i=1}^{n}\left(1 - \frac{\left|{f_1}_i - {f_2}_i\right|}{\left|{f_1}_i\right| + \left|{f_2}_i\right|}\right)}{n}}$$

Root Mean Squared Error

$$\mathrm{E}(f_1, f_2) = \sqrt{\frac{\sum_{i=1}^{n}({f_1}_i - {f_2}_i)^2}{n}}$$

Normalized Root Mean Squared Error

$$\mathrm{E}(f_1, f_2) = \frac{\sqrt{\frac{\sum_{i=1}^{n}({f_1}_i - {f_2}_i)^2}{n}}}{\max(f_1) - \min(f_2)}$$

Results

8 subjects recruited (1 female)

Ages 33.4 ± 10.9

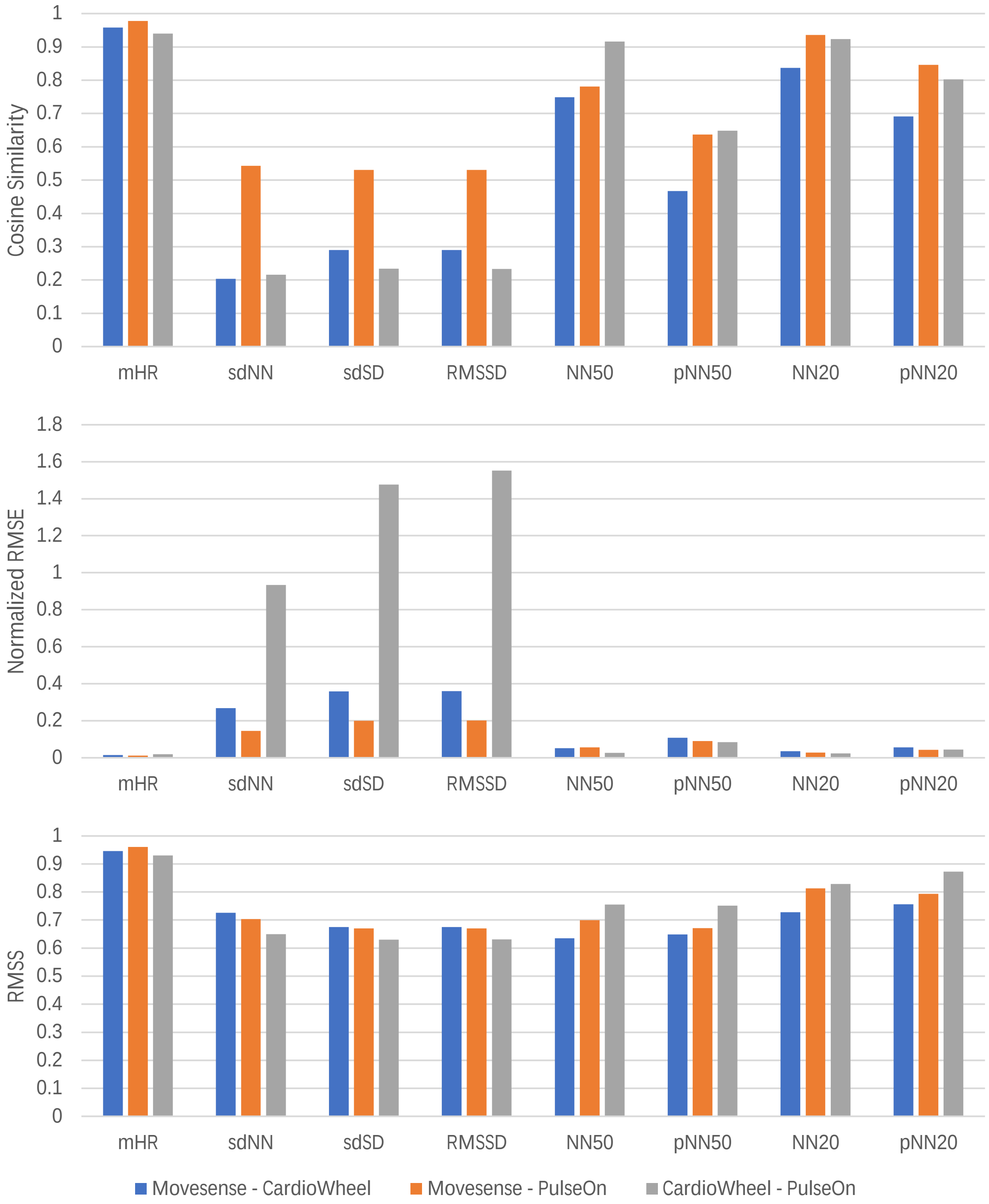
More than 4 years of driving experience

16 sessions

8 hours of data from each device

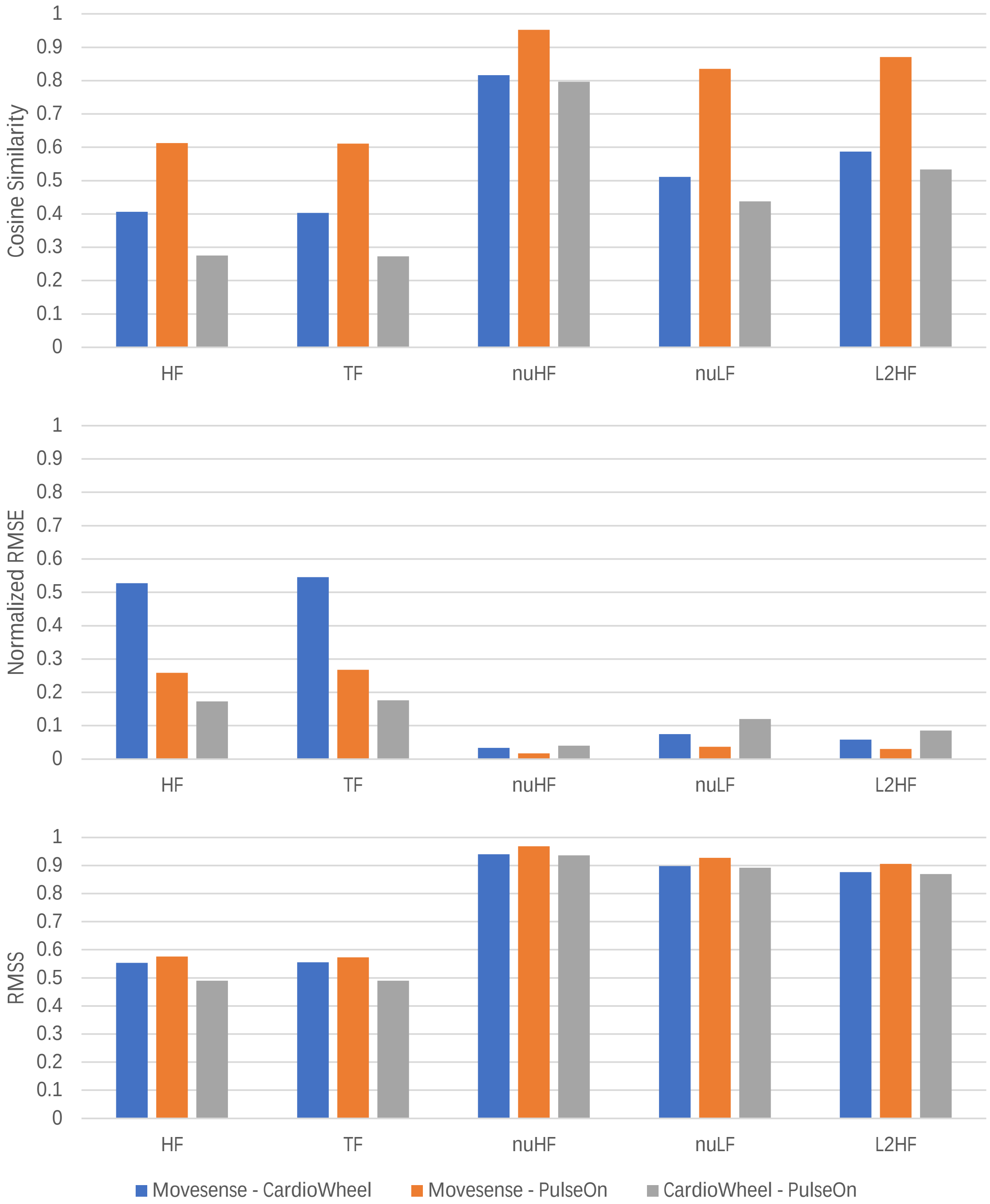
Results

Time Domain Features

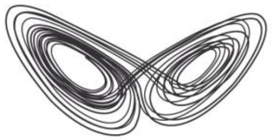


Results

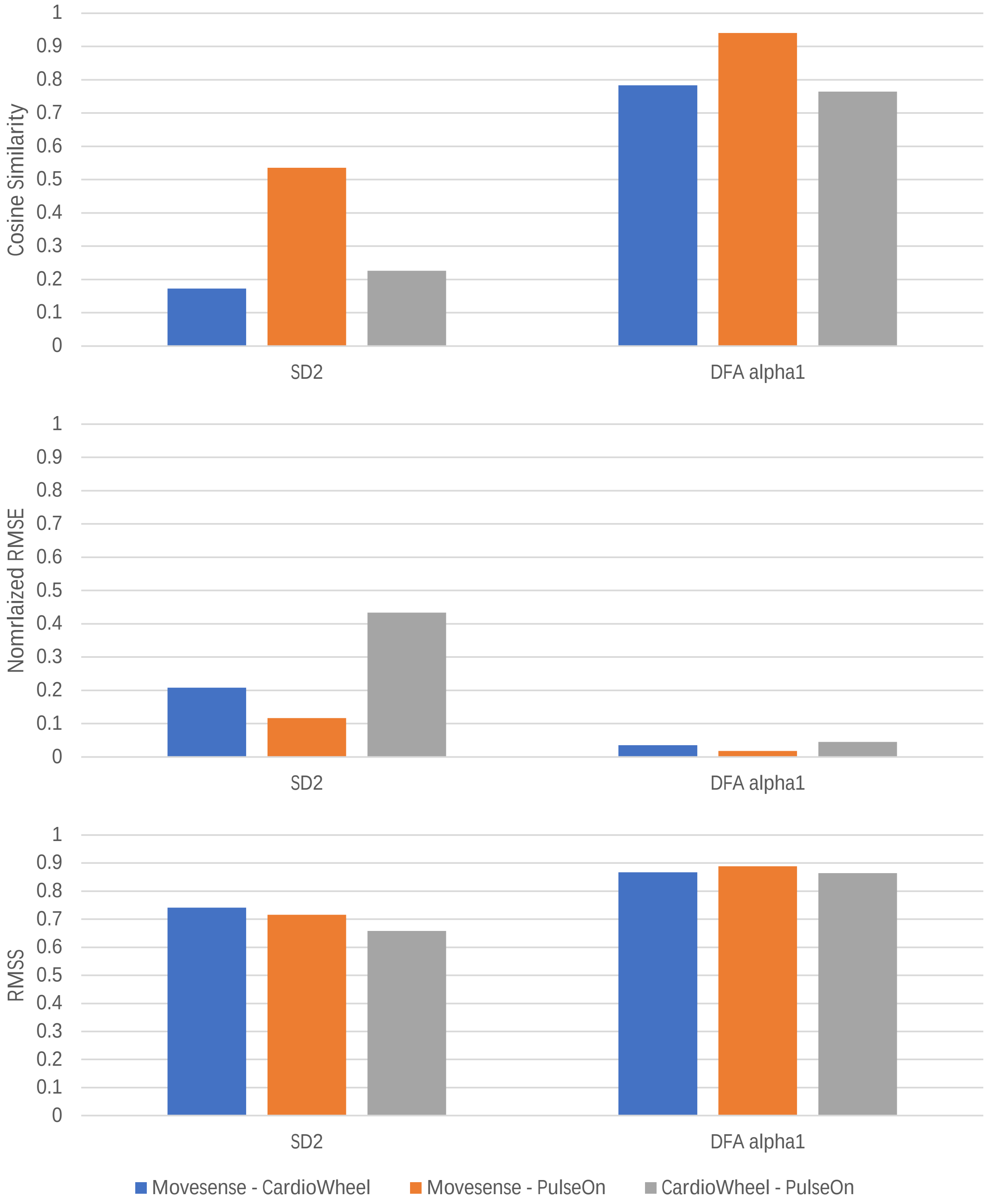
Frequency Domain Features



Results



Non-Linear Domain Features



Conclusions

- 9 out of 15 features presented high levels of agreement between devices.
- Features with lower performance are associated with short-term fluctuations and precise point measurements of IBIs.
- Changing devices, and the sampling frequency used, changes the uncertainty of measured IBIs.
- Signal loss is the major source of inter-device HRV disagreement.

Conclusions

- Peripheral Cardiac Signal integration for driver monitoring shows potential as a platform for a sensor agnostic system.

- While a high temporal resolution is advantageous, filtering out for signal loss segments is the most crucial step to ensure the validity of HRV features calculated.

Future Work