Detecting Stressful Driving Situations Using Wearable PPG Sensors: A Case Study

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Abstract. Stress remains a key issue in long-distance driving, where prolonged periods behind the wheel can lead to fatigue, reduced attention, and increased risk of accidents. This study explores an approach for detecting potentially stressful situations using pulse rate variability (PRV) metrics extracted from photoplethysmography (PPG) signals. Data gathering involved PPG signals with video recordings for validation. After applying a Min–Max standardization to align individual differences, a Z-score method flagged outliers whenever the values of the PRV parameters deviated more than three standard deviations from the mean. Events were only considered if these outliers persisted for at least one second, reducing the impact of brief fluctuations not related to genuine stress. To make the results more interpretable, outliers occurring within three seconds of each other were merged into single episodes. This process provided a clearer picture of sustained stress, rather than isolated spikes. A final comparison with video footage confirmed that many flagged intervals corresponded to visibly tense driver reactions or challenging driving conditions, suggesting a reasonable alignment between physiological data and observable stress cues. In general, the findings highlight the importance of combining PPG-based PRV measurements, time-based outlier clustering, and video validation to detect moments of elevated stress. This integrated methodology has potential in applications such as advanced driver assistance systems, driver training programs, and other interventions aimed at improving safety and reducing risk on long journeys.

Keywords: PPG · photoplethysmography · Stress Detection · PRV Analysis · HRV Analysis · Long-Distance Driving.

1 Introduction

Long-distance driving can lead to prolonged mental and physical strain on the driver, increasing the likelihood of fatigue, reduced attention, and slower reaction times [26]. Over extended periods behind the wheel, stress can accumulate and increase the risk of mistakes or accidents, placing both the driver and other road users at risk. Effective stress management during long journeys is critical for sustaining alertness, ensuring timely decisions, and maintaining overall safety on the road.

Stress is a common phenomenon that significantly affects both physical and mental well-being, including cardiac function and blood pressure. In order to accurately pinpoint stress factors, a more precise detection method is needed. Unfortunately, traditional approaches often fail to achieve satisfactory results, underscoring the importance of exploring new techniques to improve stress detection accuracy. According to [6] study, stress detection is a complex process that requires more than a single physiological signal. The article examines how various signals such as PPG, EEG, and ECG correlate with stress states. A strong correlation has been observed between cardiac indicators and stressful situations: when stress occurs, heart rate and blood pressure typically increase, whereas heart rate variability (HRV) decreases.

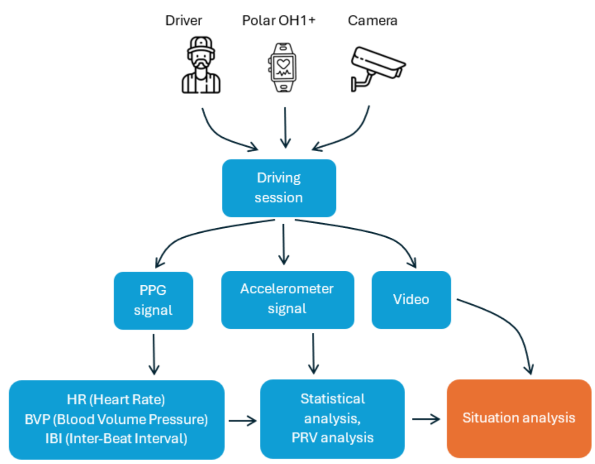

Fig. 1. A scheme of the workflow.

Additionally, pinpointing moments of unusually high stress allows these situations to be recreated in a virtual reality (VR) environment. In this controlled setting, drivers can practice coping strategies and refine their responses. This preparation can help them better manage similar circumstances in real traffic conditions. In this study to improve stress detection, the PPG signals were recorded together with accelerometer data for stress detection in long-distance driving. HRV metrics estimated from the PPG data were used to identify potential stress episodes. Each detected event was then checked against video recordings to confirm whether it matched an actual stressful moment. This approach allows more accurate stress detection by combining multiple data sources and verifying the results with real-world observations. The flowchart of this workflow is presented in Figure 1.

2 Related Work

Numerous studies support the use of heart rate variability (HRV) as an objective metric for evaluating stress. A commonly reported indicator of HRV variation is a decrease in the high-frequency band coupled with an increase in the low-frequency band [12].

While electrocardiography (ECG), which is regarded as the gold standard for HRV measurement, can be relatively intrusive, photoplethysmography (PPG) has gained attention as a promising alternative, particularly in non-medical applications. Research shows that indices of pulse rate variability (PRV) — an equivalent of HRV derived from PPG — significantly correlate with HRV derived from ECG in healthy individuals [18] [23]. Multiple studies employing PRV to detect stress induced in laboratory settings [16] [27] [1] [2] [17] or simulations [3] further corroborate these findings.

Extensive research has focused on analyzing ECG-based HRV and other physiological signals (e.g., electrodermal activity (EDA)) to assess driver stress. In the study conducted by Healey and Picard [7], a real-world driving experiment was performed in which ECG, electromyogram (EMG), skin conductance, and respiration data were recorded. The results indicated that skin conductivity and heart rate metrics exhibited the strongest correlation with driver stress levels. The dataset from this study was subsequently utilized by Munla et al. [22] and Keshan et al. [11] to explore ECG pre-processing and stress classification techniques further. Liu et al. [20] introduced an ultra-short-term HRV analysis method based on the same dataset. Moreover, HRV analysis has also been applied in the detection of fatigue. In a related study, Jiao et al. [9] [10] conducted an experiment involving urban railway transit drivers, using both HRV and electrodermal activity (EDA) to assess the drivers' fatigue and mental state changes.

Our work is primarily aligned with studies that evaluate driver stress using PRV. Lee et al. [14] introduced a wearable glove system equipped with a PPG sensor capable of accurately detecting driver stress during simulated driving conditions. Similarly, Lee et al. [13] demonstrated high accuracy in detecting drivers' emotional states—namely, relaxed, stressed, and fatigued—using earlobe PPG, upper trapezius muscle EMG, and head movement analysis.

Given that some researchers suggest a link between stress and drowsiness, we also consider studies that assess driver drowsiness. In Leng et al. [15], driver drowsiness is evaluated through a combination of features, including heart rate, PRV, respiratory rate, adjustment counter, and stress levels derived from galvanic skin response (GSR) signals. Additionally, Heydari et al. [8] identified a PRV pattern associated with the onset of sleep, indicating that PRV alone can be effectively utilized for driver drowsiness detection.

3 Data Collection

3.1 System Setups and data collection use cases

Two setups were created for data collection, both utilizing the Polar OH1+ device to capture PPG signal data. The lightweight setup employs a smartphone running the Android operating system. Figure 2 illustrates the scenario in which data collection and annotation are performed using a smartphone application. To start a driving session, the driver needs to put on the Polar OH1+ device,

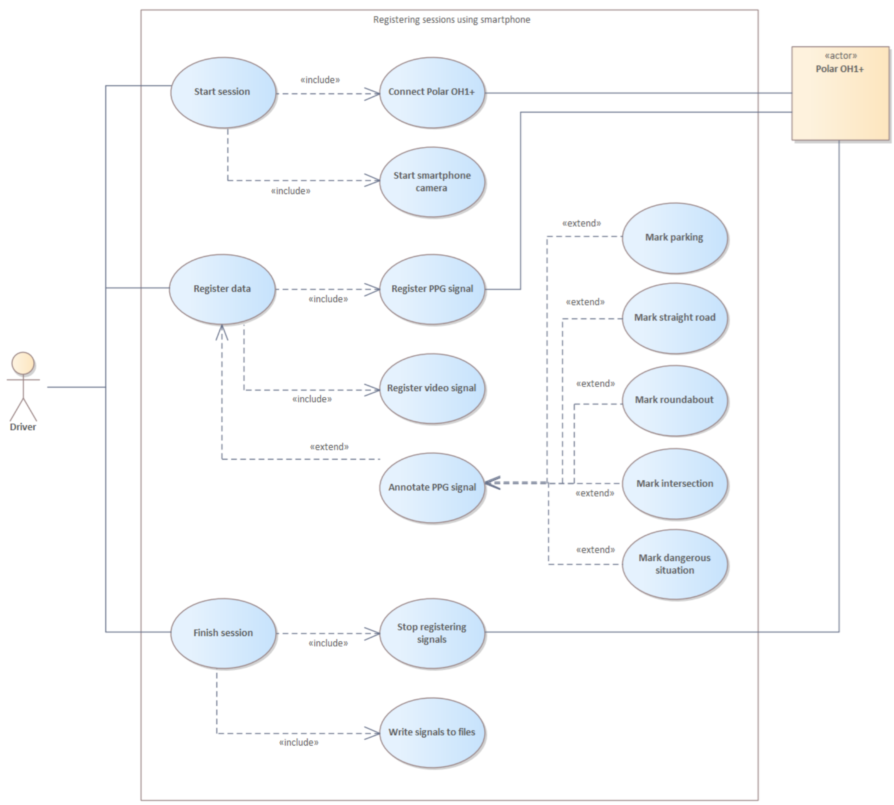

Fig. 2. Data collection and annotation using a smartphone

turn it on, and start the application. The application connects to this device and starts displaying the camera video feed. Now, the driver may click "Start session" button to start recording PPG and video signals. The application allows to perform signal annotation during the driving sessions (see section 3.2).

Another setup was designed for data collection during truck driving. A dedicated device was developed to register the PPG signal and capture the camera feed. The device includes a Raspberry Pi microcomputer and a 5G router. The Raspberry Pi collects the data and transmits it to the server via the 5G network. To ensure data security, a VPN is used for encryption.

During a focus group with expert drivers, we discovered that manual annotation is not sustainable. Therefore, this functionality was not included in the device. Figure 3 illustrates the scenario in which data collection is performed during truck driving sessions. This approach provides a solution with better us-

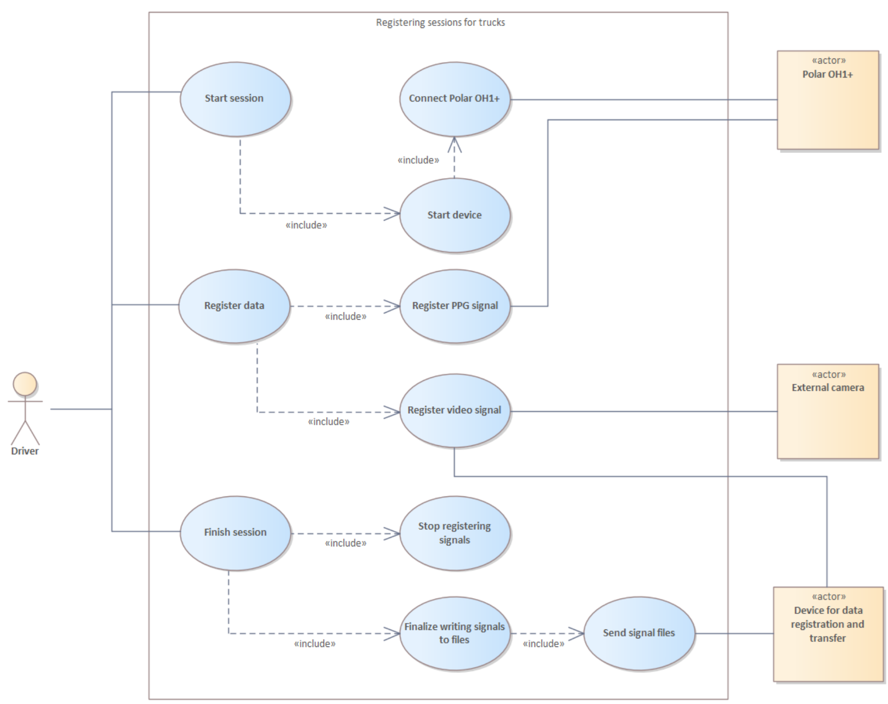

Fig. 3. Data collection for trucks

ability. The driver needs to put on the Polar OH1+ device, turn it on and push the physical button on the device to start registering data. PPG and video signal register substantial amount of data (around 700MB of video signal and 73MB for PPG signal for one hour). Therefore, the data is transferred in chunks.

3.2 Data Annotation

We used two methods for data annotation. The smartphone application supports just-in-time labelling, meaning data can be annotated in real-time during a driving session. The current driving state can be marked either by tapping the appropriate button or by using voice commands.

Initially, we tried out the manual input via buttons. However, we quickly realized that this approach is mentally demanding and can cause stress during driving, potentially leading to dangerous situations. As a result, we implemented voice command functionality:

- **initial** – indicates the standing car (driver prepares for a trip)
- **parking** – indicates the parking state (activated at the beginning and end of the trip)
- **straight** – indicates the state of driving on a straight road
- **inter** – a shortened form of “intersection”, used for better recognition; indicates intersection
- **round** – a shortened form of “roundabout”, used for better recognition; indicates roundabout
- **danger** – indicates a danger state when a traffic situation arises (e.g., lane change is blocked, honking occurs, etc.)

This approach was used for data collection and the dataset includes only the sessions annotated by using voice commands.

As mentioned before, this approach could not be applied to truck data collection. Therefore, we had to fall back on manual session labeling. We developed dedicated software to perform labelling efficiently. This software allows reviewing video footage and marking custom driving events by pressing dedicated keyboard buttons.

During further analysis, we refined the categorization of various events and situations occurring during driving sessions. The extended list of driving states (or events) is as follows:

- **lane changing** – indicates a change of lane on a road going in the same direction
- **overtaking** – indicates overtaking on a road with traffic in the opposite direction
- **roadwork** – indicates lane narrowing due to roadworks
- **accident** – indicates an accident involving another vehicle
- **stress** – indicates a subjectively assessed stressful situation caused by an unusual or unexpected event
- **other** – indicates other, previously undefined cases, which are later discussed in research team meetings

3.3 Preliminary Dataset Collected

The complete dataset comprises signals from 3,209 driving sessions, covering both data collected via the smartphone application and during truck driving sessions. However, a significant portion of the recordings are invalid and unsuitable for data analysis. Signal corruption can occur during transmission, and in some cases, the PPG signals are unusable due to improper use of the Polar OH1+ device. Out of the entire dataset, we identified 692 valid recordings suitable for data processing. From these, 476 sessions were manually labelled for further analysis.

4 Stress Estimation

4.1 Signal Quality Control

Data was recorded at around 135 Hz sampling rate, gathering PPG signals from truck drivers during long-distance trips that might include stressful situations on the road. Each recording was checked to ensure a minimum length of ten minutes, equivalent to around $10 \times 60 \times 135 = 81\,000$ samples. Recordings failing this criterion were marked as too short and excluded from analysis. Further tests were to check if every sample could be converted to a numerical type (float) and that no more than 200 samples exceeded an amplitude threshold of 1×10^7. If at least one condition was not met, the signal was flagged as invalid. This ensures high-quality data for subsequent analysis.

After signal preprocessing and outlier detection, potential stress events were matched against video recordings. In these videos, all observed stressful situations were marked together with the duration of the event. A two-minute tolerance window was applied: if a detected event coincided with a visually identified stressful situation (within two minutes), it was considered a match. This process provided a qualitative analysis that evaluated the performance of the automated detection algorithm against a human-assessed baseline.

4.2 PPG signal preprocessing and PRV computation

The average human heart rate typically lies between 0.9 and 1.7 Hz [25]. To extract pulse rate variability (PRV) from photoplethysmography (PPG) data, the signal must be processed in a way that reduces measurement errors. Although physiological factors such as breathing and vascular dynamics often appear within the 0.05–0.4 Hz range, these lower frequencies are excluded here for simplicity and to focus specifically on the PRV component.

PPG signal preprocessing and pulse recognition are performed using the NeuroKit2 [21] Python toolbox. PPG signal filtering and systolic peak detection method proposed by [4] is used, more specifically it involves 0.5-8Hz band-pass filtering with a third-order Butterworth filter, as well as artefact correction proposed by [19]. An example of such post-processed PPG signal and detected (and corrected) peaks is presented in Figure 4.

The inter-beat interval (IBI), defined as the time between consecutive heart beats, is crucial for accurate pulse rate variability (PRV) measurements. Although photoplethysmography (PPG) devices can track the IBI, they are more

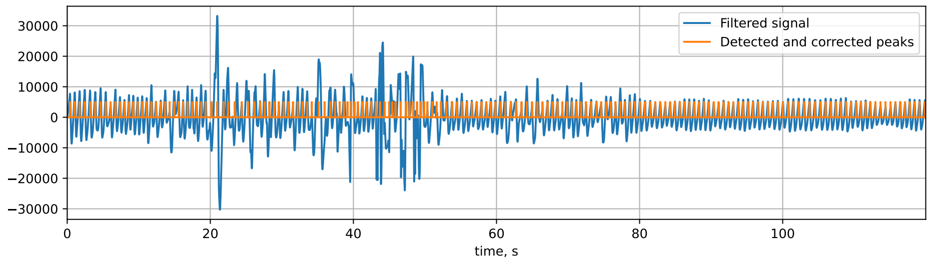

Fig. 4. An example of two minutes of filtered PPG signal with corresponding pulse peaks recognized and corrected.

sensitive to motion artifacts, ambient light interference, and missed or false beats due to contact issues, leading to reduced PRV accuracy. Nevertheless, many PPG sensors are now designed with better light shielding and improved signal processing algorithms, increasing their effectiveness for continuous PRV tracking in everyday settings [5]. They also tend to be smaller and more comfortable than electrocardiograms (ECGs), making them suitable for scenarios where a more portable or user-friendly device is needed [24].

4.3 PRV-Parameter-Correlation Based Stress Estimation

Abnormal driving situations are examined by focusing on changes in pulse rate variability (PRV) parameters. While we are dealing with PRV here, we will use "HRV" term in code and figures instead, as we are building on the NeuroKit2 [21] codebase where all the relevant methods and parameters are designated "HRV", their calculation does not depend on whether the estimated pulses come from PPG or ECG.

Special attention is given to metrics such as `HRV_SDSD`, `HRV_CVSD`, and `HRV_pNN50`, which often reveal significant shifts from typical values. These shifts have been recorded in relation to driver movements or periods of increased stress and are treated as indicators of possible deviations from a calm, stable driving state. Because the subjective experience of stress cannot be verified without driver feedback, changes introduced by body movements are also considered potential markers of abnormal conditions. Marked variations from personal baseline values are considered signals that require closer examination. Through this process, it is assessed whether stress or other factors have contributed to the observed changes. By applying this approach, a more in-depth investigation into the root causes of these changes becomes possible. Such causes may include emotional strain, driver fatigue, or various external factors.

A normalization technique is applied to address differences in PRV recordings between individuals. Parameters are centered on personal averages and adjusted according to each person's variability, which enables more precise detection of shifts from normal conditions. The risk of misclassification that is often associated with fixed thresholds is reduced by eliminating individual baselines. Observing these changes enables more focused evaluations or interventions when needed.

As a result, a clearer understanding of driving conditions can be achieved, improving overall safety.

Min-Max scaling was applied to the PRV parameters estimated from the PPG signals, transforming each metric to the [0, 1] range. The raw PPG data were then plotted to provide context for any abnormal movements or other factors that might coincide with notable shifts in the PRV metrics. Next, a Z-score approach was used to locate outliers in the PRV data, using ±3 standard deviations from the mean as a threshold. Data points beyond this threshold were marked, allowing sudden changes or anomalies to be easily identified for further analysis. The pseudocode of this methodology is presented in Algorithm 1.

Algorithm 1 Detection of abnormal situations

```
Input: hrv_param : Collection of HRV parameters
   data: dataset containing at least one lead PPG signal
   parameter: name or index of the HRV parameter to analyze
   sr: sampling rate
   ws: window size
Output: outliers: a list of data points flagged as outliers
   hrv_data ← hrv_param[parameter]
   len ← length(data)
   x ← range from (60 × sr) to len in steps of ws
   if length(hrv_data) > length(x) then
      hrv_data ← truncate hrv_data to match length(x)
   else
      x ← truncate x to match length(hrv_data)
   end if
   min_val ← minimum(hrv_data)
   max_val ← maximum(hrv_data)
   hrv_data ← (hrv_data - min_val) / (max_val - min_val)
   mean_val ← mean(hrv_data)
   std_val ← std(hrv_data)
   z_scores ← (hrv_data - mean_val) / std_val
   outliers ← |z_scores[i]| > 3
```

Potentially stressful moments were identified by monitoring a pulse rate variability (PRV) metric over time and flagging values that exceeded a statistical threshold – outliers (see examples in Figure 5). Once these points were recorded along with their timestamps, they were checked to ensure that any event of interest exceeded one second in duration. This approach helps to filter out brief, isolated fluctuations that are less likely to reflect genuine stress.

Next, a clustering method was applied to group closely spaced outliers into single events. If two or more outlier timestamps occurred within three seconds of each other, they were considered part of the same episode. The earliest timestamp in that cluster marked the event's official start time. This allows to maintain a precise record of when the stress or high intensity change first appeared.

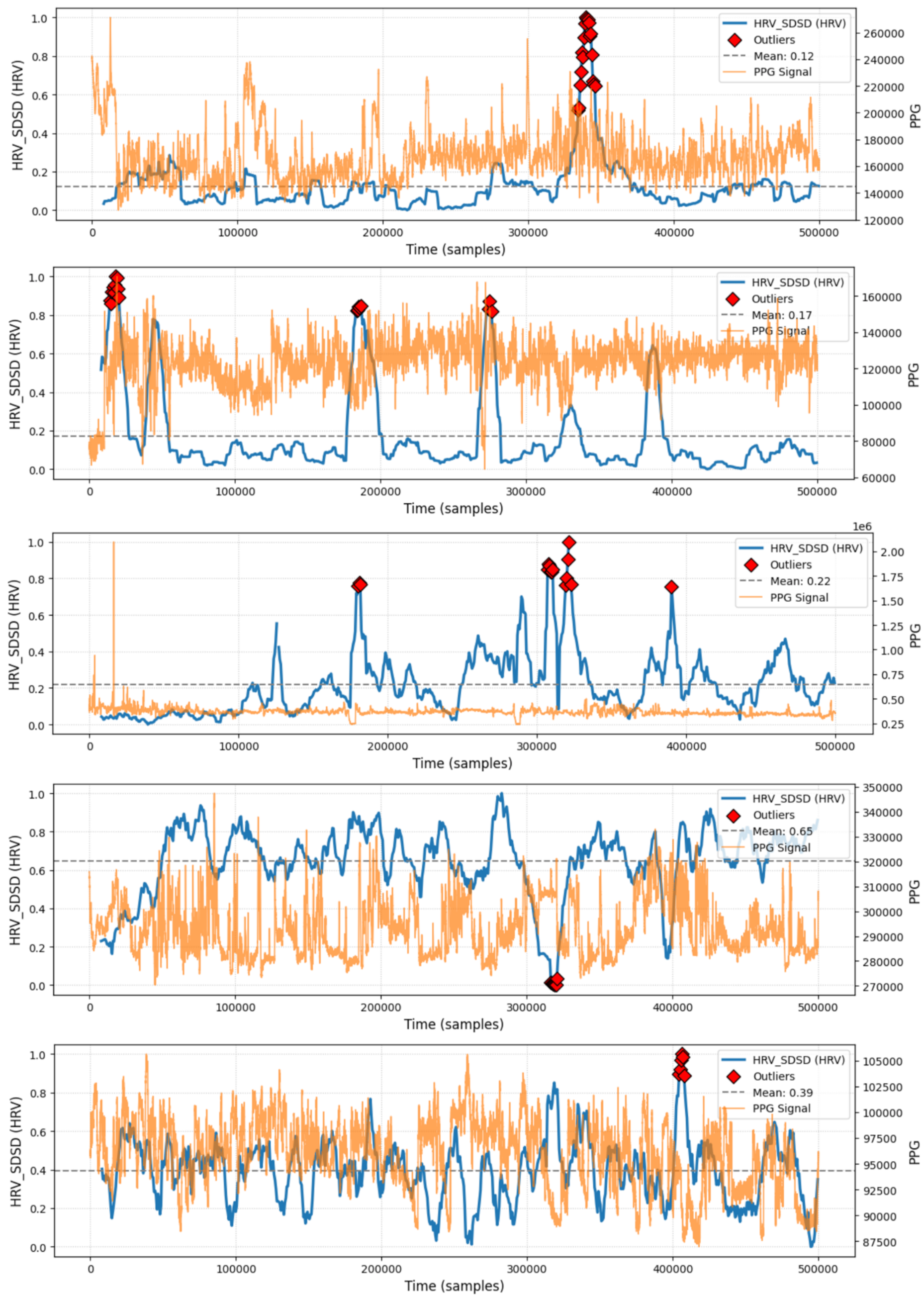

Fig. 5. PPG signals and their corresponding PRV (called HRV here) SDSD metrics examples where outliers are extracted.

By consolidating individual outliers into meaningful events, the data became more interpretable, enabling clearer identification of extended periods that may improve further investigation.

5 Discussion

The presented method relies on analyzing PRV parameters (e.g., SDSD, CVSD, pNN50) to identify abnormal states potentially linked to stress. By normalizing the data and using outlier detection, sudden changes are flagged. This clustering helps define true periods of increased stress or intense activity from less meaningful fluctuations. While the approach captures a range of significant events, it may also detect non-stressful movements, so careful interpretation is needed.

This leads to the limitation that the method does not fully differentiate between stress responses and other physical artifacts, such as driver movements, environmental or sensor noise. The system's accuracy also depends on reliable PPG recordings, which can be affected by motion or limitations in sensor contact. In addition, driver stress is subjective, and ground truth labels drawn from video review may miss subtle emotional states.

This study shows that stress-related events in driving can be identified by combining normalized PRV metrics, outlier detection, and time-based clustering. Events that last longer than one second and occur within three seconds of each other are merged, making it easier to see patterns in the data. Many of these patterns match actual behavior observed on video, suggesting that this approach is useful for detecting moments of high stress.

To enhance the robustness of stress detection, future research will explore larger and more diverse datasets. Incorporating machine learning techniques may help refine differences between stress and artifacts, leading to improved predictions. Furthermore, collecting and analyzing subjective self-report measures could deepen our understanding of how well the detected events align with each driver's experience.

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