Feasibility of Driver Monitoring for Sudden Cardiac Illness Detection

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Abstract: A relatively large proportion of fatalities on our roads are due to sudden illness in drivers, with the majority of these cases attributed to cardiovascular disease. Being able to detect and manage these sudden events could save many lives. This paper consolidates results from a literature review and three small-scale studies that investigated and developed the possibilities of detecting sudden driver illness by measuring physiological signals from cardiac activity with unobtrusive sensors including single-lead Electrocardiogram (ECG), consumer-grade pulse sensors, and research grade radar technology. In general, the experiments have shown that there is potential for the evaluated technologies to help detect and quantify cardiac illness events, but significant development is needed to implement the technologies in real-world driving. It is challenging to succeed in detecting driver states with high accuracy based on measurements of cardiac activity alone due to both individual variations in heart activity patterns and an environment that complicates measurements, and additional data from other sensors is probably needed. Physiological monitoring of drivers is challenging due to vehicle vibrations, the driver's movements and thick clothing. There is a need for further research and development of unobtrusive measurement technologies to detect driver states.

1 INTRODUCTION

A non-negligible number of deaths that occur during driving are caused by sudden illness of the driver (Halinen & Jaussi, 1994; Sjögren et al., 1996; Tervo et al., 2013). Therefore, striving towards the vision of zero traffic fatalities, the health of the driver and any sudden loss of ability to control the vehicle is an important factor to address. In most cases, the underlaying cause is related to cardiovascular disease (CVD), but other sudden pathologies such as syncope and diabetic reactions may also be of importance.

Investigations of real crash data have shown that medical conditions are a contributing factor in crash causation. In-depth at-scene investigation of 298 road crashes in the Adelaide metropolitan area in which at least one person was transported to hospital or fatally injured as a result of injuries sustained in the crash showed that a medical condition was the main causal factor in 13% of the crashes investigated (Lindsay & Baldock, 2008). Close to a third of these were cardiac-related (Lindsay & Baldock, 2008).

Moreover, studies have reported that medical conditions can be the direct cause for between 1.5 and 24.7% of all road fatalities (Halinen & Jaussi, 1994; Sjögren et al., 1996; Tervo et al., 2013). Some of these deaths are due to the disease itself and in other cases the medical condition causes a crash where the crash impact is the cause of death. Tervo et al. (2008) reported that in fatal crashes caused by medical conditions, 43% of the deaths were caused by the crash impact and 57% were caused by the disease. An in-depth study of road fatalities in older drivers in Sweden showed that 29% of all road fatalities in drivers 50 years or older were attributable to acute disease and in 9% of acute disease-triggered crashes,

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another road user was injured (Skyving et al., 2023). Almost all disease related deaths (97.5%) in this study were caused by a cardiovascular event. In most studies, cardiovascular related conditions are the dominating medical conditions related to road fatalities (Halinen & Jaussi, 1994; Lindsay & Baldock, 2008; Tervo et al., 2008). Other medical conditions include aortic rupture, cerebral circulatory conditions and epilepsy. Studies have shown that less than half of the drivers can stop the car on their own in this situation (Büttner et al., 1999; Tervo et al., 2008).

By continuously measuring the driver's vital signs while driving, it would be possible to take necessary safety measures in case a sudden deterioration is detected. Survival from a cardiovascular event is in some cases possible with fast, appropriate medical care. Being able to monitor the onset of sudden cardiovascular disease (CVD) in drivers could thus save lives by providing valuable information about the condition of the driver to first responders, helping them to prioritize and allocate resources. Driver assistance systems or automatic stop manoeuvres triggered by detection of driver incapacitation could also limit the effects of a disease episode by preventing collisions with other road users. Various types of driver monitoring systems already exist in new vehicles, and organizations like the European New Car Assessment Programme (Euro NCAP) emphasize that the next generation of driver monitoring systems should be able to detect and manage sudden sickness in drivers (Fredriksson et al., 2021). However, only a limited number of studies have examined the detection of critical medical conditions in vehicles to date.

Clinically, cardiovascular conditions such as myocardial infarction and cardiac arrest are detected by 12-lead Electrocardiogram (ECG) (Lee & Kim, 2023). From a twelve-lead ECG, where the electrodes are placed at standardized positions, very comprehensive diagnoses of cardiac infarction as well as diagnoses of other cardiopathies can be deduced. The morphology of the ECG is then an important feature of the signal. Ischemia is typically most clearly reflected in changes in ST-segment and the T-wave. Depending on the localization of the infarction in the cardiac muscle, the signs are more or less visible in different leads, thus the need for several leads for a good detection of local ischemia/infarction. Cardiac arrythmias are seen as irregular R-R-intervals and/or as lost synchronization between P-wave and R-wave, and they are important clues to cardiac problems. Arrythmia detection depends less on many leads but put other restrictions on the ECG. Assuming an absence of cardiac arrythmia, heart rate (HR), sometimes referred to as pulse rate or just pulse, can be derived easily from a good quality single ECG signal from an arbitrary lead, but there are also several other ways of recording HR and short term, beat-to-beat variations in HR, often referred to as Heart Rate Variability (HRV). As HR and HRV are influenced by a multitude of factors they alone are poor indicators of cardiac distress, but they can provide complementary information to other signs.

Measuring 12-lead ECG is not feasible in vehicles during everyday driving. Driver monitoring is therefore dependent on measurements of vital signs using technology that does not disturb or affect the driver, for example via electrodes in the steering wheel, sensors in the seatbelt or driver seat, or elsewhere in the vehicle (Arakawa, 2021). There are different types of sensors that are suitable for use in vehicles, it can be via electrodes that measure single lead ECG or HR (pulse) when in contact with the skin, via light (photoplethysmography), via radar sensors, cameras, or other technologies. Another challenge is to be able to handle shorter interruptions in the measurements and disturbances such as noise or artifacts due to non-optimal measurement conditions that may occur during driving.

The aim of this paper is to explore the possibility of detecting signs of sudden cardiovascular disease in drivers by measuring HR or ECG via sensors in the vehicle. This paper consolidates results from a literature review and three small-scale exploratory studies performed at the Department of Electrical Engineering at Chalmers University of Technology to provide a comprehensive view of the feasibility of in-vehicle cardiovascular event detection. The work focused on various aspects of cardiovascular disease (CVD) detection technologies, including how to 1) measure HR and/or ECG unobtrusively in vehicles 2) handle noise and disturbances in physiological measurements taken in vehicle environments and 3) detect specific CVDs in single-lead ECG measurements. The rationale being that HR measurements were regarded as more likely to be implemented for continuous monitoring in vehicles. However, one-lead ECG, for instance via steering wheel electrodes, might be possible to implement for assessment of suspected CVD when an abnormal HR has been detected. Results from these studies combined with the review of what has already been done and is currently being done in the field forms the basis for a general assessment of feasibility and direction for further research and development.

2 SMALL-SCALE STUDIES

2.1 In-Vehicle HR Measurement Using Commercial Wearables

This study tackled the problem of measuring vital data reliably in vehicles (Andersson et al., 2024). Vital data was collected in a vehicle during driving using different types of measuring equipment including ECG with gel electrodes (which was used as the gold standard), ECG via chest strap, and HR measurement with photoplethysmography (PPG). The sensitivity to noise and disturbances was compared between different technologies. The measurements taken in the car were carried out under different conditions; stationary, driving on asphalt, and driving on gravel roads. On the gravel road, measurements were carried out driving through bumps and during hard braking. Reference measurements were carried out in stationary vehicles with and without the engine running.

The measurements were carried out with commercially available equipment; a Movesense chest strap with electrodes and an Inertial measurement unit (IMU) integrated in the strap (Movesense Oy, Vantaa, Finland), a wrist-worn Polar Vantage M (Polar Electro Oy, Kempere, Finland), which measures HR using PPG, and a Vitaport II single-lead ECG which measures a lead-II ECG using gel electrodes placed on the chest (Temec Technologies, Heerlen, Netherlands).

The signals were visually inspected to identify when noise, artifacts and other disturbances occurred. Signal processing was then performed to reduce noise and extract relevant information from the signals. Basic filtering was done using bandpass, notch and Savitzky-Golay filters. This was tested on signals from all sensors to investigate how well different types of noise can be handled. The Pan-Tompkins algorithm was applied to calculate HR by detecting the peaks of the QRS complex in ECG signals (Pan & Tompkins, 1985). The method uses bandpass filtering and derivation, followed by squaring and integrating the signal.

Baseline drift and noise from the car's vibrations were evident in the signals. Baseline drift was reduced by signal processing with bandpass filters with successful noise reduction in all cases. High frequency noise and vibrations could be reduced by Savitzky-Golay filtering with a reduced amplitude in the signals after filtering. The R-peaks of the ECG were easy to identify in the filtered signals, showing that the noise is not problematic to reduce, and that pulse identification can be easily done. Motion artifacts were also present in all measurements. They were difficult to filter out and problematic because they can distort the signals and make it difficult to correctly identify the HR and arrhythmias.

The chest strap and wrist worn PPG sensor gave the same average HR but there were differences in individual HR values. The wrist worn PPG sensor showed greater variability and was consistently deficient in measuring the HR correctly in shorter time intervals. Thus, wrist worn PPG is less reliable for detection of short-term abnormal HR.

2.2 Unobtrusive HR Measurement Using Radar Technology

The aim was to investigate the potential for detecting signs of sudden illness in the form of arrhythmia using radar technology by measuring HR (Björkman et al., 2022). This included determining the appropriate position of the radar, developing the signal processing for both high and low HRs to be detected, and investigating whether it was possible to measure HR when the subject was wearing a jacket and performed movements that mimic driving.

The radar sensor was the AWR1642BOOST manufactured by Texas Instruments. The AWR1642BOOST is a Frequency Modulated Continuous Wave (FMCW) radar that operates at 77 GHz and supports a bandwidth of 4 GHz. Three different radar sensor positions were examined: in front of the chest, next to the left side of the chest and behind the left side of the back (Figure 1). For each position, measurements were performed at normal HR and at high HR (> 100 beats per minute) created by physical exertion. Measurements with normal HR and high HR were conducted under stationary and moving conditions (steering wheel movements). In addition, two different jackets were used, a thinner and a thicker jacket.

To study how accurately the radar could detect the heart rhythm, a lead-II ECG measured with gel electrodes on the chest was used as a reference (PLUX Biosignals, Lisbon, Portugal). Signal processing was then used to extract information about the HR from the radar signal.

HR detection had the highest accuracy when the radar sensor was placed behind the left side of the back. In a car, this corresponds to the radar being implemented in the driver's backrest. Regular HR in the range of 55-140BPM could be detected with an overall accuracy of 91% when the radar was placed behind the back and the subjects sat still without a jacket.

Figure 1: Experimental setup with the radar sensor placed behind the participant.

The result also showed that it is possible to use the FMCW radar to measure the HR even though the subject is wearing a jacket. However, the results indicate that different materials can affect the accuracy. The results from measurements with steering wheel movements showed that the radar follows the HR from the ECG poorly when automatic filtering is used. With manual filtering it was possible to achieve a higher accuracy of 82%.

2.3 CVD Detection Based on Single-Lead ECG

The study by Widengård et al. (2024) focused on developing algorithms to detect CVD using databases of physiological data (ECG) with signals from patients affected by cardiovascular disease. With recent advances in machine learning, many studies have shown that computerized algorithms can perform ECG-based detection of CVD with high accuracy (Ansari et al., 2023; Feng et al., 2019; Gibson et al., 2022; Kora, 2017; Liu et al., 2018; Martin et al., 2021). In this study, existing algorithms were further developed to work with single-lead ECG, which is more realistic to implement in vehicles.

The ECG data used in this work were taken from the database "Physikalisch-Technische Bundesanstalt (PTB) Diagnostic ECG Database", abbreviated PTB (Bousseljot et al., 1995), as well as "PTB-XL, a large publicly available electrocardiography dataset", abbreviated PTB-XL (Wagner et al., 2020) both via PhysioNet (Goldberger et al., 2000). These open datasets contain ECG data from healthy subjects as well as subjects with various cardiovascular diseases. The recordings were divided into training, validation and test data. To avoid data leakage, the division was made so data from the same patient did not end up in both training and test data.

Two different types of deep learning models were tested: Convolutional Neural Network (CNN), and Recurrent Neural Network (RNN). Several versions of the algorithms were developed with the starting point in the structure described in the report by Liu et al. (2018). To validate the algorithms, four different measures were used; accuracy, sensitivity, specificity, and F1 measures. In addition, the generalizability of the best performing algorithm was evaluated by training it on the PTB-XL dataset and then evaluating with test data from another dataset, the PTB dataset.

CNN Version 2 showed the best results of the algorithms developed (Table 1). The algorithm also had good performance when trained with one dataset and evaluating with another. This suggests that the algorithm is robust against different types of datasets, and not overfitted or subject to data leakage.

The results for CNN version 2 are relatively similar to the results of previous studies that used neural networks for heart attack detection (Feng et al., 2019; Gibson et al., 2022; Liu et al., 2018). All algorithms were tested with single-lead data from ECG lead I, but the algorithms were also tested with data from ECG lead II, with no significant difference in performance. The position of the myocardial infarction determines the propagation of the changes in the ECG signal, which allows localization of the myocardial infarction (Morris & Brady, 2002). This also means that some heart attacks do not cause changes in all ECG leads. By only using one lead there is a risk of missing out on information that would have been visible in another lead.

3 DISCUSSION AND STATE-OF-THE-ART

Driver monitoring systems for the detection of driver

Table 1: Results from the algorithm evaluation.

Algorithm	Accuracy	Sensitivity	Specificity	F1
CNN Version 1 (training and evaluation using PTB)	0,839	0,80	0,86	0,845
CNN Version 2 (training and evaluation using PTB-XL)	0,92	0,95	0,90	0,93
CNN Version 2 (training using PTB-XL, evaluation using PTB)	0,83	0,97	0,76	0,81
RNN	0,49	0,50	0,42	0,668

incapacitation require the ability to unobtrusively monitor the driver's condition. Systems for the detection of sudden cardiovascular disease in drivers are based on monitoring vital signs linked to the activity of the heart, mainly ECG and pulse. Driver health monitoring systems are thus dependent on the ability to measure these vital parameters reliably in vehicles. Any available technique will be a compromise of many aspects such as usability, sensitivity, specificity, latency of detection, etc. Being able to detect a specific condition at a specific time is one of the biggest challenges with driver monitoring in general. From the vehicle manufacturers' perspective, it is not always the detection of a specific condition that is the most important, but the ability to handle an incapacitated driver, regardless of the cause. New vehicles are already equipped with many sensors, such as cameras, radar for passenger detection, etc. It can therefore be a challenge to bring in additional sensors, but also an opportunity to use sensors that already exist.

The results from the small-scale studies show that there is potential for continuous monitoring of driver vital signs for CVD detection in the future, but substantial further development of in-vehicle HR and ECG monitoring technologies is needed. Andersson et al. (2024) showed that commercially available wearable sensors can be used to monitor mean HR in real-world driving. However, wrist worn PPG was not able to detect sudden changes in HR and may thus be less suitable for arrhythmia detection. Furthermore, in all measurement technologies, noise and disturbances that do not occur periodically and that arise from sudden events were difficult to handle. Björkman et al. (2022) showed that it is possible to measure HR in a wide frequency range with radar technology in a laboratory setting, which suggests that there is good potential to detect arrhythmia. However, there are still several challenges with signal processing before radar can be implemented in a vehicle. Among other things, it is necessary to develop the method further so that it becomes more robust and can measure continuously. Widengård et al. (2024) showed that if a single-lead ECG of good signal quality is available, it is possible to detect CVD (myocardial infarction) with high accuracy in ECG data from lead I with a machine learning algorithm. Furthermore, a CNN was considered the most appropriate machine learning algorithm for this purpose.

In a controlled environment and without restrictions on how to apply sensors, there are excellent methods for rapid detection of cardiovascular disease states. ECG recordings offer the possibility to detect CVD based on the morphology of the signal, whereas HR sensors limit the possibilities for CVD detection to detection of abnormalities in the heart rhythm. Recent studies show that it is possible to detect myocardial infarction with single-lead ECG (Gibson et al., 2022; Hannun et al., 2019). Abnormalities in various vital parameters are common hours before a heart attack and clear deteriorations can be found before cardiac arrest (Andersen et al., 2016; Churpek et al., 2012; Kang et al., 2016; Oh et al., 2016). With access to HR only or lower quality data, there are still opportunities to detect cardiovascular problems, but likely with lower sensitivity and specificity. Additional difficulties in the vehicular environment are the fact that in real-world driving, the measurement must be carried out in an unobtrusive manner. The collected signals are often plagued with various types of disturbance and noise that make further analysis very difficult. For example, motion artifacts are of great importance for the quality of the signals (Kawasaki & Kajiwara, 2023) and the traffic environment can influence signal quality (Leicht et al., 2022). Wearable sensors often provide more robust measurements of HR than remote sensing in a vehicle environment (Arakawa, 2021; Leicht et al., 2022), although with the disadvantage that it requires the driver to put on the equipment.

Leonhardt et al. (2018) published an extensive review of different methods for unobtrusive vital sign monitoring in an automotive environment. The most explored monitoring technologies were ECG (conductive, capacitive or hybrid), ballistocardiography, optical methods (PPG, PPG imaging, far infrared imaging, other camera-based methods), magnetic induction, and radar-based methods. Some of the techniques have been more extensively studied than others and the review provides a thorough comparison between methods. A general conclusion was that all methods were fragile and sensitive to disturbances. Relatively few of the methods have been tested in environments close to realistic conditions. Most early tests were in laboratory settings and without the influence from movement.

Previous studies have shown that it is possible to detect HR with remote sensing, including radar technology (Qiao et al., 2022; Schires et al., 2018; Tang et al., 2017). However, few studies have used radar technology to investigate the possibility of detecting CVD. Radar-based systems can be used to detect both breathing rate and HR, but they tend to be very sensitive to both body and vehicle motion. Tang et al. (2017) proposed a method using two radar sensors, one in front of the person and one at the back. Utilizing the fact that movements of the entire body tend to give an out-of-phase signal whereas movements of heart and lung give an in-phase signal.

In a review article by Arakawa (2021), different approaches to measuring drivers' HR were analyzed. A steering wheel sensor with electrode measurement and steering wheel sensor with LED sensor managed to measure HR accurately when both hands were on the wheel. Steering wheel electrodes have the potential to be used for single-lead ECG measurement but with the disadvantage that the hands must always be kept on the steering wheel. Another method was a car seat with a 24 GHz doppler sensor and accelerometer. This car seat was able to measure HR accurately within 5-10 beats per minute depending on the type of driving. Arakawa (2021) found that wearables such as rings and watches could measure HR with good reliability with the disadvantage that the driver have to wear them. Finally, it was reported that several studies used video cameras to measure HR by measuring color changes in people's faces. However, this method has not been tested in vehicles. Arakawa (2021) also states that pulse measurements alone today are not enough to assess the driver's state of health.

Ultimately, the goal of the sensors is to provide signals that can be processed into information pertinent to the detection of driver health status. Signal processing including preprocessing, parametrization/information enhancement, and finally information extraction/disease detection is key. Preprocessing is primarily necessary to increase the signal-to-noise ratio (SNR). Low SNR is clearly one key obstacle in all the reviewed methods. Few of the sensors described in the literature have been tested in a car during driving; and those that have been subjected to realistic conditions have demonstrated unsatisfactory performance. Parametrisation is based on the notion that some specific aspect or aspects of a signal carries relevant information. For instance, HR, HRV or ECG morphology as potential indicators of cardiac problems. The intended parametrization may put requirements and limitations on the preprocessing. If the sought parameter is HR only a narrow band filtering may be a good component in the preprocessing, but such filtering may extinguish all possibilities to capture ECG morphology. Maximizing the SNR in the sense signal power divided with noise power is counterproductive as the maximum power of the signal does not necessarily coincide with power of the morphology alterations. All good signal processing is therefore based on a clear idea of the information bearing part of the signal and knowledge of the interfering signal components.

A powerful method to reduce noise from the signal is adaptive filtering which is based on the idea of placing a second transducer, a reference transducer, in close proximity to the original, signal transducer (Eilebrecht et al., 2012). The purpose of the reference sensor is to get a signal that mainly registers noise, and no signal. Ideally, the difference between the signals from the two sensors would give a clean signal. In reality, an appropriate filter will be inserted after the reference transducer; whose task is to adjust the amplitude and phase of the reference signal to mimic the noise from the signal transducer. The filter is adaptively adjusted to changes in transmission characteristics during recording (Widrow et al., 1975).

Sensor fusion is a potential method that can be applied to deal with poor signal quality. Future research may benefit from including several vital parameters to obtain a more complete understanding of the physiological processes. Combining more vital parameters can create a stronger basis for identifying CVD. For instance, if abnormal vital signs are detected the driver could be asked to put both hands on the steering wheel to enable a single-lead ECG measurement for more detailed health assessment. Another possibility is to connect mobile devices to the vehicle, in this way measurements from smart watches or other wearables can be used in the assessment. The focus of this report is on cardiovascular events, but it is worth noting that both epileptic seizures and strokes can affect HR and HRV (Chen et al., 2014; Nei, 2009; van Elmpt et al., 2006; Zangróniz et al., 2017; Zijlmans et al., 2002). This opens for the possibility that also some cases of severe cerebral attacks could be detected via heart signals.

The way forward is therefore to use physiological signals that contain as much information as possible and that can realistically be acquired routinely during driving. The diagnostic qualities of any single one of these signals will likely be too low, and in periods the signal-to-noise will be very poor. However, combining several signals from different sources may compensate for the shortcomings of individual technologies. Suggested next steps are to test and evaluate sensor tools allowing detection of morphological changes in single lead ECG, HR recording, analysis of HRV, and recording of respiration rate. In parallel, the types of interference that affect the different sensors should be studied to look for means of acquiring a good reference signal, allowing adaptive noise cancelling. When the sensor data acquisition is optimized for each individual sensor, sensor fusion algorithms can be developed that extract the physiologically relevant parameters. Lastly, the decision system that can provide the final decision whether the driver is in full health or actions are required needs to be developed.

A major challenge for the development and evaluation of sensors and algorithms is that sudden illness events while driving are rare and they cannot be manipulated experimentally for validation of the systems as is done, for example, when testing fatigue warning systems. Early development must rely on data measured under other conditions or simulated data. An important limitation is that the studies by Andersson et al. (2024) and Björkman et al. (2022) use only measurements from healthy individuals, which limits the possibility to generalize to real disease situations. Future studies should include data from people diagnosed with arrhythmia to assess whether these conditions can be detected in the signals. Another challenge is to minimize the number of false positives as well as false negatives. Vehicle support systems such as automatic stop maneuvers or automatic alarms should not be activated unless it is a real emergency. This underscores the need to carefully consider the pros and cons of different detection methods to ensure proper interpretation and management of CVD events.

The traffic safety and societal benefit of being able to detect sudden CVD onset in drivers is mainly linked to two scenarios. The first is to integrate driver monitoring with support systems into the vehicle so that the vehicle can take control and perform a safe stop. This would reduce the risk of collisions with other road users and the risk of single-vehicle accidents. The second aspect is about being able to inform emergency responders about the driver's condition to allocate appropriate resources to the scene. A recent project called TEAPaN (Traffic Event Assessment, Prioritizing and Notification) explored how such traffic incident information could be used for prioritization of emergency resources (Söderholm, 2023). The project designed and explored an IT-infrastructure and incident alert handling solution directly interfacing with prehospital care resources. Detecting a medical condition before the driver is completely incapacitated can provide the opportunity to handle the medical emergency at an early stage. Early detection would also increase the possibility of survival if the right care can be given more quickly. Both actions, stopping the vehicle and calling for emergency care, can have far-reaching consequences. It is not possible to achieve 100% sensitivity and 100% specificity for this type of detection. False CVD detection can potentially lead to the vehicle making unnecessary and dangerous maneuvers and/or sending false alarms to dispatch centers. False alarms are costly and can mean that resources that could have saved lives elsewhere are blocked.

In the study by Widengård et al. (2024), the recordings in the PTB and PTB-XL databases were often taken several days after the onset of CVD, which is important to take into account when analyzing and drawing conclusions about the performance of the algorithm. Moreover, the datasets were recorded in a clinical environment, i.e. not in vehicle environment which is the intended environment for the practical implementation of the algorithm. For further development of a machine learning algorithm with the aim of detecting acute CVD, a large amount of new data is required. Optimally, this data would contain real-time infarcts and be collected in a vehicle environment where characteristic noise and motion artifacts occur. However, such data collection is very difficult to implement.

Privacy and regulatory issues are other important areas to consider when handling health data. Health monitoring would involve the storage of sensitive personal data. Therefore, all data will probably need to be processed locally in the vehicle to reduce the risk of exposing (sensitive) personal data. The ability to turn off or deny monitoring can also be a solution to privacy issues. Diagnostic tools are regarded as medical devices and the regulations surrounding medical devices are extensive. If a detection system in a vehicle makes a medical decision, the device needs to be tested and approved as a medical device. Whether a detection system that warns of abnormal vital parameters in a driver is a medical device has not been investigated here.

4 CONCLUSIONS

The results showed that there are significant challenges in building a functional system to detect sudden cardiovascular disease in drivers, and substantial development work remains. Provided there is a high-quality ECG signal, the prospects for detecting heart attacks are promising, and a high-quality pulse signal enables the detection of arrhythmias in drivers. Further development work is required to ensure sufficiently high sensitivity and specificity in real cases of illness. However, the biggest obstacle is that reliable unobtrusive technologies for measuring ECG morphology and HR in the vehicle environment are not yet available. Arrhythmias can be detected using wearables such as chest straps whereas sensors not worn by the driver but integrated into the vehicle are sensitive to noise and interference. To enable the detection of sudden illnesses in vehicles, more vital parameters need to be examined, and multiple measurement systems need to be integrated to provide sufficient and reliable data. The results indicate that there is a need for further research and development of unobtrusive measurement methods to detect driver states.

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