Proc. of the International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME)
16-18 November 2022, Maldives

Combining Vehicle BUS and Vital Sign Sensors for Continuous Health Monitoring During Driving: Concept and First Results

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***Abstract*—Continuous health monitoring is the key to change the paradigm in medicine from diagnostics & therapy to prediction and prevention. As humans, on average, spend about 1 hour per day in a car, we target vital sign recording in the vehicle. The different BUS systems in the vehicle deliver information that will help to distinguish automatically artifacts due to movement from pathologic irregularities of the signals. In our research car, the Drivetrain controller area network (CAN), the Suspension System and Driver Assistance CAN, and the Comfort CAN provide 33 electronic control units (ECU) with about 3,700 signals. Furthermore, we suggest redundancy for vital sign recording. We integrate electrocardiography (ECG) and photoplethysmography (PPG) in the steering wheel, imaging PPG in the windscreen, and phonocardiography (PCG) in the seatbelt. Our preliminary results obtained from steering wheel-based ECG deliver reliable recordings from about 45.62 % of the driving time. We expect an increase in that portion of our redundant sensing approach. However, as compared to the current selective measures of less than 60 sec, 20 min to 30 min per day may help to prevent significant adverse health events such as stroke and heart failure as well as those arising from chronic illnesses.**

Keywords—vital signs, health monitoring, steering wheel, electrocardiography, sensor fusion

I. Introduction

The World Health Organization (WHO) reports that 17 Mio. deaths are caused by cardiovascular diseases [1]. Each year, 270,000 strokes occur in Germany with about 200,000 individuals experiencing their first event [2]. 20% of these are caused by atrial fibrillation (AF) [3], and 2 Mio. Germans are suffering from AF [4]. Furthermore, stroke is the third most cause of death yielding total costs of € 18 billion per year [5].

On the other hand, continuous health monitoring may help to prevent adverse health events by lowering their prevalence. For instance, Gheorghiade & Pang [6] and Steinhubl et al. [7] have shown that early intervention increases the therapeutic outcome and decreases the mortality rate in heart failure or stroke, respectively. This optimizes the assignment of medical resources. Unobtrusive sensors in private spaces, e.g., apartments or vehicles, may early detect subtle changes in the health conditions of the occupant [8]. Advantageously over the smart home, the position and pose of vehicle occupants are rather constant (e.g., upright seating position) and the vehicle's interior is rather static (e.g., no furniture movements).

In this paper, we focus on the vehicle. In Germany, a person spends about 43 minutes per day in a vehicle [9]. We want to use this travel time for meaningful health monitoring, in particular, for AF detection and stroke prevention.

So far, the driver state monitoring focuses on the driving style, the driver-control behavior, and the driver's driving capability. So far, most work aims to detect driver drowsiness as emergency prevention [10,11].

However, the described methods and sensory capabilities have not been researched regarding continuous health monitoring. As compared to driving assistance systems, the reliability of continuous health measures for medical checkups must not range up to 99.9%. In contrast, we can accept much lower rates as long as we can reliably distinguish between disturbed and clear data.

In 1997, WHO defined health and well-being as the quality of life (WHOQOL) within six domains. Four of them are already evaluated for in-vehicle monitoring [12]:

1. *Environmental*: temperature, air quality, humidity, weather, light conditions, and traveling speed are captured for in-car well-being and driver's assistance systems [13].

2. *Behavioral*: cockpit and panel usage, eye movement, physical activities such as driver control behavior, and driver states like drowsiness reflect the driver's attention level [14].

3. *Physiological*: vital signs (primary: heart rate (HR), respiratory rate (RR), blood pressure (BP), and body temperature (BT); secondary: oxygen saturation, and blood glucose level) and other biosignals (e.g., electro-dermal activity (EDA)) characterize the physical health of a person [15].

4. *Psychological*:

In this paper, we focus on HR and heart rate variability (HRV) for AF detection and stroke prevention.

The current state of driver monitoring includes eye- and face-tracking and steering wheel, pedal, and lane movements to detect tiredness in the early stages. Only a few works focus on unobtrusive vital-sign monitoring in automotive environments [16]. For instance, Gomez-Clapers & Casanella have attached electrodes for electrocardiography (ECG) to the steering wheel and derived the HR [17]. The HARKEN project integrated ballistocardiography (BCG) into the seat belt [18] and Walter et al. have integrated capacitive ECG (cECG) [19], again to derive the HR. Kuo et al. have used image-based photoplethysmography (iPPG) for drivers' HR detection [20]. Lazaro et al. have applied radar from the seat backrest for heart and respiratory rate detections [21]. Vavrinsky et al. have integrated one-lead ECG, galvanic skin response (GSR), and temperature sensors into each side of the steering wheel [22]. Kowalczuk et al. have recognized emotions with a red, green, and blue (RGB) camera [23].

However, all this work intents to capture the momentary health state to feed driver's assistance systems or to handle a safe transition between different levels of autonomous driving rather than to identify subtle changes in the long term for a specific individual and predict future health to prevent adverse events (e.g., a stroke).

II. Materials and Methods

For a continuous medical assessment in the vehicle, several problems are unsolved. The dynamic environment in a vehicle causes several disturbances, e.g., vibrations of the car, motion of the driver, and changes in light conditions. Hence, the signal quality is changing over time and a single sensor is unreliable [19],[16]. We want to combine multiple sensors from inside and outside environment, engine and driving situation, as well as health (sensor fusion) and analyze the data.

A. Health sensors

In previous work [24], we have developed an ECG recording device that integrates into the steering wheel of our research car (VW Tiguan, Volkswagen AG, Wolfsburg, Germany). In particular, we have designed 3D-printed flexible and elastic electrodes for contact measures and connected them via adhesive electrodes (AgCI electrodes, 110 Covidien, Dublin, Ireland) to an ECG sensor (Explorer Kit, Biosignalplux, Lisbon, Portugal), as visualized in Figure 1.

Fig. 1. Research car with steering wheel-integrated contact ECG.

While this device delivers reliable data at rest, the driving situation may significantly disrupt the signal such that the computed HR or HRV is erroneous. The difficulty is to distinguish artifacts caused by the driving situation (e.g., car or driver's movement) from correctly measured irregularities of the beating heart. We suggest two solutions

1. *Redundancy*: we apply different types of sensors based on different effects to measure the same vital signs (HR and HRV);

2. *Complementarity*: we apply additional information derived from sensing environmental and behavioral parameters (inside and outside environment, engine and driving situation).

According to Leonhardt et al. [16], the HR is usually computed from the detected beats in electrical (ECG, cECG), mechanical (BCG), acoustical (phonocardiography, PCG), and optical (iPPG) signals. In our previous work, we deployed acceleration sensors into the seatbelt of the car, but the signal quality–in particular during the ride–turned out to be rather poor [25]. Kado et al. used iPPG based on near-infrared (iPPG-NIR) [26] and Pereira et al. applied thermal imaging (iPPG-T) to derive the heart rate [27]. Additionally, we have systematically reviewed optical devices for the recording of vital signs [28]. As a result, we suggest the following devices (Table I).

TABLE I. Redundant devices for HR and HRV

Type	Position	Vendor & Model
ECG	Steering wheel	Biosignalplux SensPro-ECG1
PPG	Steering wheel	BiosignalPlux SensPro-SPO2
iPPG-NIR	Windscreen	Raspberry Foundation NoIR Camera V2
iPPG-T	Windscreen	Pimoroni MLX 90640
iPPG-RGB	Windscreen	Raspberry Foundation Camera 2
PCG	Seatbelt	Thinklabs One Stethoscope

B. Vehicle sensors

All driving conditions such as road surface, traffic volume, temperature, and humidity (inside and outside), as well as light and illumination impact vital sign measurements [16],[19]. According to [12], we group in-vehicle sensors by assignment and application:

1. *Functional sensors* such as pressure and air-mass flow are needed for the control and regulation systems,
2. *Sensors for safety and security* are related to the passenger's protection and include airbag and electronic stability control (ESC), and
3. *Sensors for vehicle monitoring* such as onboard diagnosis (OBD), fuel consumption, and passenger information (i.e., number of passengers and seatbelts fastened) are needed for maintenance.

In our research car, the Drivetrain controller area network (CAN) BUS has 10 electronic control units (ECU) with about 500 signals, the Suspension System and Driver Assistance CAN have 13 ECUs (~2000 signals), and the Comfort CAN has 10 ECUs (~1200 signals). We have tested the CAN as well as the Onboard Diagnostics System 2 (OBD2) access in several thousand measurement hours in various vehicles [29]. Table II collects some appropriate sensors, but we consider all data from these CAN bus systems because it is an open research question, which sensors are most suitable to identify artifacts in biosignals. Nonetheless, we will disregard all signals from the Extended CAN and the Sensor Fusion CAN, as they are partly redundant or considered peripheral.

TABLE II. SENSORS FOR ENVIRONMENTAL AND BEHAVIORAL DATA.

Type	Position	Vendor & Model
Accelerometer	Pedal	Bosch
Accelerometer	Vehicle's center of gravity	Kisler Peripheral Sensor
Steering angle	Steering wheel	Bosch
Capacitive sensor	Steering wheel	Bosch
External camera	Windscreen	Valeo FAS Front amera
Front radar	Front bumper	Continental Mid Range H01

We derive behavioral parameters not only from pedal and steering wheel movements but also from manual adjustments of interior climate, sound, light, and seat adjustments. This indicates short- and long-term changes in the driver's behavior. To categorize the driving style as {*quiet, normal, aggressive*}, we record the synchronized BUS systems in real-time.

C. Sensor fusion

We have designed and implemented a platform that not only supports data access via the CAN-BUS but also synchronizes the medical signal recordings (Fig. 2). The core idea is to combine USB and CAN BUS hardware early, yielding time synchronization of all sensors on the BUS level already before it is sent to the server for storing. The central component is a USB / CAN / USB chain using PCAN USB (PEAK, Germany) and VN 1630 (Vector Informatik, Germany).

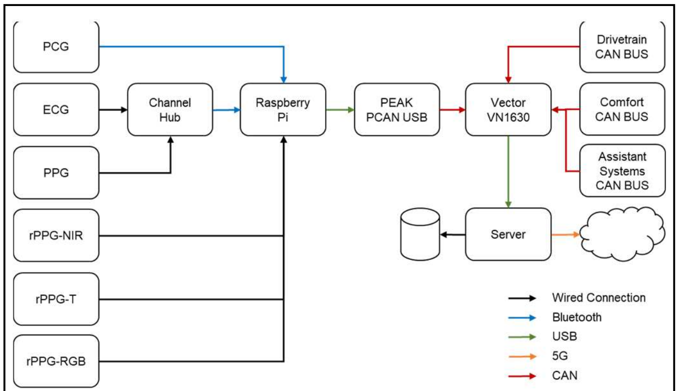

Fig. 2. Sensor fusion.

D. Signal processing

Münzner et al. [30] distinguish three fusion approaches using convolutional neural networks (CNN):

- early fusion merges the signals after the first layer;
- sensor-based late fusion merges the signals in the dense layer with one convolutional layer per signal, and
- signal-based late fusion has an additional convolutional layer per signal.

Tejedor et al. review sensor fusion for heartbeat detection and recommend an algorithm with CNN-based information fusion, which is generalizable regarding the input modalities [31]. Based on this work, we implement a hybrid algorithm using all three fusion approaches (Fig. 3) [32]. In the end, a majority vote identifies the segments with reliable heartbeats. This voting function is independent of the CNN and processes the output vector for making the final decision if a segment contains no heartbeat (class 0) or one heartbeat (class 1) based on a majority vote.

Unobtrusive measurements acquired during driving are noisy, and periods of reliable measures must be detected automatically. To ensure reliability and accuracy for health monitoring, the signal quality assessment (SQA) is important: SQA allows for a determination of signal segments, in which the SNR is adequate for measurements of vital signs. The SNR calculates the power of the signal P_S divided by the power of the noise P_N:

$$\mathrm{SNR} = 10\,\lg\left(\frac{P_S}{P_N}\right)\mathrm{dB} \tag{1}$$

We calculate the SNR of the steering wheel ECG based on the ECG frequency and use the MATLAB function periodogram to estimate the power spectral density.

III. RESULTS

Figure 4 depicts a sequence of 15 min. The estimated HR (orange) is computed from the steering wheel-based ECG and compared with a ground truth obtained from body-attached wet ECG electrodes (Reference ECG, blue). It is important to observe the red-marked periods on the time axes, indicating

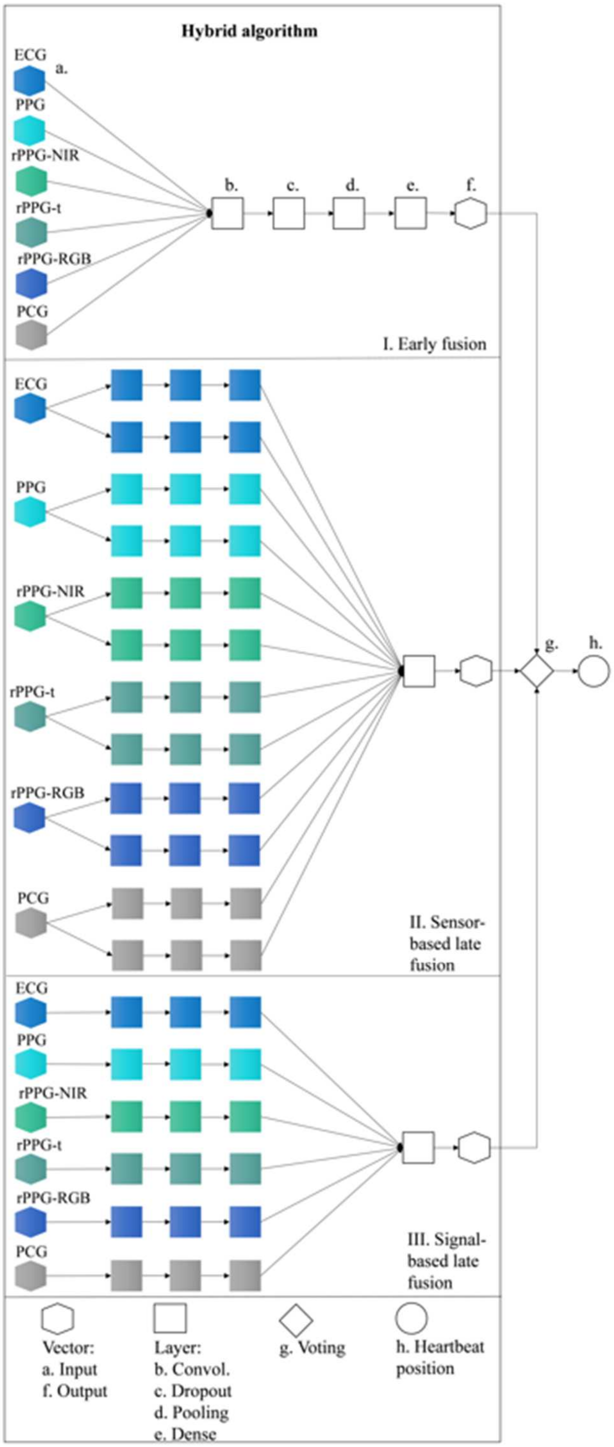

Fig. 3. Schematic diagram of hybrid CNN-based algorithm.

periods of unreliable measures. Figure 4 also emphasizes the high correlation between estimated and reference HR measures.

Our preliminary results indicate that steering wheel-based ECG delivers reliable recordings from about 45.62 % of the driving time [24].

IV. Discussion and Conclusion

In this work, we have presented a technical solution for the time-synchronized recording of CAN BUS and vital sign data within the driving vehicle. To overcome the problem of distinguishing artifacts from correctly recorded signal irregularities (relevant pathological indicators) we suggested redundancy and complementarity.

However, our work has several limitations. So far, the approach is not implemented completely. We expect an increase in the portion of reliable recording by our redundant sensing approach.

Nonetheless, today's systems support selective recordings only, which usually are restricted to 60 s or less. In contrast, our approach delivers 20 min to 30 min per day and, therefore, may help to prevent significant adverse health events such as stroke and heart failure as well as those arising from chronic illnesses.

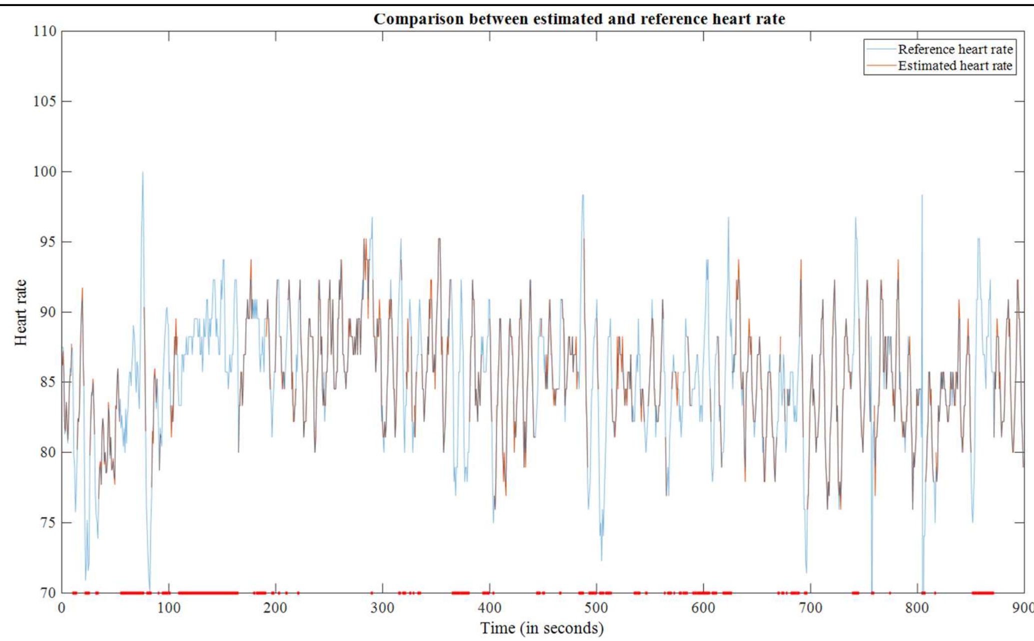

Fig. 4. Results of the printed and flexibel ECG electrodes.

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