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Evaluating the Measurement of Driver Heart and Breathing Rates from a Sensor-Equipped Steering Wheel using Spectrotemporal Signal Processing

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Abstract— **Driver's status and behaviours such as inattention, drunk driving, or sleeping while driving play important roles in approximately half of all automobile crashes. For this reason, the last decade has seen an emergence of non-intrusive driver status monitoring systems with the ultimate goal of reducing the number of such accidents. From the different number of proposed methods, the use of the physiological signals, specifically the electrocardiogram (ECG), has shown useful. The acquisition of ECG signals during driving, however, presents a challenge due to movement artifacts, such as car and driver motion, and a good contact of the sensing electrodes, e.g., embedded on the driver seat. In this paper, we evaluate the ECG signals acquired from electrodes placed on the steering wheel under three aspects: (i) quality of the acquired signals; (ii) their usability to estimate an average and an instantaneous heart rate, and (iii) their usability to estimate the driver's breathing rate via innovative spectrotemporal processing of the acquired signals. Experimental results show that ECG signals obtained from the steering wheel have quality inline with that obtained from a benchmark chest ECG device, allow for both average and instantaneous heart rate to be measured, as well as breathing rate to be extracted.**

Index Terms— **Driver status monitoring, electrocardiogram, stress, drowsiness, spectrotemporal signal processing**

I. Introduction

With an increasing number of cars and trucks on the roads, there is an increase also in related problems such as traffic, air pollution and car crashes. According to the National Highway Traffic Safety Administration, in 2016 there were over 7 million car crashes in the U.S.A. alone [1]. An earlier study showed that driver status factors, such as inattention, drunk driving, or sleeping while driving amounted to over 45% of the reported crashes [2]. As consequence, a key element in the reduction of such accidents has been to monitor driver mental states, such as, attention level, mental workload, fatigue, drowsiness, and stress, to name a few. To this end, diverse driver status monitoring (DSM) systems have been proposed. Depending on their approach, DSM systems can be divided into two main categories: (i) systems that rely on the analysis of images captured from the driver to detect head position, facial direction, blinking rate and eye lid movements, to infer the driver's status; and (ii) system that rely on acquiring physiological signals such as electrocardiogram (ECG), photoplethysmogram (PPG), electrodermal activity (EDA), breathing signal, and electroencephalogram (EEG).

Camera-based methods are non-invasive, however, their performance can be compromised by changes in background and illumination conditions [3]; and can potentially compromise the privacy of the driver [4]. Physiological signals, in turn, have been used to measure correlates of fatigue, drowsiness [5], stress [6], and mental workload [7], [8]. However, measurement of such physiological signals within a car interior is very challenging, particularly if sensing is to be done in an unobtrusive manner and not relying on the driver to wear any special gear, such as a breathing rate belt or an EEG cap [9]. As such, most available systems have relied on ECGs and used heart rate variability as a correlate of varying mental states.

The ECG signal is produced by the electrical activity of the heart every beat. Although it is a repetitive signal, the rate of repetition, or heart rate (HR), can vary slightly with each beat, thus giving origin to the so-called instantaneous heart rate (iHR). The temporal dynamics of the iHR, in turn, is a measure of heart rate variability (HRV), which has been used as a valuable tool to monitor the autonomic nervous system through the sympathetic-vagal balance [10], [11]. Regarding DSM systems, the ECG signal has been used to assess stress [12], mental workload [13], as well as drowsiness and fatigue [14]. Moreover, the ECG can be used to derive other important metrics such as the breathing rate (BR) [15], which has been shown to increase as stress and workload increase [8]. As such, ECG acquisition can play an important role in driver status monitoring. In addition, ECG has also been shown to be a useful tool for driver biometrics recognition [16].

ECG signals can be acquired with electrodes placed on the steering wheel and/or on the driver seat. With the latter, the quality of the signal can be affected by artifacts due to car- and driver-motion, as well as posture and size of the driver [17]. On the other hand, electrodes placed on the steering wheel are subject to artifacts during steering actions. To the best of our knowledge, the assessment of the quality of the ECG signals acquired with electrodes on the steering wheel has not been addressed, nor have their use for extracting breathing rates from the ECG been explored. To overcome this limitation, we present a modified steering wheel to acquire ECG signals and: (i) explore the quality of the obtained signals; (ii) evaluate their usability to estimate average HR and iHR; and (iii) evaluate their usability to

Fig. 1. Car simulator used in the experiments. Steering wheel was equipped with electrodes to monitor driver ECG

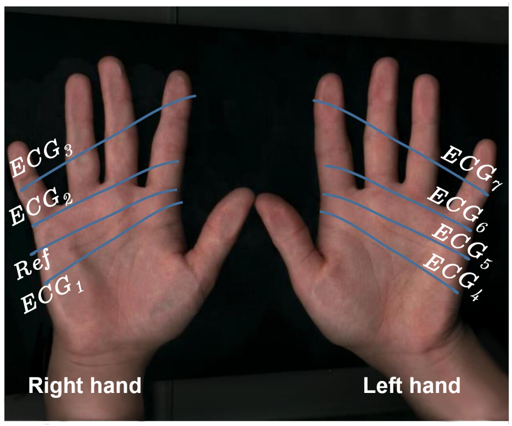

Fig. 2. Position on hands where electrodes on the steering wheel would touch.

derive an accurate BR.

The remainder of this paper is organized as follows. Section II presents the Material and Methods used, Section III the experimental results and a discussion, and paper conclusions are presented in Section IV.

II. Methods and Material

This section describes the experimental protocol using a car simulator, the sensor-equipped steering wheel, and the signal processing methods used.

A. Experimental protocol

Five participants underwent a driving task using a car simulator that required drivers to repeatedly make lane changes on the same straight road. The designated lane change areas were indicated by signs on the highway, and the lane change procedure was a self-paced action as the participant decided when exactly to do so. The participant was prompted to make the lane changes quickly but accurately. The speed of the car was kept constant and the participant did not change speed. The same road was looped after the participant has performed the 4 lane changes. Participants performed at least 10 trials, each trial had a duration of approximately 5 minutes. The car simulator used in the experiments is depicted by Figure 1 where the sensors have been embedded on the steering wheel.

Eight electrodes were placed on the steering wheel with the goal of making contact with the participants hands according to the locations shown in Figure 2. As one electrode served as reference (Ref), a total of seven physiological signals were obtained (ECG_1 to ECG_7). Additionally, benchmark ECG (ECG_{gt}) and respiration (RSP_{gt}) signals were acquired from each participant, with electrodes placed on the right clavicle and the lowest left rib for the ECG signal, and respiratory effort sensor (Spes Medica SRL, Italy) for the respiration signal. Physiological signals acquired with the electrodes on the steering wheel were sampled at 256 Hz, while ECG_{gt} was sampled at 2048 Hz. Physiological signals were acquired with a multimodal biosensing recorder (Bitbrain Technologies S.L., Spain). ECG signals were bandpass filtered with a zero-phase FIR filter with a bandwidth from 4 to 30 Hz to remove baseline wandering and preserve most spectral content of the QRS complex [10], [18]. The benchmark respiration signals were lowpass filtered with a zero-phase FIR filter with 3 Hz cutoff frequency.

B. Average HR measurement

Measurement of heart rate from noisy ECG signals can be challenging. Here, we rely on a recently-proposed method based on spectrotemporal signal processing to measure average HR in an artifact-robust manner. The so-called modulation spectrogram is computed based on the steps shown in Figure 3. First, time domain signal $x(t)$ is mapped to a time-frequency representation $X(t, f)$. This can be achieved with the short-time Fourier transform (STFT) (or any other time-frequency transformation such as the continuous wavelet transform). Next, this time-frequency representation is further processed by carrying out a Fourier transform (FT) on the spectral magnitude time series for a particular frequency bin. This second transform characterizes the second-order periodicity of the signal and results in a (conventional) frequency vs. (modulation) frequency representation called 'the modulation spectrogram' $X(f, f_{mod})$. As the modulation spectrogram representation relies on the FT, it can be directly implemented in hardware by making use of efficient hardware implementations of the fast Fourier transform (FFT) algorithm [19]. The modulation spectrogram has been used to accurately measure the quality of ECG signals [20], as well as to extract breathing rate information modulated onto the ECG signal [21].

Once the modulation spectrogram representation is computed, the average HR is obtained following two steps: *i*) the modulus of the modulation spectrogram is averaged across the conventional frequency axis for the major spectral components that comprise the QRS complex, i.e., 4 - 30 Hz. *ii*) The peak in the averaged modulation spectrum represents the HR. In our experiments, the ECG signals were analyzed in segments of 10 s with an overlap of 50%. The STFT was computed with a window length of 125 ms with 75% overlap. To validate the usability of the ECG signals from the steering wheel, the root-mean-squared error (RMSE) between the benchmark and measured ECGs was computed

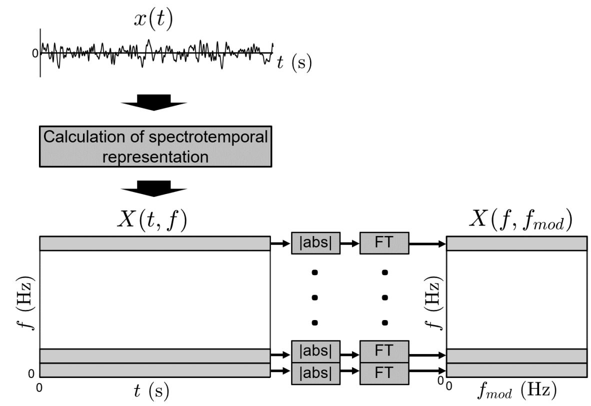

Fig. 3. Signal processing steps involved in computation of the so-called modulation spectrogram.

for each trial. For each participant, the signal that achieved the lowest RMSE value across all trials was considered to be the best ECG_{sw} for a given participant.

C. ECG signal quality

While the RMSE of the average HR provides some insight into the usability of the signals acquired from the steering wheel, we further measured the quality of the ECG_{sw} signal using the recently-proposed modulation spectral based quality index (MS-QI) [20]. This index is based on the modulation spectrogram representation of the ECG signal, where ECG components can be accurately separated into signal and artifacts, thus can be used to blindly measure the ECG signal-to-noise ratio (SNR). In [20], MS-QI values geq 0.5 were shown to correspond to high quality ECG signals, with values between $0.35 - 0.5$ showing acceptable quality. Similar to the average HR, the MS-QI was computed in segments of 10 s with an overlap of 50%. More details can be found in [20].

D. Instantaneous HR

Using the modulation spectrogram method described above, we are able to obtain an average HR roughly every 4 seconds. Recent work, however, has shown that for more accurate heart rate variability (HRV) monitoring, instantaneous HR (iHR) measures are desirable [22]. For this reason, we also compared the iHR time series derived from the ECG_{gt} and ECG_{sw} signals. The iHR time series was obtained from the RR-interval time series obtained with the Pan-Tomkin's algorithm for detection of QRS complexes [23], [24]. The iHR time series was resampled at 4 Hz.

E. Average breathing rate

Given the relevance of the breathing rate (BR) for driver status monitoring, we evaluated three different methods that exploit the influence of the respiration process on the cardiac activity signal to derive the BR from both the ECG_{gt} and the ECG_{sw} signals. In method 1, the BR is estimated with the spectral analysis of the changes of the RR-interval time series (also know as RR tachogram) due to the respiratory sinus arrhythmia (RSA) [15], [25]. Method 2 is based on the CTW-based modulation spectrogram of the ECG signal as presented in [21]. Lastly, with method 3, the changes in amplitude in the R-peaks are used to estimate the respiratory signal and from it BR [15]. A BR estimate was obtained for a 120-s window with a shift of 30 s.

TABLE I

AVERAGE RMSE ACROSS TRIALS FOR AVERAGE HR (GIVEN IN BEATS PER MINUTE), BETWEEN BENCHMARK ECG AND THE SEVEN STEERING WHEEL ECGS. VALUES IN PARENTHESES REPRESENT THE STANDARD DEVIATION OF THE RMSE VALUES.

Steering wheel signals	**Participant**				
	1	2	3	4	5
ECG_1	33.9 (3.0)	38.7 (4.3)	33.3 (4.0)	35.9 (7.4)	34.4 (2.9)
ECG_2	40.0 (3.8)	13.8 (14.9)	48.2 (4.5)	41.6 (4.3)	45.5 (4.7)
ECG_3	33.2 (4.3)	41.7 (2.1)	35.4 (4.0)	39.0 (3.5)	33.9 (4.0)
ECG_4	36.5 (13.1)	11.3 (15.8)	26.1 (5.5)	22.5 (3.1)	16.5 (18.0)
ECG_5	0.39 (0.08)	0.64 (0.58)	13.6 (7.3)	6.2 (8.0)	5.7 (7.6)
ECG_6	0.39 (0.09)	0.62 (0.58)	13.8 (6.6)	6.3 (8.0)	5.1 (8.0)
ECG_7	9.3 (8.8)	6.6 (12.7)	22.3 (5.8)	6.2 (8.1)	6.6 (8.7)

III. EXPERIMENTAL RESULTS AND DISCUSSION

A. Average HR

The average HR was computed in 10-s segments every 5 s for the ECG_{gt} signal, as well as for the seven ECG signals acquired with the electrodes on the steering wheel, thus resulting in over 62 HR values per trial. Table I presents the average RMSE across trials per participant for each of the ECG signals acquired from the steering wheel. For each trial, the electrode or electrodes with the lowest RMSE were considered to be the best signal to estimate the average HR. Figure 4 depicts which electrodes were the most useful. As expected, only electrodes placed on the hand that is opposite to the hand with the reference electrode were useful. Moreover, in most of the cases the signals ECG_5 and ECG_6 obtained the best results. Finally, a single best ECG signal, ECG_{sw}, was selected per participant. Table 2 reports the Spearman's correlation values obtained between the average HR obtained with the ECG_{gt} signal and the ECG_{sw} per participant.

B. ECG signal quality

Figure 5 presents the distribution of the MS-QI values obtained for the benchmark ECG (ECG_{gt}) and the best signal ECG_{sw} per participant. As can be seen, the benchmark ECG mostly surpassed the high quality threshold of 0.5, and the steering wheel signals the acceptable threshold of 0.35, thus suggesting the usefulness of the implemented setup.

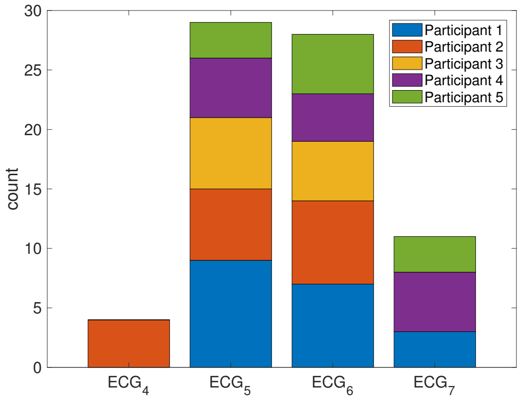

Fig. 4. Histogram of channels with the lowest RMSE across participants.

TABLE II

BEST SIGNAL ECG_{sw} FOR EACH PARTICIPANT AND ITS CORRESPONDING CORRELATION TO THE BENCHMARK ECG_{gt}

Participant	Best signal ECG_{sw}	Spearman's correlation
1	ECG5	0.981
2	ECG6	0.979
3	ECG5	0.861
4	ECG5	0.887
5	ECG6	0.954
Average ± std	—	0.933 ± 0.05

C. Instantaneous HR

Motivated by the MS-QI results, we evaluated the usability of the ECG signal from the steering wheel to detect the occurrence of each R-peaks in order to derive an iHR time series. To gauge the accuracy, we measure the Spearman correlation between the measure iHR from the steering wheel ECGs and the benchmark ECG. These results are presented in Table III. As can be seen, for most participants, this was made possible and correlations as high as 0.995 could be achieved, thus suggesting that accurate HRV metrics could be extracted from the steering wheel sensors and used for driver monitoring. The worst case scenario occurred with Participant 3 where a correlation of approximately 0.8 was attained. On average, iHR series could be achieved with a correlation over 0.93 with the benchmark ECG; such results are very encouraging.

D. Average breathing rate

Lastly, Table IV presents the estimated BR from the ECG_{gt} signal and the ECG_{sw} signal using each of the three methods described previously. As can be seen, Methods 1 and 3 performed better across participants. Overall, from the ECG_{sw} signal, an accurate BR could be derived with RMSE values between 0.8 bpm and 4.0 bpm. When combined with accurate HRV measures, BR can be used for multimodal driver assessment.

TABLE III

CORRELATION BETWEEN THE IHR TIME SERIES DERIVED FROM THE ECG_{gt} AND ECG_{sw} SIGNALS.

Participant	Best signal ECG_{sw}	Spearman's correlation
1	ECG5	0.995
2	ECG6	0.985
3	ECG5	0.793
4	ECG5	0.961
5	ECG6	0.871
Average ± std	—	0.921 ± 0.08

IV. CONCLUSION

In this paper, we presented the non-intrusive acquisition of ECG signals from an automobile driver through electrodes placed over the steering wheel. By using the modulation spectrogram representation, the acquired signals were processed and their usability to estimate average heart rate (HR), instantaneous HR, and to extract breathing rates was evaluated. The presented results show that from recorded signals, it was possible to estimate HR with a high degree of confidence, with correlations around 0.93 with a benchmark ECG worn by the drivers. Moreover, the analysis showed that the electrode locations for the signals ECG_5 and ECG_6 carried the greatest amount of information across trials and across subjects. For BR estimation, in turn, three methods were tested and two showed to achieve acceptable results, with an RMSE as low as 0.8 breaths-per-minute being achieved. In this preliminary work, the proposed driving test facilitated the acquisition of electrophysiological signals. As such, a more demanding driving test, e.g., with 90 degrees turns would elicit more realistic signals in which the hands may come off the steering wheel. In this scenario, better assessment of the stability of the methods could be measured and the evaluation on the complementarity of the ECG signals would be useful to develop methods that adaptively measure HR and BR from different sensors over time. This is left for future work.

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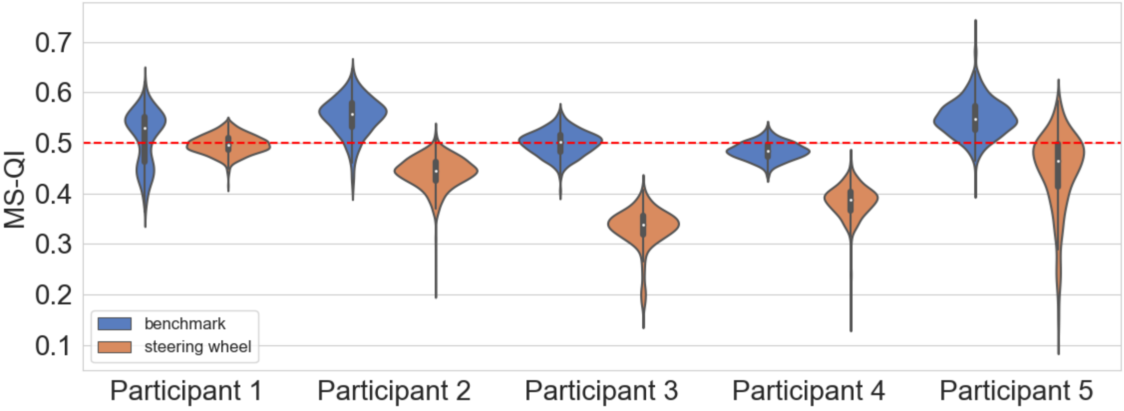

Fig. 5. MS-QI values for the benchmark ECG and the best ECG signal from the steering wheel per participant.

TABLE IV

RMSE VALUES FOR BR (GIVEN IN BREATHS PER MINUTE) BETWEEN MEASURED AND BENCHMARK BR. THE VALUES IN BOLD INDICATE THE LOWEST RMSE VALUE FOR EACH COMBINATION OF ECG SIGNAL AND BR MEASUREMENT METHOD.

Participant	Method 1		Method 2		Method 3	
	BR from ECG_{gt}	**BR from ECG_{sw}**	**BR from ECG_{gt}**	**BR from ECG_{sw}**	**BR from ECG_{gt}**	**BR from ECG_{sw}**
1	2.6	**2.7**	5.9	9.4	**1.5**	3.6
2	3.0	**3.3**	3.3	5.9	**2.7**	4.5
3	**1.1**	**2.0**	2.6	3.5	2.3	4.9
4	**0.5**	**0.8**	0.9	4.5	1.3	3.2
5	5.8	6.7	6.7	7.3	**3.0**	**4.0**
Average ± std	2.6 ± 2.1	3.1 ± 2.2	3.9 ± 2.4	6.1 ± 2.3	2.1 ± 0.7	4.0 ± 0.7

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