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Reading the human in the driver seat

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Abstract: Unobtrusive physiological sensors that seamlessly integrate in the automotive environment provide a novel way to measure driver's health and well-being. A driver pilot was conducted to test the accuracy of some new unobtrusive and wearable physiological sensors that currently are under development. Six drivers drove a pre-defined route twice, once during light and once during dark conditions. The drive included different road types to be able to identify possible differences in measurement precision. Heart rate measurements were done using a standard ECG method as well as via two types of unobtrusive measurements. These included a watch equipped with a photo-plethysmograph and a driver seat that was equipped with capacitive ECG sensors. Skin conductance levels were measured by means of dry sensors at the finger and a wristwatch was used for unobtrusive skin conductance measurements. Results show high intraclass correlation between the unobtrusive and reference physiological measurements while driving in different conditions. This evaluation demonstrates the potential for unobtrusive tracking of driver's health and well-being in the car.

Keywords: Driver monitoring, health & well-being, unobtrusive sensors, physiology

1. Introduction

Modeling the car and its environment gets a lot of attention and has become sophisticated. The model of the human being inside the car is, however, much less advanced yet and still plays a minor role in advanced driver assistance systems. Nevertheless, the condition of the driver can have a big influence on the performance of the car, as well as on comfort and safety. Moreover, many car brands see health & well-being as the next step - after safety - in their continuous improvement of the automotive environment. To illustrate, from an insight and marketing study, eight topic clusters in the health and well-being domain for human centric automotive were identified and some promising concepts were verified [1]. These eight topics range from "taking care of yourself on the go" to "providing mobile emergency care". In most of the identified topic clusters, sensing physiological parameters to track and improve the health and well-being of the driver played an important role.

In order to get insight into physiological input data about the driver - for driver assistance systems and other automotive health & well-being applications - we have started driving tests with a variety of physiological sensors.

Ideally, the physiological sensors to be used would be unobtrusive and contactless. There are some promising examples, like the vital signs camera developed by Philips [2], but a single type of sensor is rarely sufficient for an application and often it turns out difficult to achieve the required automotive robustness. Therefore, we broadened our scope to unobtrusive but not necessarily contactless sensors. To illustrate, Healey and Picard (2000) [3] were one of the first to equip a car with a variety of physiological sensors, among which heart rate and skin conductance level sensors, to measure driver stress. Results show that the input from a combination of signals leads to higher recognition performance (88%) of stress compared to the best single feature (62%). Therefore, triangulation of different sensor data is proposed to create the required for reliability to infer any health or well-being measurement from automatic measurements indicating the driver's condition [4].

The choice of objective automatic measurement of the driver condition depends on the application. Namely, physiological features have been shown to correlate with several different human conditions. An extensive amount of research for mainly cognitive (i.e., fatigue and mental workload [5]) or affective (i.e., mood or emotions) instead of healthcare-related applications has already been conducted in driver simulators. For example, it has been shown that during anger inducing rides, a positive calm, compared to a negative, activating in-car environment can reduce cardiovascular load, measured by among others blood pressure and heart rate [6]. Also, in difficult driving situations, induced calmness is able to lower sympathetic nervous system activity (i.e., measured with skin conductance) which is related to arousal [7].

Evaluations of physiological measurements in real cars are conducted less often. During studies in real cars, increases in heart rate have been reported in a drive through the wood compared to a baseline driving condition [8]. More recently, [9] included several physiological sensors in a real car to measure driving workload. They found higher skin conductance level (SCL) values in the 30 km/hour part of the drive compared to driving on a freeway. Cardiovascular and skin conductance measures hence show to be potentially meaningful for assessing driver conditions during simulated and real drives for a variety of applications. In most of the driving studies conducted, however, obtrusive and wired ways to measure physiological signals were used. These include the above examples and illustrate that the focus of pervasive adaptive driver support systems that include physiological measurements still is at the measurement quality and interpretation level.

In order to get experience with and insights into relevant input data about the driver for driver assistance systems and other automotive health & well-being applications, we have started driving tests with a variety of unobtrusive and wearable sensors. In this paper we show a pilot in which the performance and accuracy of unobtrusive physiological measurements of drivers is evaluated. For this purpose, two types of unobtrusive physiological measurement devices that are currently being developed at Philips Research are included: heart rate and skin conductance level measurements.

For unobtrusive heart rate measurement a photoplethysmography (PPG) embedded in a wrist watch was used (e.g., [10]). Besides PPG measurements, the watch has an accelerometer in order to acquire information about possible movement artefacts. Capacitive ECG is the second method we included to unobtrusively measure heart rate in the car. The advantage of capacitive ECG is that it is contactless i.e., the driver does not have to wear a sensor; instead, the sensors can be connected to the driver seat. Both PPG sensors and capacitive ECG sensors are highly susceptible to movement artefacts. Therefore, we expected higher accuracy of the signal when less movement of the car is present.

Unobtrusive skin conductance measurements were done with the discrete tension indicator (DTI-2) [11]. The DTI-2 sensor bracelet measures skin conductance at the wrist, besides measuring skin temperature and wrist movement. Skin conductance level is a tonic, slowly varying signal. Therefore, the signal is expected to be less influenced by motion artefacts created by different road types.

Because our interest concerns real-life data, we let the test participants drive in a normal car (equipped with sensors) on public roads, instead of using a driving simulator or closed driving track. Although as a consequence the test conditions can be controlled to a lesser extent, we believe that this is outweighed by the benefits of information about real-life usage and robustness. To identify the accuracy on different types of road, the drive passed different segments including an industrial area, highway, city drive, residential area drive. In addition, the drives were conducted during day as well as during night time to be able to investigate the impact of light and dark on the driver and the measurements.

2. Method

2.1 Participants and design

Six Philips Research employees (4 males, 2 females, average age 33 years, SD=7 years) participated in the driving evaluation. The participants had their driving license for on average of 14.8 years (min 7 years, max 27 years). They had driven on average 1483 km per year for the last few years (min 2000 km/year, max 30000 km/year). Each participant signed an informed consent before participating.

Each session started with a 3 minute baseline measurement in the car. The driving evaluation followed a within-subject design, so that all participants drove twice; once in light conditions and once in darkness. The order of the driving conditions (light / dark) was counterbalanced over participants.

2.2 Drive

A Ford Focus station wagon (year 2013) with manual gear was used for the driving test. The drive consisted of a predefined 14.5 km long, 30 minute drive including four different road types divided in seven sections (see Figure 1, Table 1). The drive was in an area that was familiar to the drivers.

Table 1 A description of the different road types, the maximum speed (S, km/hour), and mean duration (D, min.sec) of the 14.5 km long drive.

Section	S	D	Description
1 Industrial1	50	2.46	From the starting point to the high way
2 Highway	80	2.41	Highway Eindhoven towards city center Veldhoven
3 City Drive 1	50	4.32	From highway toward city center Veldhoven
4 Residential1	30	1.19	City center Veldhoven, many bumps
5 City drive 2	50	8.4	Urban ring from Veldhoven towards Eindhoven
6 Residential2	30	4.2	Road with many bumps
7 Industrial2	50	3.0	Back to end point and parking

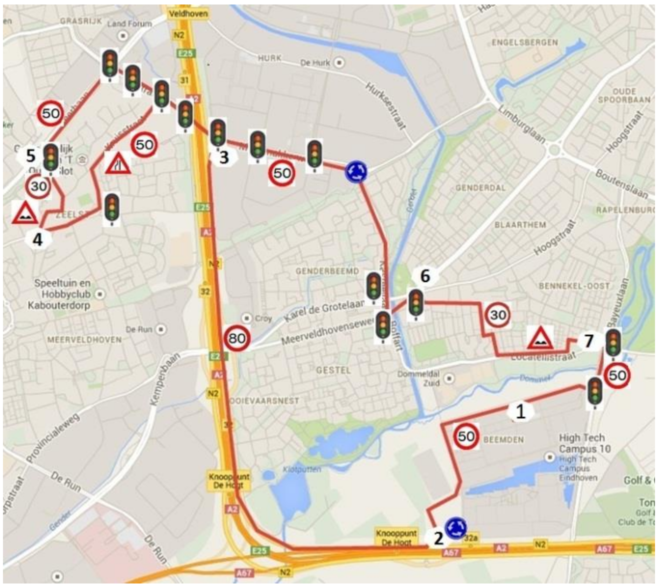

Figure 1 The 14.5 km, 30 minute drive in Eindhoven area. The numbers indicate the start/end of a drive segment.

2.3 Subjective measurements

The three dimensions of the Bond and Lader mood questionnaire were assessed before and after the drive [12]. The questionnaire contains 16 items, referring to 3 dimensions, i.e. alertness (9 items), contentedness (5 items), and calmness (2 items). The questions were presented on a 10 cm VAS scale. After the drive a 1-dimensional effort scale was used to assess the drivers effort levels during each driving segment. The driver was asked to answer on a continuous scale from 1 till 100, representing the 1-10 cm VAS scale in millimeters. These calmness ratings were normalized using z-transformations to allow inter participant comparisons.

2.4 Heart rate measurements

Three different measurement techniques were used to acquire heart rate (See Figure 2). First, the NeXus-10 device (MindMedia B.V., Roermond, the Netherlands) was used in standard Lead II electrode placement to measure ECG (sample frequency 1024 Hz) in the standard lab way (Stern, Ray & Quigley, 2000). The measurements were taken using Ag-AgCl disposable sensors, containing a solid gel. The signal was pre-processed by automatically detecting the R peaks from the raw ECG signal after filtering the signal (0.05-40 Hz). After automatic detection the signal was visually inspected for errors: misdetected peaks were corrected manually. Successively, the distances between the successive R peaks, the interbeat intervals (IBI), were calculated to determine the heart rate (IBI/60).

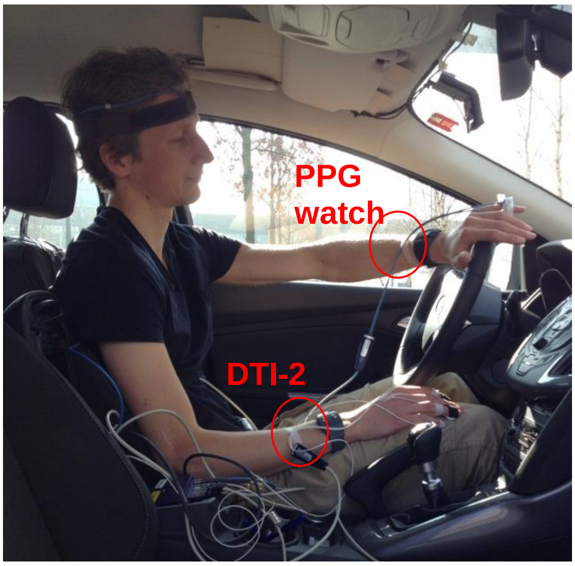

Figure 2 The sensors connected to a driver. The PPG watch to measure heart rate can be seen on the left wrist. The DTI-2 sensor bracelet to measure skin conductance can be seen at the right wrist. The small blue box is the NeXus device which is used for the wired reference measurements**.**

Second, a wristband equipped with a photoplethysmograph (PPG) was used to measure heart rate. The PPG device is being developed at Philips Research and also includes a 3D accelerometer. This is based on the same technology that Philips has licensed to power up sport watches such as the MIO Alpha, Adidas MiCoach SmartRun, TomTom Cardio Runner [13]. The optical device projects light to the skin and measures the reflection of the blood to acquire the PPG signal. The PPG wrist device was connected to the left wrist of the drivers. Two types of software analysis methods were used for the analysis of the PPG signal. In the first method, automatically detected interbeat intervals (IBI's) were only trusted and incorporated in further analyses, when movement levels of the wristband did not pass a set threshold. This threshold was set very low to guarantee correct detection of IBI's. The detected IBI's were then recalculated to heart rate in beat per minute (PPG_IBI). The second method always output average heart rate measurement per one second intervals (PPG_HR). This algorithm averages heart rates over a moving window of a few second intervals which made it more robust against motion.

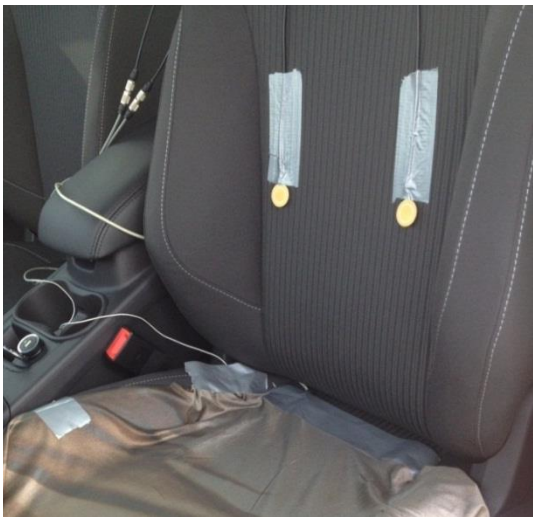

Figure 3 The two sensors of the capacitive ECG are connected to the back of the chair. The cloth acting as ground plate can be seen on the chair.

Third, heart rate was measured via capacitive ECG (cECG). cECG was measured by integrating two capacitive sensors and a ground plate in the car seat (sample frequency 1024 Hz, see Figure 3). Because the sensor electrode is coupled capacitively to the skin, the sensor can measure heart rate through clothing. From the sensors the data were transmitted to the NeXus 10-device. For the current pilot set-up no mechanical amplification of the raw capacitive ECG signal was included in the car. As a result, the normally visible large heart peaks (R peak) known from ECG measurements appeared smaller in the capacitive ECG measurements. This did made it harder to distinguish R peaks from the rest of the signal and especially from movement artefacts. Therefore, for this evaluation automatic detection of R peaks was done using the three lead ECG placement electrodes as a reference. The algorithm searched for R peaks in the cECG signal only at places 50 ms before and after an R peak was detected in the reference ECG signal. Additionally, detected R peaks were solely accepted if they had a cross correlation of 0.7 and higher with the detected R peaks in the lead II ECG signal. Successively, the HR was calculated from the IBI's (IBI/60).

2.5 Skin conductance measurements

Skin conductance level (SCL) measurements in the standard recording manner were done with the NeXus 10 device (sample frequency 1024 Hz). The sensors included dry Ag-AgCl finger electrodes which were attached to Velcro strips. The electrodes were strapped around the middle phalanxes of the middle and little finger of the right hand, in such a way that the driver was not restricted in a using the steering wheel and gears.

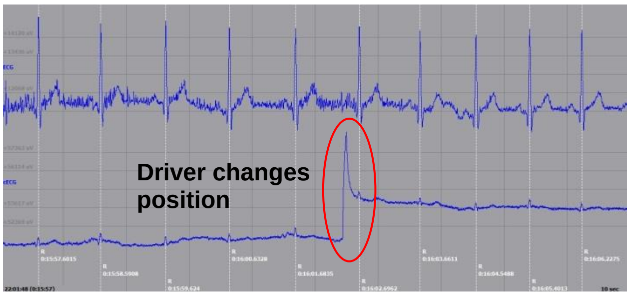

Figure 4 The top figure shows the reference ECG signal and the bottom figure shows the capacitive ECG signal. Halfway the signal, an example of a movement artefact in the capacitive ECG signal can be seen. The white dotted lines show the detected R peaks.

The discrete tension indicator 2 (DTI-2) wrist band was used for unobtrusive measurements of skin conductance (sample frequency 10 Hz) [11]. The DTI-2 is being developed by Philips Research and combines multiple sensors measuring not only skin conductance but also 3D acceleration, skin temperature and ambient light. The wrist band was attached to the right wrist of the driver.

Small movement artefacts were removed from the reference_SCL and the DTI_SCL by a low-pass filter at 0.5Hz. To be able to compare the signal over different participants, the skin conductance level was normalized using z-scores by taking the mean and standard deviation of the whole signal i.e., baseline and drive. Successively, the mean normalized SCL per segment was determined.

2.6 Other physiological measurements

The physiological measurements of skin temperature and respiration were additionally acquired during the drive. They are not fully analyzed yet at this point in time.

2.7 Protocol

After reading the information letter and signing the informed consent the participants were seated in the car. Then the participant adjusted the seat and mirrors to the driver preferences and the sensors were attached. The participant was then asked to sit calm and relax for three minutes without speaking and with the car engine switched on in order to take a baseline measurement. Next, the participant filled out the mood questionnaire after which he was asked to start to drive as he would normally do while following the directions of the GPS system. The experimenter was seated in the back of the car and accompanied the participant during the drive. They both did not speak during the drive to not interrupt the physiological measurements. When the drive was finished the participant filled out the mood questionnaire once more. Then the sensors were detached and the participant was thanked for his participation. The protocol was repeated for the second measurement which solely differed in the measurement conditions (dark/light).

3. Results

Missing data occurred for the physiological data of one participant during the light condition. The analyses were applied to the remaining data. The physiological measurements of skin temperature and respiration that were additionally acquired during the drive are not fully analyzed yet at this point in time. At a first glance this data appear to contain less interesting information.

3.1 Subjective effort measurements

The subjective effort acquired after each driving segment at the end of the drive showed a significant main effect of the driving section (generalized linear model $F(6,69)=2.41$, $p=.036$). Effort ratings were higher in the first industrial drive compared to the cityDrive_2 and the industrial drive_2. The industrial drive_2 had lower effort ratings compared to the city drive_1 and the residential are_2. Effort levels in the first driving section were highest and lowest in the last section. This could be due to the experiment setup and getting used to the car. No differences were found in the light and dark conditions (generalized linear model $F(1,69)=0.00$, $p=1.0$). Therefore, the combined effort measurements are: Industrial1 0.55/ high way -0.22/ city drive1 0.21/ residential1 0.01/ city drive2 -0.34/ residential2 0.44/ industrial2 -.071. No significant intraclass correlations were found between the effort ratings and the physiological measurements.

No multivariate differences in the pre and post mood measurements were found in the light and dark conditions ($F(3,8)=.250$, $p=.86$**)**. The pre and post mood measurements solely showed a marginal increase in alertness pre compared to post drive (alertness pre M= 45.4 (SD=3.0), post M=60.8 (SD=11.7); Contentedness pre M=68.5 (SD=5.4) post M=67.1 (SD=14.9); Calmness pre M=62.8 (SD=12.6), post=58.1 (SD=9.7).

3.2 Heart rate measurements

As expected, all the R peaks could be detected from the reference and the Lead II ECG placement, independent of the road section. The percentage of detected R peaks of the capacitive ECG and the PPG_IBI are shown in Table 3. The PPG_HR always provided HR output every second and therefore had full data coverage. From Table 3 it appears that the percentage detected IBIs of the PPG signal was highest in the baseline condition. It has to be noted that especially in the cECG measurements a large variability existed between the percentages of detected IBI's (see also Figure 5).

As hypothesized the areas with most movement noise, the residential areas, turn out to cause most difficulties for the reliable detection of successive R peaks, hence IBI's. During the drive no differences could be detected in the number of detected heart rates in the light compared to the dark conditions (cECG light M=58% (SD=9%), dark M=53% (SD=11%); PPG_IBI light 16% (SD=10%), Dark M=11% (SD=8%)).

The average heart rates for each driving segment are presented in Figure 6. Errors in the detected heart rates were calculated by taking the mean absolute difference between the ECG reference and the other heart rate data (see Table 4). The standard deviations of these errors were calculated to indicate the precision. Significant intraclass correlations (all $p<.001$) of the reference HR with the other HR measurements were found: cECG $r=.998$; PPG_IBI $r=.830$; PPG_HR $r=.951$.

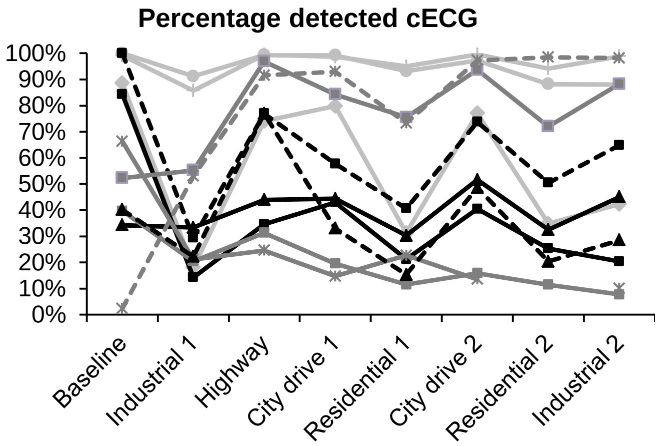

Figure 5: The percentage of detected IBI's of the Capacitive ECG (cECG). Each line represents the data of one session.

Table 3: The percentage of detected IBI's of the capacitive ECG (cECG) and the PPG IBI algorithm compared to the reference ECG measurement. The PPG_HR had continuous data coverage and was therefore not included in this table.

	cECG			**PPG_IBI**		
	mean	min	max	mean	min	max
Baseline	64	2	100	94	79	100
Industrial 1	40	14	91	9	0	22
Highway	68	25	99	20	0	70
CityDrive 1	61	15	99	17	2	36
residential 1	46	12	95	0	0	0
CityDrive 2	64	14	100	27	0	55
Residential 2	53	11	99	4	0	24
Industrial 2	54	8	99	16	0	46

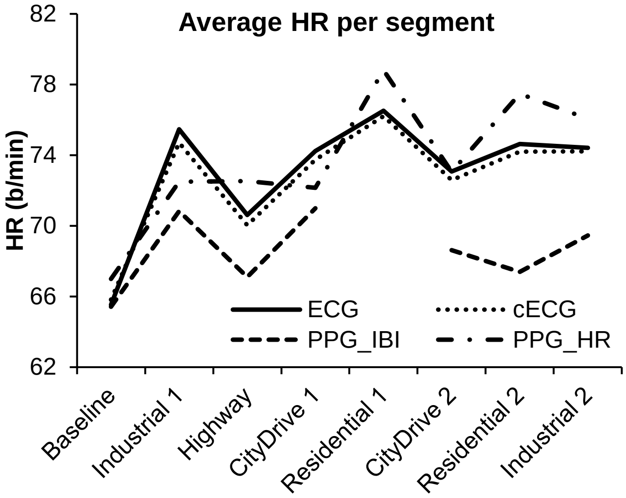

Figure 6: The average HR measured via the reference ECG, capacitive ECG (cECG), and the PPG. The PPG wrist signal has been analyzed in two ways, via exact successive detected IBI's (PPG_IBI) and via the continuous averaged HR (PPG_HR). No HR's were detected in the Residential 1 for PPG_IBI, therefore a HR prediction is missing.

Table 4: The mean absolute differences (MAD) and their standard deviation (SD) in heart rate (beat / minute) compared with the reference heart rate taken from the ECG.

	cECG		**PPG_IBI**		**PPG_HR**	
	MAD b/pm	**SD b/pm**	**MAD b/pm**	**SD b/pm**	**MAD b/pm**	**SD b/pm**
Baseline	1.30	2.24	0.21	0.20	1.48	2.61
Industrial 1	0.77	0.70	3.66	3.78	5.11	4.38
Highway	0.59	0.55	4.21	6.87	5.12	4.11
CityDrive 1	0.58	0.51	3.23	1.73	3.22	2.80
residential 1	0.62	0.40	NaN	NaN	5.07	5.83
CityDrive 2	0.52	0.50	3.59	4.02	2.45	2.83
residential	0.56	0.52	5.36	2.71	2.69	2.55
Industrial 2	0.42	0.49	3.03	1.86	3.02	2.94

3.3 Skin conductance measurements

A significant intraclass correlation (r=.57, p<.001) was found between the normalized SCL values measured at the fingers (Reference_SCL) and at the wrist (DTI_SCL). This implies that both signals follow a similar pattern. Figure 7 shows the normalized values of the SCL.

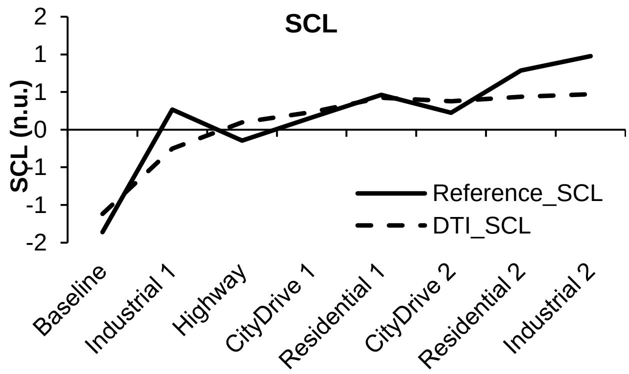

Figure 7: The average normalized skin conductance level per driving segment. The reference SCL is measured at the fingers. The DTI SCL is measured at the wrist.

4. Discussion

Health & well-being of the driver will become increasingly important in cars of the future. As a result unobtrusive measurements of driver physiology will be incorporated in future cars. In that way our cars could help us to continuously track our health, or provide feedback when our mental load or fatigue levels are increasing. Short-term measurements of driver stress and health pattern could lead to early recognition of changes in driver's condition which can be used to provide feedback on the current driving situation. Measurement information over a longer time period like weeks or months, which can be acquired during daily or weekly drives, can potentially indicate changes in driver's health situation. By creating awareness of this situation the car could possibly initiate changes in lifestyle patterns. The pilot study described in this paper showed a first evaluation of the reliability of a set of currently available wearable sensing methods of heart rate and skin conductance. Both heart rate and skin conductance measurements showed a high inter class correlation with the reference measurements.

As expected, the accuracy of the watch equipped with a PPG sensor showed a dependency on the amount of movement artefacts. This is illustrated during the baseline measurement where almost 100% correct detection of all successive heart beats

(IBI's) were found. Also, the detection of IBI's was worse while driving through the residential areas showing the sensitivity of the wristwatch to motion artefacts. This led to the highest precision in heart rate predictions in the baseline part, and additionally implies that the correct number of detected IBI's influenced the precision of calculation of the average heart rate.

Because the PPG watch uses light to measure the PPG this sensor was the sensor in this pilot that could possibly show differences in precision in light or dark circumstances. The results do not show any difference, indicating that the Philips technology integrated in the watch can be used independent of ambient light conditions

The second heart rate algorithm that is embedded in the PPG watch continuously provides as output a heart rate estimation based on the whole PPG signal. The precision of this signal might sometimes be slightly less; however, this is compensated by far lower dependency on movement artefacts resulting in continuous data coverage. In applications that only require heart rate information, for example for well-being purposes, the continuous heart rate algorithm might give enough information. Contrary, for a large range of health applications, heart rate variability might be required, in order to for example, determine cardiac load or different types of stress. This variability measurement will only be reliable with a large coverage and precision of successively detected heart peaks (i.e., R-peaks, hence IBI's). The continuous heart rate algorithm might not suffice in that case.

The capacitive ECG measurements showed a high precision in the detected heart peaks compared to the reference ECG. There appears, however, large between-measurement variability in the capacitive measurements, i.e., large differences in the number of detected R-peaks were found between participants. This result is almost certainly caused by the position of the driver in the seat or the body composition of the driver. For example, when a person bends forward, or the shape of the driver makes the connection with the sensors disappear, no heart peaks can be detected. Possible design solutions to increase the data coverage include the enlargement of the sensor size to increase the contact area with the driver. Also the number of sensors can be increased as well as their placement to cover a larger area of the car back and seat. In this way the best signal can be selected continuously.

The most prominent artefacts of the capacitive ECG were caused by severe movements of the car, i.e., in residential areas with many traffic bumps. This made it more difficult to distinguish heart-peaks from (movement) noise. Adding an amplifier to the sensor may facilitate recognition in these more challenging road conditions in the future.

In accordance with lab studies, skin conductance levels of the wrist show the same response patterns compared to those at the fingers [14]. The only difference between the two measurement locations is the measurement range; the amplitude of the skin conductance at the fingers is larger. In this pilot possible measurement artefacts could have arose from the finger measurements, in cases the drivers pressed the fingertips to the steering wheel too hard. Even though we had tried to prevent this as much as possible by sensor placement and driver instructions this could still have happened. This is especially visible in the driving parts that had the highest indicated effort and could imply that the drivers pressed the steering wheel harder during these sections (and thereby increasing measurements). It shows that objective measurements can sometimes be less accurate or even impossible in real world situations. Future studies could try to find ways to overcome this issue, by for example using unobtrusive instead of obtrusive skin measurement ways of the condition of the driver.

The current pilot evaluation aimed to show the accuracy of unobtrusive wearable physiological measurements in the car. Therefore, the route was designed to have different road surfaces hence noise, it was also designed in an area the drivers knew well, and the drive was short so that no changes in for example fatigue were expected. As a result, drivers did not indicate the drive as difficult. Also, differences in effort ratings were only at the first section of the drive (higher ratings) and at the last section (lower ratings) of the drive. The effect is most probably caused by getting familiar with the driving setup instead of with the actual road segment. Average heart rate and skin conductance measurements did not show large variations between the different road segments. In a follow up study a route could be designed in more extreme cases that targets to find correspondence of subjective feelings, cognitions or health situations and seamlessly integrated physiological measurements. For example, much longer drives or drives in unfamiliar areas could be included in a study. Another option is to run this evaluation test with a larger number of participants (larger than 6) to increase the power of the analysis.

5. Conclusion

This pilot evaluation showed a first step in evaluating the feasibility of wearable measurements of physiological signals in the car. Significant correlations between the obtrusive reference and the unobtrusively acquired heart rate and skin conductance measurements were found. For the capacitive ECG, we've additionally indicated some design improvements which should increase the detection of a continuous signal and improve the signal to noise ratio. The measurements from the wrist watches also show large correlations with the reference, and they both already have the computations embedded in the device. Therefore, depending on the application under investigation, they seem to be for a large extent already suited for continuously daily life driver assessment. For the detection of critical health applications, such as a cardiac load or an heart attack, however, the reliability and robustness of all sensors need to be extremely high, and higher than is currently obtained.

6. Acknowledgement

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8. Glossary

ECG: ElectroCardioGram
cECG: Capacitive ECG
IBI: Interbeat interval
PPG_HR: Continuous heart rate estimation acquired from photoplethysmograph measurements
PPG_IBI: Heart rate acquired from successively detected R peaks (IBI's) measured photoplethysmograph measurements
SCL: Skin conductance level
VAS: Visual Analog Scale