Chapter 1

Non-Invasive Psycho-Physiological Driver Monitoring through IoT-Oriented Systems

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The definition, analysis, and implementation of in-vehicle monitoring systems that collect data which are informative of the status of the joint driver-vehicle system, represent a topic of strong interest from both academic players and industrial manufacturers. Many external factors, such as road design, road layout, traffic flow and weather can influence and increase driving-related stress, potentially increasing risks. The ubiquitous diffusion of Internet of Things (IoT) technologies allows to collect heterogeneous data that can build the foundation for driver's psycho-physiological characterization, with the aim of improving safety and security while driving. This chapter evaluates and discusses the feasibility and usefulness of a non-invasive IoT-oriented driver monitoring infrastructure aiming at collecting physiological parameters (such as Heart Rate Variability, HRV) that may be adopted as biomarkers of the driver's psycho-physiological state in different driving scenarios.

1.1 Introduction

Driving is one of the major experiences linking together people: every day, while travelling by car, drivers are exposed to different events and situations, which can impact on their psycho-physiological state. External factors such as road design (motorways vs. rural roads vs. city roads, etc.), road layout (straight vs. curves, steep road vs. downhill road, etc.), traffic flow (high vs. low) and weather can

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influence and increase driving-related stress. To this end, literature studies examined the relationship between traffic conditions and stress levels and, as expected, they found that driving-related stress is greater in high traffic jam areas rather than in low congestion ones [1, 2, 3]. Moreover, it has been observed that these stressful situations may alter the driver's psycho-physiological state.

In this regard, Heart Rate Variability (HRV) represents an indirect and non-invasive measurement of beat-to-beat temporal changes in Heart Rate (HR), which reflects cardiac autonomic influences, particularly of vagal origin, at the sinoatrial node of the heart. HRV analysis has been extensively applied in various research fields, including psycho-physiology, cardiology and psychiatry, and has been increasingly recognized as a biomarker of health and stress. In fact, a healthy subject is characterized by higher levels of resting HRV, which are in turn associated with better flexibility and adaptability to environmental challenges [4]. Moreover, HRV analysis is able to index psycho-physiological states during stressful conditions or mental efforts (such as during driving activities) [4]. Indeed, lower tonic HRV has been associated with psycho-social stress and mental workload [5, 6, 7], whereas higher HRV reflects the capability of an individual to successfully adapt to external stimuli and manifesting itself in a reduction in daily performance [8]. An example of the potential utility of HRV as a biomarker of physiological driver's state is shown in [9], where driving-related stress is associated with a reduction in HRV indexes of vagal tone.

From a more technological perspective, the definition and analysis of monitoring systems inside vehicles which are able to simultaneously collect physiological indexes and useful data to determine the status of the driver-vehicle system is a topic of strong interest. The final aim for both academic players and industrial manufacturer is to improve safety and security while driving for both drivers and passengers [10]. Furthermore, recent technological progress has introduced new possibilities with respect to traditional manual driving, especially with regard to mechanisms aiming at vehicle—e.g., cars, trucks, etc.—driving assistance, such as *on-board* Advanced Driver-Assistance Systems (ADAS) [11]. In detail, examples of ADAS mechanisms equipping modern vehicles are Anti-lock Braking System (ABS) [12], Adaptive Cruise Control (ACC) [13], Electronic Stability Control (ESC) [14], Lane Departure Warning System (LDWS) [15], Forward Collision Warnings (FCW) [16], Traffic Sign Recognition (TSR) [17], automotive night vision [18], alcohol ignition interlock devices [19], collision avoidance systems [20], and driver drowsiness detection [21]. Then, as a common objective, all these ADAS aim to compensate for human errors, in order to reduce road fatalities—activating alarms or, when necessary, taking control of the vehicle itself.

Furthermore, focusing on a more general perspective, in the last years the ubiquitous diffusion of the Internet of Things (IoT) paradigm [22] has influenced and changed our lifestyle, thanks to the ability to interconnect heterogeneous devices (such as sensors, actuators, or more in general, *smart objects* [23, 24]), combining different technologies and communication protocols to build services for end users [25]. Thanks to this heterogeneity, IoT applications are innumerable—nowadays often requiring to outsource some processing efforts to Cloud-based infrastructures [26]—

and, among different possible scenarios, one of the most relevant is linked to the automotive industry, with the aim of acquiring a better knowledge of the driver-vehicle system as a whole.

Then, looking at the interaction level of all these paradigms, the majority of existing ADAS do not take into account aspects related to the psycho-physiological state of the driver. This would require continuous monitoring and understanding of the the driver's physical, emotional, and physiological state, an effective communication of the ADAS decisions to the driver, or a direct action on the vehicle. Although a monitoring system with these characteristics is very challenging to obtain, ADAS provided with information about the driver's psycho-physiological state could take more contextualized actions, implementing complex decisions that are compatible with the driver's possible reactions. Another aspect that should be considered in the field of *in-vehicle* monitoring systems, is the degree of intrusiveness of the sensors employed for collecting driver's physiological parameters, which in fact should not interfere—or minimize as much as possible their interference—with the driving activity, and therefore should be selected accordingly.

Due to these premises, the aim of this chapter is twofold: (i) propose a non-invasive IoT driver monitoring infrastructure, aiming at collecting data useful to estimate the psycho-physiological status of the driver, as a base for subsequent actions, and (ii) evaluate the usefulness of HRV parameters as biomarkers of a driver's psycho-physiological state in different driving scenarios.

The rest of the chapter is organized as follows. A review of heterogeneous technologies for human driver monitoring is presented in Section 1.2. Section 1.3 describes the in-vehicle IoT monitoring system and the experimental setup. In Section 1.4 a preliminary evaluation of collected data is presented. Finally, some conclusions and propose future research directions are drawn in Section 1.5.

1.2 Heterogeneous Driver Monitoring

When considering technologies for human driver monitoring activities, a focal point that should be taken into account is the extent to which the end user (i.e., the driver) takes up these technologies. This is strictly dependent on their unobtrusiveness, i.e., their capacity to be perceived by the user as not infringing upon his/her privacy or interfering with his/her driving activity. Taking these aspects into account, IoT sensing devices can be adopted as monitoring technologies and could be selected on the basis of their mobility degree. *Mobile sensors* (e.g., wearable and sensors-equipped smartphones), have become practical and appealing—thanks to the miniaturization of the components—and could also be exploited for monitoring driver's behavior and physiology [27]. On the other hand, *stationary sensors* are typically installed in the environment that needs be monitored (e.g., in the vehicle's cabin) and act without any physical contact with the user, thus being well suited for *unobtrusive* monitoring—an example of a stationary sensor may be a video and/or thermal camera positioned in the vehicle's cabin.

1.2.1 Wearable and Inertial Sensors

One of the uprising unobtrusive ways to monitor individual physiological parameters while driving is through the collection and analysis of biological signals. For example, the Electrocardiogram (ECG) gives uniqueness, universality, and permanence [28] in the measurement, thanks to its working principle by which the biometric signal is the result of the electrical conduction through the heart needed for its contraction [29]. Then, ECG analysis directly inside the vehicle's cabin may be useful for assessing parameters (e.g., HRV) related to both mental and physical stress, and workload [30, 31, 32] for automatic vehicle settings customization (e.g., biometric authentication for ignition lock [33]). Moreover, the respiratory signal may be exploited in order to obtain additional physiological indicators (e.g., the Respiratory Rate, RR) that are useful in the automotive scenarios. In particular, these data could be informative of the driver's workload and stress status. Nevertheless, it could be interesting to investigate how the combination of these measurements with vision data (either by normal or thermal cameras) would allow to estimate a classification index for workload or stress level of the driver [34]. Additional mobile sensing elements (often worn by the person to be monitored) are Inertial Measurement Units (IMUs), which allow the estimation of the driver motion level through 3-axes internal accelerometers and gyroscopes. More in detail, IMUs allow both motion and attitude/pose estimations, but they require to be carefully chosen and calibrated—because of bias instability, scaling, alignment, and temperature dependence. All these issues should be carefully considered especially in operating areas which require limitations in IMU's size, weight and cost limitations.

With particular regard to the automotive field, inertial sensing mechanisms can intervene in different scenarios, from driver's movements monitoring when seated in the vehicle's cabin to safety areas—like vehicle dynamics control (e.g., Electronic Stability Control, ESC) and passenger restraint systems (e.g., seat-belt pretensioner and airbags).

1.2.2 Camera Sensors

With regards to unobtrusive and stationary sensing technologies to be used in driver monitoring contexts, a particularly interesting one can be found in imaging-based solutions, such as video cameras. Unfortunately, as for sensing mechanisms discussed in Section 1.2.1, even video cameras are not exempt from drawbacks, especially depending on swinging lighting and atmospheric conditions—which may interfere with driver's movements monitoring and physiological signal recognition. Considering these aspects, a way to overcome this limitations is the deployment of thermal cameras, being more robust to adverse light conditions compared to canonical imaging sensors. More in detail, Long Wavelength Infrared (LWIR) cameras [35] can detect objects in different environmental conditions (e.g., rain, darkness, in the presence of fog, etc.), are unaffected by sun glare (improving situational awareness [36]), and are more robust against reflections, shadows and car headlights [37]. Even in this case, the price to be paid is that the thermal camera's video resolution is typically lower than that of traditional video sensors. Nevertheless, more recent thermal cameras

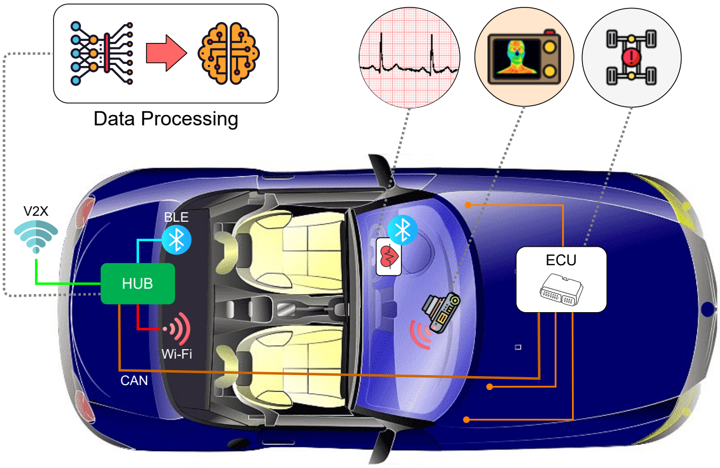

Figure 1.1 In-vehicle IoT-oriented monitoring architecture.

are able to produce high quality video streams. Finally, in addition to the driver's monitoring based on thermal cameras, a useful integration could involve the use of normal and general-purpose imaging sensors, such as *in-vehicle* fixed cameras, or the front camera of a smartphone [38, 39]. In detail, these additional video sensing elements can integrate the experimental data obtained by thermal cameras, thanks to their well-known portability, thus representing an optimal way for gathering information [40].

1.3 In-Vehicle IoT-oriented Monitoring Architecture

1.3.1 Experimental Setup

Given the different monitoring entities discussed in Section 1.2, the non-invasive IoT-oriented driver monitoring architecture proposed in this chapter is shown in Figure 1.1. In order to collect the driver's physiological data, an Equivital EQ02 LifeMonitor [41] sensor belt has been adopted. This wearable sensing device is composed by two elements: (i) a chest belt containing fabric electrodes placed in good contact with the driver's skin, and (ii) a Sensor Electronics Module (SEM) collecting ECG and respiratory signals, skin temperature, and 3-axis accelerometer data. Then, as shown in Figure 1.2, on a practical side the belt securely holds the SEM on the driver's body through a specific pocket on the left side of the belt itself.

Moreover, in order to collect thermal information from the body (i.e., face) of the driver and the surrounding environment, a FLIR One Pro LT [42] thermal camera has been included in the experimental IoT-oriented monitoring architecture. In detail, this video-capturing device is intended to work as an external "dongle" to be plugged into a smartphone (running either Android or iOS as operating system) and subsequently positioned and installed inside the vehicle, as shown in Figure 1.3. To this end, it is necessary to carefully and accurately define the position of the smart-

Figure 1.2 Equivital EQ02 LifeMonitor sensor belt positioning.

Figure 1.3 FLIR One Pro LT thermal camera positioning inside the vehicle.

phone connected with the thermal camera; this is as much true as it represents a trade-off between the quality of the framing—further image processing and analysis tasks require a frontal viewpoint—and the degree of obtrusiveness for the driver's perspective toward the windscreen.

1.3.2 HRV Analysis

The experimental testbed has been used to obtain high quality ECG recordings under stationary conditions, in order to perform a first HRV analysis. In detail, ECG signals are digital waves converted through specific processing tasks and, aiming at obtaining a good time resolution, a sampling rate of at least 250 Hz is recommended. Then, HRV is quantified by analyzing the variations of time intervals between consecutive normal heart beats. To this end, an inter-beat interval may be defined as the time between consecutive R waves peaks of the ECG (R-R interval), while the time-

Table 1.1 HRV indexes considered in the time domain.

Variable	Description	Physiological Origin
SDNN	Standard Deviation of the R-R intervals	Cyclic components responsible for heart rate variability
RMSSD	Root Mean Square of Successive Differences between adjacent R-R intervals	Vagal tone
pNN50	Percentage of successive RR interval differences exceeding 50 ms	Vagal tone

Table 1.2 HRV indexes considered in the frequency domain.

Variable	Description	Physiological Origin
VLF	Very Low Frequency (< 0.04 Hz)	Long-term regulation mechanisms, thermoregulation and hormonal mechanism
LF	Low Frequency ($0.04 \div 0.15$ Hz)	Mix of sympathetic and vagal activity
HF	High Frequency ($0.15 \div 0.4$ Hz)	Vagal tone

course of the R-R interval is called *tachogram* and further quantitative analysis of this curve will allow the estimation of HRV parameters. HRV analysis is performed by applying time-domain and frequency-domain methods.

Time-domain parameters are calculated with mathematical approaches to measure the amount of variability present in a specific time period in a continuous ECG signal. The most frequent time domain indexes adopted for HRV analysis are detailed in Table 1.1: (i) Standard Deviation of the R-R intervals (SDNN), (ii) Root Mean Square of Successive Difference between adjacent R-R intervals (RMSSD), and (iii) percentage of successive RR interval differences exceeding 50 ms (pNN50). In detail, the SDNN estimates overall HRV and includes the contribution of both branches of the Autonomic Nervous System (ANS) to HR variations. The RMSSD estimates vagally-mediated changes in HR [43]. Finally, the pNN50 quantifies the percentage of successive R-R interval differences that are larger than 50 ms and reflects the vagal tone [43].

Instead, frequency-domain analysis requires to filter the signal into different bands. In fact, the power spectral analysis decomposes a time-dependent fluctuating signal into its sinusoidal components, allowing to detect and quantify the amount of cyclical variation present at different frequencies [44]. Moreover, it provides information on how the power is distributed as a function of frequency. Thus, in a

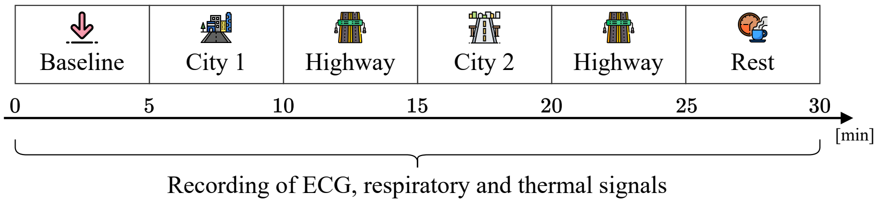

Figure 1.4 Operating driving protocol adopted in the experimental driver monitoring.

typical power spectral density curve, three main frequency bands can be identified, as detailed in Table 1.2: (i) Very Low Frequency (VLF), (ii) Low Frequency (LF), and (iii) High Frequency (HF) bands. The VLF component reflects R-R interval variations that are due to long-term regulation mechanisms (e.g., thermoregulation and hormonal mechanisms). The LF band reflects a mix between sympathetic and vagal influences. The HF band reflects vagal tone and is linked to respiratory-related changes in cardiac autonomic modulation [45].

1.4 Experimental Performance Evaluation

1.4.1 Operating Protocol for Data Collection

In order to collect information on the driver's psycho-physiological state in different driving scenarios, driving tests should be performed according to a well-defined operating protocol. Both smooth and fast driving should be included in the analysis to evaluate the driver's response to different external stimuli, associated to different amount of perceived stress. All these tests should then take place on both urban and highway roads in situations of smooth and heavy traffic.

The experimental driver monitoring has been conducted on a 26-years-old Italian female subject, separating the driving protocol into six time intervals, as shown in Figure 1.4: (i) baseline, (ii) first city driving, (iii) first highway driving, (iv) second city driving, (v) second highway driving, and (vi) rest phase. Each driving period had a duration of at least 5 min, in the end resulting in a total driving time of 30 min. In order to collect driver's physiological data, the Equivital EQ02 LifeMonitor sensor was worn by the subject throughout the driving test and the FLIR One Pro LT thermal camera was used to simultaneously record temperature-related information.

The overall route covered during the experimental campaign inside the city of Parma, Italy, is shown in Figure 1.5. During the baseline period, the vehicle's engine was off and the subject was asked to sit still inside the vehicle to acquire baseline data. During city and highway driving phases, urban and ring roads were covered with an average speed of 50 km/h and 90 km/h, respectively. Finally, at the end of the route, data recording continued for at least 5 min during recovery conditions, with the driver inside the car.

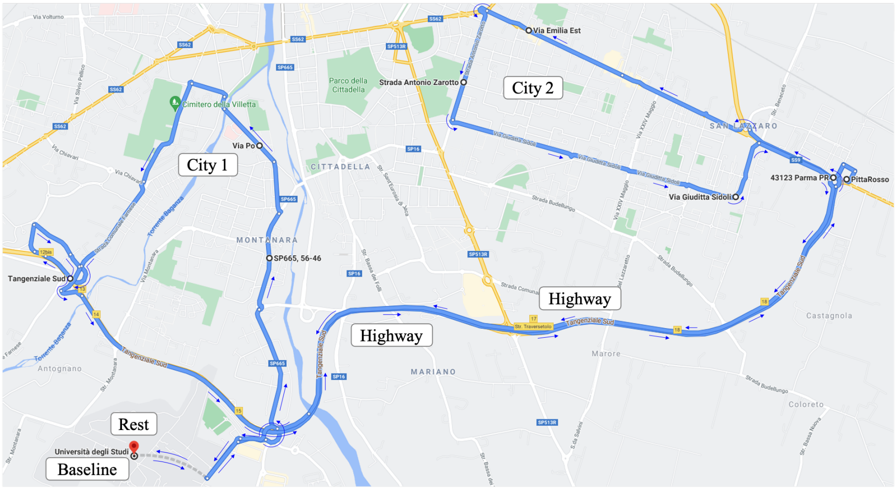

Figure 1.5 Urban and highway roads traveled in the city of Parma, Italy, during the experimental driver monitoring.

1.4.2 HR and HRV Data

ECG and respiratory signals were exported from the wearable sensor by means of its software manager, denoted as Equivital Manager. Then, raw ECG and respiratory data obtained from the EQ02 LifeMonitor equipment were amplified, digitized, and analyzed by means of the LabChart Pro 5.0 software [46]. More in detail, each raw ECG signal was manually inspected to ensure that all R-waves were correctly detected and to exclude artifacts before further analysis. Then, for each recording period, ECG signals were split in 5-min epochs and, for each epoch, HR has been calculated by plotting the number of R waves per time unit (dim: beats per minute [bpm]), together with the estimation of time- and frequency-domain HRV indexes (namely, RMSSD and HF). Finally, as for the ECG signals, for each recording period, respiratory signals were split in 5-min epochs, and RR was calculated for each epoch.

1.4.3 Experimental Results

In Figure 1.6, average HR temporal dynamics (dim: [bpm]) are shown. In detail, at the beginning of the recording session, the subject showed a HR value equal to 85 bpm. Then, HR increased during the first city driving phase and remained constant throughout the rest of the drive. Finally, at the end of the driving session, in the rest phase, HR returned back to baseline levels.

RMSSD values (dim: [ms]) are shown in Figure 1.7. At the beginning of the driving session, the average RMSSD was equal to 34 ms. Then, the RMSSD decreased during both city and highway driving phases, till increasing back to baseline levels during the rest phase, similar to what was observed for HR.

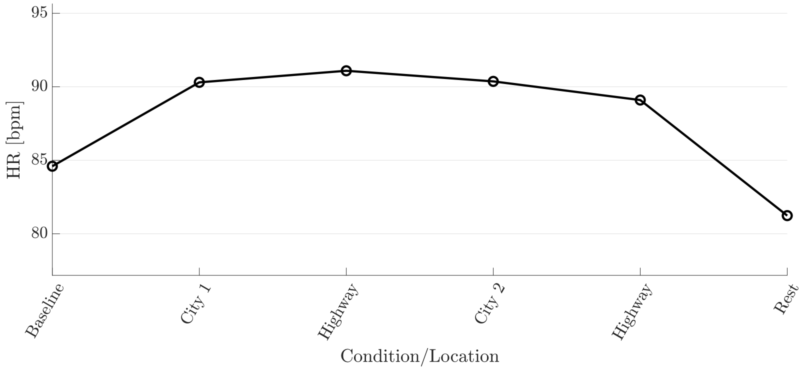

Figure 1.6 *Experimental HR values obtained during the driving route.*

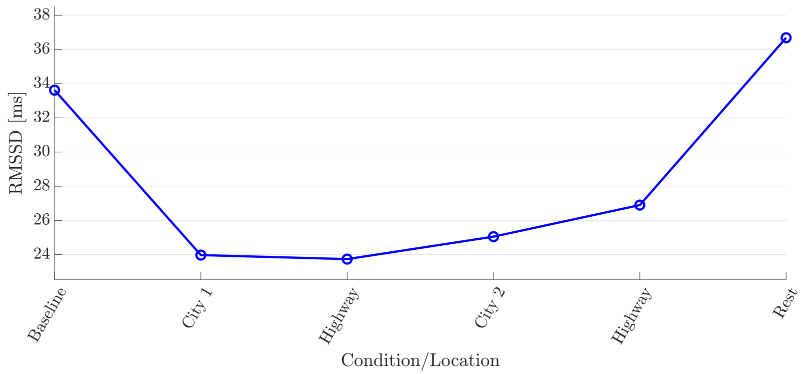

Figure 1.7 *Experimental RMSSD values obtained during the driving route.*

In Figure 1.8, the values of HF (dim: [ms^2]) are shown. As for RMSSD, the driving phase was characterized by a reduction of HF values in both city and highway scenarios, thus suggesting a decrease in parasympathetic modulation.

Finally, the average RR values (dim: counts per minute [cpm]) are shown in Figure 1.9. RR interval was steady during the overall recording session.

These preliminary results suggest that the driving experience can modulate the psycho-physiological state of the driver, as hinted by the reduction in HRV parameters associated with the increase of HR. Therefore, further driving recording sessions with a larger sample size are needed to confirm these results and indicate the extent to which HRV parameters may vary according to the psycho-physiological state of the driver in different driving scenarios. Moreover, future integration of thermal imaging data would provide a clearer picture of the physiological correlates of drivers' mental effort.

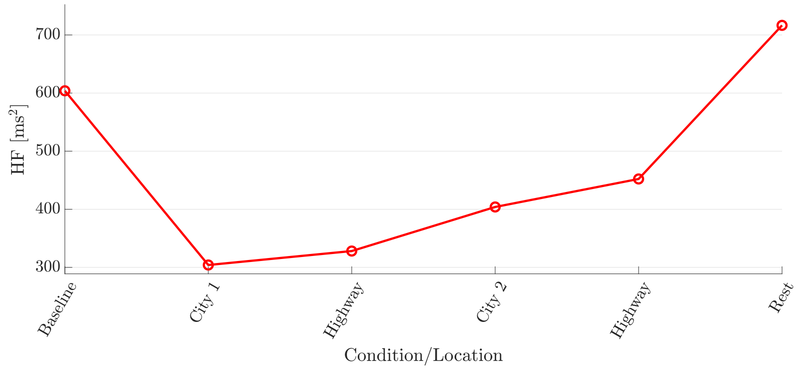

Figure 1.8 Experimental HF values obtained during the driving route.

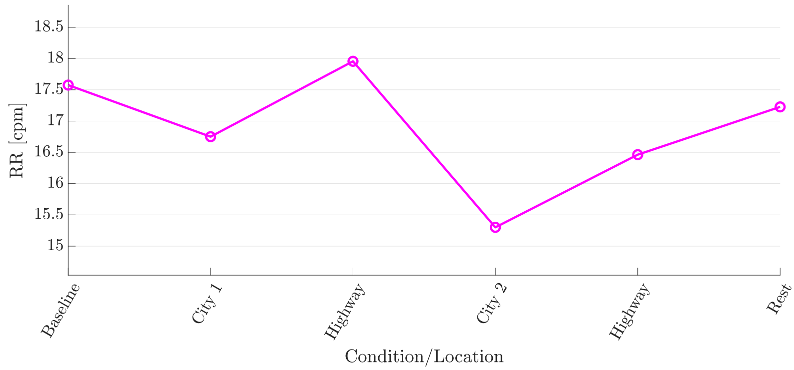

Figure 1.9 Experimental RR values obtained during the driving route.

1.5 Conclusions and Future Works

In this chapter, a preliminary non-invasive infrastructure for in-vehicle driver monitoring of the psycho-physiological status of the driver is presented. This infrastructure is based on an IoT sensor network composed by a wearable sensor belt, worn by the driver, and a thermal camera, installed in the vehicle's cabin framing the driver. Then, the protocol adopted for experimental data acquisition campaigns, together with ECG and respiratory signals collection and analysis during different driving scenarios, have been described. While additional experimental recordings are needed to confirm these experimental results and to allow a better investigation on the effects of driving activities on autonomic neural modulation of the cardiac function, the preliminary results on the utility of HRV parameters as biomarkers of a driver's psycho-physiological state are promising.

Future activities will involve the integration of thermal camera-based data and the improvement of the IoT communication infrastructure in order to integrate additional data sources, e.g., data collected directly from the on-board vehicular bus and emitted from the vehicle's Electronic Control Unit, ECU, possibly in real time.

Acknowledgments

The work of the Authors is supported by the European Union's Horizon 2020 research and innovation program ECSEL Joint Undertaking (JU) under grant agreement No. 876487, NextPerception project - "Next Generation Smart Perception Sensors and Distributed Intelligence for Proactive Human Monitoring in Health, Wellbeing, and Automotive Systems." The JU received support from the European Union's Horizon 2020 research and innovation programme and the nations involved in the mentioned projects. The work reflects only the authors' views; the European Commission is not responsible for any use that may be made of the information it contains. The work of L.D. is partially funded by the University of Parma, under "Iniziative di Sostegno alla Ricerca di Ateneo" program, "Multi-interface IoT sYstems for Multi-layer Information Processing" (MIoTYMIP) project.

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