Contactless Heart Rate Measurements using RGB-camera and Radar

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Abstract: The detection of vital parameters with traditional approaches, as the electrocardiograph, requires to appropriately place electrodes in direct contact with patients' skin, often causing irritation. On the other hand, contactless measurement of physiological parameters provides an unobtrusive and comfortable instrument for subjects' conditions monitoring, with application to home monitoring of aging people and in particular to those suffering of heart disease. In this paper two contactless techniques are proposed, based on radar technology and on video processing from an RGB camera. In order to validate their precision, the proposed methods are compared with three wearable low cost devices, taken as a reference for the outcomes. The developed approaches prove to achieve excellent performances, with an estimated mean relative error of 0.55% with respect to a commercial cardiac strap device.

1 INTRODUCTION

The Heart Rate (HR) measurement represents an important indicator of people's health condition. In the last years, research about contactless HR estimation methods gained an increasing attention, especially since they can represent a non-invasive alternative to conventional devices to detect different pathologies related to cardiac problems before getting a clinical diagnosis. Clinical devices in fact are often expensive and usually require the physical presence of patients in the hospital environment, which may be a difficulty especially for the elder people. Furthermore, clinical examination are equipped with electrodes that may react with the patient's skin and in some case cause significant damages. In addition other available contact sensors require exact positioning, while contactless methods allow to obtain a precise measurement also for patients that are not completely autonomous. Aging population represents the category of people who can take the most advantage of the use of contactless HR monitoring devices directly in their homes, where a complete electrocardiogram (ECG) recording may not be easy to perform. A continuous HR contactless monitoring can find an application in several contexts, for example in driving conditions (Lee et al., 2018), or to indicate a mental stress state (Kumar et al., 2007).

The design of contactless HR detection algorithms with a high accuracy is still an open problem. As a benchmark, the reliability of their performance is usually compared with those derived from standard methods, such as electrocardiography (ECG), or from other provably reliable non-invasive technologies, such as wearable devices (Georgiou et al., 2018).

Several methodologies for contactless HR have been proposed over the years. Consolidated systems exploit the use of the Microwave Impulse Radar (MIR) (Michahelles et al., 2004) or the Ultra Wideband (UWB) radar (Paulson et al., 2005; Zetik et al., 2007), which are non invasive and non contact methods based on very short radar impulses. These techniques use a wider bandwidth than conventional radar systems, enabling a positive impact on the information content of the received signal, proportional to the bandwidth of the low power transmitted signal. An alternative solution is given by the use of automotive radars. These sensors work in the mmWave range, with very high bandwidth and low cost. Also thanks to their operating frequencies, automotive Radars have a very small dimension, thus allowing to easily use them for healthcare applications (Wang et al., 2015; Hsu and Tseng, 2016).

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Another well-known short-range contactless HR estimation approach is represented by image and video processing (Li et al., 2014; Rouast et al., 2018; Sanyal and Nundy, 2018). It is mainly based on the detection of changes in the skin color due to the blood flow, which is usually imperceptible to the human eye. Since people's faces are an uncovered area, the face acquisition with an RGB camera is suitable for HR extraction by video processing. The Eulerian Video Magnification (EVM) method allows to enhance the skin color due to the blood flow, and it is a widely used approach in several studies (Alghoul et al., 2017; Gambi et al., 2017; Bennett et al., 2017; Aubakir et al., 2016).

Starting from the above considerations, this paper develops and deepens the work shown in (Ciattaglia et al., 2019), by the proposition of two methods to estimate HR through different contactless technologies. In particular, we consider signals obtained from an automotive radar and from video, which are elaborated to detect the HR of subjects with different characteristics. For the implementation of the proposed methodologies we exploit low cost commercial devices originally designed for other purposes, showing that we are able to achieve good precision performances. In order to estimate their accuracy, we compare the results obtained with those measured with more standard and provably precise contactless technologies, such as a pulse oximeter, a Polar wearable sensor and a Garmin smartwatch, which can be easily self-applied in a domestic context. Besides the measurement of the average value of the HR in a fixed interval, we also prove that by exploiting the considered contactless methodologies it is possible to assess the time variation of the HR, achieving a small and in some case negligible error with respect to more conventional technologies.

2 RELATED WORK

The use of radar systems in contexts other than the original one, such as the ambient assisted living, has seen an important technological advancement in the last years. Recently, these systems have attracted the attention of the medical field, thanks to their ability to provide high precision measurements at a reduced cost. In particular, a special interest has raised about the remote monitoring of vital parameters (Pisa et al., 2016). In (Wang et al., 2013; Lin et al., 1979) vital signs are extracted by using a Continuous Wave (CW) radar, while the same analysis is performed through an impulsive Ultra wideband (UWB) radar in (Ren et al., 2016) and a Frequency-Modulated Continuous-Wave (FMCW) radar in (Wang et al., 2015; Muñoz-Ferreras et al., 2019). The operational frequency of this kind of radar is in the range 24-80 GHz (De Ponte Müller, 2017); the use of such high frequencies allows measurements with good resolution, thus making it possible to analyze variations in very small displacements, such as those produced by the heartbeat.

Examples of remote monitoring of the heart pulse through the Photoplethysmography (PPG) are given in (Li et al., 2014; Rouast et al., 2018; Verkruysse et al., 2008). The PPG signal can be extracted through a pulse oximeter by exploiting a lightweight optical device (Tremper, 1989) for measuring oxygen saturation and heart beats in clinical use. Recently has been proved that PPG signal can be measured using a digital camera and the ambient light as an illumination source. When the digital camera is used to acquire a video, Videoplethysmography (VPG) (Rumiński, 2016; Couderc et al., 2015; Gambi et al., 2017) is defined as the signal derived by the RGB frame sequences processing.

In the paper here presented, we describe the VPG signal extracted from the subjects' face, using a face detection process (Viola and Jones, 2004), through the luminance component obtained by transforming the RGB in YIQ (Y-luminance, IQ chrominance) space color. The Regions of Interest Region of Interests (ROIs) are selected manually and they represent a percentage of a detected face; these ROIs are applied for every subjects under tests in the same way. Deep learning is exploited in (Hsu et al., 2017; Sebe et al., 2019) to track the better facial ROI by using a set of landmarks, but, differently from this work, the authors use an approach based on Independent Component Analysis (ICA) (Alghoul et al., 2017) or by extracting the sample mean sequences of the R, G, and B channels. On the contrary, in this study we adopt the EVM approach to highlight the blood flow after the heart pumping. The EVM method allows to amplify the color values assumed by the pixels in a specific frequency band. This means that our algorithm is able to recognize a periodic variation in a sequence, and amplifies that variations in the frequency range selected in the input.

The rest of the paper is organized as follows. In Sec. 3 radar setup and signal processing are described, also considering a Multiple-Input Multiple-Output (MIMO) configuration, while in Sec. 4 the video signal processing developed is presented. Sec. 5 contains the results obtained and the comparison between the considered measurement techniques. Final considerations and remarks are provided in Sec. 6.

3 HEART RATE ESTIMATION FROM RADAR

The use of radar systems to determine the physiological parameters of a subject is implemented with the application of a technology that comes from the automotive world. Automotive radars are in fact capable of achieving extremely high precision at reduced costs. In our tests we exploit the AWR1843 radar provided by Texas Instruments (Instruments, 2019), a MIMO radar with a fully integrated system containing a RF section, a DSP processor, an analog-to-digital converter (ADC) and a micro-controller; 4 receivers and 3 transmitters are available. A scheme of the device is reported in Fig. 1.

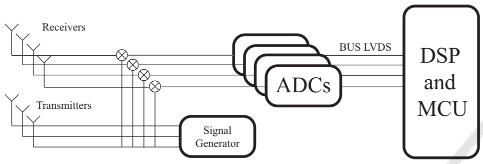

Figure 1: AWR1843 scheme.

A high precision in the definition of the target position is needed for the subject's HR detection, since, as described in the following, the heart activity is studied through the analysis of the phase of the signal Fast Fourier Transform (FFT). Accuracy can be improved by exploiting MIMO. Moreover, as discussed in (Lee et al., 2019), MIMO turns out to be extremely effective for the simultaneous monitoring of the HR of two subjects, thanks of the possibility of identifying the angular dimension of the subject.

A description of the MIMO technology applied to radar systems is contained in (Fishler et al., 2004). Differently from classic communication systems application, the main goal in a radar context is to increase the angular resolution without adding complexity to the system. As stated in (Jian and Stoica, 2009), the result is a virtual receiving antenna, whose characteristics depend on the position of the transmitter and the receivers.

3.1 Radar Signal Processing

As described in (Ciattaglia et al., 2019), the HR extraction procedure from radar works as follows. The radar transmits a sequence of chirps divided into frames. Each chirp is designed to be able to precisely detect the position of a subject. It is possible to use only one frame for each chirp, thus not creating a data overhead during the processing phase. It is important to carefully set the duration of each chirp and the number of the contained frames within it, since these values directly impact on the sample rate of the HR. From (Instruments, 2019) the sampling frequency along the slow time can be written as

$$f_{sampling[HR]} = \frac{k}{t_{periodicity}}, \quad (1)$$

where k is the number of chirps inside one frame and $t_{periodicity}$ represents the frame duration.

For a better target position identification the MIMO technology is applied. Using this technique is possible to identify not only the distance but also the angle position, this is an improvement of the algorithm accuracy (Ding et al., 2016; Xiong et al., 2018).

A Field Programmable Gate Array (FPGA) is used to collect the samples of the beat signals from the ADCs. These signals come from four receivers' lines, and it is possible to store the samples in a data cube. This cube is depicted in Fig. 2. Samples of a single chirps are stored along the fast time, samples of different chirps are stored along the slow time, while samples of different receivers are stored along the spatial sampling. The fast time is used to detect the range distance of the subject, the spatial sampling and the slow time detect the angle and the velocity, respectively.

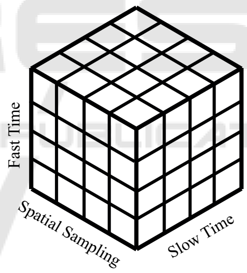

Figure 2: MIMO Data Cube.

By performing a bi-dimensional FFT on the Fast Time - Spatial Sampling plane, we obtain information about the subject position for each transmitted chirp. In our tests the target is static and there is no great variation in the FFT of the different chirps. In Fig. 3 we show an example of this FFT, where the red square represents the subject.

Once evaluated the target position, it is possible to apply the algorithm for the extraction of the HR. The displacement variation due to the heart contraction is far below the radar range resolution, thus making the phase analysis the only way of extracting the HR. The HR in fact produces a phase modulation of the FFT signal corresponding to the target position, as described in (Ding et al., 2016). After this identification is possible to extract the signal of interest along the slow time. The information is inside the phase, for

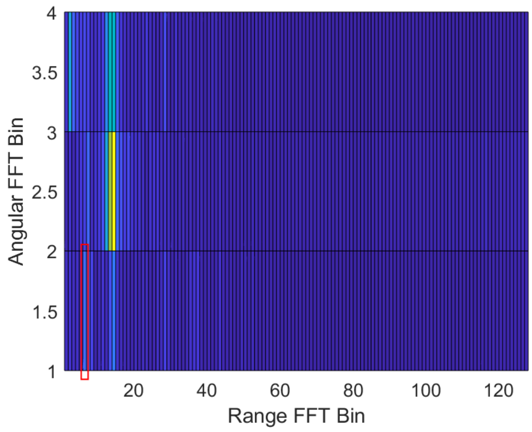

Figure 3: Subject position identification.

Table 1: Filters parameters.

Parameter	Value
Filter Type	FIR Equiripple
f_{stop1}	0.8 Hz
f_{pass1}	1.1 Hz
f_{stop2}	2.5 Hz
f_{pass2}	2.8 Hz

this reason a phase extraction and unwrap operation are needed. After having obtained the phase signal we can filter it in the range of the heartbeat, i.e. between 60 beats/min and 150 beats/min. The values used in our setting are reported in Tab. 1.

4 HEART RATE ESTIMATION FROM VIDEO

This section describes the techniques and algorithms applied for HR extraction through the video processing of a subject's face, by exploiting the face detection and the slight variations in skin color, generated by the blood flow in the tissues, amplified with the EVM method. The entire algorithm is briefly presented in Fig. 4.

The video is captured with GoPro Hero 6 with a frame rate of 60 fps (2400 frames for a sequence of 40 seconds) and resolution 1920×1080 pixels. Each frame composing the video is converted from RGB to YIQ space color to process only the luminance signal (Y), which constitutes the Videoplethysmographic (VPG) signal.

The face detection algorithm is derived by Viola and Jones approach. A face detector of at most 300×300 pixel is applied in order to extract the face of the subjects under test. The variations in skin color,

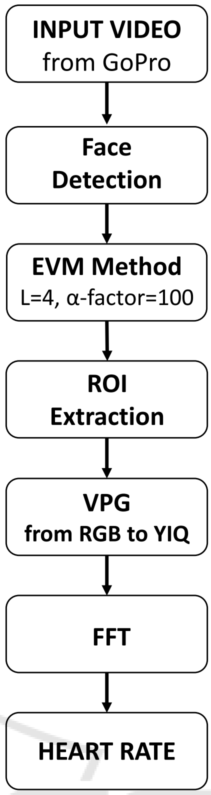

Figure 4: Main scheme of the video signal processing algorithm.

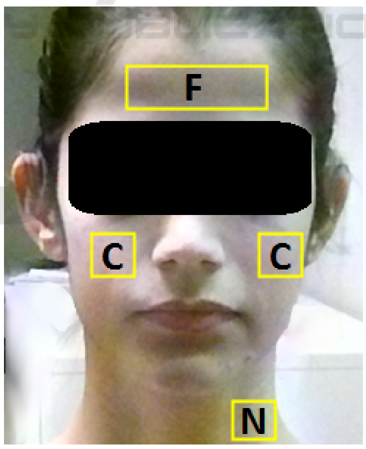

Figure 5: ROI selection on a subject's face. F stand for Forehead, C for Cheek and N for Neck.

imperceptible to human eye, reveal the subject HR thanks to the support of technological innovation. In particular, in each frame of the acquired video, we applied the EVM method (Wu et al., 2012), which allows to amplify skin color with the blood flow following the pumping of the heart, by deploying advanced image processing techniques. The algorithm analyses the sequences of frames by performing a spatial decomposition and a time filtering to determine the skin color changes in a specific frequency range. In the spatial decomposition, realized with four levels of a Gaussian pyramid in which the higher level is the smallest one, each image is down-sampled so that, starting with a level of 300×300 px, the higher level has 18x18 pixel size. The time filtering is developed on each spatial band with Infinite Impulse Response (IIR) band-pass filters to extract the frequency bands of interest.

As regards the emphasis on the skin colours variation, the main principle underlying the EVM consists in the amplification of the color values assumed by the pixels in a selected area or ROIs, realized by a specific parameter, i.e. the magnification factor or α-factor, set to 50. The selected ROIs are constituted by the forehead, cheeks and neck. The mean luminances extracted in each ROI must be added up to realize a total ROI and to process the VPG signal. As shown in Fig. 5 ROIs are chosen by setting the percentages of the box identified by the face detector and the ROIs size are respectively 90×30, 30×30 and 30×26 pixels. The VPG signal corresponds to the average values of the Y-component of all the pixels values inside the selected ROIs. We are able to extract the subject HR by setting the plausible cut-off frequencies for a healthy subject, which in this work correspond to (50 bpm/60) Hz for the lower and to (174 bpm/60) Hz for the higher, and applying first a third order Butterworth band-pass filter and then a FFT.

5 EXPERIMENTAL RESULTS

Experimental tests were conducted at the ICT Laboratory of the Polytechnic University of Marche on a set of 15 Caucasian and Asian people of different age and weight. Radar and GoPro Hero 6 were placed on two tripods, radar at a distance of about 20 cm from the subject's chest and GoPro at about 50 cm from the subject's face. The subjects under test were in a standing position. The used measurement setup is depicted in Fig. 6. During the video acquisition, the subjects were asked minimize their movements in order to avoid noisy signals or face tracking errors. Videos are captured in indoor conditions, hence we used a standard lamp (see Fig. 6) in addition to the ceiling light to better illuminate the subjects' faces.

Radar configuration parameters are reported in Tab. 2; it is possible to note that the heartbeat of the subject is sampled with a frequency of 20 Hz, which is a much larger value than Nyquist's limit.

In Tab. 3 we report the characteristics of the subjects participating to the tests and in Tab. 4 the results of the corresponding average heartbeat obtained with both the considered methods, radar (indicated as R) and video (V) processing, with respect to values given by Pulse Oximeter (POx). Since the EVM method amplifies the skin color, the subjects' characteristics are described to highlight any possible influence on the HR estimation. People with beard or make-up may generate a greater error in the VPG processing. The average heartbeat has been evaluated by considering the peak value obtained after applying a FFT to the entire signal. The peak value in frequency is then multiplied by 60 to convert it in bpm.

Figure 6: Measurement setup.

Table 2: RADAR parameters.

Parameter	Value
t_{chirp}	15.7 ms
Bandwidth	3.99 GHz
$t_{periodicity}$	50 ms
No. chirps in frame	1
No. samples in chirp	128
$f_{sampling}$	4 MSps
R_{max}	4.2184 m
$f_{samplingHR}$	20 Hz
Used TX and RX	TX1/RX1-RX4

In Figs. 7 and 8 we show an example of the amplitude (or luminance) evolution of the VPG signal as a function of time, where 40 seconds of acquisition are considered, and frequency for subject 14 in Tab. 4. Fig. 8 underlines the presence of a peak, which corresponds to the maximum value of the HR, that is equal to 92 bpm.

The relative percent errors $Er\%$ between different methods shown in Tab. 4 are calculated as follows

$$Er\% = \frac{|Ref - A|}{Ref} \cdot 100, \quad (2)$$

where Ref is the reference value and A is the value

Table 3: Characteristics of the subjects under test.

S	Age	Weight	Characteristics
1	22	66	Caucasian
2	22	85	Caucasian, Beard
3	37	75	Caucasian, Make-up
4	28	58	Caucasian, Beard
5	27	54	Caucasian, Make-up
6	26	54	Caucasian
7	37	75	Caucasian, Tanned skin
8	25	74	Caucasian, Beard
9	24	75	Asian
10	25	64	Caucasian
11	45	70	Caucasian
12	31	70	Caucasian, Beard
13	29	63	Caucasian
14	29	63	Caucasian
15	36	58	Caucasian, Make-up
16	29	50	Caucasian

Table 4: Tests Results.

S	V	POx	R	$\mathbf{Er}_{\mathbf{\|P-R\|}}\%$	$\mathbf{Er}_{\mathbf{\|P-V\|}}\%$
1	77	76	77	1.05	1.32
2	99	102	98.4	3.53	2.94
3	96	93	91	1.94	3.23
4	65	67	70	3.88	2.99
5	61	64	64	0.62	4.69
6	72	73	73	0.27	1.37
7	90	93	92.4	0.65	3.23
8	77	72	71	1.67	6.94
9	74	73	72	1.37	1.37
10	79	81	83	2.22	2.47
11	79	78	79	1.54	1.28
12	103	103	104	0.97	0.00
13	72	72	67	6.67	0.00
14	92	93	82	12.26	1.08
15	81	83	80	3.13	2.41
16	70	71	72	1.41	1.41

estimated using the contactless approach. The Mean Relative Errors (MREs) (Srivastava, 2014), computed by averaging the relative percentage errors $Er\%$, between Radar and Pulse Oximeter and VPG and Pulse Oximeter, are reported in Tab. 5, showing that errors obtained are very similar. The small errors measured also prove that both contactless methods can be used as a valid alternative to the Pulse Oximeter.

Table 5: Results and characteristics of the subjects under test.

MRE POx-R	MRE POx-V
2.76%	2.35%

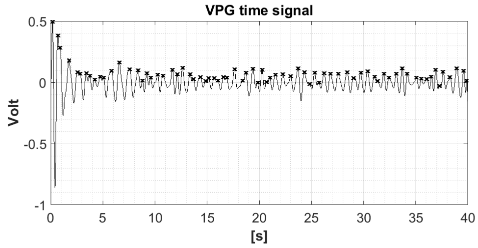

Figure 7: VPG signal extracted in terms of amplitude as a function of time.

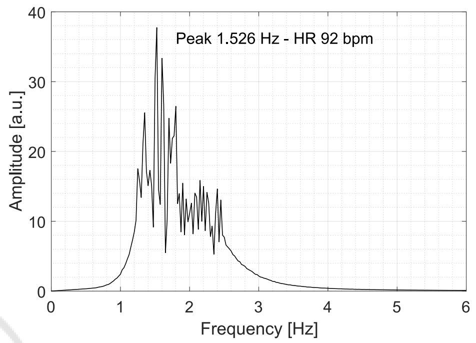

Figure 8: VPG signal extracted in terms of amplitude as a function of frequency. The peak at 1.526 Hz corresponds to 92 bpm.

A second kind of analysis is then carried out by analysing the time evolution of the VPG and Radar signals. As a reference, we considered the results obtained from two additional devices, a Polar H7 Bluetooth smart heart rate sensor, in association with the smartphone application Heart Rate Monitors, and a Garmin Vivoactive 3 smartwatch. They are both cheap but highly reliable HR monitoring devices.

The variability of HR is captured in the entire temporal sequence according the approach described in the following. Acquisitions of 40s were taken by simultaneously placing the Radar and the GoPro, wearing the Polar using a chest strap and the Garmin smartwatch. We investigated the FFT in the frequency domain by segmenting the VPG and Radar signals in the time domain in portions of 10 seconds, with 1 second of overlapping windows. The result is then interpolated and filtered using a Savitzky-Golayand (Theodor, 1996) filter, a Finite Impulse Response (FIR) optimal filter that minimizes the least-squares error in a polynomial fitting applied to noisy data. Finally, the outcome is compared to those extracted using the wearable devices.

The beats values resulted from the time domain analysis are shown in Fig. 9. All the examined curves lead to similar trends in their second part (which corresponds to 20-40 seconds of acquisition), although the radar exhibits a maximum value slightly shifted with respect to the other methods. However, we also observe that radar trend significantly differs from the others in the first 20 seconds of observation, and this is probably due to the fact that the algorithm used for radar signal processing is sensitive to the inevitable micro oscillations of subjects in standing position. On the other hand, the error measured on the radar is limited with respect to the Polar, which represents our main and most precise reference, as shown in Tab. 6.

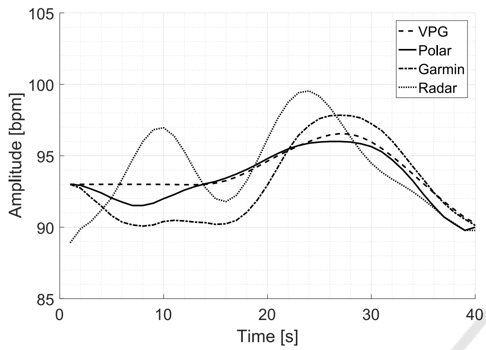

Figure 9: Comparison between contactless measurements and wearable devices.

Tab. 6 also reports MREs calculated comparing different methods, where *P* stands for Polar sensor and *G* for Garmin smartwatch. The minimum error achieved between Polar and VPG signal proves that the video contactless HR estimation represents a very precise approach. Radar shows a greater error with respect to other methods, but even in the worst case it remains below the threshold of 3%, thus demonstrating good overall performances.

Table 6: MRE between Polar (P), Garmin (G), VPG (V) and Radar (R) estimated values. The first letter indicates the reference device.

Methods compared	MRE value
P-G	1.74%
P-V	0.55%
G-V	1.93%
P-R	2.09%
G-R	2.92%
V-R	1.93%

5.1 Discussion

The proposed contactless approaches for HR measurement have proved to be valid and effective methods, with the advantage of an ease-of-installation in a home environment, thus allowing the monitoring of the elderly people in a simple way to reproduce. The cheapness of the commercial devices, such as the Go Pro RGB camera or the radar used in this work, makes also easy to reproduce the setup in different rooms of the house, in order to extend the HR monitoring to a domestic environment. The main error sources of the considered measurements are probably represented by the noise caused by the subjects' movements during the HR detection and by the distances between people and contactless devices. These distances can be further reduced, especially in a domestic scenario. In addition, the radar captures other signals which overlap to the HR, being focused on an area not sufficiently small. However, this problem can be avoided by applying a proper filtering.

6 CONCLUSIONS AND FUTURE WORK

Different contactless methodologies to estimate heart rate have been proposed. The application of these methodologies has relevance especially in contexts where the user is not able to properly handle the measurement devices, as the non-contact measurement provides for the user a simple positioning, even seated. We exploited low cost devices, in particular an automotive radar and a commercial camera, to extract physiological parameters from a set of 15 subjects with various characteristics. In order to validate our results, we have compared them with provably reliable technologies and we have shown that it is possible to assess the time variation of the heart rate with a small and in some case negligible error. The errors of 0.55% obtained with VPG approach and 2.09% using radar, compared with the Polar H7, taken as reference device, have proven the system precision and reliability of the developed methods. Further analyses could involve the evaluation of the proposed approaches by using an extended data-set comprising of different characteristics of the subjects, including ethnicity and lifestyle.

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