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Duration of photoplethysmographic signals for the extraction of Pulse Rate Variability Indices

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ABSTRACT

Pulse rate variability (PRV) assesses the changes in pulse rate through time when pulse rate is extracted from pulsatile signals such as the photoplethysmogram (PPG). PRV has been used as a surrogate of heart rate variability (HRV), but there is evidence of differences between these two variables. It has been hypothesised that these differences may arise from physiological processes or from technical aspects that may affect the reliable extraction of PRV indices from PPG signals. Moreover, there are no guidelines for the extraction of PRV information from pulsatile signals, which hinders the comparison among PRV studies and the understanding of physiological changes that may affect PRV. In this study, the effects of using PPG signals with different duration for the extraction of time-domain, frequency-domain and Poincaré plot indices from PRV was studied. Using simulated PPG signals with known PRV content and varying duration, it was found that PRV indices can be reliably estimated from signals as short as 90 s. This indicates that PRV indices can be extracted from ultra-short PPG signals. Although further validation with real data is needed, it can be concluded that acquiring shorter segments of PPG can be used for PRV analysis, allowing for a more efficient acquisition and processing of this variable.

1. Introduction

Pulse rate variability (PRV) describes the changes in pulse rate through time. It is extracted from pulsatile signals such as the photoplethysmogram (PPG) and has been proposed as a surrogate to heart rate variability (HRV), which is measured from the electrocardiogram (ECG) and reflects changes in cardiac autonomic activity [1,2]. PPG is nowadays probably the most widespread used physiological signal, since it is relatively easy to acquire, non-invasive and cost effective [3]. Hence, PRV has become particularly interesting for the monitoring and prediction of mental and somatic diseases [1], and its validation is crucial for the advancement of the technique and its applications.

However, the relationship between PRV and HRV is still not entirely clear. Some studies have found that PRV and HRV have similar trends but are not entirely the same, and have concluded that these differences may (1) originate from physiological processes [4–8], which could mean that PRV has potential applications when compared to HRV; or (2) arise from technical aspects in the extraction of PRV from PPG signals, such as the sampling rate used for the acquisition of the signal, the algorithms used for the detection of inter-beat intervals (IBIs) and the fiducial points used for the extraction of PRV traces [1]. Moreover, there are no guidelines for the extraction of PRV indices from pulsatile signals, which makes it difficult to compare and validate results from different studies.

One important factor for the extraction of PRV information from PPG signals is to understand how long PPG segments should be to obtain reliable PRV indices. This is essential especially for the extraction of PRV from wearable and embedded devices, which have limited computational and power resources, and from smartphone-based PPG technologies. Also, utilising shorter segments in PRV analysis will enable for a larger resolution in the measurement of indices in real time. The standard length of signals suggested for short-term HRV and PRV analysis is 5 min [9], but some researchers have found a relatively good behaviour in the extraction of indices from ultra-short-term segments, although further studies are needed to better understand the validity of these indices to extract physiologically valuable information [10–12].

The aim of this study was to evaluate how the length of the PPG signal affected the assessment of time-domain, frequency-domain and Poincaré plot indices from PRV. This was done using simulated PPG signals with different signal quality, varying lengths, and simulated but physiologically-plausible PRV content. It was hypothesised that PRV extracted from signals shorter than 5 min could be feasible for the reliable estimation of PRV content, when compared to indices extracted from the generated PRV trace with a duration of at least

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30 min. The use of simulated PPG signals and PRV information allows for the direct comparison of the expected results to the extracted PRV information, instead of using HRV information as a gold standard. Thus, this allows for a direct analysis of how the length of the signal affects PRV analysis, controls for the physiological differences that may be included in the comparison against ECG-derived HRV indices, and delivers valid statistical results due to the larger databases that can be generated. Moreover, understanding how these technical factors may affect PRV, regardless of HRV, is a step forward in the establishment of guidelines for the assessment of PRV indices from PPG signals, which could diminish the errors in PRV analysis. This, in turn, will open the doors to a better understanding of the physiological factors that affect PRV, its relationship to HRV, and the potential applications of the technique.

2. Materials and methods

The simulation and processing of PPG signals and PRV was performed in MATLAB (version 2020b), while statistical analyses were done in RStudio (version 1.4.1717).

2.1. Signal simulation

PPG signals were simulated using a modified version of the model proposed by Tang et al. [13,14]. In their model, a single cardiac cycle was simulated using the sum of two Gaussian functions with parameters set to simulate excellent and acceptable quality PPG signals. The values they proposed for the parameters describing the Gaussian functions, i.e., their amplitudes (a_i), width (b_i) and mean value (μ_i), were found by determining the optimal values when comparing the simulated cardiac cycle to annotated PPG signals from the MIMIC III database [15–17]. In the modified version of this model, instead of altering the quality of the PPG waveform it is possible to determine the ratio of the a parameters, r, from the two Gaussian functions, which alters the amplitude of the Gaussian functions and, therefore, the quality of the PPG cycle, determined by the presence or absence of a dicrotic notch, and its amplitude. The b and μ parameters were selected according to what has been suggested in the original model for the excellent quality PPG. The resulting model for the PPG cycle is shown in (1), where θ corresponds to the four quadrant inverse tangent of the cosine and sine functions of the duration of the cycle.

$$z = a_1\left(e^{-\frac{(\theta-\mu_1)^2}{2b_1^2}}\right) + a_2\left(e^{-\frac{(\theta-\mu_2)^2}{2b_2^2}}\right), a_2 = \frac{a_1}{r} \tag{1}$$

Then, the simulated cardiac cycles were appended and the resulting signal was detrended and low pass filtered using a second-order Butterworth filter with cutoff frequency of 15 Hz. The duration of each of the appended cardiac cycles was modified in order to include PRV information on the PPG signal. This was done by simulating PRV information as a sum of sinusoidal waves with randomly generated parameters that fall inside plausible physiological values for PRV. Table 1 summarises the ranges used for the random generation of these parameters. The average pulse rate (PR) was generated with values between 40 and 200 beats per minute, while its standard deviation was between 0.05 and 0.08 s. The fundamental frequency for the sine waves in the low frequency band was randomly selected between 0.04 and 0.15 Hz, while in the high frequency band these values were between 0.15 and 0.4 Hz.

The resulting function for the randomly generated PRV information is shown in (2). As can be seen, a total of four sinusoidal waves were summed, each of them with different fundamental frequencies, two for each of the main frequency bands as found in PRV analysis. It has been shown that the main physiological contributor to HRV, and probably PRV, is respiratory sinus arrhythmia (RSA), although other physiological processes, such as neural activity of the sympathetic and parasympathetic branches of the ANS, affect these variables [18,19].

Table 1
Ranges for the Pulse Rate Variability (PRV) parameters randomly generated to obtain PRV gold standard traces.

Parameter	Range	Units
Low frequency peak location (LF)	0.04–0.15	Hz
High frequency peak location (HF)	0.15–0.40	Hz
Average pulse rate (PR)	40–200	Beats per minute (bpm)
Standard deviation of pulse rate (SD)	0.05–0.08	s

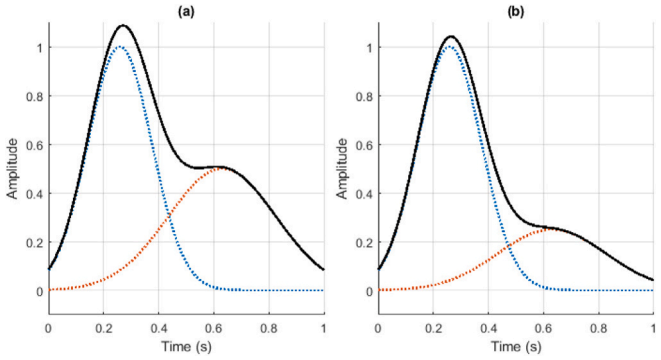

Fig. 1. Photoplethysmographic cardiac cycles generated using the proposed mode, using ratios of value (a) $r = 2$ (excellent quality), and (b) $r = 4$ (acceptable quality). The blue and orange dotted lines illustrate the two Gaussian functions generated, while the black continuous line shows the result of summing these two Gaussian functions, i.e., z.

Hence, more than just one sinusoidal wave was included in the model for each frequency band, increasing the complexity of the gold-standard PRV and simulating the real behaviour of HRV and PRV spectra, in which more than one frequency component can be observed.

$$PRV = \frac{60}{PR} + SD\sum_{i=1}^{2}(\sin(2\pi LF(i)t) + \sin(2\pi HF(i)t)) \tag{2}$$

In this study, two groups of PPG signals were simulated, according to the ratio r used to simulate the amplitude of the Gaussian functions. Excellent quality PPG signals were simulated with ratios of $r = 2$, while acceptable quality PPG signals were considered as those with $r = 4$. The base cardiac cycles for these two values of r are illustrated in Fig. 1. The main difference between these signals can be observed in the notoriety of the dicrotic notch, i.e., its amplitude when compared to the amplitude of the systolic peak. Fig. 2 depicts excellent and acceptable PPG signals simulated using the model with the specified r values, and with randomly generated PRV information.

In this study, 110 PRV traces with at least 30-min duration were generated and used to simulate excellent and acceptable quality PPG signals with varying lengths. From each of these, long PPG signals were generated, which were then segmented into shorter PPG segments. PPG segments had a minimum duration of 30 s, and a maximum of 20 min (1200 s), increasing in steps of 30 s. These gave a total of 40 segments with different lengths related to each of the generated 30-min PRV traces, for a total of 4400 signals. The 30-min PRV traces were used as gold-standard for statistical comparisons. This was done in order to understand how short the PPG segments need to be to reflect similar behaviour as longer PPG segments for PRV analysis. PPG signals were simulated using a sampling rate of 256 Hz, which has been shown to be a good sampling rate for PRV analysis from PPG signals [20,21].

2.2. Pulse rate variability assessment

Cardiac cycles were extracted from simulated PPG signals using the D2Max algorithm described in [22], which is based on the generation of blocks of interests based on two moving averages, which are designed based on the expected duration of cardiac cycles and the a point in the

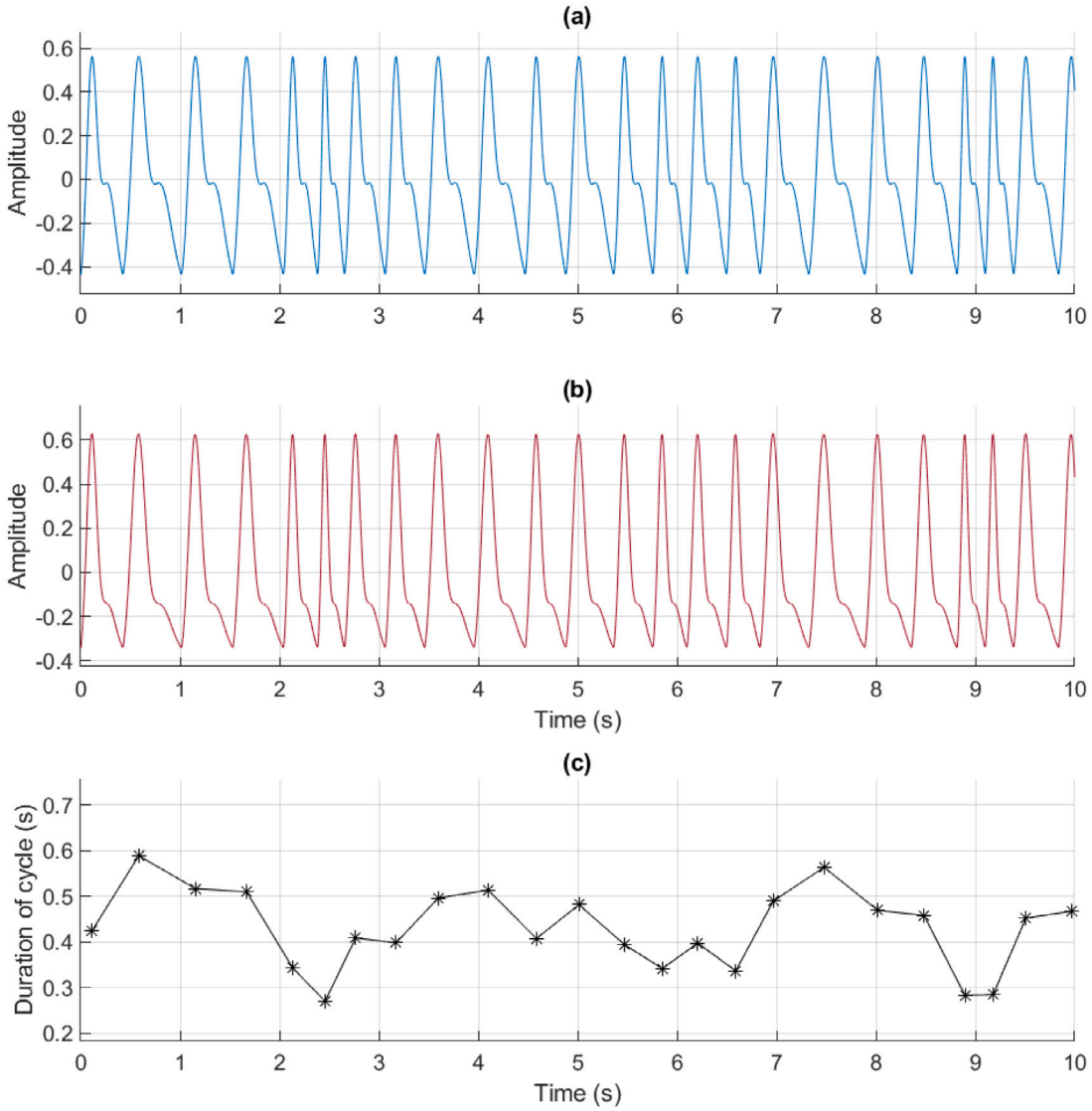

Fig. 2. Example of photoplethysmographic (PPG) signals simulated using the proposed model and randomly generated pulse rate variability (PRV) information. (a) PPG signal with excellent quality ($r = 2$). (b) PPG signal with acceptable quality ($r = 4$). (c) PRV information used for the generation of these signals.

second derivative of the PPG signal. The location of the systolic peak from the PPG signal was determined as the location of the maximum point in each block of interest. This algorithm has been found to have a good performance for PRV analysis [20]. IBIs were then obtained as the time difference between consecutive *a* points detected from each of the identified cardiac cycles. The *a* point corresponds to the location of the first local maxima in the second derivative of the PPG cardiac cycle. IBIs longer than 1.25 times the median duration of all the IBIs were corrected by looking for additional cardiac cycles in each of these longer windows. IBIs shorter than 0.75 times the median duration of IBIs were also detected and discarded.

Time-domain, frequency-domain and Poincaré plot PRV indices were extracted, both from the IBIs time-series and from the gold-standard PRV traces. From the time-domain, the mean duration of IBIs (AVNN), their standard deviation (SDNN), the root-mean squared value of sequential differences (RMSSD) and the proportion of sequential differences longer than 50 ms (pNN50) were obtained.

Spectral analysis was performed using Fast Fourier Transform (FFT). In the case of extracted IBIs time-series, the FFT was done after applying a cubic-spline interpolation with 4 Hz rate, and with 512 data points, for a frequency resolution of 0.0078 Hz. From all the analysed PRV time-series, both simulated and extracted, the very-low frequency (VLF, $f \leq 0.04$ Hz), low-frequency (LF, 0.04 Hz $< f \leq 0.15$ Hz), high-frequency (HF, 0.15 Hz $< f \leq 0.40$ Hz) and total power (TP, 0.04 Hz $\leq f \leq$ 0.40 Hz) bands were measured. Relative indices, i.e., the normalised LF and HF (nLF and nHF, respectively) and the ratio between LF and HF (LF/HF) were also extracted. The centroid of LF, HF and TP bands was measured, and their x and y coordinates were obtained (cLF_x, cLF_y, cHF_x, cHF_y, cTP_x and cTP_y). Although VLF was not included in the model for PRV simulation, it was extracted in an attempt to understand if, even in its absence, technical processes may affect the behaviour of this index when extracted from shorter PPG signals.

Finally, non-linear measures were obtained using 1-lag Poincaré plots. From these, the area of the ellipse (S), the minor and major axes of the ellipse (SD1 and SD2, respectively) and the ratio between axes (SD1/SD2) were extracted.

2.3. Statistical analysis

The differences between indices obtained from the extracted PRV traces and from gold standard traces were measured, and Friedman rank sum tests were implemented to evaluate how these differences were affected by the duration of the signals. This was considered as an appropriate non-parametric alternative to a 2-way ANOVA, where the

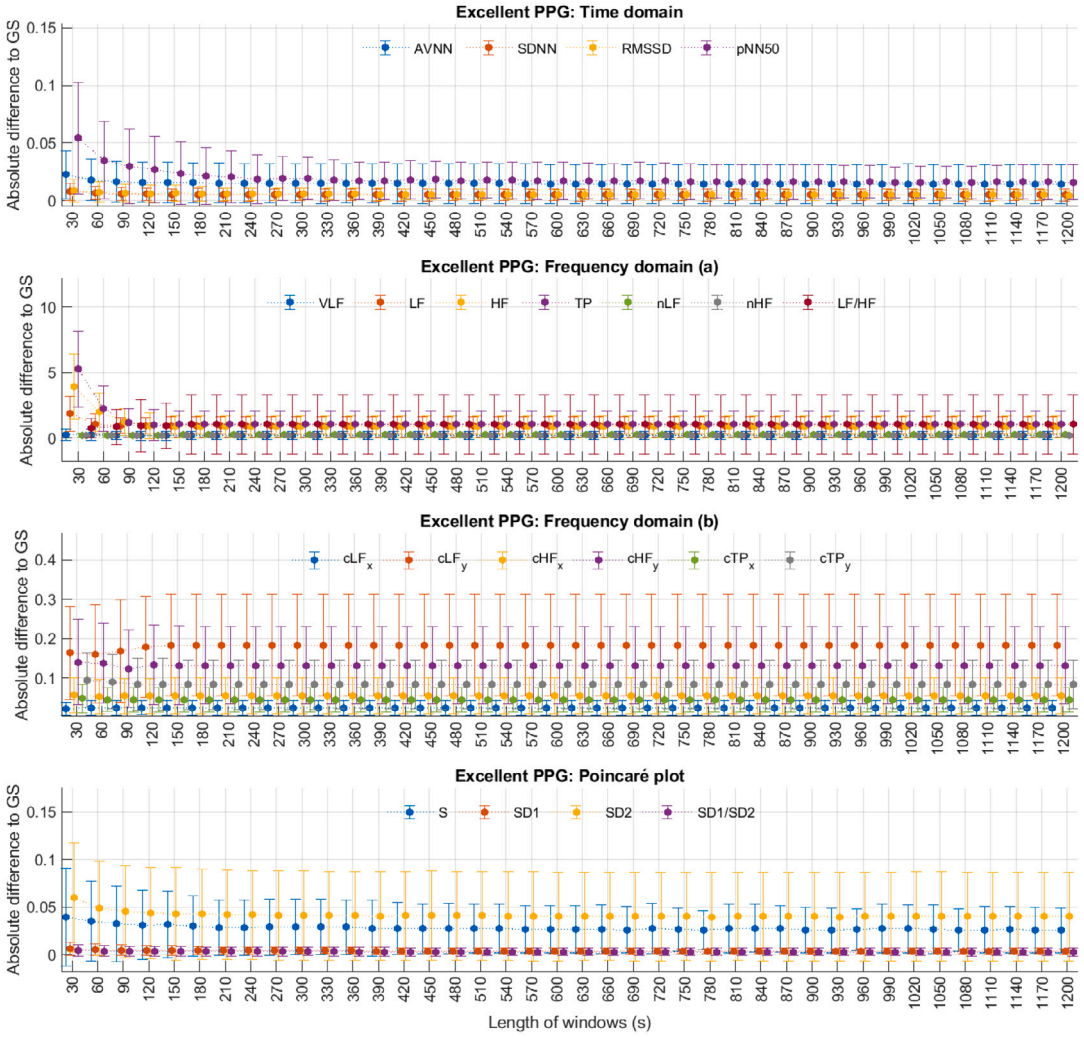

Fig. 3. Mean and standard deviations of the differences between indices extracted from measured and gold-standard pulse rate variability traces.

utilisation of the same PRV traces for the generation of PPG signals with different duration was considered as blocking factor and controlled for. Wilcoxon rank sum tests with Bonferroni correction were used for post-hoc comparisons.

3. Results

Fig. 3 shows the behaviour of PRV indices measured from excellent quality PPG signals with varying length. Statistical analyses showed non-significant differences among lengths for RMSSD (p-value = 0.217), nHF (p-value = 0.902), LF/HF (p-value = 0.0.150), cHF_x (p-value = 0.062), cHF_y (p-value = 0.136), cTP_x (p-value = 0.984), S (p-value = 0.832), SD1 (p-value = 0.217) and SD1/SD2 (p-value = 0.261). The mean value of the differences for time-domain (AVNN, SDNN, RMSSD, pNN50), non-centroid related frequency domain (VLF, LF, HF, TP, nLF, nHF, LF/HF) and Poincaré plot indices (S, SD1, SD2, SD1/SD2) tend to be smaller in PPG signals with duration longer than 120 s, as well as their standard deviations. The higher mean differences were observed in the extraction of non-centroid related frequency-domain indices. In the case of centroid-related frequency-domain indices, the trend is opposite, with lower differences for y-coordinates with shorter signals, while values related to x-coordinates remain relatively stable regardless of the duration of the signals. These indices seem to be less affected by technical aspects than y-coordinates of centroids.

In the case of acceptable quality PPG signals, Friedman rank sum tests showed non-significant differences among lengths for nHF (p-value = 0.604), cLF_x (p-value = 0.113), cHF_x (p-value = 0.343), cHF_y (p-value = 0.355), cTP_x (p-value = 0.691) and cTP_y (p-value = 0.939). The behaviour of the mean values and standard deviations (Fig. 4) is similar as that observed with excellent quality PPG signals: The differences become smaller and less variable with PPG signals longer than 120 s, and differences become stable with durations longer than 300 s. Again, differences are larger for non-centroid related frequency-domain indices, while the same behaviour can be observed in centroid-related indices.

In both cases, the results obtained for VLF need to be taken with care. Since this frequency component was not simulated as part of the proposed PRV model, it should not be present in the extracted spectra. However, it was assessed as an attempt to understand how technical aspects may affect it. It was observed that there were differences between VLF extracted from the gold standard and from the measured PRV traces, indicating that care should be taken to these technical aspects, which may include the frequency resolution and the algorithm used to obtain the frequency spectrum. However, this is not particularly valuable regarding the duration of the PPG signal, hence this index was not included in the subsequent analysis.

Since the aim of this study was to determine how long PPG segments need to be for reliable estimation of PRV indices, the minimum length at which no significant differences were observed for each index and each PPG signal quality were obtained from the post-hoc comparisons (Table 2). It was observed that pNN50, HF, and TP needed at least 90

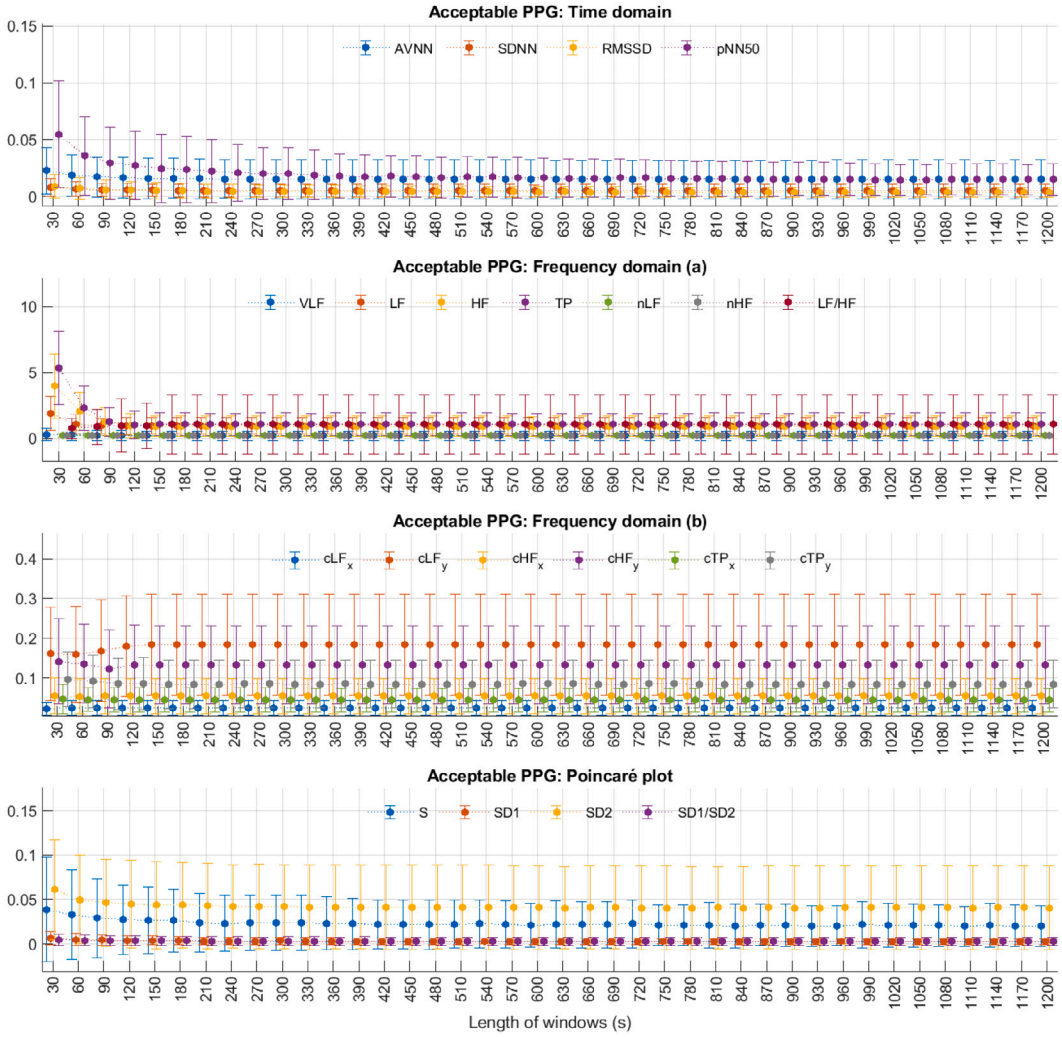

Fig. 4. Mean and standard deviations of the differences between indices extracted from measured and gold-standard pulse rate variability traces.

s long PPG signals. Hence, PPG signals of at least this length should be considered for reliable PRV estimation.

4. Discussion

Given the growing interest in acquiring and analysing PPG signals using everyday devices, such as smartwatches, or smartbands or video-based PPG signals from smartphones, as well as using PRV for the extraction of physiological information in a continuous manner, there is an acute interest in understanding how short the analysis window should be in order to obtain reliable PRV information. In the case of HRV, the standard is to use windows as short as 5 min [9], although shorter segments of ECG signals have been proposed for ultra-short HRV analysis [10]. The results of this experiment suggest that PPG signals as short as 90 s, for obtaining time-domain, frequency-domain and Poincaré plot indices, give sufficiently reliable results, and that the differences to gold-standard indices stabilise using PPG signals longer than 300 s.

It has usually been accepted that frequency-domain indices are more affected by the duration of the PPG signals used for PRV analysis than time-domain and non-linear indices, although further validation and analysis of ultra-short-term indices extracted both from HRV and PRV are needed [18]. From the results obtained in this study, it can be concluded that the differences between indices obtained from longer duration gold standard traces and PRV indices measured from ultra-short term signals of at least 120 s duration are comparable, and that these differences become stable when measured from signals longer than 5 min. However, these results should be considered with care given the simulated nature of the signals used, and the fact that physiological processes are not considered in this study. The effects of using ultra-short signals for PRV analysis could be larger in diseased subjects or while executing different experimental protocols that may alter PRV behaviour, and care should be taken given the effects of outliers in ultra-short-term recordings [18].

As should have been expected, indices related to long-term changes in PRV, i.e., AVNN, LF- and TP-related indices, and SD2, are importantly affected by the duration of the signal, mostly showing larger differences to gold-standard and more variability as shorter segments are employed. This could be explained by the nature of these indices, which are related to long-term changes in PRV, and as explained by Shaffer and Ginsberg [18] most of these indices are not comparable between long-term and short-term analysis results. However, these are not the only indices that show important differences when shorter segments are used, and pNN50, HF, S and y-coordinate related centroid indices show important differences to the gold standard as the window becomes shorter.

Previous studies have reported on the validity of ultra-short-term measurements for HRV or PRV. Baek et al. [23] obtained 5-min PPG signals from 467 healthy volunteers with a wide range of ages, and partitioned them into 270, 240, 210, 180, 150, 120, 90, 60, 30, 20 and 10 s segments. PRV indices were extracted from these short segments as well as the 5-min original signals, which were used as gold

Table 2
Minimum length of photoplethysmographic signals where post-hoc comparisons did not show significant differences between indices extracted from measured and gold-standard pulse rate variability traces, both with excellent and acceptable quality.

Index	Minimum length without significant differences (s)	
	Excellent PPG	Acceptable PPG
AVNN	60	60
SDNN	30	30
RMSSD	30	60
pNN50	**90**	**90**
LF	60	60
HF	**90**	**90**
TP	**90**	**90**
nLF	30	30
nHF	30	30
LF/HF	30	30
cLF_x	30	30
cLF_y	30	30
cHF_x	30	30
cHF_y	30	30
cTP_x	30	30
cTP_y	30	30
S	30	30
SD1	30	60
SD2	60	60
SD1/SD2	30	60

standard, and compared using correlation analysis, Kruskal-Wallis tests and Bland-Altman analysis. They found that the minimum duration of PPG segments varied according to group age and index, with a minimal duration of 10 s for AVNN; 20 s for HF; 30 s for RMSSD; 60 s for pNN50; 90 s for LF, nLF, nHF, and LF/HF; 240 s for SDNN; and 270 s for VLF. Most of these results are in line with those found in the current experiment, where it was found that shorter segments can be used to extract PRV indices, and the differences in the suggested lengths could be explained by the fact that these authors used shorter segments as gold-standard than what was used in this experiment, and the effects of physiological factors that are not considered using simulated data, as well as the amount of variability included in the simulated PRV information. Regardless, these authors suggest the reliability of obtaining most PRV indices from ultra-short PPG signals. Similarly, Finžgar and Podržaj [11] investigated the feasibility of assessing ultra-short-term PRV from video PPG, and compared their results to most of the previous studies using video-based PPG and ultra-short recordings. Although their results suggest that SDNN, RMSSD and pNN50 could be reliably extracted from ultra-short PPG segments (10 s, 30 s and 60 s), their gold standard was indices extracted from 60 s segments, which should not be considered as acceptable. Hence, the validity of their results is under question and further analyses should be performed in the area of video-based PRV analysis. Nonetheless, other studies have suggested the validity of using segments as short as 60 s for PRV analysis in healthy fit subjects [23,24].

Recently, similar studies have been reported for ECG-derived ultra-short-term HRV analysis. Kim et al. [12] showed that ultra-short-term HRV could be assessed under static conditions with ECG signals with duration between 30 and 240 s, while under dynamic conditions longer segments are needed, even with unreliable results for some indices regardless of the duration of the segments for ultra-short-term analysis. Gallardo et al. [25] extracted LF/HF and SD1/SD2 from HRV traces with varying lengths, and concluded that signals with duration of 180 s and 120 s, respectively, should be considered as the minimum reliable duration for ultra-short-term HRV analysis. Finally, Canino et al. [26] evaluated the feasibility of using 120 s ECG signals for the extraction of ultra-short-term HRV indices under different physiological conditions and data pre-processing techniques, and found that indices carry information related to different physiological states, although were not strongly predictors of aerobic fitness in healthy men, and found that most indices are robust to artifact correction procedures.

This study has some limitations. Firstly, simulated PPG signals with simulated PRV information were used in this study. This was done for two main purposes. It is simpler to obtain larger number of samples using simulated data, which gives statistical validity to the experiment. Also, by simulating PRV information it was possible to obtain a gold standard that was not HRV information obtained from the ECG. As mentioned, physiological aspects may explain part of the differences between HRV and PRV, hence comparing them in order to establish methodologies and strategies for obtaining PRV information is not ideal. Regardless of the benefits, using simulated PPG signals may not represent the entire variation of the PPG morphology and PRV changes, and the results from these experiments need to be validated using real PPG data. The simulation of PRV information may also affect the results obtained. However, PRV was simulated using physiologically feasible values. Future studies should optimise the PRV model to have a better reflection of real PRV information, using alternative models such as the integral pulse frequency modulation model [27]. It is important to note that the inclusion of four sinusoidal waves (2 for LF, and 2 for HF) in this model was intended only for increasing the complexity of the PRV information, rather than to suggest that this is the real behaviour of PRV and its related physiological processes. Hence, it is critical to validate this model or utilise a more robust model, especially for frequency-domain analyses. Secondly, this study considered noise free signals. This was done in order to have a level of control on the extraction of PRV information from PPG signals. Future studies should consider including noise to the signal to evaluate its effects on PRV analysis and the results found in this study. Moreover, although it was found that short segments reliably reflect the behaviour of PRV information extracted from these signals, the results need to be further validated using data obtained from healthy and ill subjects, in order to understand the effects of physiological processes that take part on PRV changes.

5. Conclusion

The reliable extraction of PRV information from short PPG signals is crucial for the continuous estimation of PRV in real-life scenarios and for its applications in wearable and consumer devices. According to the results found in this study, PPG segments should be longer than 90 s for reliable estimation of all time domain, frequency domain and Poincaré plot PRV indices, which is in line with several of the results reported in the literature. Nonetheless, further studies with real data both from healthy and unhealthy populations are needed to understand the differences among ultra-short-, short- and long-term PRV indices, and how and when could shorter segments of PPG signals be used for reliable estimation of PRV.

CRediT authorship contribution statement

Elisa Mejía-Mejía: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Panicos A. Kyriacou:** Conceptualization, Resources, Writing – review & editing, Supervision, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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