# Can PPG be used for HRV analysis?

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*Abstract*— **Heart rate variability (HRV) represents one of the most promising markers of the autonomic nervous system (ANS) regulation. However, it requires the acquisition of the ECG signal in order to reliably detect the RR intervals, which is not always easily and comfortably available in personal health applications. Additionally, due to progress in single spot optical sensors, photoplethysmography (PPG) is an interesting alternative for heartbeat interval measurements, since it is a more convenient and a less intrusive measurement technique. Driven by the technological advances in such sensors, wrist-worn devices are becoming a commodity, and the interest in the assessment of HRV indexes from the PPG analysis (pulse rate variability – PRV) is rising.**

**In this study, we investigate the hypothesis of using PRV features as surrogates for HRV indexes, in three different contexts: healthy subjects at rest, healthy subjects after physical exercise and subjects with cardiovascular diseases (CVD). Additionally, we also evaluate which are the characteristic points better suited for PRV analysis in these contexts, i.e. the PPG waveform characteristic points leading to the PRV features that present the best estimates of HRV (correlation and error analysis). The achieved results suggest that the PRV can be often used as an alternative for HRV analysis in healthy subjects, with significant correlations above 82%, for both time and frequency features. Contrarily, in the post-exercise and CVD subjects, time and (most importantly) frequency domain features shall be used with caution (mean correlations ranging from 68% to 88%).**

## I. Introduction

Heart rate variability (HRV) parameters quantify the change of time periods between consecutive cardiac cycles. It has been proven to be a valuable tool to characterize and understand the regulation of the cardiovascular system by the autonomic nervous system (ANS) [1]. In HRV analysis, the RR intervals obtained from the ECG are required [2]. Nevertheless, in principle, any signal providing accurate inter-beat heartbeat intervals could be used instead. A promising alternative technology is PPG, which can potentially provide similar results compared to a HRV analysis. However, since pulse signals are used, it shall be called pulse rate variability (PRV) instead [3]. Due to its technological and practical advantages, PPG is becoming increasingly popular in wrist-worn devices for pulse rate detection [3, 4], driving the interest for PRV analysis (rather than HRV) in different physiological, demographic and biometric circumstances. The PRV may achieve better estimates than HRV under some circumstances, such as when the ECG is subject to ECG-specific electrical artifacts, e.g., during clinical interventions [4].

Recent research has shown a sufficient accuracy of PRV compared to HRV in healthy mostly young subjects at rest [3], with high correlations (r) of both time and frequency domain parameters ($r > 0.94$, p-value $< 0.0001$) [5], and suitable limits of agreement: from [-0.1, 0.1] $min^{-1}$ (in heart rate – HR) to [-7.0; 19.8] % (in pNN50) and from [-1.38; 0.9] n.u. (in low/high frequency ratio – LF/HF) to [-202; 343] $ms^2$ (in low frequencies – LF) [6]. In non-stationary conditions, like the tilt table test, similar results were found [7].

It has also been shown that PRV-derived parameters tend to overestimate HRV values representing physiological processes related with short-term variability [3], but without impairing the evaluation of ANS in individuals at rest: absolute differences from 0.0±0.7 $min^{-1}$ (in HR) to 6.4±0.8% (in pNN50), and from 0.31±0.21 n.u. (in LF/HF) to 54±44 $ms^2$ (in HF) [6]. A major challenge for using PPG in HRV analysis is its sensitivity to motion artifacts [3, 5]. Suppression of these artifacts by improved algorithms is a popular research topic [8]. A complementary strategy for artifact suppression deals with acquisition from other body sites, like the earlobe [5, 6] or inside the auditory canal [9]. Often, an acceleration signal is synchronously acquired as well [5, 8], enhancing the deletion of motion artifacts using sensor fusion approaches.

Rauh *et al.* [6] achieved appropriate limits of agreement between the ECG-derived HR and the PPG-derived pulse rate (PR) in healthy subjects for paced breathing. However, worse ranges were observed for some parameters (from [-0.4, 0.5] $min^{-1}$ – HR – to [-10.2; 21.3] % – pNN50 – in the time domain, and from [-4.56; 3.31] n.u. – LF/HF – to [-715; 1260] $ms^2$ – LF – in the frequency domain), which was interpreted as a higher influence of breathing effects on the PPG compared to the ECG. Similar results were reported during obstructive sleep apnea events [10]. Furthermore, Han *et al.* [11] found that different breathing patterns lead to unequally altered characteristics of HRV and PRV. Breathing frequency had a higher impact than breathing volume. It was also demonstrated that the agreement between HRV and PRV-derived frequency features diminishes (e.g., a decrease of 28% in HF) during the Stroop Color-Word Test, when compared to resting conditions [12].

Since moderate physical or mental stress has been associated with a compromised agreement between PRV and HRV [3], the aim of this study is to extend these observations and to compare the HRV and PRV parameters, extracted using a time-variant analysis, in three experimental settings:

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healthy subjects at rest, healthy subjects after physical exercise and subjects with cardiovascular diseases (CVD).

## II. Collected Data

Three datasets were collected at the "Centro Hospitalar de Coimbra" covering different populations and circumstances: case 1) 33 healthy subjects at rest; case 2) same subjects as in case 1, after moderate physical exercise on a treadmill and; case 3) 35 subjects with CVD (such as hypertension, acute infarction, heart failure and coronary artery disease) at rest in supine position. Our datasets comprise ECG and PPG signals collected from all enrolled individuals using a HP-CMS monitor extended with a data logger functionality. The PPG signal (@125Hz) was recorded from the tip of the index finger using an infrared transmission finger probe, while the ECG waveform (MLII lead) was digitized at 500Hz. The biometric characteristics of the enrolled subjects (51 male and 17 female) are:

- **Cases 1 and 2 -** Age: 29.72±8.54 years; BMI: 24.48±2.41 kg/m$^2$;
- **Case 3 -** Age: 58.97±17.22 years; BMI: 25.38±3.10 kg/m$^2$.

Since our data analysis is based on a sliding window of 180 sec. with increments of 5 secs., the minimum length of the analyzed signals must be at least 185 secs. to retrieve two data points. This requirement could not be achieved for some subjects, which had to be excluded from the analysis: case 1) Patient 19; case 2) Patients 3, 4 and 5; case 3) Patients 4 and 34.

## III. Methods

### A. Assessment of Heart Rate obtained from ECG R-peaks and Pulse Rate from different PPG characteristic points

In HRV and PRV analysis, it is essential to first extract the HR and the PR. HR was calculated from detected consecutive R-peaks in the ECG signal, while PR was inferred as the time span between the characteristic points of two consecutive PPG pulses.

Characteristic points for PRs were as follows: 1) the onset of the PPG pulse – $PPG_{onset}$; 2) time instant corresponding to 20% of the PPG pulse's total amplitude, at the systolic rise – $PPG_{20\%}$; 3) time instant corresponding to the local maxima of the PPG pulse's first derivative – $PPG_{deriv}$; 4) time instant corresponding to 50% of the PPG pulse's total amplitude, at the systolic rise – $PPG_{50\%}$; 5) time instant corresponding to 80% of the PPG pulse's total amplitude, at the systolic rise – $PPG_{80\%}$ and; 6) the peak of the PPG pulse – $PPG_{peak}$.

### B. HRV and PRV analysis

Using a 180 sec. sliding window, shifted by 5 sec. increments, time and frequency domain HRV and PRV features were extracted using the same algorithm. Noisy segments and signal artifacts in the ECG and PPG signals were carefully removed from the analysis.

We analyzed the following six time domain features: Mean – mean of the time intervals within the sliding window; SDNN – standard deviation of normal-to-normal (NN) intervals; SDSD – standard deviation of successive differences between adjacent NN intervals; RMSSD – square root of the mean squared differences between adjacent NN intervals; NN50 – number of interval differences of successive NN intervals greater than 50ms; pNN50 – ratio between NN50 and the total number of NN intervals [3].

Additionally, four frequency domain parameters were extracted from the analysis of the estimated spectra (Burg's method [13]): aVL – normalized area of the spectrum of very low frequency (VLF) band (0.003-0.04 Hz); aLF – normalized area of the spectrum of low frequency (LF) band (0.04-0.15 Hz); aHF – normalized area of the spectrum of high frequency (HF) band (0.15-0.4 Hz); RaLH – ratio between aLF and aHF [3]. While the HF component is widely accepted as a marker of parasympathetic activity (and influenced by the respiratory activity), the LF component is thought to be the result of both sympathetic and parasympathetic activities [1, 14]. RaLH is commonly defined as a marker of sympatho-vagal balance [14].

### C. Statistical Evaluation Methods

In this study, we evaluate the accuracy of the extracted PRV features (in the time and frequency domains, extracted from different characteristic intervals) by comparing them to the reference HRV features, extracted from the analysis of the ECG signal. Data were synchronized in time, ensuring the correct correspondence between the analyzed features. This comparison was performed using the Spearman's rank correlation (SRC), the normalized root mean squared error (NRMSE) and the Wilcoxon's rank sum test (WRST). MATLAB R2014b® was used for signal processing and subsequent data analysis.

First, a one-sample unequal-tailed Kolmogorov-Smirnov test (KST) was performed in each set of parameters' values to test if the data belong to a standard normal distribution (at the 5% significance level). The results show that almost none of our data fulfilled this criterion. Exceptions were observed in cases: 1) patient 20 / feature pNN50 (p-value = 0); 2) patients 1, 2, 17 and 30 / feature pNN50 (p-value = 0), and patient 2 / feature RaLH (p-value $\in$ [0.0482, 0.1565]). Therefore, non-parametric methods were used to assess the agreement between the extracted features and to test the hypothesis that those features came from the same distribution.

Using a two-tailed SRC we aim to assess the agreement between the HRV and PRV features, i.e. the existence of a monotonic relationship between them. The normalized error between each PRV feature and its homologous HRV feature was assessed using the NRMSE, defined as:

$$NRMSE = \frac{\sqrt{\frac{1}{N}\sum_{m=1}^{N}(PRV_{feat_i}^{j}[m] - HRV_{feat_i}[m])^2}}{\overline{HRV_{feat}}}, \quad (1)$$

where $HRV_{feat_i}$ is the $i^{th}$ extracted feature (e.g.: aVL,…, pNN50) from the ECG analysis, $PRV_{feat_i}^{j}$ is the $i^{th}$ extracted feature from the analysis of the $j^{th}$ PPG interval (e.g.: $PPG_{onset}$,…, $PPG_{peak}$) and $\overline{HRV_{feat}}$ is the mean of the values of the HRV-derived feature. To test if the HRV and PRV features came from the same population, i.e. could be classified as samples from continuous distributions with equal medians (p-value < 0.05), a two-sided WRST was performed.

## IV. Results and Discussion

Our results are summarized in Figure 1 and Figure 2, which present the average of the results (SRC and NRMSE) presented TABLE I and TABLE II of the APPENDIX, obtained for each feature category (time and frequency domains) and according to the different PPG characteristic points and to the different datasets.

Almost all correlation values were statistically significant (p-value < 0.05), except for those found to belong to a standard normal distribution (the KST exceptions discussed in section III C. Statistical Evaluation Methods).

From Figure 1, it is possible to observe that under ideal conditions, i.e. healthy patients at rest (case 1), the agreement between the features extracted from HRV and PRV analysis is high (SRC ∈ [82.4±17.1; 90.6±6.2] %) in the majority of the analyzed parameters. Exceptions were found for NN50 and pNN50 (see TABLE I). Contrarily, in cases 2 and 3, the agreement between the analyzed features decreases drastically (SRC ∈ [68±9.7; 80.6±16.2] %). An exception was found for the frequency domain features in case 2, which range from 81.9±13.4 % to 88±8.4 %. It is also shown that the agreement between PRV and HRV features tend to decrease from case 1 to case 3, and that the achieved correlations within frequency domain features present higher values when compared to the time domain features (except for case 3).

Regarding the estimation error of the PRV features, it is possible to observe from Figure 2 that the time domain features extracted from PRV analysis achieved the lowest estimation errors (comparing to frequency features), in each of the three cases (NRMSE ∈ [5.3±3.9; 15.6±18.3] %), being the case 2 where the worst estimates were achieved (NRMSE ∈ [13.7±14.6; 15.6±18.3]). As for the frequency features, it is shown that there is a drastic increase in the estimation error from case 1 (NRMSE ∈ [14.7±5.3; 17.4±6.4] %) to case 3 (NRMSE ∈ [38.9±8.5; 47.1±13.2] %).

From the analysis of each specific feature in the time domain, one observes in TABLE I and TABLE II that the direct comparison between HRV and PRV signals (specified as HRV-PRV) returns excellent estimation errors (NRMSE ∈ [1.3±0.6; 2.8±2.6] %), followed by high correlations (SRC ∈ [88.6±16; 98.3±2.1] %) in the three cases under study. This observation shows a close agreement and high similarity between the estimated PRV and HRV signals under different physiological conditions. It is also noticed that the features presenting better accuracy (i.e. lowest NRMSE) are the mean (NMRSE ∈ [0.1±0.1; 0.4±0.6] %) and SDNN (NMRSE ∈ [2.6±2; 8.7±8.2] %).

It shall be noticed that the NN50/pNN50 features present a very low agreement in all the three cases, ranging from 36.2±46.2% to 69.1±30.6% (see TABLE I.), representing one of the main contributes to the decrease in the global correlation of the time domain features depicted in Figure 1. Nevertheless, these two features presented a good estimation error (NRMSE ∈ [5.7±3.6; 10.6±7.7] %). In order to investigate the reason for such observations, a histogram of the error ($HRV_{feat_i} - PRV^{j}_{feat_i}$) for each feature of each PRV interval was calculated, showing an overestimation of the

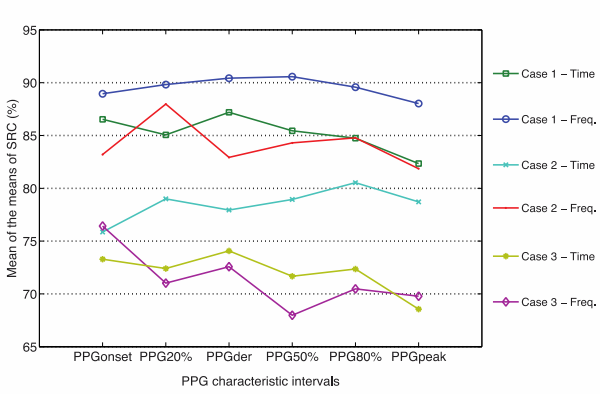


Figure 1. Mean of the Means of SRC (%) between ECG-derived and each PPG interval-derived features, in time and frequency (freq.) domains.

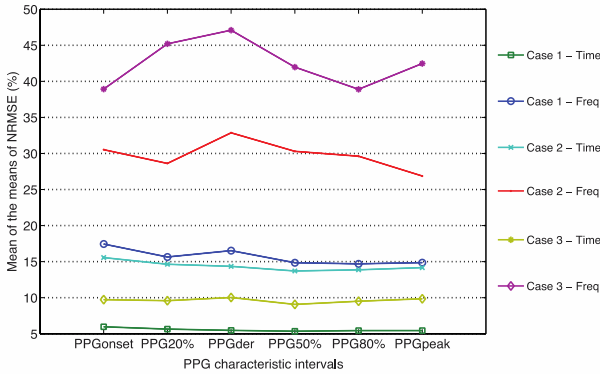


Figure 2. Mean of the Means of NRMSE (%) between ECG-derived and each PPG interval-derived features, in time and frequency (freq.) domains.

PRV features, as mentioned in the literature [3, 6], but not for NN50 and pNN50. Moreover, the tails of their histograms are longer, with more widespread values. One possible reason for the low correlation within these two features relies on the fact that they are based on the counting of interval differences among a very short amount of time (50 ms), which is approximately 5% of the RR interval (considering an HR of 60 $min^{-1}$). Therefore, it is expected that even the smallest estimation error produces a highly negative impact on the agreement of these features with their reference.

Regarding the frequency domain features, the RaLH presented a more complex behavior, since the accuracy in the estimation of this feature is highly dependent on the estimation errors of both aLF and aHF, a high uncertainty in the estimation of one of these features results in a dramatic increase in the estimation error of the RaLH. It is also shown in TABLE I that the agreement between the frequency features and their reference decreases from VLF (aVL) to HF (aHF). This trend is also clear when inspecting the estimation error, with a special emphasis to the aHF, where the NRMSE is clearly higher in all the three cases.

Issues for HF-related features have been previously found already [3, 4, 12]. Many PPG artifacts (e.g. motion artifacts) influence the HF component, as well as stronger breathing patterns induced by exercise or mental stress (such as in case 2), which induce higher uncertainty in the estimation of this feature. Similarly, in case 3 subjects (older subjects and with CVD), abnormal patterns in breathing and in the Frank-

Starling mechanism (which cause stronger fluctuations in HR/PR) [3, 6], as well as the existence of a poorer blood perfusion and a lower compliance (stiffer arteries), can represent an obstacle to the correct detection of the PPG characteristic points. Moreover, elderly subjects are known to have distinct skin characteristics that prevent the reflectance/ transmittance of light to the photo-detector (mimicking a low-pass filter behavior), which can also prevent the correct characterization of the PPG pulse. These aspects increase the uncertainty in the calculation of the heartbeat intervals and consequently have a negative impact on the agreement between aHF estimated from PRV and the reference HRV.

Analyzing the characteristic points that achieved the best results, it is possible to observe, from Figure 1 and Figure 2, a small variation in the correlation and NRMSE values (ap. < 3%), for the various PPG characteristic points of case 1. The only exception was observed in the correlation of time domain features for the $PPG_{peak}$. As for the cases 2 and 3, although the NRMSE within time domain features increases when compared to case 1, it is shown in Figure 2 that it remains with a low range of values ([9±5.9; 15.6±18.3] %). A lower agreement within these features was observed, being the best values achieved for $PPG_{80\%}$ (after-exercise individuals) and for $PPG_{deriv}$ (subjects with CVD). In these cases, a higher range of correlation values was also seen for the frequency domain features (SRC ∈ [68±9.7; 88±8.4] %), suggesting that the selection of a suitable PPG characteristic interval is much more important in these sets, than in healthy individuals.

The characteristic points exhibiting the best estimation error (NRMSE) were, in general, the $PPG_{50\%}$, $PPG_{80\%}$ and $PPG_{peak}$, while the agreement between features did not follow a consistent pattern, depending on the context and analyzed feature category. However, there is more accordance between the intervals with best correlation and with best NRMSE in case 1 subjects, rather than in the remaining cases.

$PPG_{peak}$ underperformed in almost all cases. One plausible reason for this is the change in the characteristics of the PPG pulse, leading to a very broad maximum of the PPG pulse and preventing the correct estimation of PR intervals and, consequently, the derived PRV features. Effects such as breathing are reported to have a strong influence on PR detection accuracy [6, 11].

Finally, one must notice that in cases 1 and 2, the WRST of PRV and HRV features always stated that the tested features came from continuous distributions with equal medians. In case 3, the same results were observed, with an exception to 3 subjects and a marked decrease in the performed tests' p-value.

The spread between the least and the most accurate values suggest that the choice of the best characteristic point is dependent on the physiological condition of the subject and on the analysis' context, which highlights the need for an automatic decision-making algorithm to select the most suitable PPG intervals. To our knowledge, in such a system, the SRC may provide better guidelines, since the trend between HRV and PRV features can be corrected through algebraic means.

## V. Conclusion

This study focuses on the evaluation of commonly used HRV features calculated from PR signals, both in frequency and time domains. This was achieved by comparing HRV and PRV-derived parameters (including HR and PR) using the Spearman's rank correlation (SRC), the normalized rout mean square error (NRMSE) and Wilcoxon's rank sum test (WRST).

Our results confirm that the majority of PRV indexes may be used as surrogates for ECG-based HRV in healthy subjects at rest, as reported in the literature [3, 5, 6, 7]. Accurate results can be observed in subjects after exercise, especially for aVL, aLF, HRV-PRV, Mean and SDNN. However, in CVD patients, we found a lower performance in the estimation of PRV features, with an exception to the abovementioned features, where some acceptable results were achieved. Low agreement and/or high estimation errors within aHF, NN50 and pNN50 were identified and justified.

In general, time domain features present a mean NRMSE below 15% in the three case studies, whereas frequency domain features show such a result in healthy subjects at rest only. As for the achieved correlation values, the features extracted from CVD patients are the only ones with results below 75%. Therefore, time domain features may be used for PRV analysis covering the three presented protocols, whereas frequency domain features require more caution.

Our results show that, for healthy subjects at rest the most suitable characteristic point (highest agreement with the reference) is $PPG_{deriv}$, while for healthy subjects after exercise the best characteristic point is $PPG_{20\%}$. As for the subjects with CVD, the characteristic point achieving the highest agreement was the $PPG_{onset}$.

Summing up, this study provides a ranking of PRV parameters, which might be used depending on the obtained PPG characteristic interval and analyzed context.

Future work will focus on the adaptation of our previous algorithm for syncope prediction [15] to resort only on PPG analysis including PRV, which will benefit from our findings in this study.

## Appendix

TABLE I. Spearman's Rank Correlation (%) between ECG-Derived Features and each PPG Interval-Derived Features

| *Feature* | **Intervals between characteristic PPG points** | | | | | |
|---|---|---|---|---|---|---|
| | $PPG_{onset}$ | $PPG_{20\%}$ | $PPG_{deriv}$ | $PPG_{50\%}$ | $PPG_{80\%}$ | $PPG_{peak}$ |
| **Dataset: Case 1** | | | | | | |
| aVL | 97.1±4.6 | 96.5±9.7 | 95.2±18.6 | 97.9±3 | 96.4±8.1 | 97.7±3.4 |
| aLF | 95.6±7.8 | 96.2±4.9 | 95.3±10.6 | 95.5±8.6 | 96.4±7.2 | 92±17.4 |
| aHF | 81.3±31.7 | 83.9±20.2 | 87.1±19.9 | 83.9±23.1 | 84.9±21.7 | 81.2±23 |
| RaLH | 81.8±22.6 | 82.7±21.8 | 84.1±20.7 | 85±19.9 | 80.6±29.4 | 81.2±29.2 |
| HRV-PRV | 98.2±2 | 98.1±2.4 | 98.1±2.2 | 98.3±2.1 | 98.1±2.4 | 97.9±2.4 |
| Mean | 99.3±2 | 98.8±4.3 | 99.5±1 | 99.4±1.8 | 99.2±2.6 | 98.6±4 |
| SDNN | 93.6±21.1 | 93.4±18.8 | 93.2±23.4 | 91.8±23.3 | 93.2±17.4 | 93.6±17.3 |
| SDSD† | 89.3±13.9 | 90.6±13 | 90.7±11.2 | 87.9±18 | 90.9±12.1 | 87±15.2 |
| NN50* | 68±22.7 | 61.9±32.1 | 69.1±30.6 | 66.4±30.6 | 60.4±34.2 | 56.1±37.5 |

| Dataset: Case 2 | | | | | | |
|---|---|---|---|---|---|---|
| aVL | 98.5±2.3 | 98.6±2.3 | 98.6±2.2 | 99.1±1.5 | 98.9±1.9 | 98.9±1.8 |
| aLF | 86.5±34.5 | 88.9±28.9 | 87.1±30.9 | 86.8±30.1 | 86.7±29.2 | 84.4±38.8 |
| aHF | 79.7±27.6 | 89.3±16.2 | 77.2±30.8 | 86.4±19 | 83±38.9 | 82.8±24.5 |
| RaLH | 68.1±34.4 | 75.1±27 | 68.8±34.9 | 64.9±40.4 | 70.5±37.5 | 61.3±46.5 |
| HRV-PRV | 97.5±2.2 | 97.5±2.3 | 97.6±2.4 | 97.5±2.5 | 97.4±2.6 | 97.2±3.1 |
| Mean | 99.9±0.4 | 99.8±0.5 | 99.7±1 | 99.7±1 | 99.7±1 | 99.6±1.1 |
| SDNN | 98.8±4 | 97.5±7.7 | 99±3.9 | 97.3±9 | 98.8±4 | 97.5±7.7 |
| SDSD† | 62±54.3 | 72.6±41.4 | 63.5±49.4 | 66.7±46.6 | 72.5±43.3 | 72.6±40.8 |
| NN50* | 55.3±40.5 | 56.5±36.6 | 60.7±30.3 | 62.4±40.4 | 61.8±30.3 | 55.7±39.7 |
| **Dataset: Case 3** | | | | | | |
| aVL | 85.1±21.2 | 81.1±35.5 | 83.9±30.8 | 78.8±37 | 84.4±28.7 | 85.1±28.8 |
| aLF | 81.5±27.3 | 79.3±35.8 | 78.3±37.9 | 76.5±41 | 74.5±43 | 70.6±51.1 |
| aHF | 71.3±42.1 | 56.7±53.9 | 62.2±51.2 | 57.5±53 | 55±56.8 | 56.3±56.3 |
| RaLH | 67.8±37.9 | 67±36.1 | 65.9±38.9 | 59.1±42.9 | 68±38.8 | 67.1±38.5 |
| HRV-PRV | 89.1±15.6 | 89.5±15.9 | 89±15.7 | 89.3±15.7 | 89.4±16.1 | 88.6±16 |
| Mean | 96±6.8 | 95.7±9.4 | 95.2±9.1 | 95.2±8.9 | 96.2±6.7 | 94.9±7.9 |
| SDNN | 92.9±9.4 | 90.4±14.6 | 87.4±22.4 | 87.3±21 | 85.7±26.3 | 87.6±23.7 |
| SDSD† | 73.9±35.7 | 75.8±26.7 | 75±29.4 | 73.1±31.1 | 72.6±32.7 | 68.2±42.7 |
| NN50* | 43.6±42.8 | 39.8±42.6 | 48.4±38.4 | 41.9±49.2 | 45±44.3 | 36.2±46.2 |

*and pNN50; †and RMSSD

TABLE II. NRMSE (%) BETWEEN ECG-DERIVED FEATURES AND EACH PPG INTERVAL-DERIVED FEATURES

| *Feature* | Intervals between characteristic PPG points | | | | | |
|---|---|---|---|---|---|---|
| | $PPG_{onset}$ | $PPG_{20\%}$ | $PPG_{deriv}$ | $PPG_{50\%}$ | $PPG_{80\%}$ | $PPG_{peak}$ |
| **Dataset: Case 1** | | | | | | |
| aVL | 11.3±10.9 | 11.3±9.9 | 10.5±13.4 | 10.1±8.3 | 9.1±5.5 | 13.2±14.2 |
| aLF | 11.5±10.6 | 9.7±5.8 | 10.1±6.5 | 10.3±7.4 | 10.4±8.1 | 11.6±10.8 |
| aHF | 26.4±21.5 | 23±20.6 | 24.9±19.1 | 21.1±11.7 | 22.2±13.8 | 18.1±11.1 |
| RaLH | 20.6±9.6 | 18.6±10.2 | 20.6±11.4 | 17.9±8.9 | 17.1±10 | 16.6±7.9 |
| HRV-PRV | 1.3±0.8 | 1.3±0.9 | 1.3±0.9 | 1.3±0.9 | 1.3±0.9 | 1.4±0.9 |
| Mean | 0.1±0.1 | 0.1±0.1 | 0.1±0.1 | 0.1±0.1 | 0.1±0.1 | 0.1±0.1 |
| SDNN | 3±2.5 | 2.6±2 | 2.7±1.8 | 2.7±1.8 | 2.7±1.9 | 2.6±2.1 |
| SDSD† | 12.6±6.7 | 11.4±7.5 | 11.4±6 | 10.5±6.3 | 10.4±6.2 | 10.7±7 |
| NN50* | 6.1±3.6 | 6.4±3.4 | 5.7±3.6 | 6.2±3.7 | 6.6±3.8 | 6.3±3.6 |
| **Dataset: Case 2** | | | | | | |
| aVL | 15.5±16.7 | 17.3±39.1 | 21.9±63.5 | 24.2±68.8 | 22.5±65 | 22.3±73.3 |
| aLF | 13.4±10.5 | 12.9±9.2 | 21.9±50.7 | 14.3±17.1 | 13.8±11.8 | 14.5±13.5 |
| aHF | 63.2±65.7 | 57.8±63.8 | 60.4±64.8 | 54.7±48.9 | 55.6±71.4 | 44.3±41.3 |
| RaLH | 30±20.3 | 26.5±19.5 | 27.3±20.2 | 28±19.5 | 26.6±20.3 | 26.4±18.1 |
| HRV-PRV | 1.3±0.6 | 1.4±0.9 | 1.3±0.8 | 1.4±0.8 | 1.4±0.9 | 1.4±1 |
| Mean | 0.1±0.1 | 0.1±0.1 | 0.1±0.1 | 0.1±0.2 | 0.1±0.1 | 0.1±0.1 |
| SDNN | 3.1±2.9 | 3.1±3.6 | 4.4±10.5 | 3.8±7.2 | 3.7±6 | 3.6±7.4 |
| SDSD† | 44.1±42.8 | 40.1±40.4 | 37.8±34.6 | 36.3±34.7 | 36.2±34.8 | 37±37.1 |
| NN50* | 8.2±5.3 | 8.9±5.3 | 9.6±5.5 | 9.1±5.5 | 9.8±5.9 | 10.1±5.5 |
| **Dataset: Case 3** | | | | | | |
| aVL | 28.8±33.4 | 36.4±40.9 | 38.8±43.2 | 33.5±33.6 | 32.6±34.1 | 30.9±29.7 |
| aLF | 27±24 | 31.6±41.3 | 33.2±31.6 | 31.4±36.3 | 29.5±31.9 | 39.8±44.8 |
| aHF | 55.4±57 | 67.2±112.7 | 67.8±93.7 | 50.2±39.1 | 50.9±42.3 | 54.7±66.2 |
| RaLH | 44.5±31.4 | 45.6±37.6 | 48.6±37.9 | 52.8±48.1 | 42.6±32.6 | 44.5±37.1 |
| HRV-PRV | 2.6±2.5 | 2.7±2.5 | 2.8±2.6 | 2.6±2.4 | 2.6±2.3 | 2.8±2.5 |
| Mean | 0.2±0.3 | 0.2±0.3 | 0.4±0.6 | 0.3±0.4 | 0.3±0.5 | 0.3±0.3 |
| SDNN | 6.6±4.9 | 7±5.8 | 8.6±7.7 | 7.4±6.4 | 7.5±7 | 8.7±8.2 |
| SDSD† | 20.1±18 | 19.3±16.1 | 20.5±16.7 | 16.9±12.6 | 17.8±13.6 | 18±16.1 |
| NN50* | 9.3±6 | 9.3±5.9 | 8.7±5.7 | 9.7±6.9 | 10.3±7 | 10.6±7.7 |

*and pNN50; †and RMSSD

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