

# Arterial Pulse Rate Variability Analysis for Diagnoses

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## Abstract

Heart rate variability (HRV) provides an estimate of sympathetic and parasympathetic influences on the heart rate. Although HRV has been extensively studied, sustained clinical use is still outstanding.

The noninvasive, convenient, and inexpensive arterial pulse originate from heartbeats, but has not been studied in a systematic fashion except in rudimentary ways. In this paper, we present Pulse Rate Variability (PRV) as an alternative to HRV. We give evidence for the detection of disorders in patients using PRV, paving the way for future clinical use.

## 1 Introduction

The analysis of Heart Rate Variability (HRV) is important when studying the autonomic nervous system because it helps in evaluating the equilibrium between the sympathetic system (which accelerates the heart rhythm), and parasympathetic system (which decelerates the heart rhythm) in cardiac pacemaker cells [13]. The instantaneous heart rate, and the duration of the heart beat-to-beat intervals (denoted RR) is a consequence of the above interacting systems.

Human heart rate is affected by a variety of physiological parameters. Other important factors include age, sleep-wake cycle, disease present, and gender. It is now well known that the properties of HRV may play important role in the better prognosis in patients with heart failure [16], diabetes [4] and autonomic dysfunction. It is generally believed that the variations between consecutive beats are critical, rather than simply the heart rate. First appreciated in 1965 [5], the clinical importance of HRV became apparent in the late 1980s. Over the last 3 decades, special attention has been given to the improvements in analysis of the HRV in terms of cost, ease, and accuracy.

Related, but inexpensive, physiological signals derived from the finger plethysmogram, and the arterial blood pressure have been studied in [8, 3]. The arterial pulse, on the other hand, has not received signifi-

cant recognition due to lack of quantitative basis. We have developed a data acquisition system named *Nadi Tarangini* [7] for obtaining clean, and accurate pulse waveforms. It incorporates pressure transducers, an ADC, and storage and analysis capabilities. A sample waveform is shown in Figure 1.

As shown, a pulse cycle consists of a Systolic wave (S), and a Diastolic wave (D). We extract the arterial pulse intervals (termed API in [9]) using a complex frequency b-spline wavelet by finding the peaks in the S waves [6].

Historically, the pulse has in fact been extensively used in diagnosis. The *Indian Traditional Medicine* believes that the function of entire human body is governed by *Tridosha* [14], by sensing pulse at three pre-defined positions on wrist. The pulse identifies the presence and location of disorders in a patients body [14], unlike ECG which mainly reflects the electrical activity of the heart, and thus the pulse contains much more useful information than ECG.

**Contributions:** We introduce PRV analysis on the API by computing several (see Table 1) time-domain, frequency-domain, and nonlinear measures [13]. Interestingly, we show that these measures show variations with respect to age similar [2] to previously established results in the domain of HRV analysis. We also compute measures indicating the presence and absence of disorders. Our results show the efficacy of PRV analysis akin to HRV [1] in clinical use.

The rest of the paper is organized as follows. §2 introduces the PRV measures. We provide our experimen-

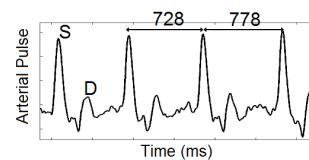


Figure 1. A sample pulse waveform. At first glance, pattern of the pulse seems to repeat itself, the intervals usually change in a complex and irregular way.

Variable	Units	Description
Time Domain Measures		
AVPP & SDPP	ms	Mean and standard deviation of all API
SDAPP		Standard deviation of the mean of API in segments
ASDAPP		Mean of the standard deviation of API in segments
RMSSD	ms	The root mean square of differences of successive API
PP50 count		No. of consecutive PP intervals that differ more than 50 ms
pPP50	%	The percentage value of consecutive API that differ more than 50 ms
PP triangular index		The integral of the sample density distribution (SDD) of API divided by the maximum of the density distribution
TIPP	ms	Baseline width of the minimum square difference triangular interpolation of the maximum of the SDD of API
Frequency Domain Measures		
Peak frequency	Hz	Peak frequencies of the PSD estimate for VLF, LF, and HF frequency bands (see §2.2)
Power	$ms^2$ , %	Respectively for VLF, LF, and HF frequency bands
Power	n.u.	Respectively for LF, and HF frequency bands in normalized units
LF/HF	%	Ratio of LF and HF frequency band power
Nonlinear Measures (Poincaré plot)		
centroid		The centroid of the ellipse (see §2.3)
SD1	ms	The standard deviation perpendicular to the line-of-identity
SD2	ms	The standard deviation along the line-of-identity
SD1/SD2		SD1 to SD2 ratio

**Table 1. PRV measures in different domains.**

tal results for variations in the measures with our data in §3 along with discussion and future scope. Finally we conclude in §4.

## 2 Pulse Rate Variability

A number of measures are used in HRV (and now in this paper, PRV) analysis. Some of these describe short-term variability while other depict long-term variability [13]. Table 1 gives the PRV measures we have used.

### 2.1 Time Domain Measures (TDM)

These are the simplest measures calculated directly from the raw API time series, or the differences between API. Also, the major advantage of geometric methods (PP triangular index & TIPP) lie in their relative insensitivity to the quality of the API series [10].

### 2.2 Frequency Domain Measures (FDM)

It has been widely accepted that the 0.05Hz oscillations are related to the thermoregulatory system, the 0.1Hz oscillations to the vasomotor activity, and the 0.25Hz oscillations to the respiratory activity [12]. Though the pulse signal is a regularly sampled (at 500Hz) data, the API is inherently irregularly spaced in time. Therefore, we firstly interpolate this irregularly time-sampled API series before the computation of the FDM measures.

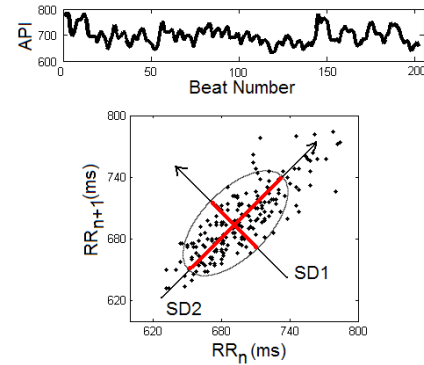
The power spectral density (PSD) is computed using the fast Fourier transform (FFT) nonparametric model, and the parametric autoregressive (AR) model. We consider the commonly used frequency bands as very low frequency (VLF, 0–0.04Hz), low frequency (LF, 0.04–0.15Hz), and high frequency (HF, 0.15–0.4Hz). The representation of LF and HF in normalized units emphasizes the controlled and balanced behaviour of the two branches of the autonomic nervous system [10].

### 2.3 Nonlinear Measures

Pulse intervals contain nonlinear properties because of the complex regulation mechanisms controlling it. It has been speculated that the analysis of HRV based on the methods of nonlinear dynamics might elicit valuable information for the assessment of the risk of sudden death [13].

We use the easy to comprehend nonlinear method of the Poincaré plot. This is a graphical presentation of the correlation between consecutive API. It summarizes the entire recording (short or long), making it possible to extract the information on both short as well as long time behaviour of the system (pulse action in this case) [11]. A typical healthy API time series and its Poincaré plot are shown in Figure 2. Further, in Figure 3, a portion of an arrhythmic pulse is shown. Here the third beat is missing (every now and then). The Poincaré plot in this case shows a different coverage of points.

In the Poincaré plot, the points towards the top right indicate two consecutive increasing intervals (i.e., the pulse rate is decreasing), while the bottom-left points



**Figure 2. A sample API signal and its Poincaré plot. SD1 and S2 are the dispersions of points perpendicular and along the axis of line-of-identity.**

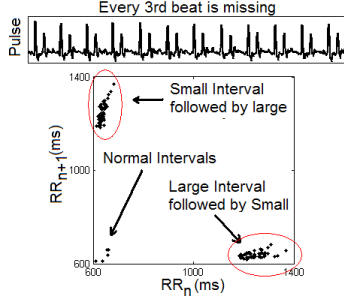


Figure 3. Poincaré plot of an arrhythmic pulse.

indicate two consecutive decreasing intervals (i.e., the pulse rate is increasing). A common way to describe the geometry is to fit an ellipse on the line-of-identity at  $45^\circ$  to the normal axis [10]. SD1 and SD2 thus are the lengths of the two axes of the ellipse. The Poincaré plot summarizes the entire data as SD1 indicates the short-term variability (mainly caused by respiratory sinus arrhythmia), and SD2 indicates the long-term variability.

### 3 Results and Discussion

**Data.** The pulse waveforms were recorded using *Nadi Tarangini* [7]. In this study, we had a total of 158 waveforms from 64 volunteers with varying ages, and either having a specific disorder or no disorder. (Some volunteers were recorded multiple times). The volunteers were instructed to breathe normally & without deep breaths. We then extracted peaks in these signals using a complex frequency b-spline wavelet [6]. The length of each waveform is at least 250, and the distances in them form the API time series.

#### 3.1 Variation with Age

As age increases, the heart rate and thus the pulse rate decreases. In other words, it results in increase of the pulse intervals. This can be verified in the Poincaré representation as shown in Figure 4. The elliptical area shifts along the line-of-identity as the age increases from 2 months to 45 years.

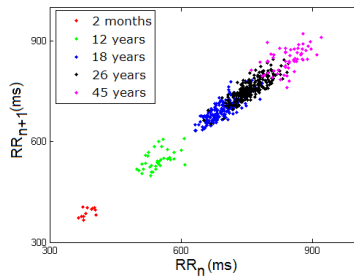
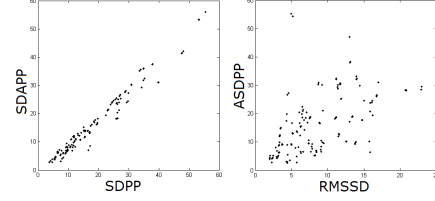


Figure 4. Shift of elliptical area on the Poincaré plot as age increases

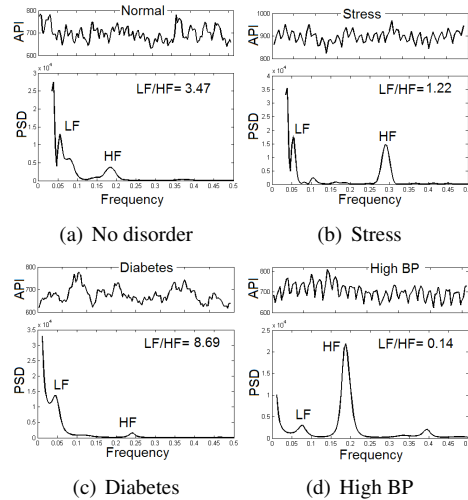


(a) Strong (b) Weak  
Figure 5. Correlation among PRV measures

#### 3.2 Features for Classification

Table 2 indicates correlation coefficients (CC) among various time-domain, frequency-domain and non-linear measures of the APIs. CC measures the strength and direction of a linear relationship between two variables. Higher +ve values (approaching 1) indicate strong correlation, lower values (approaching 0) indicate weak correlation, while -ve values indicate negative correlation. We observed that few measures have a strong correlation which has implication for classification using methods such as the Support Vector Machine. On the other hand, a few are not related at all as shown in Figure 5. For example, it can be observed that the LF/HF ratio is not correlated to any other measure. Representative examples of power spectrums of the PRV for various disorders are shown in Figure 6[a-d]. Only two frequency bands are studied here, LF and HF. We applied this easy, alternative PRV method to many volunteers and observed that most of the results of LF/HF measure are consistent with the HRV results obtained earlier in the literature.

**Future scope.** Recent studies [11] [9] [15] have tried to make use of the PRV. But more rigorous studies are needed to determine the sensitivity, specificity, and predictive value of PRV in the identification of individuals at risk. The PRV analysis can also be suitably used in



(a) No disorder (b) Stress (c) Diabetes (d) High BP  
Figure 6. Power Spectrums (FFT (top row), AR (bottom row)).

	SDRR	ASDRR	SDARR	RMSSD	pPP50	PP Tri. Index	TIRR	LF/HF	SD1	SD2
SDRR	1.00	0.70	0.98	0.88	0.79	-0.21	0.87	0.18	0.88	0.99
ASDRR		1.00	0.63	0.52	0.56	0.036	0.73	0.044	0.52	0.73
SDARR			1.00	0.89	0.80	-0.22	0.87	0.20	0.89	0.96
RMSSD				1.00	0.84	-0.26	0.74	0.061	1.00	0.79
pPP50					1.00	-0.05	0.79	0.15	0.84	0.74
PP Tri. Index						1.00	0.0058	0.12	-0.26	-0.17
TIRR							1.00	0.24	0.74	0.88
LF/HF								1.00	0.06	0.20
SD1									1.00	0.79
SD2										1.00

**Table 2. Correlation coefficients for the PRV measures in Table1.**

conjunction with HRV to collect information on the peripheral circulation.

#### 4 Conclusion

The Heart Rate Variability (HRV) measures have been earlier used to a limited extent to assess the role of autonomic nervous system fluctuations with various cardiovascular and non-cardiovascular disorders. In this paper, we presented the pulse rate variability measures and showed that the pulse intervals have the capability to capture similar effects. Unlike the HRV measurement, PRV measurement is noninvasive, inexpensive, and easy to obtain.

We presented several techniques. Specifically we showed that the Poincaré plots shift along the line-of-identity as the age increases. By considering the ratio of the resulting major and minor axes, we showed the quantitative difference between the normal and arrhythmic pulse. Classification accuracy of healthy and unhealthy subjects can be improved by the absence or selection of certain time-domain and frequency-domain measures used in the literature based on whether they have correlation or not.

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