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Dynamic Phase Extraction: Applications in Pulse Rate Variability

Christopher H. Li[1] · Franklin S. Ly[2] · Kegan Woodhouse[2] · John Chen[2] · Zhuowei Cheng[3] · Tyler Santander[4] · Nirmit Ashar[3] · Elyes Turki[1] · Henry T. Yang[2] · Michael Miller[4] · Linda Petzold[2,3] · Paul K. Hansma[1,5]

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Abstract

Pulse rate variability is a physiological parameter that has been extensively studied and correlated with many physical ailments. However, the phase relationship between inter-beat interval, IBI, and breathing has very rarely been studied. Develop a technique by which the phase relationship between IBI and breathing can be accurately and efficiently extracted from photoplethysmography (PPG) data. A program based on Lock-in Amplifier technology was written in Python to implement a novel technique, Dynamic Phase Extraction. It was tested using a breath pacer and a PPG sensor on 6 subjects who followed a breath pacer at varied breathing rates. The data were then analyzed using both traditional methods and the novel technique (Dynamic Phase Extraction) utilizing a breath pacer. Pulse data was extracted using a PPG sensor. Dynamic Phase Extraction (DPE) gave the magnitudes of the variation in IBI associated with breathing (ΔIBI) measured with photoplethysmography during paced breathing (with premature ventricular contractions, abnormal arrhythmias, and other artifacts edited out). ΔIBI correlated well with two standard measures of pulse rate variability: the Standard Deviation of the inter-beat interval (SDNN) ($\rho = 0.911$) and with the integrated value of the Power Spectral Density between 0.04 and 0.15 Hz (Low Frequency Power or LF Power) ($\rho = 0.885$). These correlations were comparable to the correlation between the SDNN and the LF Power ($\rho = 0.877$). In addition to the magnitude ΔIBI, Dynamic Phase Extraction also gave the phase between the breath pacer and the changes in the inter-beat interval (IBI) due to respiratory sinus arrythmia (RSA), and correlated well with the phase extracted using a Fourier transform ($\rho = 0.857$). Dynamic Phase Extraction can extract both the phase between the breath pacer and the changes in IBI due to the respiratory sinus arrhythmia component of pulse rate variability (ΔIBI), but is limited by needing a breath pacer.

Keywords Respiratory sinus arrhythmia · Lock-in amplifier · Pulse rate variability · Photoplethysmography

Introduction

Recent experiments have reawakened interest in the phase relationships caused by the delay between the modulation of the heart rate from the breath and the breath (Fisher & Lehrer, 2021; Lehrer et al., 2020). Lehrer et al. have shown the phase shift at the breathing rate that yields the maximum power in heart rate variability varies systematically with age (Fisher & Lehrer, 2021; Lehrer et al., 2020). This report builds upon those papers and the largely-ignored work on phase by Angelone and Coulter, who demonstrated over 50 years ago that there is an intricate relationship between phase, heart rate variability amplitude, and breathing rate (Angelone & Coulter, 1964). In this paper we introduce a method to accurately and efficiently extract the phase of the respiratory sinus arrythmia (RSA) induced variations in inter-beat interval (IBI), measured with

✉ Christopher H. Li
christopher02px2017@gmail.com

1 Department of Physics, University of California, Santa Barbara, Santa Barbara, USA

2 Department of Mechanical Engineering, University of California, Santa Barbara, Santa Barbara, USA

3 Department of Computer Science, University of California, Santa Barbara, Santa Barbara, USA

4 Department of Psychological & Brain Sciences, University of California, Santa Barbara, Santa Barbara, USA

5 Neuroscience Research Institute, University of California, Santa Barbara, Santa Barbara, USA

photoplethysmography, relative to the breath. For the sake of clarity and succinctness, in this paper we will define the change in IBI due to RSA as the *change in IBI* (ΔIBI).

Our Dynamic Phase Extraction (DPE) method is based on lock-in amplifier technology. The lock-in amplifier is a powerful instrument commonly used in astronomy, physics, and engineering that can isolate signals a millionth the amplitude of the noise.

We propose that this method could be used for analyzing the wave characteristics of RSA and may be useful for biofeedback studies of pulse rate variability. Broadly, pulse and heart rate variability (HRV) is negatively associated with a multitude of ailments and physical states, including chronic pain (Evans et al., 2013; Tracy et al., 2016), post myocardial infarction death rate (Carny et al., 2001; Hohnloser et al., 1997; Sosnowski et al., 2002), anxiety (Chalmers et al., 2014; De Souza et al., 2014; Goessl et al., 2017), diabetes (van Ravenswaaij-Arts, 1993), and sympathetic nervous system activation (Evans et al., 2013; Sztajzel, 2004; van Ravenswaaij-Arts, 1993); conversely, it is positively associated with athletic performance (Kiviniemi et al., 2007; Plews et al., 2013). Some fluctuations in the very low frequency (VLF) range (< 0.04 Hz) have been positively associated with sympathetic nervous system activation, with some further complexities in chronic heart failure patients (Sztajzel, 2004). This has led to many papers seeking optimization parameters, and extensive work has been done in developing biofeedback and breathing protocols to improve and optimize heart rate variability (Lehrer et al., 2013; Lehrer & Slime, 2007; Goessl et al., 2017), as well as the development of consumer devices that measure and utilize pulse rate variability, e.g. HeartMath, Whoop, Fitbit.

Previous work has modeled the cardiac system as a two-closed-loop system, with the brain, baroreceptors, vascular tone control system, blood pressure control system, and heart rate control system as its constituents. Vaschillo (2002) emphasized the importance of phase delays in his work on biofeedback and approached the system from an engineering perspective, where often the most important components of a feedback system are the phase relationships. This is reason enough to investigate phase relationships, but there has been even more work motivating an investigation into the phase relationships in HRV.

There is evidence to suggest that the delay causing the phase shift between the changes in IBI and breathing rate exists because a delay results in more efficient pulmonary gas exchange (Hayano et al., 1996; Giardino et al., 2003), and that the changes in IBI are just the apparent manifestations of a system that optimizes this gas exchange (Sin et al., 2010). Thus, we are interested in finding two parameters: the phase between IBI and breathing, and the peak-to-peak amplitude of the inter-beat interval, ΔIBI, as defined in Fig. 1.

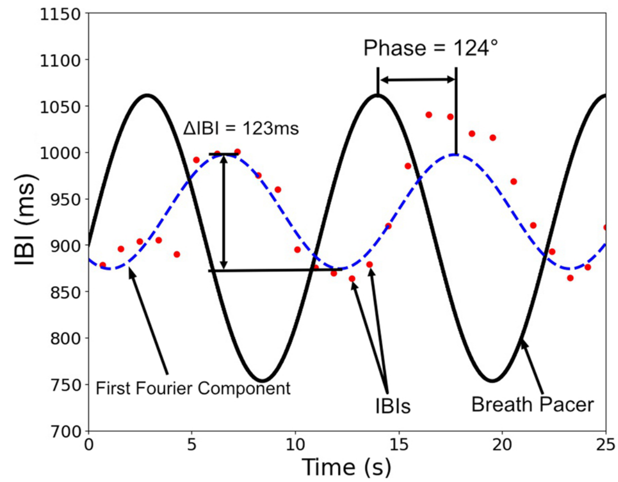

Fig. 1 Dynamic Phase Extraction (DPE) can give the phase and magnitude (ΔIBI) of the variation in Inter-beat Interval (IBI) due to Respiratory Sinus Arrhythmia (RSA). We define the phase as a shift to the left being negative, and a shift to the right being positive, in agreement with standard physics and engineering convention. The phase and ΔIBI are determined by DPE, which pulls out the first Fourier component of the IBI Interval curve, as shown with the blue dashed line

Notably, the preponderance of extant literature measures HRV by electrocardiography (ECG). Here, however, we use photoplethysmography (PPG) to measure pulse rate variability. While we acknowledge limitations to this approach (e.g., difficulties in precisely capturing the timing of peak-to-peak events), PPG is nevertheless the most accessible form of measuring pulse rates. Our future research hopes to use the technique in various applications where ECG is unfeasible.

Here we introduce and discuss the Dynamic Phase Extraction (DPE) method and demonstrate its ability to extract the phase relationships from PPG data. We also compare the measure for the magnitude of pulse rate variability, ΔIBI, that it generates to other methods of extracting pulse rate variability (the LF Power and Standard Deviation of the IBI) and compare the phase that it extracts to the phase extracted using the Fourier transform. ΔIBI is defined as the peak-to-peak amplitude of the waves in the IBI interval vs. time curve. We extracted the phase and amplitude of the pulse rate variability, compared it to other methods of measuring pulse rate variability and phase, and found good agreements between them.

Methods

Participants

We collected data from six healthy young adults (5 men and 1 woman, aged between from 19 to 26). All procedures were approved by the UC Santa Barbara Human Subjects Committee.

Data Acquisition Procedures

A custom built PPG sensor was used to obtain pulse data. A chest strap with an integrated FUTEK LSB 200 load cell, an instrument that measures force using a Wheatstone bridge and strain gauges, was used to obtain breathing data. These were used because they were conveniently available in the lab; however, any linear chest circumference measurement and pulse rate measurement could be used.

The PPG sensor was attached to the left index finger using a Velcro strap. The voltage powering the LED in the PPG sensor was adjusted until a pulse waveform that occupied about a third of the voltage range on the measurement device with clear peaks was measured. The chest strap was wrapped around the thorax to measure chest movement, and the output was run through a low-pass filter and then to an amplifier. Voltage values from the PPG sensor and chest strap were read using a Wemos LOLIN32 board sampling at 2000 Hz and recorded by a computer.

Each subject was tested for at least 8 different breathing rates, ranging from 2.4 to 57 breaths per minute. IBIs were eliminated without replacement if they were more than double or less than half of the previous pulse rate. In order to calculate the phase and perform Fourier transforms, each IBI interval was interpolated between to ensure consistent time interval spacing.

Participants were instructed to follow a sine wave breath pacer at the desired breathing rate, and to breathe in as the sine wave increased and breath out as the sine wave decreased. Recording sessions were 12 min total, with 2 min for each breathing rate. Multiple sessions were recorded for each subject, with the goal of finding a breathing pace where a local maximum of ΔIBI could be seen.

The chest strap data was used to verify that the participant followed the breath pacer, this was done visually, just to make sure that the subject took a breath every cycle of the pacer. Inter-beat Interval (IBI) data were extracted by passing the pulse data through a peak detection program and then using those peaks to determine IBI.

Dynamic Phase Extraction and Analysis

The lock-in amplifier is an instrument commonly used in engineering and physics. Here, we apply the principles of lock-in amplifier technology, specifically dual-phase lock-in amplifiers, in the DPE method to extract the phase of the IBI variations relative to the breath pacer. The method can be broken down into a few simple parts.

First, a reference signal is fed into any system which will process and return a signal. In this case, the reference signal is a breath pacer, the system is the human body, and the signal is the Inter-beat Interval. The signal is then processed in two ways: "in-phase" and "quadrature". For the in-phase processing (Fig. 2a), the signal is inverted every time the reference signal crosses zero, as seen in the third panel of

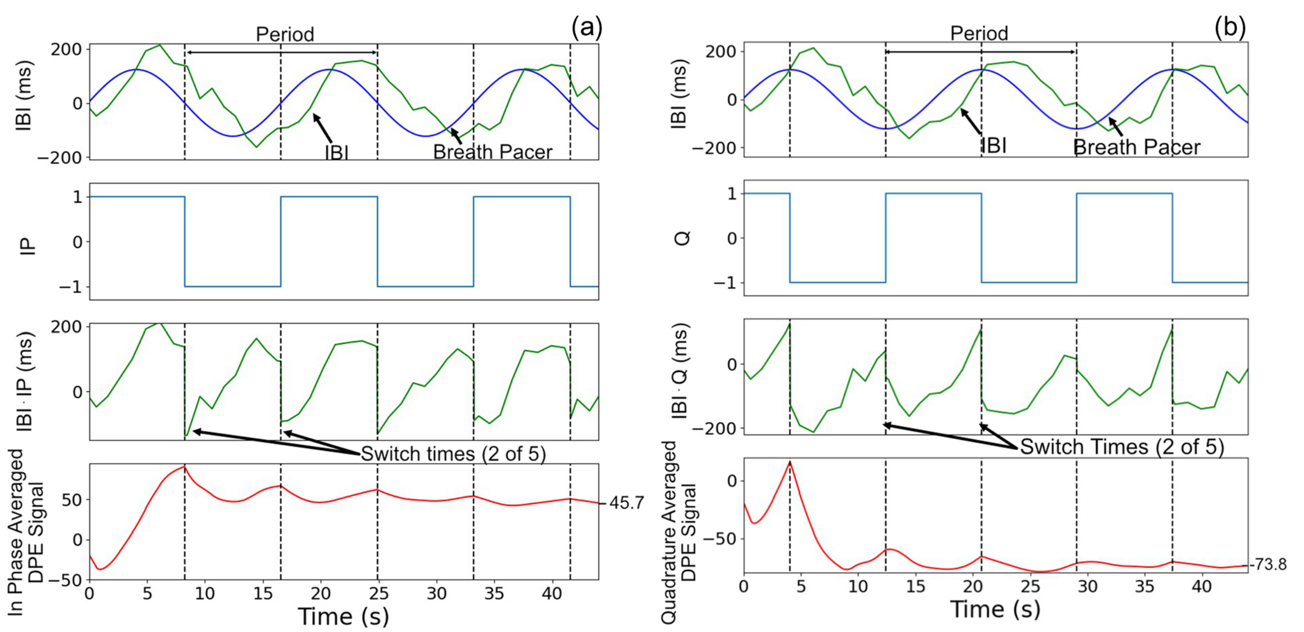

Fig. 2 The Dynamic Phase Extraction (DPE) method extracts an In-phase Averaged Signal and a Quadrature (90 degrees out of phase) Averaged Signal. These are used to calculate the amplitude and phase of the Interbeat Interval (IBI) relative to a Breath Pacer. The average value of the pulse rate was subtracted out to only reflect the changes in IBI

Fig. 2a. Similarly, for the quadrature signal (Fig. 2b), the signal is inverted every time the reference signal has a peak or a trough, as seen in the third panel of Fig. 2b. The in-phase and quadrature signals are then continuously time-averaged, as seen in the fourth panels of Fig. 2a and 2b. In practical terms, we can simply perform a numerical summation.

$$A_0 = \frac{1}{N}\sum_{i=1}^{N} \mathrm{IBI}_i \mathrm{IP}_i, \tag{1}$$

$$A_{\pi/2} = \frac{1}{N}\sum_{i=1}^{N} \mathrm{IBI}_i \mathrm{Q}_i. \tag{2}$$

In the sum, $\mathrm{IP_i}$ is positive for the first half of the reference signal, and negative for the second half (as seen in the second panel of Fig. 2a). Similarly, $\mathrm{Q_i}$ follows the second panel of Fig. 2b, where it starts positive and switches sign every half-wave. i indexes the ith heart beat from where you start counting, and N is the total number of heart beats. After evaluating $\mathrm{A_o}$ and $\mathrm{A_{\pi/2,}}$ using Eqs. (1) and (2), we can calculate the phase and amplitude (ΔIBI) as follows:

$$\text{Phase} := \phi = \operatorname{arctan2}\left(A_0, A_{\pi/2}\right) = -\operatorname{arctan2}(45.7, -73.8) = 58.2°, \tag{3}$$

$$\Delta\mathrm{IBI} := 2A = \pi\sqrt{A_0^2 + A_{\pi/2}^2} = \pi\sqrt{73.8^2 + 45.7^2} = 86.8 \text{ ms}, \tag{4}$$

whereΔIBI is the peak-to-peak amplitude of the signal, A_0 is the in-phase value, and $A_{\pi/2}$ is the quadrature value. The function arctan2 gives the angle of a ray through the origin to a point (x,y) relative to the x-axis. It is used because the normal arctan only ranges from -90^o to $+90^o$, while arctan2 ranges from -180^o to $+180^o$. We are justified in using these formulas as DPE extracts the first Fourier component at the reference frequency. This can be seen by converting our sum (Eqs. (1) and (2)) to an integral:

$$A_0 = \frac{1}{T}\int_0^T IBI(t)IP(t)dt,$$

$$A_{\pi/2} = \frac{1}{T}\int_0^T IBI(t)Q(t)dt.$$

If IBI(t) is periodic, its Fourier decomposition is given by:

$$IBI(\omega t) = \sum_{i=1}^{\infty} a_i \sin(i\omega t) + b_i \cos(i\omega t).$$

We can neglect the constant value in the Fourier transform because it is exactly equal to the average value, which we subtracted out of the IBI.

However, when we integrate with the in-phase and quadrature signals, the sines and cosines cause anything other than a wave at the same frequency as the reference to diminish as $1/T$, thus only the $I=1$ terms are left. We can choose to start anywhere—in other words, may keep only the sine terms without loss of generality. Thus, we are left integrating:

$$A_0 = \frac{1}{T}\int_0^T a_1 \sin(\omega t - \phi)\mathrm{IP}(\omega t)dt + = \frac{2a_i}{\pi}\cos(\phi),$$

$$A_{\pi/2} = \frac{1}{T}\int_0^T a_1 \sin(\omega t - \phi)\mathrm{Q}(\omega t)dt + = -\frac{2a_i}{\pi}\sin(\phi).$$

We can use the result of this integration to easily derive Eqs. (3) and (4).

In general, DPE will have a reasonable phase after two breaths, but inevitably, the more breaths that are taken, the better the precision of the method will be. The trade-off between time and precision is important to consider when measuring phase, and depends strongly on the application of DPE.

Results

First, we investigated how changes in the Breathing Rate (Breaths per Minute) of the breath pacer modulated the amplitude, ΔIBI, and Phase, as shown in Fig. 3.

This allowed us to identify the breathing rate that maximizes ΔIBI (Fig. 4). If we compare multiple trials to each other, we can locate what phase an individual's ΔIBI is maximized at, and compare said phase to other individuals. Aside from the applications in pulse rate variability, the DPE method can be applied to any physiological signal that varies at the same frequency as a reference signal.

As shown in Fig. 5, it is possible to extract phases relative to the breath from different physiological systems—even if they are noisy or have other signals mixed into them. It is evident that the pulse and the phase of the R–R interval are different. This is because, although the R–R interval is extracted from the pulse, breathing has a different phase relationship to the *pulse* specifically than it does to the R–R interval. Although the shapes don't resemble sine waves, plugging them into the DPE method as one would with the IBI yields the phase of the fundamental Fourier component of the signal relative to the reference signal.

Futhermore, we demonstrate that there is an upward trend in phase as we increase the breathing rate. However, as the breathing rate increases, the phase increases slower, indicating that the change in phase isn't a simple delay in the breathing, but rather, is some more complicated function of breathing. We note that this general trend was not

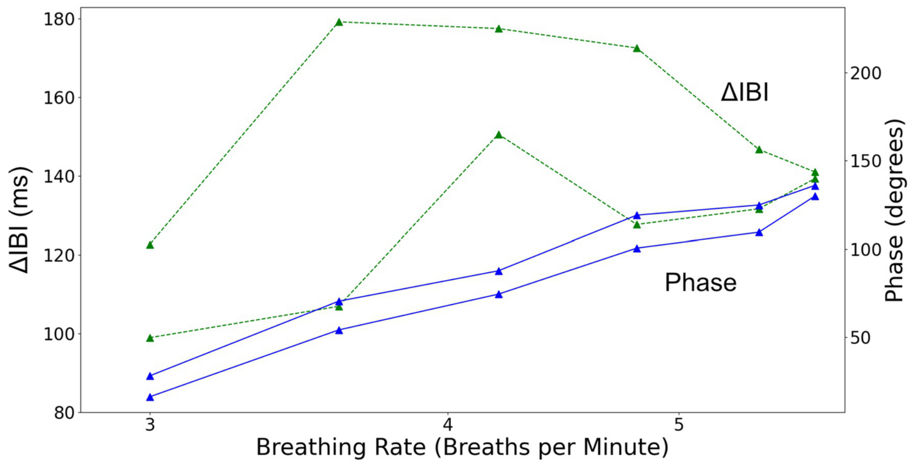

Fig. 3 ΔIBI and phase as a function of Breathing Rate for a young, athletic person. The maximum ΔIBI occurs around 100*o* Phase. The x-axis is plotted on a log scale. Multiple runs are reported

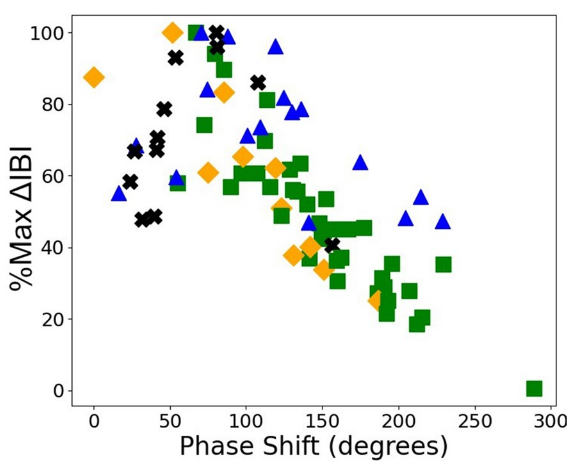

Fig. 4 Different people (shown by different symbols and colors) can have slightly different phases at their maximum ΔIBI

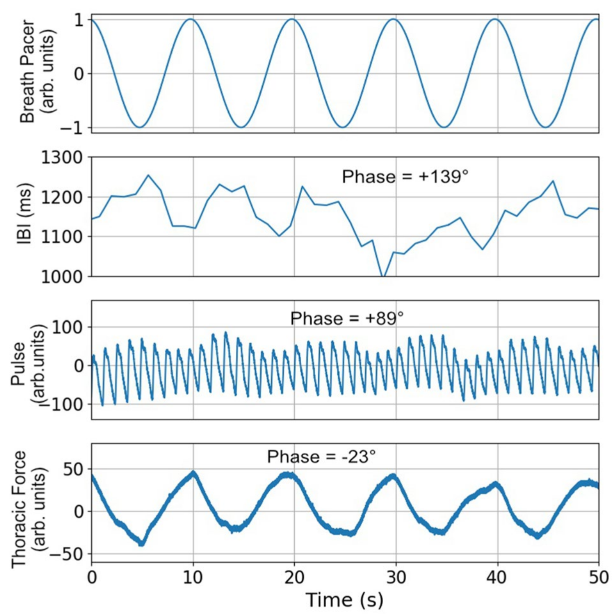

Fig. 5 Dynamic Phase Extraction (DPE) can measure the phase and amplitude of the IBI Interval, Pulse Waveform, and Thoracic Force on a chest strap. In general, DPE can measure the phase and amplitude of any signal that is the same frequency as a reference signal. In this case, all phases are calculated with reference to the breath pacer

observed in the single female participant, although we cannot determine whether this is due to gender or is simply an outlier. There is also a variation in the phase measured at each breathing rate. Whether this is truly a meaningful variation or an artifact due to measurement noise remains unclear. More research is needed before any conclusions are warranted.

Correlations with Standard Methods

Our results for ΔIBI correlate well with other standardized measures of pulse rate variability (PRV). Here, we compare our method of analysis to the LF Power, a common frequency domain analysis method for HRV, and the standard deviation of the inter-beat interval (SDNN), a common time-domain analysis method (Task Force, 1996; Shaffer & Ginsberg, 2017). We performed these comparisons by calculating ΔIBI, SDNN, and LF power for each data set recorded, and plotting the value obtained for each data record with respect to each other measure obtained from the same data set. The breathing rates were paced but varied, in order to verify that the method generalized well across breathing rates (Figs. 6, 7).

Notably, we observed an offset from zero (Fig. 8) due to SDNN being based on the standard deviation (which will pick up any variance due to noise in the data), while the DPE naturally filters the noise out. There is also a spread in the data; however, this spread is also present when correlating SDNN to the LF Power (Fig. 9). All correlations were assessed via the nonparametric Spearman method and were significant at $p < 0.00001$.

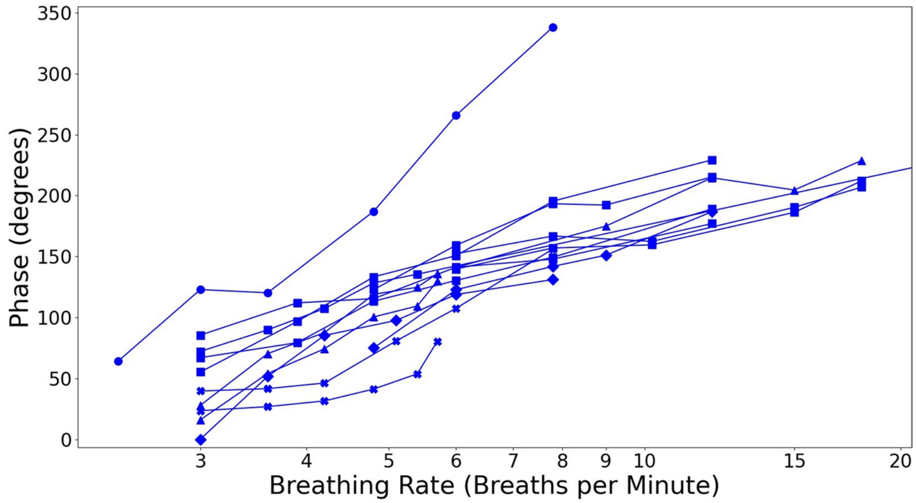

Fig. 6 The phase relationships of the population, plotted on a logarithmic xscale, there is a general upwards trend in phase as breathing gets faster

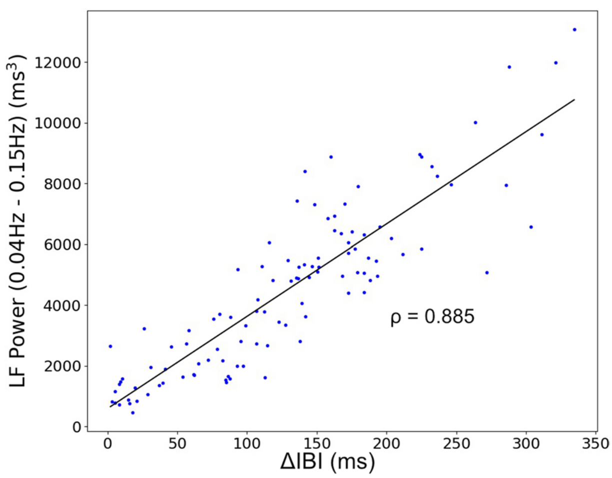

Fig. 7 Δ*IBI* from DPE correlates with the LF Power (0.04–0.15 Hz) (ρ = 0.885)

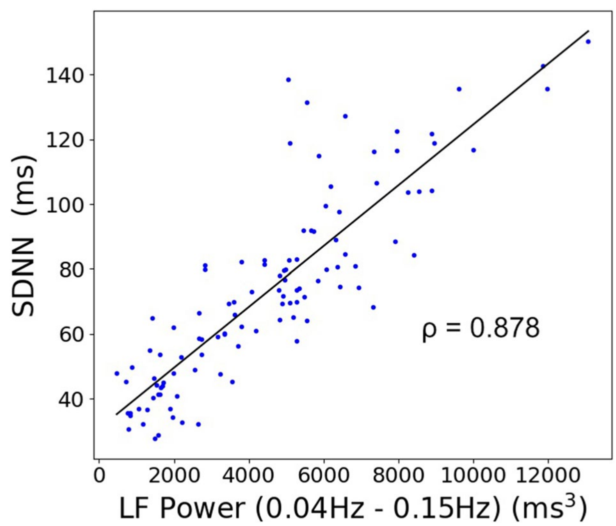

Fig. 9 The correlation between two conventional measures of pulse rate variability, LF Power and SDNN, ρ = 0.877, is comparable to the correlation of each of them with the novel measure, Dynamic Phase Extraction (DPE) (Figs. 6 and 7)

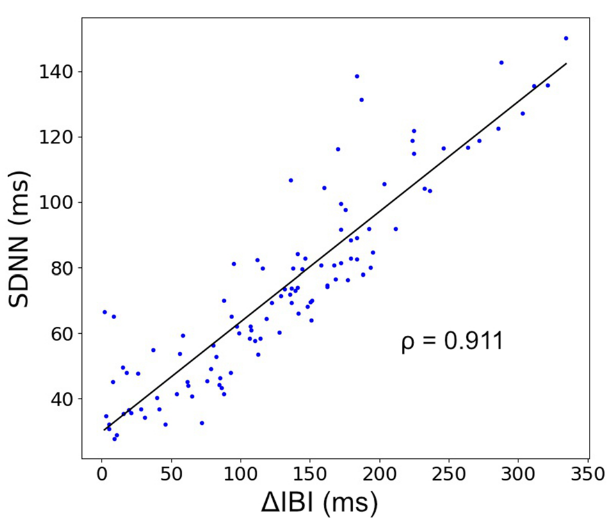

Fig. 8 Δ*IBI* from DPE correlates well with SDNN (ρ = 0.911)

In order to confirm that these correlations were a result of our method's sensitivity to the RSA—and not some other source of variance in the LF band—we took the Fourier transform of the pulse rate and verified that the largest peak was at the respiratory rate. Figure 10 presents a set of power spectra for typical trials.

In most cases, the primary source of power does appear to arise from RSA; however, there is a baseline level of power, and the harmonics are also somewhat visible (Fig. 10). Furthermore, at very low breathing rates, power from the VLF band (< 0.04 Hz) may contaminate the estimate (although at such low breath frequencies, it becomes very difficult for an individual to keep breathing at the necessary pace).

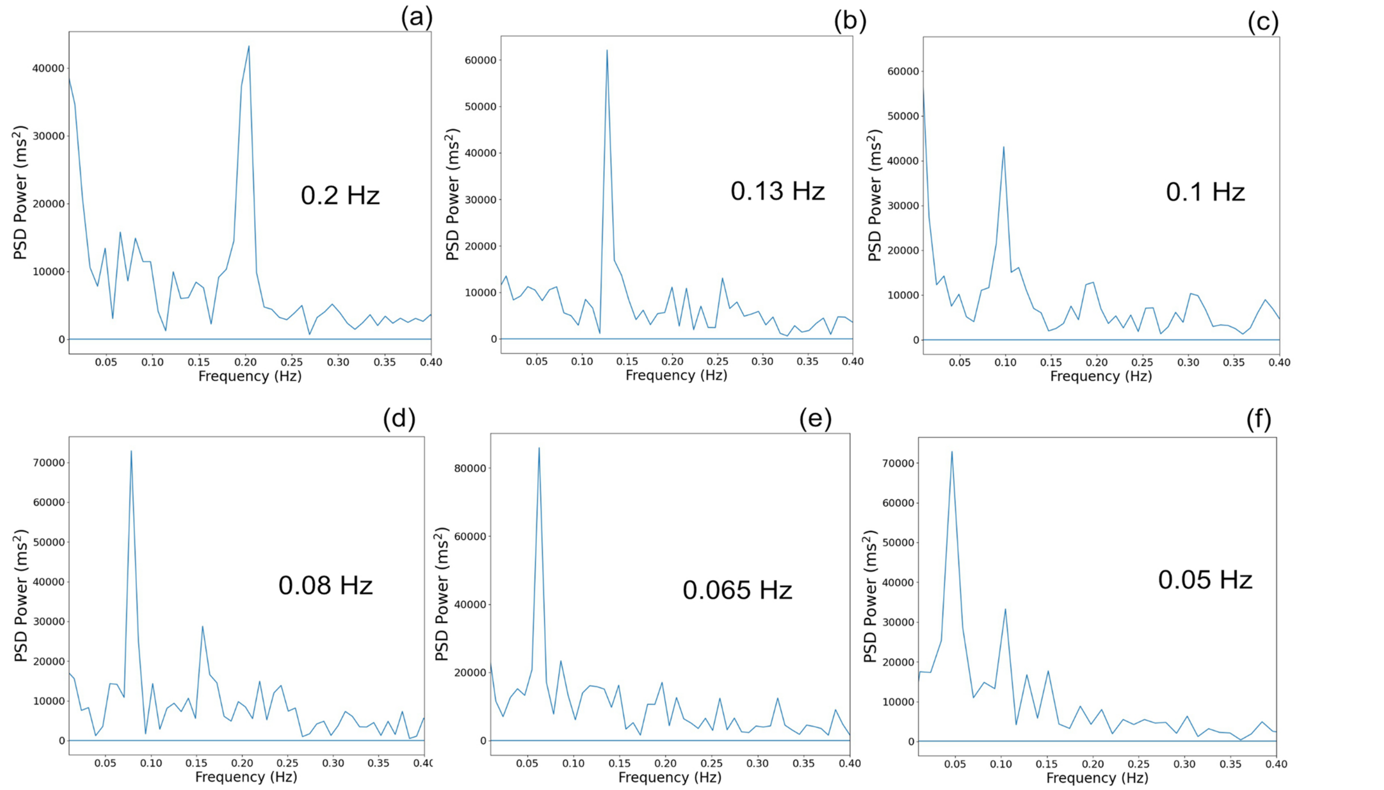

Fig. 10 The Fourier transforms of a typical set of data, with the breathing rates indicated on each of the graphs. The dataset shows that the primary source of power comes from frequencies close to the breathing rate. Each subfigure **a**–**f** represent is a different trail with a breathing rate set to the frequency in the figure

While there are no standardized methods of phase extraction, one approach for extracting phase relationships utilizes the Fourier transform. In general, the Fourier transform of a time series yields a complex function—the modulus of the values in frequency space gives the power density at that frequency, while the argument of the values in frequency space gives the phase shift of said frequency. In other words, the phase shift, ϕ, can be calculated from the Fourier transform of a function $f(t)$:

$$\phi(\omega) = arctan2\left(\frac{Im\left(\hat{f}(\omega)\right)}{Re\left(\hat{f}(\omega)\right)}\right)$$

where $\widehat{f}(\omega)$ denotes the Fourier transform of a function $f(t)$. Specifically for our case, to find the phase shift of the value in question, we perform a Fourier transform on the pulse rate that we extract from the PPG signal, and then find the peak within ± 0.01 Hz of the breathing rate. We then identify the phase shift of that peak and show that our DPE method is strongly correlated to the traditional Fourier technique (Fig. 11).

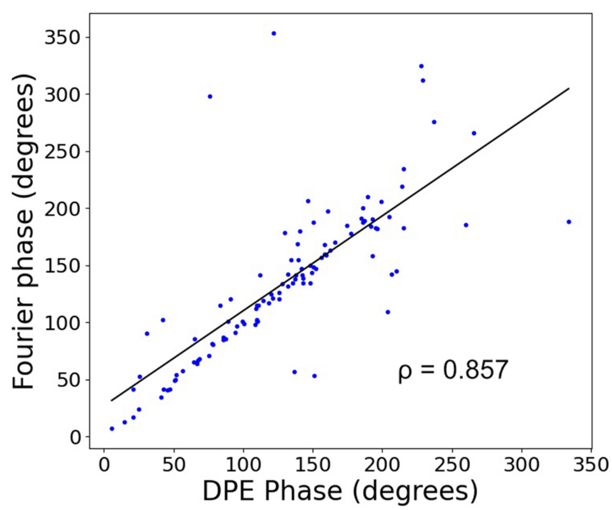

Fig. 11 The phase extracted using DPE correlates well with the phase extracted using Fourier Transform methods (ρ = 0.857)

Discussion

Dynamic Phase Extraction (DPE) is a powerful methodology that can determine the phase of a signal relative to a reference signal and extract the amplitude of the fundamental Fourier component of the signal at the frequency of the reference signal. There has recently been a resurgence of interest in phase, and several groundbreaking studies have shown that phase can be used to determine the breathing rate that gives the maximum variation in heart rate variability in the LF (0.04–0.15 Hz) band (Fisher & Lehrer, 2021; Lehrer et al., 2020; Lehrer & Gevirtz 2014). Our results, using DPE analysis of PPG data, agree with previous estimates of where maximum HRV amplitude is in relationship to the phase (Lehrer et al., 2020). The magnitude extracted by DPE also demonstrates a significant correlation to other standardized methods of measuring pulse rate variability, namely SDNN and LF Power ($\rho = 0.911$ and $\rho = 0.885$, respectively), and the phase agrees well with that extracted via Fourier transform techniques ($\rho = 0.857$). This suggests that DPE is an effective measurement technique for analyzing changes in inter-beat intervals due to respiratory sinus arrythmia as measured with PPG.

We note that PPG has nontrivial limitations relative to ECG estimates of heart rate variability. Constant et al. have emphasized that *pulse rate variability* (PRV)—an analogue for heart rate variability measured using PPG—is not a surrogate for HRV measured via ECG. In particular, they found that respiratory PRV does not precisely reflect respiratory HRV in standing healthy subjects and in patients with low HRV. Accordingly, Yuda et al. (2020) suggest that it is more appropriate to recognize PRV as a different biomarker than HRV. The literature at large, however, is more conflicted: a number of influential studies have persisted in using *HRV* for PPG-derived signals to emphasize that they are often similar to ECG estimates, especially in the frequency domain (Batista et al., 2021; Bozkurt et al., 2019; Chrousos et al., 2022; Jhang et al., 2021; Lam et al., 2020; Natarajan et al., 2020; Rubins et al., 2019; Vescio et al., 2018; Yu et al., 2020).

There are differences between PPG and ECG sensors, particularly with respect to the RSA spectrum. However, this tends to manifest in an overestimation of the power in the high frequency band (Constant et al., 1999), while most data taken in this study is in the LF band. Furthermore, other studies have found that PPG and ECG measurements of heart rate/pulse rate variability are well correlated during rest (Charlot et al., 2009; Lin et al. 2014). There is also a delay in where the peaks are detected between PPG and ECG sensors. This delay is on the order of 0.1 s (Dunn et al., 2019). For our application, we are interested in phase delays, and therefore do not investigate non-resting participants. Our ultimate goal is to develop more accessible techniques to assess pulse rate variability. As such, in this context, we believe that PPG is suitable for use.

Additionally, there are some mathematical niceties to consider for the numbers to make sense. The formula $\sqrt{A_{\pi/2}^2 + A_0^2}$ gives the RMS amplitude of the changes in the Inter-beat Interval, with no assumption of the waveform. But if one wants to convert to peak-to-peak amplitude, one needs to know the waveform. For example, the IBI pattern during paced breathing is visually similar to a sine wave, thus we multiply by π, as in Figs. 1 and 4. In multiplying by π there is an inherent assumption that the waveform is a sine wave. Strictly speaking, this doesn't change any of the correlation coefficients, but it does link the number generated by DPE to a physical attribute (the peak-to-peak amplitude).

In terms of usage, the primary limitation of this method is that it requires a breath pacer. The most common methods for determining the heart/pulse rate variability are to perform a Fourier transform and integrate the power within the target frequency band (0.04–0.15 Hz) (Task Force, 1996; Shaffer & Ginsberg, 2017; Lehrer & Gevirtz, 2014) or to perform time-domain analysis involving some statistical methods, eg SDNN (the standard deviation of the time between heartbeats) (Task Force, 1996, Shaffer & Ginsberg, 2017; Lehrer & Gevirtz, 2014). These methods do not require a breath pacer, and as such are easier to implement. The primary benefit of using DPE is that it can extract the phase efficiently after a breath is taken, while simultaneously providing a measurement for the amplitude of the signal at the desired frequency, making it ideal for biofeedback.

Conclusion

In this paper we introduce a novel technique, Dynamic Phase Extraction (DPE), that can detect the magnitude (ΔIBI) and phase of a signal relative to a reference signal. ΔIBI correlated well with other standard measures of respiratory sinus arrythmia ($\rho = 0.885$ for LF power and $\rho = 0.911$ for SDNN). We apply this technique to PPG data to determine the magnitude and phase of the IBI, pulse, and thoracic force as measured with a chest strap relative to a breath pacer. In the case of the IBI, the magnitude detected by this novel technique correlates well with pulse rate variability as determined by conventional time and frequency-based techniques. The phases detected by our new technique are consistent with what has been reported with other techniques, and correlates well with the phase extracted using Fourier techniques ($\rho = 0.857$). The phases between various parameters may give important clues to the detailed operation of the physiological feedback loops that are critical for health.

Work beyond the scope of this initial report on the Dynamic Phase Extraction method would be needed to determine if this method is also useful for ECG data and, if that is successful, to determine how the parameters from Dynamic Phase Extraction in PPG compare to ECG.

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Declarations

Conflict of interest The authors of this paper report no conflicts of interest.

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