

# Pulse Transit Time Based Respiratory Rate Estimation with Singular Spectrum Analysis

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Total Tables: 1

Total Figure: 9

## Abstract

Respiratory rate (RR) is an important vital sign which is difficult to measure accurately and unobtrusively in routine clinical practice. Pulse transit time (PTT) can be easily accessible from unobtrusively acquired electrocardiogram (ECG) and photoplethysmogram (PPG) signals. PTT technique is a novel method to estimate and monitor blood pressure (BP) and RR. This study aimed to estimate continuous RR using PTT with singular spectrum analysis to extract respiratory components. The performance of the proposed method was validated on 17 subjects who carried out a trial including spontaneous breathing and controlled deep breathing. Three types of estimated RR parameters such as average RR by power spectral density (PSD) ( $RR_{PSD}$ ), number of breaths ( $RR_{\#}$ ), and instantaneous RR ( $RR_{inst}$ ) were compared with their corresponding reference RR that was calculated from the reference respiratory signal obtained via a respiratory belt. We demonstrated that PTT reliably tracked respiratory variation with a root mean square error of 0.84, 1.11 and 0.74 breaths/min for  $RR_{PSD}$ ,  $RR_{\#}$  and  $RR_{inst}$  estimations, respectively. Furthermore, RR estimated by PTT was in general more accurate than those by other respiratory indicators that were extracted from single ECG or PPG, including heart/pulse rate interval, QRS area and PPG amplitude. Our findings suggest the feasibility of using PTT derived from ECG and PPG for continuous noninvasive and unobtrusive estimation of RR, plus potential extra vital signs monitoring including BP and heart rate with only two sensing modalities.

**Keywords** Respiratory rate · Pulse transit time · Singular spectrum analysis · Blood pressure

## 1 Introduction

Respiratory rate (RR), defined as the number of breaths a person takes in one minute (breaths/min), is one of the primary vital signs apart from heart/pulse rate (HR/PR), blood pressure (BP) and body temperature. RR varies in response to metabolic demand and the normal range for an adult is 12 to 20 breaths/min at rest. Elevated or reduced RR may be an indicator of respiratory dysfunction [1, 2]. The most common and basic methods for RR assessment are through counting the chest wall movements via observation or auscultation with a stethoscope. These methods provide only a snapshot rather than real-time continuous measurement. Moreover, these methods suffer from problems, like poor reproducibility in the

clinical settings [3]. Instrumental RR measurement methods, such as detection of respiratory gas variations (*e.g.* through flow, temperature, humidity,  $O_2$  or  $CO_2$ ), mechanical effort measured with strain gauges or impedance, provide continuous and more reliable RR measurements. However, these methods are usually obtrusive and cumbersome to apply, particularly for non-ventilated patients. Their routine application is therefore limited [4].

Accurate RR estimation techniques that are noninvasive and continuous are thus in high demand. There have been a number of studies on the indirect RR estimation from vital signs such as electrocardiogram (ECG), photoplethysmogram (PPG) or arterial BP that can be collected noninvasively and even unobtrusively [5, 6]. A common method for such RR measurement is to analyze HR/PR variability obtained from ECG/PPG signal. Although thoracic or abdominal respiratory belts are arguably less intrusive than ECG electrodes and finger PPG for breathing monitoring, the latter are more potential for unobtrusive sensing with the development of flexible and stretchable wearable health sensors [7]. Pulse transit time (PTT), defined as the propagation time of a pulse wave traveling

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1 between two sites in the cardiovascular system, can be  
2 derived from ECG and PPG signals. PTT is a popular  
3 indicator of BP changes, since PTT is an index of  
4 arterial stiffness which is closely related to arterial  
5 pressure [8]. The usage of PTT for BP estimation has  
6 been widely investigated and always been of great  
7 interest to the researchers [9, 10]. Information of  
8 respiratory activity can be extracted from PTT [11],  
9 but the use of PTT to estimate RR remains  
10 underexplored. One study by Pitson *et al.* [12] reported  
11 that PTT can provide a noninvasive estimate of  
12 inspiratory effort as well as a measure of arousals that  
13 may benefit the management of obstructive sleep  
14 apnea. Other studies have investigated the potential of  
15 PTT to evaluate respiratory effort associated with  
16 intrathoracic pressure changes [13, 14]. The  
17 relationship between PTT and RR or respiratory signal  
18 has also been studied. For example, Johansson *et al.*  
19 described the correlation between PTT and RR under  
20 different BP levels [15]. The study by Chua *et al.*  
21 demonstrated that PTT-derived respiratory frequency  
22 was well correlated with that derived from inductance  
23 plethysmography in patient with obstructive sleep  
24 apnea [16]. However, only the relative variance of  
25 PTT with respiration was analyzed, but not the  
26 quantitative estimate of RR. It remains unclear  
27 whether PTT can accurately estimate RR continuously  
28 and reliably in various situations.

29 One of our recent preliminary study has reported  
30 the use of PTT as a measure of RR, and estimated RR  
31 with a fusion algorithm using the combination of HR  
32 interval (HRI) and PR interval (PRI) [17]. This  
33 approach was validated with the CapnoBase dataset  
34 [18] and the results indicate that RR estimation by PTT  
35 was feasible for ventilated patients. Nevertheless, the  
36 capability of PTT to estimate RR for spontaneous  
37 breathing still remains to be investigated. In addition,  
38 most of previous studies used the raw PTT instead of  
39 extracting the respiratory component for the  
40 estimation of RR [19-22]. We hypothesize that the RR  
41 estimations using respiratory component extracted  
42 from PTT would be more accurate than that from the  
43 raw PTT.

44 Singular spectrum analysis (SSA) is a  
45 nonparametric spectral estimation method based on  
46 the singular value decomposition that can decompose  
47 the original time series into a sum of independent and

interpretable components such as a slowly varying  
trend, oscillatory components and noise [23]. SSA can  
be used for finding trends of different resolution,  
filtering of noise, extraction of oscillatory  
components, finding structure in short time series, and  
so on. For filtering, SSA has the advantage over  
bandpass filter for specific purpose, because the SSA  
filters often correspond with narrowband quasi-period  
oscillations that come from anywhere in the full  
frequency spectrum of the signal trace rather than  
representing high- and low-pass limits.

In this study, we attempt to employ SSA to extract  
respiratory component from PTT. The aim of this  
study is to explore the utilization of PTT for RR  
measurement in different breathing conditions, such as  
spontaneous breathing and controlled deep breathing.  
We employ SSA to characterize respiratory  
component of PTT, and experimentally validate its  
performance for RR measurement with the  
comparison to those estimated with other respiratory  
indicators that were extracted from ECG and PPG.

## 2 Methods

### 2.1 Subjects and experiment

The experiment was conducted on 17 healthy subjects  
(59% male with mean age  $24.6 \pm 2.1$  years and body  
mass index (BMI) of  $19.66 \pm 2.21 \text{ kg/m}^2$ ) without  
history of cardiac or respiratory diseases. All the  
subjects volunteered to participate the study and gave  
their informed written consent prior to participation in  
the study. We conduct our studies in compliance with  
the principles of the Declaration of Helsinki, and the  
study has been approved by Joint Chinese University  
of Hong Kong – New Territories East Cluster Clinical  
Research Ethics Committee (CREC Ref. No.:  
2015.301).

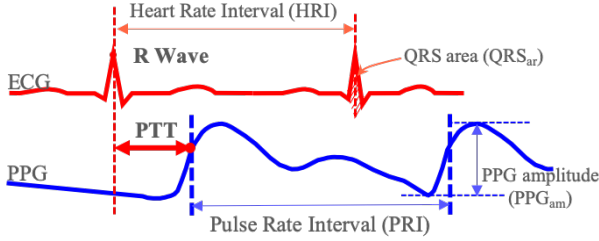
Single-lead ECG electrodes were placed on the  
chest of the subjects and the PPG signal was recorded  
with a reflectance probe that consists of an infrared  
LED (SFH 4250, 850nm) and a phototransistor (SFH  
320) placed on the left index fingertip. Reference  
respiratory effort was measured using a gas pressure  
sensor-based respiration monitor belt (Vernier  
Software & Technology). All signals were recorded  
simultaneously at a sampling rate of 1000 Hz.

The subject followed a strict breathing protocol.  
Data were collected firstly from subject breathing  
spontaneously at rest while seating for 5 min, which

was followed by cyclic deep breathing for 2 min with a controlled breathing rate of 6 breaths/min.

## 2.2 Calculation of PTT and other ECG and PPG derived indicators for respiratory extraction

PTT was calculated as the time interval between the peak of the R wave of ECG signal and maximal upslope of PPG signal for every cardiac cycle (Fig. 1). To compare the performance of PTT for RR estimation, other respiratory indicators were also extracted from ECG or PPG signal, including HRI, PRI, QRS area of ECG waveform ( $QRS_{ar}$ ), and PPG amplitude ( $PPG_{am}$ ). Since PTT is an intermittent variable, it was interpolated to 1000 Hz with a spline function, so did HRI, PRI,  $QRS_{ar}$  and  $PPG_{am}$ .



**Fig. 1.** Calculation of pulse transit time (PTT), heart rate interval (HRI), pulse rate interval (PRI), QRS area ( $QRS_{ar}$ ) and PPG amplitude ( $PPG_{am}$ ) from ECG and PPG signals.

## 2.3 Respiratory component extraction with singular spectrum analysis

As a powerful technique applicable for dynamical systems and signal processing, SSA is used to extract respiratory variations from the respiratory indicators including PTT, HRI, PRI,  $QRS_{ar}$  and  $PPG_{am}$ . SSA technique consists of two complementary stages: decomposition and reconstruction [26]. At the first stage we decompose the respiratory series and at the second stage we reconstruct the series with components that represent the respiratory variations in the respiratory series. We then use the reconstructed series for respiratory estimation. The main steps of the SSA algorithm are briefly described as follows:

**Embedding:** Consider the interpolated respiratory series as a time series with a length of  $T$ , e.g.  $PTT = (PTT_1, \dots, PTT_T)$ . Fix  $L$  the window length ( $L \leq T/2$ ) and let  $K = T - L + 1$ . Then the embedding process transfers a one-dimensional time series into the trajectory matrix, which is also a Hankel matrix, i.e.  $X \in M_{L,K}^{(H)}$  and  $X = (PTT)$ . In this study, the value of  $L$

was set to 8 and 10 for spontaneous and controlled breathing, respectively.

**Decomposition - step 1:** The matrix  $XX^T$  is computed for applying singular value decomposition. The eigenvalues and eigenvectors of the matrix  $XX^T$  are computed and represented in the form  $XX^T = PAP^T$ , where  $\Lambda = \text{diag}(\lambda_1, \dots, \lambda_L)$  is the diagonal matrix of eigenvalues of  $XX^T$  and  $\lambda$  is ordered such that  $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_L \geq 0$ , an  $P = (P_1, P_2, \dots, P_L)$  is the orthogonal matrix of eigenvectors of  $XX^T$  corresponding to these eigenvalues.

**Decomposition - step 2:** Selection of eigenvectors and the resultant sum of 1-rank matrices. If we denote  $V_j = X^T U_j / \sqrt{\lambda_i}$ , then the singular value decomposition of the trajectory matrix can be written as:

$$X = \sum_{j=1}^r X_j$$

where  $X_j = \sqrt{\lambda_i} U_j V_j^T$  ( $j = 1, \dots, d$ , where  $d = \max(i, \text{such that } \lambda_i > 0) = \text{rank } X$ );  $X_j$  are matrices with rank 1;  $U_j$  and  $V_j$  that are called “factor empirical orthogonal function” and “principal components” stand for the left and right eigenvectors of the trajectory matrix, respectively;  $\sqrt{\lambda_i}$  ( $i = 1, \dots, d$ ) are the singular values of the matrix  $X$  and the set  $\{\sqrt{\lambda_i}\}$  is the spectrum of the matrix  $X$ .

**Reconstruction - step 1:** The elementary matrices  $X_j$  were split into groups, with matrices in each group being summed. Let  $I = \{i_1, \dots, i_r\}$  be a group of indices  $i_1, \dots, i_r$  ( $r = 2:3$  and  $r = 2$  for spontaneous and controlled breathing). Then the matrix  $X$  corresponding to the group  $I$  is defined as  $X = X_{I1} + X_{I2} + \dots + X_{Ii}$ , and

$$X_I = \sum_{j \in I} X_j$$

**Reconstruction - step 2:** The one-dimensional series are reconstructed with components that represent the respiratory variations in the respiratory series through computing the matrix:

$$\tilde{X} = \sum_{k=1}^l P_{ik} P_{ik}^T X$$

and the one-dimensional extracted respiratory series can be approximated by averaging over the diagonals of the matrix  $\tilde{X}$ .

## 2.4 Respiratory rate estimation

The extracted respiratory component was segmented using a 60s window with 5% overlap (3s). For each

time window, we derived three types of RR: 1) the one that derived from the maximum peak of the power spectral density (PSD) ( $RR_{PSD}$ ) where the PSD was estimated using Welch's method; 2) the number of breaths in one minute ( $RR_{\#}$ ), which was calculated by automatically counting the number of peaks in a window with the peak being detected with an adaptive threshold method; and 3) the instantaneous RR ( $RR_{inst}$ ), which was measured as the average instantaneous rate for each window, where the instantaneous rate was calculated as the time interval between two peaks divided by 60. The corresponding reference RRs were calculated from the recorded respiratory signal using the same method described above.

## 2.5 Data analysis

The performance of the RR estimation with PTT, SSA processed PTT, HRI, PRI, QRS<sub>ar</sub>, and PPG<sub>am</sub> was evaluated against the RR measured from the reference respiratory signal. The mean and standard deviation (SD) of the difference between the estimation and the reference values, the root mean squared error (RMSE) and mean absolute error (MAE) were calculated for the evaluation of accuracy performance. The formulas of these metrics are as below:

$$\text{Error mean} = \sum(Y_{esti} - Y_{refi})/n$$

$$\text{Error SD} = \sqrt{((Y_{esti} - Y_{refi})^2/(n-1))}$$

$$\text{MAD} = \sum|Y_{esti} - Y_{refi}|/n$$

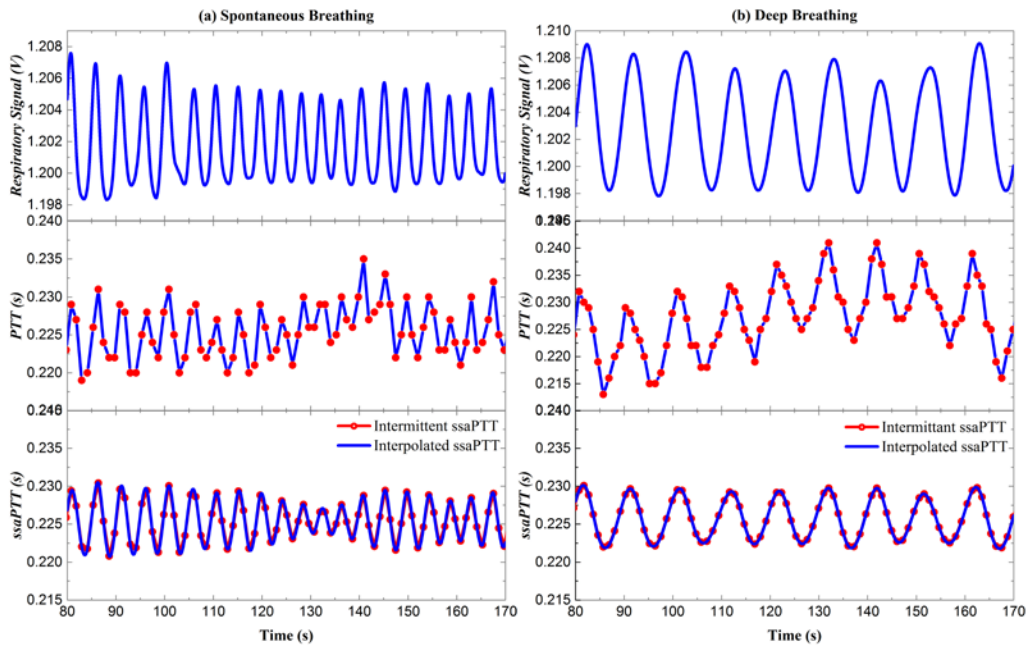
$$\text{RMSE} = \sqrt{((Y_{esti} - Y_{refi})^2/n)}$$

where  $Y_{esti}$  and  $Y_{refi}$  are the estimation and reference values of RR, respectively, and  $i=1, \dots, n$ . In addition, the Bland-Altman plot was used to compare the estimation of RR with the reference RR with the analysis of limits of agreement. The significance of level was tested using the Kruskal-Wallis ANOVA test. A statistical significance level is assumed at 0.05.

## 3 Results

### 3.1 Relationships of PTT and the singular spectrum analysed PTT with respiration

As can be observed from Fig. 2, PTT fluctuated with respiratory signal with its changes being in accord with the phase of each breathing cycle either for spontaneous breathing or controlled deep breathing. Specifically, the interpolated PTT altered during each breath cycle with its amplitude increasing during inspiration and decreasing during expiration. However, time-varying components slower than that of the respiratory exhibited in PTT in both situations. With SSA, PTT was decomposed and reconstructed to contain the principal component of the respiration. Obviously, after processed with SSA, PTT (ssaPTT) aligned better with the respiratory signal than the raw PTT. It is, therefore, expected that the ssaPTT would predict RR with a better accuracy.

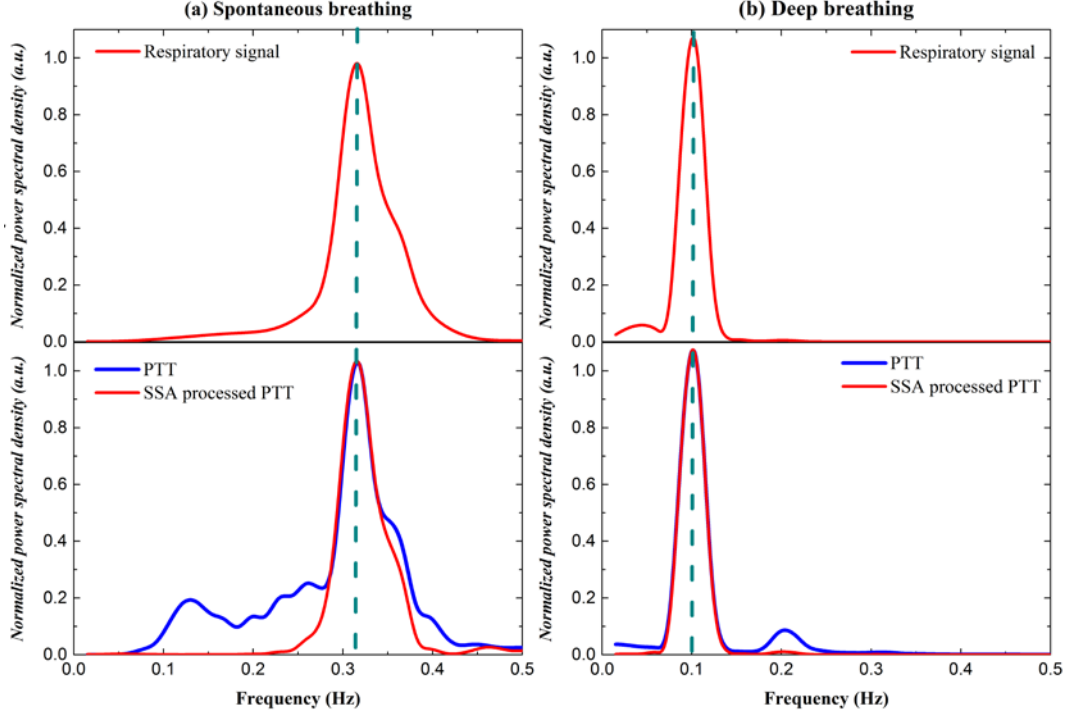


**Fig. 2.** Variations of the pulse transit time (PTT, middle panel), singular spectrum analysis (SSA) based PTT (ssaPTT, lower

1 panel) with the reference respiratory signal (upper panel) for a representative subject under (a) spontaneous breathing and  
 2 (b) controlled deep breathing.

3 The normalized PSD of PTT, ssaPTT and the  
 4 reference respiratory signal for a representative sample  
 5 illustrated in Fig. 3 further suggests the efficiency of  
 6 the SSA method to extract robust respiratory  
 7 component from PTT. For spontaneous breathing (Fig.  
 8 3a), PTT showed a wider spectral range (0.1–0.4 Hz)  
 9 with a specific focus on the breathing spectrum (~0.32 Hz).

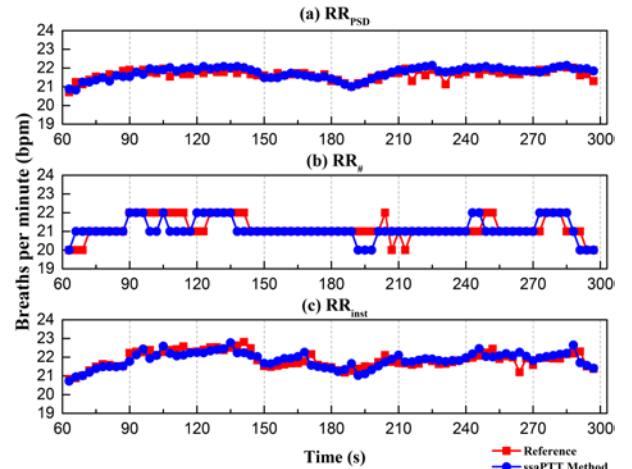
While under controlled breathing rate, PTT exhibited a higher frequency peak (0.2 Hz) apart from the controlled frequency, *i.e.* 0.1 Hz. Owing to SSA, the extracted PTT respiratory component would be detected more reliably and the cycle-by-cycle breathing rate will be calculated more easily and more accurately.



**Fig. 3.** The normalized power spectral density (PSD) of the reference respiratory signal (upper panel) and the pulse transit time (PTT, lower panel, blue) and SSA processed PTT (lower panel, red) under (a) spontaneous breathing and (b) deep breathing.

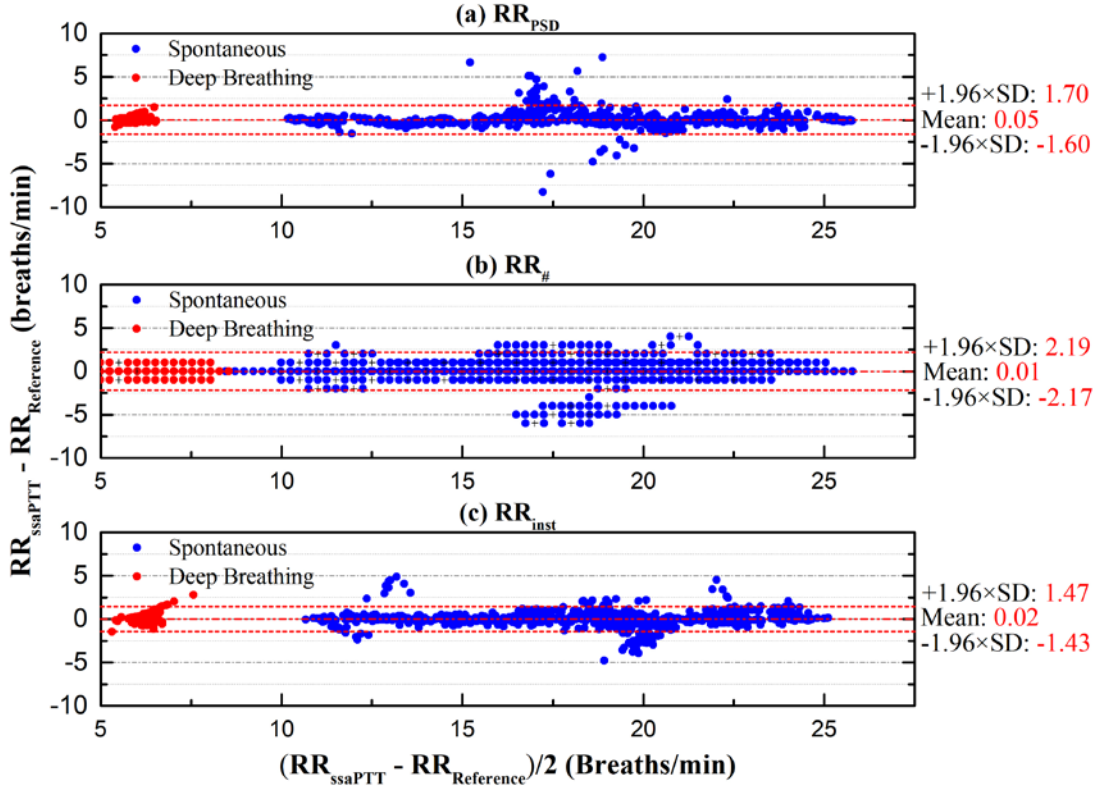
### 3.2 RR Estimation with PTT

There was a total of 1485 windows of PTT data for RR estimation. The estimated RR from ssaPTT followed very well with the reference RR for all of the three types of RR (Fig. 4). Further, the overall estimation difference biases of  $RR_{PSD}$ ,  $RR_{\#}$  and  $RR_{inst}$ , were all around zero, with the 95% limits of agreement fell within the range of -1.60 to 1.70 breaths/min, -2.17 to 2.19 breaths/min, and -1.40 to 1.47 breaths/min, respectively (Fig. 5). It can be obviously observed that the estimation performance with PTT under controlled deep breathing was better than that under spontaneous breathing, as the differences of the estimation and the reference in the latter situation were almost all within the limits of agreement.



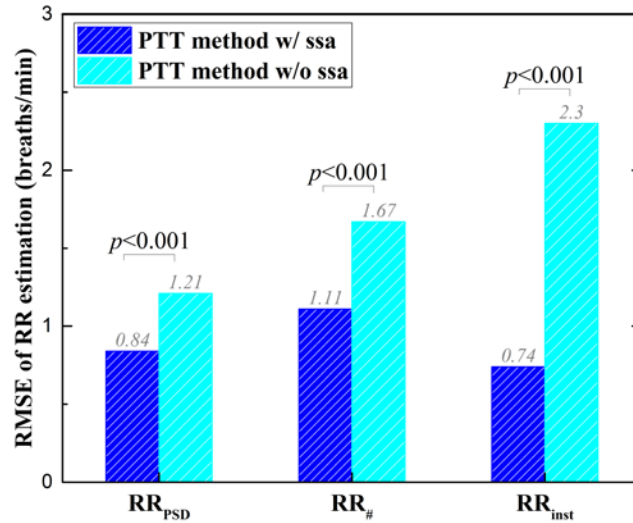
**Fig. 4.** Cycle-by-cycle respiratory rate (RR) estimation by singular spectrum analysis (SSA) processed pulse transit time (ssaPTT, blue) against the reference (red): (a) average RR that was estimated from PSD –  $RR_{PSD}$ , (b) the number of breaths per minute –  $RR_{\#}$ , (c) instantaneous RR –  $RR_{inst}$ .





**Fig. 5.** Bland-Altman plot of differences between respiratory rate (RR) estimation by singular spectrum analysis (SSA) processed pulse transit time (ssaPTT) method and reference method vs. the mean of these two measurements, with the representation of the error mean (red dashdot) as well as the limits of agreement (red dash line) for (a) average RR that was estimated from PSD –  $RR_{PSD}$ , (b) the number of breaths per minute –  $RR_{\#}$ , and (c) instantaneous RR –  $RR_{inst}$ .

In comparison to the method using raw PTT, the one with ssaPTT achieved significantly lower RR estimation errors for all types of RR estimation (Fig. 6). The error was reduced to less than or around 6 breaths/min with the process of SSA.



**Fig. 6.** Root mean square error (RMSE) of respiratory rate (RR) estimations with original pulse transit time (PTT, blue) and singular spectrum analysis (SSA) processed PTT (cyan).

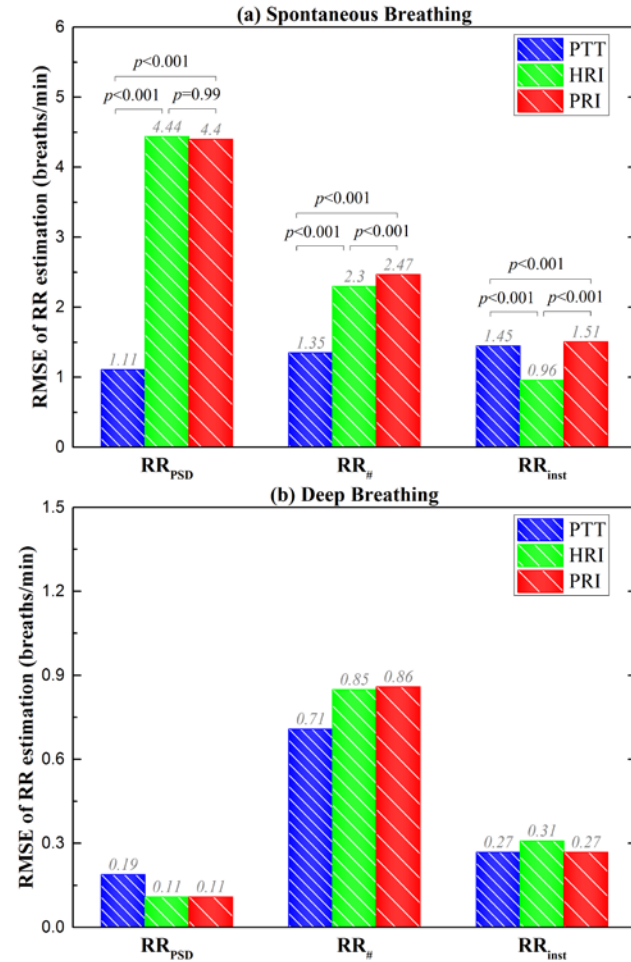
### 3.3 Performance of RR estimation with PTT with comparison to other respiratory indicators derived from ECG and PPG

To further assess the performance of PTT, PTT was compared with HRI, PRI,  $QRS_{ar}$ , and  $PPG_{am}$  for RR estimation. Since SSA processed PTT has a better performance for RR estimation, we have processed all the other respiratory indicators with SSA for estimating RR. Among all these RR estimations including both the spontaneous and controlled breathing, the RR estimations with PTT achieved the best performance in terms of the accuracy and precision, with significantly lower mean error, SD, RMSE and MAE, as illustrated in Table 1. In particular, it performed the best for  $RR_{PSD}$ . Being time interval respiratory indicators, the performance of PTT was first compared with those of HRI and PRI for RR estimation under spontaneous breathing and controlled breathing, respectively. As shown in Fig. 7, PTT was significantly superior to HRI and PRI for RR estimations particularly under spontaneous breathing.

**Table 1.** Accuracy and precision for respiratory rate (RR) estimations by respiratory indicators including pulse transit time (PTT), heart rate interval (HRI), pulse rate interval (PRI), ECG QRS area (QRS<sub>ar</sub>), and PPG amplitude (PPG<sub>am</sub>).

	Method	Accuracy: Mean error (breaths/min)	Precision: Standard Deviation (breaths/min)	Accuracy: RMSE (breaths/min)	Accuracy: MAE (breaths/min)
<b>RR<sub>PSD</sub></b>	<b>PTT</b>	<b>0.05</b>	<b>±0.84</b>	<b>0.84</b>	<b>0.34</b>
	HRI	-0.78	±3.22	3.31	1.12
	PRI	-0.80	±3.18	3.27	1.09
	QRS <sub>ar</sub>	0.17	±5.10	5.10	2.84
	PPG <sub>am</sub>	-0.15	±3.22	3.22	1.45
<b>RR<sub>#</sub></b>	<b>PTT</b>	<b>0.01</b>	<b>±1.11</b>	<b>1.11</b>	<b>0.64</b>
	HRI	-0.45	±1.75	1.81	1.08
	PRI	-0.56	±1.85	1.93	1.15
	QRS <sub>ar</sub>	-1.36	±3.10	3.38	1.89
	PPG <sub>am</sub>	-0.85	±2.11	2.28	1.38
<b>RR<sub>inst</sub></b>	<b>PTT</b>	<b>0.02</b>	<b>±0.74</b>	<b>0.74</b>	<b>0.40</b>
	HRI	-0.27	±1.06	1.09	0.53
	PRI	-0.33	±1.09	1.14	0.56
	QRS <sub>ar</sub>	-0.29	±3.02	3.03	1.77
	PPG <sub>am</sub>	-0.09	±1.77	1.78	1.10

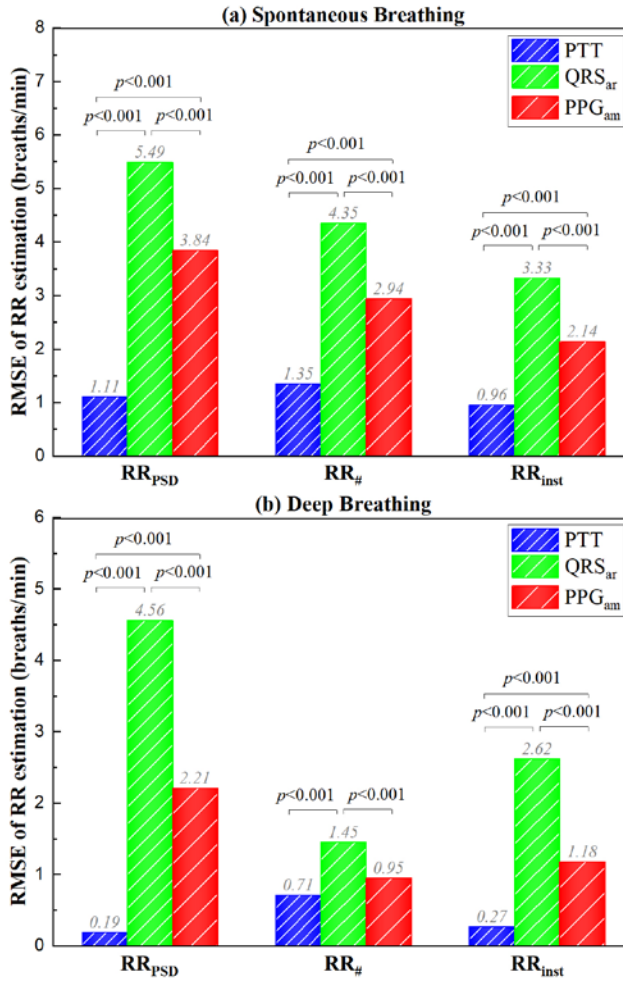
RR<sub>PSD</sub>: average RR that was estimated from PSD; RR<sub>#</sub>: the number of breaths per minute; RR<sub>inst</sub>: instantaneous RR; RMSE: root mean squared error; MAE: mean absolute error



**Fig. 7.** Root mean square error (RMSE) of respiratory rate (RR) estimations with pulse transit time (PTT, blue) compared to those estimated by heart rate interval (HRI, green) and pulse rate interval (PRI, blue) under (a) spontaneous breathing and (b) controlled deep breathing.

There was a striking difference between PTT and that of HRI and PRI for RR<sub>PSD</sub>, with the error for PTT was around one breaths/min as opposed to around 4.5 breaths/min for HRI and PRI. For RR<sub>#</sub>, the error of the estimate using PTT was about one breaths/min less than those using HRI or PRI. But for RR<sub>inst</sub>, HRI obtained the lowest error, with the one with PTT comparable to that of PRI. However, it is noticeable that the performance of PTT was comparable to that of HRI and PRI under controlled deep breathing.

Further, we compared the performance of PTT with QRS<sub>ar</sub> and PPG<sub>am</sub> for RR estimation. The results in Fig. 8 demonstrate that PTT was more accurate than both the QRS<sub>ar</sub> and PPG<sub>am</sub> for estimating all type of RR parameters either for spontaneous breathing or controlled breathing. The differences are most significant for RR<sub>PSD</sub> estimation. It is worth nothing that PPG<sub>am</sub> in general achieved better performance than QRS<sub>ar</sub> both under spontaneous breathing and controlled breathing.



**Fig. 8.** Root mean square error (RMSE) of respiratory rate (RR) estimations with pulse transit time (PTT, blue) compared to those estimated by ECG QRS area (QRS<sub>ar</sub>, green) and PPG amplitude (PPG<sub>am</sub>, red) under (a) spontaneous breathing and (b) controlled deep breathing.

## 4 Discussion

In this study we investigated PTT for the estimation of RR with SSA, in which PTT was acquired from ECG and PPG. We demonstrated high accuracy of continuous RR measurements using SSA processed PTT under spontaneous breathing and controlled deep breathing. The comparison of the performance of PTT with other ECG or PPG derived respiratory indicators, including HRI, PRI, QRS<sub>ar</sub> and PPG<sub>am</sub> also indicates the superiority of PTT for spontaneous continuous RR estimation. As PTT is also a powerful indicator for cuffless BP, the configuration of ECG and PPG noninvasively or unobtrusively would thus be capable of monitoring three vital signs, *i.e.* BP, RR, PR/HR at the same time.

Our recent study on PTT for RR estimation on ventilated subjects showed that PTT is able to track respiratory variation and estimate RR [17]. The present study further highlights the ability of PTT to estimate spontaneous RR. Using PTT for estimating  $RR_{PSD}$ ,  $RR_{\#}$  and  $RR_{inst}$  obtained acceptable accuracy with RMSE less than 1 breaths/min. Of note, there seems time lag between the estimated RR and the reference as shown in Fig. 4. The cause for such “delay” is presumably the phase shift between the respiratory signal and the interpolated ssaPTT, which might be observed from Fig. 2. The valley of the PTT was originally corresponding to the peak of the respiratory waveform, and the waveform of the interpolated ssaPTT was therefore reversed upside down to minimize the estimation bias. When the method of SSA was employed to extract the respiratory component, the estimation error was improved by about 2.5 breaths/min with contrast to that without SSA processing. This demonstrates the oscillatory components extraction and filtering capabilities of SSA method. As PTT features the slow variations of BP as well as the elements of respiratory spectrum, SSA could isolate the arterial-related composition efficiently such that the breathing component was enhanced.

Regarding different modes of breathing, *i.e.*, spontaneous breathing and controlled deep breathing, the PTT method achieved lower error for RR estimates in the latter condition. This could possibly be attributed to stronger modulation of respiratory sinus arrhythmia (RSA) under controlled breathing than the spontaneous condition. This was consistent with findings reported by other studies, in which a strong relationship between PTT changes were observed under paced respiration [11].

RR estimation with PTT outperformed other respiratory indicators that were extracted from either ECG or PPG, particularly under spontaneous breathing. The reason is presumably the enhanced effect of respiration on PTT. Because PTT as an indirect predictor of BP, could reflect the effect of respiration that was due to both the direct mechanical pressure in the chest and the effect of respiratory sinus arrhythmia. The effect of respiration on BP, particularly SBP, depends on two aspects. The first is direct effect of respiration (DER) through the





- 1 We investigated the usage of PTT for RR estimation
- 2 with SSA. We demonstrated that PTT varied with
- 3 respiration in each breath cycle, and its components
- 4 after decomposition and reconstruction with SSA
- 5 achieved promising accuracy for estimating RR. PTT
- 6 can accurately track RR under spontaneous breathing
- 7 and it in general demonstrates better performance than
- 8 other respiratory indicators that were derived from
- 9 either ECG or PPG. Potential application of PTT could
- 10 include continuous and unobtrusive measurement of
- 11 RR for diagnosing and monitoring respiratory
- 12 dysfunction and provide extra monitoring of BP and
- 13 HR/PR using only ECG and PPG.
- 14
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- 20
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