# Application of Empirical Mode Decomposition to Cardiorespiratory Synchronization

**Ming-Chya Wu and Chin-Kun Hu**

**Abstract** A scheme based on the empirical mode decomposition (EMD) and synchrogram introduced by Wu and Hu [Phys. Rev. E **74**, 051917 (2006)] to study cardiorespiratory synchronization is reviewed. In the scheme, an experimental respiratory signal is decomposed into a set of intrinsic mode functions (IMFs), and one of these IMFs is selected as a respiratory rhythm to construct the cardiorespiratory synchrogram incorporating with heartbeat data. The analysis of 20 data sets from ten young (21–34 years old) and ten elderly (68–81 years old) rigorously screened healthy subjects shows that regularity of respiratory signals plays a dominant role in cardiorespiratory synchronization.

**Keywords** Empirical mode decomposition · Intrinsic mode functions · Cardiorespiratory synchrogram

## 1 Introduction

Physiological systems are nonlinear, and biomedical signals are apparently random or aperiodic in time. These systems can serve as a playground for the study of analysis techniques of nonlinear dynamics. Recently, the study of oscillations and couplings in these systems has gained increasing attention [1–19]. Among these, the nature of the couplings between human cardiovascular and respiratory systems has been widely studied [18–26], and is known to be both neurological [1] and mechanical [2]. The interactions between the two systems result in the well-known modulation of heart rates, known as respiratory sinus arrhythmia (RSA). Recent studies suggest that beside modulations, there is also synchronization between them.

Almasi and Schmitt reported that there are voluntary synchronization between subjects' breathing and cardiac cycle [3], in which subjects, signaled by a tone derived from the electrocardiograms (ECGs), inspired for a fixed number of heart

M.-C. Wu (✉)
Research Center for Adaptive Data Analysis, National Central University, Chungli 32001, Taiwan
e-mail: mcwu@ncu.edu.tw

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beats followed by expiration for a fixed number of heart beats [3]. Recently, Schäfer et al. [5, 6] and Rosenblum et al. [7] applied the concept of phase synchronization of chaotic oscillators [15] to analyze irregular non-stationary bivariate data from cardiovascular and respiratory systems, and introduced the cardiorespiratory synchrogram (CRS) to detect different synchronous states and transitions between them. They found sufficient long period of synchronization and concluded that the cardiorespiratory synchronization and RSA are two competing factors in cardiorespiratory interactions. Latter, Tolddo et al. [8] found that synchronization was less abundant in normal subjects than in the transplant patients, which indicated that the physiological condition of the latter promotes cardiorespiratory synchronization. More recently, Kotani et al. [14] developed a physiologically model to study the phenomena, and showed that both the influence of respiration on heartbeat and the influence of heartbeat on respiration are important for cardiorespiratory synchronization.

Up to now, cardiorespiratory synchronization has been reported in young health athletes [5, 6], healthy adults [9–11], heart transplant patients [9], infants [12], and anesthetized rats [13]. Since the studies are based on measured data, the data processing method plays a crucial role in the outcome. An essential task for the studies is to process such signals and pickup essential component(s) from experimental respiratory signals dressing with noise. Except for the Fourier spectral analysis which has been widely used, to date there have been several approaches to preprocess real data for this purpose [27–33]. Most of these approaches require that the original time series should be stationary and/or linear, while respiratory signals are noisy, nonlinear, and non-stationary. As a result, a number of filters may be used to filter out noises from real data, while the capabilities and effectiveness of the filtration are usually questionable. There is also no strict criterion to judge what is the inherent dynamics and what is contribution of the external factors and noise in measured data. Improper approaches might lead to misleading results.

To overcome above difficulties, Wu and Hu [26] suggest using the empirical mode decomposition (EMD) method proposed by Huang et al. [34] and the Hilbert spectral analysis,[1] as a candidate for such studies. Unlike conventional filters, the EMD provides an effective way to extract respiratory rhythms from experimental respiratory signals. The EMD uses the sifting process to eliminate riding waves and make the wave-profiles more symmetric. The expansion of the turbulence data set in EMD has only a finite-number of locally non-overlapping time scale components, known as intrinsic mode functions (IMFs). These IMFs form a complete set and are orthogonal to each other. The adaptive properties of EMD to empirical data make it easy to give physical significations to IMFs, and allow us to choose a certain IMF as a respiratory rhythm [26]. As an IMF is selected for the respiratory rhythm, one can further use CRS to detect synchronization. In this article, we will review the scheme proposed by Wu and Hu [26], and focus on the application of EMD

[1] Besides the Hilbert spectral analysis, one can also use other methods to process the data obtained from EMD, see e.g. Refs. [17, 18].

to cardiorespiratory synchronization. Details of the study will be referred to their original paper [26].

This article is organized as follows. In Section 2, we introduce the EMD method. In Section 3, the EMD is used to extract the respiratory rhythm from experimental data and the Hilbert transform is used to calculate the instantaneous phase of the respiratory time series. The CRS is then constructed by assessing heartbeat data on the phase of the respiratory signal, and is used to visually detect the epochs of synchronization in Section 4. In Section 5, we investigate the correlation between regularity of respiratory signals and cardiorespiratory synchronization. Finally, we discuss our results in Section 6.

## 2 Empirical Mode Decomposition

The EMD is an empirically based data-analysis method. It was developed from the assumption that any data consists of different simple intrinsic modes of oscillations. The essence of the EMD is to identify the intrinsic oscillatory modes by characteristic time scales in the data empirically, and then decompose the data accordingly [34]. This is achieved by "sifting" data to generate IMFs. The IMFs obtained by the EMD are a set of well-behaved intrinsic modes and are symmetric with respect to the local mean and have the same numbers of zero crossings and extrema. The algorithm to create IMFs in the EMD has two main steps [26, 34]:

*Step-1*: Identify local extrema in the experimental data $\{x(t)\}$. All the local maxima are connected by a cubic spline line $U(t)$, which forms the upper envelope of the data. Repeat the same procedure for the local minima to produce the lower envelope $L(t)$. Both envelopes will cover all the data between them. The mean of upper envelope and lower envelope $m_1(t)$ is given by:

$$m_1(t) = \frac{U(t) + L(t)}{2}. \tag{1}$$

Subtracting the running mean $m_1(t)$ from the original time series $x(t)$, we get the first component $h_1(t)$,

$$h_1(t) = x(t) - m_1(t). \tag{2}$$

The resulting component $h_1(t)$ is an IMF if it is symmetric and have all maxima positive and all minima negative. An additional condition of intermittence can be imposed here to sift out waveforms with certain range of intermittence for physical consideration. If $h_1(t)$ is not an IMF, the sifting process has to be repeated as many times as it is required to reduce the extracted signal to an IMF. In the subsequent sifting process steps, $h_1(t)$ is treated as the data to repeat steps mentioned above,

$$h_{11}(t) = h_1(t) - m_{11}(t). \tag{3}$$

Again, if the function $h_{11}(t)$ does not yet satisfy criteria for IMF, the sifting process continues up to $k$ times until some acceptable tolerance is reached:

$$h_{1k}(t) = h_{1(k-1)}(t) - m_{1k}(t). \tag{4}$$

*Step-2*: If the resulting time series is an IMF, it is designated as $c_1 = h_{1k}(t)$. The first IMF is then subtracted from the original data, and the difference $r_1$ given by

$$r_1(t) = x(t) - c_1(t). \tag{5}$$

is the residue. The residue $r_1(t)$ is taken as if it were the original data, and we apply to it again the sifting process of *Step-1*.

Following the procedures of *Step-1* and *Step-2*, we continue the process to find more intrinsic modes $c_i$ until the last one. The final residue will be a constant or a monotonic function which represents the general trend of the time series. Finally, we obtain

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n, \tag{6}$$

$$r_{i-1}(t) - c_i(t) = r_i(t). \tag{7}$$

The instantaneous phase of IMF can be calculated by applying the Hilbert transform to each IMF, say the $r$th component $c_r(t)$. The procedures of the Hilbert transform consist of calculation of the conjugate pair of $c_r(t)$, i.e.,

$$y_r(t) = \frac{1}{\pi} P \int_{-\infty}^{\infty} \frac{c_r(t')}{t - t'} \mathrm{d}t', \tag{8}$$

where $P$ indicates the Cauchy principal value. With this definition, two functions $c_r(t)$ and $y_r(t)$ forming a complex conjugate pair, define an analytic signal $z_r(t)$:

$$z_r(t) = c_r(t) + i y_r(t) \equiv A_r(t) e^{i\phi_r(t)}, \tag{9}$$

with amplitude $A_r(t)$ and the instantaneous phase $\phi_r(t)$ defined by

$$A_r(t) = \left[c_r^2(t) + y_r^2(t)\right]^{1/2}, \tag{10}$$

$$\phi_r(t) = \tan^{-1}\left(\frac{y_r(t)}{c_r(t)}\right). \tag{11}$$

## 3 Data Acquisition and Processing

The empirical data consisting of 20 data sets were collected by the Harvard medical school in 1994 [35]. Ten young (21–34 years old) and ten elderly (68–81 years old) rigorously-screened healthy subjects underwent 120 minutes of continuous supine resting while continuous ECG and respiration signals were collected. The continuous ECG and respiration data were digitized at 250 Hz (respiratory signals were latter preprocessed to be at 5 Hz). Each heartbeat was annotated using an automated arrhythmia detection algorithm, and each beat annotation was verified by visual inspection. Among these, records f1y01, f1y02, . . ., f1y10 were obtained from the young cohort, and records f1o01, f1o02, . . ., f1o10 were obtained from the elder cohort. Each group of subjects includes equal numbers of men and women.

The respiratory signals represent measures of the volume of expansion of ribcage, so the corresponding data are all positive numbers and there are no zero crossings. In addition to respiratory rhythms, the data also contain noises originating from measurements, external disturbances and other factors. In this work we apply the EMD [34] to preprocess the data. From to the decomposition of EMD, one can select one component as the respiratory rhythm according to the criteria of intermittencies of IMFs imposed in *Step-1* as an additional sifting condition [26]. Note that among IMFs, the first IMF has the highest oscillatory frequency, and the relation of intermittence between different modes is $\tau_n = 2^{n-1}\tau_1$ with $\tau_n$ the intermittence of the $n$th mode. More explicitly, the procedures of data processing are as follows. (i) Apply EMD to decompose the data into several IMFs. The decomposition acquires input of the criterion of intermittence as the parameters in the sifting process, and we use the time scale of a respiratory cycle as the criteria. Since the respiratory signal was preprocessed to a sampling rate of 5 Hz, there are (10–30) data points in one cycle.[2] Then, for example, we can use $c_1$: (3–6), $c_2$: (6–12), $c_3$: (12–24), etc. After the sifting processes of EMD, the original respiratory data is decomposed into $n$ empirical modes $c_1, c_2, \ldots, c_n$, and a residue $r_n$. (ii) Visually inspect the resulting IMFs. If the amplitude of certain mode is dominant and the wave-form is well distributed, the data is said to be well decomposed and the decomposition is successfully completed. Otherwise, the decomposition may be inappropriate, and we have to repeat step (i) with different parameters.

Figure 1 shows the decomposition of an empirical signal with a criterion of the intermittence being (3–6) data points for $c_1$, and $(3 \times 2^{n-1}–3 \times 2^n)$ data points for $c_n$'s with $n > 1$. Comparing $x(t)$ with $c_i$'s, it is obvious that $c_3$ preserves the main structure of the signal and is dominant in the decomposition. We thus pickup the third component $c_3$, corresponding to (12–24) data points per respiratory cycle, as

[2] The number of breathing per minute is about 18 for adults, and about 26 for children. For different healthy states, the number of respiratory cycles may vary case by case. To include most of these possibilities, we take respiratory cycles ranging from 10 to 30 times per minute, and each respiratory cycle then roughly takes 2–6 seconds, i.e., (10–30) data points.

the respiratory rhythm. After one of IMFs is selected as the respiratory rhythm, we can proceed in the next step to construct CRS.

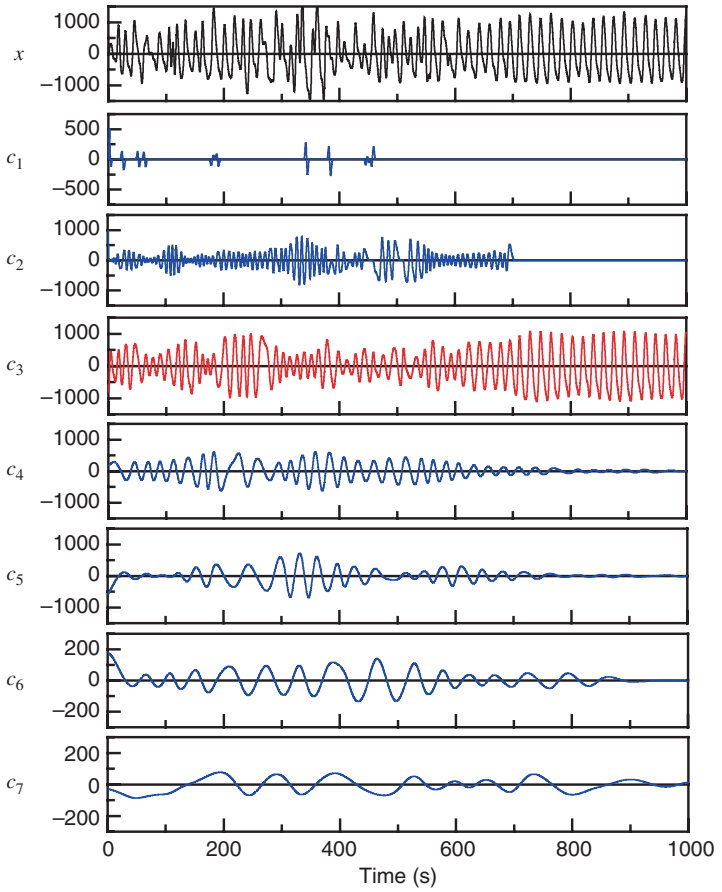


**Fig. 1** Example of EMD for a typical respiratory time series data (flo01). The criteria for intermittence in the sifting process is (3–6) data points per cycle for $c_1$. Signal $x(t)$ is decomposed into 14 components including 13 IMFs and 1 residue. Here only the first 7 components are shown. After Ref. [26]

## 4 Cardiorespiratory Synchrogram

Cardiorespiratory synchronization is a process of adjustment of rhythms due to interactions between cardiovascular and respiratory systems. These interactions can lead to a perfect locking of their phases, whereas their amplitudes remain chaotic and non-correlated [4]. If the phases of respiratory signal $\phi_r$ and heartbeat $\phi_c$ are coupled in a fashion that a cardiovascular system completes $n$ heartbeats in $m$

respiratory cycles, then a roughly fixed relation can be proposed. In general, there is a phase and frequency locking condition [4–6]

$$|m\phi_r - n\phi_c| \leq \text{const.}, \tag{12}$$

with *m, n* integer. According to Eq. (12), for the case that ECG completes *n* cycles while the respiration completes *m* cycles, it is said to be synchronization of *n* cardiac cycles with *m* respiratory cycles. Using the heartbeat event time $t_k$ as the time frame, Eq. (12) implies the relation

$$\phi_r(t_{k+m}) - \phi_r(t_k) = 2\pi m. \tag{13}$$

Furthermore, by defining

$$\Psi_m(t_k) = \frac{1}{2\pi}[\phi_r(t_k) \text{mod} 2\pi m] \tag{14}$$

and plotting $\psi_m(t_k)$ versus $t_k$, synchronization will result in *n* horizontal lines in case of *n:m* synchronization. By choosing *n* adequately, a CRS can be developed for detecting the synchronization between heartbeat and respiration [5, 6].

Example of 3:1 synchronization with $n = 6$ and $m = 2$ is shown in Fig. 2a, where phase locking appear in several epochs, e.g. at 2800–3600s, and there are also frequency locking, e.g. at 400s, near which there are *n* parallel lines with the same positive slope. For comparison, we also show the results of the same subject in 1800–3600s, but with respiratory signals without filtering, preprocessed by the standard filters and the EMD in Fig. 2b. The windows of the standard filters are

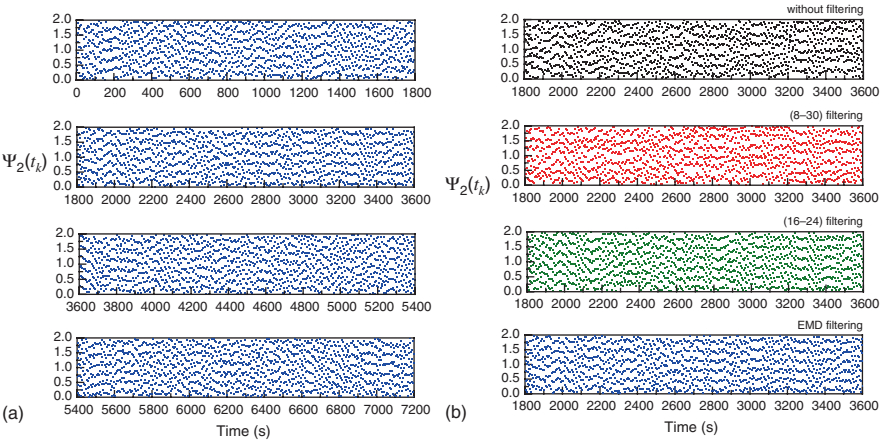


**Fig. 2** Cardiorespiratory synchrogram for a typical subject (f1o06). (**a**) Empirical data are preprocessed by the EMD. There are about 800s synchronization at 2800–3600s, and several spells of 50–300s at other time intervals. (**b**) Comparison of the results without filtering (*top one*), preprocessed by the standard filters with windows of (8–30) and (16–24) cycles per minute (the second and the third ones), and the EMD method (*bottom one*). After Ref. [26]

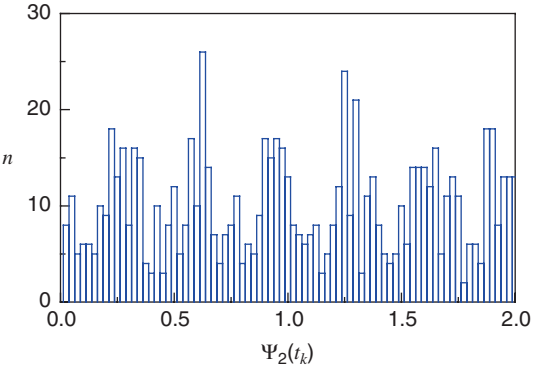


**Fig. 3** Histogram of phase for the phase locking period from 2800s to 3600s for a typical subject (f1o06) shown in Fig. 2a. After Ref. [26]

(8–30) and (16–24) cycles per min. In general, some noise dressed signals can still show synchronization in some epochs but the Hilbert spectral analysis failed at some time intervals (e.g., around 3400–3600s of the case without filtering), and over-filtered signals reveal too strong synchronization (filter with window of 16–24). In other words, global frequency used in standard filters may dissolve local structures of the empirical data. This does not happen in the EMD filtering.

Figure 3 shows the histogram of phases for the phase locking period from 2800 to 3600s in Fig. 2a. Significant higher distribution can be found at $\psi_2 \approx 0.25, 0.6, 0.9, 1.25, 1.6, 1.9$ in the unit of $2\pi$, indicating heartbeat events occur roughly at these respiratory phase during this period. Following above procedures, we analyze data of 20 subjects, and the results are summarized in Table 1. The results are ordered by

**Table 1** Summary of our results. 20 subjects are ordered by the strength (total time length) of the cardiorespiratory synchronization. After Ref. [26]

| Code | Sex | Age | Synchronization |
|---|---|---|---|
| flo06 | F | 74 | 3:1(800s, 300s, 250s, 150s, 100s, 50s) |
| f1y05 | M | 23 | 3:1(350s, 300s, 200s, 100s) |
| f1o03 | M | 73 | 3:1(200s, 50s, 30s) |
| f1y10 | F | 21 | 7:2(200s, 50s), 4:1(50s) |
| f1o07 | M | 68 | 7:2(120s, 100s, 80s) |
| f1o02 | F | 73 | 3:1(100s, several spells of 50s) |
| f1y01 | F | 23 | 7:2(several spells of 30s) |
| f1y04 | M | 31 | 5:2(80s, 50s, 30s) |
| f1o08 | F | 73 | 3:1(50s, 30s) |
| f1y06 | M | 30 | 4:1(50s, 30s) |
| f1o01 | F | 77 | 7:2(several spells of 50s) |
| f1y02 | F | 28 | 3:1(50s) |
| f1y08 | F | 30 | 3:1(50s) |
| f1o10 | F | 71 | 3:1(30s) |
| f1o05 | M | 76 | No synchronization detectable |
| f1y07 | M | 21 | No synchronization detectable |
| f1y09 | F | 32 | No synchronization detectable |
| f1y03 | M | 34 | No synchronization detectable |
| f1o09 | M | 71 | No synchronization detectable |
| f1o04 | M | 81 | No synchronization detectable |

the strength of the cardiorespiratory synchronization. From our results, we do not find specific relations between the occurrence of synchronization and sex of the subjects as in Refs. [5,6]. Here we note that if we use other filters to the same empirical data, we will have different results depending on the strength of synchronization. Wu and Hu [26] found that from the aspect of data processing that could preserve the essential features of original empirical data, the EMD approach is better than Fourier-based filtering.

## 5 Correlation and Regularity

As noted above, data processing method plays a crucial role in the analysis of real data. Over-filtered respiratory signals may lose detailed structures and become too regular. It follows that final conclusions are methodological dependent. One might then ask how the results depend on the data processing methods. This problem arises when one addresses the issue of existence or strength of the cardiorespiratory synchronization, and the answers may be helpful for understanding the mechanisms of the synchronization.

In general, the existence of cardiorespiratory synchronization is confirmed simply when it is observed in enough subjects analyzed by various approaches. The existing studies have positive answers on its existence [5, 6, 9–13]. Nevertheless, the strength of synchronization for these subjects may depend on the methods used, and need further investigations. For this purpose, we test the correlations between cardiac and respiratory signals as well as their regularities. We first consider two data sets: (f1o06.res, f1o06.hrt) and (f1y05.res, f1y05.hrt). Here notation "code.signal" indicates one code and its corresponding signal. Both of these two data sets, f1o06 and f1y05, have been analyzed to show 3:1 synchronization in some periods. The synchronization exhibited by these two data sets in an interval from 2000s to 3600s is shown respectively in Fig. 4a and b. We interchange the respiratory and cardiac time series of them to be (f1o06.res, f1y05.hrt) and (f1y05.res, f1o06.hrt), and then construct their synchrograms. The results are shown in Fig. 4c and d, respectively. There are still phase locking appearing in shorter spells for the "mixed" data, such as at 3000s of Fig. 4c and at 2000s of Fig. 4d. This implies the synchronization should be detectable provided that there are characteristic features coupled between respiratory and cardiac signals. Therefore, emergence of short shells of synchronization does not necessarily imply true coupling between cardiovascular and respiratory systems. If cardiorespiratory synchronization exists in a subject, the cardiovascular and respiratory systems must correlate with the same variation scheme of intermittence such that synchronization can appear again and again in some time intervals. Hence, the phase locking in the synchrogram of Fig. 2a, where synchronization disappears and recovers repeatedly at 1800–3600s due to the variation of intermittence of respiratory time series indicates true cardiorespiratory synchronization.

Next, we test the dependence of the results on the regularity of signals. In our study, cardiac signals are regular enough [26], which implies the regularity of

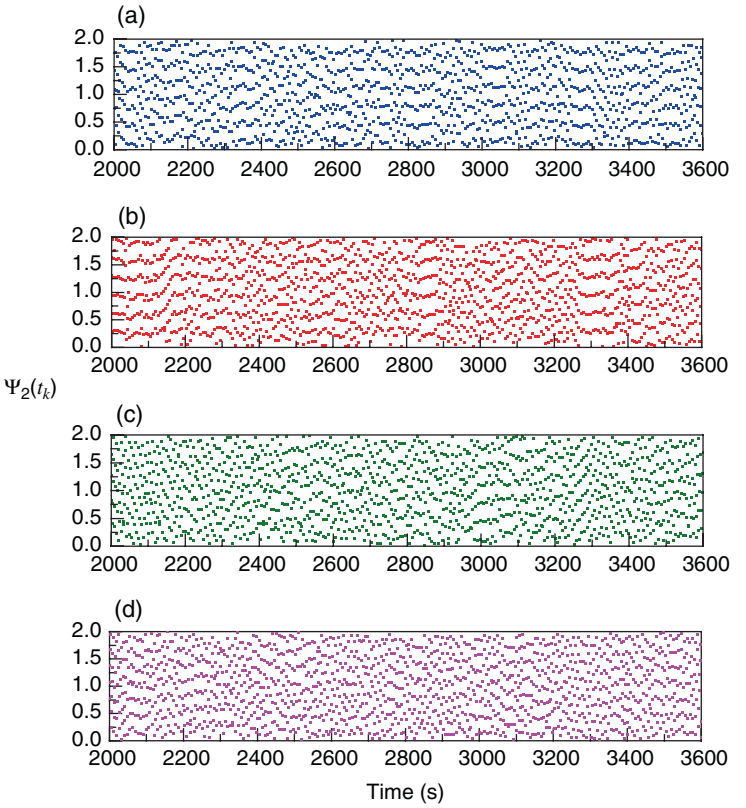


**Fig. 4** Cardiorespiratory synchrogram for data sets (**a**) (f1o06.res, f1o06.hrt), (**b**) (f1y05.res, f1y05.hrt), (**c**) (f1o06.res, f1y05.hrt), (**d**) (f1y05.res, f1o06.hrt), at period 2000–3600s. After Ref. [26]

cardiac signals is not necessarily related to the strength of synchronization. In contrast to cardiac signals, real respiratory signals are essentially irregular. Here we will not measure regularity of respiratory cycles directly, but compare synchronization in CRS for various sets of cardiac and respiratory time series. We introduce an artificial respiratory signal generated by a generic cosine wave $s(S_0, T, t)$,

$$s(S_0, T, t) = S_0 \cos\left(\frac{2\pi t}{T}\right), \tag{15}$$

where $S_0$ is the amplitude and $T$ is the period. The frequency of this wave is fixed and the phase varies regularly. We first construct the synchrogram for [$s(S_0, T, t)$, f1o06.hrt]. The results are shown in Fig. 5, in which different periods $T = 15$, 16, 17, 17.6, 18 have been used. According to Fig. 5, the cardiac signals for this subject are rather regular, and a fixed heartbeat frequency can last relatively long time, even if it changes finally. When $T$ is a multiple of 3, such as $T = 15$ and

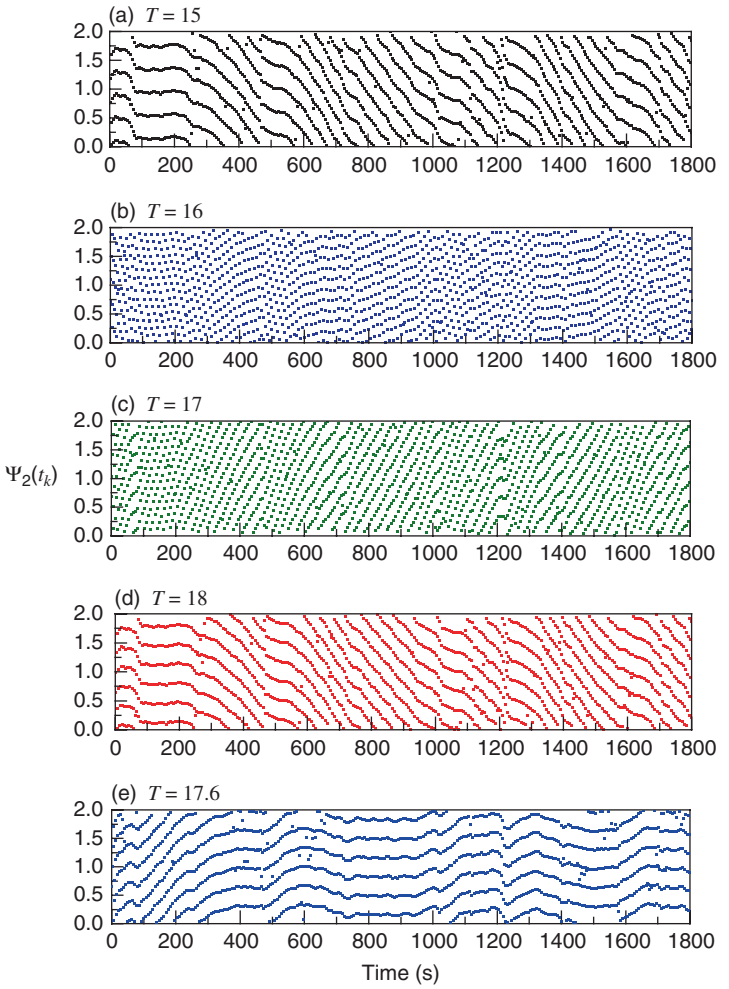


**Fig. 5** Cardiorespiratory synchrogram for data sets [$s(S_0 = 1000, T, t)$, f1o06.hrt] with (**a**) $T = 15$, (**b**) $T = 16$, (**c**) $T = 17$, (**d**) $T = 18$, and (**e**) $T = 17.6$. After Ref. [26]

$T = 18$, there are synchronization spells observed at the period from 100s to 220s, and phase locking at the other epochs. For $T = 17.6$, phase locking can be observed at most epochs of the period. Here we should note that, comparing Figs. 2(a) and 5, a short spell from 100 s to 220s appears as phase locking corresponds to respiratory intermittence $T = 18$. However, a short spell from 1220s to 1350s corresponds to respiratory intermittence roughly about $T = 17.6$. Even the intermittence varies, the synchronization persists. This indicates the existence of correlations.

Comparing the patterns of the periods where synchronization occurs in Fig. 5 and the corresponding periods in Fig. 4, we find that cardiac signals are regular enough such that synchronization occurs at the framework of regular time series,

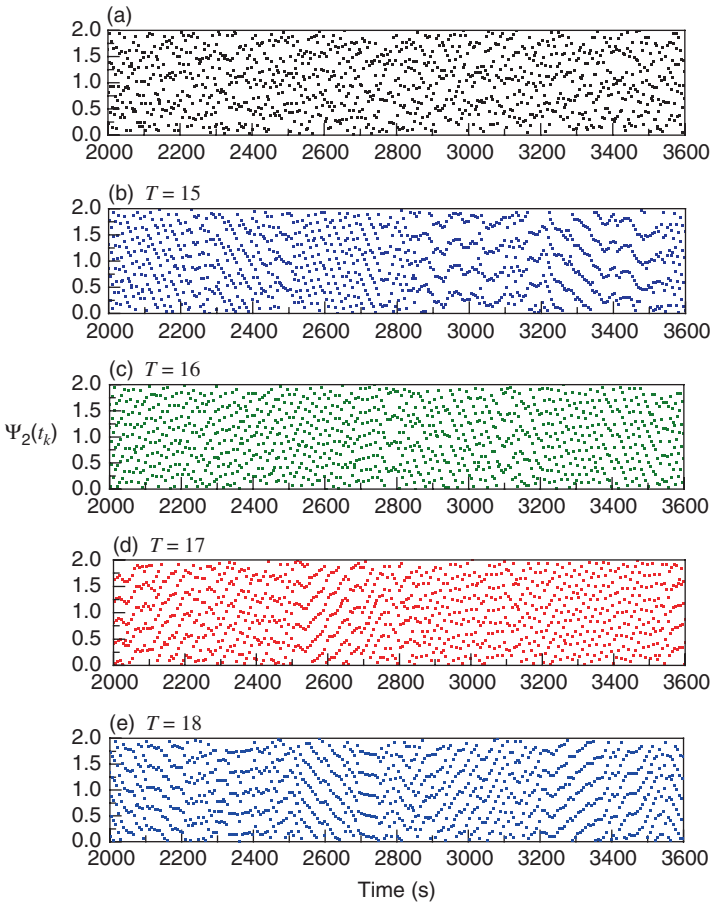


**Fig. 6** Cardiorespiratory synchrogram for data set (**a**) (f1o09.res, f1o09.hrt), and data sets [$s(S_0 = 1000, T, t)$, f1o09.hrt], with (**b**) $T = 15$, (**c**) $T = 16$, (**d**) $T = 17$, and (**e**) $T = 18$. After Ref. [26]

and respiratory cycles are not regular enough such that there is weaker or even no synchronization in the corresponding periods. To have more results for comparison, we examine another subject having data set (f1o09.res, f1o09.hrt), which has no synchronization at all in the preceding analysis. The synchrogram for data set (f1o09.res, f1o09.hrt) is shown in Fig. 6a, and data sets [$s(S_0, T, t)$, f1o09.hrt] with $T = 15, 16, 17, 18$ are respectively shown in Fig. 6b–e. We find that there are short spells phase locking or frequency locking appear, and the length of the spells depend on the period $T$. Therefore, more regular respiratory signals have better manifestation of synchronization.

From above investigation, we conclude that: (i) In most cases, cardiac oscillations are more regular than respiratory oscillations and the respiratory signal is the key factor for the strength of the cardiorespiratory synchronization. (ii) Cardiores-

piratory phase locking and frequency locking take place when respiratory oscillations become regular enough and have a particular frequency relation coupling with cardiac oscillations. We observed the intermittence of respiratory oscillation varies with time but synchronization persists in some subjects, such as codes f1o06 and f1y05. This confirms correlations in the cardiorespiratory synchronization. (iii) Over-filtered respiratory signals may be too regular, and in turn, appear to have stronger synchronization than they shall have. Therefore, if the Fourier based approach with narrow band filtration is used, some epochs of phase locking or frequency locking should be considered as being originated from these effects.

## 6 Discussion

We have reviewed the scheme introduced by Wu and Hu [26] to study cardiorespiratory synchronization. The scheme is based on the EMD and CRS. The advantage of using the EMD is that it catches primary structures of respiratory rhythms based on its adaptive feature [34, 36]. By imposing the intermittency criteria based on physiological condition revealing from empirical time series, this feature allows us to effectively keep the signal structures and avoid the introduction of artificial signals easily appear in the Fourier-based filters with priori bases [26]. Furthermore, the introduction of IMFs in EMD provides a reasonable definition of instantaneous phase. This advantage is helpful for drawing reliable conclusions on the studies of empirical data. The study supports the existence of the cardiorespiratory synchronization. However, no difference in synchronization between two different age groups and two different sex groups were found. At the current stage, even cardiorespiratory synchronization has been observed in a number of studies, there is still no confident conclusion on its dependence on sex and age due to few subjects were studied and most of them were performed in different physiological stages. Furthermore, the statistics of our results indicates that most synchronization exhibits 3:1 (8 subjects), 4:1 (1 subjects) and 7:2 (4 subjects) synchronization, which is consistent with the report of Ref. [12] that mature physiological subjects (adults) have larger probabilities of 3:1, 4:1, and 7:2 synchronization than 5:2 synchronization.

From a physiological viewpoint, it is difficult to precisely identify the mechanisms responsible for the observed non-linear interactions. From our studies, we found that cardiac oscillations are more regular than respiratory oscillations, and cardiorespiratory synchronization occurs at the period when respiratory signals become regular enough. In other words, the regularity of respiratory signals contributes dominantly to the synchronization. Cardiorespiratory synchronization and RSA are two competing factors in the cardiorespiratory interactions. This observation is consistent with the results reported in Refs. [21, 37].

Finally, it should be remarked that the technique used in this work can also be applied to the analysis of other time series, such as financial time series [38–40]. It is also interesting to extend the technique to analyze signals from many-body systems and study their synchronization.

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