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Quantification of Cardiorespiratory Interactions Based on Joint Symbolic Dynamics

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Abstract—Cardiac and respiratory rhythms are highly nonlinear and nonstationary. As a result traditional time-domain techniques are often inadequate to characterize their complex dynamics. In this article, we introduce a novel technique to investigate the interactions between R–R intervals and respiratory phases based on their joint symbolic dynamics. To evaluate the technique, electrocardiograms (ECG) and respiratory signals were recorded in 13 healthy subjects in different body postures during spontaneous and controlled breathing. Herein, the R–R time series were extracted from ECG and respiratory phases were obtained from abdomen impedance belts using the Hilbert transform. Both time series were transformed into ternary symbol vectors based on the changes between two successive R–R intervals or respiratory phases. Subsequently, words of different symbol lengths were formed and the correspondence between the two series of words was determined to quantify the interaction between cardiac and respiratory cycles. To validate our results, respiratory sinus arrhythmia (RSA) was further studied using the phase-averaged characterization of the RSA pattern. The percentage of similarity of the sequence of symbols, between the respective words of the two series determined by joint symbolic dynamics, was significantly reduced in the upright position compared to the supine position (26.4 ± 4.7 vs. $20.5 \pm 5.4\%$, $p < 0.01$). Similarly, RSA was also reduced during upright posture, but the difference was less significant (0.11 ± 0.02 vs. 0.08 ± 0.01 s, $p < 0.05$). In conclusion, joint symbolic dynamics provides a new efficient technique for the analysis of cardiorespiratory interaction that is highly sensitive to the effects of orthostatic challenge.

Keywords—Heart, Heart rate variability, Coupling, Breathing frequency, Respiratory sinus arrhythmia.

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INTRODUCTION

The association between cardiac and respiratory rhythms has long been recognized.[31,43,44] Some of the conventional signal-processing techniques such as power spectral density and cross-correlation analysis have shown linear dependencies between heart and respiratory rate.[1,4] However, as these biological signals are inherently nonlinear, nonstationary, and contain superimposed noise, the techniques mentioned above often prove to be inadequate for characterizing their complex dynamics.[23,39] Dynamic relationships between heart rate and respiratory rate were assessed by various approaches, and consequently there is still substantial terminological and conceptual indifference in this field. For this reason, we consider it important to clearly define terms used in the current work. We will use *cardiorespiratory interaction* as the most generalized umbrella term. The best known phenomenon of cardiorespiratory interaction is respiratory sinus arrhythmia (RSA)[9]—cyclic oscillation of HR, with acceleration during the inspiratory phase and deceleration during expiration.[8] Neural RSA mechanisms are well established: it is vagally mediated, with inputs to cardiac vagal neurons from both central pattern generator[35] and from peripheral airways and lung stretch receptors.[46]

Cardiorespiratory phase coordination/synchronization is a phenomenon, which was initially described as short intermittent periods[22,44] during which the phases of heart rate and respiratory rate coincide with different integer ratios known as phase locking ratios.[13,31,43] Cardiorespiratory phase coordination/synchronization has been reported in healthy adults,[28,31] athletes,[43,44] infants,[34] and in anesthetized[45] and conscious rats.[26] Rodent studies demonstrated that the underlying mechanism could be the excitatory effects from arterial baroreceptors of the central respiratory pattern generator.[48]

Cardioventilatory coupling (CVC) is another concept, which specifically refers to the influence of timing of breathing on cardiac activity.[17,19,47] CVC is quantified based on the temporary alignment between the R waves of the electrocardiogram (ECG) and inspiratory onsets, using the R-peak to inspiratory-onset interval plot. Galletly and Larsen showed that during anesthesia CVC places the heart beats and inspiratory onsets such that they are maximally affected by vagal modulation of RSA implying common physiological roles and significant relationship between CVC and RSA.[18]

Although the physiological significance of various aspects of cardiorespiratory interaction are not completely understood, it has been suggested that RSA enhances pulmonary gas exchange and thereby improves the energy efficiency of pulmonary circulation.[21] The quantification of cardiorespiratory interaction appears to have clinical merit for risk stratification of cardiac mortality,[24,32] and diagnosing obstructive sleep apnea.[3,15,25]

In this study, we were interested in a new and relatively simple approach that could also provide us with some additional information about cardiorespiratory interactions. While assessment of coherence function can lead us to the detection of changes in cardiorespiratory interaction with postural changes, it lacks the temporal information contained in the pattern of either the R–R intervals and respiratory phases or their interaction. The concept of symbolic dynamics allows for an easy interpretation of physiological data by a simplified description of the system's dynamics and offers a framework for exploring the nature of a system through a means of simplified analysis.[2,5,6,30,49] By employing a coarse-graining procedure some of the time series' detailed information is lost while the robust properties of the dynamics are preserved.[6,49] In this article, we introduce a novel approach to quantify cardiorespiratory interaction that is based on the joint symbolic dynamics of respiratory phase and heart rate.

The aim of this study was to develop a framework for quantifying cardiorespiratory interaction using symbolic dynamics. We hypothesized that a symbolic approach would provide a new powerful tool to study the changes in cardiorespiratory interaction and evaluated this technique in healthy subjects during orthostatic challenge.

METHODS

Subjects/Experimental Protocol

Thirteen healthy subjects (5 males, 8 females) participated in this study. The age of the subjects ranged between 19 and 24 years. The study conformed to the principles outlined in the Declaration of Helsinki and was approved by the institution's human research ethics committee. Subjects gave informed consent.

The protocol included 10 min of recording for different body postures. A group of eight subjects (4 males, 4 females) was investigated in the supine position and while standing during spontaneous normal breathing. A second group of five subjects (1 male, 4 females) underwent graded head-up tilt test at angles: 0, 30 and 60° during controlled metronomic breathing at 15 bpm. The subjects were instructed not to speak and to remain absolutely motionless during the recording.

Herein, ECG (leads I and II) and respiratory signals (from abdomen impedance belts) were sampled at 1 kHz and recorded using a PowerLab data acquisition system (ADInstruments, Sydney, Australia) and the ChartPro 6.0 software (ADInstruments, Sydney, Australia).

Data Analysis

ECG

Custom written computer software developed under MATLAB® was used to detect the R-peaks from the recorded ECG signal using parabolic fitting, where a parabola of the length based on the sampling frequency is fitted around the R-wave to determine the R-wave maximum. The R–R time series, as obtained from R–R tachogram, were visually scanned for artifacts. Ectopic beats were replaced with the average RR interval calculated from the beats prior to and after the ectopy.

Respiration

Respiratory signals were low-pass filtered at 1.0 Hz to remove noise, using a zero-phase forward and reverse digital filter, which first filtered the raw signal in the forward direction using a fourth order Butterworth filter, and subsequently filtered the reversed signal. The resultant signal has zero-phase distortion. Custom written computer software developed under MATLAB® was used to detect inspiratory onsets for each respiratory cycle. First, the offset of the signal was removed by subtracting the mean value. Subsequently, the inspiratory and expiratory onsets were determined as the zero-crossings of the first derivative of the respiratory signal. All zero-crossings <1.0 s apart were considered as artifacts and hence discarded. The inspiratory onsets of respiration were later used to calculate the average respiratory time period.

We used the Hilbert transform to calculate the phases of the respiratory signal. For a discrete signal

$x[n]$ with samples N, if the discrete Fourier transform is given as

$$F(x[n]) = X[k] = \sum_{n=0}^{N-1} x[n]e^{-jnk\frac{2\pi}{N}}, \quad k \in \{0, N-1\}$$

then the discrete Hilbert transform can be defined as

$$H(x[n]) = \hat{x}[n] = \frac{1}{N}\sum_{k=0}^{N-1} \hat{X}[k]e^{jnk\frac{2\pi}{N}}, \quad k \in \{0, N-1\},$$

where for N—even

$$\hat{X}(k) = \begin{cases} -jX[k], & k = \left\{1, \frac{N}{2} - 1\right\} \quad \text{for } N \text{ even} \\ jX[k], & k = \left\{\frac{N}{2} + 1, N-1\right\} \quad \text{for } N \text{ even} \end{cases}$$

where the continuous and Nyquist components are excluded (for $k = 0$ and $k = N/2$).

While for N—odd

$$\hat{X}(k) = \begin{cases} -jX[k], & k = \left\{1, \frac{N-1}{2}\right\} \quad \text{for } N \text{ odd} \\ jX[k], & k = \left\{\frac{N+1}{2}, N-1\right\} \quad \text{for } N \text{ odd} \end{cases}$$

where the continuous component is excluded.

If k_i is the kth sample of ECG corresponding to the appearance of an ith R-peak, then $\varphi_r(k_i)$ represents the kth phase of respiration at the instant of the ith R-peak. In this article, the parameter RP represents the series of respiratory phases at the instants of R-peaks.

Calculation of Time Delays for Enhanced Detection of Coordination

The most common and widely used tool for the calculation of time delay is the cross-correlation function. The linear association between the respiratory phases, $\varphi_r(k)$, and R–R intervals, RR, can be assessed by determining the Pearson correlation coefficients for the correlation between RR and cos $\varphi_r(k)$, $r_{RC} =$ c(RR(i), cos $\varphi_r(k_i)$), RR and sin $\varphi_r(k)$, $r_{RS} =$ c(RR(i), sin $\varphi_r(k_i)$), and cos $\varphi_r(k)$ and sin $\varphi_r(k)$, $r_{CS} =$ c(cos $\varphi_r(k_i)$, sin $\varphi_r(k_i)$), and subsequently the angular–linear correlation coefficient, r_{RCS}, defined as[50]

$$r_{RCS} = \sqrt{\frac{r_{RC}^2 + r_{RS}^2 - 2r_{RC}r_{RS}r_{CS}}{1 - r_{CS}^2}}.$$

The parameters r_{RC}, r_{RS}, and r_{CS} are substituted by $r'_{RC} = \mathrm{c}(\mathrm{RR}(i + \tau), \cos\varphi_r(k_i))$, $r'_{RS} = \mathrm{c}(\mathrm{RR}(i + \tau), \sin\varphi_r(k_i))$, $r'_{CS} = \mathrm{c}(\cos\varphi_r(k_i), \sin\varphi_r(k_i))$ to introduce a delay of τ R-peaks, where $\tau = -6, -5, \ldots, 0, \ldots, +5, +6$ beats. The time delay between respiration and heart beats is illustrated in Fig. 1.

Circular statistics analysis was performed using the CircStat MATLAB® toolbox and codes described in Berens.[7]

The negative delays in the R–R time series were achieved by shifting the respiratory phases while preserving the original R–R intervals. For our analysis, we selected the τ-delayed RR time series that provided the highest correlation between the delayed R–R intervals and respiratory phases.

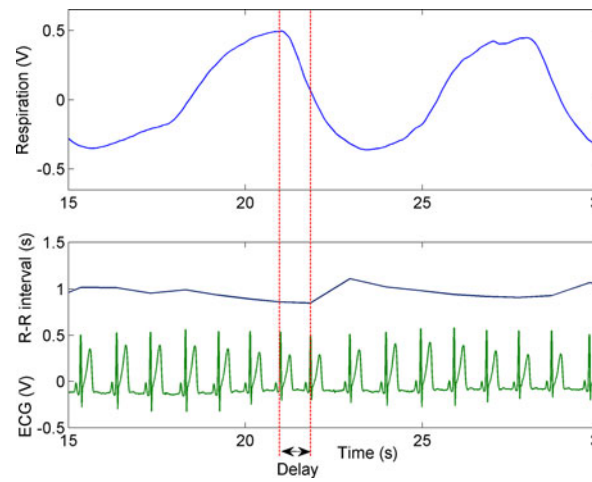


FIGURE 1. Respiratory signal (top panel) and ECG signal together with R–R interval (bottom panel). The delay is calculated as the time between the expiratory onset of respiration and the start of the increase in R–R interval.

Joint Symbolic Dynamics

Symbolic analysis involves transformation of time series into a series of discretized symbols to extract information about the behavior of the system generating the time series. In this process, the phase space of the dynamical system is partitioned into a finite number of cells in order to obtain a coordinate grid of the phase space. Using the method of time delayed phase space embedding the time series generated by a dynamical system would form an orbit, known as a phase trajectory, within a closed and bounded space. Each cell visited by the trajectory at a time instant can be denoted by a specific symbol among a set of defined symbols. Subsequently, the phase space trajectory can be mapped onto a symbol space by generating a sequence of symbols corresponding to partitions in the space defining each state of the system.[16,27,37] This is illustrated in Fig. 2.

Phase space embedding requires knowledge of the system's dimension, which is difficult to obtain from physiological data. In this article, we follow a more pragmatic approach, using an embedding delay of one and varying the embedding dimension with the aim to optimize the classification of our experimental data.

From the vectors of the R–R time series and the series of respiratory phases φ_r at the instants of R-peaks, RP, two symbolic sequences, s^{HR} (HR denoting the heart rate) and s^{RP}, can be formed using

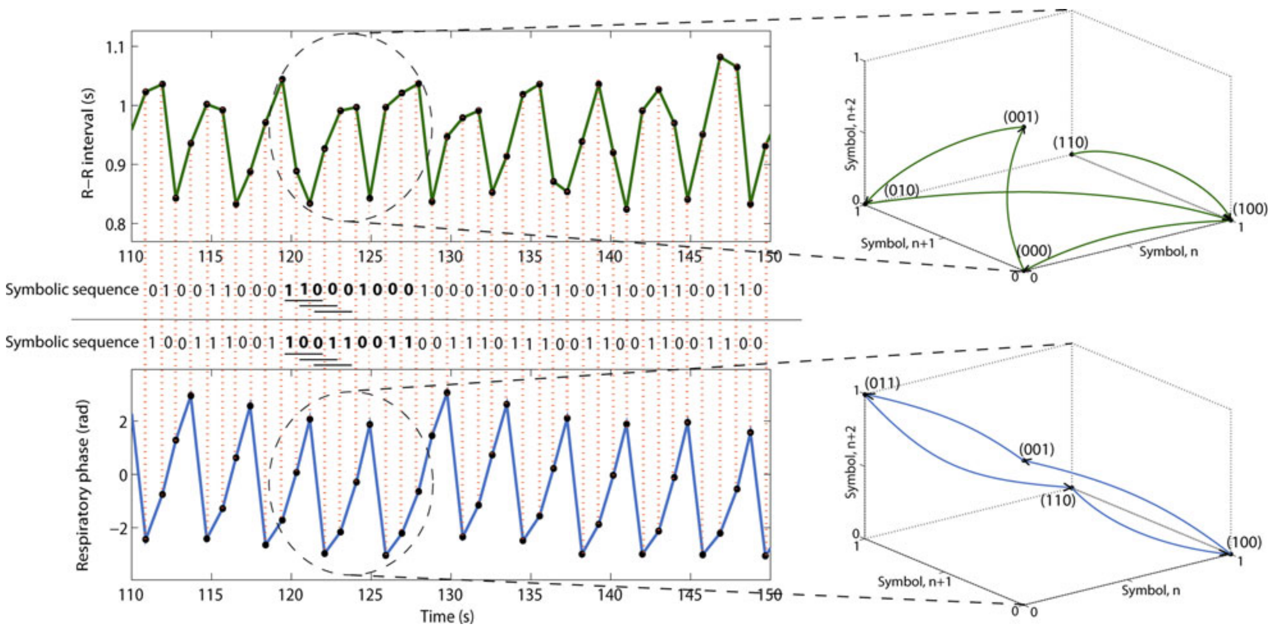


FIGURE 2. Schematic illustration of symbolic dynamics. The top left panel shows the R–R intervals as obtained from the time points of R-peaks, while the bottom left panel represents the respiratory phase cycle and the respiratory phases at the time points of R-peaks (dots represent the time points while dotted lines show the correspondence between the two time series). Both the time series can be transformed into symbolic sequences as defined in the "Methods" section. In this study, three consecutive symbols were used to form words (underlined in the symbolic sequence). The right panel illustrates the phase space representation of symbolic dynamics using 10 consecutive cardiac cycles (shown in bold symbols in the left panel).

the transformation rule below, based on the differences between successive R–R intervals and R-instant respiratory phases, respectively,

$$s_i^{\mathrm{HR}} = \begin{cases} 0 & \text{if} \quad RR_{i+1} - RR_i > V \\ 1 & \text{if} \quad RR_{i+1} - RR_i < V \\ 2 & \text{if} \quad RR_{i+1} - RR_i = V \end{cases}$$

$$s_i^{\mathrm{RP}} = \begin{cases} 0 & \text{if} \quad |RP_{i+1}| - |RP_i| > 0 \\ 1 & \text{if} \quad |RP_{i+1}| - |RP_i| < 0 \\ 2 & \text{if} \quad |RP_{i+1}| - |RP_i| = 0 \end{cases},$$

where V is a threshold value.

For the purpose of this study, we have used $V = 0$, 2, 4, 6, 8 and 10 ms.

Using the symbol vectors s^{HR} and s^{RP}, we constructed series of words (bins), w_k^{HR} and w_k^{RP} of lengths $k = 1, 2, \ldots, 5$—containing k successive symbols. Consequently, 3^k different word types were obtained for each vector.

After applying the delay in R–R intervals leading to the highest correlation between respiratory phases and delayed R–R intervals, the interaction between R–R intervals and respiratory phases during supine and upright posture was studied using symbolic dynamics for the lengths of words and threshold values mentioned earlier. Subsequently, the word length and threshold value that provided the highest significance level was chosen for our analysis.

The interaction between cardiac and respiratory cycles was studied by comparing the jth ($j = 1, 2, \ldots, n$, where n is total number of words) word from the distributions, w_{lj}^{HR} and w_{lj}^{RP}, of a particular word length l. If the sequence of symbols in w_{lj}^{HR} corresponded to w_{lj}^{RP} (i.e., $w_{lj}^{\mathrm{HR}} = w_{lj}^{\mathrm{RP}}$), the two words and hence the cardiac and respiratory epochs were considered to be coordinated. The total interaction was calculated by dividing the total count of coordinated words by the total number of words and subsequently determining the percentage of interaction for different body postures.

Theoretically, the cardiac and respiratory cycles are also considered to be coordinated when the two series are in complete phase opposition. In this study, however, we limited the assessment of cardiorespiratory interaction to the case of identical words in both the series, such that the proposed approach resembles the concept of RSA.

Phase-Averaged RSA Pattern Analysis

The pattern of RSA was evaluated by selective averaging of R–R interval changes from multiple respiratory cycles over the respiratory phase. As explained in more detail in Gilad *et al.*[20] for all n respiratory cycles, the R–R intervals in each respiratory cycle were interpolated into 50 data points using cubic spline interpolation. The 50 data points for each of all the n respiratory cycles correspond to 2π

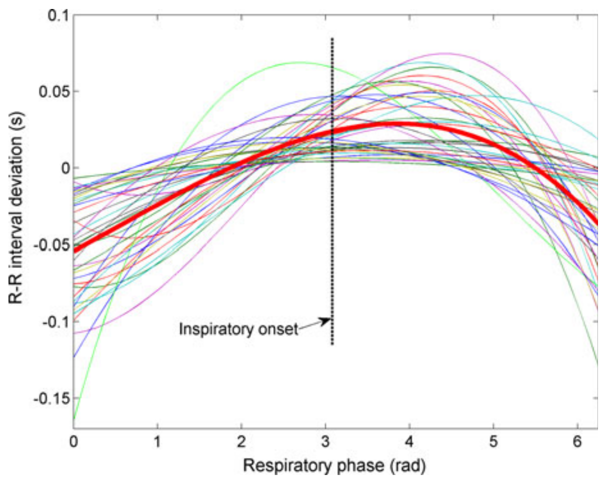


FIGURE 3. Respiratory sinus arrhythmia (RSA) of a subject during supine position for 39 respiratory cycles clustered together (thin lines) and the overall RSA (thick line) obtained by averaging the clustered RSA. Each thin line indicates the R–R interval deviation for one respiratory cycle. The origin is the expiratory onset of respiration.

(Fig. 3)—the origin in the figure being the expiratory onset of respiration. The overall RSA pattern was obtained by taking the average of all the RSA patterns for n respiratory cycles (Fig. 3). For the purpose of our analysis, we defined two RSA parameters: RSA amplitude and phase. The RSA amplitude was calculated by taking the difference between the maximum and the minimum peaks of the overall RSA pattern. The phase of RSA was defined as the respiratory phase at the point of maximum overall RSA.

Statistical Analysis

GraphPad Prism version 5.01 for Windows (GraphPad Software, San Diego, CA, www.graphpad.com) was used for statistical analysis. The interaction between cardiac and respiratory rhythms between different body postures was compared using non-parametric repeated measure analysis of variance (Wilcoxon matched pairs test, Friedman test, and Dunn's multiple comparison test). Values with $p < 0.05$ were considered statistically significant. Data were expressed as mean ± standard deviation (SD).

RESULTS

Effect of Changes in Body Posture on R–R Interval

The change in body posture from supine to upright was associated with significant shortening of R–R intervals (0.87 ± 0.07 vs. 0.67 ± 0.05 s, respectively, $p < 0.001$). Increase in head-up tilt angles from 0 to 30 and 60° also showed significant shortening in R–R intervals (0 vs. 30 and 60°: 0.90 ± 0.06 vs. 0.83 ± 0.05 and 0.71 ± 0.05 s, $p < 0.01$ and $p < 0.001$, respectively).

TABLE 1. Mean values (±SD) of the respiratory intervals during supine and upright postures in eight subjects.

Subjects	Respiratory interval (s)	
	Supine	Upright
Subject 1	2.69 ± 0.2	3.24 ± 0.1
Subject 2	3.91 ± 0.2	4.37 ± 0.2
Subject 3	5.95 ± 0.7	5.29 ± 0.2
Subject 4	3.83 ± 0.4	4.01 ± 0.1
Subject 5	4.71 ± 0.6	5.09 ± 0.5
Subject 6	3.64 ± 0.7	3.79 ± 0.5
Subject 7	4.37 ± 0.3	4.98 ± 0.2
Subject 8	3.48 ± 0.1	3.57 ± 0.3

Effect of Changes in Body Posture on Respiratory Interval

In spontaneously breathing subjects, the average respiratory interval increased with the change in body posture from supine to upright for all but one subject, in whom a slight decrease in respiratory interval was observed (subject 3: supine vs. upright: 5.95 ± 0.7 vs. 5.29 ± 0.2 s), see Table 1. Due to this variation in one subject, the overall difference in respiratory intervals with the change in body posture did not reach statistical significance.

Symbolic Dynamics Approach: Optimization of Word Length and Threshold Value and Cardiorespiratory Interaction

The interaction between respiratory phases and delayed R–R intervals was determined by calculating the percentage of similarity of the sequence of symbols between the respective words of the two series. The word length and threshold values were optimized using the recordings of eight subjects obtained during standing and in the supine position. The analysis of variance p value between standing and supine recordings was the output variable under consideration. A word length of three provided consistently low p values for different threshold values (Fig. 4). Setting the threshold value to 6 ms (Fig. 4, upper panel) and the word length to three, provided the most significant result ($p = 0.008$). The suitability of this parameter setting was validated with the second data set consisting of recordings during graded head-up tilt (Fig. 4, bottom panel). The word types span over a 27 × 27 vector matrix from $[000,000]^T$ to $[222,222]^T$ (Fig. 5). There was a significant decrease in cardiorespiratory

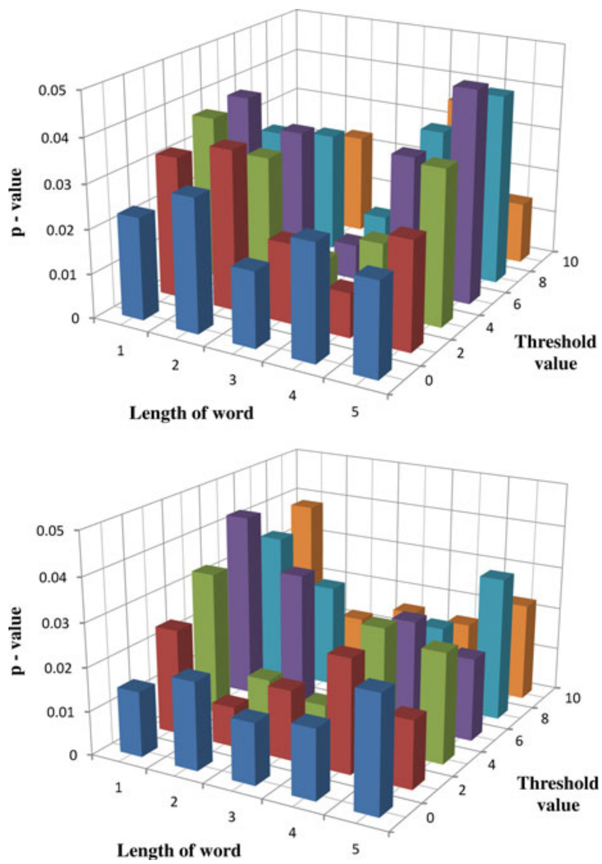


FIGURE 4. Wilcoxon test results (*p* values) obtained from cardiorespiratory interaction analysis for different lengths of words and threshold values in two groups of subjects: Group 1—supine vs. upright posture with spontaneous normal breathing (upper panel); Group 2—head-up tilt test (0° vs. 60°) with controlled metronomic breathing (lower panel).

interaction with the change in body posture from supine to upright (26.4 $\pm$ 4.7 vs. 20.5 $\pm$ 5.4%) during spontaneous breathing (Fig. 6). Head-up tilt during controlled breathing also showed a significant decrease in cardiorespiratory interaction (0 vs. 60°: 41.8 $\pm$ 5.3 vs. 23.5 $\pm$ 6.1%), as seen in Fig. 6.

Effect of Changes in Body Posture on RSA

The magnitude of RSA maxima in upright posture was significantly lower than in supine posture (0.08 $\pm$ 0.01 vs. 0.11 $\pm$ 0.02 s, $p < 0.05$, respectively) see Fig. 7, upper panel. On the other hand, the phase of the RSA pattern maxima was significantly higher in upright posture as compared to supine posture (5.1 $\pm$ 0.7 vs. 4.0 $\pm$ 0.6 rad, $p < 0.05$, respectively), see Fig. 7, bottom panel.

Increase in head-up tilt angles from 0 to 60° also resulted in significant decrease in magnitude and significant increase in phase of the RSA pattern maxima (magnitude: 0.12 $\pm$ 0.02 vs. 0.07 $\pm$ 0.01 s, $p < 0.05$ and phase: 2.97 $\pm$ 0.73 vs. 4.51 $\pm$ 0.23 rad, $p < 0.05$, respectively), see Fig. 8.

Correlation Between Results Obtained Using Symbolic Dynamics and RSA Analysis

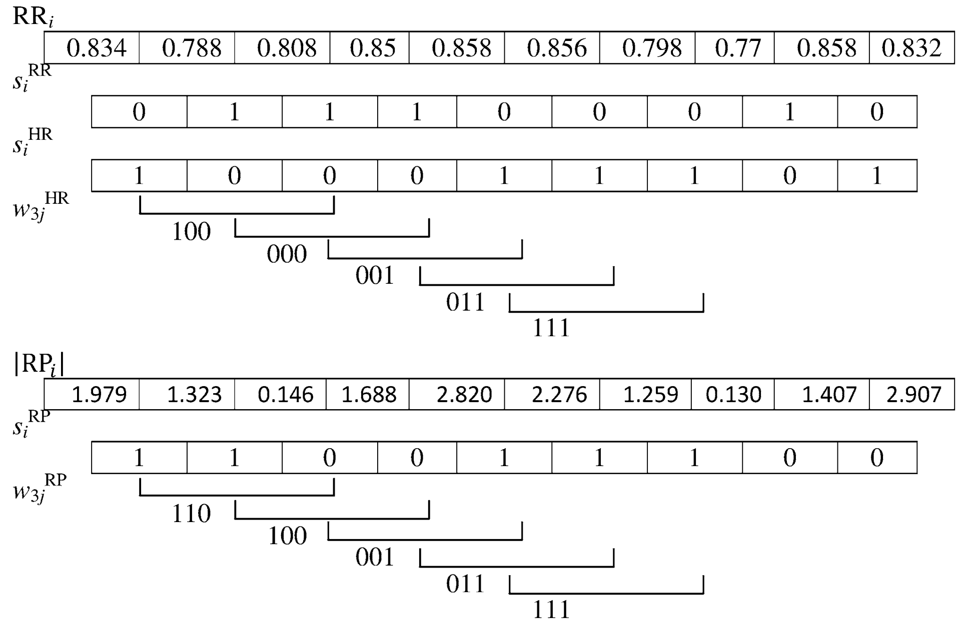
The cross-correlation between the results of cardiorespiratory interaction analysis for each body posture obtained using joint symbolic dynamics approach and RSA pattern analysis was calculated and presented in Table 2. Although correlations were observed between the measures obtained using the two techniques, the results of cross-correlation analysis were not statistically significant.

DISCUSSION

In this article, we introduced a novel approach for the investigation of interaction between cardiac and respiratory cycles based on their joint symbolic dynamics. Our main finding is that the joint symbolic dynamics approach reveals significant differences in the cardiorespiratory interaction in different body postures. It appears that JSD is more sensitive to postural changes than phase-averaged RSA pattern analysis.

Symbolic dynamics has become a standard tool for the identification and interpretation of key dynamic structures and behaviors of dynamical systems, particularly when studying chaotic systems.[16,27,37] Analysis of respiratory data by symbolic dynamics has been suggested to provide better results than time-domain analysis.[12] In a study by Caminal *et al.*,[12] the transformation of respiratory time series into symbols and their analysis was based on different parameters—a nondimensional parameter α, the number of overlapped symbols in consecutive words τ, and the probability threshold of word occurrences p_{TH}—whose values had to be selected appropriately. Our study uses a novel methodology that is based on the changes in consecutive respiratory phases corresponding to the changes in R–R intervals and involved optimization of the transformation rules, threshold values and word lengths and delay. The optimum word length identified in this study was three and is well in line with several previous studies that used a pragmatic approach instead of true phase space embedding.[6,11,12]

In this study, we found that introducing a time delay between cardiac and respiratory symbol strings increases the amount of observed cardiorespiratory interaction. It has recently been demonstrated that introducing a time delay may be useful to detect coordination between two time series when the coupling of the underlying systems includes a delay.[41]



w_{3j}^{HR} \ w_{3j}^{RP}	000	001	010	011	100	101	110	111	200	…	211	…	222
000													
001		*											
010													
011				*									
100	+												
101													
110					+								
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200													
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FIGURE 5. Transformation of R–R intervals (RR_i) and respiratory phases (RP_i) into symbol vectors, s_i^{RR}, s_i^{HR}, and s_i^{RP}, and words of length 3, w_{3j}^{HR} and w_{3j}^{RP}, respectively. The words can be placed in a 27 × 27 table matrix. In the table, the star indicates that sequence of symbols in w_{3j}^{HR} corresponds to w_{3j}^{RP} and hence is considered coordinated. The plus sign indicates the pair of words with a difference in sequence of symbols.

In this study, we obtained the highest correlation between R–R intervals and respiratory phases through a delay of usually one heart beat in the R–R time series, which is apparent in the example displayed in Fig. 1. Consequently, we delayed the R–R time series accordingly for subsequent symbolic cardiorespiratory interaction analysis.

Our results show that the upright posture, as compared to supine, causes a shortening in R–R intervals with no significant change in respiratory intervals, which is consistent with the findings by Gilad *et al.*[20] It is well known that a postural change from supine to upright causes a decrease in vagus nerve activity and an increase in sympathetic nerve activity[10,38,40] and this is the most likely cause of the decrease in R–R interval.

Using a symbolic dynamics approach, a significant decrease in cardiorespiratory interaction was observed in the upright position and also with increasing tilt angles compared to supine posture. This finding is in line with several other studies that used different approaches to investigate cardiorespiratory interaction during head-up tilt. Porta *et al.*[36] used a nonlinear

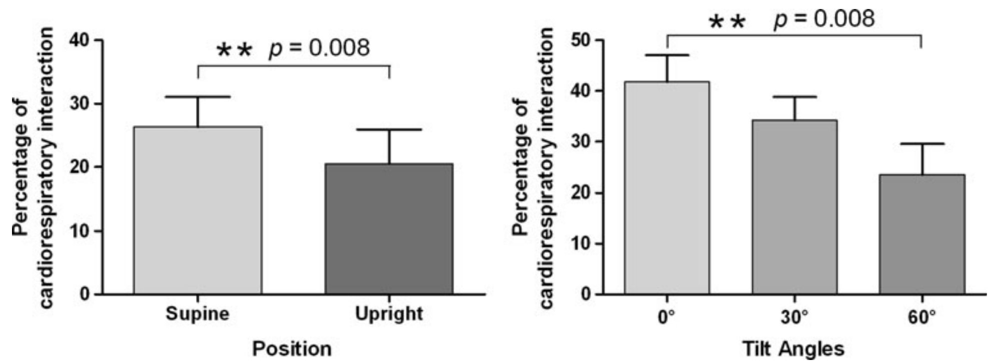

FIGURE 6. Percentage of cardiorespiratory interaction using the symbolic dynamic approach for the supine and upright postures (top) and different graded head-up tilt (bottom).

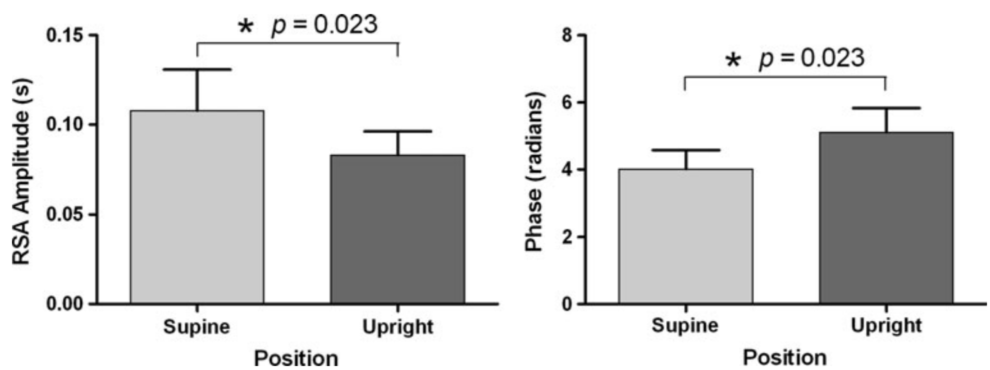

FIGURE 7. Amplitude (top) and phase delay (bottom) of RSA of healthy subjects in supine and upright postures.

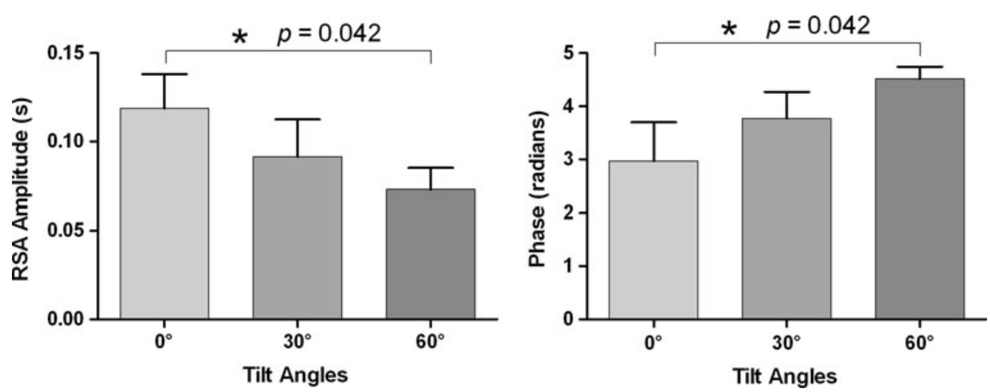

FIGURE 8. Amplitude (top) and phase delay (bottom) of RSA in healthy subjects during graded head-up tilt.

approach to assess the casual interactions between heart period and respiration based on the evaluation of conditional entropy. Censi *et al.*[14] employed a multivariate embedding approach, and Krishnamurthy *et al.*[29] investigated coherence spectrum of heart rate variability and respiration.

Our analysis of the phase-averaged RSA pattern confirms previous studies.[20,42] The upright position was associated with a decrease in amplitude of RSA indicating less influence of respiration on heart rate in upright posture. The phase delay of the RSA pattern with regard to the respiratory signal was significantly

TABLE 2. Correlation between the results of cardiorespiratory interaction analysis obtained using joint symbolic dynamics approach and RSA pattern analysis.

	Joint symbolic dynamics approach					
RSA pattern analysis	Supine	Upright	0°	30°	60°	*p* values
Supine	0.12					0.19
Upright		0.09				0.11
0°			−0.30			0.29
30°				−0.39		0.18
60°					−0.27	0.23

higher in the upright posture, compared with the supine posture and is in line with the findings by Gilad *et al.*[20]

Comparing the results obtained by the analysis of symbolic dynamics to those obtained with the phase-averaging method, the significance level was higher when using the novel method ($p = 0.008$ vs. $p = 0.023$ in group 1, and $p = 0.008$ vs. $p = 0.042$ in group 2, respectively), suggesting improved performance in detecting changes in cardiorespiratory interactions. In addition, the lack of correlation between the symbolic dynamics measure and the amplitude and phase of the RSA pattern suggest that the proposed methodology provides additional information about the cardiorespiratory coordination—hence establishing a framework for further studies.

LIMITATIONS

The results in this study were obtained by analyzing the data from a small number of subjects. Although the study was sufficient to detect statistically significant differences, the results need to be validated using another group of subjects. For the quantification of symbolic dynamics, we considered only patterns that resemble RSA due to its predominant role in cardiorespiratory interaction. Future work should extend this approach to bidirectional interactions.[33]

CONCLUSION

The proposed methodology shows significant differences in cardiorespiratory coordination in different body postures and appears to be more sensitive to postural changes than phase-averaged RSA analysis. The joint symbolic dynamics of heart rate and respiratory rate provide a new representation of cardiorespiratory interaction and offers additional information.

ACKNOWLEDGMENTS

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CONFLICT OF INTEREST

There is no conflict of interest.

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