Analysis of Non-Linear Respiratory Influences on Sleep Apnea Classification

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Abstract

In this paper we propose the use of Kernel Principal Component Regression (KPCR) in order to model the nonlinear interaction between heart rate (HR) and respiration. We used wavelets in order to decompose the respiratory signal in 2 different frequency bands; namely, the low frequency band (LF) 0-0.078Hz, and the high frequency band (HF) 0.078-2.5Hz. We used the decomposed respiration as regressors in the KPCR model. Using the results provided by KPCR we computed the coupling between HR and the respiration in the LF and HF bands, separately. We evaluated the predictive power of these scores using the Physionet Sleep Apnea Dataset. In addition, we compare these results with the ones previously reported in our group, where we used a linear model based on orthogonal subspace projections and wavelet regression. We found that the features extracted using the nonlinear model improved the classification rate for apneic episodes when compared to the linear model, AUC =92.36 vs AUC = 88.29%.

1. Introduction

In the framework of cardio-respiratory coupling, the goal is to quantify the influence of the respiration in the heart rate (HR) in order to use this information as a monitoring parameter. In general, this relationship is altered during episodes of breathing disorders. For example, an elevated coupling in the low frequency range (LF) between HR and respiration was observed during obstructive apnea episodes, when compared with normal breathing patterns [1].

In the literature there exist a multitude of studies that employ linear methods to evaluate the relation between HR and respiration [2, 3]. These studies have shown that, under normal breathing, a linear relation might be enough in order to assess the cardio-respiratory coupling. This might be due to the fact that during normal breathing the effect of the respiration on the HR is strongly observed, specifically in the respiratory sinus arrhythmia (RSA).

However, during apnea episodes, the mechanical effort and the consequent physiological reactions might disrupt the normal coupling between respiration and HR [1]. These effects challenge the cardio-respiratory coupling inducing, possibly, nonlinear elements in their relation. In a previous work we presented a linear algorithm for the quantification of the coupling between HR and respiration. The performance of this algorithm was tested in the framework of obstructive apnea classification [4].

In this study, the main goal is to investigate the use of kernel principal component regression (KPCR) as a nonlinear model for the assessment of cardio-respiratory coupling, and to evaluate which is the added value of the use of nonlinear methodologies for the automatic classification of obstructive sleep apnea episodes, comparing the results provided by this methodology with the ones previously reported for our group.

2. Modeling of cardio-respiratory interactions using KPCR

Kernel Principal Component Regression (KPCR) is the nonlinear extension of Principal Component Regression (PCR) [5]. In this study, we use KPCR in order to solve a nonlinear regression problem between HR and the respiratory signal (R). The nonlinear regression problem is formulated as follows:

$$HR(n) = \varphi^T\left(\left[\mathbf{R}_{\mathbf{LF}}(n) \quad \mathbf{R}_{\mathbf{HF}}(n)\right]\right)\omega + \varepsilon, \quad (1)$$

where $\mathbf{R}_{\mathbf{LF}}[n] \in \Re^{m+1}$ and $\mathbf{R}_{\mathbf{HF}}[n] \in \Re^{m+1}$, are vectors containing the present and m past samples of the low and high frequency components of the respiratory signal, respectively, m is the maximum number of delays in the model, ε is the error term, $\varphi(.) \in \Re^{d}$ represents the nonlinear transformation, $\omega \in \Re^{d}$ is a vector of regression coefficients, and T represents the transpose operator.

The matrix form of (1) is:

$$\mathbf{HR} = \Phi\omega + \boldsymbol{\varepsilon}, \quad (2)$$

where $\mathbf{HR} \in \Re^N$, with N the number of observations, the i^{th} row of $\Phi \in \Re^{N \times d} = \varphi([\mathbf{R_{LF}}(i) \quad \mathbf{R_{HF}}(i)])^T$.

Since the matrix $\mathbf{\Phi}$ might suffer of multicollinearity, we can change the formulation presented in (2) using the criteria employed in PCR. Therefore, using $\Phi = U\Lambda V^T$, we can reformulate the regression problem in (2) using a new matrix $B = \Phi V$. The matrix B has orthogonal columns, avoiding problems due to multicollinearity. Replacing B in (2) we obtained:

$$\mathbf{HR} = B\gamma + \boldsymbol{\varepsilon}, \qquad (3)$$

with $\gamma = V\omega$. The solution to (3) is given by:

$$\hat{\gamma} = \Lambda^{-1} B^T \mathbf{HR}, \qquad (4)$$

However, since the nonlinear transformation, $\varphi(.)$, is unknown, we cannot compute B directly. But, using the kernel trick $k(x_i, x_j) = \varphi^T(x_i).\varphi(x_j)$, we obtain that $\mathbf{K} = \Phi\Phi^T$, where $\mathbf{K} \in \Re^{N \times N}$ is the kernel matrix. Using the SVD decomposition of Φ, we obtain that $\mathbf{K} = U\Lambda^2 U^T$. Therefore, we do not need to know the nonlinear transformation, since we can compute an approximation of B using the eigenvalue decomposition of the kernel matrix, solving (4).

In this study we use the RBF kernel function:

$$k(x_i, x_j) = e^{\left(\frac{\|x_i - x_j\|_2^2}{\sigma^2}\right)},$$

where σ represents the kernel bandwidth and is a parameter that should be tuned in order to solve the regression problem. We use 10-fold cross-validation in order to find a suitable σ and solve the KPCR problem.

3. Data

We use concomitant measurements of ECG and Nasal breathing obtained from 8 recordings from the Physionet Sleep Apnea Database [6, 7]. The tachogram was computed from the ECG, and it was resampled, together with the respiratory signal, to 5Hz. We decomposed the respiratory signal using a 5th level stationary wavelet transform. From this decomposition we used the approximations as a reference for the low-frequency band, and the 5th-3rd level details as a base for the high-frequency band.

We divided the signals in segments with a duration of 1-minute. The 8 recordings contain a total of 1328 minutes from which 489 contain apnea episodes and 839 are normal segments. For each segment we solved a KPCR model, as explained in section 2.1. Additionally, for each segment, we also computed a coupling coefficient that quantifies the strength of the relation between HR and respiration, in each frequency band.

4. Algorithm and feature extraction

In this study we used a delay of 15 samples in order to formulate the KPCR model for cardio-respiratory interactions, presented in equation (2). Additionally, we assumed that the component of the HR that depends on the respiratory signal, can be further decomposed as the sum of the components related to the low and high frequencies of the respiration, as follows: $\mathbf{HR} = \mathbf{HR_{LF}} + \mathbf{HR_{HF}}$. In order to decompose the estimated HR, we need to find a suitable basis for the subspaces spanned by the low and high frequencies of the respiratory signal.

Taking into account that the columns of the kernel matrix span the column space of the nonlinear transformation matrix Φ, we propose to build a basis for the low and high frequency components of the respiration using kernel evaluations of the kernel function.

Consequently, we form the basis for the low and the high frequencies of the respiratory signal as follows:

$$\mathbf{K_{LF}}(i,j) = \varphi^T([\mathbf{R_{LF}}(i) \quad \mathbf{R_{HF}}(i)])\varphi([\mathbf{R_{LF}}(j) \quad 0])$$
$$\mathbf{K_{HF}}(i,j) = \varphi^T([\mathbf{R_{LF}}(i) \quad \mathbf{R_{HF}}(i)])\varphi([0 \quad \mathbf{R_{HF}}(j)])$$

where $\mathbf{K_{LF}}(i,j)$ is the $\{i,j\}$ element of the kernel matrix that spans the column space of the nonlinear transformation of the respiratory low frequencies and $\mathbf{K_{HF}}$ is the kernel matrix that spans the column space of the nonlinear transformation of the respiratory high frequencies.

Since $\mathbf{R_{LF}} \perp \mathbf{R}_{HF}$, we assume that $\mathbf{HR_{LF}} \perp \mathbf{HR_{HF}}$. Therefore, we can construct orthogonal projectors using $\mathbf{K_{LF}}$ and $\mathbf{K_{HF}}$, such that:

$$\begin{aligned} \mathbf{HR_{LF}} &= \mathbf{P_{LF}}\mathbf{HR} \\ \mathbf{HR_{HF}} &= \mathbf{P_{HF}}\mathbf{HR} \end{aligned}, \qquad (6)$$

with $\mathbf{P_{LF}} = \mathbf{K_{LF}}\left(\mathbf{K_{LF}^T}\mathbf{K_{LF}}\right)^{-1}\mathbf{K_{LF}^T}$, the orthogonal projector on the respiratory low frequencies subspace, and $\mathbf{P_{HF}} = \mathbf{K_{HF}}\left(\mathbf{K_{HF}^T}\mathbf{K_{HF}}\right)^{-1}\mathbf{K_{HF}^T}$ the orthogonal projector on the respiratory high frequencies subspace. We are aware that the orthogonality might not be preserved after

the nonlinear transformation, but in our simulations it seems to be a valid approximation.

We propose to use the normalized magnitude of the projections of the HR, onto the respiratory LF and HF components, as a measure of the strength of the nonlinear cardio-respiratory coupling in the different frequency bands. These features were used as input for the detection of sleep apnea events.

5. Results

In Figure 1, the decomposition of the heart rate in the components related to the LF and HF is depicted for a normal segment and an apnoeic segment. In the figure it can be observed that the component of the HR related to the low frequency components has larger amplitude in the apnoeic episode than in the segment with normal breathing. Additionally, the bottom plots in Figure 1, show the box plots of the features extracted from the projection. The box plots indicate that during normal breathing, the coupling between low frequencies and respiration is lower than during apnea. In contrast, in the high frequency band this coupling seems larger during normal breathing than during apnea, however, the differences where not significant.

In Table 1, the median values and the 25, and 75 percentiles for the extracted features are displayed.

Table 1. Median, 25 and 75 percentiles of the coupling coefficients between the LF and HF respiratory bands and the HR.

Band	Normal Segment	Apnoeic Segment
LF	0.01 (0.00 – 0.08)	0.35 (0.17 – 0.56)
HF	0.14 (0.06 – 0.25)	0.09 (0.02 – 0.24)

Finally, we have compared the predictive value of the coupling coefficients in the LF obtained using a linear method previously developed in our group, with the ones obtained using the proposed methodology. In Figure 2, the ROC for a linear classifier based on thresholding of the feature values for the linear and nonlinear

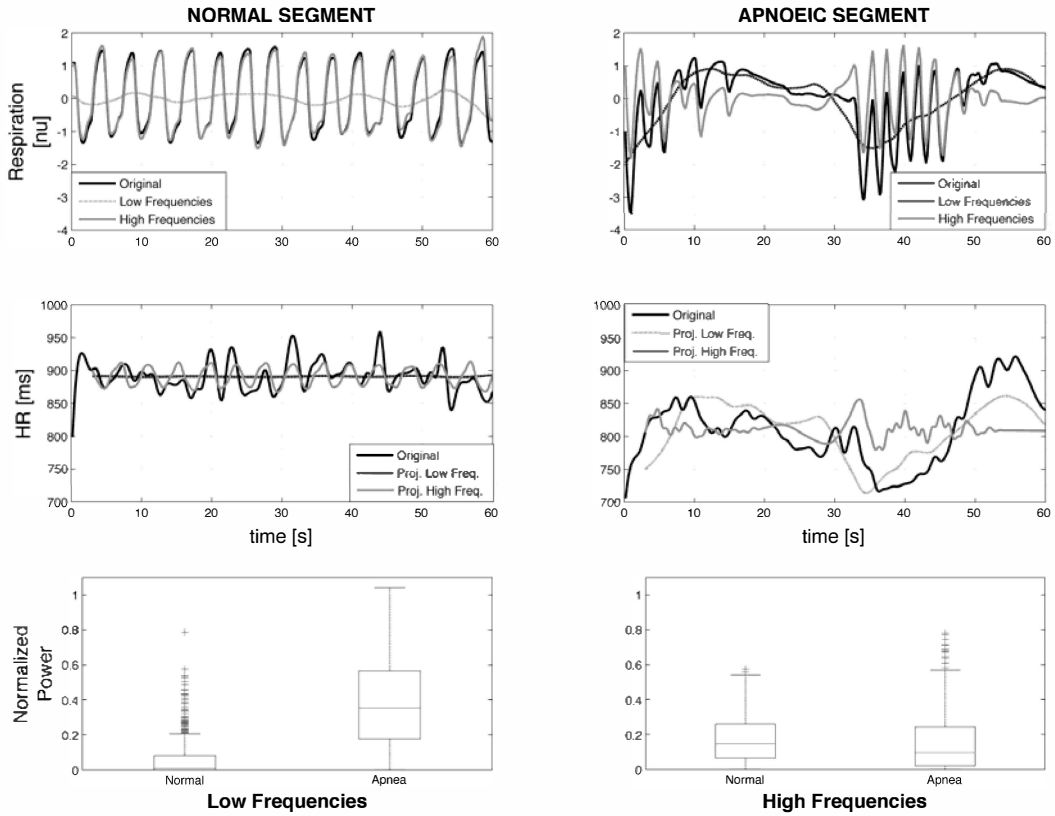


Figure 1. Representative segments of Normal and Apnoeic activity. Respiration is shown in the upper figures together with the components in the low and high frequencies. In the middle figure the HR activity is presented with the nonlinear contributions of the respiratory low and high frequencies respectively. In the bottom figures the box-plot of the normalize power in low and high frequencies for both populations is shown.

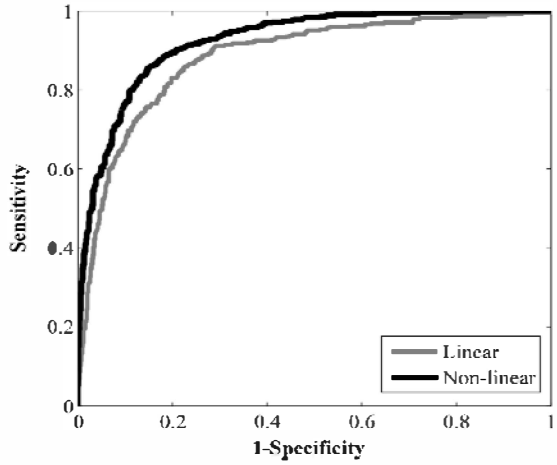


Figure 2. ROC curve for the LF coupling coefficients between HR and respiration assessed using linear and nonlinear methodologies.

methodologies are shown. The obtained AUC for the linear features was 88.29%, while the nonlinear feature presented an AUC of 92.36%. The results indicate that the proposed methodology outperforms the linear approaches.

6. Discussion and conclusion

In this study we proposed a methodology in order to assess, in a nonlinear framework, the coupling between respiration and heart rate. We have shown that the use of this novel nonlinear method outperforms the results obtained using a linear approach, in the framework of apnea classification.

Interestingly enough, when comparing the features obtained a linear methodology and the ones obtained using the proposed nonlinear method, we observed that during normal breathing, the projections in the LF and HF of the respiratory signal were similar for the linear and the nonlinear methods. However, during the apnoeic episodes, the projections obtained using the nonlinear method differed significantly from the ones obtained by the linear methodology.

In this study, we have assumed a fixed order model for the regression problem. This order might change between normal and apnoeic episodes, and even between consecutive segments. Therefore, the order of this model should also be included in the optimization function used to solve the KPCR problem. Additionally, we have assumed that orthogonality of the respiratory signals, LF and HF, is preserved after the nonlinear transformation. This might not be true, but in our experiments this assumption is fairly correct. A more robust approach should include the use of oblique projectors.

To conclude, we have presented a novel method that is able to decompose the HR into the nonlinear contributions of the low and high frequencies of the respiratory signals. We proposed to use the magnitude of these components as a measure of the coupling between the HR and the respiration. We show that this metric outperforms linear methodologies, currently used to quantify the cardiorespiratory coupling.

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