An improved ECG-Derived Respiration Method using Kernel Principal Component Analysis

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Abstract

Recent studies show that principal component analysis (PCA) of heart beats generates well-performing ECG-derived respiratory signals (EDR). This study aims at improving the performance of EDR signals using kernel PCA (kPCA). Kernel PCA is a generalization of PCA where nonlinearities in the data are taken into account for the decomposition. The performance of PCA and kPCA is evaluated by comparing the EDR signals to the reference respiratory signal. Correlation coefficients of 0.630 ± 0.189 and 0.675 ± 0.163, and magnitude squared coherence coefficients at respiratory frequency of 0.819 ± 0.229 and 0.894 ± 0.139 were obtained for PCA and kPCA respectively. The Wilcoxon signed rank test showed statistically significantly higher coefficients for kPCA than for PCA for both the correlation (p = 0.0257) and coherence (p = 0.0030) coefficients. To conclude, kPCA proves to outperform PCA in the extraction of a respiratory signal from single lead ECGs.

1. Introduction

Respiration is often jointly recorded with the heart rate, e.g. in studies for ambulatory and home monitoring of chronic diseases, stress testing, heart rate variability analysis and sleep apnea detection. In order to obtain a respiratory signal, impedance sensors, pressure sensors and a thermistor in the nose are used. However, these methods need extra equipment in addition to the sensors needed to obtain an electrocardiogram (ECG), increasing both the discomfort during the measurements and the cost of the study. For these reasons, it is advantageous to investigate how a respiratory signal can be extracted from the recorded ECG. The extracted respiratory signals are called ECG-derived respiration or EDR signals and arise from the movement of electrodes with respect to the heart during respiration. This causes changes in the electrical impedance, which modifies the ECG [1].

Developing new EDR methods has challenged many researchers. The most commonly used single lead EDR methods are based on (a) filtering of the ECG in the respiratory frequency band, (b) the amplitude of the R peak, and (c) the area under the QRS complex [1–4]. Recently, Langley *et al.* introduced the use of principal component analysis (PCA) on heart beats to analyze beat-to-beat variations, where the largest variations in the QRS morphology are assumed to be caused by respiration. Therefore, an EDR signal can be generated by the coefficients of the first principal component [5]. The performance of this method proved to be higher than previously described methods. However, PCA is restricted to linear transformations, which means that the direction of the highest variance due to the respiration is assumed to be linear. In order to discard this assumption, an expansion of PCA to kernel PCA (kPCA) is proposed. Kernel PCA is a generalization of PCA where nonlinearities in the data are taken into account for the decomposition and is hypothesized to improve the performance of EDR signals.

2. Methods

2.1. Data

For this study, the data from the Fantasia database from PhysioNet [6] are used. The dataset consists of simultaneously recorded ECG and respiratory signals of 20 young (21–34 years old) and 20 elderly (68–85 years old) healthy subjects, with a sampling frequency of 250 Hz. During the recordings, the subjects watched the movie *Fantasia* (Disney, 1940) in supine resting position. From the 120 minutes of recordings, 5 minutes were randomly selected.

2.2. (Kernel) principal component analysis

In order to derive a respiratory signal from the ECG, firstly, the input matrix X for (k)PCA is constructed. Figure 1 shows the outline of the input matrix; all R peaks (n) of the ECG are detected and a fixed window around each

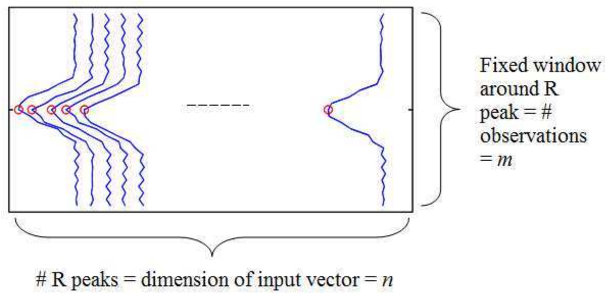

Figure 1. Input matrix X of (k)PCA including the windows around each R peak.

R peak is selected. In this study, the windows contain only the QRS complexes, i.e. 60 ms before and 60 ms after the R peaks (m). Next, all windows are assembled in a matrix and all means are subtracted, resulting in the $m \times n$ input matrix X, with m the number of samples around the R peak and n the number of R peaks detected.

1. **PCA**
Applying (linear) PCA to the input matrix results in n eigenvalues and n corresponding eigenvectors. Langley *et al.* prove that the first eigenvector, which indicates the direction of the highest variance, is related to the respiration (EDR$_{PCA}$).

2. **kPCA**
Schölkopf *et al.* introduced kernel PCA as a nonlinear form of PCA [7]. In kPCA, the input data are mapped to a higher dimensional space via a nonlinear transformation, given by the kernel function. In this higher dimensional feature space, PCA is applied. Due to this nonlinear transformation, kPCA is able to include nonlinearities. In Figure 2 the performance of PCA and kPCA, when using data with nonlinearities, is presented. The results show clearly that kPCA outperforms PCA.

In this study the implementation of kPCA from the toolbox LS-SVMlab v1.7 (Leuven, Belgium), with a Radial Basis Function kernel (RBF kernel), is used [8]. When using an RBF kernel, the parameter σ^2, i.e. the variance of the Gaussian kernel, needs to be tuned. However, as this is a case of unsupervised learning, choosing an optimal σ^2 is a problem without any clear solution so far. In these preliminary results, σ^2 is set according to a rule of thumb: $\sigma^2 = m\cdot$ mean(var(X)).

Nonetheless, as the nonlinear transformation used in kPCA is unknown, it is impossible to transform the eigenvector from the feature space to the input space. However, due to the kernel trick, it is possible to approximate the reconstructed data in the input space [9]. Taking this into account, reconstruction of the input data using the first eigenvector in the feature space will indicate the direction of the maximal variance in a higher dimensional space, yielding an EDR signal (EDR$_{kPCA}$).

2.3. Comparison of performance

In order to evaluate the performance of kPCA as a method for ECG-derived respiration, the EDR signals are resampled by cubic spline interpolation (10 Hz). The similarity of the resampled EDR signal with the reference respiratory signal is expressed by means of the correlation coefficient (c) and the magnitude squared coherence coefficient at respiratory frequency (msc). The non-parametric Wilcoxon signed rank test evaluates the pairwise comparison of the performance with PCA and kPCA. $P < 0.05$ is considered statistically significant.

3. Results

Figure 3 shows an example of the EDR signals determined from the application of PCA and kPCA on the input matrix X of subject `f1y05m`. Whereas PCA fails to retrieve all respiratory cycles (c = 0.311, msc = 0.511), kPCA finds all cycles and clearly improves the derived respiratory signal (c = 0.753, msc = 0.958).

Figure 4 gives an overview of the performance of all subjects. Overall correlation values of 0.630 $\pm$ 0.189 and 0.675 $\pm$ 0.163, and coherence values of 0.819 $\pm$ 0.229 and 0.894 $\pm$ 0.139 (mean $\pm$ std) were obtained for PCA and kPCA respectively. The Wilcoxon signed rank test showed p-values of 0.0257 and 0.0030 for the correlation and coherence coefficients respectively, indicating statistically significantly higher coefficients for kPCA than for PCA.

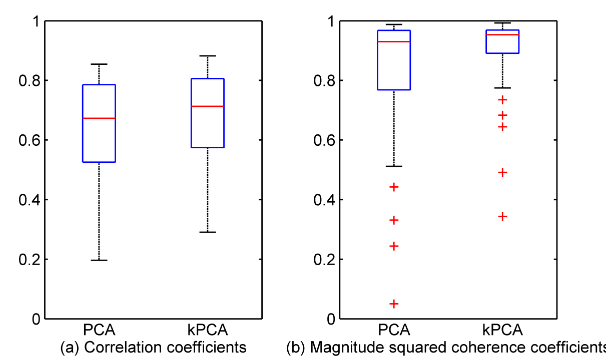

Figure 4. Boxplots of (a) correlation and (b) coherence coefficients of EDR$_{PCA}$ and EDR$_{kPCA}$ with the reference respiratory signal.

4. Discussion and conclusion

This study aimed at investigating whether kernel PCA could be a meaningful improvement for ECG-derived respiration compared to the existing methods, in particular the one using PCA. The performance of both kPCA and PCA

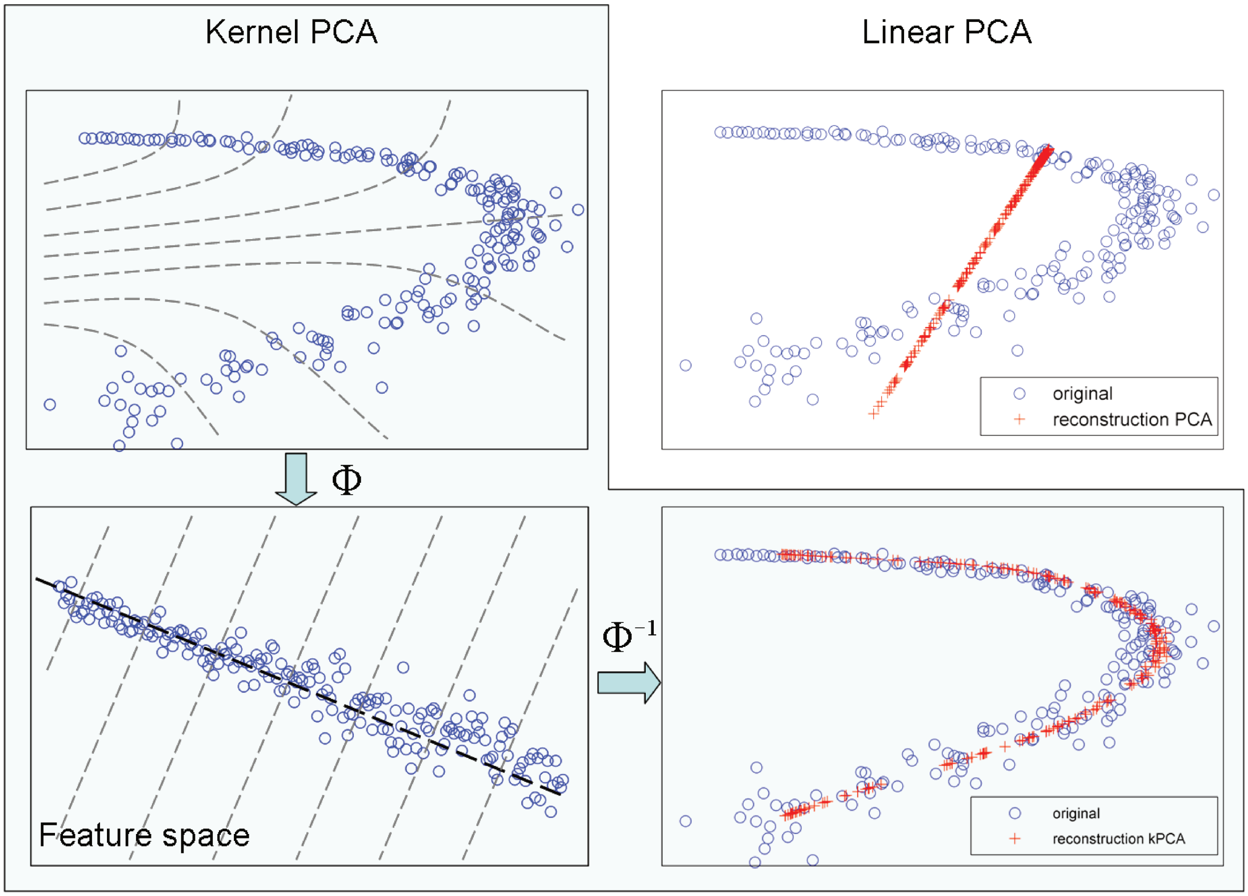

Figure 2. Toy example demonstrating the idea of kPCA (*left*): by the use of a nonlinear kernel function, PCA is implicitly performed in a higher dimensional space (feature space), which is nonlinearly related to the input space [7]. The reconstructed data (*right*) show the power of kPCA, whereas reconstruction using the first eigenvector in linear PCA fails to capture the nonlinearity. Φ indicates the nonlinear tranformation.

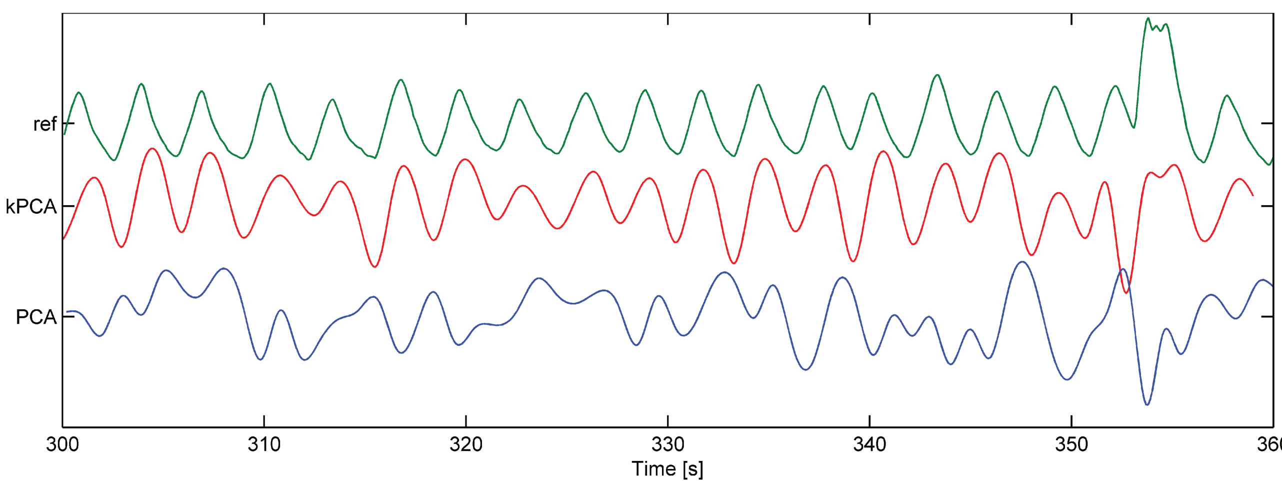

Figure 3. EDR signals of subject `f1y05m` from 300 s to 360 s (*from top to bottom: reference respiratory signal;* EDR_{kPCA}; EDR_{PCA}).

was assessed by means of the correlation and coherence coefficient.

Kernel PCA proved to be an important improvement for ECG-derived respiration; it manages to use the non-linear interactions between respiration and the ECG, resulting in statistically significantly better EDR signals than other EDR techniques. However, kPCA is more complex in its implementation than PCA; several choices need to be made concerning the type of kernel (polynomial, RBF ...) and their parameters (order, $\sigma^2 \ldots$). In this study, an RBF kernel with σ^2 according to a rule of thumb was used. Although σ^2 was not optimized, the resulting EDR signals are good. However, σ^2 is an important parameter and the performance of the method is greatly affected by changes in its value. Furthermore, as explained, the eigenvector is only known in the feature space and reconstruction is needed in order to obtain the EDR signal. Ongoing research tries to resolve these issues, but anyhow, even without optimization of all parameters, kPCA outperforms PCA in the estimation of EDR signals.

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