Application of Kernel Principal Component Analysis for Single Lead ECG-Derived Respiration

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***Abstract*—Recent studies show that principal component analysis (PCA) of heart beats is a well-performing method to derive a respiratory signal from ECGs. In this study, an improved ECG-derived respiration (EDR) algorithm based on kernel PCA (kPCA) is presented. KPCA can be seen as a generalization of PCA where nonlinearities in the data are taken into account by nonlinear mapping of the data, using a kernel function, into a higher dimensional space in which PCA is carried out. The comparison of several kernels suggests that a radial basis function (RBF) kernel performs the best when deriving EDR signals. Further improvement is carried out by tuning the parameter σ^2 that represents the variance of the RBF kernel. The performance of kPCA is assessed by comparing the EDR signals to a reference respiratory signal, using the correlation and the magnitude squared coherence coefficients. When comparing the coefficients of the tuned EDR signals using kPCA to EDR signals obtained using PCA and the algorithm based on the R peak amplitude, statistically significant differences are found in the correlation and coherence coefficients (both $p < 0.0001$), showing that kPCA outperforms PCA and R peak amplitude in the extraction of a respiratory signal from single lead ECGs.**

***Index Terms*—ECG-derived respiration (EDR), kernel principal component analysis (kPCA).**

I. Introduction

RESPIRATION is an interesting physiological process to monitor as it plays an important role in sleep apnea detection, stress testing and many other applications. A respiratory signal is usually obtained using specialized equipment, like a spirometer, inductive plethysmograph and impedance pneumograph. However, due to increasing costs in the health care industry, there is a growing need to be more cost-effective. This is expressed by a large interest to derive a respiratory signal from another (recorded) physiological signal, which has the additional advantage of being more comfortable for the patient as less sensors need to be attached. Moreover, looking for a surrogate respiratory signal has the benefit of not interfering with natural breathing, in contrast to spirometry. One of the most commonly used recordings to derive a respiratory signal from, is the electrocardiogram (ECG). This electrophysiological signal is measured non-invasively via a few electrodes, and it is often recorded simultaneously with respiration as it contains much information about the autonomic nervous system, and most importantly, it has a close interaction with respiration.

Respiratory sinus arrhythmia (RSA), a well-known phenomenon in heart rate variability (HRV), describes how respiration modulates the heart rate; during inspiration, the heart rate increases, whereas expiration is coupled with a decrease of the heart rate [1]. This interaction causes respiration to be a main modulator of HRV. However, respiration alters the ECG recordings in a different way as well due to the movement of the thorax associated with breathing, the so-called 'mechanical' interaction. This is caused by two factors: (1) the volume changes in the lungs that alter the electrical impedance, and (2) the changing position of the electrodes with respect to the heart, both resulting in modulations in the morphology of the heart beats in the ECG [2]. Due to these interactions, it is feasible to derive a surrogate respiratory signal from the ECG, termed ECG-derived respiration (EDR). Based on the interactions between respiration and the ECG, a wide range of EDR algorithms have already been developed. Most methods use the amplitude of the R peak [3], [4] or the area under the QRS complex [5], [6]. A few researchers developed EDR algorithms based on RSA or filtering of the ECG in a predefined respiratory frequency band [4], [7]. Recently, Langley *et al.* introduced the use of principal component analysis (PCA) to look into morphological beat-to-beat variations [8]. Their hypothesis was based on the changing correlation between ECG features, such as the QRS complex, at several heart beats. An EDR signal arises from the coefficients that describe the beat-to-beat variability of the principal components. Langley *et al.* prove that PCA outperforms the EDR algorithm based on RSA when analyzing beat-to-beat variations. However, using PCA, the relation between respiration and ECG is assumed to be linear. To tackle this assumption, we propose to use kernel PCA (kPCA) instead of (linear) PCA. Kernel PCA can be seen as a generalization of PCA where nonlinearities in the data are taken into account when the variance is maximized. In this way, nonlinear interactions between respiration and the ECG are included in the construction of a surrogate respiratory signal. KPCA is hypothesized to improve the performance of EDR signals, in particular the EDR signals obtained using PCA and the R peak amplitude.

This paper is organized as follows. In Section II the methodology of the research is presented, starting from the description of the used database. Next, PCA as EDR algorithm is explained and a demonstration of how kPCA deals with nonlinear data structurs is given. Further, kPCA is described in detail and presented as an improved algorithm for deriving

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surrogate respiratory signals that benefit from the nonlinear relation between the ECG and respiration, including a report of the model selection. The methodology is completed with the description of the R peak amplitude as EDR algorithm and the assessment of the performance of the different EDR algorithms. In Section III, the results when comparing different kernel functions, and when comparing kPCA, linear PCA and R peak amplitude are evaluated. Section IV presents a discussion of the obtained results, followed by a conclusion regarding the improvement of our proposed EDR method in Section V.

II. Methods

A. Data

The data from the Fantasia database, available at PhysioNet, are used in this study [9]. This database includes simultaneously recorded lead II ECG and respiratory signals of 20 young (21–34 years old) and 20 elderly (68–85 years old) healthy subjects, with a sampling rate of 250 Hz. Respiration was measured via a belt over the thorax. No respiratory pattern was imposed. All subjects were in supine resting position and watched the movie *Fantasia* (Disney, 1940) to avoid drowsiness. Per subject, 5 minutes of the total recordings were selected in such way that no movement artifacts in the respiratory signal were present.

B. (Kernel) Principal Component Analysis

Principal Component Analysis is a method that linearly transforms the input space in such a way that the first principal component accounts for the highest variance of the data. Therefore, PCA is mostly used to reduce the dimensionality of multivariate data. Langley *et al.* use PCA to find respiratory-induced modulations in ECG features like the QRS complex, P or T wave, by looking for the direction of the highest variance, i.e. the first eigenvector. This eigenvector is used to construct an EDR signal.

However, PCA is restricted to linear transformations. In order to improve the EDR signals, we propose to use kernel PCA, a generalization of linear PCA to a nonlinear setting which was introduced by Schölkopf *et al*. In kernel PCA, the data are mapped to a possibly higher dimensional feature space F, which is nonlinearly related to the input space. PCA is then performed in F [10]. Fig. 1 demonstrates with a toy example how nonlinear data structures benefit from kPCA. KPCA as EDR method is carried out using least squares-support vector machines (LS-SVM) which are implemented in the freely available toolbox LS-SVMlab v1.8 (http://www.esat.kuleuven.be/sista/lssvmlab/, Leuven, Belgium) [11]. The EDR algorithm is described as follows:

1) Construction of the Input Matrix: Firstly, an input matrix $\mathbf{X}$ for (kernel) PCA is constructed via the following steps: (a) detection of all R peaks (n) via the Pan-Tompkins algorithm [12] and visual verification of all detections; (b) selection of a fixed window around each R peak (m): 60 ms before and 60 ms after each R peak are selected to capture the QRS complexes; and (c) assembly of all windows in one matrix with dimensions $m \times n$ and centering of every column. Fig. 2 shows the outline of the resulting input matrix $\mathbf{X}$. Note that ectopic beats are manually excluded from the input matrix.

2) Principal Component Analysis: The EDR signals using linear PCA are obtained by calculating the covariance matrix $\mathbf{C}$ of input matrix $\mathbf{X}$: $\mathbf{C} = \frac{1}{m}\sum_{j=1}^{m} \mathbf{x}_j \mathbf{x}_j^T$, leading to an $n \times n$ matrix. Subsequently, the eigenvalue problem $\lambda \mathbf{v} = \mathbf{C}\mathbf{v}$ is solved, resulting in eigenvalues $\lambda \geq 0$ and eigenvectors $\mathbf{v} \in \mathbb{R}^n \backslash \{0\}$. The first eigenvector $\mathbf{v}^1$ is defined as the EDR signal [8].

3) Kernel Principal Component Analysis: As previously explained, a nonlinear transformation Φ maps the input data into a higher dimensional feature space F and PCA is then carried out in that feature space [10].
For the input data $\{\mathbf{x}_k\}_{k=1}^m$, $\Phi(\mathbf{x}_k)$ represents the mapped data in F. The covariance matrix $\bar{\mathbf{C}}$ of the eigenvalue problem $\lambda \mathbf{v} = \bar{\mathbf{C}}\mathbf{v}$ is

$$\bar{\mathbf{C}} = \frac{1}{m}\sum_{j=1}^{m} \Phi(\mathbf{x}_j)\Phi(\mathbf{x}_j)^T \tag{1}$$

with eigenvalues $\lambda \geq 0$ and eigenvectors $\mathbf{v} \in F \backslash \{0\}$. We can write an equivalent system

$$\lambda(\Phi(\mathbf{x}_k) \cdot \mathbf{v}) = (\Phi(\mathbf{x}_k) \cdot \bar{\mathbf{C}}\mathbf{v}) \text{ for } k = 1, \ldots, m. \tag{2}$$

Then, consider the coefficients α_i for $i = 1, \ldots, m$ such that

$$\mathbf{v} = \sum_{i=1}^{m} \alpha_i \Phi(\mathbf{x}_i), \tag{3}$$

and define an $m \times m$ kernel matrix $\mathbf{K}$ by

$$K_{ij} := (\Phi(\mathbf{x}_i) \cdot \Phi(\mathbf{x}_j)). \tag{4}$$

Combining (2), (3) and (4) leads to

$$m\lambda \mathbf{K}\boldsymbol{\alpha} = \mathbf{K}^2\boldsymbol{\alpha}, \tag{5}$$

with $\boldsymbol{\alpha}$ a column vector with entries $\alpha_1, \ldots, \alpha_m$. Finding solutions for the eigenvalue problem $m\lambda\boldsymbol{\alpha} = \mathbf{K}\boldsymbol{\alpha}$, solves (5). To extract the principal components, the projection of the image of a test point $\Phi(\mathbf{x})$ onto the eigenvectors $\mathbf{v}^k$ in F is computed via

$$(\mathbf{v}^k \cdot \Phi(\mathbf{x})) = \sum_{i=1}^{m} \boldsymbol{\alpha}_i^k (\Phi(\mathbf{x}_i) \cdot \Phi(\mathbf{x})). \tag{6}$$

Remark that to solve the equations, the nonlinear transformation Φ is never applied explicitly, only the dot products are required. For that reason, kernel functions $k(\mathbf{x}_i, \mathbf{x}_j)$ can be used [13]. The dot product matrix is then given by $K_{ij} = k(\mathbf{x}_i, \mathbf{x}_j)$.

Applying (4), called the kernel trick, implies that it is not needed to construct the nonlinear transformation explicitly and thus results in the fact that the nonlinear transformation is unknown. This poses a problem in this context since the EDR signal is constructed from the first eigenvector in the input space, but kPCA yields eigenvalues and eigenvectors in the feature space F. However, it is possible to find an approximation of the reconstructed data using a limited number of eigenvectors. This process is called pre-imaging and is computed as described in [14] via the function `preimage_rbf` of the LS-SVMlab toolbox. Taking this into account, by reconstructing

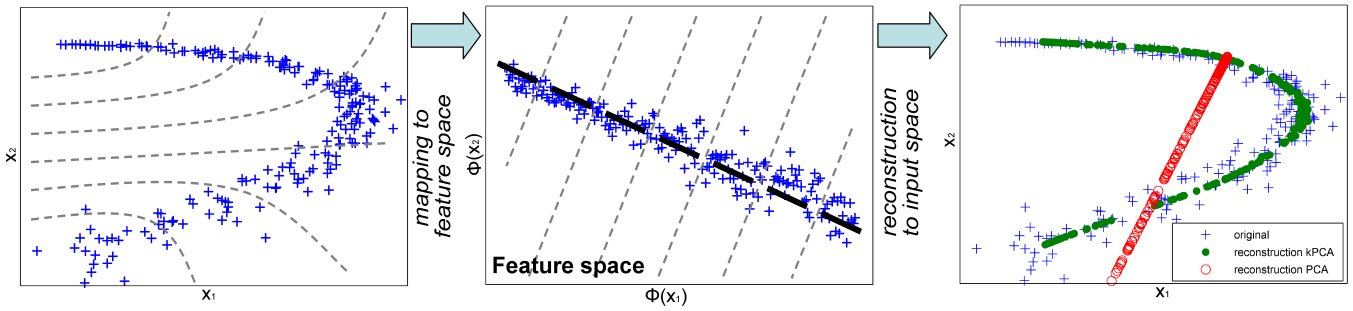


Fig. 1. Toy example showing the idea of kernel PCA: first, a nonlinear transformation Φ maps the input data to a feature space where PCA is implicitly performed. In this case, the data are denoised using only a few eigenvectors for the reconstruction of the data from the feature space to the input space. Unlike kPCA, PCA fails to detect the nonlinearity of the data.

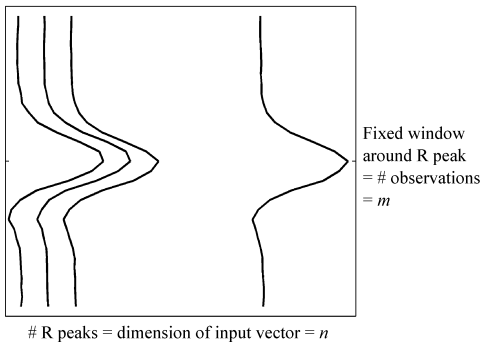


Fig. 2. Structure of input matrix $\mathbf{X}$.

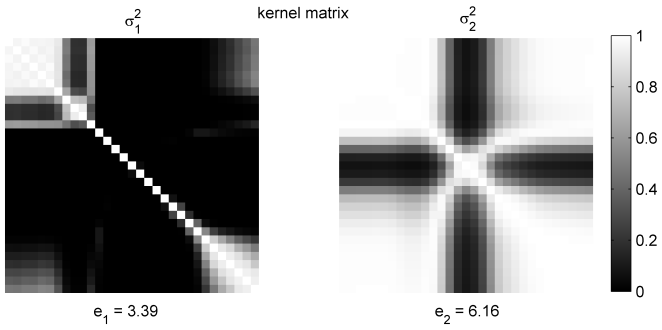


Fig. 3. Entropy e of the kernel matrix for two values for σ^2, σ_1^2 and σ_2^2.

the input data using the first eigenvector in the feature space, we can get an indication of the direction of the maximal variance in a higher dimensional space. Note that reconstruction using one eigenvector results in projections of the data that are all the same among the rows. The reconstructed observations are thus identical. An EDR signal is then obtained using one row of the reconstructed observations.

Kernel PCA is described in more detail by Schölkopf *et al.* in [10].

4) Model Selection: The nonlinear transformation Φ is given by kernel functions $k(\mathbf{x}_i, \mathbf{x}_j)$. Two types of kernel functions are evaluated:

- polynomial kernel: $k(\mathbf{x}, \mathbf{y}) = (\mathbf{x}^T\mathbf{y} + t)^d$, with $t \geq 0$ the intercept and d the degree of the polynomial;
- radial basis function (RBF) kernel: $k(\mathbf{x}, \mathbf{y}) = \exp(-\frac{\|\mathbf{x}-\mathbf{y}\|_2^2}{2\sigma^2})$, with σ^2 the variance of the Gaussian kernel.

These kernel functions have specific parameters that need to be tuned. However, as this is a case of unsupervised learning, choosing optimal parameters is still an ongoing research topic with no clear solution so far. Therefore, to select a suitable kernel function, they are first evaluated using a fixed set of parameters, after which an optimization of the relevant parameter will take place. In case of the polynomial kernel, t is set to 1[1] and values of $d = 2$ and $d = 3$ are assessed, further noted as EDR$_{poly(d=2)}$ and EDR$_{poly(d=3)}$ respectively. Polynomial kernels of higher degrees are not considered as they become too complex. For a first indication of the performance of RBF kernels (EDR$_{RBF}$), the value for σ^2 is chosen according to a rule-of-thumb: $\widehat{\sigma^2} = m$·mean(var($\mathbf{X}$)).

As will be shown in Section III-A, an RBF kernel produces the best results. In order to further tune the relevant parameter σ^2, we propose two selection criteria. Both options first apply kPCA to a range of 1000 values for σ^2 going from $\widehat{\sigma^2}/100$ to $\widehat{\sigma^2} \cdot 100$. Selection of a value for σ^2 is based on different criteria:

- Entropy (EDR$_{ent}$): the entropy e of the kernel matrix $\mathbf{K}$ for each σ^2 is calculated according to $e = -\sum(p \cdot log_2(p))$, where p contains the histogram counts of the kernel matrix which is taken as an image. The value for σ^2 with the highest entropy is selected, given that the entropy gives information about diversity of the kernel matrix, and thus the discriminative power of the kernel function. Fig. 3 shows the kernel matrices for two values for σ^2, σ_1^2 and σ_2^2, with their corresponding entropies e_1 and e_2. As e_2 is larger than e_1, σ_2^2 is selected for the application of kPCA.
- Eigenvalue (EDR$_{eig}$): the difference between the first eigenvalue and the sum of the remaining eigenvalues for each σ^2 is evaluated. The value for σ^2 that produces the largest difference, is selected. In this way, the variance represented by the first eigenvector is maximized and the EDR signal will be generated using that eigenvector. Fig. 4 displays the eigenvalues of the kernel matrices for two values for σ^2, σ_1^2 and σ_2^2. The plot shows that most of

[1]We tested other values for t as well, but t did not seem to be a critical parameter as all obtained EDR signals appeared to be same.

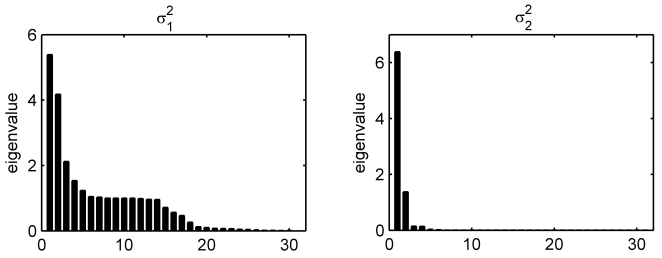


Fig. 4. Eigenvalues of the kernel matrix for two values for σ^2, σ_1^2 and σ_2^2.

the variance is captured in the first eigenvector in the case that σ_2^2 is used, whereas the eigenvalue distribution when using σ_1^2 indicates that the other eigenvectors account for a large part of the variance as well.

Algorithm 1 summarizes the successive steps of the EDR method based on kPCA described above.

Algorithm 1 ECG-Derived Respiration using Kernel PCA

Input: single lead ECG.

Output: EDR signal.

1) Construction of the $m \times n$ input matrix $\mathbf{X}$ based on the ECG;
   a) Detection of the R peaks (n R peaks);
   b) Selection of a fixed window around each R peak (m samples);
   c) Assembly of all windows (see Fig. 2) in a matrix $\mathbf{X}$ and centering of every column;
2) Definition of a range of values for σ^2 going from $\widehat{\sigma^2}/100$ to $\widehat{\sigma^2} \cdot 100$, with $\widehat{\sigma^2} = m \cdot \text{mean}(\text{var}(\mathbf{X}))$;
3) Application of kPCA using an RBF kernel for every value of σ^2 in the predefined range, yielding a solution for (5);
4) Selection of σ^2 (σ^2_{select}) by maximizing:
   a) the entropy of the kernel matrix; or,
   b) the difference between the first eigenvalue and the sum of the remaining eigenvalues;
5) Reconstruction (pre-imaging) of the data using the first eigenvector that results from the application of kPCA using an RBF kernel with σ^2_{select}, yielding $\mathbf{X}_{rec}$;
6) Definition of the EDR signal as one row of the reconstructed observations of $\mathbf{X}_{rec}$.

C. R Peak Amplitude

In addition to the EDR algorithm using PCA, the algorithm using the amplitude of the R peak (EDR_{Ramp}) is included in the comparison of EDR algorithms. EDR_{Ramp} is determined as the amplitude of the R peaks in the baseline-corrected ECG. The baseline wander is removed using 2 median filters, as described by de Chazal *et al.* [5]. The ECG signal is first filtered with a median filter of 200 ms to remove the QRS complexes and P waves. The filtered signal is then processed using a median filter of 600 ms to remove the T waves. The resulting signal represents the baseline and is subtracted from the original ECG signal. From this baseline-corrected ECG, EDR_{Ramp} is constructed from the R peaks that are detected as described above.

D. Comparison of EDR Methods

In order to compare the different EDR signals resulting from (k)PCA and the R peak amplitude with the simultaneously recorded reference respiratory signal, the EDR signals are first resampled at 10 Hz by cubic spline interpolation and the reference signal is downsampled to 10 Hz. The similarity is expressed by means of the correlation coefficient c and the magnitude squared coherence coefficient msc. The correlation coefficient is determined as the maximum cross-correlation over a lag range of 10 samples such that possible phase delays are taken into account. The magnitude squared coherence $C_{xy}(f)$ is computed via

$$C_{xy}(f) = \frac{|P_{xy}(f)|^2}{P_{xx}(f)P_{yy}(f)} \tag{7}$$

with $P_{xx}(f)$ and $P_{yy}(f)$ the power spectral densities of x and y respectively, and $P_{xy}(f)$ the cross power spectral density of x and y. The spectra are calculated via Welch's method using a 1024 point fast Fourier transform (FFT), a periodic Hamming window of a length such that eight equal sections of x and y are obtained, and an overlap of 50%.

As no fixed respiratory frequency was imposed, msc is determined as the mean magnitude squared coherence in a range around the fundamental respiratory frequency (f_R). The range is derived from the power spectrum of the reference respiratory signal and is determined by the frequencies around f_R which have at least half of the maximum power. In this way, only the frequencies that represent most of the power of the respiratory signal are taken into account in the calculation of msc.

E. Statistical Analysis

The performance of the EDR signals using different types of kernels in kPCA and using PCA and the R peak amplitude are compared using Friedman's test, which is a non-parametric statistical test that is similar to the parametric two-way analysis of variance. Tukey's honestly significant difference criterion is used to take multiple comparisons into account. A $p < 0.05$ is considered statistically significant.

III. Results

A. Comparison of EDR Signals using Different Kernel Functions

Fig. 5(a) shows the EDR signals and reference respiratory signal of subject `f1y07`. $\text{EDR}_{poly(d=2)}$ ($c = 0.73$, $msc = 0.89$) and $\text{EDR}_{poly(d=3)}$ ($c = 0.73$, $msc = 0.89$) are almost identical. Both signals resemble the reference signal, but visual evaluation of EDR_{RBF} indicates a better performance, which is also represented by a slightly higher correlation and a higher magnitude squared coherence coefficient ($c = 0.76$, $msc = 0.95$). Fig. 5(b) marks the frequency range over which the coherence is averaged. The coherences of the different kernel

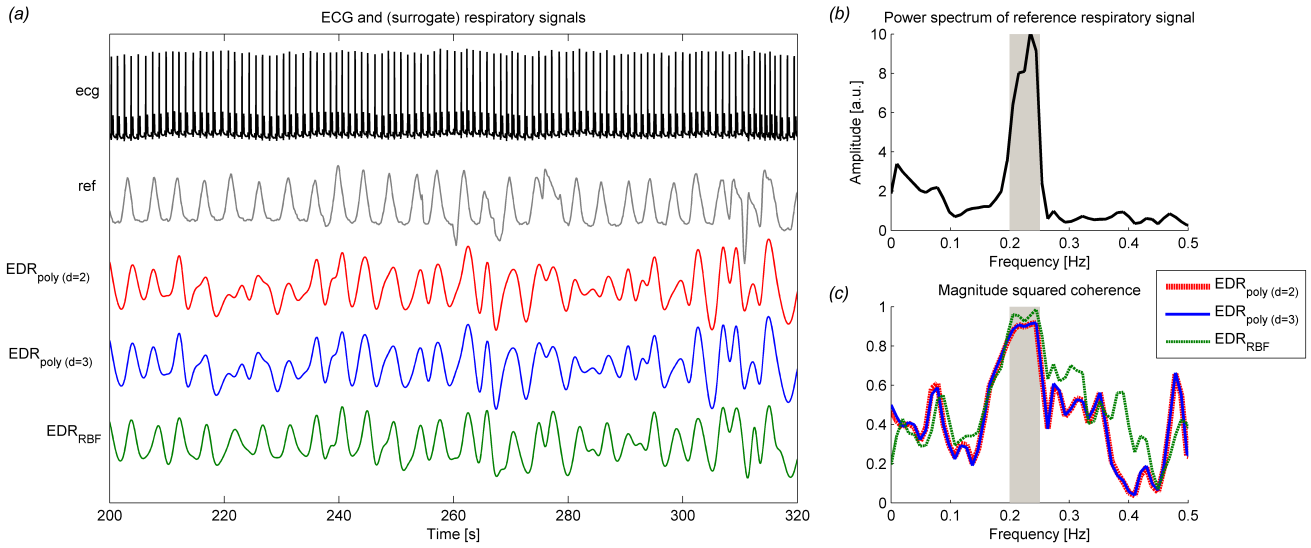


Fig. 5. EDR signals of subject `f1y07`; (a) EDR signals shown from 200 s to 320 s *(from top to bottom: the ECG signal; the reference respiratory signal (ref); EDR signal using a polynomial kernel of degree 2 ($EDR_{poly(d=2)}$); polynomial kernel of degree 3 ($EDR_{poly(d=3)}$); and RBF kernel (EDR_{RBF}))*; (b) Power spectrum of the reference respiratory signal, computed from 200 s to 500 s. The grey area indicates the frequencies around the fundamental respiratory frequency f_R that contain at least half of the maximum power; (c) Magnitude squared coherence of the EDR signals and the reference respiratory signal, computed from 200 s to 500 s.

functions with the reference respiratory signal are given in Fig. 5(c), showing a higher coherence when an RBF kernel is used.

The distributions of the correlation and the coherence coefficients of all subjects are shown in Fig. 6. Among the correlation coefficients of the different kernel functions, no statistically significant results are obtained. Friedman's test only finds a significant difference in the magnitude squared coherence coefficients ($p = 0.0003$), showing statistically higher coefficients for EDR_{RBF} than $\text{EDR}_{poly(d=2)}$ and $\text{EDR}_{poly(d=3)}$.

B. Comparison of EDR Signals using kPCA, Linear PCA and R Peak Amplitude

As kPCA using an RBF kernel gives promising results for obtaining EDR signals, further 'optimization' of this method is carried out by tuning the parameter σ^2 via a selection criterion based on the entropy and a criterion based on the eigenvalues. Both tuned EDR methods (EDR_{ent} and EDR_{eig}) are compared with the algorithm proposed by Langley *et al.* using linear PCA (EDR_{PCA}) and with the commonly used algorithm based on the R peak amplitude.

The EDR signals of subject `f1y07` are shown in Fig. 7. Both selection criteria for σ^2 yield similar EDR signals; they both resemble the reference respiratory signal ($c = 0.76$ and $msc = 0.96$ for both EDR_{ent} and EDR_{eig}). Fig. 8 shows the behavior of the kernel matrix entropy and the distances of the eigenvalues for different values of σ^2, indicating that both selection criteria lead to similar σ^2-values. Linear PCA and R peak amplitude lead to EDR signals with correlation and coherence coefficients of $c = 0.66$ and $msc = 0.88$, and $c = 0.47$ and $msc = 0.77$ respectively.

When comparing the performances over all subjects, Friedman's test shows significant differences in both the correlation and coherence coefficients of the four EDR methods

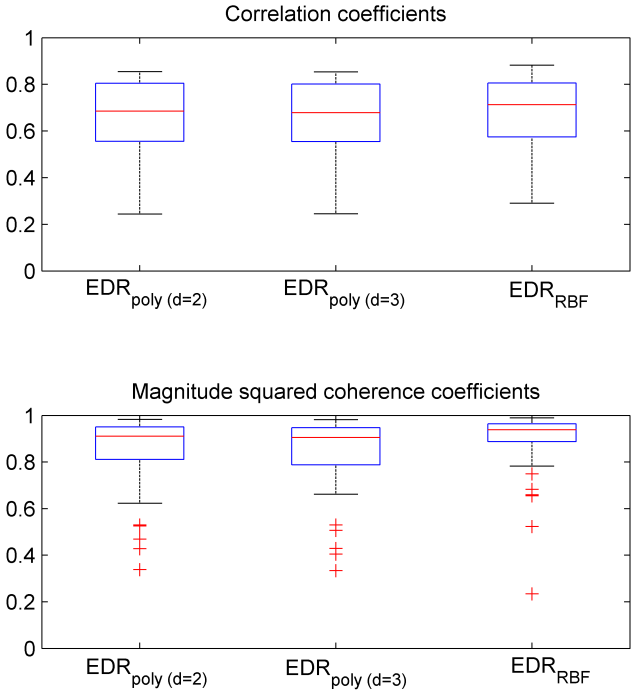


Fig. 6. Comparison of EDR signals obtained with a polynomial kernel ($d = 2$ and $d = 3$) and an RBF kernel, expressed in terms of the correlation coefficients and the magnitude squared coherence coefficients. Each box plot indicates the median (50th percentile) and interquartile range (25th and 75th percentile). The maximum whisker length is 1.5 times the length of the box. Points exceeding the maximum whisker length are drawn as outliers.

($p < 0.0001$ in either case). EDR_{ent} and EDR_{eig} are statistically significantly better than EDR_{PCA} and EDR_{Rampl}. The algorithm based on linear PCA shows also a significantly better performance over the R peak amplitude in terms of the

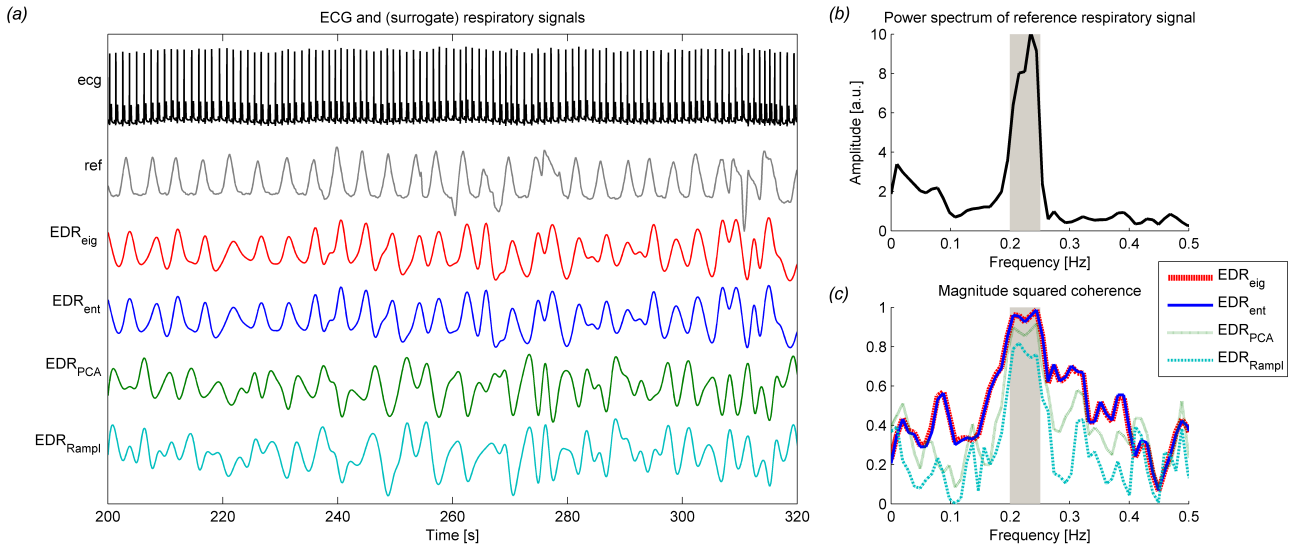


Fig. 7. EDR signals of subject `f1y07`; (a) EDR signals shown from 200 s to 320 s *(from top to bottom: the ECG signal; the reference respiratory signal (ref); EDR signal using an RBF kernel with σ^2 optimized via the eigenvalue criterion (EDR_{eig}); via the entropy criterion (EDR_{ent}); using linear PCA (EDR_{PCA}); and using the amplitude of the R peak (EDR_{Rampl})*; (b) Power spectrum of the reference respiratory signal, computed from 200 s to 500 s. The grey area indicates the frequencies around the fundamental respiratory frequency f_R that contain at least half of the maximum power; (c) Magnitude squared coherence of the EDR signals and the reference respiratory signal, computed from 200 s to 500 s.

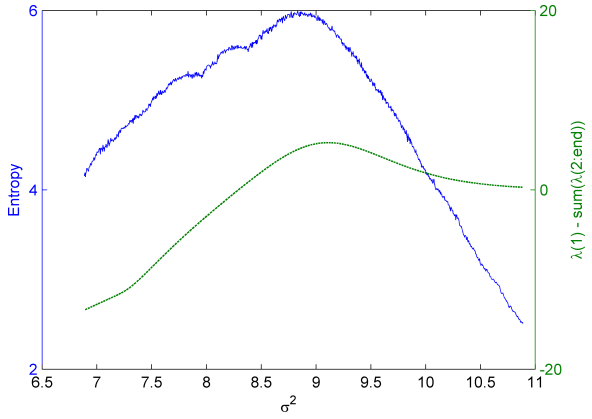


Fig. 8. Demonstration of the selection criteria for choosing a suitable σ^2 for the RBF kernel. The figure shows the behavior of the entropy of the kernel matrix (*solid line*) and the difference between the first eigenvalue and the remaining eigenvalues (*dashed line*) for several σ^2-values.

magnitude squared coherence coefficients. From these results, we can conclude that kPCA using an RBF kernel outperforms PCA and R peak amplitude. However, no difference is found between both tuning methods for σ^2. Fig. 9 shows the distributions of the correlation and coherence coefficients using box plots.

IV. Discussion

A. ECG Feature Selection

In this study, the only selected ECG feature for construction of the input matrix $\mathbf{X}$ is the QRS complex. We tested the selection of the whole beat (WB) as well, given that the performance of this feature in linear PCA is similar to the QRS complex [8]. However, those EDR signals fail to resemble the respiratory signals. The lack of synchronization in samples further away from the R peak seems to play a crucial role as kPCA is more prone to these time alignments.

B. Selection of σ^2

Two criteria for selecting a suitable σ^2 are proposed, both yielding good EDR signals. However, the chosen σ^2 is not always optimal and better results might be obtained using other values for σ^2. Nevertheless, the obtained respiratory signals outperform EDR signals resulting from algorithms like the amplitude of the R peak and PCA, even though σ^2 is not optimal. Determining this selection criterion in unsupervised learning is thus an important research topic that can greatly influence the performance of this algorithm.

C. Performance of Kernel PCA as EDR Algorithm

In order to assess the performance of kPCA as EDR algorithm, the comparison with two frequently used EDR algorithms, linear PCA and R peak amplitude, was made. Kernel PCA showed to outperform both methods. However, many other single lead EDR algorithms exist, such as the algorithms based on the area under the QRS complex [5], [6], based on RSA [4] and based on filtering of the ECG [7], which are possibly more robust than the methods evaluated in this paper. Hence, a validation study that includes all established single lead EDR algorithms is recommended to review the performance of kPCA.

D. Computational Effort

Kernel PCA as EDR algorithm is computationally more expensive than PCA or R peak amplitude. In order to assess the extra computational effort of kPCA with respect to PCA, we evaluated the computation time of both EDR algorithms.

Computations were executed on an Intel(R) Core(TM)2 Quad CPU Q9650 processor with 3 GHz using MATLAB R2010a (MathWorks, NA, USA). The two EDR signals were ten times calculated in every subject, starting from the input matrix $\mathbf{X}$. The overall average computation time of EDR_{ent} and EDR_{eig} are respectively 1.254 s and 0.874 s. The difference in computation time is caused by the calculation of the kernel matrix for every value of σ^2 in the entropy case. This step accounts for over 90% (1.149 s) of the total computation time, whereas iterations based on the eigenvalues cost about 0.724 s. The pre-imaging step takes on average 0.104 s. On the other hand, EDR signals obtained using PCA are acquired in a considerably smaller computation time of 0.007 s.

These results shows that kPCA is less suited for real-time calculation of the surrogate respiratory signal compared to other EDR algorithms. However, for most applications, the higher computational effort is acceptable. To reduce the computation time, we suggest to use the eigenvalue criterion as this is faster and has no disadvantage compared to the entropy criterion.

However, when longer segments are analyzed, kPCA has an advantage over PCA. In this paper, we only computed the EDR signal of segments of 5 minutes. Longer segments will increase the computation time. In linear PCA, the covariance matrix needs to be calculated, yielding an $n \times n$-matrix. The number of R peaks that can be included is thus subject to the available memory in MATLAB. Kernel PCA on the other hand solves the eigenvalue problem of the kernel matrix $\mathbf{K}$ with dimensions $m \times m$, which is independent of the number of R peaks.

E. Failure of EDR Algorithms

In some cases, kPCA using different values for σ^2 does not succeed in producing a good EDR signal, and both PCA and R peak amplitude fail likewise. This failure might be due to the fact that the orientation of the ECG lead vector and the orientation of the electrical axis of the heart are very close, causing an apparent doubling of the respiratory frequency in the EDR signals. The use of other ECG leads should improve the quality of the EDR signals.

We also hypothesize that the type of breathing influences the performance of the EDR algorithms; most persons breathe via the chest. However, some persons, such as sportsmen and musicians, are trained to breathe via the abdomen. Both breathing types have other mechanisms to allow filling and emptying of the lungs. The different mechanical movements might cause an altered relation between the ECG and the respiratory influence.

The placement of the electrodes, the used ECG leads and the abdominal and thoracic effort during breathing are thus important factors that need to be taken into account. Future studies need to focus on these issues.

V. Conclusion

Kernel Principal Component Analysis proved to be a promising algorithm to obtain ECG-derived respiratory signals. The comparison of different types of kernel functions led to the selection of a radial basis function kernel. However, the parameter σ^2, indicating the variance of the RBF kernel, needed to be optimized, which is a difficulty in unsupervised learning. We proposed two criteria, based on entropy and the difference in eigenvalues, to select a suitable value for σ^2. KPCA using an RBF kernel function and selection of σ^2 according to both criteria showed to outperform linear PCA and R peak amplitude and kPCA using other kernel functions as methods for ECG-derived respiration. These results encourage the use of kernel PCA as improved EDR algorithm in applications like sleep apnea detection or home monitoring.

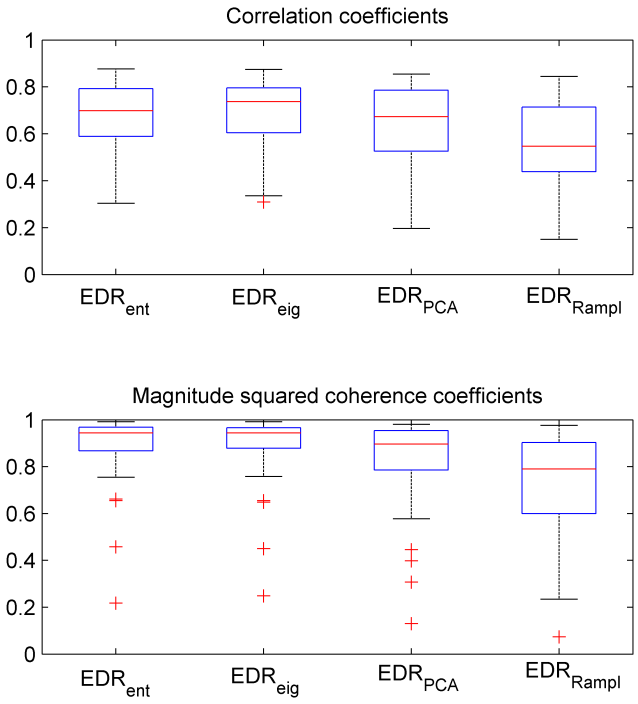


Fig. 9. Comparison of EDR signals obtained with an RBF kernel with σ^2 tuned according to the entropy and eigenvalue criteria, with linear PCA and with the R peak amplitude, expressed in terms of the correlation coefficients and the magnitude squared coherence coefficients.

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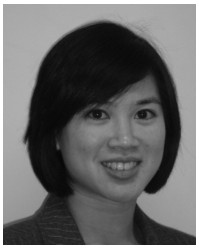
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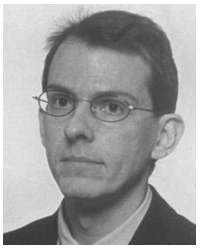
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