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Estimation of Respiration rate from ECG Using Canonical Components Analysis and Ensemble Empirical Mode Decomposition

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Abstract

Electrocardiogram and Respiratory signal are correlated to each other. In this paper respiration rate has been estimated from ECG. We purpose a novel combination of Ensemble Empirical Mode Decomposition (EEMD) and Canonical Correlation Analysis (CCA) in order to remove the artifacts and we have estimated the respiratory rate from the denoised ECG by creating the envelope of the denoised signal. The canonical components corresponding to the artifacts were removed on the basis of correlation coefficient of denoised signal and ground truth signal. The MIT-Polysomonographic and Apnea-ECG databases of physionet bank were used to acquire the ECG signals. Real time Baseline wander noise from MIT-NSTDB was added to each record and the respiratory rate determined was compared with the corresponding respiratory signals. The average snr improvement in case of denoising using EEMD-CCA is 20.8989db. The average BPM error in respiration rate derived from ECG denoised from EEMD is $\pm$ 2.7 *BPM.*

Keywords: *Ensemble Empirical Mode Decomposition (EEMD); Canonical Correlation analysis(CCA); Intrinsic Mode Function(IMF); Canonical Component(CC).*

1. Introduction

The respiratory signal and Electrocardiogram are correlated to each other due to the presence of heart and lungs in the thoracic cavity. The chest movements affect the ECG signal. These mechanical actions of respiration results in the frequency modulation of the ECG signal. These interactions have some recognizable effects which results in baseband and lateral band at each side of the cardiac harmonic in the ECG spectrum [1]. Due to the presence of this type of interaction the ECG can also be used to analyze the respiratory information. As the traditional methods of respiration rate acquisition are cumbersome, ECG signal provides an easy and best alternative.Various techniques have been applied by several authors in order to determine the respiration rate information from ECG signal. DevyWidjajaet al [10] applied the Kernel Principal Component Analysis in order to extract ECG-Derived respiration rate from a single lead ECG signal. K.VenuMadhavet al [11] estimated the respiration signal from ECG signal, Blood pressure(BP) signal and Photoplethysmographic (PPG) signal using EMD. Several approaches have been made using wavelet decomposition in estimating the respiration signal. Marco A.F. Pimentel et al presented a Gaussian process framework for the estimation of the respiratory rate from the different sources of modulation in a single lead ECG signal. All these approaches were based on various signal processing techniques with different levels of complexity. The proposed method is based on the use of combination of Ensemble Empirical Mode Decomposition and Canonical Correlation Analysis. This method uses the base source separation property of CCA in order to perform the denoising in

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the initial stage which results in promising results in the process of estimation respiration rate from ECG.

2. Methods

2.1 Ensemble Empirical Mode Decomposition

EEMD gives true Intrinsic Mode Functions (IMFs)as the mean of the corresponding IMFs obtained via EMD over an ensemble of trails, generated by adding different realizations of white noise of finite variance to the original signal x[n] [2, 3]. EEMD algorithm can be described as:

1. Generate $x^i[n] = x[n] + w^i[n]$, where $w^i[n]$ (i =1……, I) are different realizations of white Gaussian noise.
2. Each $x^i[n]$ (i = 1; : : : ; I) is fully decomposed by EMD getting their modes $IMF_k^i[n]$, where k = 1,..,K indicates the modes.
3. Assign $IMF^{\sim}{}_k$ as the k-th mode of x[n]; obtained as the average of the corresponding

$$IMF_k^i : IMF^{\sim}{}_k\,[n]=\frac{1}{I} IMF_k^i[n]. \quad (1)$$

So for each one a residue is obtained as

$$r_k^i[n] = r_{k-1}^i[n] - IMF_k^i[n] \quad (2)$$

The amplitude of white to be added also plays an important role . If the amplitude of the added noise is too small relative to the original signal no effect on mode mixing prevention can be achieved, on the other hand if it is too large it would result in redundant IMF components [4]. In [2], the amplitude of the added white noise was set as 0.2 times the standard deviation of the original signal.

2.2 Canonical Correlation Analysis

CCA was developed by H. Hotelling . Although being a standard tool in statistical analysis, where canonical correlation has been used for example in economics, medical studies, meteorology and even in classification of malt whisky, it is surprisingly unknown in the fields of learning and signal processing. CCA is another technique which employs the Blind source separation (BSS)method for separating a number of mixed or contaminated signals [9]. CCA solves the BSS problem by forcing the sources to be maximally autocorrelated and mutually uncorrelated[6] . Given an input signal **x**, let **y** be a linear combination of neighboring samples (**y(t)=x(t+1)+ x(t-1)**). Consider the linear combinations of the Components in **x** and **y** , called the canonical variates.

$$x = w_x^T(x - \hat{\boldsymbol{x}}) \quad (3)$$
$$y = w_y^T(y - \hat{\boldsymbol{y}}) \quad (4)$$

CCA finds the weight matrices w_x and w_y that will maximize the correlation ρ between x and y;

$$\rho = \frac{w_x^T c_{xy} w_y^T}{\sqrt{w_x^T c_{xx} w_x w_y^T c_{yy} w_y}} \quad (5)$$

Where c_{xy} is the between sets covariance matrix and c_{xx} and c_{yy} are the non singular within sets covariance matrices.The calculation of the maximum of ρ can be found by setting the derivatives of (5) to zero with respect to w_x and w_y :

$$c_{xx}^{-1} c_{xy}^{-1} c_{yy}^{-1} c_{yx}^T \widehat{w}_{x=}\rho^2 \widehat{w}_x \quad (6)$$

$$c_{yy}^{-1}c_{yx}^{-1}c_{xx}^{-1}c_{xy}^{T}\widehat{w}_{y}=\rho^{2}\widehat{w}_{y} \quad (7)$$

Here, w_x and w_y can be determined as the eigenvectors of the matrices $c_{xx}^{-1}c_{xy}^{-1}c_{yy}^{-1}c_{yx}^{T}$ and $c_{yy}^{-1}c_{yx}^{-1}c_{xx}^{-1}c_{xy}^{T}$, respectively, and the corresponding eigenvalues ρ^2 are the squared canonical correlations. The first pair of variates are the eigenvectors of w_x and w_y that correspond to the largest square correlation coefficient (or eigenvalue) ρ_{max}^2. The canonical correlation analysis technique, therefore, creates a weight matrix $W_x = [w_{x1}, w_{x2}, \ldots\ldots, w_{xm}]$ that can be used to serve the recorded sources into the self-correlated and mutually uncorrelated sources.

2.3 EEMD-CCA

The EEMD-CCA technique operates in a similar manner to the EEMD-ICA technique. The single channel signal **x** is again converted into a multichannel signal **X** using the EEMD algorithm. The IMF determined to be artifacts are removed and then the remaining channels are used in conjuction with the unmixing**W**, determined using the CCA algorithm, to identify the underlying source signals $\widehat{\boldsymbol{S}}$. Similar to the EEMD-ICA algorithm, the sources corresponding to artifacts are set to zero and then the original multichannel signal is reconstructed, minus the artifact components, using the inverse of the unmixing matrix $\mathbf{W}^{-1}$creating the matrix $\widehat{\boldsymbol{X}}$. The original single-channel signal without the artifacts $\widehat{\boldsymbol{x}}$ can be determined by adding the new IMFs components in the $\widehat{\boldsymbol{X}}$matrix[7].

2.4 Algorithm

There are two stages in the algorithm, one is ECG denoisng and the other is estimation of respiration rate from denoised ECG. The steps involved in this algorithm areexplained below:

1. Firstly a clean ECG signal was taken from the various databases available on [7].
2. Then a real time baseline wander was added to the ECG signal in order to create itnoisysignal. The baseline wander noise was taken from MIT-BIH Noise Stress Test Database (MIT-NSTDB).
3. After this correlation coefficient was calculated in between clean ECG signal(ground truth signal (GT)) and noisy signal.
4. Then the noisy signal was fed to the EEMD algorithm. The amplitude of the white noise, added in case of EEMD while calculating true IMFs, was taken as 0.2 time the standard deviation of the noisy signal.
5. The IMFs obtained after EEMD were fed to the CCA algorithm. The canonical components which were regarded as artifacts, on the basis of correlation coefficient with the ground truth reference, were set to zero.
6. The remaining canonical components were used to reconstruct the signal by passing them through the inverse of unmixing matrix. Then the denoised signal was obtained by adding these newly obtained IMFs.
7. The comparison of these techniques was done by calculating the signal to noise ratio both after and before the denoising process.
8. Then the envelope of the denoised ECG signals was obtained through R-peak detection.
9. This envelope was considered as the estimated respiratory information and it was compared with original respiratory signals corresponding to the ECG signal.

The comparison was done by calculating the breathes per minute of both the original and the estimated respiratory signal.

3. Simulation and Results

In the proposed method ECG signals were taken from the Physionet.Two databases were used , MIT-Polysomnographic database and Apnea-ECG database. The sampling rates of signals are digitized at 250 Hz in MIT-Polysomnographic database and the sampling rate of signals is 100 Hz in Apnea-ECG database. Four records were taken from both the databases including ECG and their corresponding respiratory signals. The duration of samples taken is one minute.

The results were computed in both thestages,denoising and estimation of respiratory rate. The comparison parameters for denoising parameters are signal to noise ratio and correlation coefficient both before and after the denoising process. The comparison parameter is breathes per minute (BPM).

Signal to noise is given by the formulae given below

$$snr_{bef} = 10\log\left(\frac{\partial^2{}_x}{\partial^2{}_{ebef}}\right) \quad (8)$$

$$snr_{aft} = 10\log\left(\frac{\partial^2{}_x}{\partial^2{}_{eaft}}\right) \quad (9)$$

$$\Delta snr = snr_{aft} - snr_{bef} \quad (10)$$

$\partial^2{}_x$is the variance of the ground truth signal,$\partial^2{}_{ebef}$is the variance signal of the error signal beforedenoising,$\partial^2{}_{eaft}$is the variance of the error signal after denoising. Error signal is the difference between the ground truth signal and noisy signals before and after the denoising process.The correlation coefficients calculated at both the input and the output stage of the denoising process. These coefficients are given as under

COR_NOISY= correlation coefficient between noisy and ground truth signal.

COR_DEN= correlation coefficient between denoised and ground truth signal.

Table 1. Performance of EEMD-CCA Algorithm in Denoising of ECG from Apnea andMit-Polysomonographic Database

Record	Samples Taken	Amplitude of the white noise	Canonical Components set to zero	COR_NOISY	COR_DEN	snr_{bef}	snr_{aft}	Δsnr
$A01_{er}$	6000	13.840	1-9	0.7365	0.9513	1.727	22.998	21.271
$A02_{er}$	6000	10.885	1-8	0.5101	0.9316	-10.682	18.657	29.340
$A04_{er}$	6000	16.485	1-11	0.8231	0.9736	7.4377	29.107	21.669
$C03_{er}$	6000	12.6236	1-8	0.6708	0.9524	-1.8896	22.990	24.879
$B01_{er}$	6000	15.0767	1-10	0.7838	0.9685	4.6515	27.290	22.638
slp01a	15000	09.176	1-9	0.5507	0.9370	-8.386	20.494	28.880
slp59	15000	12.914	1-8	0.8042	0.9723	6.0858	28.608	22.522
slp01b	15000	09.115	1-9	0.5394	0.9308	-8.8641	19.098	27.962
slp67x	15000	13.859	1-9	0.8326	0.9539	8.0923	23.596	15.504
slp66	15000	12.998	1-9	0.8070	0.9612	6.2496	25.4499	19.200

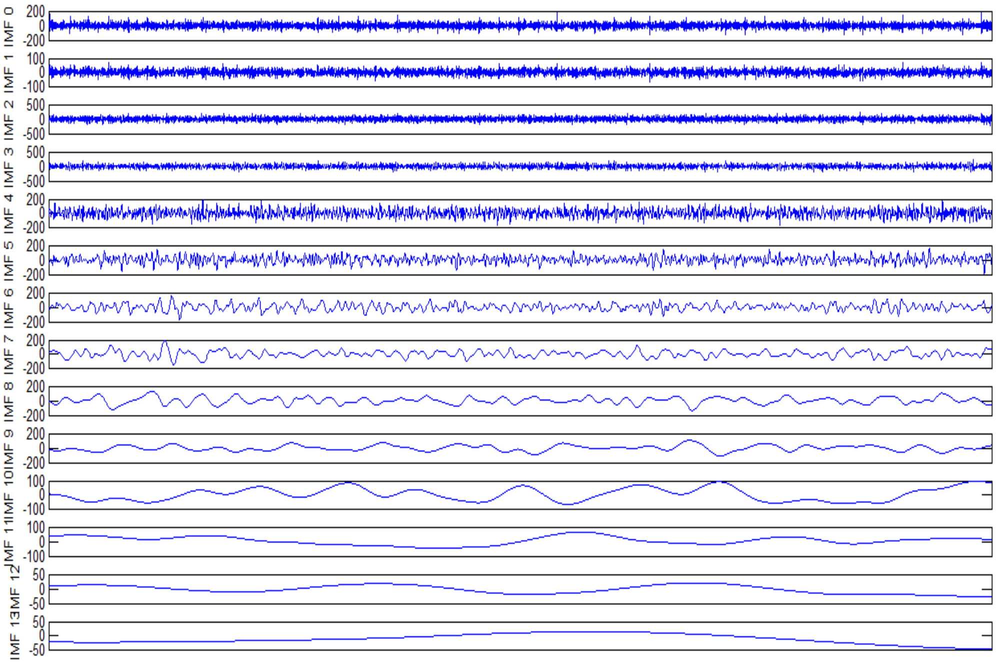

Figure 1. Different IMFs Obtained after Performing EEMD

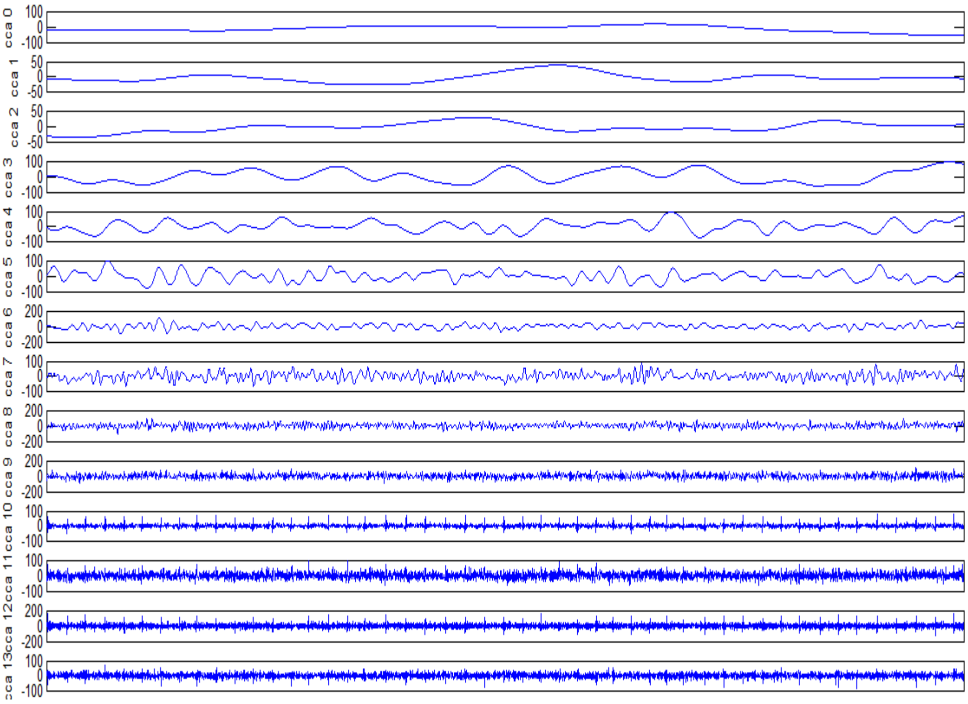

Figure 2.Different Canonical Components Obtained after Performing CCAon IMFsObtained from EEMD

Table 2. Estimation of Respiration rate after Denoising ECH Signal through EEMD-CCA Algorithm in Case of Apnea and Mit-polysomonographic Database

DATABASE	Record	Sample Taken	Time Duration	Original Respiratory Signal (BPM)	Estimated Respiratory Signal (BPM)
APNEA ECG	$A01_{er}$	6000	1 min	14	12
	$A02_{er}$	6000	1 min	21	26
	$A04_{er}$	6000	1 min	17	14
	$C03_{er}$	6000	1 min	14	14
	$B01_{er}$	6000	1 min	16	14
MIT POLYSOMONOGRAPHIC	slp01a	15000	1 min	13	12
	slp59	15000	1 min	18	17
	slp01b	15000	1 min	11	11
	slp67x	15000	1 min	15	14
	slp66	15000	1 min	19	14

The table 1 gives various parameters of thedenoising ECG signals taken from Apnea-ECG and MIT-Polysomonographydatabase. The performance of the algorithm in estimating the respiratory rate is depicted in table 2.

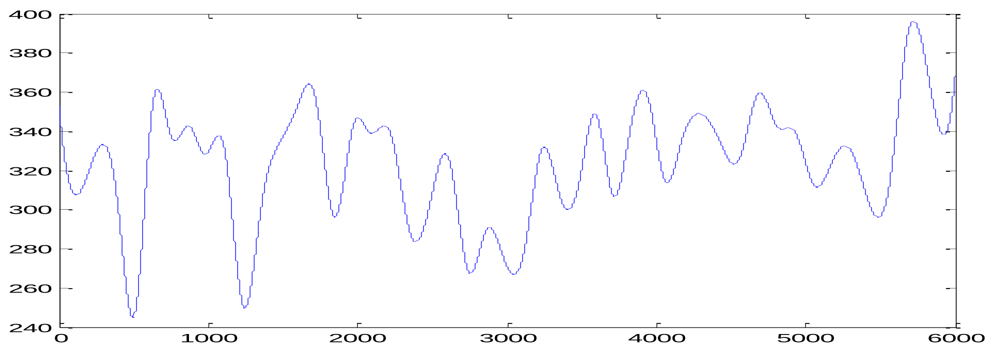

Figure 3 Estimated Respiratory Rate of C03er (Apnea-ECG database) after EEMD-CCA

The graphical analysis shown in the above figures depict the various outputs obtained at the different stages of the proposed method. Figure 1 shows the true IMFs obtained after performing the EEMD of the noise contaminated signal. Figure 2 shows the results of performing CCA on the obtained IMFs which were obtained in the previous stage. Finally the estimated respiration signal of $C03_{er}$ has been shown in the figure 3.

4. Conclusion

The proposed method shows that respiration signal can be easily estimated from the ECG signal using the Canonical correlation analysis as a BSS process, which is used for respiratory disorders estimation like sleep apnea and dyspnea. Though the ECG signal is single channel signal but by using the EEMD for the generation of multichannel signal CCA can be easily used. The error in the estimated respiratory rate information is also less i.e. $\pm$ 2 BPM. The combination of EEMD-CCA shows promising results in the denoising stage. The average *snr* improvement in case of EEMD-CCA is 20.8989 db.

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