RSA Estimation

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1 Introduction

Respiratory Sinus Arrhythmia (RSA), is the naturally occurring change in the interval between heartbeats in response to pulmonary breathing [Grossman and Taylor, 2007]. Often seen as the causal effect of the Para-sympathetic nervous system it constitutes the High Frequency(HF) component of the Heart rate Variability (HRV) signal. In the power spectrum of the tachogram, the Low Frequency(LF) power is constituted by the power in the frequencies between (0.05-0.15 Hz) where as in the HF spectrum it is seen as the power in the frequency ranges of 0.20-0.45 Hz. HF power is mainly affected from respiration changes, increasing during inspiration and decreasing while expiring. Considered as a gateway for the Vagal outflow the exact mechanism and physiological origins of RSA is much debated. Among the major theories one relates it with a central mechanism, another with a blood volume and baroreflex mechanism.

Generally, the HF power peak corresponds to the RSA but since RSA is dependent on the respiration rate of the subject at times the RSA might overlap with the LF range distorting the spectral characteristics of the tachogram. Hence, it is imperative to separate the respiratory influences from the tachogram to ensure respiration free HRV features. Since RSA can be extracted easily and non-invasively it is often useful as an index of the cardiovascular system Tiinanen et al. [2009] , mainly used as a clinical marker for a particular health related condition Mirmohamadsadeghi [2017]. Very recently,Silvilairat et al. [2016] showed the RSA can serve as an index to early detection of cardiac iron accumulation before myocardial dysfunction. Due to its partly Autonomic and partly respiratory origin RSA is considered as a biological marker to emotions,sleep apnea stages, Mental tasks and other Long-stating psycho-physiological conditions.

In this work we propose a knowledge based dictionary approach to extract the RSA component from the Heart Rate(HR) time series. We develop a RSA specific dictionary that takes into account the characteristics signal structure in time. Since the Sinus rate is assumed to increase with respiration and decrease with expiration, similar to the characteristics of the respiratory signal we use a sinusoid as our atom , the fundamental element in the dictionary. The use of the functional form of the respiratory signal is also inspired by the fact that the respiratory signal has been often used as the surrogate signal to estimate RSA in adaptive filtering techniques.

2 Previous work

One of the earliest method to estimate RSA by adaptive filtering was first proposed by Widjaja et al. [2014] using a lattice adaptive filter. Later, Tiinanen et al. [2008] used Least mean square(LMS) algorithm to remove the RSA influence from the tachogram. Independent component analysis(ICA) was used by Tiinanen et al. [2009] to separate the tachogram into two frequency dependent components defined by their respective frequency bands. Bakshi [1998] removed the drawbacks of conventional PCA enhancing its robustness by decreasing its sensitivity to outliers in the data. With the introduction of the scaling functions in the wavelets, the maximization problem of the PCA changes to a constrained optimization problem as only the distance between the points within that scale need to be maximized rather than all the points. This reduces is its sensitivity to outliers. This makes it one of the primary candidates for its use in computing the component of the tachogram that is directly related to respiration. Another, method which also uses the respiratory signal as a surrogate was developed by Caicedo et al. [2012]. It uses the reference signal to derive an orthogonal subspace representing the respiratory activity. The original tachogram is the projected into the derived subspace to estimate the respiratory component.

3 Sparse representation of Respiratory Sinus Arrhythmia (RSA)

In this section, we present the proposed dictionary based approach for extracting the arrhythmic component of the Heart rate time series or the R-R time series.

3.1 Dictionary design

Due to its ability to model a signal as a linear combination of small number of atoms,sparse signal representations techniques can model the implicit variability within a time series with much less number of atoms than the size of the actual signal itself. As mentioned earlier we use the characteristic structure of the respiratory signal. The variations and trends in the respiratory time series is modelled by smooth, phase-shifted sinusoidal Waveform. The atoms in the dictionary are allowed to have a frequency range from 0.20-0.45 Hz. The amount of frequency decimation to capture the frequency range is calculated from the length and the sampling frequency of the HR time series. To capture the initial phase misalignment for a particular frequency every atom in the dictionary is given phase shifts ranging from 0 to 2π.

In Mathematical notation,

$$g_n(t) = sin(2\pi f_i t + \phi_i^j(t))u(t) \tag{1}$$

$$f_i \in \{0.20, 0.21, 0.22, \ldots, 0.45\}, \phi_i^j \in \{0, \pi/4, 2\pi/4, \ldots, 2\pi\} \tag{2}$$

where u(t) is the Heaviside unit step function , the variable i denotes the $\imath^t h$, frequency component , the variable j denotes the $\jmath^t h$ phase shifted sinusoid for the $\imath^t h$ frequency component.

3.2 Signal Approximation

The aforementioned RSA dictionary is used to estimate and extract the RSA from the Heart Rate time series f(t). We can express the approximation as a finite linear combination of the fundamental dictionary elements. The approximate mathematical notation for the formulation can be given as:

$$f(t) \approx \hat{f}_N(t) := \sum_{n=1}^{N} c_n f_n(t) \tag{3}$$

where $g_n(t)$ represent the n^{th} selected atom from the dictionary and c_n the corresponding scalar co-efficient of the atom. The problem of selecting an appropriate corpus of atoms from a dictionary is combinatorially exhaustive and is considered a NP-hard problem. There are many approximating strategies to circumvent the approximation problem. Here, we follow Orthogonal Matching Pursuit(OMP) to reach to a sub-optimal solution by approximating the signal in an iterative manner Pati et al. [1993]. As an iterative greedy approximation algorithm , at each iteration , OMP selects the atom which provides the maximum correlation with the current signal residual R_n^f. At every iteration n, OMP selects the atom which has the maximum co-relation with the the current signal residual R_n^f.

$$R_n^f = f - f_n, f_n = \mathbf{G_n}(\mathbf{G_n}^T * \mathbf{G_n})^{-1}\mathbf{G_n}^T f \tag{4}$$

here G_n is the matrix of selected atoms till the n^{th} iteration, whereas f is the sampled version of the signal $f(t)$, and f_n is the approximation of the input signal after n iterations of the OMP.

3.3 Evaluation criteria

For evaluating the efficacy of the proposed algorithm we use the metrics proposed in Tiinanen et al. [2009] and further analyze our estimate in terms of co-relation and coherence between the original,residual tachogram (after removing RSA) and the respiratory signal. A higher co-relation co-efficient will be expected in the original tachogram with respect to the residual tachogram. Since the RSA peak can overlap in the LF as well as in the HF range, the metric considered by Tiinanen et al. [2009] have calculated the power spectral densities in both the bands. Power Spectral Densities(PSDs) were calculated for the original HR series using the Welch's method. The original signal is divided into longest possible segments but not exceeding 8 segments with a 50% overlap of the present segment with the previous one. Center frequencies(CFs) were defined as maximal peak frequencies within a particular band. CFs were detected in HF segment as well as the LF segment before and after the removal of RSA. The metrics computed from the original tachogram before removal of RSA were considered to be Baseline estimates. An appropriate spectral estimate would ensure the CFs in the original and the residual tachogram are aligned. Therefore, the location of the CFs in the original and the residual tachogram can be used as one of the metrics in evaluating the efficacy of the spectral estimation.

Generally, the respiratory influence lies in the HF range but at times can overlap with the LF frequency ranges as well. After removal of RSA the extracted power in the original tachogram is reduced at the respiration range. This reduced power in the residual tachogram can be used as another metric for evaluating the proposed model. The reduction in power compared to the baseline power seems significant in all the cases. Statistical difference was calculated non-parameterically using the Wilcoxon Signed rank test. Our estimates of the LF and the HF power for the residual tachogram follow closely with that of the surrogate signal based estimate using the adaptive filtering technique. Spectral indices were calculated for Baseline,Proposed method and LMS filtering.

4 Data description and pre-processing

The dataset used here was a multimodal dataset for analysing human affective states [Koelstra et al., 2011]. The DEAP dataset had 40 one minute long music videos watched by 32 participants. There were other physiological signal besides the PPG signals. We used the PPG and the respiratory belt signal for our development and evaluation purpose. The original Heart rate time series was extracted by detecting the peaks of the PPG signal. The Hear Rate(HR) time series extracted was further band pass filtered to remove the low frequency drift or baseline wandering.

5 Results

The CF estimates for the LF as well as the HF spectrum in the residual tachogram show that the estimated Center Frequencies lie very close to the center frequencies in the original tachogram. Indicating the fact that the CF of the estimated RSA spectrum is aligned with the HF peak of the original tachogram.

As also shown in figures the estimated HF spectrum is similar in shape or a replica of the original HF spectrum. The knowledge based dictionary approach seems to have estimated the RSA spectrum quite well whereas in case of the LMS filtering based approach, which uses the respiratory signal as the reference signal seems to have over estimated the HF power spectrum. This over estimation leads to distortion of the spectral estimation indices as is evident in the

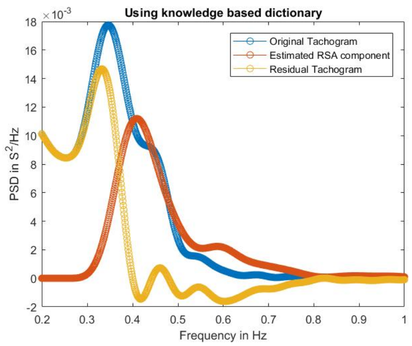

Figure 1. PSD of the Original Tachogram, RSA estimate and the Residual Tachogram using knowledge based dictionary approach.

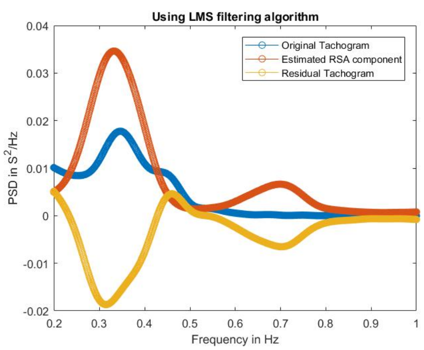

Figure 2. PSD of the Original Tachogram, RSA estimate and the Residual Tachogram using LMS filtering algorithm.

PSD of the residual tachogram. In the LF range, LMS based adaptive filtering and the Knowledge based dictionary approach seems to have estimated the power quite well.
[1]

DEAP dataset			
HRV parameters	Baseline	LMS filtering	Proposed Method
$LF(ms^2)$	5.0168	3.9941*	5.0168
$HF(ms^2)$	0.0554	-0.1155*	0.0451*
Center Frequency-LF(Hz)	0.0800	0.0815	0.0800
Center Frequency-HF(Hz)	0.2734	0.3244	0.2498

[1] *indicates pValue<0.05 when compared with the baseline

6 Conclusions and future Work

In this paper we developed a sparse representation model for modeling RSA time-series by the use of appropriately designed dictionaries, that take into account the nature and the functional form of the RSA signal. The obtained results indicate that the proposed model captures the spectral characteristics of the signal.

As a part of our future work we plan to test our model quantitatively and qualitatively on different data-sets. We further plan to use the developed model for removal of RSA as a preliminary step in our generative model for modelling heart period responses.

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