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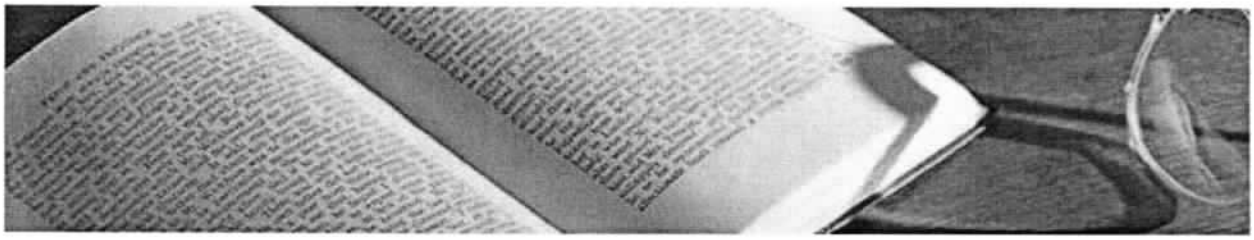

The Analysis of Heart Rate Variability using Independent Component Signals

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Keywords

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Abstract

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ABSTRACT
Assuming that the fluctuations in the RR intervals or in (RR, QT) intervals of an ECG signal correspond to measures or sensor signals of a linear mixing model the independent components or source signals are computed. To extract the independent signals we propose a modified version of the algorithm AMUSE. A preliminary experimental study show that the estimated independent components are in fact related with the Low Frequency (LF) and other with the High Frequency (HF) fluctuations of heart rate variability.

KEY WORDS
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1 Introduction

The spectral analysis of of heart rate fluctuations can be used to assess autonomic regulation [3]. The spectral heart rate has been separated into three frequency bands: Very Low Frequency band (VLF range below 0.04Hz), Low Frequency band(LF range 0.04-0.15HZ) and high-frequency band (HF range 0.15- 0.4HZ). The high frequency fluctuations (HF) are recognized to reflect parasympathetic nervous activity (PNA) while the interpretation of low-frequency fluctuations (LF) are associated to sympathetic nervous activity (SNA) and parasympathetic nervous activity (PNA). The spectral studies are usually driven by the RR intervals detected on a ECG signal or by study the blood pressure [3, 1].
More recently there is a signal processing technique called blind source separation and/or independent component analysis that is concerned with the separation of signals into independent components or sources signals. Hence it is interesting to known if independent component analysis can contribute to the interpretation of LF and HF fluctuations of cardiovascular signals and if they can be related to SNA and PNA. The independent component analysis strategy applied to RR and QT sequences was proposed by Vetter [8, 10]. Vetter uses a Principal Component Analysis (PCA) followed by generalized eigendecomposition to extract the independent signals. In this work we follow the strategy proposed by Vetter to increase the data dimension but the processing is reduced to generalized eigendecomposition of a matrix pencil. In the next sections we will present the proposed method and compare it with Vetter's work. Then the proposed method is applied to RR and (RR,QT) sequences to compute independent signals. The spectral analysis of the independent signals is presented and discussed.

2 Methods

Let us consider a noisy, linear and m-dimensional mixing model given by

$$x(k) = Hs(k) + r(k) \tag{1}$$

where $x(k) \in \Re^m$ are the m observed/measured noisy signals or linear mixtures, $H \in \Re^{m \times n}$ representing an unknown mixture matrix, $s(k)$ are the n hidden independent signals and $r(k)$ are the additive noise.

The problem is to find out the source independent signals $s(k)$ having only the observed signals $x(k)$. There are several proposals to solve this problem when $m \geq n$, whose performance is very dependent on the proper estimate of the noise amount [2, 9]. Some of the proposed methods are based on the generalized eigendecomposition of a matrix pair (R_1, R_2) [6]. For instance the algorithm AMUSE is a second order method where the matrix R_2 is a correlation matrix and R_1 is a time-delayed correlation matrix [2, 7]. The transpose of eigenvector matrix of the generalized eigendecomposition will be the separation matrix (W), i.e. $s(k) \approx Wx(k)$.
The generalized eigendecomposition is usually addressed as a two step procedure. The first step is very similar to a PCA where a standard eigendecomposition of a correlation matrix (R_2) is performed. Using the results of this eigendecomposition the matrix R_1 (or the raw data) is linearly transformed, and the second standard eigendecomposition is computed. The separation matrix (W) is calculated with the results of both eigendecompositions [2, 7]. We follow a similar strategy using a new data vector $\tilde{x}(k)$, that contains the original signals $x(k)$ and its delayed versions. In the

next sections we will present the two step of the modified AMUSE algorithm:

- computing the standard eigendecomposition of R_2 reducing the number of signals by the use of a variance criterium
- transform the data or $R_1$and then compute another eigendecomposition.

2.1 First Step

In the first step we increase the data's dimension and compute a new data vector as follows:

$$\tilde{x}(k) = [x_1(k), ..., x_1(k+lag), ..., x_m(k), ..., x_m(k+lag)]^T \quad (2)$$

the new data $\tilde{x}(k) \in \Re^j$, where $j = (lag + 1)m$. With the new data set the correlation matrix is computed on a segment of data of length N, according to the following expression

$$R_2 = \frac{1}{N} \sum_{k=0}^{N-1} \tilde{x}(k)\tilde{x}^T(k) \quad (3)$$

Assuming that the signals are not correlated with noise signals, the correlation matrix is symmetric positive definite the eigenvectors (ν_i) and eigenvalues (λ_i), are computed. The eigenvalues are organized in descending order ($\lambda_1 > \lambda_2 > ... > \lambda_j$) and l most significant are chosen according to the following criterium

$$\frac{\lambda_1 + \lambda_2 + ... + \lambda_l}{\lambda_1 + \lambda_2 + ...\lambda_j} > TH \quad (4)$$

Then, we are only interested in the eigenvectors corresponding to the directions of higher variance of the signals. The threshold (TH) should be chosen so that the maximum energy of the signals is preserved. The transformation matrix is then computed by the following equation

$$Q = \wedge^{-\frac{1}{2}} \vee^T \quad (5)$$

where $\wedge$ is an $l \times l$ matrix with the chosen eigenvalues on the diagonal and $\vee$ is an $j \times l$ matrix containing the corresponding eigenvectors on the columns. The data is then transformed by $\hat{x} = Q\tilde{x}$. Each $\hat{x}_i$, $i = 1, .., l$, is the projection of the signals onto the directions of the chosen eigenvectors (ν_i) as it is suggested in [8], but the projection is also normalized by $\lambda_i^{-\frac{1}{2}}$. With this normalization the next step can be a standard eigendecomposition instead of generalized eigendecomposition as proposed by Vetter.

2.2 Second Step

This stage is characterized by the estimation of the independent components from the new matrix of orthogonal mixtures. In the second stage of this method, a new time-delayed correlation matrix, R_x is calculated from the prewhitened data vector found in the previous step, after that an eigenvalue decomposition is made

$$R_x = \frac{1}{N} \sum_{k=1}^{N} \hat{x}(k)\hat{x}^T(k-p) = QR_1Q^T \quad (6)$$

The time delayed correlation matrix can be computed on the extended data set

$$R_1 = \frac{1}{N} \sum_{k=1}^{N} \tilde{x}(k)\tilde{x}^T(k-p) \quad (7)$$

So computing the time-delayed correlation matrix R_1 and transforming it using matrix Q as indicated in eqn. 5 or transform the data are equivalent operations. The eigenvectors of the standard eigendecomposition of R_x form the columns of the orthogonal matrix U computed in this step. The separation matrix will be

$$W = U^T Q = U^T \wedge^{-\frac{1}{2}} \vee^T \quad (8)$$

3 Results

We use ECG signals of two young normal subjects from POLY/MEDLAV database[5]. One lead of the stored ECG signal was processed by a wavelet transform based automatic delineation system [4]. Then each heart beat is

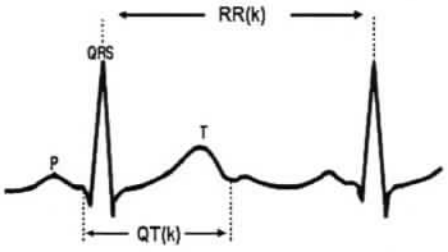

Figure 1. Schematic representation of ECG signal: RR(k)-time distance between two consecutive R waves ; QT(k) - time distance between Q wave and T wave

characterized by two sequence whose values are the time distance between consecutive R waves (RR) and Q and T waves (QT) as illustrated in Figure 1. The ECG signals of two subjects were chosen because the corresponding respiration signals have spectral contents in distinct bands:

- ECG1 - in the low frequency band (LF)
- ECG2 - in higher frequency (HF)

The proposed algorithm was applied using as input RR and (RR,QT) sequences, i.e. $x(k) = [RR(k)]$ or $x(k) = [RR(k), QT(k)]^T$. In all the experiments the free parameters of the algorithm are: $lag = 7$, $TH = 0.95$ and $p = 1$.

The computed independent component signals are not correlated in time domain and suffer from an indetermination on its amplitude as it is expected on these methods. Then in order to achieve a direct comparison they are normalized to unitary variance and amplitude in range [-1,1]. However in HRV studies the frequency contents in distinct bands is the relevant information. So, the results presented here will show the frequency contents of each independent signal. The frequency contents of the signals is studied by the Welch method. Then, the frequency contents of the independent signals are compared graphically and correlation coefficients are also computed.

3.1 RR time series

For these experiments,with the input vector $\tilde{x}(k) \in \Re^8$, the number of independent components, $s(k)$ computed is different for the ECG signals of the two subjects as can been see in Figure 2. The RR sequence presents a component

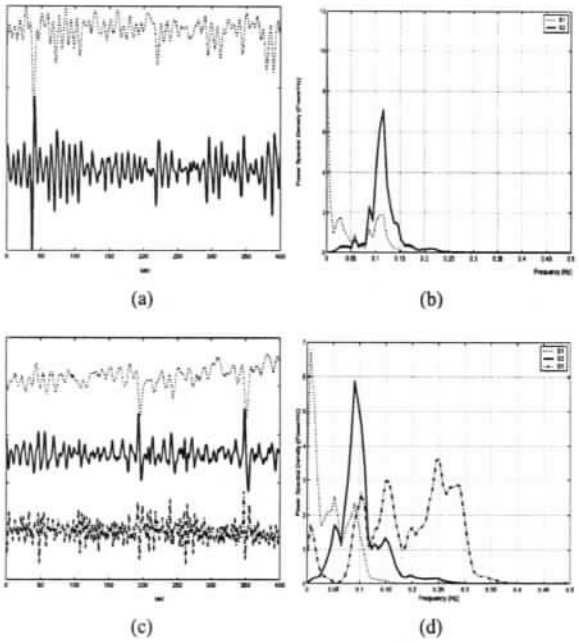

Figure 2. ECG1: (a)-Independent Components, (b)-Spectral contents of independent components; ECG2: (a)-Independent Components,(b)-Spectral contents of independent components

with high frequency information if the respiratory signal has also high frequency contents. Nevertheless we can see that in both cases the components computed have distinct frequency ranges . The Table 1 also show that these components which have a correlation coefficients equal to zero in the time domain they also have a small value when the coefficients are computed in the frequency domain.

	ECG1			ECG2		
	S_1	S_2	S_3	S_1	S_2	S_3
S_1	1	0.26	-	1	0.38	0.13
S_2	0.26	1	-	0.38	1	0.33
S_3	-	-	-	0.13	0.33	1

Table 1. Correlation coefficients between frequency contents of independent components when the input is RR sequence

3.2 RR-QT time series

For these experiments,with the input vector $\tilde{x}(k) \in \Re^{16}$, and three independent components computed and its frequency contents is distinct frequency ranges as seen in Figure 3.

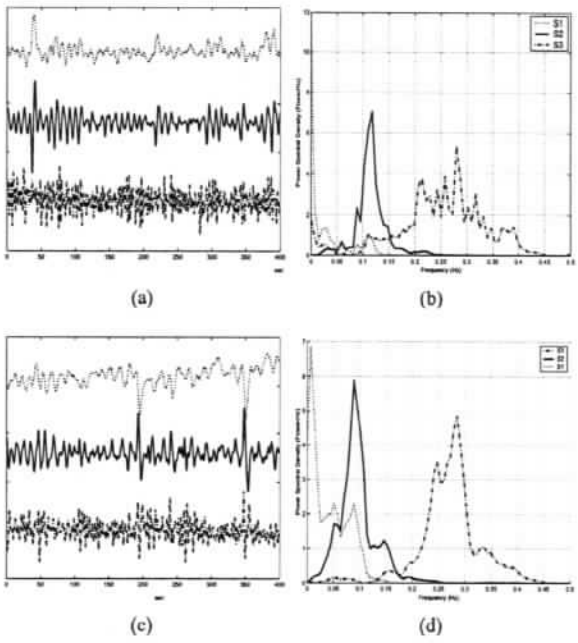

Figure 3. ECG1: (a)-Independent Components, (b)-Spectral contents of independent components; ECG2: (a)-Independent Components,(b)-Spectral contents of independent components

In table 2 we can see the correlation between the frequency contents of the components independents and as before the values are very low.
For both signals comparing the two components (LF and VLF) are very similar to the ones computed with RR sequence as we can see comparing the figures2 and 3. In fact, the correlation coefficients computed between VLF or LF components using RR or (RR,QT) sequences are ≥ 0.95. The signal ECG1 now presents a third component repre-

	ECG1			ECG2		
	S_1	S_2	S_3	S_1	S_2	S_3
S_1	1	0.10	0.09	1	0.38	0.14
S_2	0.10	1	0.03	0.38	1	0.13
S_3	0.09	0.03	1	0.14	0.13	1

Table 2. Correlation coefficients between frequency contents of the independent components when the input is RR and QT sequences

senting the high frequency band which was not found when the input was only the RR sequence, what suggests that RR and QT reflect different influences of PNA and SNA. In spite of a third component appearing for ECG2, both with inputs RR and (RR,QT), the dissimilarity found in shape and dispersion of the spectra reinforces the supposition of different effects. This hypothesis was already stated in [1] when studying the dynamic relation between HRV and QTV using a very different approach; furthermore our results are consistent with the ones presented in that paper, for the same signals.

4 Conclusions

In this work we presented a modified version of algorithm AMUSE that can be applied when the number of mixed signals is lower then the number of sources. The algorithm has free parameters (lag, TH, p) that influence the algorithm performance. In this work those parameters are chosen experimentally, but further work is need to find a methodology to compute those values.

In what concerns the application of the technique to the HRV study those preliminary results are similar to the ones presented by Vetter. It is important to notice that Vetter used a pre-processing (re-sampling and bandpass filtering)step of the RR and QT sequences and generalized eigendecomposition after PCA. In this work the generalized eigendecomposition was applied directly to the measured sequences. Nevertheless, the methods should be studied in a larger set of data, validated by comparison with more traditional approaches and improved by the inclusion of other related signals, such as blood pressure.

The results obtained including the QT series on the input indicates that RR and QT reflect different influences of PNA and SNA, allowing to access complementary information. This preliminary experimental study suggests that the independent component analysis can be a very useful tool to study HRV and QTV and motivates further work in the study of autonomic regulation.

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