Denoising of Heart Rate Variability Signals During Tilt Test Using Independent Component Analysis and Multidimensional Recordings

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Abstract

Vasovagal Syncope (VVS) represents the most frequent cause of loss of consciousness. Additionally to its clinical usefulness, the tilt test is a good quality physiological gold standard for the spectral analysis of Heart Rate Variability (HRV). Noise removal in HRV signals is problematic, due to the presence of ectopic beats and non-stationary short-term trends. Given current Tilt Test systems simultaneously record several physiological signals, we hypothesize that independent component analysis (ICA) may separate physiological from mostly-noise components, and denoising can be properly done. Four-dimensional recordings (HR, systolic/diastolic blood pressure, and ejection volume) were obtained during 50 Tilt Test. After ICA decomposition, a 5th order median filter was applied to the noisiest component, prior to signal reconstruction. In order to check the denoising performance, a gold-standard was made by manually removing ectopic beats and artifacts from the original signals by an expert. For comparison purposes, a 5th order median filter was also applied separately to the HR signal. The spectrum analysis showed that denoising of multidimensional recordings with ICA during Tilt Test yields HRV signals with lower distortion at HF band.

1. Introduction

Syncope is a temporary loss of consciousness and posture, described as *fainting*, that is usually related to temporary insufficient blood flow to the brain [1]. Syncope has in fact enormous medical, social, and economic impact. Only in United States, around one million patients are annually evaluated for this disorder. It has been also estimated that 3% to 5% emergency department visits and 1% to 6% of hospital admissions are for evaluation of Syncope [2]. Also 20% of adults have suffered a sudden fall at least once in their life [3]. Vasovagal Syncope (VVS) is a special case of Syncope that accounts for about a 40% of all Syncope, and it represents the most frequent cause of loss of consciousness [2]. VVS is a form of neurally-mediated reflex Syncope, which consists of a sudden drop in blood pressure with an associated fall of HR. Physiologically, this event is the result of a peripheral vasodilatation and increase of the sympathetic modulation, and all these phenomena are regulated by the Autonomous Nervous System [4]. Additionally, VVS presents some management difficulties, due to it diagnosis is made by discarding other problems, and it has been reported that significant unnecessary diagnostic testing can be made in patients with VVS [5].

The incorporation of the Tilt Table Test as a tool to diagnose patients with unknown originated Syncope has become a standard, due to its important diagnostic value [1]. This test consists of a tilt-table that is capable of moving from supine to vertical position, and physiological parameters can be monitored during the test. Additionally to its clinical usefulness, the Tilt Test is a good quality physiological gold standard for the spectral analysis of Heart Rate Variability (HRV) signals. However, noise removal in HRV signals is problematic, due to the presence of ectopic beats, device artefacts, and non-stationary short-term trends. Moreover, conventional filtering can not be used in this setting, due to its distorting effect on the High-Frequency (HF) of HRV.

During the last years, Independent Component Analysis (ICA) techniques have received special attention and development [6][7]. ICA techniques have been widely used in feature extraction problems [8] and blind source separation, especially in problems with multidimensional physiological data recordings [9][10]. Given that current Tilt Test systems record simultaneously other physiological signals (such as blood pressure or Cardiac Ejection Volume), and given that the physiological HF variations also influence some of these signals, we hypothesize that a static ICA may yield a mostly-noise component, in which denoising could be properly done, while minimizing the distortion on the physiological HF variations shared by the different components.

This paper is structured as follows. In Section 2, we present a short introduction to ICA techniques from an application point of view. In Section 3 we describe the clinical data, obtained during Tilt Test, that were used in the study, and the signal processing that has been used to denoise HRV signals. In the result section, the effectiveness of the ICA-based method is analyzed and compared to conventional filtering of HRV. Finally, conclusions and future work are summarized.

2. Independent component analysis

ICA algorithms are included in a group of techniques generally called Blind Signal Separation, and in practical terms, they allow us to separate the original source signals from their corresponding observed and mixed signals, with little a priori available information. More precisely, ICA is a method for finding underlying factors or components from multivariate (multidimensional) statistical data. What distinguishes ICA from other methods is that it looks for components that are both statistically independent and non-Gaussian.

ICA has been applied to audio processing, financial trend data, antenna array processing for beamforming, coding/encoding, and medical data, among many other fields. Probably the most famous example of application is the classical Cocktail-Party Problem, which is the case of trying to obtain the individual conversations from the mixed ones in a Cocktail-Party.

In mathematical terms, ICA can be seen as the process of obtaining the independent components, if any, of an observed multivariable signal *X,* taking into account that these variables are a linear combination of other variables, the so-called source variables *S*. Our problem can be formulated as follows,

$$x_1(t) = a_{11}s_1(t) + a_{12}s_2(t)$$
$$x_2(t) = a_{21}s_1(t) + a_{22}s_2(t)$$

where $x_i(t)$ is the i[th] variable of the original signal, and $s_i(t)$ is the i[th] variable of the source signal, to be estimated. By using matrix notation, the previous equation system can be expressed as

$$x = As$$

where x is the vector of observed variables $x_i(t)$, s is the vector of source variables $s_i(t)$, and A is a 2x2 array known as *mixing matrix*.

The solution of this problem consists on finding A^{-1}. The way to solve this problem uses certain well-known statistical properties, such as that the distribution of a sum of independent random variables trend toward a Gaussian distribution under certain conditions. These main principles, together with some other numerical developments, transform the ICA problem into an optimization problem with a given objective function. The objective function and the optimization algorithm used yield several possible implementations [11].

3. Methods

3.1. Independent component analysis algorithm

Several ICA implementations have been developed by others, and they are currently available for Matlab or C environments, some of them being strongly tested and widely used for many scientific applications. In our study, we used the FastICA algorithm developed by Laboratory of Computer and Information Science of the Helsinki University of Technology [11].

3.2. Protocol and data acquisition

The multidimensional signal recordings and their corresponding clinical data were obtained from consecutive Tilt Table Test register in *Hospital Virgen de la Arrixaca*. Patients had been referred when suspicion of neurally-mediated syncope. Tilt Table Test protocol employed is next described. After ten minutes of supine rest, the patient was tilt to 60% head-up position during at least 20 minutes. If no syncope-symptom was evidenced during first tilt-phase, sublingual nitroglycerine was then supplied. After a 15 minutes second tilt-phase without symptoms, the test was finished and taken as negative. Tilt test was taken as positive and stopped when experienced syncope. Presyncope was defined as typical symptoms (with no loss of consciousness) and a drop of HR or Systolic Arterial Pressure (SAP) below 70 mmHg. In this study, we defined 3 different phases for a separate analysis: Before Tilt (BT), After Tilt and before nitroglycerin (AT), and Circa Syncope (CS).

The HR, SAP, Diastolic Arterial Pressure (DAP), and

Cardiac Ejection Volume (CEV) were registered in Task-Force Monitor 3040 (CNSystems, Graz, Australia). This system includes multiple surface channels of ECG, from which the HR signal was obtained using the RR intervals. SAP and DAP were the maximum and the minimum, respectively, of the continuous blood pressure signal obtained from a finger blood pressure monitoring system (pletismography). Finally, CEV signals were estimated using the impedance of specific ECG leads.

3.3. Data selection and processing

Out of two hundred recordings from a Tilt Test data base, we selected those meeting the following criteria: having at least one ectopic beat, and no trailing missing values. Before applying the ICA transformation and the denoising filter, initial signal pre-processing was performed to avoid numerical errors by removing samples with individual missing values. The three intervals from the three previously defined phases were selected for each record, i.e., BT, AT, and CS. No distinction between positive (Syncope) and negative (non Syncope) test was subsequently taken into account. Finally, we analyzed 50 multidimensional Tilt Tests, consisting on simultaneously recorded signals of HR, SAP, DAP, and CEV.

We used a conventional ICA algorithm for obtaining 4 different independent sources. We observed that ectopic beats were mostly moved to the IC that was most related to HR, but HF pattern of HR was also present in some of the other components, see Fig. 1. Therefore, we denoised the multidimensional recordings by median filtering (order 5) the IC whose major contribution was due to HR. The resulting signal after the median filtering was transformed back into the original domain to obtain the ICA Filtered Signal (IFS), see Fig. 2.

To evaluate the results, a Gold-Standard (GS) for spectral analysis was created by manually removing ectopic beats in all HR signals. Additionally, to evaluate the improvement, a fourth signal was created by using a (order five) median filter to the original observed signals (Median Filter Signal, MFS).

Normalized High Frequency Power (NHFP) Ratio P_{ratio} was defined as follows to quantify the analysis:

$$P_{ratio} = \frac{P_{HF}}{P_{HF} + P_{LF}}$$

where

$$P_{LF} = \int_{0.04}^{0.15} power\_spectrum$$

$$P_{HF} = \int_{0.15}^{0.4} power\_spectrum$$

Effectiveness reached by all methods was measured by paired Student's t-test among the P_{ratio} obtained for GS and for all other signals.

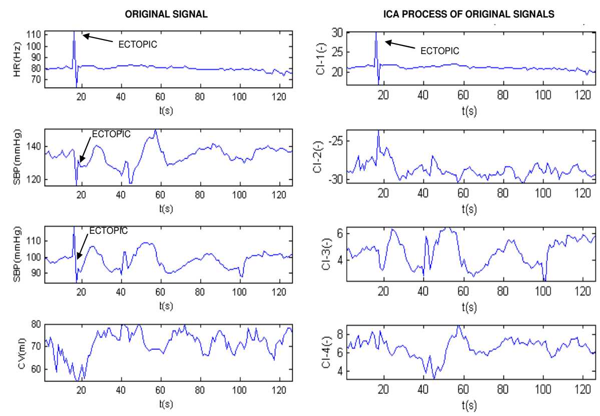

Figure 1. Example of original signals (left) and independent components obtained (right), before filtering the noisy component (CI-1).

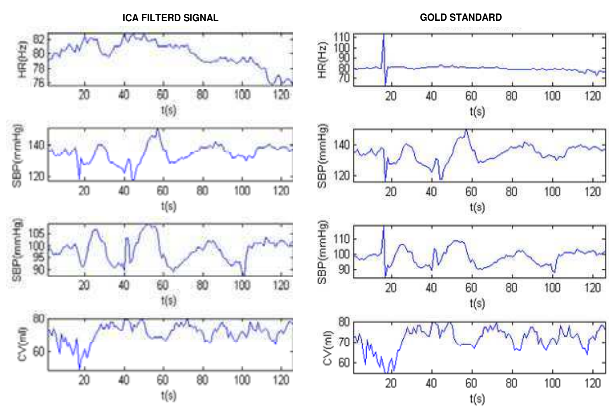

Figure 2. Example of recovered IFS (left) and GS signals (right).

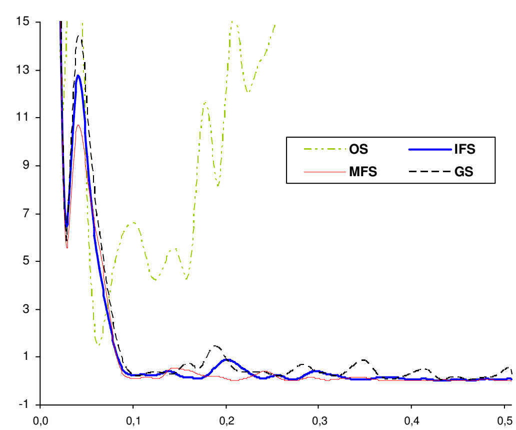

Figure 3. Example of NHFP spectrum comparison of original signal (OS), IFS, IMS, and GS.

Table 1. P_{ratio} Statistical Analysis, all signals, all

segments. Mean, Standard Deviation, and P values from t-test analysis comparison against GS.

	BEFORE TILT			AFTER TILT			CIRCA SYNCOPE		
	Mean	St.Dev.	P	Mean	St.Dev.	P	Mean	St.Dev.	P
OS	0,55	0,21	0,00	0,56	0,19	0,00	0,50	0,25	0,00
GS	0,44	0,21		0,37	0,20		0,36	0,21	
IFS	0,28	0,17	0,00	0,22	0,13	0,00	0,38	0,20	**0,33**
MFS	0,16	0,12	0,00	0,14	0,10	0,00	0,14	0,11	0,00
IFS vs MFS	**0,12**	**0,05**	**0,00**	**0,08**	**0,03**	**0,00**	**0,24**	**0,09**	**0,33**

4. Results

Independent component containing mostly ectopic beats, artefacts, and noise, could be automatically identified in all cases. Given that HF band is the most affected spectral region when filtering and denoising, we compared the NHFP between the GS and each of the other signals, for each selected segment. IFS spectrum usually followed the GS shape closer than the MFS. Also, the MFS lost significant power density in the LF, and little information remained in HF, as seen in the example in Fig. 3.

P_{ratio} of all signals was statistically compared against the GS. The results obtained showed that P_{ratio} was always in IFS significantly closer to GS than MFS in terms of mean. NHFP was always significantly affected by ectopic beats. Recovering of NHFP was poor in median filtering of the HR channel, and improved in ICA-based denoising. ICA-based denoising during CS (the most non-stationary and noisy period) was not significantly different from the GS.

5. Conclusions

We used ICA decomposition as a previous transformation to efficiently denoise multidimensional records during Tilt Test. Denoising with ICA in multidimensional recordings during Tilt Test yields HRV signals with lower distortion level at HF band. This is due to the capability of ICA to separate in part the physiological content which is common to physiological signals from the noise.

Method has to be required not to be different from the GS not only during CS, but also in all cases. Other processing schemes with BSS techniques should be explored in order to obtain a more efficient decomposition of multi-variable signals, resulting in a more effective denoising. In particular, PCA, Kernels, and SVM techniques could be explored.

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