Applying Independent Component Analysis to Heart Rate and Blood Pressure Variations

HW Chiu, CY Hsu

Taipei Medical University, Taipei, Taiwan

Abstract

The variations of heart rate (HR) and blood pressure (BP) reflect autonomic control. Most studies used spectral analysis and time-domain statistics to assess autonomic functions. Such methods provide some parameters to represent sympathetic and vagal activities. Independent component analysis (ICA) is a statistical signal processing method for blind separation. Assume that HR and BP pressure variations are linearly composed by some independent hidden signals and these hidden signals represent some meaningful physiological signals such as cardiac nervous outflow and hormonal level. Applying ICA to HR and BP variations signals will be expected to extract these hidden signals. In this study, the HR and BP variations data of six subjects were measured and the beat-to-beat RR intervals, systolic BP, and diastolic BP were considered as the mixed signals to be decomposed. The results from ICA showed that these signals were decomposed to noise component, dominate oscillation component and slow-changed component. Dominate oscillation component is similar to the spectral component observed from traditional spectral analysis but show a de-noised form. The physiological meaning of slow-changed component remains to be further studied. This study shows that ICA will be helpful for HR and BP variation analysis.

1. Introduction

Since Akselrod et al. [1] revealed that spectral analysis of heart rate variations (HRV) could be a quantitative probe for cardiovascular control, using the HRV analysis to assess the autonomic nervous function has been a useful tool in many clinical studies. Moreover, blood pressure variation (BPV) is also considered to reflect cardiovascular control and hence it is used as an important index for cardiovascular mortality assessment [2]. Some parameters extracted from HRV or BPV are used to represent some non-observed physiological signal level. For example, the standard deviation of RR-intervals (SDNN) by time-domain HRV analysis and the high-frequency power (HF) of RR-interval series by frequency-domain HRV analysis are the indicators for parasympathetic nervous activity. However, the signals of autonomic control are not observed directly. Therefore, how to extract some hidden signals which are related more directly to autonomic outflow or show more dynamic information from the clinical cardiovascular signals is an important topic.

Independent component analysis (ICA) is a statistical signal processing method for blind separation and has been applied to many biomedical researches. It showed to be an efficient tool for artifact identification and extraction from electroencephalographic (EEG) and magnetoencephalographic (MEG) recordings [3]. In genetic research, it was used to project microarray data into statistically independent components that correspond to putative biological processes [4]. Moreover, ICA was demonstrated to identify the atrial activity source from real electrocardiogram (ECG) recordings of atrial fibrillation [5]. In HRV analysis, investigators use the RR time series obtained from different conditions [6,7] or incorporated with QT interval series [8] to extract sub-signals related sympathetic and parasympathetic regulation mechanism. These works revealed that ICA can get more information about autonomic regulation of cardiovascular system. The BP signals and HR signals are the main external expression of cardiovascular control system. Their interaction between HR and BP provides the information about internal regulation mechanism. Assuming that some important and independent signals linearly mix to HR and BP signals is reasonable. In this study, we attempted to apply ICA in HR and BP signals to find some significant independent sources for cardiovascular control.

2. Methods

2.1. Data acquisition

Six AV block patients loaded with VDD pacemakers were included in this study. All these patients demonstrated normal atrial activity in surface ECG and absence of ventriculo-atrial conduction during ventricular pacing. Patients lay on a table and breathed normally. During the whole experimental procedure, the breathing rate had no marked change.

A Non-invasive continuous blood pressure (NICBP) device (Colin MP7000) was applied to record the BP waveforms of subjects. The lead II surface ECG and NICBP were simultaneously recorded and sampled at 500 Hz for further processing. The experimental procedure was described in previous work [9].

The RR-interval of each beat was derived from ECG and composed to be a time-series *RR[i]*. The time series for the systolic BP (SBP) and diastolic BP (DBP) of each beat were defined as the maximum and minimum values in BP waveform within each RR-interval, and were composed as *SBP[i]* and *DBP[i]* respectively.

2.2. Independent component analysis

The ICA mixing model in this study could be written as following equation

$$\begin{bmatrix} RR \\ SBP \\ DBP \end{bmatrix} = A \begin{bmatrix} IC_1 \\ IC_2 \\ IC_3 \end{bmatrix} \qquad (1)$$

Where the IC_1, IC_2 and IC_3 are the corresponding independent components. If the mixing matrix A can be estimated, its inverse can be computed and the independent components can be obtained.

Many algorithms have been proposed to find the estimation of matrix A. We used the FastICA algorithm [10] in this study. The FastICA MATLAB package [11] was downloaded to process the data in MATLAB R12 platform (The Mathworks, CA).

Moreover, the power spectral analysis was used to these originals and independent components in order to observe and compare the features in frequency domain. Spectral analysis was performed by Welch method using 128-points fast Fourier transform with 64-points overlapping and a Hanning window.

3. Results

The figure 1 and figure 2 showed the original signals of RR interval, systolic blood pressure and diastolic blood pressure of one subject and their power spectral densities, respectively. In general, the RR interval series had the most obvious high frequency fluctuation. In contrast, the DBP signals was lack of high frequency power and shows a less fluctuant pattern. The SBP signal showed both low-frequency and high-frequency fluctuations. The different low-frequency to high-frequency power ratios in HR and BP signals probably imply that HR and BP signals have different responses to cardiovascular control signals or they are controlled by different signals. In this study, we assumed that the HR and BP signals have different responses to some independent control signals.

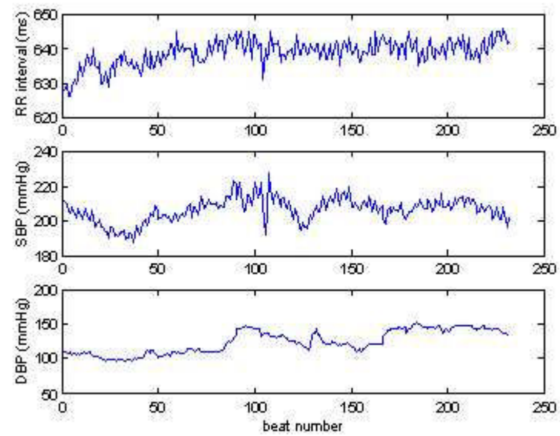

Figure 1. The original signals of RR interval (RR), systolic blood pressure (SBP) and diastolic blood pressure (DBP) used to ICA. The RR and SBP fluctuated strongly, but DBP changed more slowly.

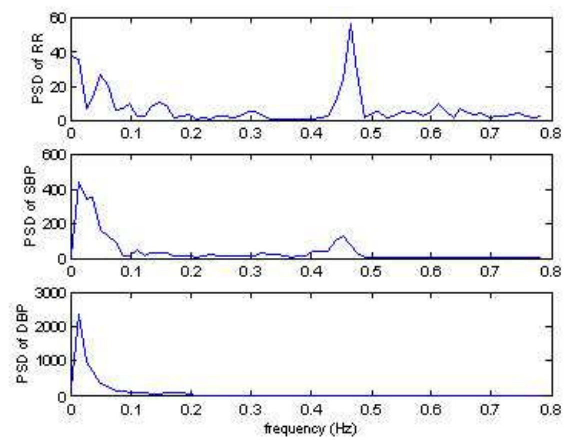

Figure 2. The power spectral densities (PSD) of RR, SBP and DBP time series. RR interval time series had significant high-frequency fluctuation, and the DBP was lack of high-frequency fluctuation.

After ICA, three independent components were obtained. Figure 3 and 4 showed these independent components and their power spectral densities, respectively. These independent sources have different dc levels, but have more similar fluctuation pattern comparing to original signals. Moreover, the one of independent component IC_1 showed a balanced low-frequency to high-frequency power ratio and a clearer spectrum. The IC_2 had less high-frequency power and showed a slow-changed pattern. Moreover, the IC_3 had a pattern similar to SBP. We expected these three components are related to sympathetic nervous signals, parasympathetic nervous signals and noise.

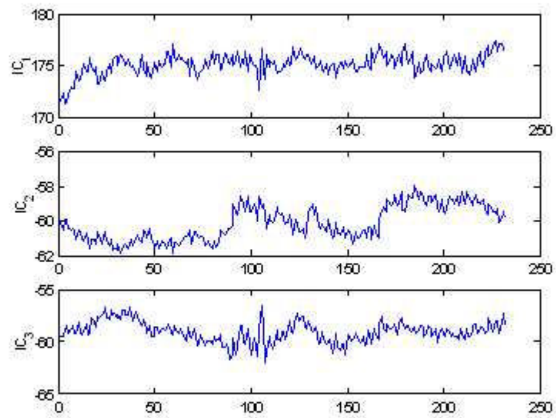

Figure 3. The independent components extracted from the signals illustrated in figure 1. These components showed more similar pattern than original signals.

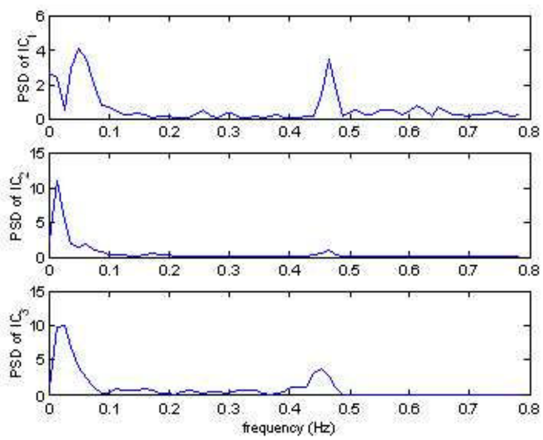

Figure 4. The power spectral densities of independent components shown in figure3. The IC_1 showed a balanced low-frequency to high-frequency power ratio.

4. Discussion and conclusions

In this study, we assumed that heart rate, systolic blood pressure and diastolic blood pressure are the mixture of some independent signals of cardiovascular control systems. Thus we expected that applying independent component analysis to these signals can extract some signals expressing the dynamics of cardiovascular control signals. The results from ICA showed that these signals were decomposed to noise component, dominate oscillation component and slow-changed component. Dominate oscillation component is similar to the spectral component observed from traditional spectral analysis but show a de-noised form. The physiological meaning of slow-changed component remains to be further studied.

Vetter et al. [12] have presented the application of ICA for reconstruction of the cardiac sympathetic nerve activity using HR and BP signals. In our study, we add another signal diastolic blood pressure to increase the number of independent components. A basic theory for HRV analysis is the bandwidth of sympathetic nervous system is lower than parasympathetic nervous system [13]. However the sympathetic activity may contribute to high frequency fluctuation of BP signals. Therefore the independent components extracted for HR and BP signals perhaps provide the more correct information for autonomic assessment.

Acknowledgements

This work was supported by the grant NSC 93-2213-E-038-007 of National Science Council of Taiwan. We also thank the Neural Networks Research Centre of Helsinki University of Technology providing the free FastICA MATLAB Package.

References

[1] Akselrod S, Gordon D, Ubel FA, Shannon DC, Berger AC, Cohen RJ. Power spectrum analysis of heart rate fluctuation: a quantitative probe of beat-to-beat cardiovascular control. Science. 1981;213:220-222.

[2] Pringle E, Phillips C, Thijs L, Davidson C, Staessen JA, de Leeuw PW, Jaaskivi M, Nachev C, Parati G, O'Brien ET, Tuomilehto J, Webster J, Bulpitt CJ, Fagard RH; Syst-Eur investigators. Systolic blood pressure variability as a risk factor for stroke and cardiovascular mortality in the elderly hypertensive population. J Hypertens. 2003;21:2251-2257.

[3] Vigario R, Sarela J, Jousmaki V, Hamalainen M, Oja E. Independent component approach to the analysis of EEG and MEG recordings. IEEE Trans Biomed Eng. 2000;47:589-593.

[4] Lee SI, Batzoglou S. Application of independent component analysis to microarrays. Genome Biol. 2003;4:R76. Epub 2003 Oct 24.

[5] Rieta JJ, Castells F, Sanchez C, Zarzoso V, Millet J. Atrial activity extraction for atrial fibrillation analysis using blind source separation. IEEE Trans Biomed Eng. 2004;51:1176-1186.

[6] Vetter R, Celka P, Vesin JM, Scherrer U. Sub-signal extraction of RR times series using independent component analysis. Proceedings of the 20th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. 1998;20:286-289.

[7] Li Z, Li B, Xie Z. Extracting and analyzing sub-signals in heart rate variability. Colloids and Surfaces B: Biointerfaces. 2005;42:131-135.

[8] Vetter R, Virag N, Vesin JM, Celka P, Scherrer U. Observer of autonomic cardiac outflow based on blind source separation of ECG parameters. IEEE Trans Biomed Eng. 2000;47:578-582.

[9] Chiu HW, Kao T, Hsiao HC, Kong CW. Cardiac aliasing in atrial rate variation response to fixed-rate ventricular pacing. Computer in Cardiology 2001;28:505-508.

[10] Hyvärinen A, Fast and robust fixed-point algorithms for independent component analysis. IEEE Trans. Neural Network 1999;10:626-634.
[11] FastICA MATLAB Package [online]. Available: HTTP:http://www.cis.hut.fi/projects/ica/fastica
[12] Vetter R, Vesin JM, Celka P, Scherrer U. Observer of the human cardiac sympathetic nerve activity using noncausal blind source separation. IEEE Trans Biomed Eng. 1999 ;46:322-330.
[13] Chiu HW, Kao T. A mathematical model for autonomic control of heart rate variation. IEEE Engineering in Medicine and Biology Magazine 2001;20:69-76.

Address for correspondence

Hung-Wen Chiu
Graduate Institute of Medical Informatics
Taipei Medical University
250 Wu-Hsing Street, Taipei, Taiwan
hwchiu@tmu.edu.tw