Development of a Blood Volume Pulse Sensor to measure Heart Rate Variability

R. Martins & J. Medeiros,

Departamento de Física, Faculdade de Ciências e Tecnologia, Universidade de Coimbra, Coimbra, Portugal

S. Palma[1] & H. Gamboa[1,2]

[1]*PLUX – Wireless Biosignals, Lisboa, Portugal*

[2]*CEFITEC – FCT – Universidade Nova de Lisboa, Lisboa, Portugal*

M. Reis,

Departamento de Engenharia Química, Faculdade de Ciências e Tecnologia, Universidade de Coimbra, Coimbra, Portugal

ABSTRACT: Biomedical systems to access physiological signals are, nowadays, in great development. In this context, non-invasive and more user-friendly methods play a role of leading impact in clinical as well as in research activities. The blood volume pulse (BVP) sensor is an example of a much more practical and easy to use method to access some cardiac variables than the electrocardiography (ECG) sensor. With the appropriate data processing algorithms, it allows the access to heart rate (HR) and heart rate variability (HRV) parameters. In the present work we developed a BVP sensor with the aim of obtaining a signal from which HRV parameters can be computed with high reliability. We acquired simultaneously BVP and ECG signals from a group of subjects and used an offline processing algorithm to compute HRV parameters from both signals. This study has shown a strong positive association between all the parameters calculated using BVP and ECG signals.

1 INTRODUCTION

The heart rate variability is an indirect measure of the activity of the autonomous nervous system and the sympathovagal balance, since heart rate is controlled by the sinoatrial node [1, 2]. It has already been proved that the analysis of HRV allows to stratify the risk after myocardial infarction and to early detect diabetic neuropathy [3, 4]. HRV describes the changes in the time intervals between successive heartbeats. Therefore, the accurate detection of heart beats' timing is of crucial importance for the HRV analysis. This detection is, generally, accomplished using the ECG signal. Nevertheless, BVP signals seem to be a very promising alternative [3, 5].

BVP sensors can be used to detect heart beats, based on a principle called photopletysmography (PPG) which consists of measuring the changes in volume using an optical method. In the particular case of BVP sensors, that measure the amount of infrared light absorbed by the blood, the changes in volume are caused by variations in blood pressure in the vessels occurring during each cardiac cycle [6, 7].

Compared with an ECG sensor, the BVP sensor has some advantages, namely it is more 'user friendly' and less obtrusive. However, since the BVP signal is affected by motion artifacts the measurements have to be performed in controlled environments. In order to evaluate the correlation between the HRV parameters computed from a BVP and ECG signals acquired simultaneously, we developed a BVP sensor to use with a *bioPLUX research* [8] system.

2 METHODS

2.1 *Acquisition system architecture*

The developed system consists in a two module BVP sensor and a signal acquisition module, as illustrated in Figure 1. The signal is acquired by the reception module of the BVP probe and conditioned by a filtering and an amplification stage. The analog signal to digital conversion and bluetooth transmission to the computer is performed using a *bioPLUX research* [8] signal acquisition system.

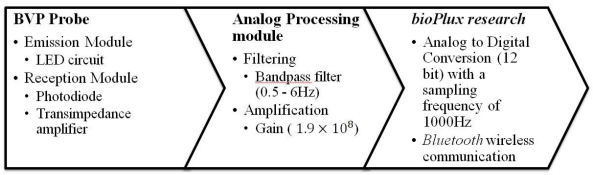

Figure 1. System architecture

2.2 *HRV algorithm*

The HRV analysis algorithm and all the digital signal processing involved in the present work was performed using custom developed Python routines (with SciPy and Numpy modules). ECG and BVP data was acquired using a *bioPLUX research* [8] system. The developed HRV algorithm follows the standards suggested by a previously published guideline [9].

In order to perform the HRV parameters' calculus, the algorithm first accesses the QRS complexes and local maxima of BVP pulses for the first 5 minutes of ECG and BVP signals, respectively. The second step consists of the calculus of R-R intervals in the ECG signal and in-

terbeat intervals in the BVP signal. HRV parameters (Table 1) are, then, computed using these values.

Table 1. HRV parameters calculated

Time Domain	Frequency Domain	Nonlinear
Mean NN (mean interbeat interval)	HF (High Frequency power)	SD1 (Short-term variability)
SDNN (standard deviation of interbeat interval)	LF (Low Frequency Power)	SD2 (Long-term variability)
RMSSD (square root of the mean squared difference of successive interbeat intervals)	LF/HF ratio	SD1/SD2 ratio
pNN50 (differences of successive interbeat interval greater than 50 ms divided by the total number of intervals)		

2.3 *Correlation Analysis*

The similarity of the HRV parameters calculated from BVP and ECG signals was assessed by performing linear regression analysis. Linear regression analysis returns the Pearson correlation coefficient and its square, r and R^2, respectively.

2.4 *Dataset and Acquisition Scenario*

To test our algorithm we collected a set of data composed of BVP and ECG signals, with variable lengths, from eighteen healthy volunteers with ages between 17 and 53 years old. Each volunteer was instrumented with our BVP sensor prototype placed on the 4th finger of the left hand and an ECG triode at V2 precordial lead connected to a *bioPLUX research* [8] data acquisition system. The acquisition of ECG and BVP signals was performed synchronously, with the subjects seated and with their left forearm on an horizontal platform. The data collected along with the correspondent ECG QRS complex annotations was made available on the Web in the Open Signals database (http://www.opensignals.net).

3 RESULTS AND DISCUSSION

The results obtained for the linear regression analysis of the HRV parameters are listed in Table 2, 3, 4.

Table 2. r and R^2 results for time domain parameters

	MEAN NN	SDNN	RMSSD	pNN50
r	1.000	0.989	0.934	0.961
R^2	1.000	0.979	0.872	0.923

Table 3. r and R^2 results for frequency domain parameters

	LF POWER	HF POWER	LF/HF RATIO
r	0.999	0.974	0.967
R^2	0.997	0.949	0.935

Table 4. r and R^2 results for nonlinear parameters

	SD1	SD2	SD1/SD2 RATIO
r	0.934	0.998	0.840
R^2	0.872	0.997	0.706

Several studies point the BVP signal as an interesting alternative to ECG signal when it comes to the measurement of HRV in home care and clinical situations [3, 10].

The results obtained show that the parameters of HRV derived from our BVP sensor are highly correlated with the parameters of HRV derived from ECG.

Analyzing the results in detail we can observe that the mean NN obtained the maximum R^2 value, showing an excellent correlation between the means calculated from the two different signals. On the other hand the SD1/SD2 ratio presents the minimum R^2 value observed and, consequently, is the least correlated HRV parameter. The best R^2 values were obtained for the frequency domain analysis parameters, which means that among the three categories of parameters computed from the BVP signal analysis, the frequency domain are highly correlated with the same parameters computed from the ECG signal.

The major limitations identified for the use of the BVP sensor are motion artifacts. To avoid noise caused by motion, the BVP signal acquisition needs to be performed under a controlled scenario. Eventual modifications of the physical packaging of the sensor could mitigate the influence of these kind of artifacts.

With the present study we can conclude that the use of the BVP sensor for the HRV analysis is a legitimate alternative and gives accurate results, highly correlated with the results obtained from ECG signal processing. Thus, our results are in accordance with the mentioned studies, indicating that BVP could be used as an alternative to the ECG for HRV analysis.

REFERENCES

[1] M.P. Tarvainen, J.P. Niskanen, J.A. Lipponen, P.O. Ranta-aho, and P. Karjalainen, “Kubios HRV - A Software for Advanced Heart Rate Variability Analysis,” IFMBE, 2008.

[2] C.D. Clifford, “Signal Processing Methods For Heart Rate Variability Analysis,” University of Oxford, 2002.

[3] G. Lu and F. Yang, “Limitations of Oximetry to Measure Heart Rate Variability Measures,” vol. 9, Sep. 2009, pp. 119-125.

[4] G.G. Berntson, T. Bigger, D.L. Eckberg, and P. Grossman, “Heart rate variability: Origins, methods, and interpretive caveats.,” Psychophysiol, vol. 34, 1997, pp. 623–648.

[5] E. Peper, R. Harvey, M. I-Mei Lin, H. Tylova, e D. Moss, “Is There More to Blood Volume Pulse Than Heart Rate Variability, Respiratory Sinus Arrhythmia, and Cardiorespiratory Synchrony?,” Biofeedback, vol. 35, 2007, pp. 54-61.

[6] R. Haahr, “Reflectance Pulse Oximetry Sensor for the Electronic Patch,” Technical University of Denmark, 2006.

[7] J.G. Webster, Design of pulse oximeters, IOP Publishing Ltd, 1997.

[8] PLUX, “bioPLUX Research,” PLUX Wireless Biosignals. Available: http://www.plux.info [Accessed April 5, 2010].

[9] Task Force of The European Society of Cardiology and The North American Society of Pacing and Electrophysiology, “Heart rate variability: Standards of measurement, physiological interpretation, and clinical use,” European Heart Journal, vol. 17, 1996, pp. 354-381.

[10] S. Lu, H. Zhao, K. Ju, K. Shin, M. Lee, K. Shelley, and K.H. Chon, “Can Photoplethysmography Variability serve as an alternative approach to obtain Heart Rate Variability information?,” Journal of Clinical Monitoring and Computing, 2008.