Blood Volume Pulse Peak Detector with a Double Adaptive Threshold

J. Medeiros & R. Martins,
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: Blood Volume Pulse (BVP) signal processing is a method to access heart rate and other cardiovascular parameters. In this work we developed an algorithm that detects the cardiac systole from the BVP signal with high accuracy. The implemented algorithm consists of a slope sum function (SSF), an adaptive threshold strategy and a backsearch routine which works as a double adaptive threshold to enhance the sensitivity of the systole detection. In order to evaluate the performance of our algorithm we synchronously acquired BVP and eletrocardiogram (ECG) signals from a group of nineteen volunteers. The QRS complexes were annotated in the ECG signals and used as reference to detect false positives and false negatives in BVP detected systoles. The algorithm detected 99.94% of the 20 210 BVP systoles evident.

Keywords: blood volume pulse sensor, pulse detector, adaptive threshold, backsearch routine, algorithm, signal processing.

1 INTRODUCTION

The BVP signal is obtainned with a photoplethysmography sensor. This sensor measures the changes in blood flow in arteries and capillaries during the cardiac cycle by shinning an infrared light-emission diode (LED) through the tissues (Peper et al. 2007 and Webster 1997). The intensity of light that travels through the tissue and is detected in the photodetector changes proportionally to the amount of blood flowing in the tissues (Haahr 2006).

Since the BVP signal reflects the blood changes that occur during a cardiac cycle it can be used as an alternative to ECG to assess instantaneous heart rate and the rr intervals. Some of the advantages of using a BVP sensor to extract the referred parameters are the fact that the sensor is non-invasive and is less obstrusive than an ECG sensor (Peper et al. 2007). Additionally, it is possible to extract from this signal other parameters, such as pulse transit time and peripheral vasodilatation (Reisner et al. 2008).

In the following sections we describe the development of an automated algorithm for detection of local maxima of the BVP pulses, which correspond to systoles in the cardiac cycle. An accurate detection of this parameter in the BVP signal is important for the computation of variables used to access the subject's health condition, such as heart rate variability (Haarh 2006; Reisner et al. 2008). Applications of this sensor and algorithm in health care range from internship and ambulatory healthcare to long-term patient monitoring. (Peper et al. 2007).

2 METHODS

2.1 *The Algorithm*

We implemented an algorithm that detects the local maxima of BVP pulses. The algorithm consists in three main steps: a slope sum function (SSF), an adaptive threshold (Zong 2003) and a backsearch routine.

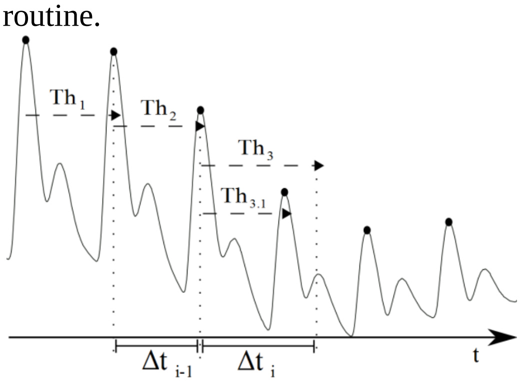

Figure 1. BVP signal with a regular pulse detection and with a backsearch pulse detection

When applied to the BVP signal, the SSF allows to keep pulses' information. The signal that results from the SSF is, then, checked for local maxima using an adaptive threshold and a decision criteria to determine whether or not a maximum occurs in each SSF pulse (Zong 2003).

When a maximum is detected, the threshold (Th) is updated according to the value of that maximum. For each SSF pulse, the algorithm performs a local search for its maximum value between the two points where the threshold is crossed.

In order to avoid the loss of maxima due to big decays in the value of the maximum between consecutive BVP pulses, we implemented a backsearch routine. When (1) is verified the backsearch is activated and a lower threshold ($Th_{3.1}$) is set (Figure 1).

$$\Delta t_i > 110\% \times \Delta t_{i-1} \quad (1)$$

2.2 *Database and Acquisition Scenario*

To test the developed algorithm we collected a set of data composed of BVP and ECG from nineteen healthy volunteers with ages between 17 and 53 years old. Each volunteer was instrumented with a finger BVP sensor placed on the 4th finger of the left hand and an ECG triode at V2 precordial lead connected to a *bioPLUX research* data acquisition system (PLUX 2010). The acquisition of ECG and BVP signals was performed synchronously, with the subjects seated and with their left forearm resting on an horizontal platform. The data collected along with the correspondent ECG QRS annotations is available on the Open Signals database (http://www.opensignals.net).

2.3 *Algorithm Evaluation Procedure*

The method used to assess the accuracy of the algorithm is based on the comparison of the number of maxima detected in the BVP signal with the number of ECG pulse annotations. The comparison was performed by visual inspection when a critical point was detected. To find a critical point we used two different approaches. In both approaches we verified if the number of maxima detected in the BVP signal was the same as the annotated in the correspondent ECG.

In the first approach, if the number of maxima in the BVP was equal to the number of ECG pulse annotations, we checked if there were some discrepancies in the time intervals between consecutive maxima in both BVP and ECG. The discrepancies were identified as critical points and visually inspected in order to decide if they corresponded or not to lost maxima in the BVP signal.

In the second approach, if the number of of maxima in the BVP was different from the number of ECG pulse annotations, we had to visually inspect the signal and look for critical points because we could not compare the time intervals directly.

We have applied this method to determine the number of true and false positives as well as true and false negatives, which will be used to evaluate the sensitivity and specificity of two versions of the algorithm: (a) with backsearch routine and (b) without backsearch routine.

3 RESULTS AND DISCUSSION

Sensitivity and specifity results of the two versions of the algorithms are listed in table 1 and 2.

Tabel 1. Sensitivity and specificity of the algorithm with the backsearch routine

	Sen (%)	Spe (%)
Gross	99.94	100
Average	99.93	100

Tabel 2. Sensitivity and specificity of the without the backsearch routine

	Sen (%)	Spe (%)
Gross	99.60	100
Average	99.58	100

The version with backsearch routine presents a sensitivity of 99.94% for the 20 210 peaks annotated in the ECG while the second version showed a sensitivity of only 99.60% for the same dataset. On the other hand, specificity was 100% for both versions.

Analyzing these results it is valid to induce that our strategy revealed high levels of performance and that the backsearch routine increased the sensitivity of the algorithm.

Our study also revealed that the algorithm's sensitivity is highly affected by physiological phenomena like Premature Ventricular Contraction (Keany and Desai 2010) which can lead to attenuation and suppression of some BVP pulses. This situation has been the cause of most of non-detected BVP pulses.

Excluding those events we can conclude that the present algorithm showed an excellent performance.

REFERENCES

Haahr, R., 2006. Reflectance Pulse Oximetry Sensor for the Electronic Patch. Technical University of Denmark.

Keany, J.E. & Desai, A.D., Premature Ventricular Contraction: eMedicine Emergency Medicine. Available at: http://emedicine.medscape.com/article/761148-overview [Accessed May 13, 2010].

Peper, E. et al., 2007. Is There More to Blood Volume Pulse Than Heart Rate Variability, Respiratory Sinus Arrhythmia, and Cardiorespiratory Synchrony? Biofeedback, 35(2), 54-61.

PLUX, bioPLUX Research. PLUX Wireless Biosignals. Available at: www.plux.info [Accessed April 5, 2010].

Reisner, A. et al., 2008. Utility of the Photoplethysmogram in Circulatory Monitoring. Anesthesiology, 108(5), 950-958.

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

Zong, W. et al., 2003. An Open-source Algorithm to Detect Onset of Arterial Blood Pressure Pulses. *Computers in Cardiology*, 30, 259-262.