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Adaptive Filtering and Characteristics Extraction for Impedance Cardiography

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Abstract

Impedance Cardiography (ICG) is a noninvasive technique for monitoring stroke volume, cardiac output and other hemodynamic parameters, which is based on sensing the change of thoracic electrical impedance caused by blood volume change in aorta during the cardiac cycle. Motion artifact and respiratory artifact can lead to baseline drift in ICG signal, particularly during or after exercise, which can cause errors when calculating hemodynamic parameters. This paper presents an LMS-based adaptive filtering algorithm to suppress the respiratory artifact of ICG signal without restricting patients' breath. Estimation of hemodynamic parameters requires error-free automatic extraction of the characteristic points. Wavelet transform is used for extracting characteristic points which include its peak point (Z), start point (B) and end point (X) of left ventricular ejection time.

Keywords: Impedance Cardiography; Adaptive Filtering; Wavelet Transform; Characteristic Points; Hemodynamic Indices; Respiratory Artifact

1 Introduction

Impedance Cardiography (ICG) is a simple, inexpensive and noninvasive method to monitor electrical impedance change of thorax which is caused by periodic change of blood volume in aorta. An appropriate thorax model can be used for estimating Stroke Volume (SV), Cardiac Output (CO) and other hemodynamic parameters [1]. A typical ICG waveform and its characteristic points is shown in Fig. 1. Points B, Z and X are the three main characteristic of ICG trace. Point B represents opening of the aortic valve, while point X denotes closing of the aortic valve. The point Z corresponds to peak of the ICG waveform, while the point X is the lowest point in the ICG waveform. The time interval between point B and point X is the Left Ventricle Ejection

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Time (LVET) [2]. SV is generally calculated using Kubicek's equation using two hemodynamic parameters: the LVET and the dz/dt_{max} of ICG [1].

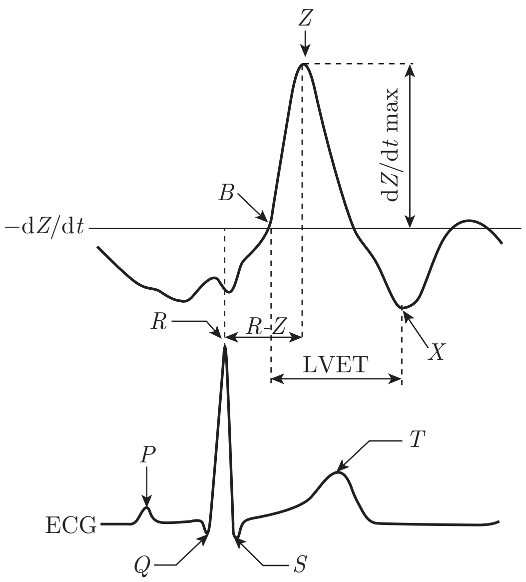

Fig. 1: A typical ICG waveform and an Electrocardiogram (ECG) waveform

The ICG signal is influenced mainly by motion artifact and respiratory artifact. Respiratory artifact is primarily caused by changes of thoracic volume during breathing, while motion artifact is generally caused by body movements and contraction of muscle. The frequency spectrum of respiratory and motion artifacts partly overlap with frequency spectrum of the ICG signal, so it is critical to remove all the artifacts. The electrical impedance change caused by blood volume change in aorta typically accounts for 2-4% of the base impedance (usually about 20ohm), while the electrical impedance change caused by the respiratory artifact and motion artifact may be 30% or even more [1]. Therefore the motion and respiratory artifacts may lead to a large baseline drift in the ICG signal, subsequently resulting in errors in characteristic points extraction and calculation of the hemodynamic parameters.

Some algorithms of removing the respiratory artifact in the ICG signal have been published. Pandey used an LMS-based adaptive filter to suppress respiratory artifact with an airflow sensor sensing breath [3]. Barros adopted an adaptive filter and a scaled linear Fourier combiner to express the ICG signal as a scaled Fourier series with a period equal to the R-R interval of ECG signal [4].

Unlike Heart Rate Variability (HRV), stroke volume variability and cardiac output variability has not been widely applied as a medical index for diagnosing cardiovascular diseases, because accurately estimating SV in a long period is very difficult [5]. This paper presents an LMS-based adaptive filtering algorithm to suppress the respiratory artifact of the ICG signal without restricting patients' breath and applies wavelet transform to extract characteristic points (B, Z and X).

The remaining portions of this paper are divided as follows: in Section 2 we analyzed signal processing technique for denoising ICG. And then we adopted wavelet transform to extract characteristic points of ICG in Section 3. In Section 4 we estimated hemodynamic parameters by classic formula. Finally, we obtained our conclusions in Section 5.

2 Signal Processing Technique

There are two major artifacts in the ICG signal: respiratory and motion artifacts. Respiratory artifacts have very low frequency (0.04-2 Hz), and the frequency of motion artifacts is about 0.1-10 Hz. The baseline drift is due to the respiratory artifacts, while the peaks variation is due to motion artifacts. ICG signal range is 0.8 to 20 Hz, therefore respiratory and motion artifacts lie within the same band [6]. In this paper particularly we are looking for respiratory artifacts suppression because these create difficulties in calculating SV and other hemodynamic indices accurately.

ICG signal is modulated by breath which can cause its fluctuation around base impedance Z_0, thus baseline drift is inevitable during exercise. Subsequently baseline drift might cause inaccurate calculations of hemodynamic parameters when the zero level is used to calculate dz/dt_{max} [7]. Therefore removing respiratory artifact from ICG signal is really important.

There are mainly five techniques of suppression of respiratory artifacts:

a) Breath holding: The easiest way to suppress these artifacts is to hold the breath. However, holding the breath during recording ICG may change SV. Another problem is when we are recording ICG after exercise it is difficult to hold the breath.

b) Ensemble averaging [8]: The bit to bit variability in the ICG will be removed in ensemble averaging technique, so it blurs the important points of ICG waveform such as B and X points. Hence it will introduce errors in calculating SV.

c) Wavelet based level dependent thresholding [8]: In wavelet based denoising selection of wavelet basis is important task. In many denoising applications it is observed that if wavelet and waveform has some similar shape, then those wavelets that give better separation of noise and signal. But selection of wavelet basis is often a difficult step in wavelet based denoising.

d) Independent Component Analysis (ICA) [9]: ICA applies to the assumption of statistical independence among different components; if the source signals do not satisfy the condition then ICA would not be able to separate the components. We still need to prove that cardiac and respiratory components can be viewed as uncorrelated.

e) Adaptive filtering: Adaptive filtering is always good in biosignal denoising, if we have a reference signal. So we need to acquire signals from two channels, one of the signals can be taken as reference input signal. Eight electrodes of the cross-shaped device are placed on the chest, as is shown in Fig. 2, four vertical electrodes and four horizontal electrodes are simultaneously used to acquire impedance signals. Because the aorta is a vertical blood vessel in the thorax, so the four vertical electrodes are used to sense ICG, while the four horizontal electrodes are used to detect respiration. Horizontal impedance can be taken as reference signal to remove respiratory artifacts.

A schematic diagram of the respiratory artifact suppression method is illustrated in Fig. 3. Input signal $x(n)$ of adaptive Finite Impulse Response (FIR) filter is the vertical impedance, and it is a mixed signal which includes ICG signal and respiratory artifact. Horizontal impedance $r_o(n)$ which is associated with the respiratory artifact is proved to be uncorrelated with ICG signal.

Horizontal impedance is found to be less than 1 Hz in frequencies, which seriously affects the accurate identification of characteristic points of ICG signal. A signal associated with the respiratory artifact can be estimated using horizontal impedance and vertical impedance together

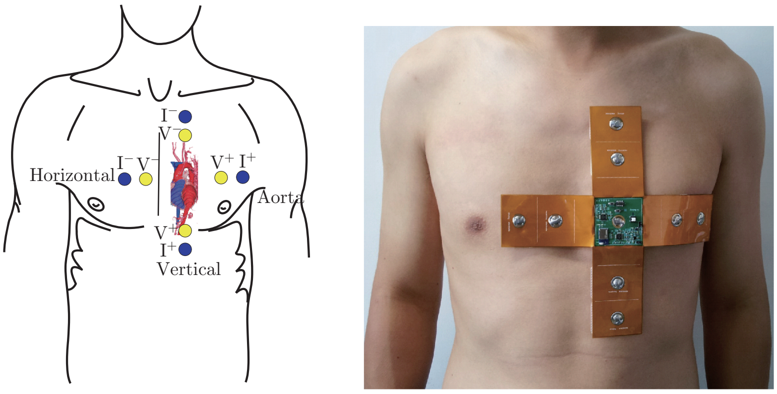

Fig. 2: Location of the electrodes

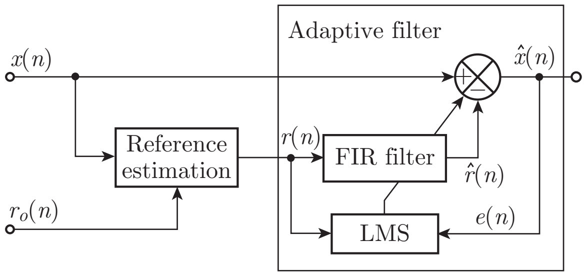

Fig. 3: LMS-based adaptive FIR filtering technique using respiration reference

and adopted as the reference input signal for the LMS-based adaptive FIR filter.

Least Mean Square (LMS) algorithm is used to control the FIR filter. The output of M-tap FIR filter with coefficients $\omega_n(k)$ is given as

$$\hat{r}(n) = \sum_{k=0}^{M-1} \omega_n(k) r(n-k) \tag{1}$$

The input $x(n)$ subtract the output $\hat{r}(n)$ to obtain the denoised output signal

$$\hat{x}(n) = x(n) - \hat{r}(n) \tag{2}$$

$\hat{x}(n)$ is used as the feedback $e(n)$ by the least mean square algorithm for estimation of the adaptive filter coefficients. An instantaneous estimate of the gradient vector is used to control adaptive filter coefficients, using the equation

$$\omega_{n+1}(k) = \omega_n(k) + \mu e(n) r(n-k) \tag{3}$$

The instantaneous estimate of the gradient vector is based on sample values of the tap input vector and the feedback for dynamic adaptation. The step-size parameter μ ($0 < \mu < 2/\mathrm{M}$) is selected for adjusting stability and convergence of the dynamic adaptive filter.

As is shown in Fig. 4, the effect of FIR adaptive filter based on LMS is very clear. The processed ICG signal has no baseline drift, which means most respiratory artifacts are removed from the ICG signal.

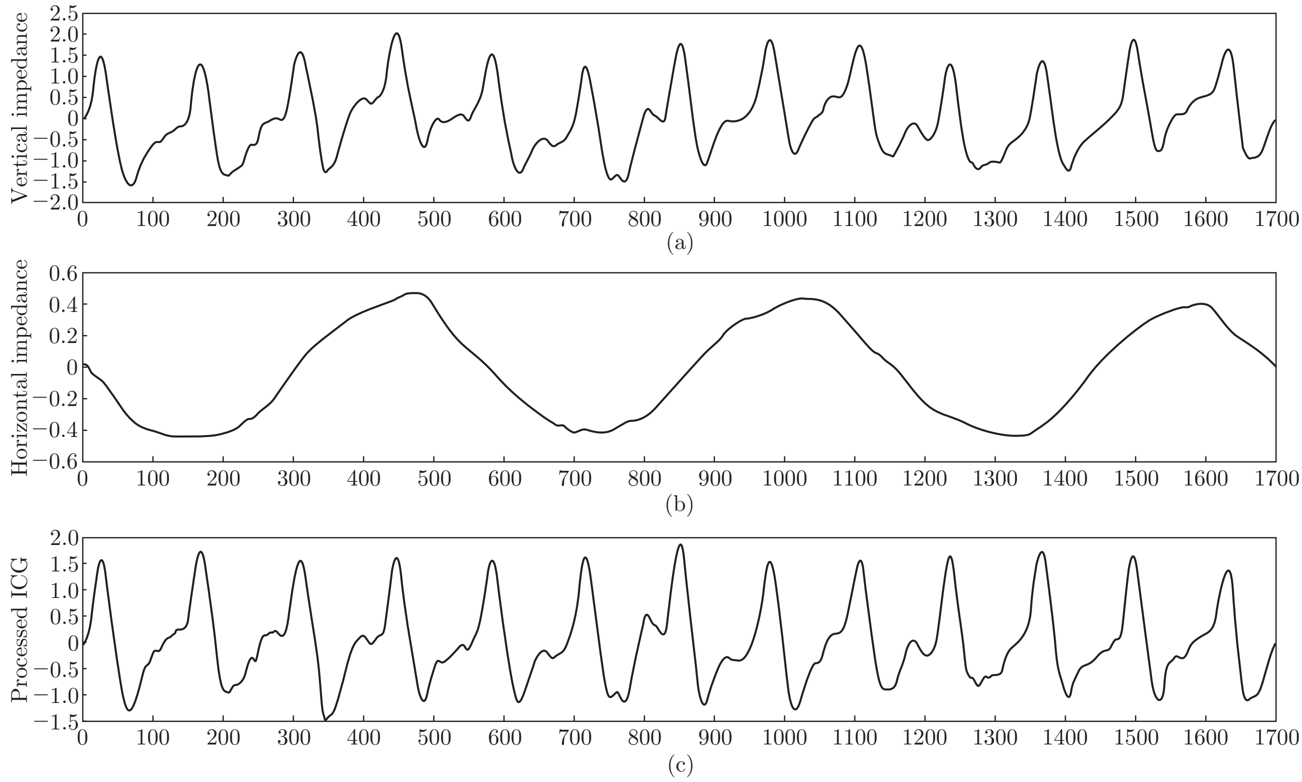

Fig. 4: Vertical impedance, horizontal impedance and ICG processed by adaptive filtering

3 Extraction of Characteristic Points

Wavelet Transform (WT) is adopted to extract characteristic points of ICG signal in this paper. Wavelet transform decomposes the ICG signal into many components at different frequency scales using filter banks. On the other hand, wavelet transform characterizes and preserves the regularities of ICG signal at different frequency scales, which can be used for extracting less prominent characteristic points [10].

3.1 Principle of Wavelet Transform

With a given mother wavelet ψ, wavelet transform of a function $f(x)$ is defined as

$$\omega_s f(x) = f * \psi_s(x) = \frac{1}{s}\int_{-\infty}^{\infty} f(t)\psi\Big(\frac{x-t}{s}\Big)dt \tag{4}$$

where s denotes the scale factor of WT. When $s = 2^j$ ($j \in Z$, Z is integral set), and the wavelet transform of $f(x)$ is defined as dyadic wavelet transform. The dyadic wavelet transform can be calculated by following two equations:

$$S_{2^j} f(n) = \sum_{k \in Z} h_k S_{2^{j-1}} f(n - 2^{j-1}k) \tag{5}$$

$$\omega_{2^j} f(n) = \sum_{k \in Z} g_k S_{2^{j-1}} f(n - 2^{j-1}k) \tag{6}$$

where S_2^j represents the smoothing operator and $\omega_{2^j} f(n)$ is the wavelet transform of digital function $f(n)$. g_k is the coefficient corresponding high pass filter, and h_k is the coefficients corresponding low pass filter.

The equivalent filters of the quadratic spline wavelet with compact support and one vanishing moment are illustrated in Fig. 5. These equivalent filters are FIR filters with a generalized linear phase. Signal can be decomposed into different scales using equivalent filters. In this paper, the ICG signal is decomposed into seven scales at different frequency.

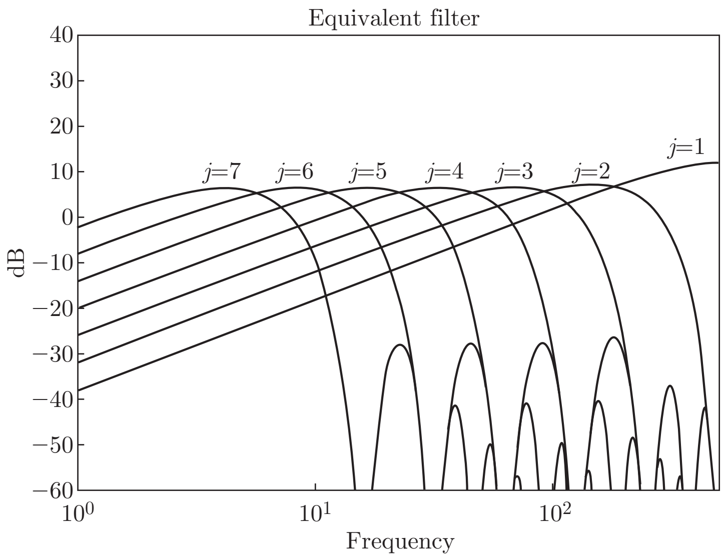

Fig. 5: The equivalent filters of quadratic spline wavelet at seven scales and different frequency

3.2 Characteristic Points Detection

Point B is located at the ascending phase of the ICG trace before point Z, and it is related to the opening of the aortic valve. Point B is generally assumed as a point occurring at the baseline (zero-crossing). Point X is described as a lowest point of ICG signal occurring after point Z in a cardiac cycle and reflects the closing of the aortic valve. The interval between the opening (B) and closing (X) of the aortic valve is defined as Left Ventricular Ejection Time (LVET). Z point, corresponding to the maximal speed of the impedance change, is located at the top position of the ICG trace. The amplitude of point Z-dz/dt$_{\max}$ is the maximal amplitude of ICG signal [11].

A minimum–maximum pair exists in the decomposed signal by quadratic spline wavelet for every uniphase wave. Therefore, some key events can be identified using these minimum–maximum pairs with convincing results. When WT is directly applied to the ICG signal processing, compared with WT in the ECG signal processing, the typical minimum–maximum pair is less prominent. The difference may be caused by different frequency ranges of ECG signal and ICG signal. High frequency components of characteristic points (eg.QRS complex) in the ECG signal are more than high frequency components of characteristic points in the ICG signal. Additionally, low frequency systolic component is one of the characteristics in ICG signal [12]. The point B is less prominent than Z and X points which both are turning points and extreme points. Nevertheless, characteristic point B in the ICG signal can be identified in the signal processed by WT.

Since point Z is the maximum point during systolic period and has low frequency component of ICG signal, it is the easiest to be extracted clearly for each cardiac cycle. The zero-crossing and minimum–maximum pairs at different scales can be examined. The results of characteristic points extraction using WT is shown in Fig. 6, the purple points are zero-crossing (B), the red points are maximum (Z), the blue points are minimum (X).

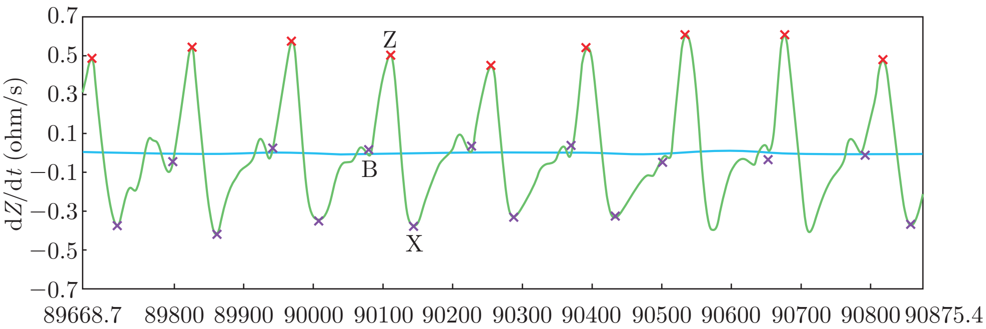

Fig. 6: The results of characteristic points extraction using WT

3.3 Evaluation Indices of Characteristic Points Detection

A visual examination of the results of the automatic detection of the characteristic points was carried out using a program based on LabVIEW which marked the detected points on the waveform itself. For a quantitative evaluation of the technique, locations of the automatically detected points were compared with the points visually located in accordance with definitions. Failure to detect a true point was counted as a Failed Detection (FD), and detection of a false point was counted as misdetection (MD). With TP as the total number of true points detected, the following performance indices were calculated [13].

$$\text{Sensitivity} = \text{TP}/(\text{TP} + \text{FD}) \tag{7}$$

$$\text{Positivepredictivity} = \text{TP}/(\text{TP} + \text{MD}) \tag{8}$$

$$\text{Detectionerror} = (\text{FD} + \text{MD})/(\text{TP} + \text{FD}) \tag{9}$$

Table 1: Evaluation indices for detection of characteristic points

Characteristic Points	Processed ICG		
	Sensitivity (%)	Positive predictivity (%)	Detection error (%)
B	94.5	93.8	11.6
Z	99.5	98.6	1.9
X	97.1	96.4	6.4

The evaluation was carried out by applying it on a total of 378 cardiac cycles in the recordings of a healthy subject. A quantitative visual examination of the automatically detected points showed a very small number of errors, and most of the errors were related to errors in the detection of the B points. A quantitative evaluation was carried out by calculating the performance indices as given in equations (7-9). The values of the indices for the detection of points B, Z and X are given in Table 1. For detection of the Z point, the technique showed excellent sensitivity (99.5%)

and very low detection error (1.9%) in the processed ICG signals. Somewhat higher errors were observed in the identification of relatively less distinct points B and X.

4 Estimation of Hemodynamic Parameters

Stroke volume is probably one of the most medically relevant hemodynamic indices obtained using ICG. The peak value dz/dt_{max} is an important parameter in the estimation of SV and other hemodynamic parameters. The equation of SV, introduced by Kubicek [12] is

$$SV = \rho \cdot \frac{L^2}{Z_0^2} \cdot LVET \cdot dz/dt_{\max} \tag{10}$$

where ρ=blood resistivity (ohm*cm), L=thoracic length between two sense electrodes (cm), Z_0=base impedance (ohm), dz/dt_{max}=maximum value of ICG waveform (ohm/s), LVET is defined as the interval between point B and point X. dz/dt_{max} can be determined by the amplitude difference between point B (baseline level) and point Z (top position).

Cardiac output is the blood volume pumped by the heart during one minute period. It is a result of SV multiplied by Heart Rate (HR). It also can be calculated as a sum of all SV values occurring during one minute period [14]. CO is related to SV as follows:

$$CO = SV \cdot HR \tag{11}$$

We can obtain dz/dt_{max} and LVET by extracting characteristic points of ICG waveform. It is assumed that L=21 (cm), ρ=135 (ohm*cm), Z_0=20 (ohm), hemodynamic parameters SV and CO can also be calculated according to the equation (10-11). The hemodynamic parameters are provided in different HR, LVET and dz/dt_{max} (Table 2). Normal range of SV is 60-100 (ml), and normal range of CO is 4800-8000 (ml/min).

Table 2: Calculated hemodynamic parameters

HR (beats/min)	LVET (ms)	dz/dt_{max} (ohm/s)	SV (ml)	CO (ml/min)
70	313	1.88	87.6	6130.7
72	318	1.90	89.9	6474.8
65	327	1.96	95.4	6200.5
69	298	1.82	80.7	5569.9
75	314	1.92	89.7	6729.8
78	295	1.83	80.3	6267.3
74	320	1.98	94.3	6978.5

We compared CO from the cross-shaped device with CO from Mindray's BeneView T5 which integrates CardioDynamics' BioZ ICG module in ten healthy people. We recorded two CO values from cross-shaped device and BeneView T5 every 10 seconds, then we calculated the correlation coefficient by recording continuously 200 CO values. The result is 0.83, higher than 0.8, so we can draw a conclusion that CO from cross-shaped device is highly-correlated with CO from BeneView T5, which implies adaptive FIR filtering based on LMS and wavelet transform is valid.

5 Conclusions

In this paper, LMS-based adaptive filtering and wavelet transform is presented to remove respiratory artifact and extract characteristic points from ICG signal respectively. Advantage of adaptive filtering is that it does not require any breath control, especially during or after exercise, when breath and cardiac activity is rapidly varying. We apply wavelet transform to detect characteristic points-"B", "Z" and "X". The WT shows significantly great performance with a high sensitivity and a low detection error. It still needs to be further evaluated by applying it to record in a clinical setting for estimating the stroke volume, cardiac output and other hemodynamic parameters.

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