Combined Linear IIR and FIR Denoising Processes Performance Study for Arm-ICG Waveform Features Determination in Ambulatory Cardiac Stroke-Volume Monitoring

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Combined Linear IIR and FIR Denoising Processes for Arm-ICG Waveform Features Determination in Ambulatory Cardiac Stroke-Volume Monitoring

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Abstract

Impedance cardiography (ICG) is a non-invasive, continuous technique for assessing cardiac parameters such as stroke volume and cardiac output. By recording ICG data on the upper left-arm along the brachial artery, a wearable sensor device could offer trend-based cardiac contractility indicators. Data from seven healthy cases were analysed, comparing simultaneous thoracic and arm ICG recordings, assisted by respective simultaneous recording of chest ECG Lead I data. Three linear, real-time, denoising methods were tested: an optimized Butterworth IIR, a 3rd order Savitzky-Golay FIR, and their combination. The combined approach consistently outperformed, exhibiting higher denoising performance metrics (p, RMS, SNR), which with an additional non-linear recursive signal-averaging denoising process, it provided accurate estimation of the cardiac stroke volume (SV), derived from Arm-ICG waveform extracted features (B and VET). This pilot study revealed a linear regression model for predicting conventional thoracic SV from estimated non-conventional arm SV, with a promising coefficient of determination (R^2) value of 0.796, in support for a versatile long-term wearable device method for CO monitoring in HF and AF affected patients.

1. Introduction

According to the World Health Organisation cardiovascular diseases (CVD) are the leading cause of death worldwide, amounting to approximately 17.5 million deaths annually. Arrhythmias are defined as a transient abnormal heart rhythm and play a key role in diagnosing heart disease. They also have significant prognostic benefits [1]. There are several types of arrhythmias, some more common than others. The most frequently diagnosed cardiac arrhythmia is known as Atrial Fibrillation (AF) and is strongly associated with increasing the risk of patients suffering from a stroke. Another most common CVD is Heart Failure (HF), which is mutually causative with AF [2, 3], and can by non-invasively assessed by means of bioimpedance sensing methods [4]. For diagnostic purposes, CVD's can be assessed using hemodynamic parameters such as stroke volume (SV) and Cardiac Output (CO). Current methods of measuring these parameters are either highly invasive or discontinuous. Impedance cardiography (ICG) offers continuous monitoring in a non-invasive manner which can derive specific hemodynamic parameters relating to the contractility of the heart, to identify any acute HF state and also diagnose life threatening arrhythmias [4]. Traditionally, ICGs are recorded using the transthoracic approach whereby electrodes are placed on a patient's thorax and neck [5]. However, in recent years, researchers [6] have reported the recording of ICGs using different points on the arm and comparing the results with those from thoracic placement.

It is important to note that when using ICG as a monitoring method, results are usually affected by signal noise. Thoracic ICG sensing methods generally pick up noises such as respiration noises, motion noises and poor electrode contact related noise. Arm ICG's are usually contaminated by motion noises, or noises associated with poor electrode contact, but are less likely to be affected by respiration noises [6]. Thus, it is vital to apply effective and robust real-time denoising filters, in order to provide a reliable ICG waveform which doctors can recognise and utilise for accurate diagnostic purposes [7]. The brachial artery ICG waveform can provide an alternative CO monitoring approach, by sensing it from the upper left-arm and process it to derive important cardiac hemodynamic indicators for the early diagnosis of HF or corroborate acute AF detection, or their treatment follow up [2].

If conventional thoracic ICG and ECG are recorded simultaneously with upper-arm ICG, a comparative assessment of the non-conventional Arm-ICG, and ICG metrics functional relationships of Thorax-ICG vs Arm-ICG can be modelled for clinical use. A variety of filters such as a Butterworth filter, a Savitzky-Golay (SG) filter, or a recursive averaging process [8], may be sufficiently effective to denoise the Arm-ICG signal to enable reliable ICG waveform metrics for CO monitoring.

2.0 Methods

2.1 ICG and ECG Data

The subjects dataset to study the accuracy of the ICG recorded on the left upper-arm, was gathered using a BioPac wireless ICG and ECG simultaneous recording system devices (BioPac Inc, California, USA) and their developed software, Acqknowledge 5.0. All subjects within this study were healthy volunteers from the research group at NIBEC, Ulster University. The subjects age range was between 23-54 years and the average age was 36 years. Within the subjects, 57% were female, and 43% were male.

Each subject case recording duration was fixed to a total of 480 seconds, at a sampling rate of 2 kHz. Each subject had one arm recording and one thoracic recording, both with simultaneous ECG recordings. Table 1 presents the study subjects sample baseline demographic characteristics.

Table 1. Patients sample demographics baseline.

Casse #	Gender % Female: 57 Male: 43	Age	Weight (kg)	Height (cm)	BMI (Kg/m^2)	Waist (cm)	L Upper-arm length (cm)
1	M	54	76	175	24.8	93	21
2	F	23	59	164	21.9	76	21
3	F	41	76	153	32.5	100	19
4	F	26	62	172	21.1	72	24
5	F	25	70	169	24.7	77	23
6	M	43	80	161	30.9	107	23
7	M	39	61	170	21.1	77	29
	Mean	**35.9**	**69.1**	**166.3**	**25.3**	**86.0**	**22.9**
	(±SD)	(11.5)	(8.49)	(7.52)	(4.67)	(13.81)	(3.18)

The ECG signal was used to extract the alignment time for signal averaging processes. A deterministic feature of ventricular depolarization was timed from the QRS complexes in the ECG data.

2.2 ICG and ECG Prefiltering Process

Both the ICG and ECG signals are subjected to noise and therefore prefiltering was a critical stage throughout this study. ICG signals, recorded from both the upper-arm and the thorax, were denoised using three linear digital filtering IIR and FIR processes, and their combination. Process 1: The signals were denoised using a 1st order high-pass Butterworth IIR-filter at 0.5Hz cut-off frequency followed by a 4th order low-pass Butterworth IIR-filter at 8Hz cut-off frequency. MATLAB coding was used to apply this technique. Process 2: The signals were denoised using a 3rd order SG FIR-filter with a window length of 351 samples. The frequency response of this particular SG filter design, suitable for human ICG waveform signal treatment [8], is shown in Figure 1, presenting low-pass

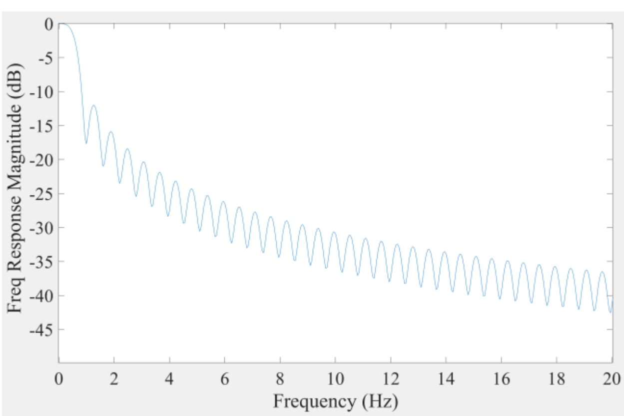

Figure 1. Frequency response magnitude (dB) of SG FIR filter design for ICG waveforms: 3rd order, 351 points size

characteristics with a -3 dB cutoff frequency at 0.61 Hz and reaching 40 dB attenuation level at 20 Hz with a 5 dB ripple amplitude. These frequency response profile aids in the suppression of noise and high-frequency fluctuations. Process 3: the signals were denoised using a combination of the band-pass Butterworth IIR-filter and the 3rd order SG FIR-filter. The denoising performance metrics of the 3 processes ere analysed and compared for selecting the best process. ECG signals on each case were conditioned using a Butterworth 1st order 0.5Hz high-pass followed by 2nd order 40Hz low-pass filters.

2.3 ICG waveform vector quality criteria

For each of the subject cases, pre-filtered 700ms ICG beat frames, on a beat-by-beat (BbyB) basis, were correlated using the Pearson Correlation coefficient (p), with the absolute reference 700ms frame (gold standard, “noiseless” ICG waveform vector), obtained by a conventional SAECG process [1], hence SAICG. Thus, the mean of computed p values for every incoming ICG beat frame (700 ms), was used as a denoising performance metric, for comparison of the 3 filtering processes. In this study, a correlation p threshold value above 0.701 or or $1/\sqrt{2}$ (-3 dB point) was used for BbyB acceptance of reasonable quality incoming ICG frame vectors. In addition to this, the noise RMS and the Signal to Noise ratio (SNR) metrics values were calculated for each accepted ICG beat frame vector, and their mean values were used later to assess the ICG waveform feature metrics (B and VET) accuracy and precision [8].

2.4 ICG waveform features metrics

An ICG signal averaging process, using chest ECG Lead I R-wave detection time event as the alignment time reference extraction using the SFP technique [8], enabled the determination of an absolute (noiseless) reference 700ms ICG vector frame. Then, two main ICG waveform feature metrics were determined to further characterise the denoising performance of each filtering process: 1, 2 and 3. The ICG waveform metric B, is the ICG main pulse peak amplitude level (Ω/s) measured on the signal averaged Arm-ICG and Thorax-ICG. The left ventricular ejection time (generally termed with the acronym VET), is the ICG waveform parameter (ms) needed to calculate the SV [8].

3. Results

3.1 FIR-filter and IIR-filter performance

The FIR-IIR filter combination was implemented and further supported by a 16th order recursive averaging process (RAv16) [8]. The Pearson correlation coefficient (p) was used as a denoising performance metric of these filtering processes. The absolute reference 700 ms window was correlated with each incoming beat, for each case. This allowed for the mean value of p to be computed for each case. The beat inclusion rate percentage (BIR%) was also calculated by including beats which had p values above the 0.701 threshold. Table 2 presents the mean p value and mean BIR% for the 7 cases, for both arm and thorax ICG. These results indicate that the cascaded combination of IIR and FIR filtering yielded Arm-ICG waveforms, which in average correlated higher with the absolute noiseless reference signal, hence, the most effective filter process.

Table 2. ICG denoising processes performance on Thorax-ICG and Arm-ICG, on the 7 subjects: mean (±SD) of p and BIR% metrics means in each subject, on a BbyB basis.

Performance metric on ICG	Butt8Hz IIR	S-Golay FIR	Butt8Hz +S.Golay
p mean: Thorax-ICG; all beats (±SD)	**0.97** (±0.02)	**0.97** (±0.02)	**0.98** (±0.02)
p mean: Arm-ICG; all beats (±SD)	**0.87** (±0.18)	**0.86** (±0.18)	**0.88** (±0.19)
BIR% mean: Thorax-ICG (±SD)	**97** (±0.02)	**97** (±0.02)	98 (±0.02)
BIR% mean: Arm-ICG (±SD)	**92** (±0.06)	**91** (±0.06)	93 (±0.06)

Additional metrics for denoising performance are the noise root mean square (RMS) and signal-to-noise ratio (SNR) mean values for all 7 cases, as presented in Table 3 for each filtering process. Again, from these metrics perspective, the highest denoising performance was for the Butter8Hz + S,Golay combined denoising Process 3.

Table 3. Arm-ICG denoising processes performance on the 7 subjects: mean (±SD) of SNR and RMS (Ω/s) metrics, mean values in each subject, on a BbyB basis.

Denoising Metric	Butt8Hz (IIR)	S-Golay (FIR)	Butt8Hz+SG (FIR)	Raw signal (no pre-filter)
Mean SNR (±SD)	**9.74** (±11.2)	**7.85** (±9.53)	**12.46** (±14.4)	**0.75** (±0.99)
Mean RMS (Ω/s) (±SD)	**0.09** (±0.03)	**0.09** (±0.03)	**0.08** (±0.02)	**0.48** (±0.28)

3.2 Functional Relationship Arm *vs* Thorax

Although the combined IIR-FIR filtering method proved satisfactory for ICG denoising, the quest for enhanced accuracy and precision in ICG waveform feature metrics prompted the application of the advanced RAv16 denoising process, as described in [8]. This iterative step was implemented for assessing the functional relationships between the Thorax-ICG and Arm-ICG waveform metrics: B, VET, and calculated SV values, are here assessed using scatter plots with respective coefficient of determination (R^2) of the linear regression model, as depicted in Figure 2.

The additional RAv16 denoising treatment led to remarkable insights into the thorax (conventional) versus arm (non-conventional) metrics prediction modelling. Specifically, the correlation coefficients were 0.97 for Metric B, 0.95 for Metric VET, and 0.89 for Stroke volume, signifying a high degree of interdependence. Furthermore, the above 0.80 values of R^2, support the goodness of the estimated linear regression models.

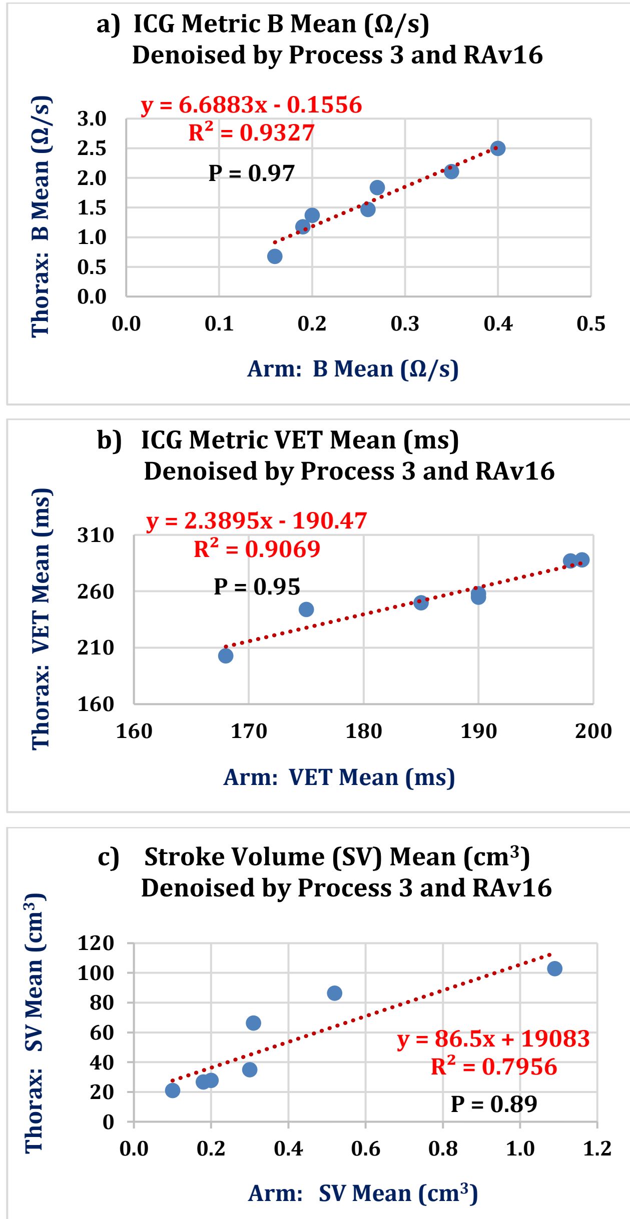

Figure 2. Scatter plots of Thorax versus Arm ICG waveform features B, VET metrics and estimated SV mean values, after ICG denoising with Process 3 and RAv16, and respective linear regression models with their R^2 values.

These findings outline the potential clinical use of the alternative, easier to practice, Arm-ICG methods for monitoring cardiac hemodynamic indicators using a wearable armband device for acute HF and AF detection.

4. Discussion

This study aimed to investigate various aspects of denoising and analysing impedance cardiography (ICG) waveforms. Denoising performance of three proposed linear pre-filtering processes (real-time) were assessed using various parameters: p, BIR%, SNR and RMS. The combined IIR-FIR (Butter8Hz+S.Golay) process was clearly the consistently best linear denoising process.

The analysis of key metrics (Metric B, Metric VET, and Stroke volume) using an additional non-linear, advanced ICG recursive averaging 16th order denoising process (RAv16) [8], which is also possible to operate at real-time, but with certain delay (16 ICG beats), for arm-ICG and thorax-ICG data, reveals promising paired metrics linear relationships, with promising coefficient of determination ($R^2 > 0.80$) linear regression modelling, also presenting high Pearson correlation coefficients ($p > 0.89$), as presented in Figure 2. Nevertheless, there are notable differences on p and BIR% denoising performance metrics mean values (see Table 2), using the selected Process 3 (best performing), with arm-ICG showing consistent lower values than thorax-ICG; as a result of the higher noise level present in arm-ICG recordings. These findings highlight the importance of considering data quality challenges associated to ICG sensing anatomical location choice in clinical and research applications.

The second branch of study investigated the relationship between thorax and arm stroke volume. Revealing promising linear proportionality between these estimated volumes, using established Kubicek's formula and ICG waveform extracted feature metrics data (B and VET). However, the scope of this pilot study is limited by the low sample size of 7 subjects and no cardiac patient groups were considered; only healthy volunteers with reasonably wide demographic characteristics.

In brief, this study delved into denoising and analysing ICG waveforms, revealing effective real-time filtering techniques, metric correlation methods, and establishing SV relationships at pilot study level of confidence. The study ultimately contributed to refining VET estimation and establishing the relationship between arm and thorax SV. This research enhanced understanding of feasible practical applications of brachial artery based alternative ICG measurements, offering insights for medical practice.

5. Conclusions

In relation to the observed Pearson correlation coefficients in our discussion, the robust positive relationships between the evaluated metrics (B, VET, and Stroke volume) when additional RAv16 denoising process is applied underscore the reliability and clinical significance of this study's insights. The good correlation p values further validate the evidence-based potential for real-world applications in non-invasive health monitoring using armband ICG sensors. Our comprehensive approach enhances the credibility and relevance of our findings, reinforcing their importance in advancing cardiovascular disease diagnosis and continuous cardiac hemodynamic indicators monitoring in healthcare.

This pilot study offers compelling evidence that points towards a promising direction for non-invasive, continuous health monitoring using armband sensors for ICG measurements. By employing a comprehensive approach involving Pearson correlation, RMS, and SNR analyses, the study successfully identified the convenient electrode placement for upper-arm ICG, ensuring the reliability of measurements. The application of Butterworth-IIR and Savitzky-Golay-FIR filtering techniques achieved good Pearson correlations (> 0.701) for both arm and thorax-ICG, thus, significantly enhancing waveform quality. Additionally, the study confirmed a robust linear regression relationship ($R^2 = 0.80$) between arm and thorax stroke volumes, bridging critical knowledge gaps related to combined filtering efficacy and specific metric calculations. These findings have wide-ranging implications, particularly in advancing non-invasive, long-term, health monitoring and the diagnosis of cardiovascular diseases.

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