# Adaptive Filtering for Respiration Influence Reduction on Heart Rate Variability

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*Abstract* —**In this paper it is described an adaptive method for Heart Rate Variability (HRV) signal filtering, which uses a noise canceller structure formed by a Finite Impulse Response (FIR) filter together with the Least Mean Squares (LMS) adaptation algorithm in order to reduce respiration influence on HRV information. Respiration and electrocardiogram (ECG) signals were obtained simultaneously using 240Hz sampling frequency during 5-minutes experiments. Respiration signal was acquired by mechanic methods whereas ECG signal was obtained using one lead electrocardiograph. After data acquisition, a tachogram was derived from ECG measurement in order to obtain the HRV signal; then Adaptive Noise Cancelling (ANC) filtering was applied, reducing artifacts due to respiration from HRV signal. This method was evaluated for spontaneous and controlled respiration frequency by comparing results from the Power Spectral Density (PSD) of HRV signal before and after filtering. At the results, it is observed that frequency components related to respiration are cancelled in the HRVs PSD, reaching an appropriate estimation of the control exerted by the Autonomic Nervous System (ANS) in the cardiac activity.**

*Keywords* —**Adaptive Filtering, Adaptive Noise Canceller, ECG, HRV, Respiration, RSA.**

## I. Introduction

The Autonomic Nervous System (ANS) is a component of the peripheral nervous system that adjusts the performance of target organs, including heart, for varying internal and external changes. ANS is subdivided into two parts, sympathetic system and parasympathetic (or vagal) system; those subsystems have antagonistic effects on the cardiac function. While the sympathetic increases the Heart Rate (HR), the vagal reduces it. [1]

Since the last three decades it has been observed an important relationship between the balance on the sympathetic-vagal tone and the cardiovascular mortality [2], this situation has led to the development of some methods that quantitatively evaluate the ANS.

A non intrusive tool that helps to assess the ANS through the sympathetic-vagal balance is the Heart Rate Variability (HRV) and its Power Spectral Density (PSD). HRV measures the time interval between two consecutive R peaks in an Electrocardiogram (ECG) register for each beat. This information is represented in a tachogram, which is a sequence of RR-intervals (RRi) extracted from the ECG, this sequence is obtained for each event, because RRi has not a constant period, tachogram is a non-uniformly sampled time series [3].

HRV changes synchronously with the respiration (for every single breath); this phenomenon is known as Respiratory Sinus Arrhythmia (RSA) and has its origin in breathing mechanics. During the inspiration, HRV is incremented, and it is reduced in the expiration [4].

As a result of RSA modulation, methods have been developed to minimize respiration effects on HRV. Several methods include the use of metronome-breathing with a fixed frequency which allows to underestimate the influence of the respiration on the HRV measurement protocols exposed in [5]-[7]. Methods that control Respiration Frequency (RF) have a major disadvantage; they change the natural behavior of the ANS functions, modifying the sympathetic-vagal balance. Another inconvenience is that, they need a conscious control on breathing; therefore, they cannot be used in sleep or coma periods.

Biomedical signals are usually contaminated and degraded by background noise whose spectrum overlaps the signal's one. In this case, using conventional linear filters with fixed coefficients would lead to unacceptable distortion of the desired signal. That is the reason why it is more appropriate to employ a filter with self-adjustable coefficients [8]. Because of their self-adjusting performance and flexibility, adaptive filters had been successfully used in diverse biomedical applications [8]-[14].

Using the Adaptive Noise Canceller (ANC) structure, it is possible to reduce the effects of the respiration over the HRV even with spontaneous respiration. This permits a better measurement in the sympathetic-vagal balance, meaning a more precise evaluation of the ANS based on the HRV.

## II. METHODOLOGY

The system developed for the implementation of the method discussed in this paper was divided in two stages: Conditioning & Acquisition and Processing, as shown in Fig. 1.

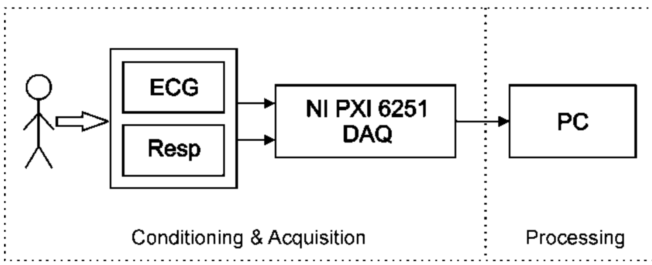


Fig. 1. System for simultaneous ECG and Respiration treatment.

### A. Signal Conditioning & Acquisition.

ECG signal consists in one lead, Lead I, which was acquired by an electrocardiogram designed and built in the Department of Electromechanic Instrumentation of the National Institute of Cardiology (INC) which has a linear voltage gain of 1000 and a bandwidth from 0.45Hz to 45Hz [5]. At the same time, the respiration signal was measured by pressure changes inside a reference balloon which is harnessed to the subject's thorax. These pressure changes reflect the thoracic cavity volume variations; during inspiration, pressure in the reference balloon increases, while in expiration, it decreases (Fig. 2). This respiration measurement method is presented as an alternative to the approaches presented in [10],[12]. The proposed technique not only measures the respiration signal, but also the inherent artifacts due to respiration mechanics; in addition, this technique is effective for nose and mouth breathing.

ECG and respiration signals were acquired simultaneously at 240 samples per second, during 5 minutes [2] through a Data Acquisition (DAQ) board NI PXI 6251 which has a resolution of 16 bits. Digitalized signals were saved as Comma Separated Values (CSV) files, for later processing.

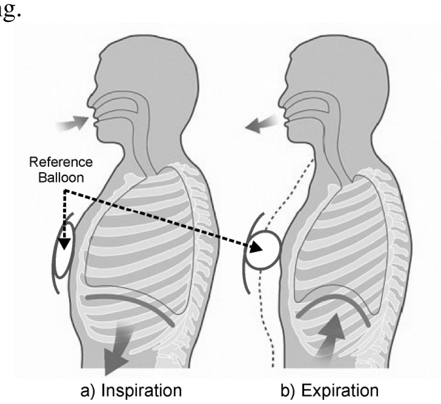


Fig. 2. Respiration measurement technique.

### B. Signal Processing.

Signal processing is carried out offline using the CSV files obtained in the previous step. Fig. 3 shows the block diagram of the Signal Processing stage.

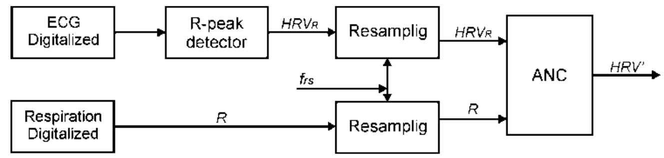


Fig. 3. Signal Processing Scheme.

ECG signal was processed using the second derivative method [15] along with thresholding and maximum detector in order to find the R peaks. After this automatic R-peak detection, it was performed a visual examination to find and remove possible false negatives and false positives. With this information, RR intervals are calculated and put together to construct tachogram signal ($HRV_R$ in Fig. 3).

$HRV_R$ is the sum of *HRV* and respiration influence ($R_i$). Because $HRV_R$ is not a uniformly sampled signal, it was required to be resampled using a frequency of 5 Hz (*frs* in Fig. 3). Parallel to this process, respiration signal (*R* in Fig. 3.) which was sampled at 240Hz, was decimated to obtain *R* signal with the same sample frequency than $HRV_R$. These resampling processes were necessary in order obtain sample to sample synchronous signals to implement the ANC structure.

Reduction of respiration influence on *HRV* was achieved using the ANC structure shown in Fig. 4 which is formed by a Finite Impulse Response (FIR) filter together with the Least Mean Squares (LMS) adaptation algorithm.

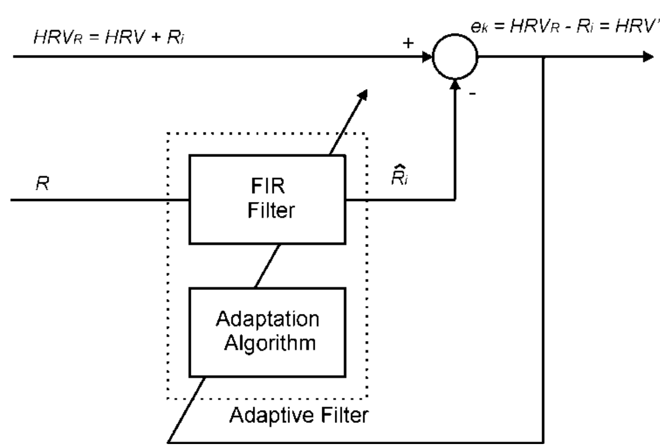


Fig. 4. Adaptive Noise Canceller structure.

The LMS algorithm adjusts the coefficients of the filter, sample to sample, in order to minimize the mean square error [8]. The upcoming coefficient weight vector is calculated using (1)

$$w(k+1) = w(k) + \mu e(k)R(k) \qquad (1)$$

where *w(k+1)* is the new weight vector at the *(k+1)th* sampling instant; $\mu$ is the step size and defines the stability and convergence rate of the adaptive filter, *w(k)* and *R(k)* are the weight vector and the delayed input vector at the *kth* sampling instant and *e(k)* is the instantaneous local error given by (2)

$$e(k) = HRV'(k) = HRV_R(k) - w^{\mathrm{T}}(k)R(k) \qquad (2)$$

where the term $w^{\mathrm{T}}(k)R(k)$ is the filter output, named as $\hat{R}_i$ and it is the estimate of $R_i$. Therefore *HRV'* is the approximation of *HRV*. The value for the step size $\mu$ was heuristically determined after a series of experiments, the optimal value found was 0.07. Delay and correlation between *R(k)* and $HRV_R$ *(k)* were used to choose the filter length. The order of the vectors and filter was set on N=300.

After implementation of the ANC, Power Spectral Density (PSD) was derived from $HRV_R$ and *HRV'* and compared. In addition Low Frequency (LF) power, High Frequency (HF) power, and LF/HF balance were calculated. LF range comprehends from 0.04 to 0.15Hz, HF band is defined from 0.15 to 0.4Hz and LF/HR balance is defined by the ratio of LF and HF power [2].

## III. RESULTS

The method explained in Section II was implemented using MATLAB, and it was evaluated by the following scenarios:

1) Controlled RF inside the HF band, 0.25Hz.
2) Controlled RF beyond HF band, 0.616Hz.
3) Spontaneous respiration.

Respiratory frequency control was guided by a visual indicator designed in LabVIEW for these tests. Results shown in Fig. 5 to Fig. 7 correspond to three 5-minutes records in sitting position.

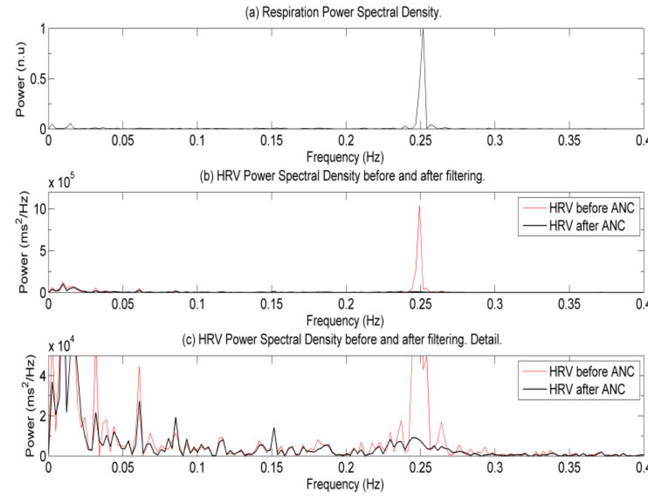


Fig. 5. Power Spectra for RF = 0.25Hz. (a) Respiration PSD, (b) and (c) HRV PSD before ANC ($HRV_{R)}$.and after ANC ($HRV'$).

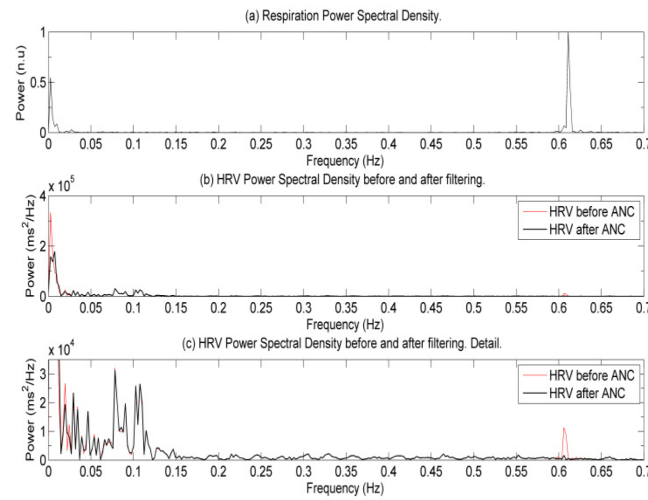


Fig. 6. Power Spectra for RF = 0.616Hz. (a) Respiration PSD, (b) and (c) HRV PSD before ANC ($HRV_{R)}$.and after ANC ($HRV'$).

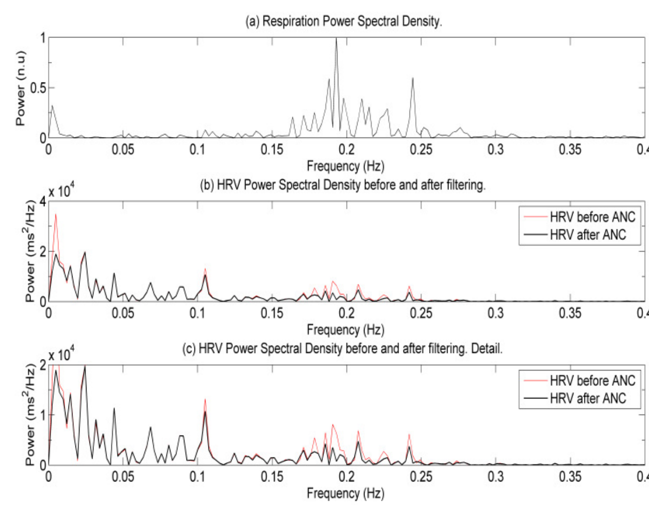


Fig. 7. Power Spectra for RF = No Controlled. (a) Respiration PSD, (b) and (c) HRV PSD before ANC ($HRV_{R)}$.and after ANC ($HRV'$).

It is visible in Fig. 5(b), Fig. 6(b) and Fig. 7(b) that ANC cancels respiration components unaffecting the spectrum corresponding to HRV signal. In the second scenario, it could be observed than the Respiration influence is not as appreciable as in scenario I where RF is located inside the HF band.

LF and HF power, and the LF/HF rate for each scenario are calculated before and after filtering with the ANC. Power measurement was made in absolute values of power ($ms^2$) and normalized units (n.u.) which represent the relative value of the band power in proportion to the total power (LF+ HF). Results are shown in Table I.

TABLE I
SPECTRUM ESTIMATION RESULTS.

| RF (Hz) | 0.25 | | 0.616 | | No controlled | |
|---|---|---|---|---|---|---|
| | Before ANC | After ANC | Before ANC | After ANC | Before ANC | After ANC |
| LF power (n.u) ($ms^2$) | 12.7 (602.46) | 47.8 (555.15) | 79.3 (807.36) | 79.1 (807.26) | 54.2 (262.38) | 64.0 (256.17) |
| HF power (n.u) ($ms^2$) | 87.3 (4137.0) | 52.1 (605.84) | 20.6 (210.65) | 20.9 (213.43) | 45.7 (221.39) | 35.6 (144.07) |
| LF/HF | 0.1456 | 0.91 | 3.83 | 3.78 | 1.18 | 1.77 |

It can be seen in Table I that LF/HF is meaningfully modified by the ANC, when respiration's frequency components are present within the bands of interest, LF and HF (from 0.4 to 4Hz).

## IV. CONCLUSION

In this paper, a novel measurement technique was utilized to register respiratory activity and movements related to it, in order to obtain a more precise estimate of the signal that affects the HRV.

The adaptive filtering proposed method has a successful performance reducing the respiration influence (RSA and respiration mechanics artifacts) from the HRV signal, which is used to analyze the sympathetic-vagal balance. In terms of computational and storage requirements, the LMS algorithm is most efficient than others such as the recursive least squares (RLS), and the Kalman filter algorithms, in addition the LMS algorithm does not suffer from the numerical instability problem inherent in the other two algorithms [8]. These reasons would lead to an easy implementation of the method exposed in this paper in portable devices.

The mentioned methodology also could be used to filter respiration influence from other physiological signals e.g. pupillary area [5] and electrogastrographic (EGG) [16]. Even more, it could be implemented in medical protocols that evaluate the ANS on patients who suffer from different pathologies that affect the correct functionality of the nervous system.

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