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Impedance Cardiography Filtering using Scale Fourier Linear Combiner based on RLS algorithm

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Abstract— **The Cardiac Output (CO) can be calculated from the thoracic cardio-impedance signal from several methods, and all of them are linked to the frequency information, information that is limited by the type of filtering used before. A methodology is proposed to evaluate the effect of the commonly used methods of filtering, and an improvement of the SFLC LMS-based algorithm by the use of RLS algorithm is also tested. Performances of algorithms are then evaluated considering different types of noise such as white noise or combination of sinusoidal noises to simulate the effect of respiration and body movements.**

I. INTRODUCTION

Impedance CardioGraphy (ICG) is a technique to obtain the cardiac output in a simple, repeatable, cost-effective and non-invasive procedure on a beat-by-beat basis. Besides these advantages, it has a major problem. ICG is particularly sensitive to noise, whether induced by a body movement, shock or simply by ventilation.

Depending on the processing, the impedance signal $Z = Z_0 + \Delta Z$ can be filtered and studied with its derivative, or the dZ/dt signal can be directly filtered to extract the fiducial points (see Fig. 1) : the opening of aortic valves (B), aortic valve closure (X) and the maximum value of dZ/dt following the opening of valves (C). To our knowledge, there are only few methods to detect these events in time (see [1] and [2]).

However, the methods of event detection require that the frequency information of dZ/dt is quite clean and not too buried in noise. Hence, we didn't focus our work on event detection, but mainly on filtering the signal.

Several studies have been carried out on this subject in order to obtain reliable measurements (see [3], [4] and [5] for example). A. K. Barros has developed the Scaled Fourier Linear Combiner (SFLC), based on an adaptive algorithm Least Mean Square (LMS) [6]. The principle of an adaptive filter is to denoise the impedance signal (Z) from a reference signal or a reference noise. A. K. Barros constructed reference signal, assumed periodic with R-R period, from a Fourier series, and the coefficients of this Fourier series are estimated using the LMS algorithm. This method allows to reconstruct the information related to cardiac cycle and to reject all the information containing frequencies different

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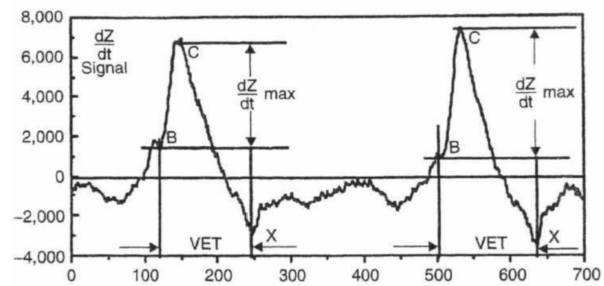


Fig. 1. Basic features of $dZ(t)/dt$ signal used for application and diagnostic purposes

than heart rate and associated harmonics: noise artifact or breathing. However, parameters of the adaptive algorithm itself may affect the quality of the reconstructed signal. About this last point, no extensive study has been carried out on the subject to our knowledge.

After recalling the principle of SFLC algorithm, we propose an improvement of it by replacing the LMS algorithm, originally used by Barros, by the Recursive Least Square (RLS) algorithm [7]. A methodology is then presented to compare different approaches. Finally, we discuss the results obtained using the different filters (SFLC-LMS and SFLC-RLS) and Ensemble Averaging (EA).

II. ADAPTIVE ALGORITHMS AND SFLC

The output of SFLC estimated from ICG (Z and its derivative dZ/dt) can be expressed during the m^{th} R-R interval (RRI) which contains L_m samples:

$$y_n = \mathbf{w}_n^{\mathrm{T}} \mathbf{x}_n,\ n = 0, \cdots, L_m - 1 \tag{1}$$

with $\mathbf{w}_n = [w_{1,n}, \cdots, w_{2H,n}]^{\mathrm{T}} \in \mathbb{R}^{2H}$, $\mathbf{x}_n = [x_{1,n}, \cdots, x_{2H,n}]^{\mathrm{T}} \in \mathbb{R}^{2H}$ and

$$x_{i,n} = \left| \begin{array}{l} \cos\left(2\pi \frac{(i+1)}{2L_m} n\right) \text{ if } i = 1,\ 3, \cdots, 2H-1 \\ \sin\left(2\pi \frac{i}{2L_m} n\right) \text{ if } i = 2,\ 4, \cdots, 2H \end{array} \right. \tag{2}$$

SFLC output approaches the input signal by a Fourier series with H harmonics and coefficients of the series are estimated in $\mathbf{w}_n$.

A. LMS Algorithm

In classical SFLC [6], $\mathbf{w}_n$ is updated using LMS algorithm:

$$\mathbf{w}_{n+1} = \mathbf{w}_n + 2\mu(d_n - y_n)\mathbf{x}_n \tag{3}$$

where d_n is the n^{th} sample of the original ICG in the m^{th} RRI. LMS algorithm minimizes iteratively the mean quadratic error between original signal and reconstructed signal by Fourier series. μ is the factor that controls the stability and the rate of convergence: the higher the value of μ, the higher the rate of convergence but the lower the stability. The parameter μ is then adjusted to manage the compromise between the stability and the rate of convergence.

B. RLS Algorithm

RLS algorithm can be summarized as

$$\begin{array}{l} \mathbf{k}_n = \frac{\mathbf{P}_{n-1}\mathbf{x}_n}{\lambda + \mathbf{x}_n^{\mathrm{T}}\mathbf{P}_{n-1}\mathbf{x}_n} \\ \xi_n = d_n - \mathbf{w}_{n-1}^{\mathrm{T}}\mathbf{x}_n \\ \mathbf{w}_n = \mathbf{w}_{n-1} + \mathbf{k}_n\xi_n \\ \mathbf{P}_n = \lambda^{-1}\mathbf{P}_{n-1} - \lambda^{-1}\mathbf{k}_n\mathbf{x}_n^{\mathrm{T}}\mathbf{P}_{n-1}. \end{array} \qquad (4)$$

The computation of $\mathbf{w}_n$ is based on the *a priori* estimation error ξ_n and the gain vector $\mathbf{k}_n$. The parameter μ in the LMS algorithm is replaced by an expression which depends on $\mathbf{P}_n$, the recursive estimation of the inverse of the correlation matrix of the input reference, and λ the forgetting factor: $0 < \lambda \leq 1$. This last parameter controls the rate of adaptation of the algorithm: the lower is λ, the higher the rate of adaptation. The parameter λ is then adjusted to manage the compromise between stability and rate of convergence.

The RLS algorithm is more complex than LMS algorithm, but it does not delay its execution in real time due to performances of existing real time systems. Moreover, the rate of convergence is faster. Finally, performance is better in stationary case.

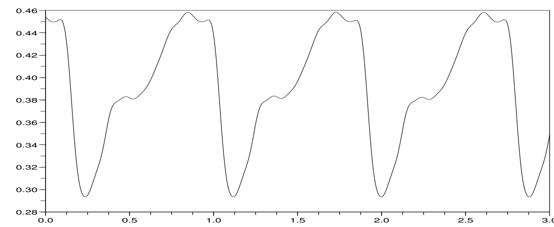
III. METHODOLOGY OF COMPARISON

In [6], A. K. Barros chose to use a noisy triangular signal to evaluate the performances of his algorithm. However, the characteristics of a cardiac signal may vary the performance as the frequency content is different from the one of a triangular signal. That's why, to propose a complete methodology to compare the performance of EA and the different SFLC algorithms -the SFLC-LMS and the SFLC-RLS-, we need reference of noise and cardiac information. We then propose to create a simulated impedance signal as similar as possible to a real impedance signal.

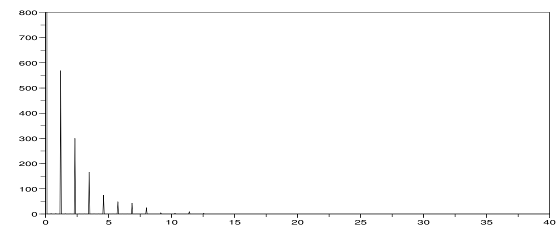
To achieve this, we acquired a signal at rest and then extracted ICG periods with almost no noise. This sample has been duplicated to obtain a signal which has been decomposed in the frequency domain. Then, we removed all the frequencies different from the fundamental frequency associated to the period and its harmonics, and reconstructed a synthesized ICG signal of 20s duration. The simulated signal has therefore all the components of a real signal, but is not noisy at all (see Fig. 2).

Similarly as in [6], we simulated:

- the noise-related breathing and movement of small amplitude from compositions of sinusoids of different frequencies (respectively lower and higher than heart rate),



(a) **Simulated Z**



(b) **Modulus of the Fourier Transform of Z**

Fig. 2. Simulated impedance signal and the modulus of its Fourier transform

- the acquisition noise with a Gaussian white noise with various variances to model different levels of noise.

In these circumstances, we tested our algorithms with different types of noise by extracting performances in terms of Signal to Noise Ratio expressed in decibel (SNR dB) and speed of adaptation.

IV. EXPERIMENTS AND RESULTS

A. Simulations

The simulated ICG signal has a sampling frequency of 1 kHz, an amplitude of 0.16 and the reference heart rate is 1.13 Hz (about 68 bpm). Regarding noise, we tested a wide range of types and amplitudes of noise. Firstly, the amplitude of noise varies to obtain SNR dB from -10 dB to 10 dB. Secondly, the type of noise can be :

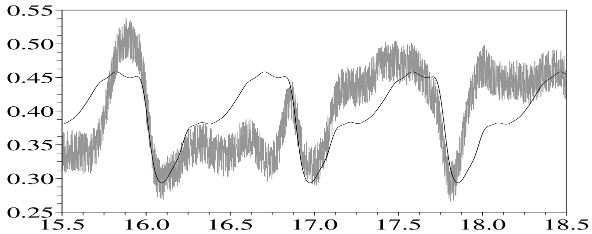
(a) either a Gaussian white noise (variance varies from 2.6×10^{-4} to 2.6×10^{-2}),

(b) a Gaussian white noise (variance varies from 4.9×10^{-5} to 4.5×10^{-3}) combined with 4 to 8 sinusoids whose frequency is below the heart rate (frequency is around 0.33 Hz and total amplitude varies from 0.05 to 0.75),

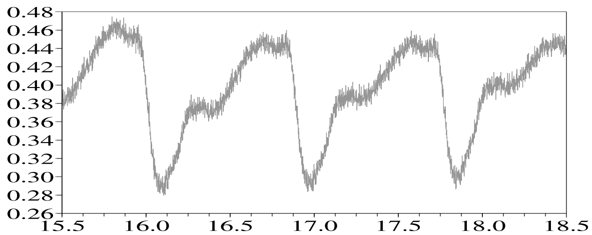
(c) or a Gaussian white noise (variance varies from 2.7×10^{-5} to 2.6×10^{-3}) combined with 4 to 8 sinusoids whose frequency is below the heart rate (frequency is around 0.33 Hz and total amplitude varies from 0.035 to 0.43) and others 4 to 8 sinusoids whose frequency is higher (frequency is around 1.3 Hz and total amplitude varies from 0.06 to 0.72).

In the (b) and (c) cases, the sum of sinusoids which have low frequencies in comparison to heart rate, simulates the ventilation while the sum of sinusoids which have high frequencies simulate the movement artifact.

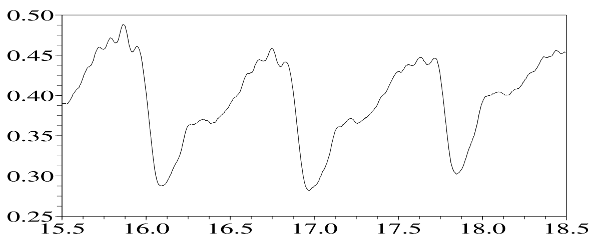
The tested algorithms are the EA, classically computed on ten cardiac periods (EA_{10}), the original SFLC



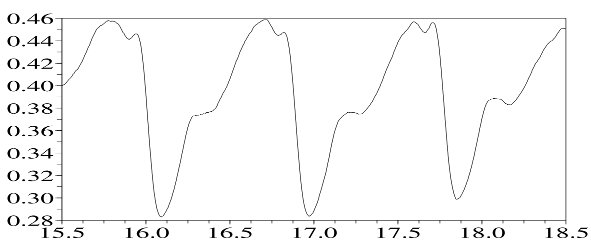
(a) Simulated Z before and after being noised.



(b) Z filtered by EA.



(c) Z filtered by SFLC LMS-based.



(d) Z filtered by SFLC RLS-based.

Fig. 3. Example of filtering on a simulated impedance signal noised by a combination of sin waves and Gaussian white noise with a SNR of 0 dB. (a) is the simulated Z before and after being noised, (b), (c) and (d) are the result after filtering with EA_{10}, SFLC LMS-based with $H = 12$ and $\mu = 0.005$, and SFLC RLS-based with $H = 9$ and $\lambda = 0.9997$

LMS-based algorithm and the new SFLC RLS-based algorithm. We have tested many combinations of parameters by varying the number of harmonics, $H \in \{9, 12, 15, 18, 21, 24\}$, and the parameters of the two algorithms: $\mu \in \{0.005, 0.01, 0.02, 0.05\}$ for LMS algorithm and $\lambda \in \{0.9993, 0.9994, 0.9995, 0.9996, 0.9997\}$ for RLS algorithm. Due to limitation of space, we only present the best results obtained with each algorithm. Nevertheless, the best configuration in most cases is $H = 12$ and $\mu = 0.005$ for the SFLC LMS-based algorithm, and $H = 9$ and $\lambda = 0.9997$ for SFLC RLS-based algorithm (see Fig. 3). In any case, SNR dB results are better using $H \in \{9, 12, 15\}$ than

TABLE I

RESULTS IN TERMS OF SNR DB AFTER FILTERING OF SNR DB WITH EACH TYPE OF NOISE AND ALGORITHM

	SNR dB	(a)	(b)	(c)
EA_{10}	-10	-0.03	4.81	5.31
	-6	3.93	8.26	8.79
	-3	6.84	10.62	11.93
	0	9.74	14.15	13.73
	3	12.42	16.11	16.81
	6	14.89	17.71	18.06
	10	17.61	19.71	19.86
SFLC LMS-based	-10	12.43	2.63	1.23
	-6	16.5	3.32	4.17
	-3	18.97	6.18	6.92
	0	21.88	8.67	9.71
	3	24.51	11.12	12.47
	6	26.62	13.65	14.87
	10	29.21	17.32	17.62
SFLC RLS-based	-10	15.19	3.96	5.37
	-6	19.42	9.91	8.23
	-3	21.88	12.78	11.43
	0	25	16.48	14.59
	3	27.9	19.39	18.03
	6	29.76	21.62	20.82
	10	33.35	26.42	23.43

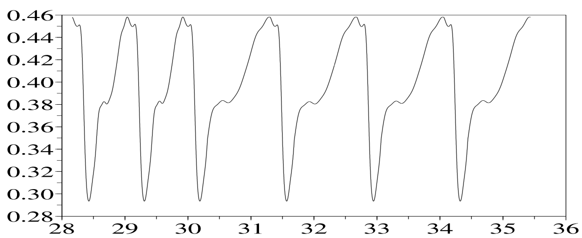
using $H \in \{18, 21, 24\}$, probably because the energy of the simulated signal is mainly represented by the first harmonics.

B. Simulation Results

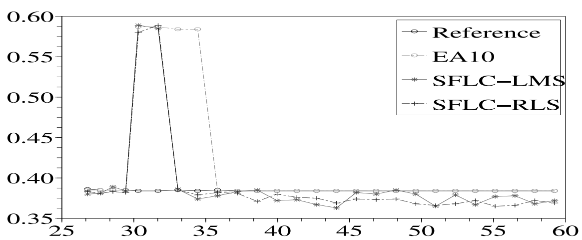
For each type of noise, twenty randomly noised signals of 20s duration were created and filtered by each algorithm. Then, the results of filtering algorithms served to calculate the SNR dB on the last 6 seconds of each signal, in order to evaluate the algorithm performances independent of their rate of adaptation. Table I summarizes the performances of algorithms in each case of noise described previously.

First, we can notice that the results of the EA method are almost similar for the (b) and (c) cases of noise (with sinusoids). In the case of a pure acquisition noise (Gaussian white noise), the results are lower than those in the other cases. An improvement of SNR dB in the (a) case could be obtained by increasing the number of periods taking into account in the EA. Nevertheless, the rate of adaptation will decrease proportionally to the number of periods.

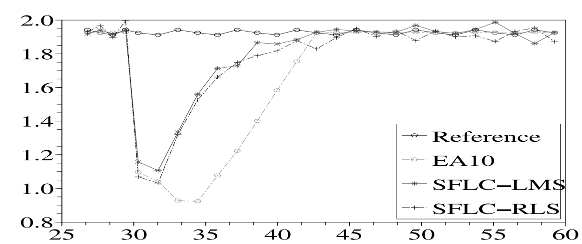
Regarding filters based SFLC, they both give excellent results in the case of acquisition noise (case (a)) with an advantage for the SFLC-RLS that increases the performances around 3 dB compared to SFLC-LMS. The difference is still more important in case of low-frequency noise (used to model ventilation) where the SFLC-RLS usually gets better results than the EA, while the SFLC-LMS has a slightly lower quality of the EA. Finally, once we combine Gaussian white noise, ventilation and movement (case (c)), the SFLC-LMS still offers lower quality than EA and SFLC-RLS. EA and SFLC-RLS show almost identical scores at lowest SNR dB noises. For highest SNR dB noises, SFLC-RLS provides the best scores. In the case of a "sinusoid" noise added to a Gaussian white noise, the performance between SFLC-LMS and SFLC-RLS ranges from 4 to 6 dB in the most



(a) Simulation of change in heart rate.



(b) Estimated Q-X period (s).



(c) Estimated $dZ/dt_{\max}$.

Fig. 4. Changes in calculated Q-X systolic period and $dZ/dt_{\max}$ value after a simulated change in heart rate. (a) represents the original signal ; (b) and (c) represent the results of calculation of Q-X period and $dZ/dt_{\max}$ after filtering with EA_{10}, SFLC-LMS with $H = 15$ and $\mu = 0.005$, and SFLC-RLS with $H = 15$ and $\lambda = 0.9997$

complex case (case (c)) and up to 9 dB in the case of a noise simulating acquisition noise and ventilation (case (b)).

To study the rate of adaptation of the different algorithms to a physiological change, we simulated a change in the heart rate from 68 bpm to 44 bpm, with a systole having the same duration and a diastole with an increased duration. No noise is added during this test. For this experiment, we only provide results using 15 harmonics as results obtained with less than 15 harmonics was poor. The main reason of these poor results is that the value of $dZ/dt_{\max}$ is systematically underestimated when using $H = \{9, 12\}$ because the Fourier series fails to adequately model the signal when the systole/diastole ratio is low. In this last case, high frequencies in comparison with heart rate appear in the signal.

Figure 4 shows simulated ICG signal (Fig. 4.a), estimated Q-X systolic periods (Fig. 4.b) and estimated $dZ/dt_{\max}$ values (Fig. 4.c). Q-X systolic periods and $dZ/dt_{\max}$ values are computed on the simulated signal and the signal filtered with the different algorithms: EA_{10}, SFLC LMS-based ($H = 15$ and $\mu = 0.005$) and SFLC RLS-based ($H = 15$ and $\lambda = 0.9997$). Compared to EA, both SFLC algorithms improve the speed of adaptation despite low μ and high λ values. We recall that it is possible to increase the rate of adaptation by increasing μ for SFLC-LMS and decreasing λ for SFLC-RLS. However, increasing the rate of adaptation also affects the quality of the estimation as both algorithms become less stable.

V. CONCLUSION AND PERSPECTIVES

In this paper, we discussed the influence of adaptive algorithms used in the SFLC filter: SFLC-RLS filter improves the performance of classical SFLC-LMS. In addition, it offers a good alternative to EA as SFLC-RLS improves SNR dB in case of Gaussian white noise and rate of adaptation performances against EA. Results are computed for simulated ICG signals in order to have ground truth for estimating SNR dB for noisy and denoised signals and physiological changes. These simulated ICG signals have been obtained from real ICG signals.

In a more general context, this study demonstrates that it is possible to improve the performance of SFLC in terms of SNR dB or rate of adaptation while keeping its overall structure. This may be done in different ways: finding other adaptive algorithms and using more pertinent reference information than R-R periods. Pertinent reference information may be improved by using information about the structure of the cardiac cycle like the durations of systole and diastole. Recently, these durations estimated using phonocardiography have been used in a modified SFLC [5]. Therefore, it could be hypothesized that this last approach could be further improved by RLS algorithm. However, ICG and phonocardiography signals are both affected by body movements ; then, another reference signal than phonocardiography has to be used, especially when the purpose is to filter ICG signal noised by body movements.

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