One-step wavelet-based processing for wandering and noise removing in ECG signals

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Abstract. This paper illustrates the application of the Discrete Wavelet Transform (DWT) to the processing of electrocardiogram (ECG) for wandering and noise suppression. The proposed scheme allows reducing the computational complexity, while its fixed-point modeling shows the expected performance of possible future portable hardware implementations. The system has been tested using synthetic ECG signals, which allow to accurately measure the effect of the proposed processing. Moreover, results from real abdominal ECG signals acquired from pregnant women are presented in order to validate the presented approach.

1 Introduction

Electrocardiogram (ECG) acquisition from the human skin involves the use of high gain instrumentation amplifiers. This fact makes the ECG signal to be contaminated by different sources of noise [1]. This circumstance is highlighted when the target is the measurement of fetal ECG signals acquired over the mother's abdomen [2]. Thus, denoising this type of signals is decisive for further parameter extraction, such as fetal heart rate estimation. Wavelet Transform (WT) [3] is a useful tool for a variety of signal processing and compression applications [4],[5]. This transform produces a time–frequency decomposition of the signal under analysis, which separates individual signal components more effectively than the traditional Fourier analysis. This fact makes WT one of the most used tools for biosignal processing, with ECG being an obvious candidate for this type of analysis. This paper proposes an arrangement of Discrete Wavelet Transform (DWT) structures for ECG signal processing, concretely for the suppression of different types of noise, including DC levels and wandering.

2 Background

The processing of ECG signals is necessary to remove contaminants from these signals that difficult visual inspection and ECG feature extraction. These contaminants have an instrumental and physiological origin [1]. Among these noises, the power line interference and the baseline wandering (BW) are the most significant. Apart from these, other noises may be wideband and complex stochastic processes that also distort the ECG signal. However, the BW and other wideband noises are not easy to be suppressed by analog hardware front-ends. Instead, software schemes are more powerful and feasible for offline processing. However, hardware platforms are the goal for portable ECG acquisition and processing systems. Thus, we studied the methods for removing these noises using hardware implementations of digital systems that allow easier suppression of the mentioned wideband noises. Concretely, Wavelet Transform [3] can be applied in many fields, being the noise suppression within specific subbands for ECG signals a highlight application [4].

BW has frequencies wandering between 0.15 and 0.3Hz. Wavelet Transform [3] can be used to remove the low frequency trend of a signal [6]. It applies wavelet decomposition until a resolution level where the approximation sequence can capture the BW, then subtracts this part from the raw ECG signal and computes wavelet reconstruction. Considering the most important frequency bands in BW are below 1 Hz, to remove wandering it should be necessary to select the resolution level so the approximation captures the ECG components for frequencies lower than 1 Hz. On the other hand, wavelet denoising has emerged as an effective method requiring no complex treatment of the noisy signal [7]. It localizes the most important spatial and frequential features of a regular signal in a limited number of wavelet coefficients. Moreover, due to the orthogonal transform, the random noise is spread fairly uniformly among all detail coefficients, assuring that wavelet shrinkage can reduce noise effectively while preserving the sharp features (peaks of QRS complex).

3 One-step DWT-based BW and noise suppression

Due to the similar wavelet structure for the application of BW and noise suppression, we propose here to apply in only one step both wavelet-based techniques. It will save important resources and/or time, which would facilitate any future hardware implementation. The required steps for the application of this approach are:

1. **Decomposition:** the wavelet decomposition is applied down to a certain level L in order to produce the approximation coefficients $a_n^{(L)}$ that capture the BW.
2. **Zeroing approximations:** the approximation $a_n^{(L)}$ is replaced by all-zero vector.
3. **Threshold details:** the level M (with $M<L$) allowing to properly distinguish the presence of partial discharges in the noisy details must be selected. Additionally, for each level from i=1 to M, the appropriate threshold limit and rule (soft or hard) are applied to the detail coefficients $d_n^{(i)}$ for better removing the noise.
4. **Reconstruction:** the wavelet reconstruction based on the zeroing approximations of level L, the modified details of levels 1 to M, and original details of levels from M+1 to L, are computed to obtain the BW corrected and denoised signal.

Thus, simultaneous BW and noise suppressions are easy to get using this wavelet-based technique for which it is necessary to select the proper parameters. The selection of the *wavelet family* has to be based on the similarities between the ECG basic structure and the wavelet functions, and the type of processing to apply. For removing BW it should be necessary to select a resolution level such its corresponding approximation captures the ECG components for frequencies lower than 1 Hz. As at each decomposition level the frequency band of the approximation is reduced to the half, the decomposition level for BW suppression can be calculated as $L = int[log_2(F_s/2)]$ where F_s is the sampling frequency. On the other hand, the maximum level for detail thresholding, M, depends on several factors such as the SNR in the original signal or the F_s. Noise content is significant in high frequency detail subbands, while most of the spectral energy lies in low frequency subbands [7]. Thus, in order to avoid losing clinically important components of the signal, such as PQRST morphologies, only high frequency detail subbands should be treated for denoising. Many methods for setting the threshold limit have been proposed [7], [11]. The most time-consuming way is to set the threshold limit on a case-by-case basis, so satisfactory noise removal is achieved. For signal denoising, once the threshold to be applied is selected, it is rescaled using noise variance. Some authors [10] use the following expression for the noise variance: $\sigma_i = median(|d_n^{(i)}|)/0.6745$. If the noise is white, the standard deviation from the details at the first level can be used to rescale the thresholds, (*simple rescaling*). If not, best results are obtained estimating the noise standard deviation at each level independently, and using each one to rescale the associated thresholds, (*multiple rescaling*). Finally, *soft* and *hard thresholding* set zeros for all details whose absolute value is less than the specified threshold and, in addition, for *soft thresholding,* this threshold is subtracted to the rest of the details.

3.2 Fixed-point modeling

In this paper, appropriate software models for the mentioned DWT-based BW and noise suppression are presented. Software models allow performing quick and simple parameter analysis of the modeled signal processing, while the translation of these models to fixed-point arithmetic allows to replicate the functioning of the appropriate hardware implementations and to analyze consequently parameters such as truncation, number of samples in the data window, most adequate sampling rates, etc. Moreover, these software models will also enable very quick tests of the required processing. MATLAB was used for the modeling and validation of the proposed one-step DWT-based processing. For fixed-point modeling, the most essential task is the right selection of word-lengths for the various variables in the system. On the other hand, two special modules required for our proposal are the DWT and the inverse DWT, which are designed to obtain high-performance results. Thus, the developed DWT and inverse DWT models include an input parameter to choose the wavelet family. Signal extension methods pad the borders of a signal to lessen discontinuity that might exist at the beginning and end of the signal and it is needed at each wavelet decomposition level. As the aim of the presented ideas is hardware development, it is important to consider the hardware implications of the extension mode. Thus, after careful evaluation, an extension mode, called *repetition padding*, is proposed in this work. It is based on the repetition of the first samples at the beginning and the last samples at the end of the signal, using the same order that these samples have in the original signal. The required resources for hardware modeling are mainly control logic and some registers. The required low-pass and high-pass filters are modeled using FIR filter banks and direct structure, while the coefficients of these filters and the tap number are determined by the wavelet function. Selecting a wavelet function of higher order requires filters of higher tap number, and thus, a higher number of resources for hardware implementation. So, it is desirable a low order wavelet function.

For evaluating the performance of the proposed floating-point models, the SNR parameter has been used: $SNR_{x/\hat{x}} = 10 \cdot log\left[\frac{\sum_i (x_n)^2}{\sum_i (x_n - \hat{x}_n)^2}\right]$. *DaIsy dataset* ECG signals [9] are targeted for evaluating the proposed floating-point wavelet models, using Daubechies order 6 as wavelet function. This dataset contains 8 leads of skin potential recordings of a pregnant woman, three thoracic and five abdominal, sampled at 250 sps rate and are 10-second long. Table 1 shows results for the parameter $SNR_{MAT/dp}$ that corresponds to the SNR between the approximation and details a_1, d_1, a_7, d_7 sequences obtained using the functions *dwt.m* and *idwt.m* available in the wavelet toolbox of MATLAB and the obtained using our floating-point models. The SNR values are very high, by the order of 300 dB, which indicates our floating-point model provides results equivalent to those obtained with wavelet toolbox functions.

On the other hand, the parameter $SNR_{\mathrm{ori/MAT}}$ is used to compare original signal with the reconstructed signals (without any processing of the data) from level 1, s_{r1}, and from 7, s_{r7} using wavelet toolbox functions, while $SNR_{\mathrm{ori/flp}}$ compares original signal with the reconstructed using our floating-point models. As Table 1 illustrates, the same RNS values for these two comparisons are obtained. Thus, results confirm the validity of the proposed floating-point wavelet models.

Table 1. Evaluation of the proposed floating-point wavelet modules.

		Real Abdominal ECG (DaISy dataset)							
	Parameter	**L1**	**L2**	**L3**	**L4**	**L5**	**L6**	**L7**	**L8**
a_1	$\mathbf{SNR_{MAT/dp}}$	315.6	315.4	313.5	315.6	316.4	316.1	313.6	315.7
d_1	$\mathbf{SNR_{MAT/dp}}$	309.0	304.0	306.7	310.3	302.7	307.1	305.5	307.8
a_7	$\mathbf{SNR_{MAT/dp}}$	307.8	296.5	306.6	313.6	303.0	300.1	302.2	305.5
d_7	$\mathbf{SNR_{MAT/dp}}$	305.4	301.4	306.1	299.6	305.4	301.8	301.5	302.9
s_{r1}	$\mathbf{SNR_{ori/MAT}}$	237.6	239.9	239.2	239.3	239.5	238.2	239.0	238.0
	$\mathbf{SNR_{ori/dp}}$	237.6	239.9	239.2	239.3	239.5	238.2	239.0	238.0
s_{r7}	$\mathbf{SNR_{ori/MAT}}$	230.2	230.0	230.2	230.7	230.1	230.3	230.0	230.1
	$\mathbf{SNR_{ori/dp}}$	230.2	230.0	230.2	230.7	230.1	230.3	230.0	230.1
s_{BW}	$\mathbf{SNR_{ori/MAT}}$	17.35	24.57	16.75	4.84	22.97	26.99	29.42	29.84
	$\mathbf{SNR_{ori/dp}}$	17.31	24.26	17.02	4.91	23.64	27.70	28.57	28.52
	$\mathbf{SNR_{ori/fixp}}$	17.22	24.28	17.01	4.91	22.07	27.62	28.65	28.60

In order to select the word-length for the DWT and inverse DWT fixed-point models, several studies varying word-lengths, from 34 to 12 bits, were made for lead-2 *DaISy dataset.* For the 16-bit fixed-point representation, the SNR between original and reconstructed signal for *J*=1 is 67.98 dB, which is an acceptable value for real signal processing systems. On the other hand, the results of another study show that if wavelet-based preprocessing for BW suppression is applied there is almost no difference in terms of SNR between the use of the predefined MATLAB functions, the proposed floating-point models and 16-bit fixed-point models, as S_{BW} results of Table 1 show ($SNR_{ori/fixp}$ compares original signal with the processed using our 16-bit fixed-point model). In addition, 16-bit fixed-point representation would offer a good balance between round-off errors and hardware implementation resources. Thus, 16-bit fixed-point representation of the data input and round-off after each level of decomposition and reconstruction was selected.

A brief analysis of the input parameters of the developed one-step BW suppression and denoising model is detailed at the following:

Wavelet function: The proposed fixed-point model allows using several wavelet families as Daubechies, Coiflets, Symlets, Biorthogonal and Reverse Biorthogonal.

Decomposition levels L and M: Our model automatically calculates the decomposition level for BW suppression according to the $L = int[log_2(F_s/2)]$. On the other hand, due to the difficulty to carry out *a priori* determination of the optimum maximum level *M* for detail thresholding, the proposed model allows selecting this parameter.

Threshold limits and rescaling: Only thresholds requiring low hardware computational cost were considered. The proposed model includes the possibility to select one of these three thresholds, *universal*, $Th_{uni} = \sqrt{2logN}$, *exponential*, $Th_{exp} = 2^{\left(\frac{i-M}{2}\right)}\sqrt{2logN}$ or *minimax* [8], $Th_{minimaxi} = 0.3936 + 0.1829 * (log(n_i)/log(2))$, where n_i represents the coefficient length at each level *i*=1, …, *M*. These thresholds require operations such as square root and logarithm that would require the use of special fixed-point algorithms for hardware implementation. However, for a prefixed signal length, *N,* it will be possible to know the coefficient length at each level, n_i. Thus, our model uses thresholds pre-computed just from *N* and *M*, since no other dependency on the signal to be denoised exists, a fact that is quite different to other proposed thresholds [7]. The following expression for estimating the noise variance $\sigma_i = media(|d_n^{(i)}|)/0.6745$ [10], and allows selecting *simple* or *multiple rescaling* [10]. The proposed rescaling can not be pre-calculated since it depends on the details. However, compared to other noise variance approximations, the complexity and the number of operations are reduced.

Threshold rules: The proposed model allows selecting *soft* or *hard thresholding*. The required operations can be easily implemented using fixed-point arithmetic.

4 Results

When working with real noisy ECG signals, it is not trivial to calculate a parameter that gives a quantitative measure about the applied technique. In order to better analyze our proposed one-step model, a separate study of BW and noise suppression has been made using synthetic ECG signals. For a quantitative evaluation of the BW suppression, we have employed synthetic ECG signals at 250, 500 and 1000 sps. Signals affected by BW are obtained adding a sine wave plus a DC level, using frequencies from 0.15 to 0.31 Hz that fit to the frequency band in real BW. Our study has estimated the BW of the signals as the approximations from level 1 to 12 and has reconstructed the signal removing the estimated BW. Table 2 resumes the main results, showing the SNRs between the synthetic and the BW corrected signal. According to the expression of *L*, for signals sampled at 250, 500 and 1000 sps, the adequate decomposition level for BW suppression will be 7, 8 and 9, respectively which is corroborated by Table 2. This study also reflects that better BW suppression (higher SNR) is achieved if the signal is sampled at higher frequency.

Synthetic ECG signals were also used to evaluate the performance of the noise suppression. These signals were contaminated adding Gaussian white noise to generate the noisy signal that is processed by the proposed model to obtain the denoised signal. This scenario is used by several authors [10] and allows visual inspection and quantitative evaluation. There are several parameters to measure the quality of the denoised signal [7], [10], as the SNR Improvement Measure SNRIMP [10]. A study using 3, 4 and 5 as maximum level for wavelet denoising, M, the three types of thresholds mentioned, *simple rescaling*, and *soft* and *hard thresholding* were carried out. A total of 12 wavelet functions were used for this evaluation. The study also considers two noise levels, approximately 15 dB and 25 dB. Table 3 shows the best results for denoising. Observing these summarized results and all the generated data, there are no large differences for the SNRIMP values of the different wavelet functions. Comparing *soft* and *hard thresholding*, *soft* gets for both noise levels higher SNRIMP using less number of levels. Regarding thresholds, Th_{exp} achieves best denoising if it is used along with *soft thresholding*, as it is the case with the combination $Th_{minimaxi}$ and *hard thresholding*. Observing all the denoised signals, it can be confirmed that *hard thresholding* almost do not decrease FQRS amplitude but for some signals introduces main discontinuities, while *soft thresholding* decrease FQRS amplitudes but no distortion is introduced. Thus, it is not possible to establish the best *threshold rule*, since it will depend on the ECG signal to be denoised.

Table 2. BW suppression analysis.

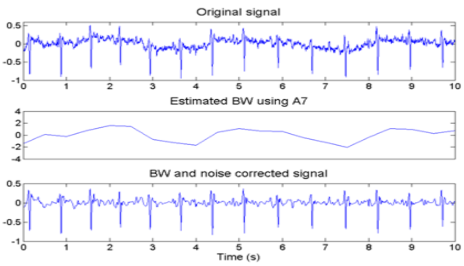
F_s (Hz)	N	F_w (Hz)	SNR for estimated BW								
			A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}
		0.15	1.866	6.563	12.579	**25.986**	25.484	7.826	-7.957	-8.948	-9.199
		0.19	1.866	6.563	12.570	**25.636**	22.445	-0.216	-8.630	-9.072	-9.193
250	**5400**	**0.23**	1.866	6.563	12.555	**24.591**	16.422	2.536	-8.981	-9.003	-9.035
		0.27	1.866	6.563	12.548	**23.882**	10.589	-7.621	-8.874	-8.943	-8.977
		0.31	1.866	6.563	12.561	**24.063**	6.442	-8.311	-8.886	-9.212	-9.339
		0.15	0.612	4.491	10.172	16.583	**30.755**	24.674	5.845	-9.762	-10.373
		0.19	0.612	4.491	10.170	16.541	**29.129**	21.425	-2.123	-10.440	-10.866
500	**10800**	**0.23**	0.612	4.491	10.168	16.485	**26.036**	14.864	0.825	-10.778	-10.796
		0.27	0.612	4.491	10.168	16.469	**25.625**	8.869	-9.412	-10.669	-10.750
		0.31	0.612	4.491	10.170	16.521	**25.237**	4.688	-10.16	-10.726	-10.064
		0.15	0.104	1.040	5.684	11.679	18.344	**33.993**	23.436	4.831	-10.805
		0.19	0.104	1.040	5.684	11.678	18.319	**31.447**	20.792	-3.154	-11.545
1000	**21600**	**0.23**	0.104	1.040	5.684	11.677	18.271	**26.531**	13.913	-0.238	-11.897
		0.27	0.104	1.040	5.684	11.677	18.255	**24.680**	7.822	-10.512	-11.771
		0.31	0.104	1.040	5.684	11.679	18.300	**25.393**	3.629	-11.258	-11.807

Table 3. Denoising evaluation using synthetic ECG signals.

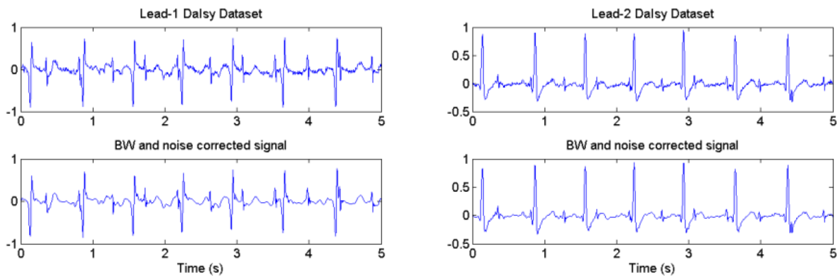
M	Threshold	Wavelet	SNR	SNRIMP	M	Threshold	Wavelet	SNR	SNRIMP
Soft thresholding 15 dB					**Hard thresholding 15 dB**				
3	Th_{exp}	coif3	21.2631	6.4015	4	$Th_{minimax}$	sym7	20.8648	5.9319
3	Th_{exp}	db7	21.4798	6.3944	5	$Th_{minimax}$	sym7	20.8288	5.8958
3	Th_{exp}	sym7	21.4286	6.3432	3	$Th_{minimax}$	sym7	20.8818	5.7964
3	Th_{exp}	db5	21.4274	6.3420	4	$Th_{minimax}$	db5	20.5822	5.7206
Soft thresholding 25 dB					**Hard thresholding 25 dB**				
3	Th_{exp}	bior3.9	29.5524	4.4960	3	$Th_{minimax}$	bior6.8	29.5025	4.5809
3	Th_{exp}	sym7	29.2657	4.3440	4	$Th_{minimax}$	bior6.8	29.5801	4.4725
3	Th_{exp}	bior6.8	29.2479	4.1915	3	$Th_{minimax}$	sym6	29.5035	4.4471
3	$Th_{minimax}$	bior3.9	29.0937	4.1720	5	$Th_{minimax}$	bior6.8	29.5436	4.4360

To study BW suppression and denoising it is also important visual inspection of the obtained signals, which in some cases is even more conclusive than quantitative measures. *DaIsy dataset* and *Physionet Dataset* [11] are targeted for evaluating the proposed one-step BW and noise suppression. *Physionet Dataset* recordings are from *Non-Invasive Fetal ECG Database* including two thoracic and four abdominal channels sampled at 1ksps rate and 60-second long. For these signals the selected parameters were wavelet function db6, *M*=3, *universal threshold*, *soft thresholding, single rescaling for DaIsy dataset,* and *multiple rescaling* for *Physionet Dataset*. Figure 1.a) includes the obtained result for lead-4, where estimated BW and BW and noise corrected signals are shown. Figure 1.b) includes results for lead-2 and lead-4.Finally, Figure 1.c) shows an example of results for ecgca 746 signal of *Physionet Dataset* including the detail of one of the fetal QRS complexes before and after processing. These figures show that the abdominal ECG signals are BW corrected and denoised while retaining its main characteristics as the fetal QRS complexes, which is very important for future parameter extraction [4].

Fig. 1. a) Lead-4 *DaIsy database*, estimated BW and BW and noise corrected signal, b) Lead-1 and Lead-2 *DaIsy database* signals and BW and noise corrected signals, c) ecgca 746 abdomen Lead-1*Physionet Dataset* signal, BW an noise corrected and signal detail.



a)



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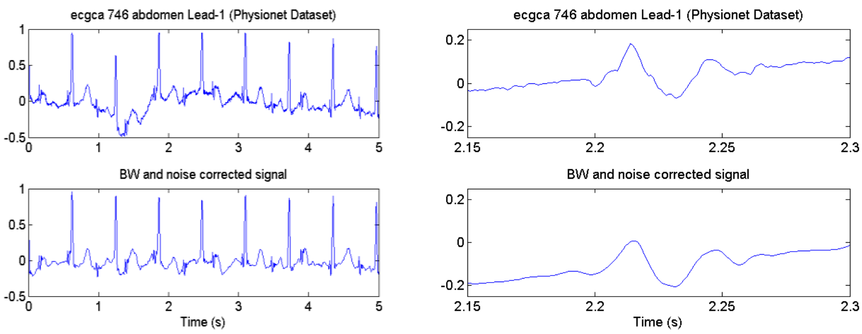

c)

5 Conclusion

This paper presents a fixed-point model for denoising ECG signals. It introduces a novel one-step wavelet-based method performing both BW and noise suppression with a sensible reduction of hardware resources. This model enables the study of different parameters that meet the specific ECG signal characteristics such as sample rate and noise levels. The presented results for synthetic ECG signals validate this method while applications on real AECG signal provided improved signals that are valid for further fetal heart rate extraction. The defined architecture also allows its hardware implementation, thus fitting portable ECG applications.

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