Comparative Analysis of Filters for Cancellation of Power-line-interference of ECG Signal

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Received: July 28, 2017 **Accepted: October 25, 2018**

Published: September 30, 2019

Abstract: *Filtering noises/artifacts from the electrocardiogram (ECG) can sustain the efficient clinical decision making. Comparative analysis of several filtering techniques is proposed: two adaptive noise cancellation techniques, Least Mean Square (LMS), Recursive Least Square (RLS); Savitzky-Golay (SG) smoothing filter and Discrete Wavelet Transform (DWT). These methods are implemented on 60 Hz Power-Line Interference (PLI), ECG signals of FANTASIA database and MIT-BIH Arrhythmia Database. Here, Short-Term Fourier Transforms (STFT) and Continuous Wavelet Transform (CWT) is introduced as a graphical tool to measure the noise level in the filtered ECG signals and also to validate the filtering performances of the proposed techniques. Statistical evaluation is also performed calculating the Signal to Noise Ratio (SNR), Mean Square Error (MSE), the Root Mean Square Error (RMSE), Peak Signal to Noise Ratio (PSNR) and Peak to Peak Amplitude (P2P) change before and after filtering of the ECG signals. The graphical results (frequency domain analysis using STFT and CWT) and statistical observation suggest that the noise cancellation performance of DWT is better, over other techniques.*

Keywords: *Power-line interference, Least mean square, Recursive least square; Savitzky-Golay smoothing filter, Discrete wavelet transform, Short-term Fourier transforms, Continuous wavelet transform, Signal to noise ratio, Mean square error, The root mean square error, Peak signal to noise ratio, Peak to peak amplitude.*

Introduction

Electrocardiogram (ECG) signal is non-stationary biosignal, which needs special attention towards noise cancellation [20, 33]. Donoho [8] and Bruce et al. [4] have proposed a powerful technique, i.e., thresholding in wavelet domain for signal noise cancellation. Analysis of heart functioning can only be possible by extracting the features from the noise free ECG signal, where filtering of ECG signal plays a significant role [19, 24]. Islam et al. [16] suggested a performance study of adaptive filtering using Least Mean Square (LMS) and Recursive Least Square (RLS) algorithm on several parameters like computational time, measure size and correlation coefficients. The ECG signal was combined with four types of AC and DC noises. These noises were nullified with the help of LMS and RLS algorithm. Hussain et al. [15] proposed a comparative study of different algorithms of adaptive filter. Normalized Least Mean Squares (LMS, NLMS) and Constrained Stability Least Mean Square (CSLMS) algorithms are used to real ECG signal from the MIT-BIH database and compared the operation of each filter outputs. Behbahani et al. [1] compared LMS algorithm of adaptive filter and the non-fault tolerant adaptive filters. Chandrakar et al. [5] used RLS based adaptive filter for the noise removal of ECG signals. Lin et al. [23] employed a PLI detector which uses optimal Linear Discriminant Analysis (LDA) algorithm for decision making during the occurance of PLI in ECG signal [23].

The last decades another approach for PLI suppression has been reported and discussed [9, 21, 22]. The main stages of the so called subtraction procedure consist of: detection of linear segments (usually PQ and TP intervals with frequency band near to zero); moving averaging over them to remove and extract the interference; calculation of phase locked interference components to be further subtracted outside the linear parts of the ECG signals (e.g., QRS complexes and some high and steep T wave).

Different approaches have already been considered for enhancing ECG signal with adaptive filters [28, 29, 32], which permit to detect time varying potentials and to cover the dynamic fluctuations of the signals. Various works have already been proposed using LMS based adaptive recurrent filter for acquiring the impulse response of normal QRS complexes and applied for arrhythmia detection in ambulatory ECG recordings respectively. Since the LMS adaptation algorithm is a simple and effective approach for Adaptive Noise Canceling (ANC) but it is not appropriate for fast-varying signals due to its slow convergence and due to the difficulty in choosing the correct value for the step size μ [10, 25, 36]. While frequency-domain representations of Savitzky-Golay (SG) filters have also been illustrated [3, 13], most presentationson SG filters (e.g., [28, 34]) have emphasized on time domain properties without reference to such frequency-domain features as pass band width or stop band attenuation. Non-stationary signals it is not tolerable to use digital filters or adaptive method because of loss in information [27, 30, 31]. Digital filters and adaptive methods can be used to signal whose statistical characteristics are stationary in many instances. Recently, the wavelet transform has been proven as a useful tool for non-stationary signal analysis.

In this context, the proposed four noise cancellations techniques, i.e., LMS, RLS, SG and Discrete Wavelet Transform (DWT) and their filtering performances are not only compared with the time domain scale, but also compared in frequency domain using Short Time Fourier Transform (STFT) and Continuous Wavelet Transform (CWT).

The baseline drift elimination was not executed to evaluate the filtering performances and to remain the signal undisturbed in power domain. The DWT as a filtering technique is proven to be a better option than other three techniques for non-stationary ECG signal.

ECG data sets

The proposed filtering techniques have been evaluated over ECG signals of 5 healthy subjects from the FANTASIA database [17] and ECG recording of 5 arrhythmic patients from MITDB [11] having a first row (signal) with the 300 samples (one complete ECG waveform). The ECG signals of both the databases are mixed with 60 Hz Power-Line Interference (PLI). These noise components are visually not identified as powerful PLI, but submerged with the ECG signals. The single ECG waveforms are selected from 5 recordings of both the databases for uniform processing and valuation. However the proposed techniques are tested over 1 hour ECG recording (Figs. 14-19). But the statistical evaluations are performed on single ECG waveform and different filtering techniques, performances are tabulated in Table 1A and B. To make uniformity in graphical decision making and analysis, the "*data # f1o07*" from FANTASIA database are selected which also suffer from 60 Hz PLI. The evaluation has been done on both the health and arrhythmic sets of databases and the observed statistical measures are tabulated (Table 1A and B).

Table 1A. Statistical observation of filtered ECG signals

Fantasia	SNR	MSE	RMSE	PSNR	P2P(A)
LMS					
f1o02	17.7201	0.0106	0.1027	67.9316	0.1958
f1o05	17.4614	0.0099	0.0996	68.2011	0.2400
f1o06	17.7696	0.0100	0.1002	68.1472	0.2032
f1o07	17.4264	0.0095	0.0976	68.3720	0.2852
f1o09	17.3190	0.0096	0.0978	68.3540	0.2903
RLS					
f1o02	22.8093	0.0034	0.0580	72.8993	0.2122
f1o05	22.7797	0.0030	0.0548	73.3920	0.2900
f1o06	22.1615	0.0037	0.0604	72.5395	0.2643
f1o07	21.8129	0.0037	0.0606	72.5145	0.2891
f1o09	21.9138	0.0035	0.0589	72.7679	0.3004
SGY					
f1o02	43.6857	2.9357e-05	0.0054	93.4877	0.1552
f1o05	36.5204	1.2824e-04	0.0113	87.0845	0.2134
f1o06	38.9705	7.6076e-05	0.0087	89.3523	0.2079
f1o07	41.2386	4.1548e-05	0.0064	91.9793	0.2219
f1o09	39.7177	5.7101e-05	0.0076	90.5983	0.0735
DWT (at Level 4)					
f1o02	45.1550	2.1140e-05	0.0046	94.9137	0.2375
f1o05	37.0775	1.1263e-04	0.0106	87.6484	0.3038
f1o06	38.9970	7.5521e-05	0.0087	89.3841	0.2268
f1o07	44.4385	2.0040e-05	0.0045	95.1458	0.2652
f1o09	41.8587	3.4938e-05	0.0059	92.7319	0.2761
DWT (at Level 8)					
f1o02	43.8693	2.8416e-05	0.0053	93.6292	0.2275
f1o05	35.7015	1.5443e-04	0.0124	86.2775	0.2938
f1o06	37.0852	1.1699e-04	0.0108	87.4831	0.2168
f1o07	42.9400	2.8295e-05	0.0053	93.6478	0.2254
f1o09	40.1881	5.1244e-05	0.0072	91.0684	0.2462

Short time fourier transform

Oppenheim et al. [27] and Press et al. [31] have stated that the STFT is the technique for non-stationary signal analysis that transforms, signal information from time domain into the time – frequency domain. The main concept of the STFT is to consider a non-stationary signal as a stationary signal over short periods of time within a window function [27, 31]. The computation of STFT can be defined as Eq. (1):

$$T(f,\tau) = \int_{-\infty}^{\infty} [x(t)w(t-\tau)]e^{-j2\pi ft}dt, \tag{1}$$

where $w(t-\tau)$ is the window function.

Table 1B. Statistical observation of filtered ECG signals

Fantasia	P2P(B)	MITDB	SNR	MSE	RMSE	PSNR	P2P(A)	P2P(B)
LMS								
f1o02	0.2469	100	17.7105	0.0104	0.1019	67.9992	0.2429	0.2434
f1o05	0.3155	105	17.5448	0.0101	0.1006	68.1150	0.2830	0.2756
f1o06	0.2488	109	17.5898	0.0102	0.1012	68.0610	0.3000	0.3144
f1o07	0.2939	111	18.0864	0.0111	0.1053	67.7181	0.1961	0.2052
f1o09	0.3063	112	17.9152	0.0112	0.1058	67.6770	0.2178	0.2280
RLS								
f1o02	0.2469	100	22.0874	0.0039	0.0622	72.2917	0.2395	0.2434
f1o05	0.3155	105	20.4877	0.0053	0.0726	70.9469	0.2554	0.2756
f1o06	0.2488	109	20.5512	0.0063	0.0791	70.1968	0.2408	0.3144
f1o07	0.2939	111	22.5345	0.0043	0.0656	71.8239	0.1618	0.2052
f1o09	0.3063	112	22.3028	0.0042	0.0645	71.9763	0.2261	0.2280
SGY								
f1o02	0.2469	100	48.6345	8.6459e-06	0.0029	98.7967	0.2200	0.2434
f1o05	0.3155	105	46.8314	1.2334e-05	0.0035	97.2539	0.2602	0.2756
f1o06	0.2488	109	51.2953	5.4558e-06	0.0023	100.7962	0.2357	0.3144
f1o07	0.2939	111	50.8260	6.1006e-06	0.0025	100.3111	0.1864	0.2052
f1o09	0.3063	112	51.3213	5.2680e-06	0.0023	100.9483	0.2049	0.2280
DWT (at Level 4)								
f1o02	0.2469	100	50.9803	5.0113e-06	0.0022	101.1653	0.2391	0.2434
f1o05	0.3155	105	50.2069	5.6485e-06	0.0024	100.6455	0.2668	0.2756
f1o06	0.2488	109	51.5212	6.0974e-06	0.0025	100.3134	0.3022	0.3144
f1o07	0.2939	111	50.5669	7.6821e-06	0.0028	99.3100	0.1912	0.2052
f1o09	0.3063	112	50.1548	8.3631e-06	0.0029	98.9411	0.2168	0.2280
DWT (at Level 8)								
f1o02	0.2469	100	49.7622	6.6721e-06	0.0026	99.9222	0.2293	0.2434
f1o05	0.3155	105	48.4097	8.5188e-06	0.0029	98.8610	0.2563	0.2756
f1o06	0.2488	109	48.2458	1.0927e-05	0.0033	97.7797	0.3015	0.3144
f1o07	0.2939	111	49.2092	8.8065e-06	0.0030	98.7167	0.1925	0.2052
f1o09	0.3063	112	48.1301	1.1029e-05	0.0033	97.7393	0.2078	0.2280

From Eq. (1) the STFT maps signal $x(t)$ into two-dimensional function in time, τ and frequency, f. The energy surface distribution of STFT called spectrogram can be computed from Eq. (2):

$$E(f,\tau) = |T(f,\tau)|^2 \ . \tag{2}$$

Here, the STFT is implemented to evaluate the changes in the input/original ECG signal and the filtered signal in frequency domain. Figs. 3, 6, 9, 12, 15 and 19 describe frequency domain changes of the filtered ECG signals as well as evaluate the performances of the different filtering methods.

Continuous wavelet transform

The CWT –$Wf(s,\tau)$ is the inner product of a time varying signal $f(t)$ and the set of wavelets $\Psi(s,\tau)(t)$ given by [12, 18]:

$$Wf(s,\tau) =< f, \Psi_{s,\tau} >= \frac{1}{\sqrt{s}} \int f(t) \Psi^{*}(\frac{t-\tau}{s}) dt. \tag{3}$$

The scaling and shifting the mother wavelet (Ψ) with factors of s and τ (with $s > 0$), respectively, generate a family of functions called wavelets given by:

$$\Psi_{s,\tau}(t) = \frac{1}{\sqrt{s}} \Psi\left(\frac{t-\tau}{s}\right). \tag{4}$$

The filtering performance and distortion level of PLI before and after noise cancellation can be analyzed in time-frequency domain (Figs. 4, 7, 10, 12, 17, 20 and 21). The noise level can be visually analyzed with changing the scale.

Adaptive noise cancellation system

Mollaei presented in his article [26] that the ANC system (Fig. 1) composed of two separate inputs, a primary input or ECG signal source which is shown as $s(n)$ and a reference input that is the noise input shown as $x(n)$. The primary signal is corrupted by noise $x_1(n)$. The signal $x_1(n)$ is highly correlated with noise signal or reference signal $x(n)$. Noisy signal $d(n)$ results from addition of primary signal $s(n)$ and correlated noise signal $x_1(n)$. The reference signal $x(n)$ is fed into adaptive filter and its output $y(n)$ is subtracted from noisy signal $d(n)$. Output of the sum block is then fed back to adaptive filter to update filter coefficients. This process is run recursively to obtain the noise free signal which is supposed to be the same or very similar to primary signal $s(n)$.

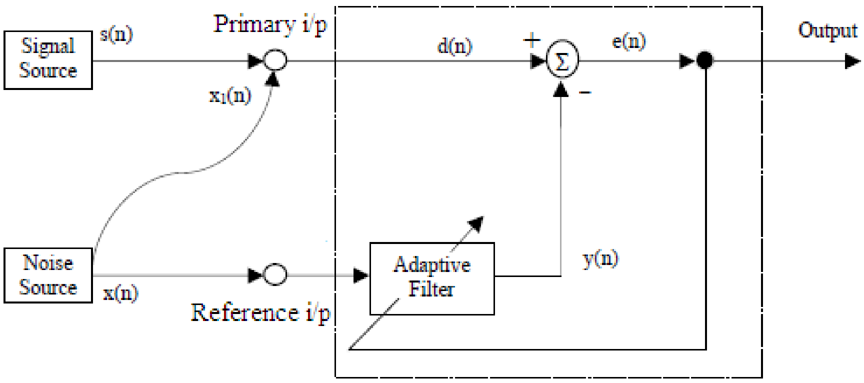

Fig. 1 ANC System

Least mean square algorithm

The LMS algorithm is also known as gradient-based algorithm [28]. Slock [34] suggested that the LMS is one of the simplest algorithms in adaptive structures and the output $y(n)$ of FIR filter structure can be formulated by Eq. (5).

$$y(n) = \sum_{m=0}^{N-1} w(m)x(n-m), \tag{5}$$

where n is the number of iteration.

Error signal is calculated by Eq. (6)

$$e(n) = \sum d(n) - y(n). \tag{6}$$

The filter weights are updated from the error signal $e(n)$ and input signal $x(n)$ as in Eq. (7).

$$w(n+1) = w(n) + \mu e(n)x(n), \tag{7}$$

where $w(n)$ is the current weight value vector, $w(n+1)$ is the next weight value vector, $x(n)$ is the input signal vector, $e(n)$ is the filter error vector and μ is the convergence factor which determine the filter convergence speed and overall behavior.

Normalized least mean square algorithm

Tandon et al., [35] discussed that, at large convergence factor μ the LMS algorithm faces gradient noise amplification problem. For rectifying such problem, NLMS algorithm is implemented where, the correction applied to the weight vector $w(n)$ at iteration $n+1$. This is "normalised" with respect to the squared Euclidian norm of the input vector $x(n)$ at iteration n. The NLMS algorithm can be viewed as time-varying step-size algorithm by formulating μ as in Eq. (8):

$$\mu(n) = \frac{\alpha}{c + \|x(n)\|^2}, \tag{8}$$

where α is the NLMS adaption constant, $0 < \alpha < 2$ and c = constant for normalization, $c < 0$. The Filter weights can be updated by the Eq. (9)

$$w(n+1) = w(n) + \frac{\alpha}{c + \|x(n)\|^2} e(n)x(n). \tag{9}$$

The LMS filter is applied to the noisy single ECG waveform and the graphical filtering evaluation is done using STFT (Fig. 3) and CWT (Fig. 4). The output filtered ECG signal shows the amplitude shifting (i.e., both elevation and deviation) in isoelectric ST segment (Fig. 2). The STFT spectrum of input-desired-output is also studied (Fig. 3), where the PLI at 60 Hz is still present in the output signal (can be compared with desired signal) which also suppressing the frequency components (i.e., ranges between 0.1 to 50 Hz). The same can be analyzed using sample versus the scale in CWT (Fig. 4), and the distortion (with small spikes) can easily be visualized (at 0-5 scale) in output signal.

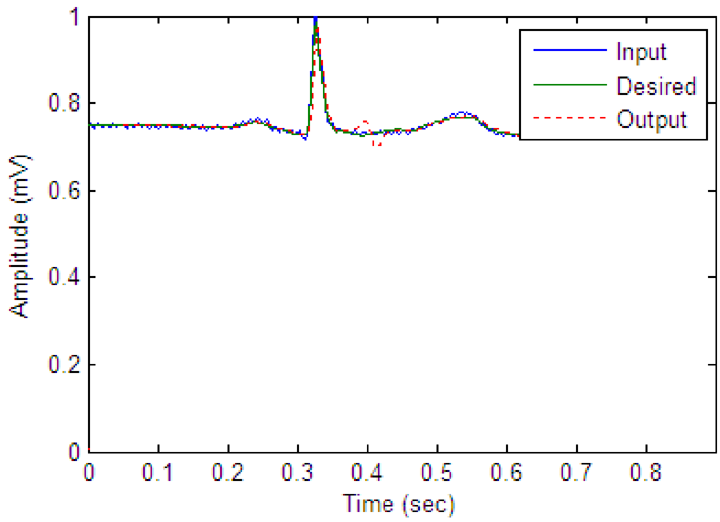

Fig. 2 Filtering with LMS for FANTASIA *data # f1o07*

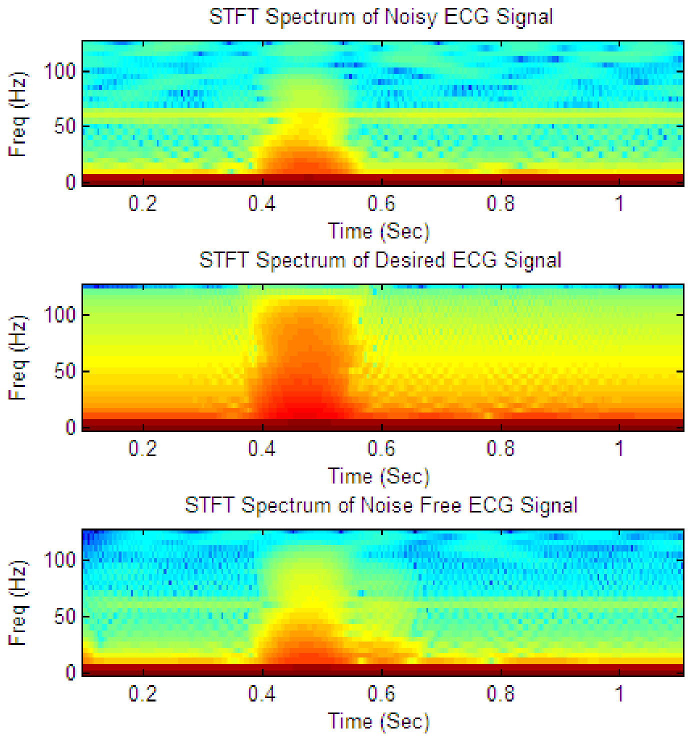

Fig. 3 Evaluation of LMS with STFT

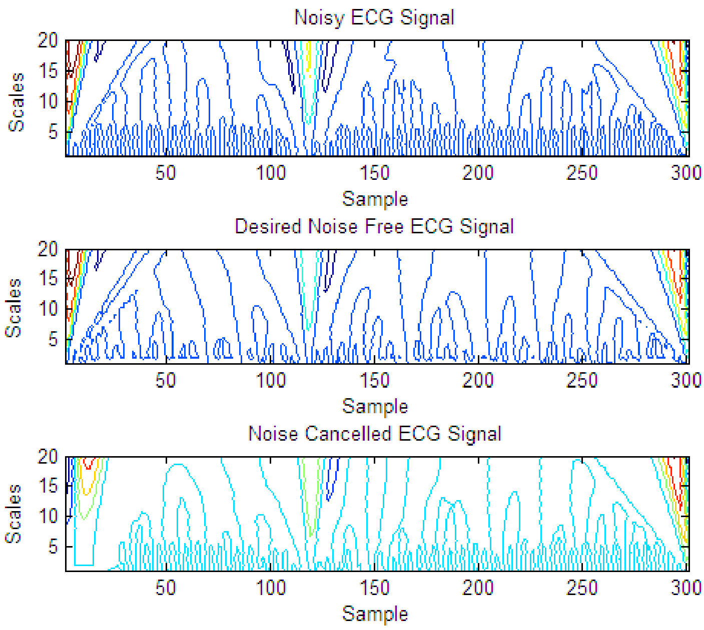

Fig. 4 Evaluation of LMS with CWT

Recursive least square algorithm

RLS algorithms perform well in time-varying conditions but the computational complexity and stability increases. The filter tap weight can be updated using the following Eq. (10):

$$w(n) = \bar{w}^T(n-1) + k(n)\bar{e}_{n-1}(n). \tag{10}$$

Eq. (11) and (12) gives the intermediated gain vector for computing tap weights.

$$k(n) = \frac{u(n)}{\lambda + x^T(n)u(n)}, \tag{11}$$

$$u(n) = \overline{w_\lambda^{-1}}(n-1)x(n), \tag{12}$$

where λ is a small positive constant very close to but smaller than 1.

The filter output is calculated from filter tap weights of previous iteration and the current input vector as in Eq. (13).

$$\bar{y}_{n-1}(n) = \bar{w}^T(n-1)x(n), \tag{13}$$

$$\bar{e}_{n-1}(n) = d(n) - \bar{y}_{n-1}(n). \tag{14}$$

RLS Algorithm requires higher memory because of estimating the previous samples of output signal, error signal and filter weight.

After implementing an RLS filter on the single noisy ECG waveform, the graphical filtering performance is analyzed using the STFT (Fig. 6) and CWT (Fig. 7). The output filtered ECG signal shows (Fig. 5) the time shifting of about 0.1 sec towards right. The STFT spectrum of input-desired-output is also studied (Fig. 6), where the PLI at 60 Hz is still present in the output signal (can be compared with desired signal) which also suppressing the frequency components (i.e., ranges between 0.1 to 40 Hz). The signal be plotted in sample versus scale using CWT (Fig. 7), and the distortion (with small spikes) can easily be visualized (at 0-5 scale) in output signal.

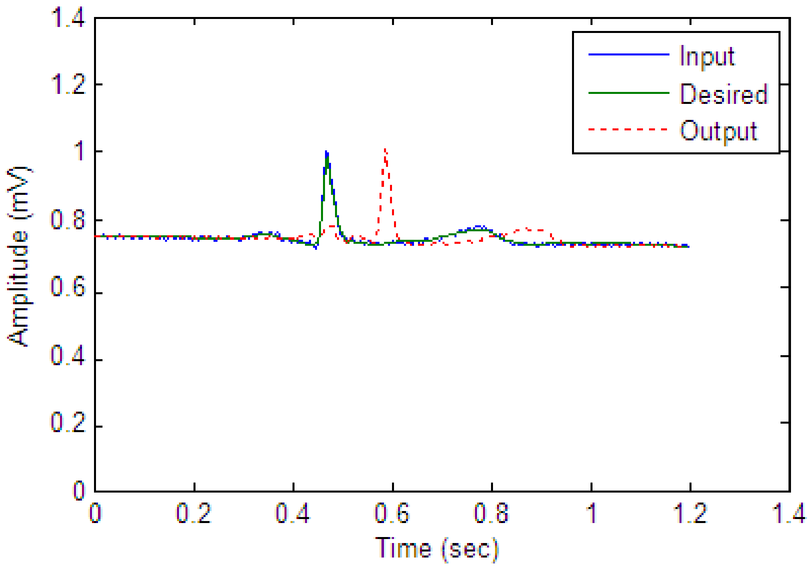

Fig. 5 Filtering with RLS for FANTASIA *data # f1o07*

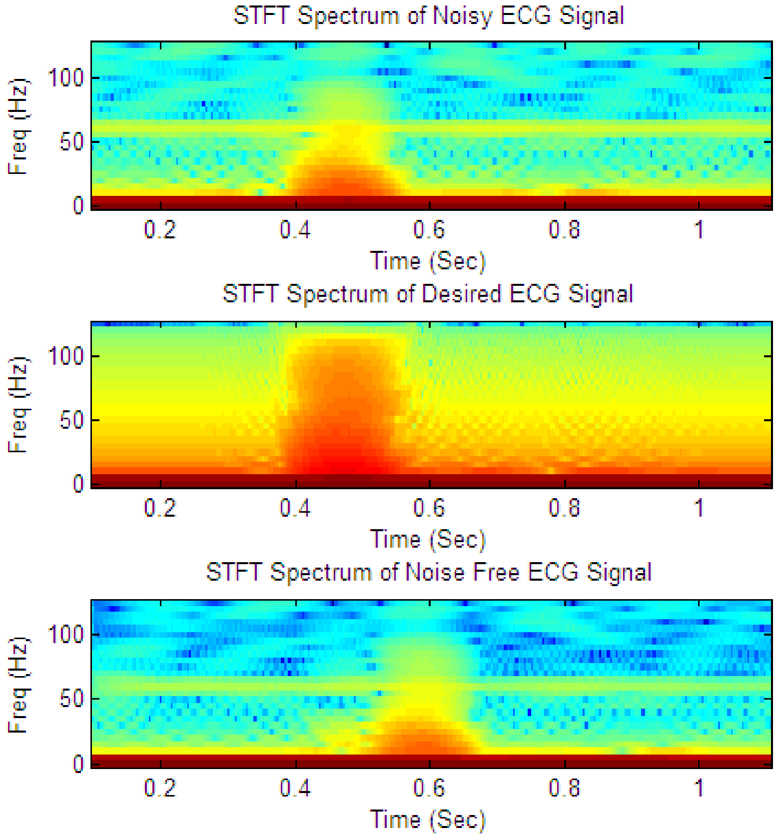

Fig. 6 Evaluation of RLS with STFT

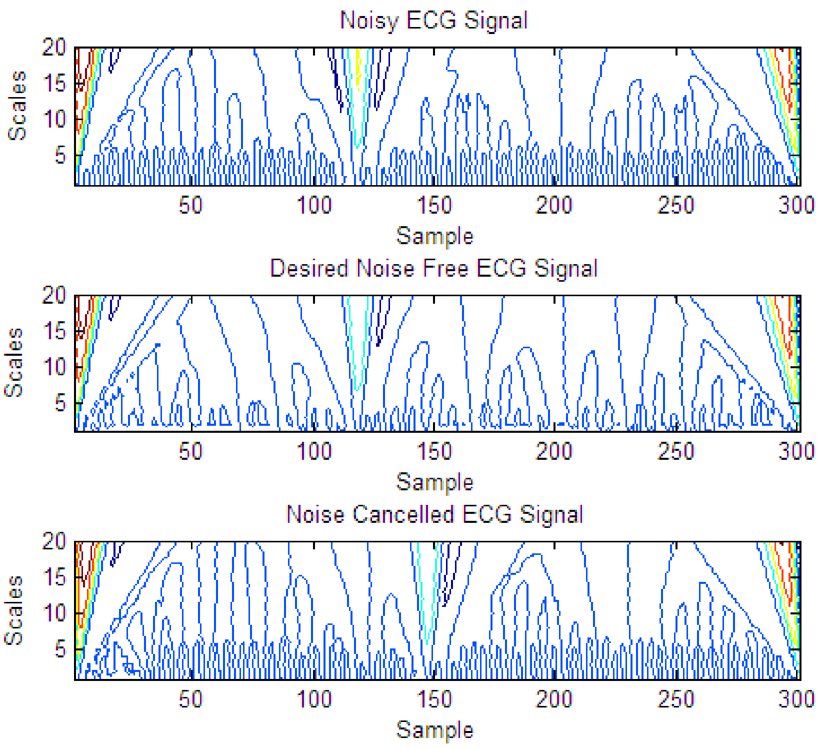

Fig. 7 Evaluation of RLS with CWT

Savitzky-golay smoothing filters

SG smoothing filters are producing a full degree of smoothing and preserving useful high frequency components of these parts of ECGs. Another feature of these filters as an FIR filter is their ability to preserve nonlinear features from a reconstructed phase space. These filters which are also known as polynomial smoothing or least-square smoothing filters are generalizations of the FIR averaging filters that optimally fit a set of data points to polynomials of different degrees.

In order to smooth parts of the ECG which lie between QRS complexes by a SG filtering method, these intervals are divided into subintervals containing an odd number of data points (span) N. The SG filter then fits the set of $N = 2M + 1$ data points x to a polynomial $\hat{x}_m$ of degree d:

$$x = [x_{-M}, \dots, x_0, \dots, x_M]^T, \tag{15}$$

$$\hat{x}_m = \sum_{i=0}^{d} c_i m^i, \quad -M \le m \le M. \tag{16}$$

The points $\hat{x}_{-M}, \hat{x}_{-M+1}, \dots, \hat{x}_M$ which are the projections of the points $x_{-M}, x_{-M+1}, \dots, x_M$ on the polynomial may be presented as follows:

$$\begin{bmatrix} \hat{x}_{-M} \\ \hat{x}_{-M+1} \\ \vdots \\ x_0 \\ \vdots \\ \hat{x}_{M-1} \\ \hat{x}_M \end{bmatrix} - \begin{bmatrix} 1 & -M & \cdots & (-M)^d \\ 1 & -M+1 & \cdots & (-M+1)^d \\ \vdots & \vdots & \vdots & \vdots \\ 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 1 & M-1 & \cdots & (M-1)^d \\ 1 & M & \cdots & M^d \end{bmatrix} - \begin{bmatrix} C_0 \\ C_1 \\ \vdots \\ C_d \end{bmatrix} \tag{17}$$

or, in short

$$\hat{x} = Sc. \tag{18}$$

Here

$$S = \left(m^i\right)_{N\times(d+1)} : -M \le m \le M : 0 \le i \le d. \tag{19}$$

The coefficients $C_0, C_1, \dots, C_d$ of the polynomials are unknown and must be determined. To determine these, the equation $x - \hat{x} = 0$ needs to be solved to find the vector C. This leads to solving the following matrix equation Sc.

$$x = Sc. \tag{20}$$

The least-square solution to an inconsistent system $x = Sc$ satisfies the following equation:

$$S^T x = S^T Sc. \tag{21}$$

The coefficient vector C and the fitted data vector $\hat{x}$ may then be calculated as follows:

$$C = (S^T S)^{-1} S^T x, \tag{22}$$

$$\hat{x} = S(S^T S)^{-1} S^T x. \tag{23}$$

SG smoothing filter is applied to the noise and the input-output relationship (Fig. 8) of time domain analysis. The filtered result shows that there is an amplitude degradation of R-peak (Fig. 8). The STFT spectrum of input (noisy) and output (noise free) ECG signal is also studied (Fig. 9), where the unfiltered PLI at 60 Hz is still present in the output signal also suppressing the frequency components (i.e., ranges between 0.1 to 30Hz). The same can be analyzed using sample versus scale in CWT (Fig. 10), and the distortion can easily be visualized (at 0-5 scale) in output signal.

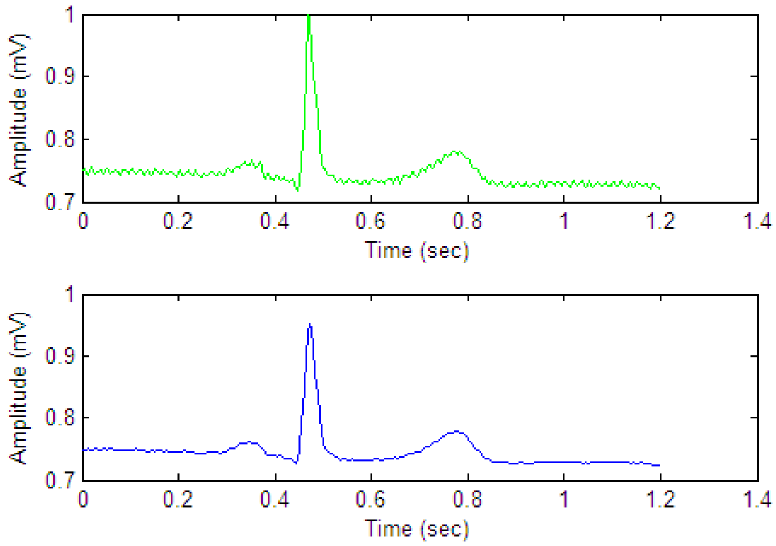

Fig. 8 Filtering with SG for FANTASIA *data # f1o07*

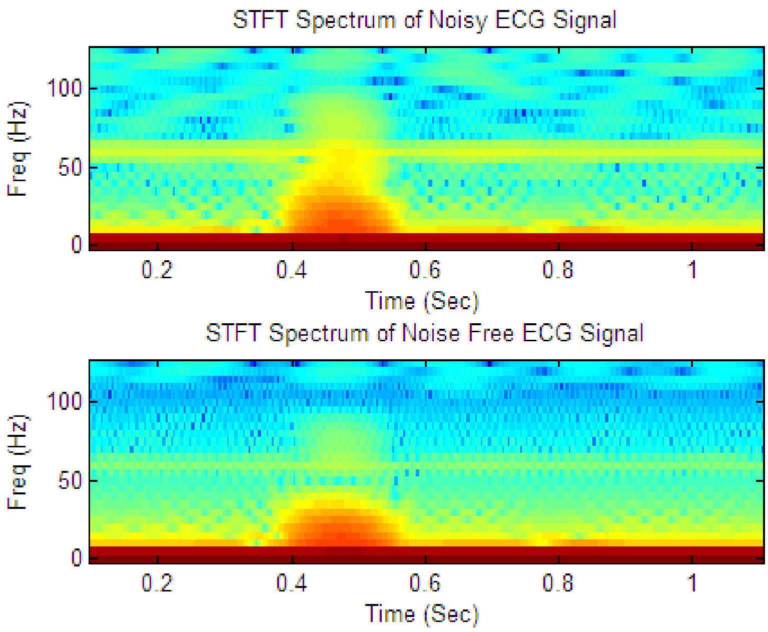

Fig. 9 Evaluation of SG with STFT

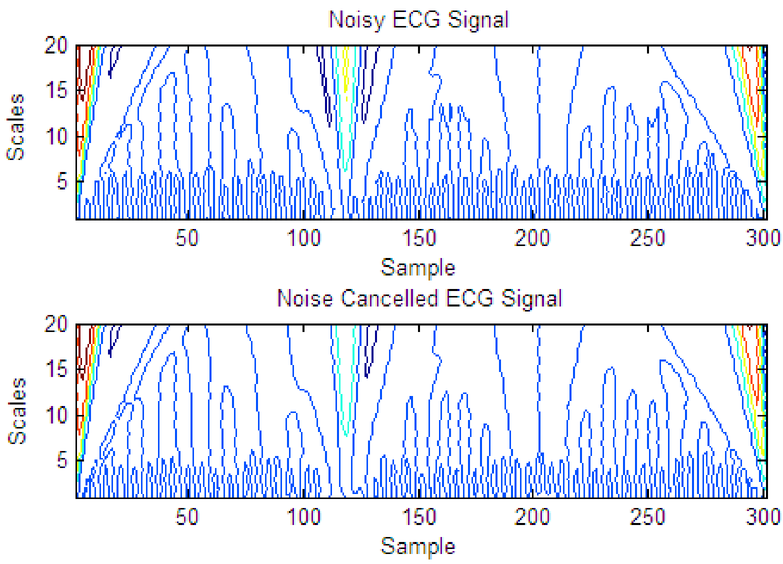

Fig. 10 Evaluation of SG with CWT

Discrete wavelet transform

Cohen et al. [7] have discussed a very common discretization of the CWT which consists of setting the scale and shift value as: $s = s_0^i$ and $\tau = k\tau_0 s_0^i$ with i and k are integers and s_0 is a real value >1. A practical choice of τ_0 and s_0 consists on setting s_0 to 2 and τ_0 to1 that is $s = 2^i$ and $\tau = k.2^i$. This is called dyadic wavelet transform and the wavelet functions become:

$$\Psi_{i,k}(t) = 2^{-\frac{1}{2}}\Psi\left(2^{-i}t - k\right). \tag{24}$$

The setting form of scale and shift parameters constitutes an orthonormal basis for $L^2(R)$ that is:

$$d_{i,k}(t) \equiv < f(t), \Psi_{i,k}(t) > \equiv \int f(t)\Psi_{i,k}(t)dt \tag{25}$$

and

$$f(t) = \sum_i \sum_k d_{i,k}(t) \cdot \Psi_{i,k}(t). \tag{26}$$

Truchetet [37] has illustrated that the DWT consists of applying the discrete signal to a bank of octave filters based on low and high pass filters $l(n)$ and $h(n)$ respectively; more precisely, the function $f(t)$ would be expressed as follows:

$$f(t) = \sum_{k=Z} a_L(k)\phi_{l,k}(t) + \sum_{j=1}^{L} \sum_{k=Z} d_j(k)\Psi_{j,k}(t) \tag{27}$$

with

$$d_j(n) =< f, \Psi_{j,n} \geq \Sigma k g'(2n-k) a_{j-1}(n), \tag{28}$$

$$a_L(n) =< f, \phi_{j,n} >= \Sigma k h'(2n-k) a_{L-1}(n), \tag{29}$$

where $\phi(t)$ is the scaling function and $\Psi(t)$ is the wavelet function, which is governed by the following condition:

$$\int \phi(t)dt = 1. \tag{30}$$

The objective of wavelet based denoising process is to estimate the signal of interest $s(t)$ (Eq. (9)) from the composite one $f(i)$ by discarding the corrupted noise $e(i)$ [14]:

$$f\ (i) = \ s(i) + \ e(i). \tag{31}$$

Donoho [8] has presented that the underlying model for the noisy signal is the superposition of the signal $s(i)$ and a Gaussian zero mean white noise with a variance of σ^2. The threshold value is computed according to the model of the signal of interest to be estimated $s(i)$ and the corrupted noise $e(i)$. Donoho and Jonhstone proposed the universal "VisuShrink" threshold given by:

$$Thr = \sigma\sqrt{2.log(N)} \tag{32}$$

In the case of white noise, its standard deviation can be estimated from the median of its detail coefficients (d_j), with $j = 1, \ldots, L$, and is computed as follows:

$$\sigma = \frac{MAD(|d_j|)}{0.6745}, \tag{33}$$

where MAD is the median absolute deviation of the corresponding sequence. Two algorithms of thresholding exist: Hard and Soft thresholding algorithms (T_{soft} and T_{hard} respectively) formulated as follows:

$$T_{soft} = sgn(x).(|x|.Thr), \tag{34}$$

$$T_{hard} = x.1(|x| > Thr). \tag{35}$$

Applying the classical wavelet denoising technique [8], i.e., the universal threshold and "soft" strategy, at level 8 appears no significant change in P and T waves whereas the R waves undergo minute distortion (amplitude loss), but at level 4, it seems to have considerably less/no loss.

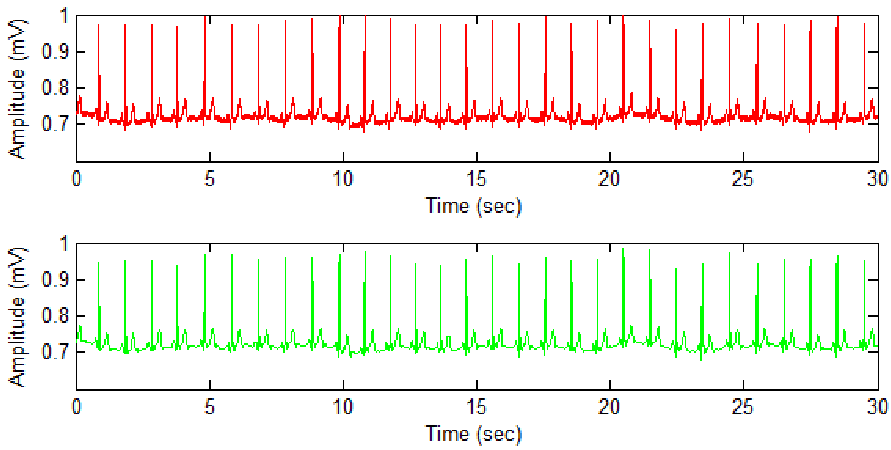

Fig. 11 Filtering with DWT at level 4 for FANTASIA *data # f1o07*
(30 sec data selected out of 1 hour recording for better visualization)

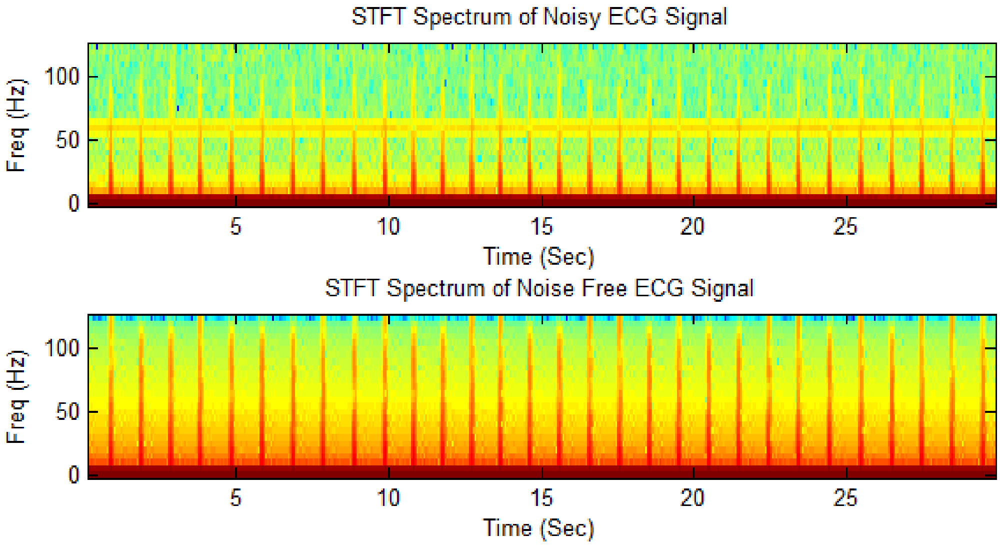

Fig. 12 Evaluation of DWT at level 4 with STFT for FANTASIA *data # f1o07*

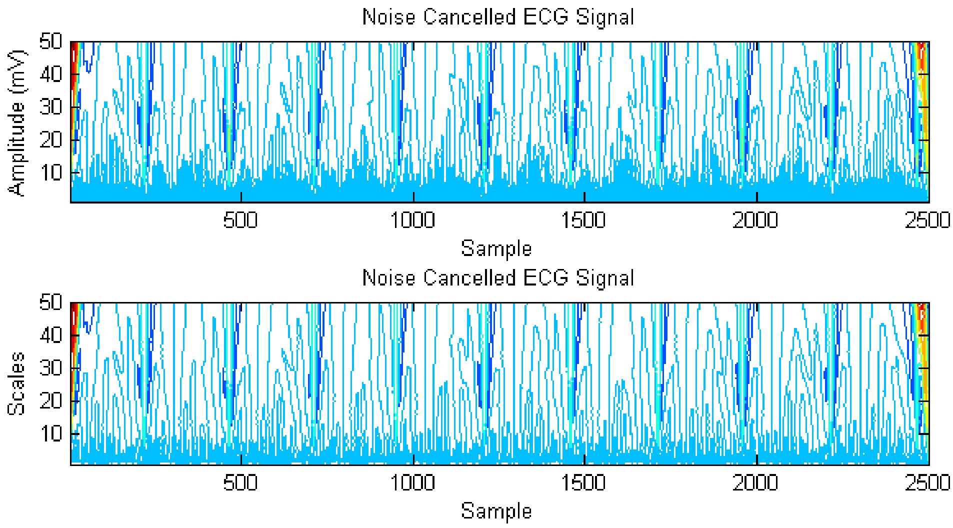

Fig. 13 Evaluation of DWT at level 4 with CWT for FANTASIA *data # f1o07*

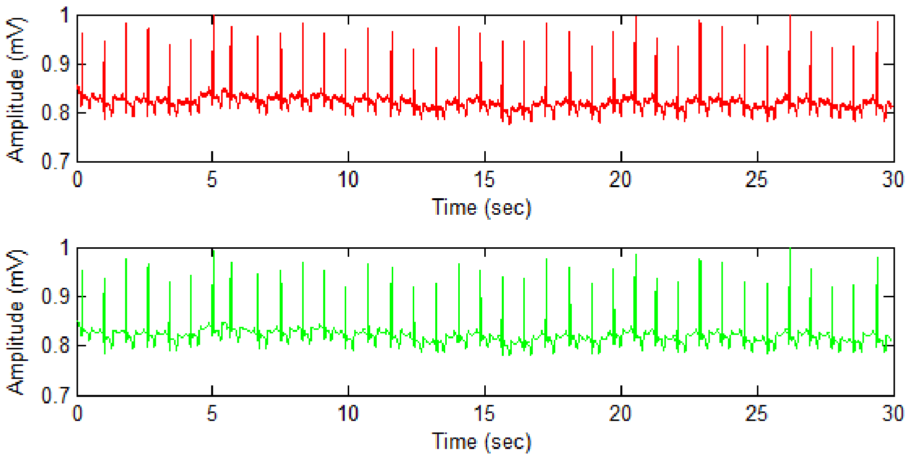

Fig. 14 Filtering with DWT at level 4 for MITDB *data # 10*1
(30 sec data selected out of 1 hour recording for better visualization)

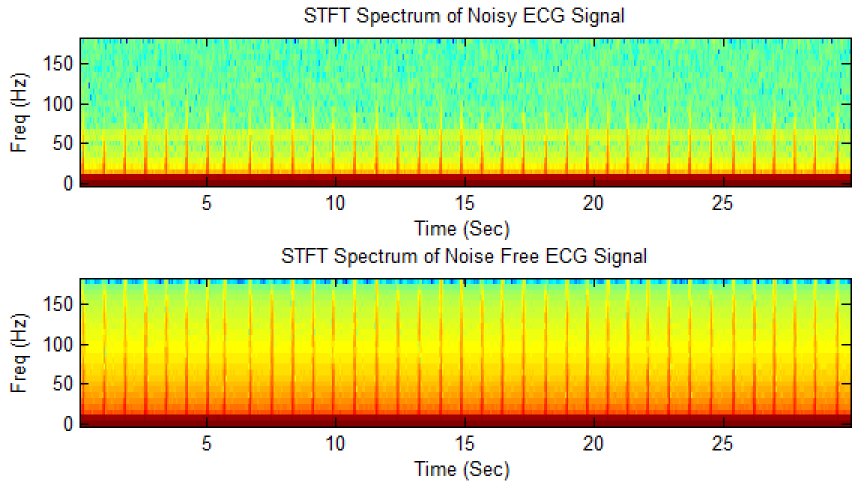

Fig. 15 Evaluation of DWT at level 4 with STFT for MITDB *data # 101*

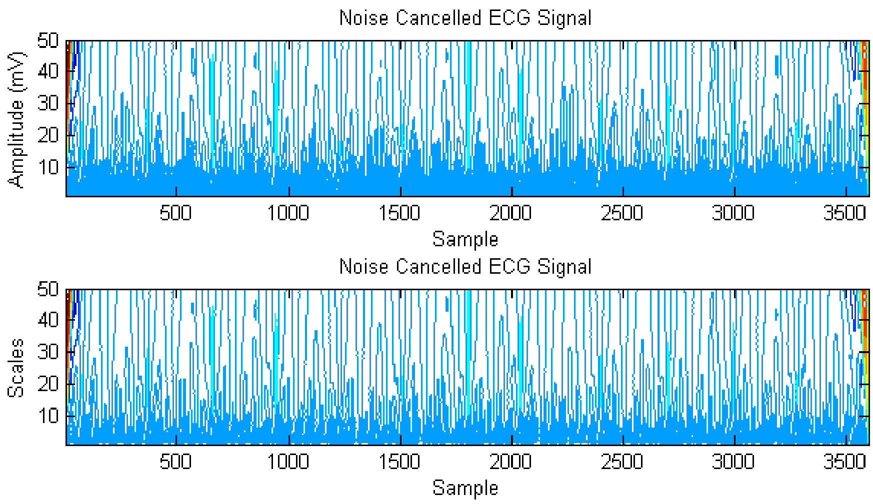

Fig. 16 Evaluation of DWT at level 4 with CWT for MITDB *data # 101*

Chouakri et al. [6], performed the filtering of MIT-BIH Arrhythmia database ECG signals using DWT with wavelet function "Symlet 8". Whereas, by determining the best suitable wavelet function for the proposed filtering approach; finally, it has led to use the wavelet function "db4" based on the reduced value of the Signal to Noise Ratio (SNR), Mean Square Error (MSE), the Root Mean Square Error (RMSE), Peak Signal to Noise Ratio (PSNR) and Peak to Peak Amplitude (P2P) values obtained. The filtering process of DWT with level 4 performs the following steps:

1. DWT to the noisy ECG signal at level 4 and identify the resulting 4 detail sequences (cD1, cD2, cD3, and cD4) and the approximation sequence (cA4);
2. To apply the DWT to the estimated Noisy signal and identify the 4^{th} level detail sequence (cDN4);
3. To generate the 4^{th} level detail sequence of the ECG free noise (cDF4) given by: $cDF4 \equiv cD4 - cDN4$;
4. To compute the used denoising threshold (T), given $T \equiv (2*\log(N))1/2 * \text{median}(\text{abs}(cD1))/0.6745$, where N is the length of the ECG signal;

5. To threshold the set of the detail sequences (cD1, cD2, and cD3), with respect to the computed threshold (T), which results the set of the sequences (cDT1, cDT2, and cDT3);
6. To reconstruct the denoised ECG signal (Fig. 20) using the Inverse Discrete Wavelet Transform (IDWT) giving the 4 detail sequences (cDT1, cDT2, cDT3, and cDF4) and the approximation sequence (cA4).

The above procedure was also applied to get level 8 noise-free ECG signals (cDF8) respectively (Fig. 18).

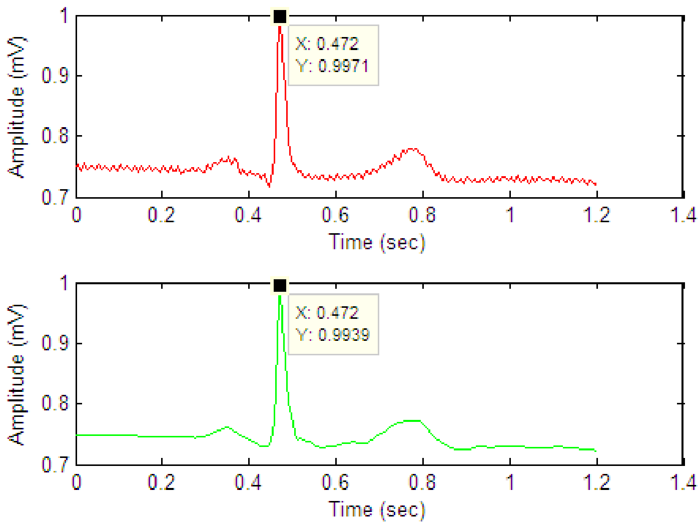

Fig. 17 Filtering with DWT at level 4 for FANTASIA *data # f1o07*

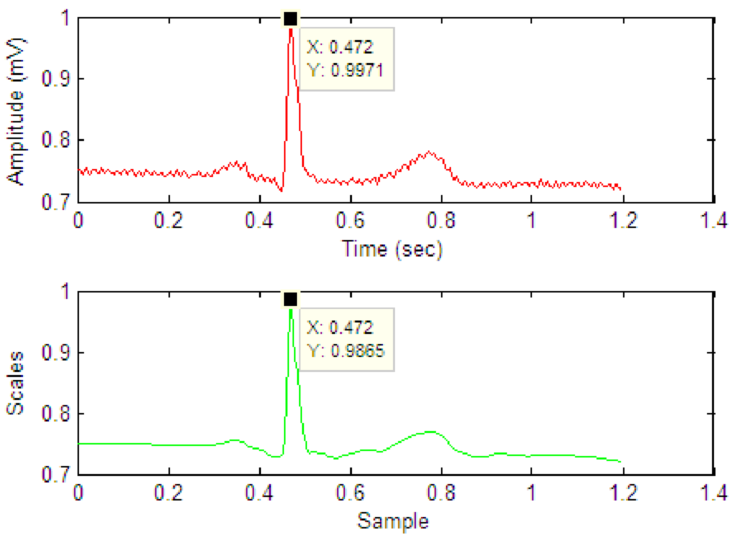

Fig. 18 Filtering with DWT at level 8 for FANTASIA *data # f1o07*

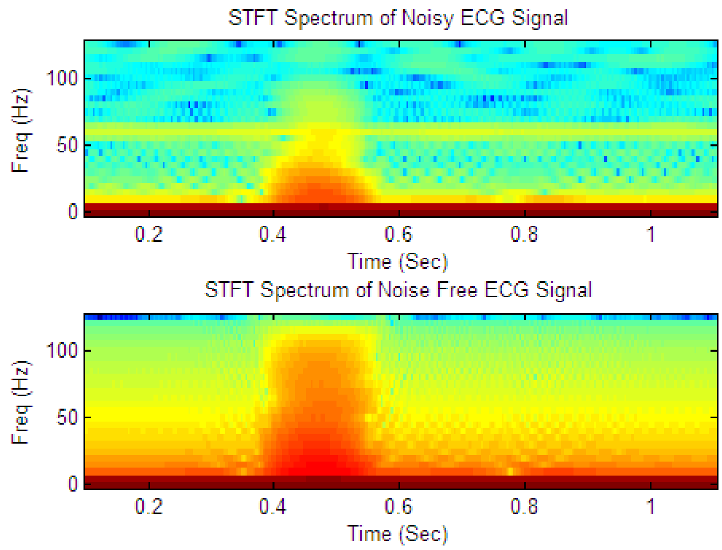

Fig. 19 Evaluation of DWT at level 4 with STFT

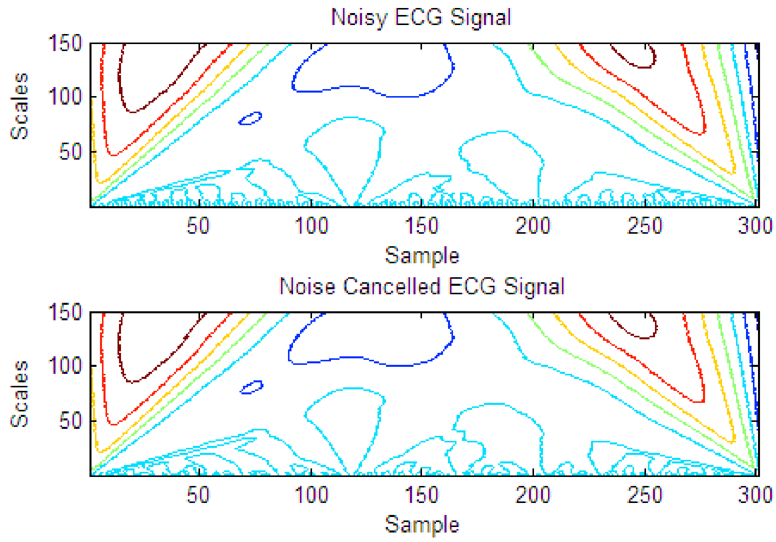

Fig. 20 Evaluation of DWT at level 4 with CWT

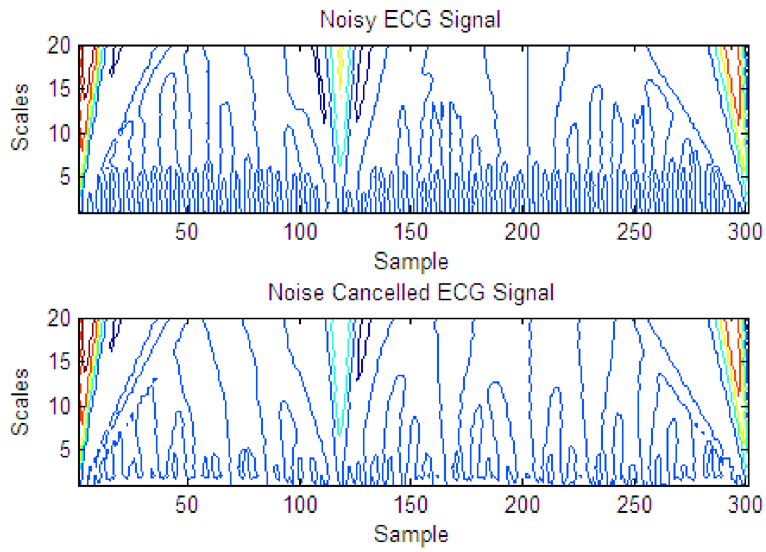

Fig. 21 Evaluation of DWT at level 4 with CWT (Zooming @ 20 scales)

Statistical analysis

Signal to noise ratio

Signal quality could be evaluated from the SNR result. System performance is better if the SNR value is higher. The SNR can be computed from the following equation as:

$$SNR = 10log_{10}\left[\frac{\sum_i^N (Filtered\ signal)^2}{\sum_i^N (Original\ signal - Filtered\ signal)^2}\right]. \tag{36}$$

Mean square error

The MSE of the filtered ECG signal may be computed from:

$$MSE = \frac{1}{N}\sum_i^N (Original\ signal - Filtered\ signal)^2. \tag{37}$$

The root mean square error

The RMSE of the noise free ECG signal is given by:

$$RMSE = \sqrt{\frac{1}{N}\sum_i^N (Original\ signal - Filtered\ signal)^2}. \tag{38}$$

Peak signal to noise ratio

PSNR calculate the peak signal to noise ration of original signal and noise free signal which can be formulated from the below equation as:

$$PSNR = 10log_{10}\left(\frac{P^2}{MSE}\right), \tag{39}$$

where P = 256, constant considered to calculate PSNR.

Peak to peak amplitude

The *Peak to peak amplitude* change can be calculated using the following equation:

$$P2P = |Max.Positive\ amplitude\ of\ signal - Max.Negative\ amplitude\ of\ signal\,|. \tag{40}$$

Here Peak to Peak Amplitude After filtering, i.e., P2P(A) and Before filtering, i.e., P2P(B) are tabulated in Table. 1.

The statistical attributes are plotted in bar charts (Fig. 22 and Fig. 23) where, the significant difference can be observed between DWT and other methods. The SNR, PSNR, MSE, RMSE values of DWT based filtered ECG signal has comparatively higher than the result obtained from other methods. The amplitude change after filtering is minimized for DWT; whereas the other three techniques have been suppressing the QRS complex during filtering of noises.

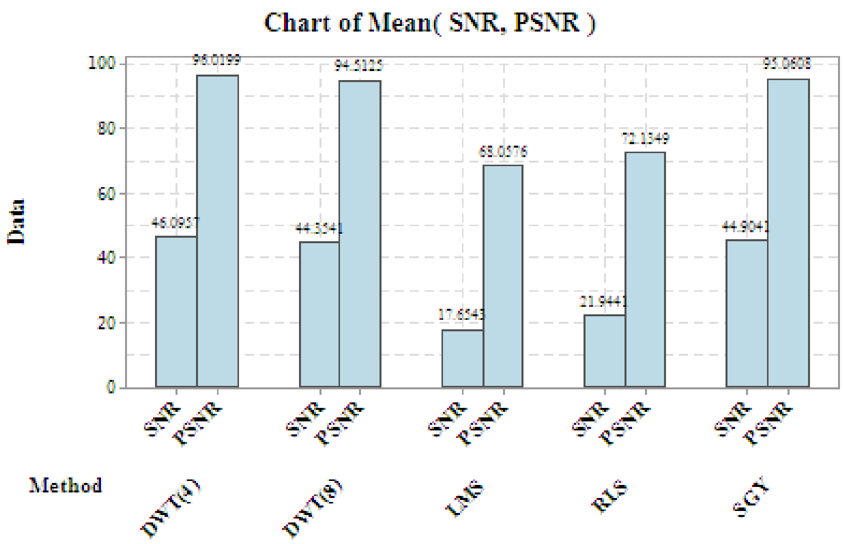

Fig. 22 Bar chart of mean (SNR, PSNR) of filters

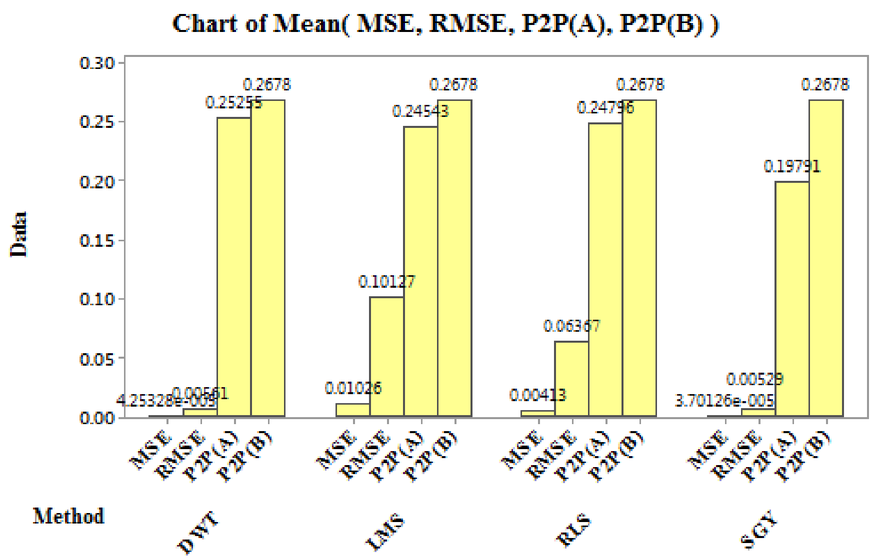

Fig. 23 Bar chart of mean (MSE, RMSE, P2P (A), P2P (B)) of filters

Naive bayes' classifiers

The applied filters and their classification, based on their filtering performances are projected on a 3D plane (Fig. 24). After filtering of ECG signal, the P2P (A) and P2P (B) versus SNR and MSE values of four different filters are introduced to the Naive Bayes' classifier [2] and the distinct probabilistic classification result is obtained (Fig. 24).

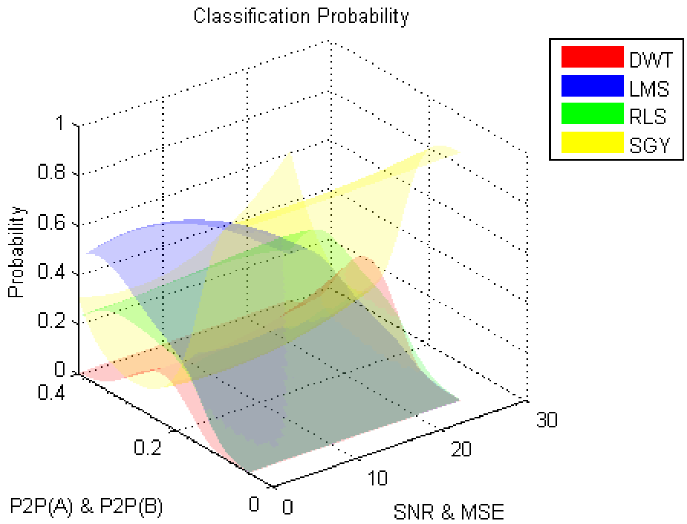

Fig. 24 Classification probability of filters

Discussion

ECG signals are non-stationary, pseudo periodic in nature and whose behavior changes with time. The unwanted additional noise or power-line artifacts corrupted the original information of the ECG signal. The presented approach discusses the performances of four noise cancellation techniques. The PL frequency and amplitude variation also presented and comparative analysis of the implanted techniques have been formulated. These implemented filtering techniques for noise cancellations also have some effect on time domain and frequency domain. Though it has already been proven that wavelet has better advantages over other methods for noise elimination, here the frequency domain analysis as well as the observational parameters were also calculated to evaluate its performance. The PLI of about 60 Hz is likely to be present (analyzed using STFT) for the LMS, RLS and SG based filtering ECG waveform and moreover the frequency component is suppressed. The possible detection of discontinuities is analyzed using CWT and its scale can be adjusted; e.g. higher scale $\Rightarrow$ stretched wavelet $\Rightarrow$ slowly changing, coarse features $\Rightarrow$ Low frequency. Fig. 20 shows the difference in discontinuity of noisy and filtered ECG signal (at scale = 150). CWT detects both the abrupt transitions and oscillations in the ECG signal. The abrupt transitions affect the CWT coefficients at all scales and clearly separate themselves from smoother signal features at small scales. Low scale $\Rightarrow$ compressed wavelet $\Rightarrow$ rapidly changing details $\Rightarrow$ High frequency. The same discontinuity changes (Fig. 21) can be clearly analyzed at scale of 20 and the significant changes in ECG signal after filtering is evaluated. The graphical results (using STFT and CWT) are statistically verified and tabulated in Table.1 and these results are comparatively analyzed with the bar charts (Fig. 22 and Fig. 23). Although the DWT is proven to be better, the level 4 and level 8 decomposition based filtering is comparatively analyzed. The QRS complex peak to peak amplitude change in the filtered ECG signal is marginally better for DWT at level 4 (Fig. 17) than level 8 (Fig. 18). This time domain maximum peak (peak amplitude) is a quantifying feature as well as correlatively supports the evaluation of frequency domain techniques. Here, the performance of filtering is only evaluated with STFT and CWT, but time domain approaches along with these frequency domain evaluations will be clubbed for different acute and chronic cardiac conditions (*like* arrhythmia) where, R-R interval changes and ectopic beats present are signals along with the noise components. Moreover, the DWT is proved to be a good approach for noise cancellation with arrhythmia signals as depicted and statistically highlighted.

Conclusions

The ECG signal gets corrupted during the acquisition process due to different types of motion artifacts and interferences *like* Power-Line Interference. Here the proposed techniques are meant for cancelling these unwanted signal components from the desired ECG signal, so that further processing and disease detection can be done uninterrupted. In the present paper effort has been made to perform the comparative analysis of two adaptive filters (i.e., LMS and RLS), SG smoothing and DWT filters for suppression of Power-Line Interference. The filtering performances (frequency domain) are analyzed graphically using STFT and CWT and statistical analysis have also implemented to validate the result. The SNR, MSE and other parameters are suggesting that the DWT filtering performance is better as compared to other methods. Fast filtration of ECG not only helps in further processing, but also improves efficiency in patient monitoring system. Here the purpose of filtering of ECG signal is to support the further diagnosis process by early and reliable analysis of cardiac abnormalities at different conditions.

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