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Power line interference cancellation from ECG signal using multiband structured sub band adaptive filter algorithm

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ABSTRACT

The Electrocardiogram (ECG) record is a procedural electrical activity of the heart which is noninvasive recording and is acquired by surface electrodes at designated locations on the skin of patient's body during which noise such as power-line interference (PLI) with 60 Hz frequency is acquired from power mains. In this research paper a new ECG enhancement design using multiband structured sub band adaptive filter (MSAF) is constructed to solve structured problems in conventional sub band adaptive filters. This paper investigates the new detailed ANC system for ECG signals with robustness based on UFB and NUFB structured MSAF using LMS algorithm. The proposed model is potentially a new realization form of algorithm which guaranteed a more stable transformation. The goal of the research is to provide solution in order to enhance the performance of ANC in terms of filter parameters which are acquired with the help of UFB &NUFB structured MSAF's using LMS algorithm. Computer simulation demonstrates that the proposed system gives improved performance and achieves good adaptation. NUFB structured MSAF algorithms are applied on ECG records obtained from standard MIT-BIH data base and the performance is compared with UFB structured MSAF algorithms in terms of parameters SNR, MSE, RMSE and distortion. The SNR for various NUFB structured MSAF's was found to be higher than the UFB structured MSAF's. The five channel NUFB structures with decimation factors (16,16,8,4,2) has on average SNR of 21.7097dB is obtained using LMS algorithm which is superior to existing algorithms.

Keywords: LMS, FB, UFB, NUFB, SAF, MSAF

1. BACKGROUND

Signals play essential part in the subject of electrical, digital, communication engineering and medical. The signals associated with scientific field are known as biomedical signals. Distinct biomedical alerts like Electrocardiogram, Encephalogram and Electromyogram are used for diagnosis as they contain lot of facts. ECG is a critical biomedical instrument for the diagnosis of cardiovascular problem that suggested to the electric interest of coronary heart recorded by way of skin electrode. The ECG is a bioelectric signal, which statistics the electrical pastime of coronary heart as opposed to time. Therefore, it is a vital diagnostic device for assessing coronary heart function [1,2]. The ECG record represents a very necessary live utilized by doctors, because it provides very important data a few patients' viscous condition and general health. The graphical record signal delivers data of the human heart, heart position, impulse starting and propagation, heart pattern and transmission of interference and drug effect on heart. Usually the band of the graphical record signal is zero.05 rate to a hundred rate. The goal of any filter is to extract helpful data from strident information. A normal fixed filter is designed in advance with knowledge of the statistics of both signal and the unwanted noise but if the statistics of the noise are not known priori, or amendment over time, the coefficients of the filter cannot be specified in advance. In these things, adaptive algorithms are needed in order to continuously update the filter coefficient [3, 4, 5].

In order to investigate the ECG record of the patient in real-time, there is a chance that the ECG signal may be corrupted with noise. The main noise(artifact)available in the ECG contains: power-line interference (PLI), baseline wander (BW), muscle artifacts (MA) and motion artifacts (EM), that are generated by patient breathing, movement, power line interference, bad electrodes and improper electrode position. these artifacts strongly influences the ST section, degrades the sign first-rate, frequency resolution, produces huge amplitude indicators in ECG that can resemble PQRST waveforms and mask tiny capabilities which might be important for clinical tracking and diagnosis [1,2]. Most types of artifacts which affect ECG record are eliminated by band pass filters which may not give good result. The noise contaminated ECG records are acquired from the standard Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH) data base. To enhance the accuracy and reliability for refine diagnosis the artefacts in ECG need to be decreased. Many methods have been implemented to eliminate the noise from noise contaminated ECG using static filters for example high pass, low pass and notch filters. However, the disadvantage of the fixed filter is that filtering or pre-processing of an ECG need to be done by understanding the noise cut off frequencies present in the signal. To overcome the restrictions of static filters, various methods have been developed. Adaptive filtering uses variety of algorithms such as LMS & NLMS algorithms etc. The performance execution of these algorithms is based on filter tap length ($\boldsymbol{M}$) and the learning rate parameter ($\boldsymbol{\mu}$). The main drawback of using FIR filter in adaptive filtering is high computational load and slower convergence [6, 7].

Figure 1 defines the essential downside and noise cancelling answer. A signal s(n) is communicated over a channel to a detector that also collectsainterferencen1(n) unrelated with the signal. The first input to the ANC is noise contaminated signal d(n)i.e. s(n)+n1(n). The second detector accepts a noise signal n2(n) unrelated with the s(n)however correlative with n1(n) that supplies the reference input to the ANC that is filtered to produce the estimate signal y(n) that's a detailed duplicate of reference input. The output signal y(n) is subtracted from signal d(n) to produce the error signal as shown in equation (1). This adaptive filter can be realized using various structures; the most frequently used structure is transversal finite impulse response (FIR). [8,9]

$$e(n)=d(n)-y(n) \qquad (1)$$

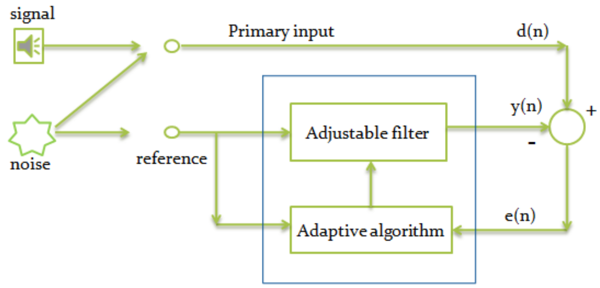

Figure 1 Adaptive Noise Canceller

Traditional filters such as adaptive filters [10], sign based normalised adaptive filters [11] were proposed in the literature to minimise artifacts. Different methodologies for ECG denoising include new variable step size NLMS [12,13] and EEMD-BLMS methods [14]. Promising performance are acquired by non linear adaptive algorithms [15,16], recently hybrid techniques have been proposed to eliminate noise from ECG signals using cascaded adaptive filters [17,18]. Filter banks (FB) decompose a digital signal into different frequency bands. On the basis of time frequency resolution, FB's can be classified into two categories *i.e.,* uniform filter banks (UFB) and non uniform filter banks (NUFB). UFB provides fixed and uniform time frequency resolution. Whereas non uniform filer bank provides non-uniform and variable time frequency resolution lead to better performance and reduced arithmetic complexity in some applications like audio analysis, ECG signal enhancement [19,20]. Different methods of decomposing signals in to sub bands have become prominent and were proposed in the literature [21, 22].

A filter bank is used to decompose a discrete time signal into several sub bands by means of a set of analysis filters. Sub band adaptive filter (SAF) structures have been proposed to overcome these problems of adaptive filters. As a result, adaptive filtering using sub band coding becomes a good option for plenty of adaptive systems. Sub band adaptive filtering belongs to two fields of signal processing namely adaptive and multirate signal processing .Recently different noise cancellation methods are proposed using SAFs include variable step size sign SAF [23], Variable individual step size SAF [24], New normalised SAF [25]. An optimised cosine modulated NUFB design approach has been proposed by Kumar,A.,G K Singh et., all [26] .This proposed method uses FBs to decimate the input signal into a number of frequency bands, each serving as an unbiased input to SAF. Sub band signals are usually down sampled in a multirate system, which leads to a whitening of the input signals and therefore an improved convergence behaviour of the adaptive filter system is expected [5,39,40,41,42]. In conventional SAF's each bound uses an individual adaptive sub filter in its own adaption that decreases the convergence rate. To solve these structured problems a multiband structured SAF (MSAF) are developed in which the full band adaptive filter's tap weight vectors are updated by a single adaptive algorithm using sub band signal [20,27]. The non-uniform filter bank SAF (NUFBSAF) is developed to achieve a better convergence performance by adapting the band width of analysis filter through proper selection of decimation factors. The objective of this paper is to develop non uniform multi band structured sub band adaptive filter which can improve the performance of the traditional ANC system, to analyse the application of SAF to the problem of noise cancellation problem in ECG.

2. PROPOSED DESIGN METHODOLOGY

LMS is most generally used adaptive algorithm than recursive least square algorithm and kalman filtering algorithm which makes use of a gradient vector to approximate a time-varying signal. A FB accommodates a set of analysis filters which decomposes the input signal of bandwidth into sub band signals. The sub bands give data from different frequency bands thus; it is conceivable to perform time and frequency dependent processing of the input signal. Since the sub bands are down sampled, processing is to be performed at a computationally efficient rate to analyze the ECG. A general objective is to create one arrangement of preprocessing filters which is useful in a noise cancellation tasks for ECG processing. In this manner, a sub band coding based adaptive algorithm calculation involves decomposing a signal into frequency sub bands and handling these sub bands as indicated by the current application. The concept of multiband structured-sub band adaptive filter (MSAF) is presented in this section.In the proposed design the primary input signal given to the first SAF consists of Noise contaminated ECG record denoted as *d(n)* in Figure.2. The secondary signal given to second SAF is noise signal $n_2(n)$ denoted as *u(n)*. The full band input signal *u(n)*, primary input signal or desired response signal *d(n)* and filter output signal *y(n)* are decomposed into *N* sub bands by means of analysis filters $H_i(z)$; for $i=0,1,2...(N-1)$.In thisFigure.2 $H_0H_1H_2....H_{N-1}$and $F_0F_1F_2....F_{N-1}$are analysis &synthesis filters of *N* channel perfect reconstruction (PR) filter bank respectively. These sub band signals are decimated to a lower rate using same factor and are processed by individual sub band adaptive sub filters $W_i(z)$.[20]

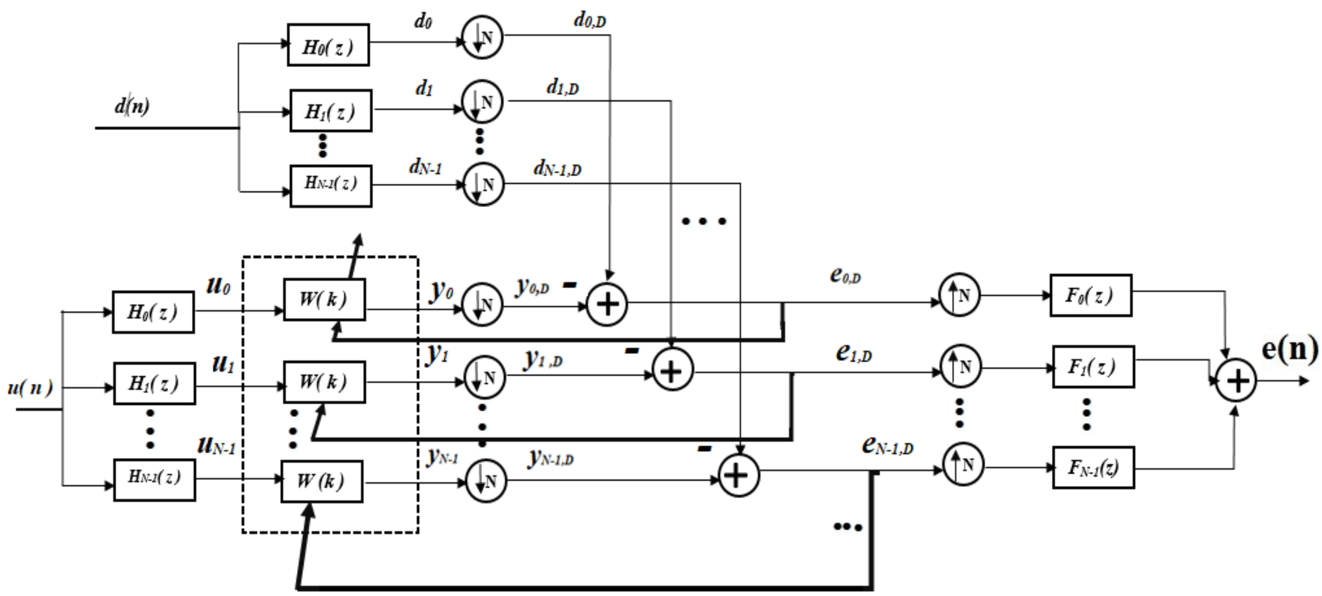

Figure 2 Block diagram of a multiband structured sub band adaptive filter (adapted from Reference [20])

Non uniform filter banks have non uniform frequency partition. One method of building NUFB is to cascade UFB in a tree structure using a two channel FB as basic building blocks. The two kinds of tree-structured filter banks are regular and irregular. In a regular sub band tree-structure, sub bands in each level are decomposed by the same filter banks where as in irregular sub band tree-structure, sub bands in each level are decomposed by different filter banks or only some sub bands are decomposed. Irregular sub band tree structure is one possible solution for non uniform filter banks as mentioned above. The distinct advantage of the equivalent form of the tree-structured FB is the possibility of realizing analysis and synthesis filters for more important tasks than simple band separation [19]. As an example of this method, NUFB with decimation factors (16,16,8,4,2) is illustrated. The proposed tree-structured non uniform filter bank's analysis section is shown in Figure 3.

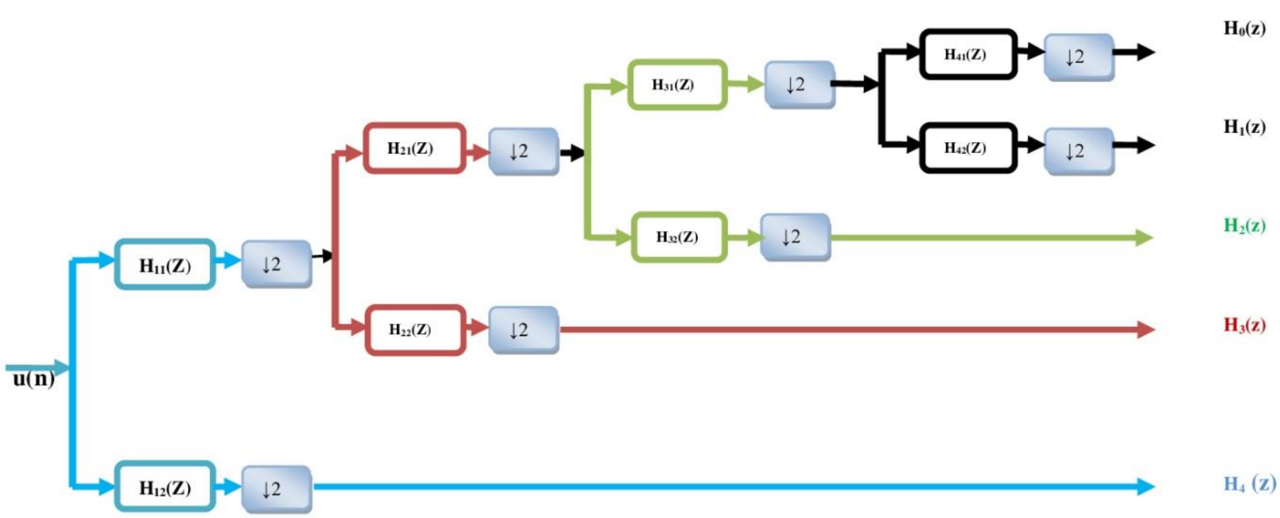

Figure 3 Proposed block diagram of a tree structured NUFB

The proposed structure makes use of low pass FIR prototype Parks-McClellan optimal equiripple filter design in both analysis and synthesis FB that give near-perfect reconstruction by permitting little measure of distortion at the output. The generalized structure of N-channel NUFB based on tree structured approach having decimation $N_0, N_1, N_2 --- N_{N-1}$ for each band then the decimation factors must fulfill the accompanying condition [21]

$$\sum_{k=0}^{N-1} \frac{1}{N_k} = 1 \quad (2)$$

In N-channel NUFB the PR is possible if

$$\sum_{k=0}^{N-1} \left|H_k(e^{jw})\right|^2 = 1 \quad \text{for } 0 \le w \le \frac{\pi}{N} \quad (3)$$

Where $H_k(e^{jw})$ is frequency response of k^{th} filter in equivalent NUFB parallel form

For tree structured NUFB design having decimation factors (16,16,8,4,2) the PR condition can be achieved by using following equation

$$\left|H_0(e^{jw})\right|^2 + \left|H_1(e^{jw})\right|^2 + \left|H_2(e^{jw})\right|^2 + \left|H_3(e^{jw})\right|^2 + \left|H_4(e^{jw})\right|^2 = 1 \text{ for } 0 \le w \le \frac{\pi}{5} \quad (4)$$

Here $H_0(z), H_1(z), H_2(z), H_3(z), H_4(z)$ analysis filters with the following relations [21]

$$\boldsymbol{H_0(z) = H_{11}(z)H_{21}(z^2)H_{31}(z^4)H_{41}(z^8)} \quad (5)$$
$$\boldsymbol{H_1(z) = H_{11}(z)H_{21}(z^2)H_{31}(z^4)H_{42}(z^8)} \quad (6)$$
$$\boldsymbol{H_2(z) = H_{11}(z)H_{21}(z^2)H_{32}(z^4)} \quad (7)$$
$$\boldsymbol{H_3(z) = H_{11}(z)H_{22}(z^2)} \quad (8)$$
$$\boldsymbol{H_4(z) = H_{12}(z)} \quad (9)$$

Where H_{11}, H_{21}, H_{31}, $H_{41}$are low pass filters in the first ,second, third and fourth stages respectively and H_{12}, H_{22}, H_{32}, H_{42} are high pass filters in the first ,second, third and fourth stages respectively.

2.1. Analysis of conventional adaptive algorithms

The traditional ANC shown in Figure.1incorporates filter whose input parameters are ***d(n)***and ***u(n)***. Here ***u(n)*** is the time delayed input vector values, $\boldsymbol{u(n) = [u(n), u(n-1), u(n-2), \ldots\ldots\ldots\ldots u(n-M+1)]^T}$, the vector $\boldsymbol{w(n) = [w_0(n), w_1(n), w_2(n), \ldots\ldots w_{M-1}(n)]^T}$ represents the coefficients of the filter at time index ***n***. The execution investigation of ordinary adaptive filter algorithms requires five particular computational strides in every emphasis as takes after.[5]

1. The estimated response ***y(n)***of the FIR filter calculated as

$$y(n) = \sum_{m=0}^{M-1} w(n)u(n-m) = w^T(n)u(n) \quad (10)$$

2. The difference between primary input signal and estimated response signal of the adaptive filter *i.e.* error signal is

$$e(n) = d(n) - y(n) \quad (11)$$

3. The minimization of the mean-square error (MSE) *i.e*. Performance function, which is defined as

$$J = E\{e^2(n)\} \quad (12)$$

4. For a given filter coefficient *w(n)* with reference input signal *u(n)* and primary input signal *d(n)* , the MSE can be calculated as

$$J = E\{d^2(n)\} - 2p^T w + w^T R w \quad (13)$$

Where *R* is the autocorrelation function of input signal calculated as

$$R \equiv E\{u(n)\, u^T(n)\} \quad (14)$$

And p is the cross-correlation array between the input signal vector and the primary input signal calculated as

$p \equiv E\{d(n)u(n)\}$ (15)

5. The filter coefficients or weight vectors of the filter are changed for the next iteration for LMS adaptive algorithm by using equations

$w(n+1) = w(n) + \mu e(n)u(n)$ (16)

Here μ is chosen such that to guarantee the stability of the algorithm in the range

$0 < \mu < \frac{2}{N * P_u}$ (17)

Here P_u is average power of the reference signal $u(n)$ calculated as

$P_u = u^T(n)u(n)$ (18)

2.2. Analysis of MSAF algorithms

Figure.2 shows two equivalent structures for the selected input portion of the multiband system as indicated that the full band adaptive filter ***W(z)***of length M is stationary (i.e. the adaptation is frozen), it can be transposed with the analysis filter bank as each sub band signal occupies only a portion of the original frequency range. The N sub band signals of MSAF algorithms requireparticular computational strides in every emphasis as takes after.[20]

It is important to note that ***n*** refers to the time index of original sequence and ***k*** denotes the time index of decimated signal.

1. The adaptive filtered output signal is

$y_i(n) = \sum_{m=0}^{M-1} w(n)u(n-m) = w^T(n)u_i(n)$ (19)

$for \; i = 0,1, \dots \dots \dots N-1$

2. The adaptive filtered decimated output signal is

$y_{i,D}(k) = y_i(kN) = \sum_{m=0}^{M-1} w(k)u(k-m) = w^T(k)u_i(k)$

$for \; i = 0,1, \dots \dots \dots N-1$ (20)

Where $w(k)$ is the weight vector of the full band adaptive filter and $u_i(k)$ is the regression (signal) vector for the i^{th} sub band at every time instant k, each sub band signal vector $u_i(k)$ is packed with N new samples and ($M-N$) old samples to produce an output sample $y_{i,D}(k)$.

3. The shift register performs both decimation and packing operations to form the sub band vectors defined in equation (21)

$u_i(k) = [u_i(kN), u_i(kN-1), u_i(kN-2) \dots \dots u_i(kN-M+1)]^T$ (21)

4. The sub band decimated error signal $e_{i,D}(k)$ is the difference between the filter output $y_{i,D}(k)$ and the desired response $d_{i,D}(k)$expressed as

$e_{i,D}(k) = d_{i,D}(k) - y_{i,D}(k) = d_{i,D}(k) - w^T(k)u_i(k)$ (22)

$for \; i = 0,1, \dots \dots \dots N-1$

5. The error signal vector for N sub bands,

$e_D(k) = [e_{0,D}(k), e_{1,D}(k), e_{2,D}(k), \dots \dots \dots \dots e_{N-1,D}(k)]^T$ (23)

6. The error signal can be expressed in a compact form as

$e_D(k) = d_D(k) - U^T(k)w(k)$ (24)

where$d_D(k)$ is N X 1 decimated desired response vector and $U(k)$ is M X N sub band signal matrix defined as follows

$$U(k) = [u_0(k), u_1(k), u_2(k), \ldots\ldots\ldots\ldots u_{N-1}(k)] \quad (25)$$

$$d_D(k) = [d_{0,D}(k), d_{1,D}(k), d_{2,D}(k), \ldots\ldots\ldots d_{N-1,D}(k)]^T \quad (26)$$

The multi band MSE functions as a performance measure for the MSAF algorithm. By means of the Wiener filter theory, the multiband MSE function can be shown to be equivalent to the classical full band MSE function. Hence, use of the multiband MSE function allows a fair comparison of the MSAF algorithm with other adaptive algorithms that are measured by the MSE function.

7. The multiband MSE function is defined as the average of the mean-squared values of the sub band estimation errors expressed as [20]

$$J_M = \frac{1}{N}\sum_{i=0}^{N-1} E\{e_{i,D}{}^2(n)\} = \sigma_d{}^2 - 2p^T w + w^T R w \quad (27)$$

8. The multiband MSE function can be written in the following parameters variance ($\sigma_d{}^2$) of the primary signal auto correlation matrix (***R***) and cross correlation matrix (***p***) expanded form:

$$\sigma_d{}^2 = E\{d^2(n)\} = \frac{1}{N}E\{\|d_D(k)\|^2\} \quad (28)$$

$$p = E\{u(n)d(n)\} = \frac{1}{N}E\{U(k)d_D(k)\} \quad (29)$$

$$R = E\{u(n)u^T(n)\} = \frac{1}{N}E\{U(k)U^T(k)\} \quad (30)$$

A recursive weight-control mechanism for the MSAF from one iteration to the next iteration, coefficients of filter should be changed in a minimal manner. This basic principle is used to design a constraint optimization criterion for deriving the adaptive algorithm. In the MSAF shown in Figure.2 with the sub band signals sets $\{U(k), d_D(k)\}$,a criterion that ensures convergence to the optimum solution after a adequate number of iterations is to have the updated tap weight vector $w(k+1)$ using LMS Algorithm in all N sub bands at each iteration $\boldsymbol{k}$ as follows

$$w(k+1) = w(k) + \mu \frac{1}{\|u_i(k)\|^2 + \alpha} e_{i,D}(k) \quad (31)$$

Where μ is learning rate parameter and it should be selected in the stability bound *i.e* equation (15)

Where α is a small positive constant used to avoid possible division by zero.

Proposed NUFB-MSAF algorithm summary

For $s = 1, 2, \ldots\ldots\ldots N$ where *s is stages*

Analysis filters $H_i(z)$

for $i=0,1,2\ldots\ldots N-1$

$H_i(z) = H_{s,l}(z^{s-i}).(z^{s-i}).(z^{s-i})\ldots.H_{s,l}(z^{s-i})$

For $k=0, 1, 2,\ldots\ldots\ldots kN$ where $kN=n$

Error estimation:

$e_D(k) = d_D(k) - U^T(k)w(k)$

Normalization matrix:

$\Lambda(k) = diag[U^T(k)U(k) + \alpha]$

Tap-weight adaptation:
$w(k+1) = w(k+1) + \mu U(k)\Lambda^{-1}(k)e_D(k)$

Input signal Band partitioning:
$U_1^T(k) = H^T A(kN)$

Desired signal Band partitioning:
$d_D(k) = H^T A(kN)$

Synthesis:
$e(kN) = Fe_D(k)$

Parameters:
l &h - Basic Low pass filter& high pass filter notation
M - Number of adaptive tap weights
N - Number of sub bands
L - Length of the analysis and synthesis filters

Variables:
$U^T(k) = [U_1^T(k), U_2^T(k-1)]$.
$U_2^T(k-1)$ - first *M-N* columns of $U^T(k-1)$
$A(kN) = [a(kN), a(kN-1), a \ldots\ldots a(kN-N-1)]$
$a(kN) = [u(kN), u(kN-1), u(kN-2), \ldots u(kN-L-1)]^T$.
$d(kN) = [d(kN), d(kN-1), d(kN-2) \ldots\ldots d(kN-L-1)]^T$.

3. RESULTS AND DISCUSSION

In this simulation the benchmark MIT-BIH arrhythmia database [28] was utilized to test the execution of various UFB & NUFB structured MSAF's adaptive algorithms for ECG denoising and it comprise of 48 half hour excerpts of two channel ambulatory ECG recordings, which were acquired from 47 subjects, including 25 men aged 32-89 years, and women aged 23-89 years. The recordings were sampled at 360 samples per second per channel with 11-bit resolution over a 10 mV range. The simulations were done by collecting 3600 samples of ECG recordings. In this simulation the proposed methodology has been implemented using Parks-McClellan optimal equiripple linear phase (real, symmetric coefficients) low pass FIR filter design with length 32,cut off frequency 100 Hz and sampling frequency 360 Hz. A data set of five ECG records: data100, data105, data108, data203 and data228 are considered to guarantee the consistency of the results. The secondary noise signal $n_2(n)$ shown in Figure.1 is taken from noise generator. A synthetic PLI with 1mv amplitude is simulated for PLI cancellation. In order to test the filtering capability in non-stationary environment real PLI noises with 3600 samples are considered. These are taken from MIT-BIH normal sinus rhythm database (NSTDB) [29].

The proposed UFB and NUFB structured MSAF-ANC are compared quantitatively by quality assessment parameters Mean Square Error (MSE), Root Mean Square Error (RMSE), Signal-to-Noise Ratio Before Filtering (SNRBF), Signal-to-Noise Ratio After Filtering (SNRAF)and distortion are outlined in Table.1.

Table 1 Proposed design's quality assessment parameters

PARAMETERS	FORMULA
$Mean\ Square\ Error$	$\frac{1}{N}\sum_{n=0}^{N-1}[s(n)-e(n)]^2$
$Root\ M.S.E$	$\sqrt{\frac{1}{N}\sum_{n=0}^{N-1}[s(n)-e(n)]^2}$

$SNRBF$	$10\log_{10}(\frac{\sum_{n=0}^{N-1}[s(n)]^2}{\sum_{n=0}^{N-1}[d(n)-s(n)]^2})$
$SNRAF$	$10\log_{10}(\frac{\sum_{n=0}^{N-1}[s(n)]^2}{\sum_{n=0}^{N-1}[e(n)-s(n)]^2})$
$Distortion$	$10\,log_{10}\sum_{n=0}^{N-1}\sum_{n=0}^{N-1}[s(n)-e(n)]^2$

3.1. Power-line Interference (PLI) Cancellation using MSAF-LMS algorithm

In this proposed design 3600 samples of clean ECG signal records from MIT-BIH data base which are corrupted with power line interference noise with frequency60 Hz and the sampling frequency of 360Hz is applied as primary input signal to the ANC shown in Figure 1. The following figures 4-15show the PLI Noise elimination. The NUFB structured MSAF's achieve good SNR; MSE and RMSE values over UFB structured MSAF's adaptive algorithms. Table's 3-6 presents 'quantitative parameter values for five record numbers from MIT-BIH data base. The simulation results state that NUFB structured MSAF's adaptive algorithms has greater efficiency than UFB structured MSAF's adaptive algorithms. These results for MIT-BIH data base record number 105 are shown in Figures 4-15.

Table 2 Simulated SNR values in dB

SNR Values	**100**	**105**	**108**	**203**	**228**	Avg.Val
Before Filtering	0.2144	0.712	-0.0059	2.9671	-1.0532	0.5669
Three Channel(3,3,3)UFB	11.5386	11.8879	11.2808	13.7657	10.5938	11.81336
Four Channel(4,4,4,4)UFB	11.9735	12.4391	11.7256	14.0723	11.2329	12.28868
Five Channel(5,5,5,5,5)UFB	11.1846	11.6595	10.9155	13.5753	10.2149	11.50996
Three Channel(4,4,2)NUFB	14.6593	15.0662	14.4046	16.71	13.9338	14.95478
Four Channel(8,8,4,2)NUFB	15.7315	16.9193	15.4913	18.9523	14.8402	16.38692
Five Channel(16,16,8,4,2)NUFB	21.791	21.214	21.833	22.9534	20.7571	21.7097

The performance of UFB structured MSAF's and NUFB structured MSAF'susing LMS algorithms in terms of SNR are shown in Table.2. The simulation results state that NUFB structured MSAF algorithms has greater efficiency than UFB structured MSAF algorithms. As shown in Table.2 three channels UFB has on average SNR of12.44774dB for 5 records and three channels NUFB has on average SNR of 14.95478dB. Similarly for four channel UFB has on average SNR of 12.28868dB for 5 records and four channels NUFB has on average SNR is 16.38692dB, for five channel UFB has on average SNR is 11.50996dB for 5 records and five channel NUFB has on average SNR is 21.7097dB.It is clear from Table.2 that NUFB structured MSAF's adaptive algorithms outperform UFB structured MSAF algorithms in approximating the ECG noises.

Table 3 Simulated MSE values

Mean Square Error Values	**100**	**105**	**108**	**203**	**228**	Avg.Val
Three Channel(3,3,3)UFB	0.0584	0.1831	0.0557	0.457	0.0672	0.16428
Four Channel(4,4,4,4)UFB	0.062	0.186	0.0579	0.4493	0.0685	0.16474
Five Channel(5,5,5,5,5)UFB	0.0574	0.1825	0.0546	0.4515	0.0653	0.16226
Three Channel(4,4,2)NUFB	0.0884	0.2569	0.082	0.6152	0.0962	0.22774
Four Channel(8,8,4,2)NUFB	0.1631	0.4716	0.1573	1.038	0.1694	0.39988
Five Channel(16,16,8,4,2)NUFB	1.0749	1.2248	1.1383	2.414	0.9461	1.35962

Table 3 shows the performance of UFB structured MSAF and NUFB structured MSAF using LMS algorithms in terms of MSE. It is clear from Table.3 that UFB structured MSAF adaptive algorithms have minimum MSE values than NUFB structured MSAF adaptive algorithms.

Table 4 Simulated RMSE values

Root Mean Square ErrorValues	100	105	108	203	228	Avg.Val
Three Channel(3,3,3)UFB	0.2416	0.4279	0.2361	0.676	0.2591	**0.36814**
Four Channel(4,4,4,4)UFB	0.249	0.4313	0.2406	0.6703	0.2616	**0.37056**
Five Channel(5,5,5,5,5)UFB	0.2396	0.4272	0.2336	0.6719	0.2555	**0.36556**
Three Channel(4,4,2)NUFB	0.2973	0.5068	0.2863	0.7843	0.3101	**0.43696**
Four Channel(8,8,4,2)NUFB	0.4039	0.6867	0.3966	1.0188	0.4116	**0.58352**
Five Channel(16,16,8,4,2)NUFB	1.0368	1.1067	1.0669	1.5537	0.9727	**1.14736**

Table 4 shows the simulated MSE values of UFB structured MSAF and NUFB structured MSAF using LMS algorithms. It is clear from Table 4 that UFB structured MSAF algorithms have minimum RMSE values than NUFB structured MSAF algorithms.

Table 5 Simulated distortion values

Distortion Values	100	105	108	203	228	Avg.Val
Three Channel(3,3,3)UFB	-12.3381	-7.3742	-12.5378	-3.4006	-11.7291	**-9.47596**
Four Channel(4,4,4,4)UFB	-12.0774	-7.3041	-12.3732	-3.4744	-11.646	**-9.37502**
Five Channel(5,5,5,5,5)UFB	-12.4117	-7.3867	-12.6298	-3.4533	-11.8519	**-9.54668**
Three Channel(4,4,2)NUFB	-10.5349	-5.9027	-10.8634	-2.1099	-10.1704	**-7.91626**
Four Channel(8,8,4,2)NUFB	-7.8743	-3.2645	-8.0329	0.1621	-7.7096	**-5.34384**
Five Channel(16,16,8,4,2)NUFB	0.3137	0.8808	0.5625	3.8274	-0.2404	**1.0688**

Table 5 shows the performance of UFB structured MSAF and NUFB structured MSAF using LMS algorithms in terms of distortion. It is clear from Table 5 that UFB structured MSAF adaptive algorithms have minimum distortion values than NUFB structured MSAF algorithms.

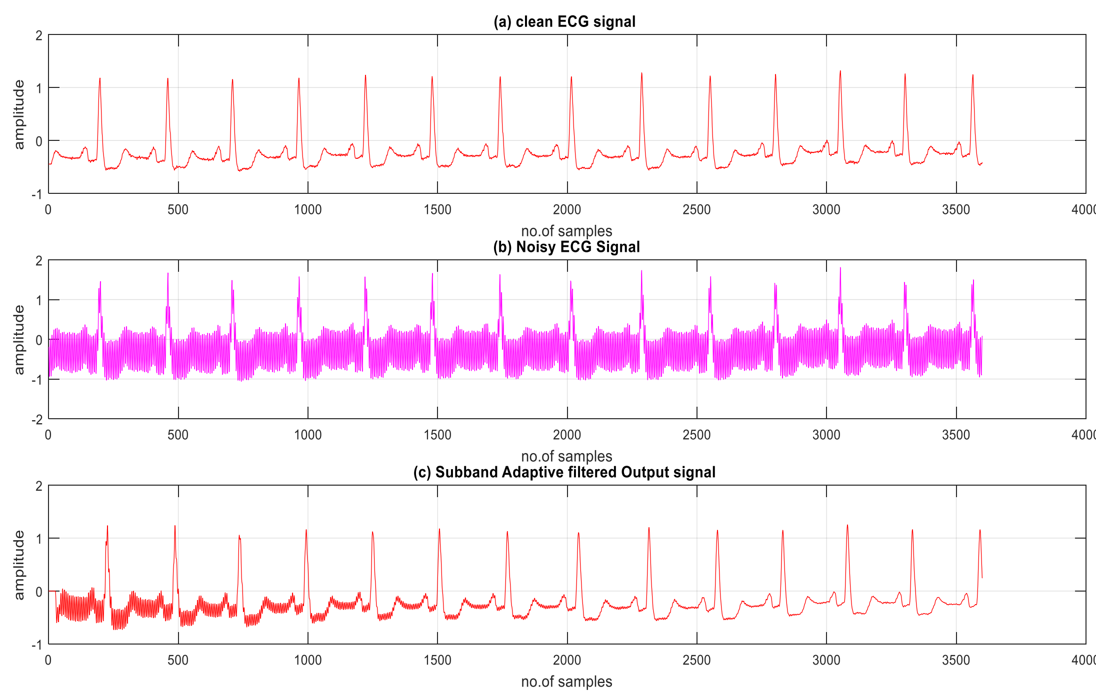

Figure 4 Simulation results using MSAF-LMS algorithm for record number 105 (i) ECG record from MIT-BIH database (red) (ii) PLI contaminated ECG record (magenta) (iii) Sub band adaptive filtered signal using three channel (3,3,3) uniform filter bank MSAF using LMS algorithm (red)

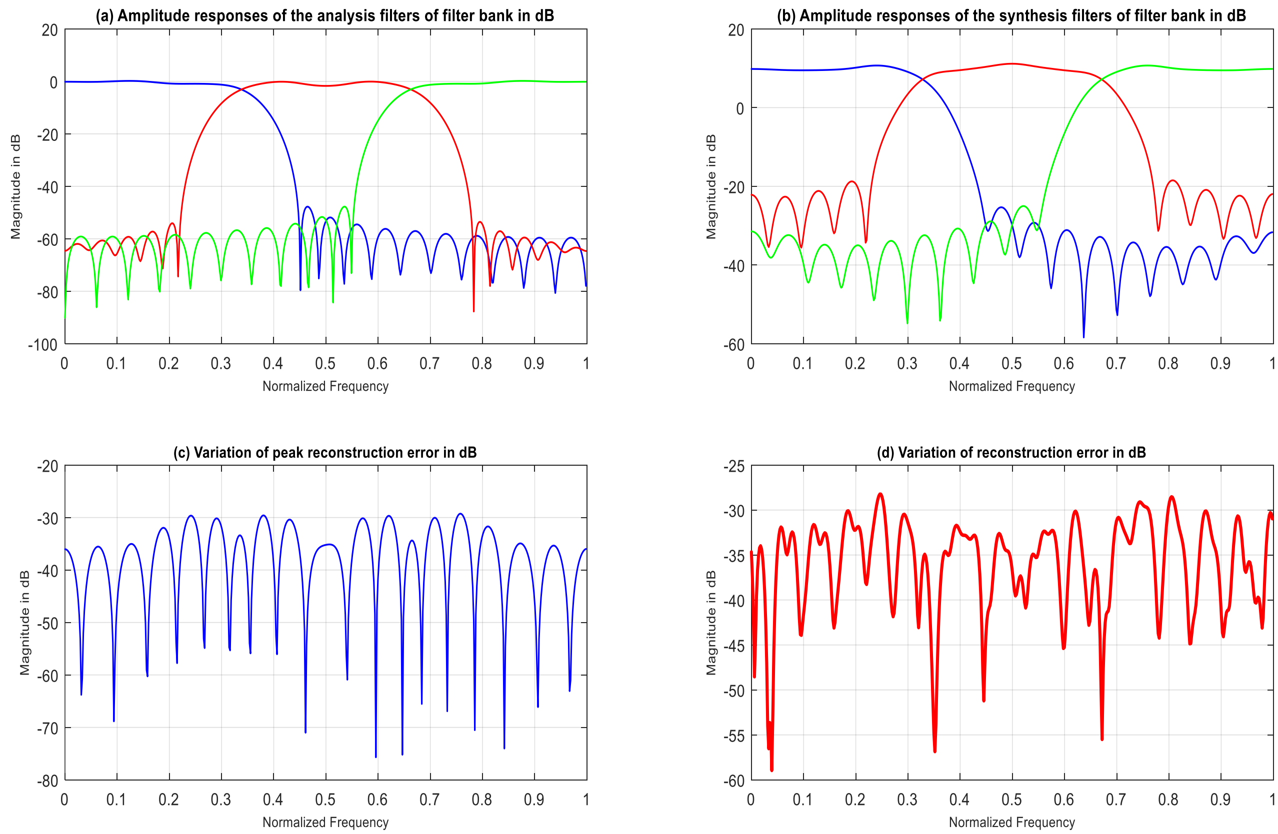

Figure 5 Three channel UFB with decimation factors (3,3,3) simulated results in dB (i) Magnitude spectrum of analysis FB (ii) Magnitude spectrum of synthesis FB (iii) Amplitude variation of PRE (iv) Reconstruction error Amplitude

The simulation results of a proposed method with proto type filter for three channel UFB with decimation factors (3,3,3) is shown in Fig.5.The peak reconstruction error (PRE) is reduced appreciably. The average PRE obtained in three channel UFB is 0.08169 dB.

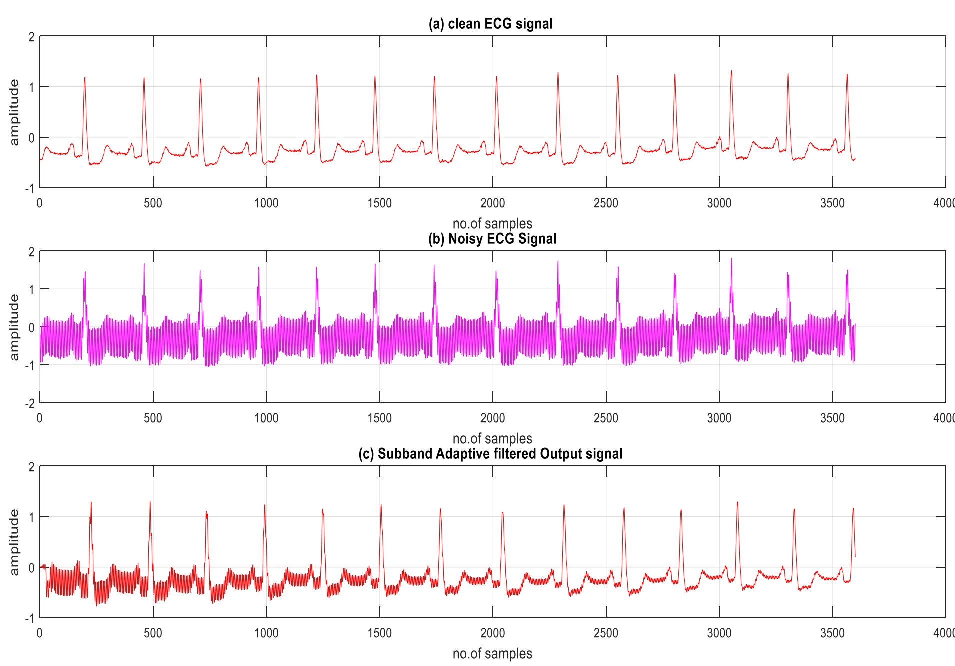

Figure 6 Simulation results using MSAF-LMS algorithm for record number 105 (i) ECG record from MIT-BIH database (red) (ii) PLI contaminated ECG record (magenta) (iii) Sub band adaptive filtered signal using four channel (4,4,4,4) uniform filter bank MSAF using LMS algorithm (red)

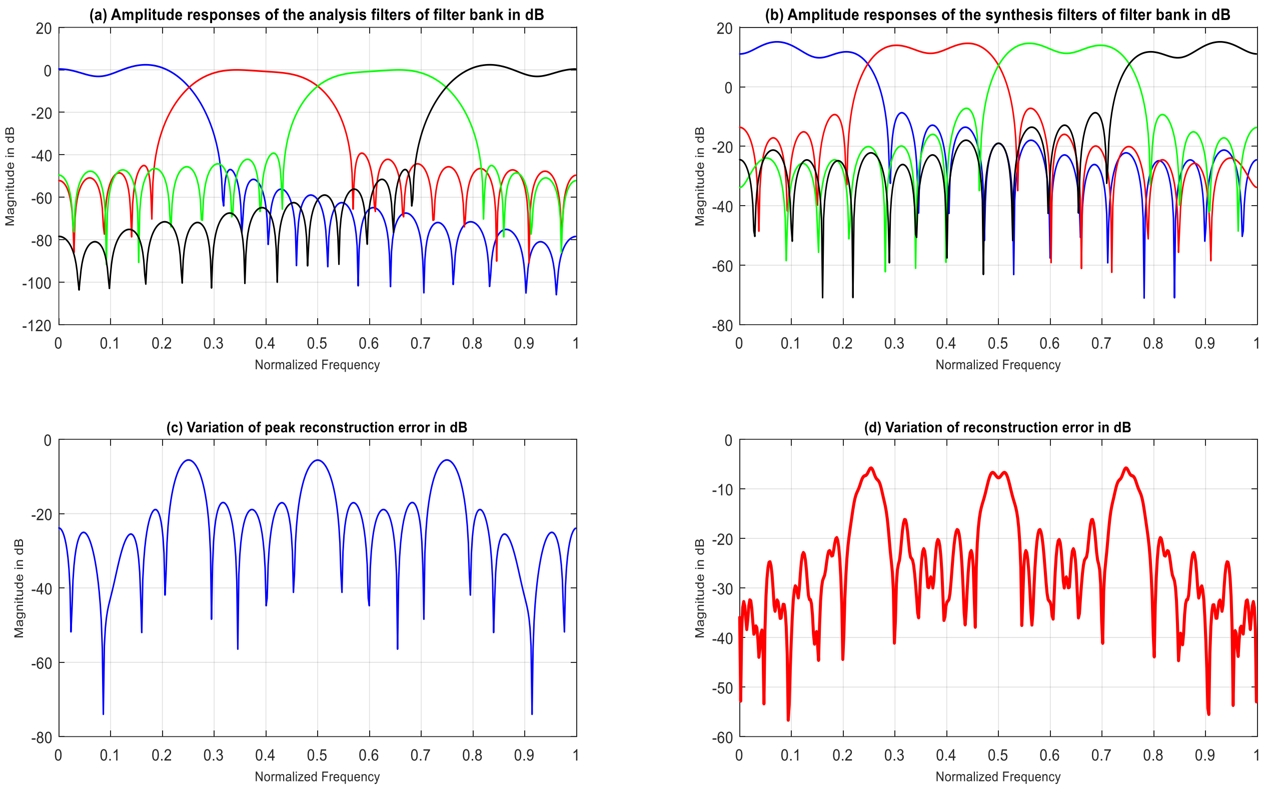

Figure 7 Four channel UFB with decimation factors (4,4,4,4) simulated results in in dB (i) Magnitude spectrum of analysis FB (ii) Magnitude spectrum of synthesis FB (iii) Amplitude variation of PRE (iv) Reconstruction error Amplitude

The simulation results of a proposed method with proto type filter for four channel UFB with decimation factors (4,4,4,4) is shown in Fig.7. The peak reconstruction error (PRE) is reduced appreciably. The average PRE obtained in four channel UFB is 0.0414dB.

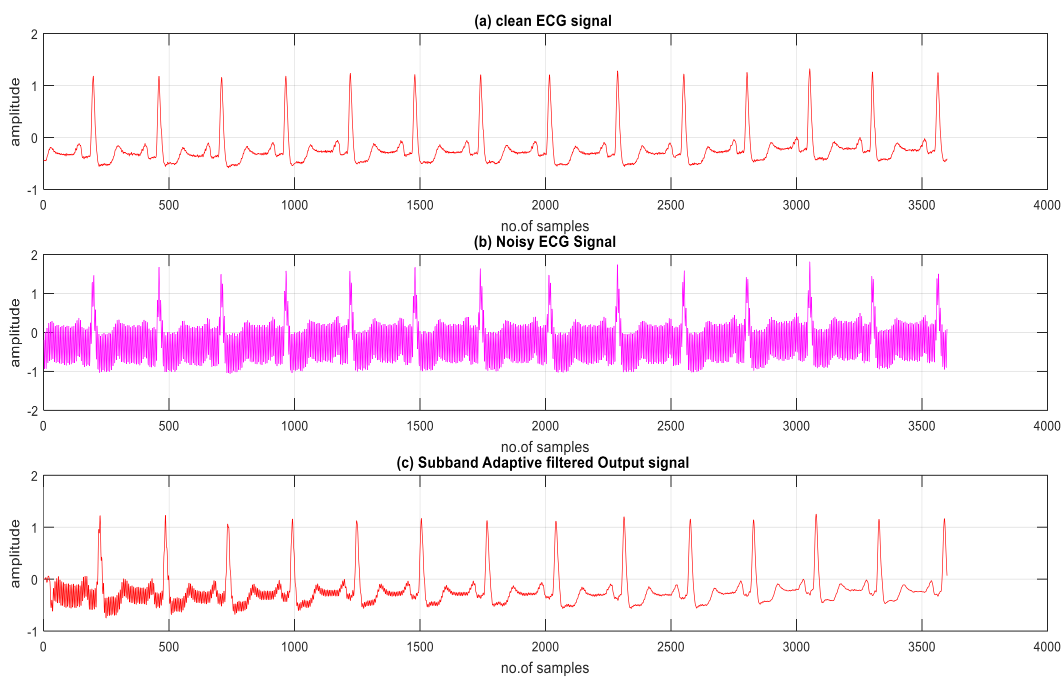

Figure 8 Simulation results using MSAF-LMS algorithm for record number 105 (i) ECG record from MIT-BIH database (red) (ii) PLI contaminated ECG record (magenta) (iii) Sub band adaptive filtered signal using five channel (5,5,5,5,5) uniform filter bank MSAF using LMS algorithm (red)

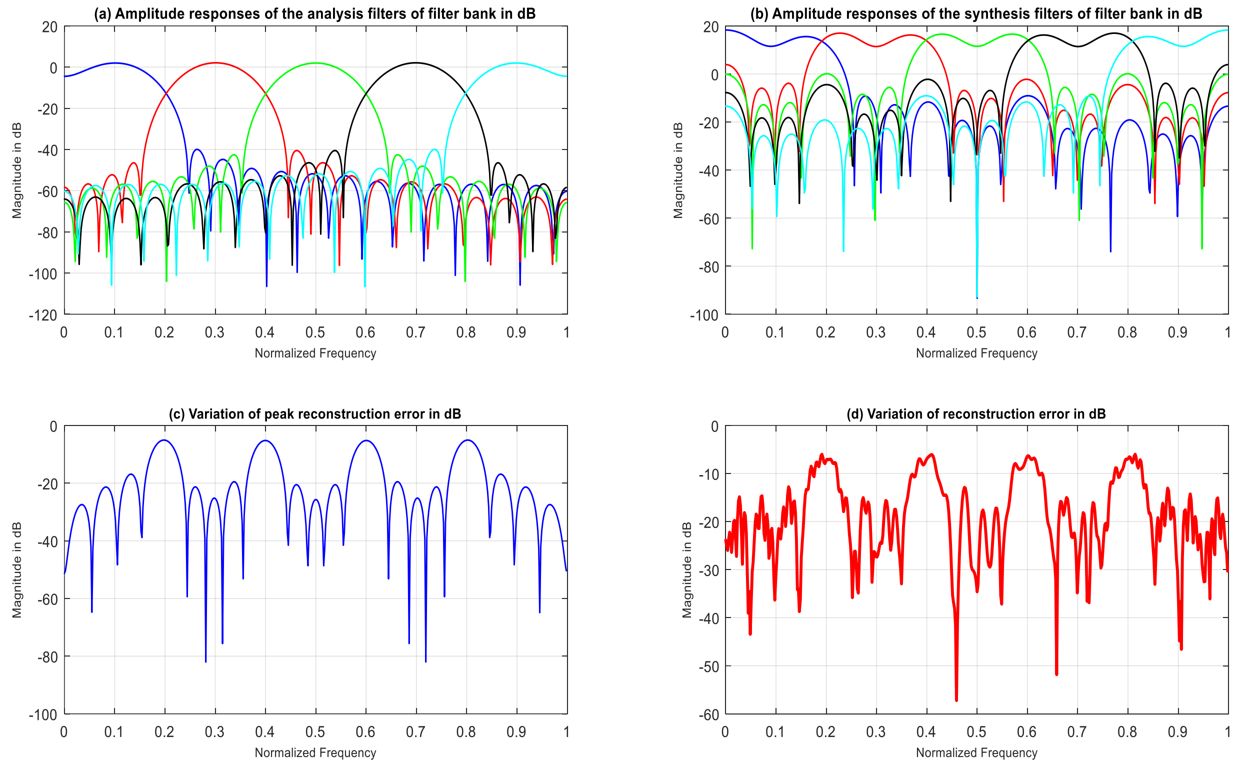

Figure 9 Five channel UFB with decimation factors (5,5,5,5,5) simulated results in dB (i) Magnitude spectrum of analysis FB (ii) Magnitude spectrum of synthesis FB (iii) Amplitude variation of PRE (iv) Reconstruction error Amplitude

The simulation results of a proposed method with proto type filter for five channel UFB with decimation factors (5,5,5,5,5) is shown in Fig.9. The peak reconstruction error (PRE) is reduced appreciably. The average PRE obtained in five channel UFB is 0.0454dB.

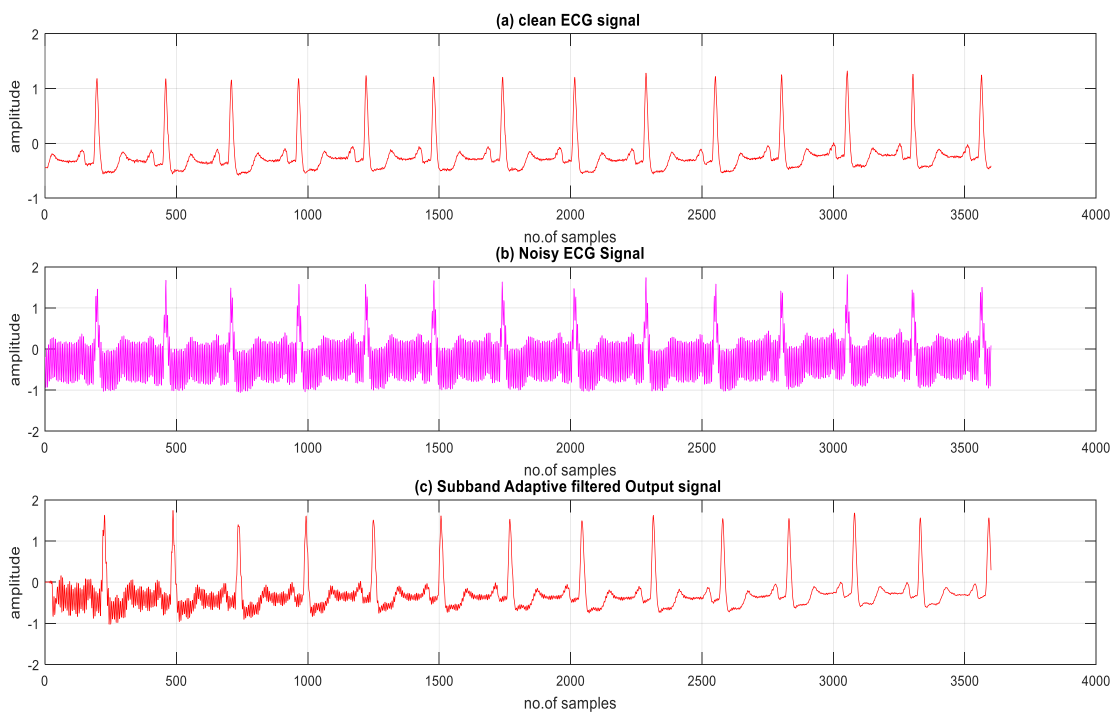

Figure 10 Simulation results using MSAF-LMS algorithm for record number 105 (i) ECG record from MIT-BIH database (red) (ii) PLI contaminated ECG record (magenta) (iii) Sub band adaptive filtered signal using three channel (4,4,2) non uniform filter bank MSAF using LMS algorithm (red)

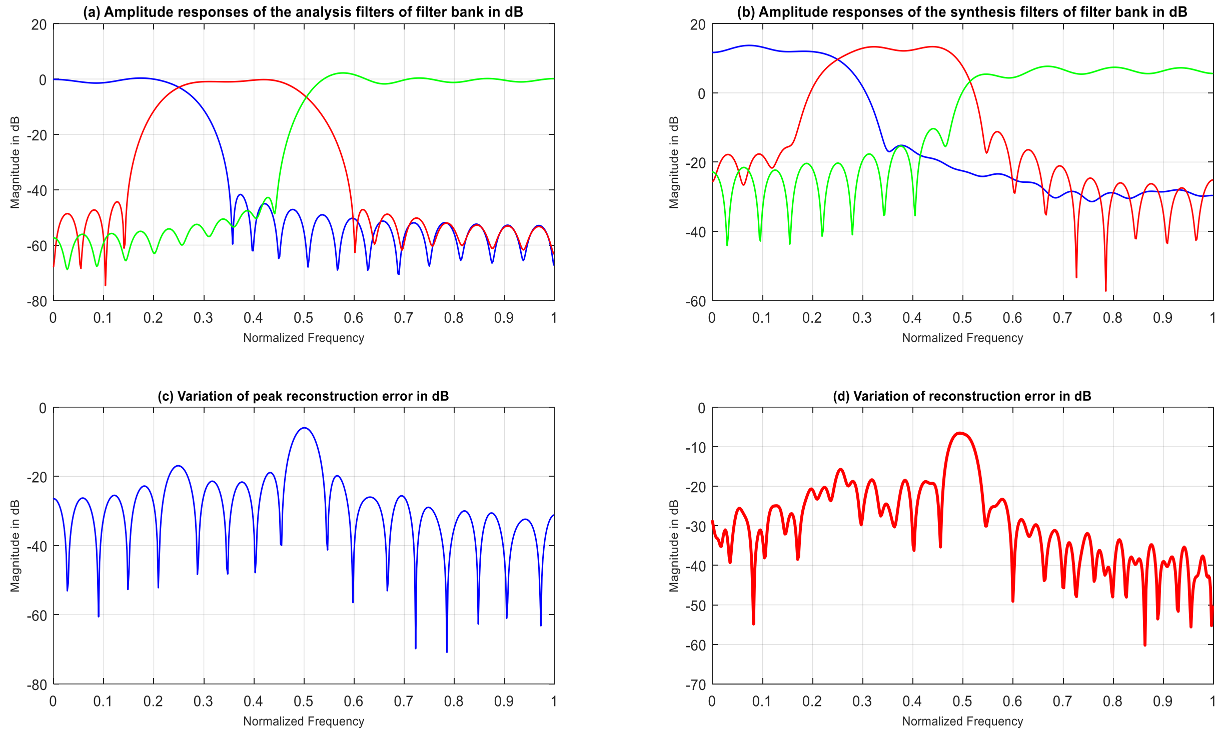

Figure 11 Three channel NUFB with decimation factors (4,4,2) simulated results in dB (i) Magnitude spectrum of analysis FB (ii) Magnitude spectrum of synthesis FB (iii) Amplitude variation of PRE (iv) Reconstruction error Amplitude

The simulation results of a proposed method with proto type filter for three channel NUFB with decimation factors (4,4,2) is shown in Fig.11.The peak reconstruction error (PRE) is reduced appreciably. The average PRE obtained in three channel NUFB is 0.03583dB.

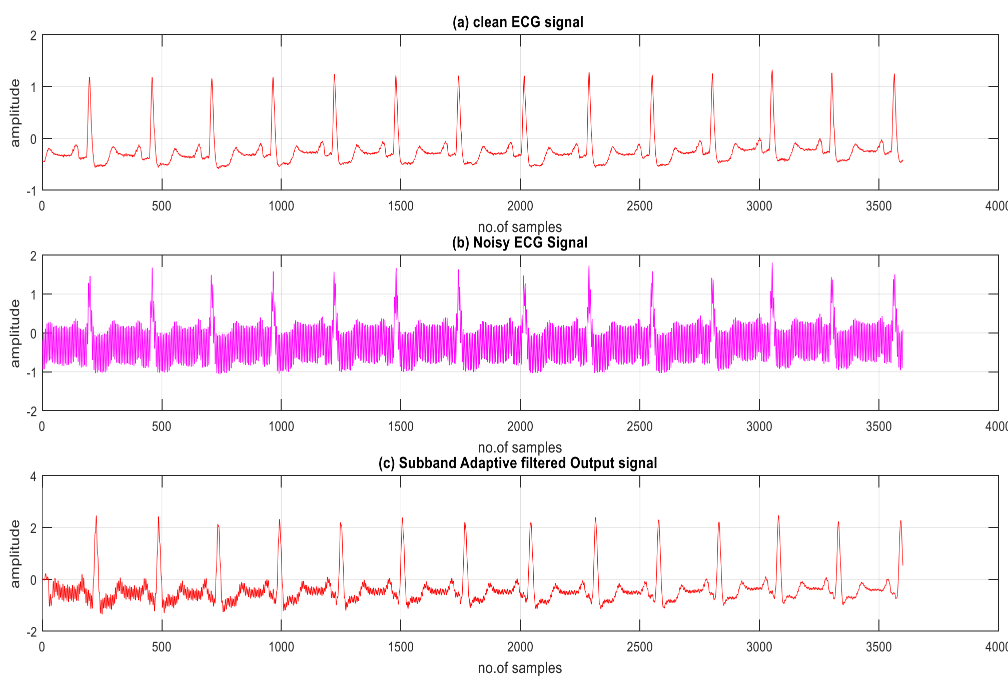

Figure 12 Simulation results using MSAF-LMS algorithm for record number 105 (i) ECG record from MIT-BIH database (red) (ii) PLI contaminated ECG record (magenta) (iii) Sub band adaptive filtered signal using four channel (8,8,4,2) non uniform filter bank MSAF using LMS algorithm (red)

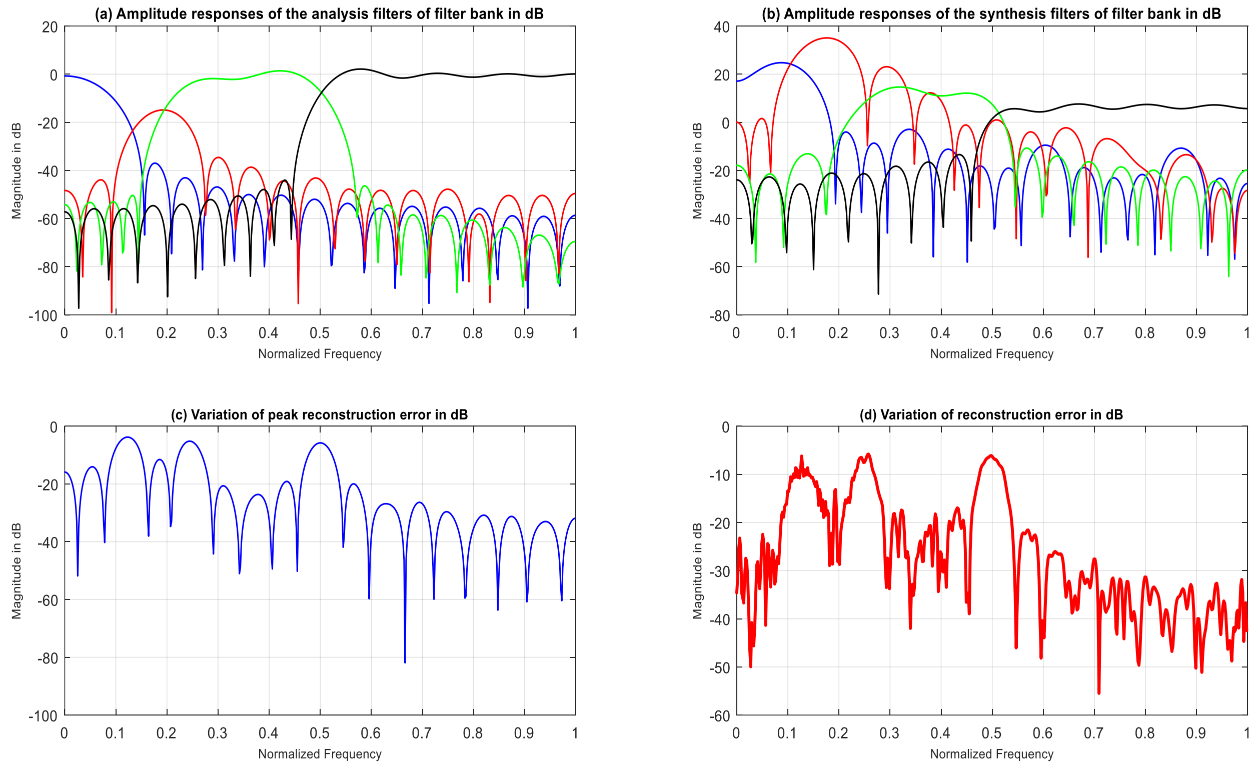

Figure 13 Four channel NUFB with decimation factors (8,8,4,2) simulated results in dB (i) Magnitude spectrum of analysis FB (ii) Magnitude spectrum of synthesis FB (iii) Amplitude variation of PRE (iv) Reconstruction error Amplitude

The simulation results of a proposed method with proto type filter for four channel NUFB with decimation factors (8,8,4,2) is shown in Fig.13.The peak reconstruction error (PRE) is reduced appreciably. The average PRE obtained in four channel NUFB is 0.023393dB.

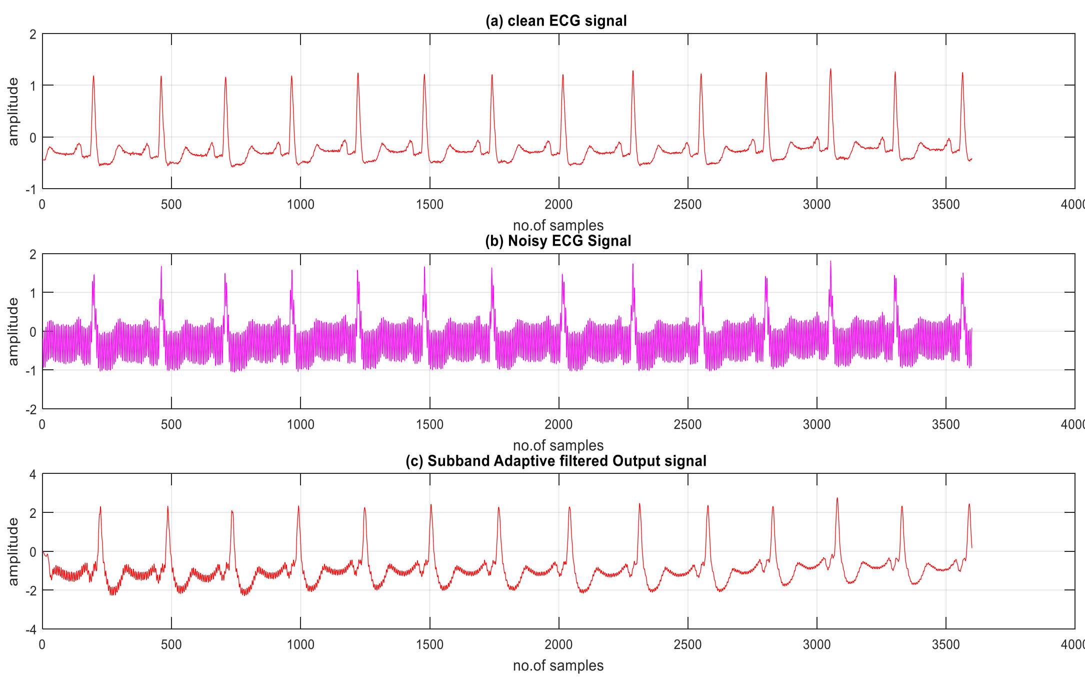

Figure 14 Simulation results using MSAF-LMS algorithm for record number 105 (i) ECG record from MIT-BIH database (red) (ii) PLI contaminated ECG record (magenta) (iii) Sub band adaptive filtered signal using five channel (16,16,8,4,2) non uniform filter bank MSAF using LMS algorithm (red)

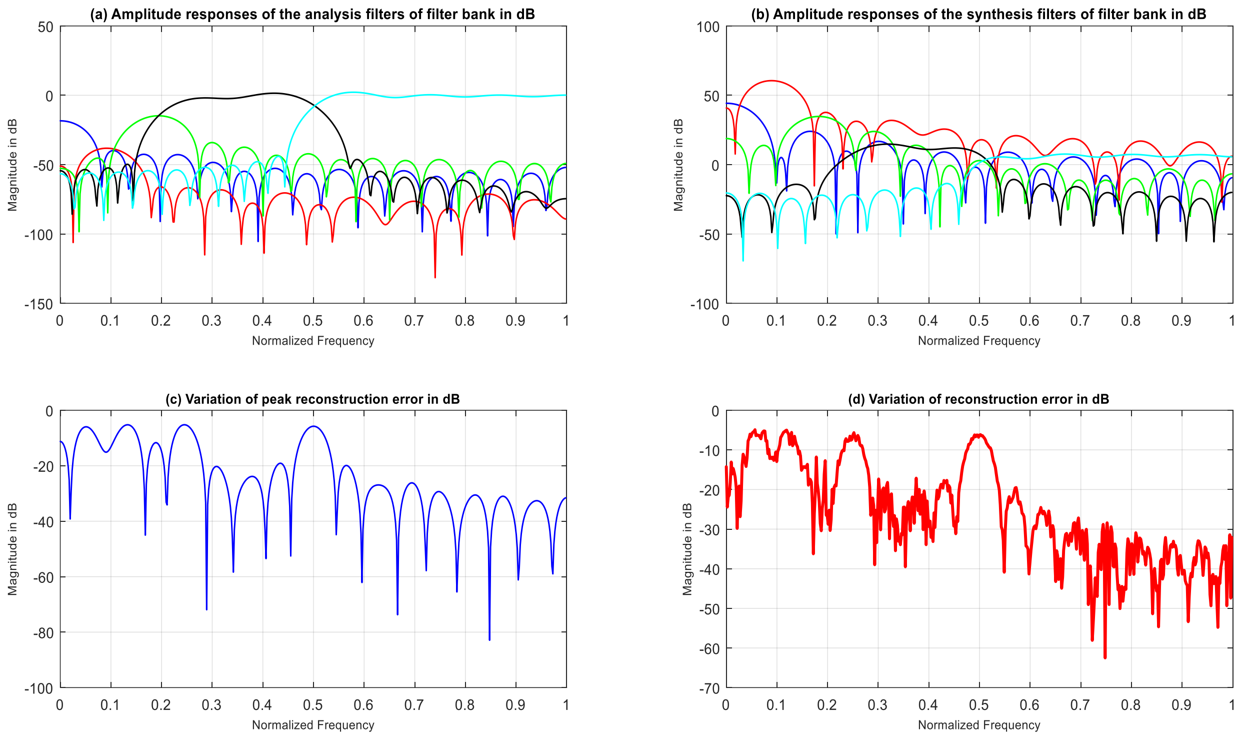

Figure 15 Five channel NUFB with decimation factors (16,16,8,4,2) simulated results in dB (i) Magnitude spectrum of analysis FB (ii) Magnitude spectrum of synthesis FB (iii) Amplitude variation of PRE (iv) Reconstruction error Amplitude

The simulation results of a proposed method with proto type filter for five channel NUFB with decimation factors (16,16,8,4,2) is shown in Fig.11. The peak reconstruction error (PRE) is reduced appreciably. The average PRE obtained in five channel NUFB is 0.0288dB.

The simulation results of a proposed method using LMS adaptive algorithm with proto type filter for three channel, four channel and five channel UFB's and NUFB's are shown in above Figures. The peak reconstruction error (PRE) is reduced appreciably. The average PRE obtained for three channel, four channel and five channel UFB's are 0.08169 dB, 0.0414 dB and 0.0454 dB respectively. The average PRE obtained for three channel, four channel and five channel NUFB's are 0.03583 dB, 0.0238393 dB and 0.0288 dB respectively. The performance comparison with published works is shown in Table 10.

Table 10 Comparison of existing works

SNO	Author	Year	Method	SNR in dB
1	Gowri, Thumbur et.,al [14]	2014	E- VSSLMS algorithm	12.3451
2	Kærgaard, Kevin et.,al [13]	2016	EEMD-BLMS algorithm	13.1900
3	Proposed design	2018	NUFB-MSAF LMS algorithm	**21.7097**

4. CONCLUSIONS

This research paper presents the new comprehensive ANC system of ECG signals with robustness based on UFB &NUFB structured MSAF's using LMS algorithm. The proposed model is potentially a new realization structure form of ANC which guaranteed a more stable transformation in response to variants in input signal power. The theoretical analysis of NUFB structured MSAF system is carried out and simulations are performed using MATLAB. In order to analyze the performance of the proposed design a comparison has been made between six different ECG denoising schemes *i.e* three channel, four channel and five channel UFB & NUFB structured MSAFs using LMS algorithm respectively. The proposed NUFB structured MSAF system consists of reference signal and primary signal as input parameters for which adaptive filtered estimated signal, error signal and coefficients of the filter are obtained as output parameters. The performance of proposed system is compared quantitatively by parameters SNR, MSE, RMSE and Distortion. Better filtering performance results are obtained by NUFB structured MSAF using LMS algorithm and also this algorithm guarantee the better estimation of noise. Computer simulation demonstrated that the proposed system gives improved performance and achieves good adaptation. The SNR for various NUFB structured MSAF's was found to be higher than the UFB structured MSAF's. The five channel NUFB structured MSAF performs better SNR values than UFB structured MSAF using LMS algorithm.

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