

ECG Denoising using Modified-NLMS Multi band Structured Sub band Adaptive Algorithm

B.Bhaskara Rao, B.Prabhakara Rao

Abstract: Electrocardiogram (ECG) is the procedural electrical action of the heart that emerges from the heart muscle's electrophysiological design. In any case, in clinical environment all through procurement, the ECG flag is debased with various assortments of artifacts. The analysis of ECG records permits the consultants to identification many viscus disorders. However, the accuracy of such diagnostic depends on the signal quality. To effectively correct associated to preserve more underlying parts of an ECG record a powerful tool for elimination of artifact from ECG was introduced. In this research paper a brand new ECG enhancement style exploitation multiband structured sub band adaptive filter (MSAF) is built to unravel structured issues in typical sub band adaptive filter (SAF). The proposed approach is established on integrating the Modified NMLS (MNLMS) adaption technique with SAF. This paper investigates the new detailed adaptive noise canceller (ANC) system for ECG signals with lustiness based mostly on uniform filter bank (UFB) and non-uniform filter bank (NUFB) structured MSAF using MNLMS adaptive algorithm. Computer simulation demonstrates that the projected system provides improved performance and achieves good adaptation. NUFB structured MSAF algorithms are applied on graphical records obtained from standard Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH) information base and the performance is compared with UFB structured MSAF algorithms in terms of parameters signal-to-noise ratio before filtering (SNRBF) and signal-to-noise ratio after filtering (SNRAF). The Post -SNR values for various NUFB structured MSAF's was found to be higher than the UFB structured MSAF's.

Index Terms: ANC, ECG, MSAF, MNLMS, NUFB, SNRBF, SNRAF, UFB.

I. BACKGROUND

Our bodies are continuously speaking data about our health. These facts can be traped through physiological devices that estimate heart rate, blood pressure, oxygen saturation degrees, blood glucose, nerve conduction, brain interest and so on. Electrocardiogram (ECG) is a illustration of the electric hobby of cardiac tissue at some point of systole and diastole. This signal is generally acquired by way of measuring the electrical potential between particular spatial combinations of recording electrodes [1, 2].

Electrocardiography is the process of recording the electrical action of the coronary heart around duration of time

Manuscript published on 30 March 2019.

*Correspondence Author(s)

B.Bhaskara Rao, ECE Dept., Research Scholar, JNT University: Kakinada, Kakinada 533003, A.P., India

Dr.B.Prabhakara Rao, Program Director, School of Nanotechnology, IST, Kakinada 533003, India.

© The Authors. Published by Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP). This is an open access article under the CC-BY-NC-ND license http://creativecommons.org/licenses/by-nc-nd/4.0/

using electrodes positioned over the skin. General goal of appearing an ECG is to gain information about the shape and Characteristic of the heart. Clinical uses for these records are numerous and usually need information of the shape and/or Characteristics of the heart to be interpreted. An ECG tracing is affected by affected person motion. Artifacts are distorted signals resulting from secondary internal or external sources, along with power line interference (PLI), baseline wander (BW), Electromyography noise or muscle artifact (MA) and electrode movement (EM) [3]. Distortion poses large demanding situations to healthcare companies, who hire diverse techniques and strategies to securely understand those false indicators. Accurately keeping apart the ECG artifact from the true ECG signal could have a tremendous effect on patient outcomes and legal liabilities. The artifact elimination in biomedical applications could be very crucial to discriminate the important desired signal capabilities in interference. Diverse adaptive systems are initiated for interference elimination. Figure.1 defines the essential downside and noise cancelling answer [4, 5].

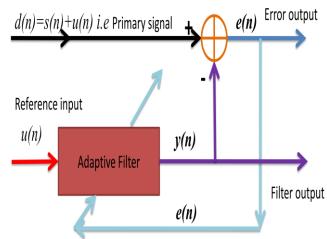


Figure.1: Basic diagram of Adaptive Noise Canceller

In order to eliminate artifact from ECG the clean ECG s(n) is added with a interference $n_I(n)$ which is uncorrelated with the s(n). The predominant input to the ANC is noise contaminated signal d(n) i.e. $s(n)+n_I(n)$. If $n_2(n)$ is another noise/artifact generated from noise source that is unrelated with the s(n) however correlative with $n_I(n)$ that supplies reference input to ANC that is filtered to produce the estimate signal y(n) that's a detailed duplicate of reference input. The response of the adaptive filter y(n) is subtracted from d(n) to yield the error function 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) [6,7].



$$e(n) = d(n) - y(n) \tag{1}$$

The adaptive filter extricates the signal or abolishes artifact by iteratively minimizing the minimum mean square error (MSE).

Traditional filters such as adaptive filters [8,9,10], sign based normalised adaptive filters [11] were initiated in the literature to minimise interference/artifacts. Dissimilar practices for ECG denoising with new variable step size NLMS [12] and EEMD-BLMS methods [13]. Promising performance are acquired by non linear adaptive algorithms [14, 15, 16], recently hybrid techniques have been proposed to suppress artifact from ECG signals using cascaded adaptive filters [17,18].

Filter banks had been delivered in an attempt to upgrade the behaviour of time area adaptive filters. The main upgrades are faster convergence and the low computational complexity due to shorter adaptive filters within the sub bands, running at a lower sampling rate. Filter banks (FB) break down an advanced signal into numerous sub band groups. Based totally on time frequency resolution, FB's can be arranged into two categories *i.e.*, uniform filter banks (UFB) and non uniform filter banks (NUFB) [19,20]. Various techniques for disintegrating indicators in to sub groups have turned out to be unmistakable and had been proposed inside the literature [21, 22].

Sub band adaptive filtering (SAF) typically employs multirate filter banks for signal decomposition and reconstruction. This approach allows for instant convergence and decreased computational complexity through use of the robust adaptive algorithms. Currently high-quality artifact elimination techniques are proposed using SAFs comprise variable step size SAF [23], Variable individual step size SAF [24], new standardized SAF [25]. An enhanced cosine modulated NUFB configuration approach has been proposed by Kumar, A., G K Singh et., all [26]. In customary SAF's each bound uses an individual adaptive sub filter in its personal unique adaption that declines the convergence rate. To solve these structured problems a multiband structured SAF (MSAF) are developed in which the entire band adaptive filter tap weight vectors are updated by a single adaptive algorithm the use of sub band signal [20, 27]. The non-uniform filter bank SAF (NUFBSAF) is developed to procure a higher convergence behaviour with the aid of adapting the band width of analysis filters through proper choice of decimation factors. The goal of this paper is to broaden non uniform multi band structured sub band adaptive filter out that could intensify the overall performance of the traditional ANC design, to examine the application of SAF to noise cancellation hassle in ECG.

II. SUB BAND ADAPTIVE FILTERING METHOD

Sub band adaptive filtering improves convergence under colored signals. 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 non stationary signal. A FB incorporates a set of analysis filters which decomposes the input signal of bandwidth into sub band signals. The sub bands supply records from extraordinary frequency bands thus; it is conceivable to function time and frequency based processing of the input signal. A common 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 totally adaptive algorithm calculation involves decomposing a signal into frequency sub bands and managing these sub bands as indicated by the current application.

The concept of multiband structured-sub band adaptive filter (MSAF) is introduced in this section. In the proposed design the desired/primary input 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 estimatedt 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 this Figure.2 $H_0,H_1,H_2,...,H_{N-1}$ and $F_0,F_1,F_2,...,F_{N-1}$ 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]

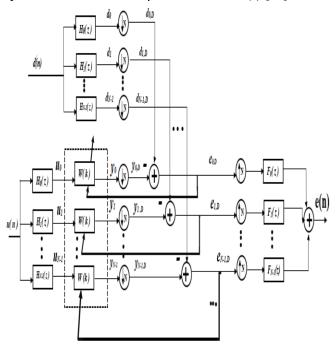


Figure.2: Block diagram of MSAF (from Reference [20])

Non uniform filter banks have non uniform frequency partition. One technique of constructing NUFB is to cascade UFB in a tree structure using a two channel FB as elementary building blocks. The distinct gain of the equivalent structure of the tree-structured FB is the possibility of realizing analysis and synthesis filters for extra vital tasks than easy band separation [19]. As an instance of this method, NUFB with decimation elements (16,16, 8,4,2) is illustrated. The proposed tree-structured non uniform filter bank's analysis section is shown in Figure.3.





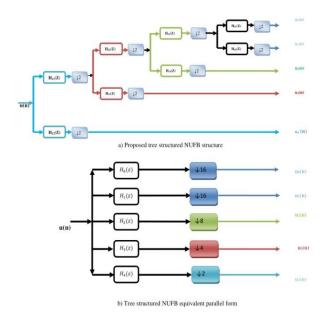


Figure.3: Proposed block diagram of (a) tree structured NUFB & (b) equivalent NUFB parallel form

The proposed structure makes use of low pass FIR filter with filter length 32,cut off frequency 100 Hz and sampling frequency 360 Hz design in both analysis and synthesis FB that give near-perfect reconstruction by permitting little measure of distortion at the output. $H_0(z)$ is the transfer function of FIR filter i.e the frequency response of low pass FIR filter and h(n) is the impulse response of $H_0(z)$ or initial FIR filter numerator polynomial coefficients which are generated by using Walsh-Hadamard transformations. These filter coefficients satisfies linear phase Walsh-Hadamard transformation codes are the most common fixed length orthogonal codes used in CDMA applications. A set of Walsh codes of length 'P' consists of the P rows of an P by **P** Walsh matrix. The generalized structure of **N**-channel NUFB based on tree structured procedure having decimation N_0 , N_1 , N_2 --- N_{N-1} for each band then the decimation factors must fulfill the accompanying condition [21].

$$\sum_{k=0}^{N-1} \frac{1}{N_k} = 1 \tag{2}$$

In N-channel NUFB the PR is possible if

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

$$|H_0(e^{jw})|^2 + |H_1(e^{jw})|^2 + |H_2(e^{jw})|^2 + |H_3(e^{jw})|^2 + |H_4(e^{jw})|^2 + |H_4(e^{jw})|^2$$

$$(4)$$

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

$$H_0(z) = H_{11}(z)H_{21}(z^2)H_{31}(z^4)H_{41}(z^8)$$
 (5)

$$H_1(z) = H_{11}(z)H_{21}(z^2)H_{31}(z^4)H_{42}(z^8)$$
 (6)

$$H_2(z) = H_{11}(z)H_{21}(z^2)H_{32}(z^4)$$

$$H_3(z) = H_{11}(z)H_{22}(z^2)$$
(8)

$$H_3(z) = H_{11}(z)H_{22}(z^2) \tag{8}$$

$$H_4(z) = H_{12}(z)$$
 (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. To evaluate performance MSAF's various UFB & NUFB structured such as three channel with decimation factors (3,3,3) UFB (TCUFB), three channel with decimation factors (4,4,2) NUFB (TCNUFB), four channel with decimation factors (4,4,4,4) UFB (FCUFB), four channel with decimation factors (8,8,4,2) (**FCNUFB**), five channel with decimation factors (5,5,5,5,5) UFB (FVCUFB) and five channel with decimation factors (16,16,8,4,2) NUFB (FVCNUFB) using different adaptive algorithms.

III. MSAF WITH MODIFIED NLMS ALGORITHM

The traditional ANC shown in Figure.1 incorporates filter whose input parameters are d(n) and u(n). Here u(n) is the time delayed input vector

 $u(n) = [u(n), u(n-1), u(n-2),u(n-M+1)]^T$ $w(n)=[w_0(n), w_1(n), w_2(n),.... w_{M-1}(n)]^T$ represents the numerator polynomial coefficients of the filter at time index n. 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 segment of the original frequency range. The N sub band signals of MSAF algorithms require-particular computational steps in every emphasis as takes after [20]. It is significant to note that n denotes the time index of original sequence & decimated signal time index is denoted by k.

Proposed algorithm summary

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

Analysis filters $H_i(z)$

for i=0,1,2....N-1

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

$$H_{i+1}(z) = H_{s,l}(z^{s-i}).(z^{s-i}).(z^{s-i})...H_{s,h}(z^{s-i})$$

For $k=0, 1, 2, \dots, kN$ 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:

1 &h - Basic Low pass & 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 $U^T(k-1)$

$$A(kN) = [a(kN), a(kN-1), a(kN-2), \dots a(kN-N-1)]$$

$$a(kN) = [u(kN), u(kN-1), u(kN-2), \dots u(kN-L-1)]^T$$
.

$$d(kN) = [d(kN), d(kN-1), d(kN-2), \dots d(kN-L-1)]^{T}.$$



ECG Denoising using Modified-NLMS Multi band Structured Sub band Adaptive Algorithm

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) in all N sub bands at each iteration k as follows

A) Modified Normalized Least Mean Square (MNLMS) Algorithm

$$w(k+1) = w(k) + \mu \frac{u_i(k)}{\|u_i(k)\|^2 + \alpha} e_{i,D}(k)$$
 (10)
Where μ is learning rate parameter and it should be selected

Where μ is learning rate parameter and it should be selected in the stability bound i.e $0 < \mu < \frac{2}{N*P_u}$, here $P_u = u^T(n)u(n)$ and α is a small positive constant used to avoid possible division by zero. These algorithms replace the filter coefficients of sub band adaptive filter the usage of the following equation.

$$w(k+1) = w(k) + \mu G(k)U(k)\Lambda^{-1}(k)e_{i,D}(k)$$
 (11)

Where $\Lambda(k)$ is normalization matrix

$$\Lambda(k) = diag[U^{T}(k)U(k) + \alpha]$$
(12)

The filter coefficients or weight vectors of the filter are changed for the next iteration for Modified Normalised Least Mean Square (MNLMS) depending on w(k). Here w(k) is Walsh-Hadamard transformation matrix defined as follows

$$w_{2P} = (w_P \ w_P; w_P - w_P); \tag{13}$$

Here initial $w_1=1$ and P is the dimension of the matrix.

IV. RESULTS & DISCUSSION

In this simulation the Physionet website MIT-BIH arrhythmia database [28] was utilized to take a look at the execution of various UFB & NUFB structured MSAF's adaptive algorithms for ECG denoising. The recordings had been sampled at 360 samples per seconds with 11-bit resolution over a 10 mV range. 'Mat' files of ECG data were used from the database to load into MATLAB. The simulations have been executed by using accumulating 3600 samples of ECG. A records set of 5 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. In order to check the filtering potentiality in shift variant domain a synthetic PLI, artificial BW, real mucle artifacts and real electrode motion atrifacts with 3600 array size are taken from Physionet website MIT-BIH normal sinus rhythm database (NSTDB) [29]. The performance of proposed UFB and NUFB structured MSAF adaptive noise cancellation systems are compared by quality assessment parameters signal-to-noise ratio before filtering (SNRBF) signal-to-noise ratio after filtering (SNRAF) are outlined as

SNR Before filtering =
$$10 \log_{10} \left(\frac{\sum_{n=0}^{N-1} [s(n)]^2}{\sum_{n=0}^{N-1} [d(n)-s(n)]^2} \right)$$
 (14)

SNR After filtering =
$$10 \log_{10} \left(\frac{\sum_{n=0}^{N-1} [s(n)]^2}{\sum_{n=0}^{N-1} [e(n)-s(n)]^2} \right)$$
 (15)

Table.1. SNR (in dB) obtained by applying UFB and NUFB structured SAF's using MNLMS algorithms

SAF's using MINLMS algorithms							
Type of	Type of FB	Rec.No	Rec.No	Rec.No	Rec.No	Rec.No	Avg.
Artifac t		100	105	108	203	228	Val
PLI	SNRBF	0.2144	0.712	-0.0059	2.9671	-1.0532	0.56688
	TCUFB	16.371 9	16.494 4	16.297 6	17.230 2	16.092 5	16.4973 2
	FCUFB	17.972 7	18.098 4	17.921 8	18.609 1	17.807 2	18.0818 4
	FVCUFB	17.396 7	17.518 5	17.339 7	18.097 4	17.187 8	17.5080 2
	TCNUFB	21.479 8	21.573 6	21.444 8	22.014 7	21.350	21.5727 6
	FCNUFB	19.477	20.018	19.383	21.158	19.137	19.8351 4
	FVCNUF B	22.836 7	22.390	22.869	23.773	22.044 5	22.7827
BW	SNRBF	5.8558	3.5196	8.5884	2.524	9.1149	5.92054
	TCUFB	8.8078	6.9116	10.808 7	6.209	11.49	8.84542
	FCUFB	8.19	6.6061	10.433 4	6.1044	10.770 9	8.42096
	FVCUFB	8.6402	7.1406	10.830 5	5.9152	11.059 6	8.71722
	TCNUFB	10.566 7	9.2235	12.963 4	8.2884	13.501	10.9086 6
	FCNUFB	13.022	11.904 6	15.565 3	11.122 4	15.810 9	13.4850 6
	FVCNUF B	19.795 8	17.419 9	21.566 9	15.939	22.648	19.4739 6
ЕМ	SNRBF	3.6096	4.1072	6.521	6.3623	2.342	4.58842
	TCUFB	16.250 9	14.106 6	8.9615	12.462 3	13.147 1	12.9856 8
	FCUFB	16.598 4	14.536 6	9.2073	12.888 8	13.495	13.3452 2
	FVCUFB	16.728 1	14.518 1	9.1277	12.766	13.691 9	13.3663
	TCNUFB	18.781 1	16.736 5	11.463	15.128 1	15.600 5	15.5418 4
	FCNUFB	21.870	19.817 3	14.451 7	18.200 9	18.608	18.5896 4
	FVCNUF B	25.693 4	22.374 2	17.480 9	19.695	23.362	21.7211 2
МА	SNRBF	4.1514	4.6489	7.0628	6.904	2.8837	5.13016
	TCUFB	14.931 7	14.308	9.2159	13.059 1	12.743	12.8515
	FCUFB	15.280 8	14.729 6	9.4417	13.492 1	13.066 5	13.2021
	FVCUFB	15.451 7	14.670 8	9.3951	13.369 4	13.306 5	13.2387
	TCNUFB	13.396 5	12.375 2	8.4101	10.858 5	12.242 5	11.4566
	FCNUFB	16.237 7	15.549	11.277	13.933	15.039 5	14.4072
	FVCNUF B	22.285	19.661	16.147	16.905	21.776	19.3547

Average SNR values shown in Table.1 are acquired by using averaging record numbers. 100m, 105m, 108m, 203m and 228m procured from MIT-BIH database. Table.1 shows the SNR values obtained for different recordings of MIT-BIH data base. The SNR values calculated by applying UFB and NUFB structured SAF's using MNLMS algorithm. As shown in Table 1. Average SNR's for 5 records obtained by applying UFB and NUFB structured SAF's using MNLMS algorithms for PLI noise has 22.78272 dB, for BW artifact has 19.47396 dB, for EM noise has 21.72112 dB and for Muscle artifact has 19.3547 dB. The computer simulations state that NUFB structured MSAFs has appreciable effectiveness than UFB structured MSAFs. Various artifact cancellations using MNLMS adaptive filtering are shown in Figures 4-7 for MIT-BIH record number 105m, by evaluating the range of data samples and magnitude (in milli volts) on x-axis and y-axis respectively. The same technique can be applied on the different MIT-BIH data base recordings with different UFB and NUFB structured SAF's. For convenience the results of only one record using only one FVCNUFB structured sub band adaptive filter are depicted

figures.

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)
© Copyright: All rights reserved.

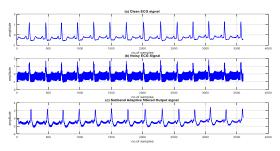


Figure.4: PLI cancellation using MSAF using MNLMS (a) clean ECG (b) PLI noise corrupted ECG (c) FVCNUFB structured Sub band adaptive filtered signal using MNLMS algorithm.

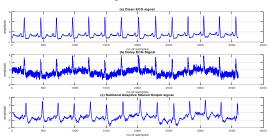


Figure.5: Adaptive filtering simulation of BW artifact removal (a) clean ECG (b) BW noise corrupted ECG (c) FVCNUFB structured sub band adaptive filtered signal using MNLMS algorithm.

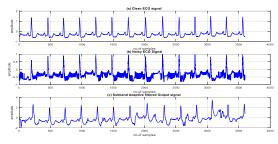


Figure.6: Adaptive filtering simulation of EM artifact cancellation (a) clean ECG (b) EM artifact corrupted ECG (c) FVCNUFB structured Sub band adaptive filtered signal using MNLMS algorithm.

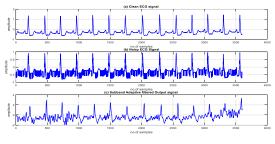


Figure.7: Adaptive filtering simulation of MA removal (a) clean ECG (b) Muscle artifact corrupted ECG (c) FVCNUFB structured Sub band adaptive filtered signal using MNLMS algorithm.

The frequency response simulation results of a proposed method with proto type filter for UFB structured SAF's and NUFB structured SAF's are shown in Figure.8.

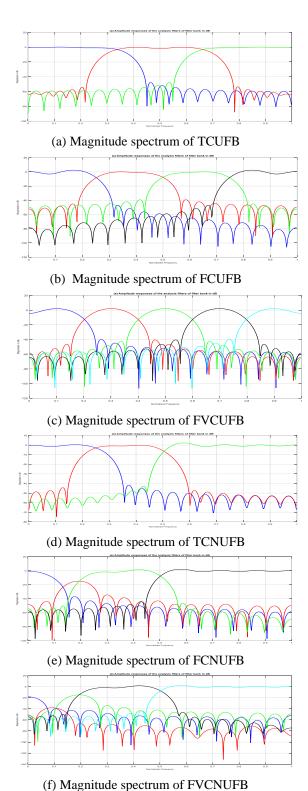
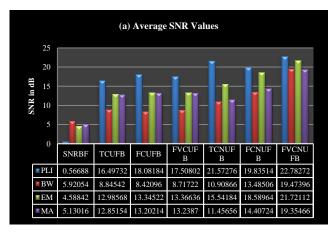
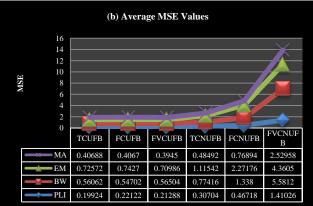
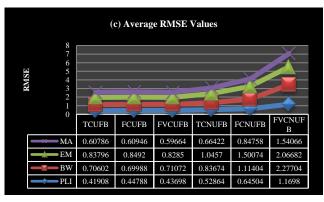


Figure.8: The frequency response of a proposed UFB structured SAF's and NUFB structured SAF's









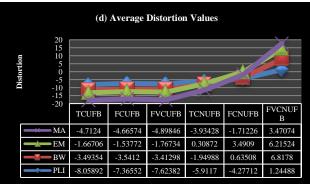


Figure.9: Artifact cancellation Using UFB& NUFB structured Sub band adaptive MNLMS algorithm simulation results (a) Average SNR values (b) Average MSE values (c) Average RMSE values (d) Average Distortion values

The perfect reconstruction error (PRE) simulation results of a proposed method with proto type filter for UFB structured SAF's and NUFB structured SAF's using MNLMS adaptive algorithms are shown in Figure.9.

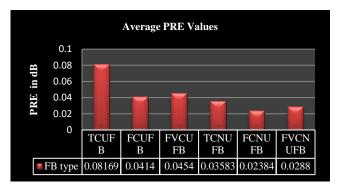


Figure.10: The peak reconstruction error (PRE) values

The perfect reconstruction error (PRE) is decreased appreciably. The average PRE got in FVCNUFB is 0.0288dB. The simulation results of a proposed method the usage of MNLMS adaptive algorithms with proto type filter for three channel, four channel and five channel UFB's and NUFB's are shown in above Figure.7. The average PRE obtained for three channel, four channel and five channel UFB's are 0.08169 dB, 0.0414 dB and 0.0454dB 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 PRE values shown in table depict that the FCNUFB has minimum PRE compared to the remaining algorithms.

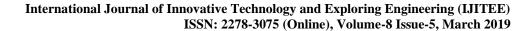
V. CONCLUSIONS

This research paper presents the new comprehensive ANC system of ECG signals with robustness based on UFB & NUFB structured MSAF's using Modified NLMS adaptive algorithms. The theoretical analysis of NUFB structured MSAF system is carried out and simulations are performed. 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 SAFs using Modified NLMS adaptive algorithms respectively. The performance of proposed system is compared quantitatively by parameter SNR. Better filtering performance results are obtained by NUFB structured SAF MNLMS adaptive algorithm and also these algorithms guarantee the better estimation of noise. Computer simulation demonstrates that the proposed system gives improved performance and achieves good adaptation. The SNR for various NUFB structured SAF's was found to be higher than the UFB structured SAF's. The five channel NUFB structured SAF performs better SNR values than UFB structured SAF using MNLMS.

REFERENCES

- Reddy, D. C. (2005). Biomedical signal processing: principles and techniques. McGraw-Hill.
- Catalano, J. T. (2002). Guide to ECG analysis. Lippincott Williams & Wilkins.
- 3. Haykin, S. S. (2008). Adaptive filter theory. Pearson Education India.
- Manolakis, D. G., Ingle, V. K., & Kogon, S. M. (2000). Statistical and adaptive signal processing: spectral estimation, signal modeling, adaptive filtering, and array processing (p. 656). Boston: McGraw-Hill.
- Paulo, S. D. (2008). Adaptive filtering: algorithms and practical implementation. The international series in Engineering and Computer Scienc, 23-50.







- Kuo, S. M., & Morgan, D. (1995). Active noise control systems: algorithms and DSP implementations. John Wiley & Sons, Inc..
- 7. Widrow, B., Glover, J. R., McCool, J. M., Kaunitz, J., Williams, C. S., Hearn, R. H., ... & Goodlin, R. C. (1975). Adaptive noise cancelling: Principles and applications. *Proceedings of the IEEE*, 63(12), 1692-1716.
- Mugdha, A. C., Rawnaque, F. S., & Ahmed, M. U. (2015, June). A study
 of recursive least squares (RLS) adaptive filter algorithm in noise
 removal from ECG signals. In 2015 International Conference on
 Informatics, Electronics & Vision (ICIEV) (pp. 1-6). IEEE.
- 9. Xiong, F., Chen, D., Chen, Z., & Dai, S. (2019). Cancellation of motion artifacts in ambulatory ECG signals using TD-LMS adaptive filtering techniques. *Journal of Visual Communication and Image Representation*, 58, 606-618.
- Sankar, A. B., Kumar, D., & Seethalakshmi, K. (2010). Performance study of various adaptive filter algorithms for noise cancellation in respiratory signals. Signal processing: An international journal (SPIJ), 4(5), 267.
- Rahman, M. Z. U., Shaik, R. A., & Reddy, D. R. K. (2011). Efficient sign based normalized adaptive filtering techniques for cancelation of artifacts in ECG signals: Application to wireless biotelemetry. Signal processing, 91(2), 225-239.
- Huang, H. C., & Lee, J. (2012). A new variable step-size NLMS algorithm and its performance analysis. *IEEE Transactions on Signal Processing*, 60(4), 2055-2060.
- Kærgaard, K., Jensen, S. H., & Puthusserypady, S. (2016). A comprehensive performance analysis of EEMD-BLMS and DWT-NN hybrid algorithms for ECG denoising. *Biomedical Signal Processing* and Control, 25, 178-187.
- 14. Gowri, T., Kumar, P. R., & Reddy, D. R. K. (2014). An efficient variable step size Least Mean Square Adaptive Algorithm used to enhance the quality of electrocardiogram signal. In Advances in Signal Processing and Intelligent Recognition Systems (pp. 463-475). Springer, Cham.
- Yazdanpanah, B., Kumar, K. S., & Raju, G. S. N. (2015, January).
 Notice of Retraction Noise removal ecg signal using non-adaptive filters and adaptive filter algorithm. In 2015 International Conference on Electrical, Electronics, Signals, Communication and Optimization (EESCO) (pp. 1-6). IEEE.
- Bhati, R., Goel, S., Kaur, G., & Tomar, P. (2016). Noise Suppression From ECG Signal Using Adaptive Filter Technique. *International Journal of Computer Science and Information Security*, 14(8), 135.
- Dixit, S., & Nagaria, D. (2017). Design and analysis of cascaded LMS adaptive filters for noise cancellation. *Circuits, Systems, and Signal Processing*, 36(2), 742-766.
- Bhaskara Rao, B., & B. Prabhakara Rao. "Performance analysis of two stage adaptive FIR Filter Algorithms for PLI and BW artifact cancellation in ECG." International Journal of Engineering & Technology [Online], 7.1.8 (2018): 123-129. Web. 17 May. 2018
- 19. Vaidyanathan, P. P. (1993). *Multirate systems and filter banks*. Pearson Education India.
- 20. Lee, K. A., Gan, W. S., & Kuo, S. M. (2009). Subband adaptive filtering: theory and implementation. John Wiley & Sons.
- Kumar, A., Singh, G. K., & Anurag, S. (2013). Design of nearly perfect reconstructed non-uniform filter bank by constrained equiripple FIR technique. *Applied Soft Computing*, 13(1), 353-360.
- Shin, J., Yoo, J., & Park, P. (2013). Variable step-size sign subband adaptive filter. *IEEE Signal processing letters*, 20(2), 173-176.
- Seo, J. H., & Park, P. (2014). Variable individual step-size subband adaptive filtering algorithm. *Electronics Letters*, 50(3), 177-178.
- Kumar, A., Singh, G. K., & Anurag, S. (2015). An optimized cosine-modulated nonuniform filter bank design for subband coding of ECG signal. *Journal of King Saud University-Engineering Sciences*, 27(2), 158-169.
- Yu, Y., Zhao, H., & Chen, B. (2016). A new normalized subband adaptive filter algorithm with individual variable step sizes. *Circuits, Systems, and Signal Processing*, 35(4), 1407-1418.
- Zhong, W., Fang, L., Zhang, Q., & Ye, L. (2017). Design of oversampled nonuniform filter banks with arbitrary rational frequency partitioning. Signal, Image and Video Processing, 11(4), 689-696.
- Abadi, M. S. E., Shafiee, M. S., & Zalaghi, M. (2018). A low computational complexity normalized subband adaptive filter algorithm employing signed regressor of input signal. EURASIP Journal on Advances in Signal Processing, 2018(1), 21.
- 28. Mark, R., & Moody, G. (1988). MIT-BIH arrhythmia database directory. Cambridge: Massachusetts Institute of Technology.
- Goldberger AL, Amaral LAN, Glass L, Hausdorff JM, Ivanov PCh, Mark RG, Mietus JE, Moody GB, Peng C-K, Stanley HE. PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic

Retrieval Number: D2802028419/19©BEIESP

Journal Website: www.ijitee.org

Signals. Circulation 101(23):e215-e220 [Circulation ElectronicPages; http://circ.ahajournals.org/content/101/23/e 215.full]; 2000 (June 13).

