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Transform-based algorithms dedicated to ECG baseline drift cancellation: A comparative study

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***Abstract*—Nowadays, Electrocardiogram (ECG) diagnosis stills to be very useful to inform about the cardiac health status of humans. However, acquiring an ECG signal in a correct manner requires that all noise sources should be reduced proficiently. Among such noise types, we attract the attention to the baseline wander (BW) that can be instigated, usually, by unreliable electrode contact placement, patient breathing, unclean skin and so on. In this context, three strategies dedicated to diminish BW contribution that are: Discrete Wavelet Transform (DWT), Discrete Cosine Transform (DCT), Fast Walsh-Hadamard Transform (FWHT) based algorithms, were experimented comparatively. Achieved simulations demonstrate, qualitatively and quantitatively, the high-performance capacity of the DWT-based strategy compared to the DCT-based technique and FWHT-based method.**

Keywords—EGC denoising, Baseline wander removing, Discrete Wavelet Transform, Discrete Cosine Transform, Walsh-Hadamard Transform.

I. INTRODUCTION

Modern healthcare technologies are made around expert systems aiming to support human physicists. However, to build such systems, a need to an accurate data acquisition platform is unavoidable. In this context, the attention is focused on ECG-acquiring systems. To guarantee a preventive or at least a correct diagnosis by a cardiologist or an aiding expert system, the numerous types of noise corrupting the acquired signal should be reduced. As it is well-known, the various noise sources can be [1]:

- Baseline wander BW originated from body respiration movements with frequencies band less than 0.5 Hz.
- Additive White Gaussian noise AWGN.
- Power-line interference PLI caused by inductive and capacitive coupling of the power supply.
- Muscle artefacts MA produced by the electrical action of muscles.

The presented work aims to compare three methods to remove the baseline wander from the ECG signal. The achieved comparison has been done and the strategies were evaluated quantitatively and qualitatively.

The organization of the paper is as follows:

Section 1 provides a brief overview of BW filtering. Section 2 describes the BW denoising techniques in detail. Section 3 presents the simulations and results. The final section presents the conclusion.

II. RELATED PREVIOUS WORKS

The literature proposes many innovative techniques for removing BW noise from the ECG signal: conventional filtering using FIR filter [2] or IIR filter [3], adaptive filtering techniques [3], [4], extended Kalman filter (EKF) [5], principal component analysis (PCA) [6], wavelet denoising [7], [8], [9], DCT-based method [10], Fourier series[11], neural network [12]and Wiener filter [13].

III. COMPARATIVE METHODS DESCRIPTION

A. DWT-based method for baseline drift removing

1) Discrete Wavelet Transform

DWT is a suitable tool for denoising signals. It can realize the time-scale decomposition of the input signal to achieve a decorrelation of the noise. A discrete signal *x[n]* can be decomposed using the multiresolution analysis (MRA) as follows [14]:

$$x(n)=\sum_{k} A_{J,k}\varphi_{J,k}(n)+\sum_{j=j_0}^{J}\sum_{k} D_{j,k}\psi_{j,k}(n) \tag{1}$$

Where: $A_{J,k}$ are the approximation coefficients, $D_{j,k}$ are the detail coefficients, additionally, $\varphi_{J,k}(n)$ and $\psi_{j,k}(n)$ are fatherlets and wavelets generated from father and mother waves correspondingly $\varphi(n)$ and $\psi(n)$.

The fast manner to calculate such coefficients is first proposed by MALLAT [14]. Accordingly, the decomposition process is realized by applying hierarchically lowpass filter *h[n]*and highpass filter *g[n]*until reaching a predefined level. A two-level decomposition process of the DWT is shown in Fig.1.

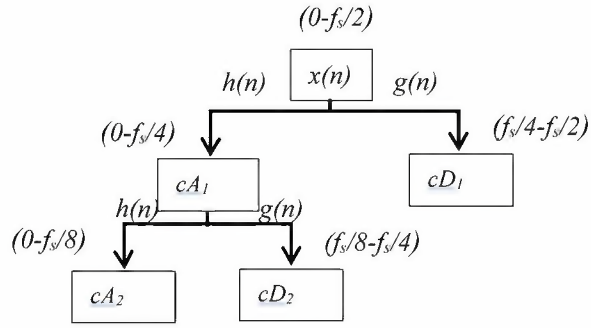

Fig. 1. The structure of a two-level pyramidal decomposition.

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The decomposition process gives coefficients that start from the last level $[A_K ,D_K ,....,D_1]$. We seek to approximate adequately the baseline wander band by the suitable wavelet approximation vector A_K, where K is produced by K levels decomposition. However, the level K can be found by[7]:

$$f_{BW\max} = \left(\frac{f_s}{2^{K+1}}\right) \Rightarrow K = \left\lfloor \log_2\left(\frac{f_s}{f_{BW\max}}\right) - 1 \right\rfloor \quad (2)$$

Where $f_{BW\max}$ is the maximum baseline wander frequency, and f_s is the sampling frequency.

This means that the cA_K vector should be nullified to suppress the contribution of the baseline drift from the noisy ECG signal and preserve the useful signal.

B. DCT-based method for baseline drift removing

1) Discrete Cosine Transform

The discrete cosine transform is considered a powerful tool for signal analysis. A general equation is written as [15]:

$$X(k) = w[k]\sum_{n=1}^{N} x[n]\cos\frac{\pi(2n-1)(k-1)}{2N} \quad /k = 1,\dots\dots,N \quad (3)$$

$$w[k] = \begin{cases} \dfrac{1}{\sqrt{N}} & k = 1 \\ \sqrt{\dfrac{2}{N}} & 2 \le k \le N \end{cases}$$

N is the length of the input signal $x(n)$. Therefore, the transform domain resulting signal $X(k)$ has the same length. The estimation of corresponding index k is expressed by :

$$k = \left\lfloor \frac{N \times f_k}{f_s / 2} \right\rfloor \quad (4)$$

Where f_s is the sampling frequency, f_k is the frequency of index k.

The baseline drift in the DCT domain is suppressed by zeroing the k index matching the frequencies of the BW [0-f_{bwmax}]. After suppressing contributing indexes [10], we perform a reconstruction operation using inverse DCT using the following equation:

$$x(n) = \sum_{k=1}^{N} w[k]X[k]\cos\frac{\pi(2n-1)(k-1)}{2N} \quad /n = 1,2...N, \quad (5)$$

2) FWHT -based method for baseline drift removing

3) Fast Walsh–Hadamard transform

The FWHT is an orthogonal transformation based on the orthogonal waveform's atoms called Walsh functions to involve frequency domain signals. The Walsh–Hadamard matrix is derived from the Kronecker product ⊗ .

$$\mathrm{H}_{2^k} = H_2 \otimes \mathrm{H}_{2^{k-1}} \text{ where } H_2 = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$$

The FWHT of the input signal $x(n)$ with N length is given as follows :

$$X\ (k) = \sum_{n=1}^{N} x(n)W_n \quad k = 1,2,3.....N \quad (6)$$

Wn is the Walsh matrix, which is generated using the Hadamard matrix employing the bit-reversal permutation and the Gray code change on the row index[16]. The Walsh function can be expressed as:

$$W_n = \prod_{i=1}^{m} (-1)^{n_i k_{m-i}} \quad / m = 2^k \quad (7)$$

The Walsh-Hadamard Transform (WHT) is a real-to-real transformation. This means that the frequency component is defined from 0 to half of the sampling frequency of the input signal. To eliminate the baseline wander, we need to nullify the contributing coefficients of the discrete WHT transform using the corresponding index k associated to the frequencies range [0-f_{bwmax}] obtained by the same equation (4).

Where f_s is the sampling frequency, f_k is the frequency of index k. Accordingly, the inverse Walch-Hadamard transform is given by :

$$x(n) = \frac{1}{N}\sum_{k=1}^{N} X\ (k)W_n \quad n = 1,2,3.....N \quad (8)$$

IV. SIMULATION AND RESULTS

We conducted multiple simulations to assess three baseline wander suppression techniques in a comparative manner using various conventional metrics. Therefore, numerous tests have been performed on two types of ECG signals:

- Real data from the MIT BIH arrhythmia database ECG recording with 360 Hz sampling frequency and 11 bits resolution[17]. These records contain inherent baseline drift noise. For our tests, we have chosen the ECG records (mitdb/121 and mitdb/115).
- Generated synthetic ECG signal with a sampling rate of 360 Hz.

It is worth noting that synthetic signals are corrupted, with generated artificial BW noise expressed by:

$$BW_{noise} = \sum_{i=1}^{5} B_i \cos(2\pi f_{0i} t) \quad (9)$$

where, B_i = [100,50,-30,50,50] and f_{0i} = [0.1,0.2, 0.3, 0.4, 0.5] Hz, respectively.

We attract attention to the fact that in the case of synthetic signals, visual inspection has been taken as a qualitative evaluation in association with a quantitative examination, considering the signal-to-noise ratio SNR and mean square error MSE. Accordingly, the used metrics are formulated as follows [11]:

$$SNR = 10\log_{10}\left(\frac{\mathrm{var}(ecg_f)}{\mathrm{var}(ecg_f - ecg_d)} \right) \qquad (10)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N-1}(ecg_f - ecg_d)^2 \qquad (11)$$

Where ecg_f is the free-noise synthetic generated signal and ecg_d is the denoised synthetic signal. However, only visual inspection was accomplished for the realistic MIT-BIH ECG signals.

Therefore, if we choose a BW band of *0.6 Hz*, the optimal estimated number of decomposition levels for the DWT-based filtering method is $L=8$, and the indexes to be suppressed are ranging from 1 to $K_{BW=}27$ (the length is taken 8192) for both DCT-based and FWHT-based filtering methods.

Several wavelet families were tested during the simulations. ‘db11’ and ‘dmey’ showed better denoising performance in the experiments, so they were selected.

In the case of FWHT-based, we suppressed more than K_{BW} indexes in order to improve the quantity of ECG-restored signal.

Fig. 2-3 compares various methods for filtering ECG baseline drift. As a result, the BW noise in the contaminated signal was significantly reduced while the original signal characteristics were preserved. As seen in Fig. 2(b) and Fig. 2(c), presenting, respectively, the recovered signals of the wavelet and the DCT-based techniques demonstrate superior quality compared to the restored signal obtained from the FWHT filtering method Fig. 2(d).

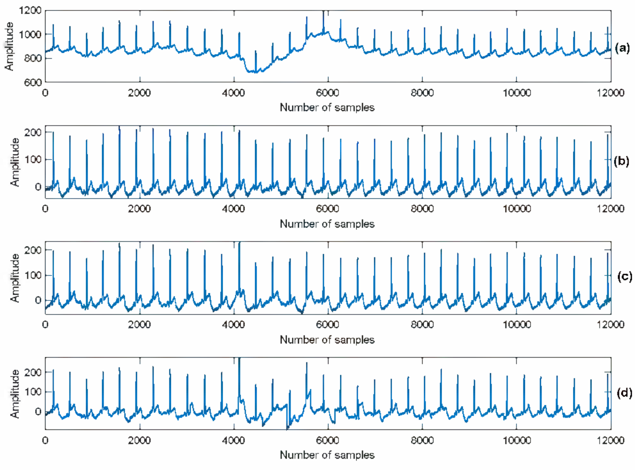

Fig. 2. Visual filtering results of denoising ECG contaminated by baseline drift: (a) the mitdb/121 ECG record originally contaminated, (b) DWT filtering, (c) DCT filtering, (d) FWHT filtering.

In the second part, the ECG BW denoising techniques have been tested on synthetic signals. Consequently, Table 1 lists the values of SNR and MSE obtained using different denoising methods. It is clear from this table that DWT-based filtering can enhance the ECG signal with better quality compared to the other techniques.

TABLE I. COMPARISON OF DIFFERENT DENOISING TECHNIQUES IN TERM OF SNR AND MSE

Technique	SNR	MSE
DWT-based denoising	28.6283	0.4967
DCT-based denoising	18.7184	4.8650
FWHT-based denoising	8.2866	53.7360

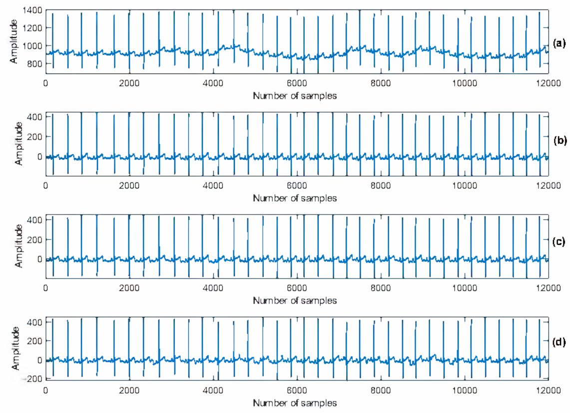

Fig. 3. Visual filtering results of denoising ECG contaminated by baseline drift: (a) the mitdb/115 ECG record originally contaminated, (b) DWT filtering, (c) DCT filtering, (d)FWHT filtering.

Additionally, Fig.4 qualitatively displays the performance of the BW-removing techniques when applied to the synthetic ECG. It can be seen that the BW noise was considerably diminished from the corrupted signals in cases of DWT and DCT-based algorithms without loss of useful medical information. Conversely, from Fig.4(e) (FWHT-based), we can observe that the ECG features are significantly reduced due to the important number of indexes suppressed.

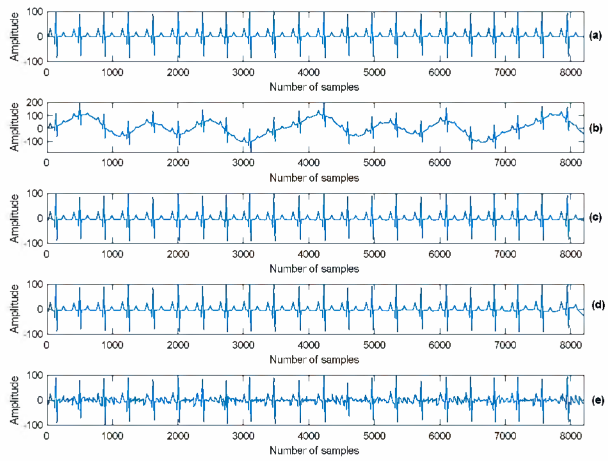

Fig. 4. Filtering of the synthetic ECG signal corrupted by baseline drift: (a) the originally synthetic ECG with zero mean, (b) corrupted signal by BW (c) DWT filtering, (d) DCT filtering, (e)FWHT filtering.

V. CONCLUSION

This paper presents a comparative review of baseline drift noise filtering methods. Consequently, the performances of DWT-based, DCT-based, and FWHT-based techniques to reduce the effect of BW in the ECG signal have been evaluated qualitatively and quantitatively. Hence, the adequate calculated level of decomposition and mother wavelet involved in the DWT-based technique make it better than the DCT-based and FWHT-based strategies in terms of the accuracy of BW noise removal.

REFERENCES

[1] R. M. Rangayyan et S. Krishnan, *Biomedical signal analysis*, Third edition. in IEEE Press series in biomedical engineering, no. 32. Hoboken, New Jersey: Wiley-IEEE Press, 2024. doi: 10.1002/9781119825883.

[2] J. A. Van Alste et T. S. Schilder, " Removal of Base-Line Wander and Power-Line Interference from the ECG by an Efficient FIR Filter with a Reduced Number of Taps ," *IEEE Trans. Biomed. Eng.*, vol. BME-32, n° 12, p. 1052-1060, déc. 1985, doi: 10.1109/TBME.1985.325514.

[3] P. G. Malghan et M. K. Hota, " A review on ECG filtering techniques for rhythm analysis ", *Res. Biomed. Eng.*, vol. 36, n° 2, p. 171-186, juin 2020, doi: 10.1007/s42600-020-00057-9.

[4] P. Laguna, R. Jane, et P. Caminal, " Adaptive filtering of ECG baseline wander," in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Paris, France: IEEE, oct. 1992, p. 508-509. doi: 10.1109/IEMBS.1992.5761083.

[5] R. Sameni, M. B. Shamsollahi, C. Jutten, et G. D. Clifford, "A Nonlinear Bayesian Filtering Framework for ECG Denoising," *IEEE Trans. Biomed. Eng.*, vol. 54, n° 12, p. 2172-2185, dec. 2007, doi: 10.1109/TBME.2007.897817.

[6] T. Mourad, " ECG Denoising based on PCA and using R Peaks Detection," in *Proceedings of the International Conference on Bio-inspired Systems and Signal Processing*, Lisbon, Portugal: SCITEPRESS - Science and Technology Publications, 2015, p. 119-125. doi: 10.5220/0004998201190125.

[7] G. Lenis, N. Pilia, A. Loewe, W. H. W. Schulze, et O. Dössel, "Comparison of Baseline Wander Removal Techniques considering the Preservation of ST Changes in the Ischemic ECG: A Simulation Study," *Comput. Math. Methods Med.*, vol. 2017, p. 1-13, 2017, doi: 10.1155/2017/9295029.

[8] W. Jenkal, R. Latif, A. Toumanari, A. Dliou, O. El B'charri, et F. M. R. Maoulainine, "An efficient algorithm of ECG signal denoising using the adaptive dual threshold filter and the discrete wavelet transform," *Biocybern. Biomed. Eng.*, vol. 36, n° 3, p. 499-508, 2016, doi: 10.1016/j.bbe.2016.04.001.

[9] M. Talbi, "New approach of ECG denoising based on 1-D double-density complex DWT and SBWT," *Comput. Methods Biomech. Biomed. Eng. Imaging Vis.*, vol. 8, n° 6, p. 608-620, nov. 2020, doi: 10.1080/21681163.2020.1763203.

[10] H. S. Shin, C. Lee, et M. Lee, " Ideal Filtering Approach on DCT Domain for Biomedical Signals: Index Blocked DCT Filtering Method (IB-DCTFM)," *J. Med. Syst.*, vol. 34, n° 4, p. 741-753, août 2010, doi: 10.1007/s10916-009-9289-2.

[11] M. Bahaz et R. Benzid, " Efficient algorithm for baseline wander and powerline noise removal from ECG signals based on discrete Fourier series," *Australas. Phys. Eng. Sci. Med.*, vol. 41, n° 1, p. 143-160, mars 2018, doi: 10.1007/s13246-018-0623-1.

[12] İ. Güler et E. D. Übeylı̇, " ECG beat classifier designed by combined neural network model," *Pattern Recognit.*, vol. 38, n° 2, p. 199-208, févr. 2005, doi: 10.1016/j.patcog.2004.06.009.

[13] A. Harkat, R. Benzid, et N. Athamena, "A Multistage Algorithm Design for Electrocardiogram Signal Denoising," *J. Circuits Syst. Comput.*, vol. 30, n° 04, p. 2150061, mars 2021, doi: 10.1142/S0218126621500614.

[14] J. T. Olkkonen, Éd., *Discrete Wavelet Transforms - Theory and Applications*. InTech, 2011. doi: 10.5772/649.

[15] Z. A. Khezzar, R. Benzid, L. Saidi, et M. K. Smail, " Envelope Detection by Shannon Energy Calculation in DCT Domain and DFS-Based Notch Filter for Interference Mitigation in GNSS Receivers," *Trait. Signal*, vol. 39, n° 3, p. 835-843, juin 2022, doi: 10.18280/ts.390308.

[16] P. Prasanna *et al.*, " Detection of Focal and Non-Focal Electroencephalogram Signals Using Fast Walsh-Hadamard Transform and Artificial Neural Network," *Sensors*, vol. 20, n° 17, p. 4952, sept. 2020, doi: 10.3390/s20174952.

[17] G. B. Moody et R. G. Mark, "The impact of the MIT-BIH Arrhythmia Database," *IEEE Eng. Med. Biol. Mag.*, vol. 20, n° 3, p. 45-50, juin 2001, doi: 10.1109/51.932724.