Synaptic Plasticity and Visual Memory in a Neuromorphic 2D Memitter Based on WS2 Monolayers

This is the author's version of the article that has been presented at IEEE ISCAS2025
The editorial version of the paper is available at http://dx.doi.org/10.1109/ISCAS56072.2025.11043932

A simple approach to ECG Motion Artifacts Reduction by MDWD Coefficients Removal

Elisabetta Spinazzola [*], Luciano Prono [*], Fabio Pareschi [*,‡], Riccardo Rovatti [†,‡], and Gianluca Setti [§,‡]
[*]DET, Politecnico di Torino, Italy - Email: {elisabetta.spinazzola, luciano.prono, fabio.pareschi}@polito.it
[†]DEI, [‡]ARCES, University of Bologna, Italy - Email: riccardo.rovatti@unibo.it
[‡]CEMSE, King Abdullah University of Science and Technology (KAUST), Saudi Arabia - Email: gianluca.setti@kaust.edu.sa

Abstract*—Motion Artifact (MA) noise is one of the most crucial components in an Electrocardiogram (ECG) signal, especially during the monitoring of normal daily activities. Because of this, they are widely investigated for optimized denoising applications, trying to maximize the physiological information while solving the noise-signal frequency overlapping. In this work, we propose a filtering approach that employs the Multilevel Discrete Wavelet Decomposition (MDWD) basis domain, in which the projections of the signal are easily separable from the noise components. Compared to other more complex denoising approaches, this method only requires the simple projection of the signal on the desired wavelet basis. We obtain the desired denoising effect through the elimination of part of the projected signal, i.e., we remove the projected coefficients with the largest scaling values. We show that these coefficients carry most of the noise introduced by MA. To validate the method and tune its parameters, we test ECG affected by MA from different datasets, proving that the reconstruction performance is on par with the state-of-the-art approaches, such as the Empirical Wavelet Transform method (EWT), while begin much simpler in practice. Moreover, while other approaches tend to destroy signal anomalies and non-idealities which are fundamental for diagnosis, our approach keeps them unaltered.

I. Introduction

Electrocardiogram signals (ECG) are the most commonly observed biosignals employed to clinically monitor the activity of the human heart, detect cardiovascular diseases, and evaluate cardiac dysfunctions [1]–[3]. Indeed, a relevant aspect is the continuous monitoring and recording of ECG physiological signals, especially during regular activities, such as fitness exercise and walking routine [4].

However, during the movements of a patient, there could often be an unavoidable displacement of the monitoring device. These minor shifts of the sensors produce artifacts during the ECG signal recording. The frequency range of this kind of noise, called Motion Artifact (MA), is known to be from 1 to $10\,\mathrm{Hz}$ [5]. Beyond the power-line interference and the baseline wander, the muscle artifacts are an important noise source that must be reduced [6]. This additional inconvenience is due to interference of the electromyography (EMG) signals, which can lead to abnormalities in the ECG recording resulting in a poor signal quality and misdiagnoses. This noise is typically included in the normal EMG frequency band from $1\,\mathrm{Hz}$ to $500\,\mathrm{Hz}$ [5].

The main problem is the overlap between the desired ECG signal frequency and the frequency range of these noise sources. In particular, the noise frequency range overlaps with the most informative frequencies of the ECGs, to the point of covering and overlapping the important information. As an example, the EMG interference leads to distortion of local waves of the ECG signals due to a frequency match in the range of $0.1\,\mathrm{Hz}$ to $100\,\mathrm{Hz}$ [6].

Literature suggests multiple different methods to denoise an ECG, from the trivial high pass filter (HP) to more complex adaptive filters [5], most of which work in the Fourier domain, but do not address the frequency overlapping phenomenon. Nonetheless, many other domains have revealed to better separate the signal from the noise, such as Discrete Fourier Transform (DFT), Discrete Cosines Transform (DCT), Discrete Wavelet Transform (DWT) or gaussian dictionaries [7]. A popular approach ECG filtering is the Empirical Wavelet Transform (EWT), which is now a gold standard in MA reduction as a fully adaptive and data-driven signal processing method [8]–[14].

However, the most sophisticated approaches require complex filtering algorithms, from iterative ones [5] to the more complex Deep Neural Networks [15]. In this work, we present a MA filtering approach based on the removal of coefficients of the signal projected onto the Multilevel Discrete Wavelet Decomposition (MDWD) basis [16]. In fact, we show that, by projecting the signal against a MDWD basis, the MA interference can be easily decoupled from the informative part of the signal. The MA is mostly encoded within the coefficients with the largest scaling factors, where the ECG data is mostly encoded in coefficients with smaller scaling factors. The application of this technique is trivial and could even be integrated in other commonly employed frameworks (e.g, a Compressed Sensing one [17]), while resulting in a performance comparable to most of the state-of-the-art denosing approaches.

We show the validity of the proposed technique using as a reference the EWT approach, both for the definition of the MA noise and as the target denoising performance. Then, the method is evaluated against commonly employed approaches such as HP filters and DWT soft thresholding [5], using both synthetic and real ECG datasets containing MA interference.

The remainder of the paper is structured as follows. In Section II we explain and show the motivation behind the use of MDWD for MA interference removal and we introduce our MDWD-based denoising approach. Then, in Section III we show the numerical results on ECG signals affected by MA compared to the most used state-of-the-art methods. Finally, the conclusion is drawn.

This is the author's version of the article that has been presented at IEEE ISCAS2025
The editorial version of the paper is available at http://dx.doi.org/10.1109/ISCAS56072.2025.11043932

II. Motivation and proposed approach

A. The Multilevel Discrete Wavelet Decomposition (MDWD)

MDWD [18] is a wavelet-based discrete signal analysis method. It can extract multilevel time-frequency features from a signal by decomposing it as low and high frequency sub-band level-by-level. The features are achieved by applying the DWT on the signal, which consists in the repeated use of Low Pass (LP) and High Pass (HP) filters. The LP filter provides the approximation coefficients $\boldsymbol{a}$ of the input signal, while the HP filter extracts detail information $\boldsymbol{d}$ from the signal. In particular, this technique exhibits good sensitivity on the low frequency signal sub-band, since only the decomposition of the approximation (low frequency) coefficients is performed multiple times by iteratively filtering the signal at each level [19], [20]. With reference to Fig. 1, we consider the input signal series as $\boldsymbol{x} = (x[1], \ldots, x[t], \ldots, x[T])$ and the decomposition level as M. Signal $\boldsymbol{x}$ is then decomposed in the coefficients series $\boldsymbol{a}_1$ and $\boldsymbol{d}_1$ by the convolution with the LP and HP filter impulse responses, respectively.

Given the coefficients $\boldsymbol{a}_1$ and $\boldsymbol{d}_1$, we obtain (by $1/2$ down-sampling) $\boldsymbol{x}_1^H$, which refers to the higher sub-band of the signal, and $\boldsymbol{x}_1^H$, which refers to its lower sub-band. The process is repeated iteratively for each i-th level of decomposition, where $\boldsymbol{x}_{i-1}^L$ is split again in approximation and detail coefficients. The i-th filtering is described as

$$\begin{aligned} \boldsymbol{a}_i[n] &= \sum_{k=1}^{K} x_{i-1}^{l}[t+k-1] \cdot l_k \\ \boldsymbol{d}_i[n] &= \sum_{k=1}^{K} x_{i-1}^{l}[t+k-1] \cdot h_k \end{aligned} \tag{1}$$

where $\boldsymbol{l} = (l_1, \ldots, l_k, \ldots, l_K)$ and $\boldsymbol{h} = (h_1 \ldots, h_k, \ldots, h_K)$ are the filter impulse responses and the filter order is $K \ll T$).

The decomposition of $\boldsymbol{x}$ is then composed of all the frequency sub-band series at the M-th level

$$\boldsymbol{X}_M = \{\boldsymbol{x}_1^H, \boldsymbol{x}_2^H, \ldots, \boldsymbol{x}_M^H, \boldsymbol{x}_1^L, \boldsymbol{x}_2^L, \ldots, \boldsymbol{x}_M^L\} \tag{2}$$

It is important to notice that we can fully reconstruct $\boldsymbol{x}$ from $\boldsymbol{X}_M$, since the decomposition is loss-less. As the level of decomposition M increases, the frequency resolution increases and the time resolution, especially for low frequency sub-series, decreases.

B. ECGs within the MDWD domain

Let us now consider a signal window $\hat{\boldsymbol{x}}$ with length n corrupted by MA interference $\boldsymbol{\nu}$

$$\hat{\boldsymbol{x}} = \boldsymbol{x} + \boldsymbol{\nu} \tag{3}$$

where $\boldsymbol{x}$ is the clean signal, i.e., not affected by MA interference. To analyze ECG signals in the MDWD domain, we generate a basis $\boldsymbol{\Psi}$ by applying the MDWD transform to each of the rows of an identity matrix. For the calculation of $\boldsymbol{\Psi}$, we set $M = 6$ levels of decomposition, which correspond to the usual number of *modes* employed by EWT for its empirical mode decomposition [8]. With this, the MWDW transform is performed by projecting the ECG on the basis $\boldsymbol{\Psi}$ as

$$\hat{\boldsymbol{\xi}} = \boldsymbol{\Psi}\hat{\boldsymbol{x}} = \boldsymbol{\Psi}\left(\boldsymbol{x} + \boldsymbol{\nu}\right) = \boldsymbol{\xi} + \boldsymbol{\Psi}\boldsymbol{\nu} \tag{4}$$

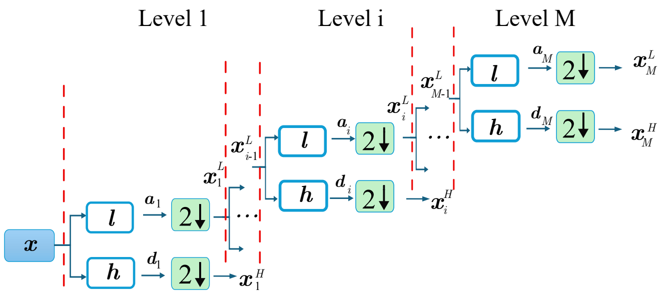

Fig. 1. MDWD algorithm. For each decomposition level, the signal is split in a low frequency and high frequency component and downsampled. This is repeated iteratively for each of the low frequency components of the signal.

where $\hat{\boldsymbol{\xi}}$ are the signal's projections' coefficients into the basis, made up of the clean signal coefficients $\boldsymbol{\xi}$ and the noise coefficients $\boldsymbol{\Psi\nu}$. Matrix $\boldsymbol{\Psi}$ is orthonormal, so the projection operation is fully reversible by multiplying with its transpose.

Then, since EWT is considered a good method to remove MA [12], we refer to the signal cleaned with this method $\boldsymbol{x}_{\text{EWT}}$ as our baseline for evaluation. From this, we define

$$\boldsymbol{\nu} \simeq \hat{\boldsymbol{x}} - \boldsymbol{x}_{\text{EWT}} \tag{5}$$

At this point, we analyze $\boldsymbol{x}_{\text{EWT}}$ and $\boldsymbol{\nu}$ projected on both the Fourier and MDWD bases and see how well the signal component can be separated from the noise component. For this analysis, we use the "Motion Artifact Contaminated ECG Database" (*MAC*) [21] from the PhysioNet database [22]. Fig. 2 shows that, by decomposing the clean-EWT signal $\boldsymbol{x}_{\text{EWT}}$ in the MDWD domain, we achieve an enhanced separation of the MA and the informative component of the signal. In fact, the MDWD projection allows to decompose in detail the signal's lower sub-band to intercept and remove the MA noise components. This is also the main difference with EWT's empirical mode decomposition.

C. Relation between wavelet coefficients and frequency

To further understand why MDWD is a powerful approach for the removal of low-frequency MA interference, we need to trace a relation between the MDWD components and the frequency sub-bands of the signal.

MDWD basis $\boldsymbol{\Psi}$ is made up of a series of wavelets, encoded in each of its columns. If we consider the Fourier domain point of view, by construction this is equivalent to building a set of band-pass filters. Each filter (or column of $\boldsymbol{\Psi}$) can be described as a discrete wavelet signal

$$\boldsymbol{\psi}_{s,b}[n] = \frac{1}{\sqrt{s}}\psi\left[\frac{n-b}{s}\right] \tag{6}$$

where ψ is the mother wavelet, s are the scale coefficients and b are the shift coefficients. Each column is identified by a specific combination of s and b, which define the filter band of each wavelet and its shift in the time domain. We can relate the scale s of each wavelet signal to its equivalent frequency F_a as

$$F_a = \frac{F_c}{s} \tag{7}$$

This is the author's version of the article that has been presented at IEEE ISCAS2025
The editorial version of the paper is available at http://dx.doi.org/10.1109/ISCAS56072.2025.11043932

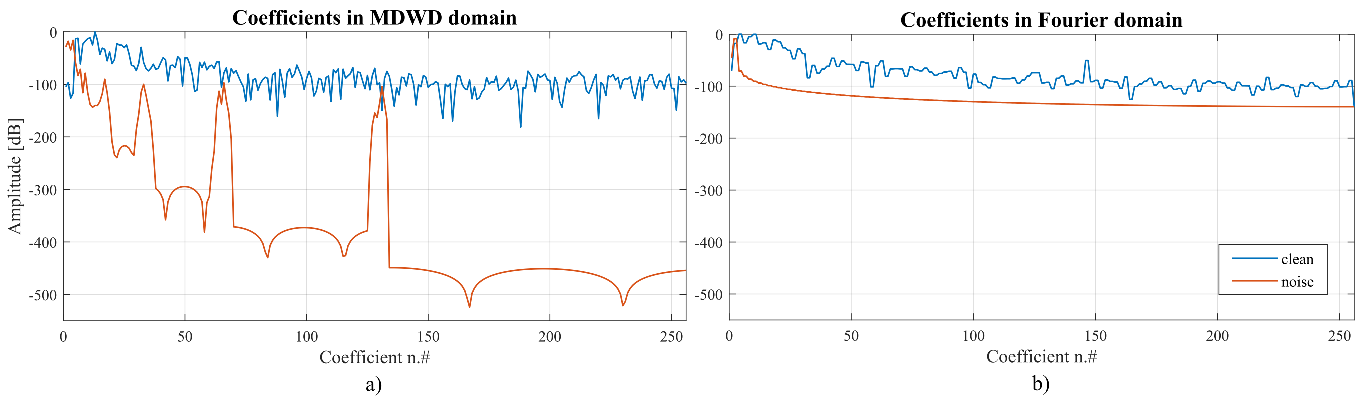

Fig. 2. The visualization of the coefficients of the clean signal, obtained by EWT, and the MA noise, either in the MDWD domain (a) and in the Fourier domain (b). The reported case refers to ECG #1 of recording "18_90wm" from *MAC* database [21]. Besides some isolated peaks, most of the signal power is concentrated in the MDWD coefficients on the left (the ones with the largest scaling factors) while they are spread more evenly in the Fourier basis.

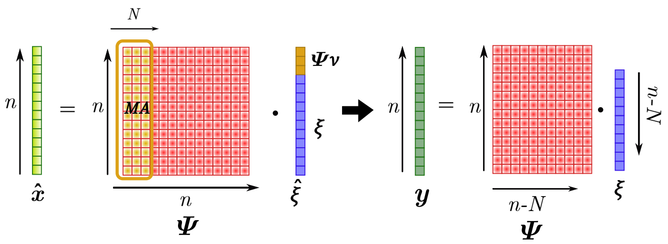

Fig. 3. The MA removal from the ECG signal is achieved by removing the first N columns from the selected sparsity basis $\boldsymbol{\Psi}$.

where F_c is the central frequency of the wavelet, which depends on the type of the employed mother wavelet (e.g., "Symlet 6" has $F_c = 0.7273\,\text{Hz}$). Now, since the scale factor s doubles for each level of the MDWD decomposition, we have that the equivalent frequencies in the MDWD domain increase exponentially for each decomposition level. This means that the MDWD coefficients associated to low frequencies are much more fine-grained compared to the coefficients in the Fourier domain, whose frequencies span linearly with the projections' coefficients.

D. *Proposed approach*

With the assumptions made previously, we can intercept the noise in the first N coefficients of $\hat{\boldsymbol{\xi}}$, that refer to the largest wavelet scaling factors. From this, we get:

$$\begin{aligned} \boldsymbol{\nu} &\simeq \boldsymbol{\Psi}^T_{1:N}\hat{\boldsymbol{\xi}}_{1:N} \\ \boldsymbol{y} &\simeq \boldsymbol{\Psi}^T_{N+1:n}\hat{\boldsymbol{\xi}}_{N+1:n} \end{aligned} \tag{8}$$

where $\cdot_{i:j}$ is the operator that selects columns from i to j of the argument matrix, n is the number of coefficients and $\boldsymbol{y}$ is the denoised signal. For the proposed algorithm, we considered signal batches of 256 samples and a $\boldsymbol{\Psi}^{n\times n}$ with $n = 256$. The method is further explained in Fig. 3.

In order to maximize the performance of the proposed approach, we need to evaluate N, which depends on the entity of the noise. The 256×256 MDWD basis matrix $\boldsymbol{\Psi}$ is constructed on $M = 6$ levels, composed by 4, 4, 8, 16, 32, 64, 128 coefficients, namely all the low-pass decompositions $\boldsymbol{x}_i^L$ (for $i = 1$ to $i = M$) and the last high-pass decomposition $\boldsymbol{x}_M^H$, as they are ordered in the basis matrix $\boldsymbol{\Psi}$. Aim of a preliminary evaluation is to get the range of values of N that intercept the MA interference.

III. Numerical results

A. *Datasets*

For the proposed method, several datasets have been investigated to evaluate and validate the algorithm:

- "Motion Artifact Contaminated ECG Database" (*MAC*): 108 short duration ECG signals recorded from a single healthy 25-year-old male performing different physical activities [21], from the PhysioNet database [22].
- Synthetically generated ECGs (*Syn*): 30 signals, at different heart rate, where MA interference was extracted from *MAC* database.
- "MIT-BIH Noise Stress Test Database" (*NST*): used as noisy signals of 12 half-hour ECG recordings and 3 half-hour recordings of noise typical in ambulatory ECG recordings [23].
- "MIT-BIH Arrhythmia Database" (*Arr*): used as the noise-free ECG signals with arrhythmia of 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects [24]. These have been used as clean signals in the validation test performed on the *NST* database.

B. *Metrics*

The MA removal performance has been calculated with the root mean square error (RMSE), correlation coefficient (CoC) and SNR improvement (SNRimp). These are defined as

$$\text{RMSE} = \sqrt{\frac{1}{T}\sum_{i=1}^{T}(x_i - y_i)^2} \tag{9}$$

$$\text{CoC} = \frac{\sigma_{\boldsymbol{xy}}}{\sigma_{\boldsymbol{x}}\sigma_{\boldsymbol{y}}} \tag{10}$$

This is the author's version of the article that has been presented at IEEE ISCAS2025
The editorial version of the paper is available at http://dx.doi.org/10.1109/ISCAS56072.2025.11043932

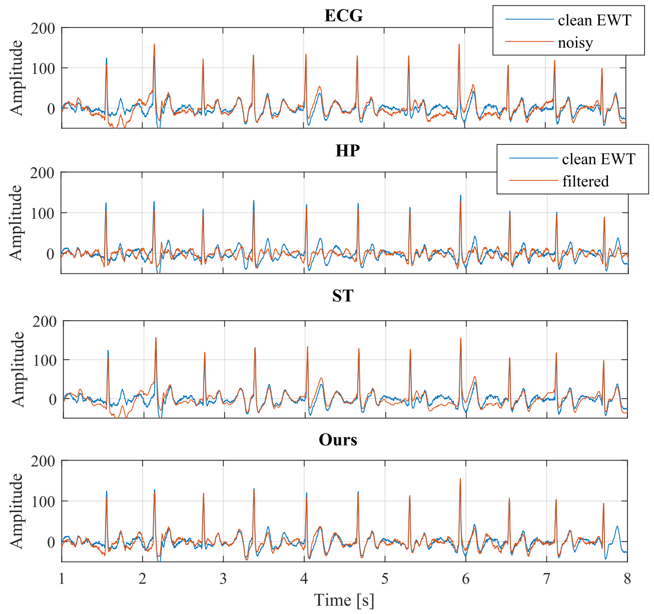

Fig. 4. Evaluation results of different MA reduction methods on *MAC* dataset's ECG #3 of recording "12_90wm". As a reference, we use the EWT-cleaned ECG. We use $N = 8$ for our approach.

$$\text{SNR}_{\text{imp}} = 10\log_{10}\left(\frac{\sum_{i=1}^{T}(\hat{x}_i - x_i)^2}{\sum_{i=1}^{T}(y_i - x_i)^2}\right) \tag{11}$$

where $\sigma_{\boldsymbol{x}}$, $\sigma_{\boldsymbol{y}}$ and $\sigma_{\boldsymbol{xy}}$ are the standard deviation of x, the standard deviation of y and the covariance of x and y, respectively.

C. Method evaluation

To evaluate the number of coefficients to discard N, we performed an evaluation on the whole *MAC* and *Syn* datasets' recordings, which we split in windows of size 256. We select different values for N and apply our denoising approach, comparing the results with the EWT-cleaned ECG signals. We obtain the optimal RMSE with $N = 4$ or $N = 8$ for 60% of the ECG windows, with $N = 16$ for 15% of the windows, $N = 32$ for the last 25%. From this analysis, we choose $N = 8$. The values of N have been selected to be compliant with the number of coefficients of each of the decomposition levels.

To further assess our choice for N, we compared the performance on the evaluation datasets with other commonly employed filtering methods, namely a simple high pass filter (HP), EWT and a soft threshold, DWT-based filter [5] (ST) that uses the "Daubechies 6" wavelet transform. We deliberately selected very simple approaches for comparison, since our method can be performed with a simple matrix projection. Fig. 4 shows how the proposed method results in cleaned signals much closer to the signal cleaned by EWT method, used as reference, compared to the other filtering methods.

D. Method validation

We performed the validation of the proposed approach on the *Arr* and *NST* datasets. In this case we have both the real cleaned signal and the signal to which noise from *NST* dataset has been added. Table I reports the validation metrics averaged on the whole datasets. For all the metrics we take into consideration, the proposed method results in a cleaned signal closer to the real clean signal.

TABLE I
AVERAGE PERFORMANCE METRICS ON THE NORMALIZED SIGNALS FROM THE NST-CORRUPTED ARR DATABASE COMPARED TO THEIR CLEAN COUNTERPART. OUR METHOD IS PERFORMED WITH $N = 8$.

Params	HP	ST	EWT	Ours
RMSE	0.6917	0.9434	0.5457	**0.4805**
CoC	0.4738	0.5240	0.2339	**0.7633**
SNR_{imp}[dB]	3.1912	0.4126	5.5002	**6.3254**

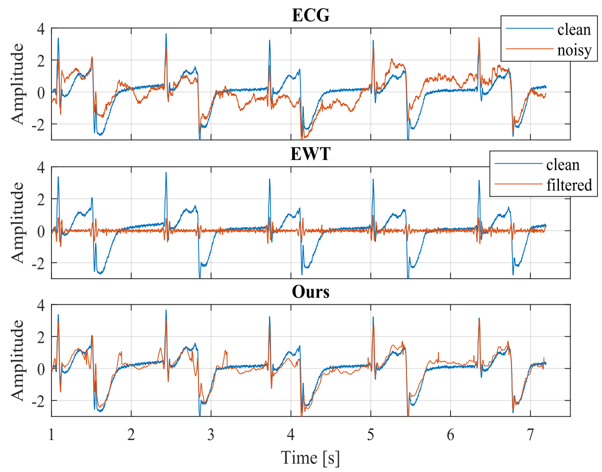

Fig. 5. The results of MA reduction on *Arr* dataset's ECG #2 of recording "207m" corrupted with MA from the *NST* database. We use $N = 8$ for our approach. While EWT completely removes the information on the arrythmia phenomenon, the proposed approach leaves it unaltered.

As a final remark, the proposed approach keeps unchanged eventual anomalies in the ECG signal, which have a high relevance in clinical analyses. Since the signal in Fig. 5 is affected by arrhythmia, it is evident that, while filtering away the MA interferences, the proposed method preserves the arrhythmia anomalies from the *Arr* dataset. This is not true for EWT, that substantially alters the morphology of the signal.

IV. Conclusion

In this work, we present a simple method for the reduction of MA interferences in an ECG signal, based on the removal of part of the projected coefficients onto a MDWD basis. This approach is much easier to implement compared to other state-of-the-art methodologies and better preserves detail information fundamental for clinical diagnosis. The approach has been evaluated and tested on multiple ECG datasets affected by MA interferences. On average, the proposed method shows a very good denoising capability, with a better performance compared to the considered state-of-the-art denoising approaches.

REFERENCES

[1] H. Xia, I. Asif, and X. Zhao, "Cloud-ecg for real time ecg monitoring and analysis," *Computer Methods and Programs in Biomedicine*, vol. 110, no. 3, pp. 253–259, 2013. doi:10.1016/j.cmpb.2012.11.008

[2] J. S. Lee, J. Heo, W. K. Lee, Y. G. Lim, Y. H. Kim, and K. S. Park, "Flexible capacitive electrodes for minimizing motion artifacts in ambulatory electrocardiograms," *Sensors*, vol. 14, no. 8, pp. 14 732–14 743, 2014. doi:10.3390/s140814732

[3] D. De Bacquer, G. De Backer, M. Kornitzer, and H. Blackburn, "Prognostic value of ecg findings for total, cardiovascular disease, and coronary heart disease death in men and women," *Heart*, vol. 80, no. 6, pp. 570–577, 1998. doi:10.1136/hrt.80.6.570

[4] G. Da Poian, C. J. Rozell, R. Bernardini, R. Rinaldo, and G. D. Clifford, "Matched filtering for heart rate estimation on compressive sensing ecg measurements," *IEEE Transactions on Biomedical Engineering*, vol. 65, no. 6, pp. 1349–1358, 2018. doi:10.1109/TBME.2017.2752422

[5] D. Berwal, V. C.R., S. Dewan, J. C.V., and M. S. Baghini, "Motion artifact removal in ambulatory ecg signal for heart rate variability analysis," *IEEE Sensors Journal*, vol. 19, no. 24, pp. 12 432–12 442, 2019. doi:10.1109/JSEN.2019.2939391

[6] S. Chatterjee, R. S. Thakur, R. N. Yadav, L. Gupta, and D. K. Raghuvanshi, "Review of noise removal techniques in ecg signals," *IET Signal Processing*, vol. 14, no. 9, pp. 569–590, 2020. doi:10.1049/iet-spr.2020.0104

[7] G. Da Poian, R. Bernardini, and R. Rinaldo, "Gaussian dictionary for compressive sensing of the ecg signal," in *2014 IEEE Workshop on Biometric Measurements and Systems for Security and Medical Applications (BIOMS) Proceedings*, 2014, pp. 80–85. doi:10.1109/BIOMS.2014.6951540

[8] J. Gilles, "Empirical wavelet transform," *IEEE Transactions on Signal Processing*, vol. 61, no. 16, pp. 3999–4010, 2013. doi:10.1109/TSP.2013.2265222

[9] S. Nagai, D. Anzai, and J. Wang, "Motion artefact removals for wearable ecg using stationary wavelet transform," *Healthcare Technology Letters*, vol. 4, no. 4, pp. 138–141, 2017. doi:10.1049/htl.2016.0100

[10] P. Mithun, P. C. Pandey, T. Sebastian, P. Mishra, and V. K. Pandey, "A wavelet based technique for suppression of emg noise and motion artifact in ambulatory ecg," in *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2011, pp. 7087–7090. doi:10.1109/IEMBS.2011.6091791

[11] F. R. Hashim, L. Petropoulakis, J. Soraghan, and S. I. Safie, "Wavelet based motion artifact removal for ecg signals," in *2012 IEEE-EMBS Conference on Biomedical Engineering and Sciences*, 2012, pp. 339–342. doi:10.1109/IECBES.2012.6498019

[12] X. Xu, Y. Liang, P. He, and J. Yang, "Adaptive motion artifact reduction based on empirical wavelet transform and wavelet thresholding for the non-contact ecg monitoring systems," *Sensors*, vol. 19, no. 13, 2019. doi:10.3390/s19132916

[13] V. G. Sirtoli, M. Liamini, L. T. Lins, M. Lessard-Tremblay, G. E. R. Cowan, R. J. Zednik, and G. Gagnon, "Removal of motion artifacts in capacitive electrocardiogram acquisition: A review," *IEEE Transactions on Biomedical Circuits and Systems*, vol. 17, no. 3, pp. 394–412, 2023. doi:10.1109/TBCAS.2023.3270661

[14] R. Ranjan, B. C. Sahana, and A. K. Bhandari, "Cardiac artifact noise removal from sleep eeg signals using hybrid denoising model," *IEEE Transactions on Instrumentation and Measurement*, vol. 71, pp. 1–10, 2022. doi:10.1109/TIM.2022.3198441

[15] H.-T. Chiang, Y.-Y. Hsieh, S.-W. Fu, K.-H. Hung, Y. Tsao, and S.-Y. Chien, "Noise reduction in ecg signals using fully convolutional denoising autoencoders," *IEEE Access*, vol. 7, pp. 60 806–60 813, 2019. doi:10.1109/ACCESS.2019.2912036

[16] M. Jallouli, M. Zemni, A. Ben Mabrouk, and M. A. Mahjoub, "Toward new multi-wavelets: associated filters and algorithms. part i: theoretical framework and investigation of biomedical signals, ecg, and coronavirus cases," *Soft Computing*, vol. 25, pp. 14 059–14 079, 2021. doi:10.1007/s00500-021-06217-y

[17] D. Donoho, "Compressed sensing," *IEEE Transactions on Information Theory*, vol. 52, no. 4, pp. 1289–1306, Apr. 2006. doi:10.1109/TIT.2006.871582

[18] S. Mallat, "A theory for multiresolution signal decomposition: the wavelet representation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 11, no. 7, pp. 674–693, 1989. doi:10.1109/34.192463

[19] G. Luo, D. Zhang, and D. Baleanu, "Wavelet denoising," *Advances in wavelet theory and their applications in engineering, physics and technology*, pp. 59–80, 2012. doi:10.5772/37424

[20] S. Prins, V. Mini, N. Mayadevi, and R. Harikumar, "Detection of broken rotor bars using multilevel wavelet decomposition," in *2018 2nd International Conference on Trends in Electronics and Informatics (ICOEI)*, 2018, pp. 621–626. doi:10.1109/ICOEI.2018.8553821

[21] V. Behravan, N. E. Glover, R. Farry, P. Y. Chiang, and M. Shoaib, "Rate-adaptive compressed-sensing and sparsity variance of biomedical signals," in *2015 IEEE 12th International Conference on Wearable and Implantable Body Sensor Networks (BSN)*, 2015, pp. 1–6. doi:10.1109/BSN.2015.7299419

[22] A. L. Goldberger *et al.*, "Physiobank, physiotoolkit, and physionet: components of a new research resource for complex physiologic signals," *circulation*, vol. 101, no. 23, pp. e215–e220, 2000. doi:10.1161/01.cir.101.23.e215

[23] G. B. Moody, W. Muldrow, and R. G. Mark, "A noise stress test for arrhythmia detectors," *Computers in cardiology*, vol. 11, no. 3, pp. 381–384, 1984. doi:10.13026/C2HS3T

[24] G. Moody and R. Mark, "The impact of the mit-bih arrhythmia database," *IEEE Engineering in Medicine and Biology Magazine*, vol. 20, no. 3, pp. 45–50, 2001. doi:10.1109/51.932724