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Noise Reduction Techniques in ECG Signal

Sakarie M. Muhumed, and Muhammad I. Ibrahimy*

Dept. of Electrical and Computer Engineering
International Islamic University Malaysia
Kuala Lumpur, Malaysia

*Corresponding author: ibrahimy@iium.edu.my

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Abstract— The problem of noise interference in ECG signals has been addressed in this paper. Specifically, a method has been developed to filter out Electromyography noise (EMG) from ECG signals. A dataset of ECG signals with varying levels of EMG noise has been collected using the MIT-BIH dataset. An algorithm has been designed and implemented using the DA FIR filter coupled with Kaiser windowing technique to filter out the noise. The algorithm has been tested on the collected dataset using MATLAB. The performance of the algorithm has been evaluated by calculating the Signal-to-Noise Ratio (SNR) and the Mean Squared Error (MSE). The effectiveness of the algorithm in reducing the EMG noise in the ECG signals has been demonstrated by the results. The algorithm's limitations and future work were discussed in this paper. Interesting future works could include using other filtering techniques to enhance the performance or deep learning techniques to improve noise cancellation. Overall, the effectiveness of using signal processing techniques to filter out EMG noise from ECG signals has been demonstrated and resulted in clearer and more accurate signals for diagnostic purposes.

Keywords: *ECG, EMG, SNR, MSE, DA FIR*

1. BACKGROUND

Electrocardiography or ECG, is a collection of records of the heart's electrical activity. Variations in the usual electrical patterns indicate different heart diseases. In their natural state, cardiac cells are electrically polarized. Compared to their outer sides, their interior sides are negatively charged. Depolarization, the primary electrical activity of the heart, can cause these cardiac cells to lose their typical negativity. A wave of depolarization can be carried across the entire heart because of the depolarization spreading from cell to cell. Keeping the electrodes on the body's surface allows one to measure the electric current produced by this wave of depolarization. After the depolarization is finished, a process known as re-polarization allows the cardiac cells to return to their usual polarity. The electrodes can also detect this [1].

1.1 Characteristics of ECG signals

The ECG recorder captures the electrical activity of the heart, represented by each heartbeat as a series of electrical waves with peaks and troughs. Any ECG offers two distinct forms of information. Whether the electrical activity is regular, sluggish, or irregular depends on how long the electrical wave passes the heart. A typical ECG signal (Fig. 1) has a dynamic range of 1 to 10 mV and a frequency ranging from 0.05 to 100 Hz. The five peaks and valleys that make up the ECG signal are denoted by the letters P, Q, R, S, and T. We also occasionally use a mountain named U.

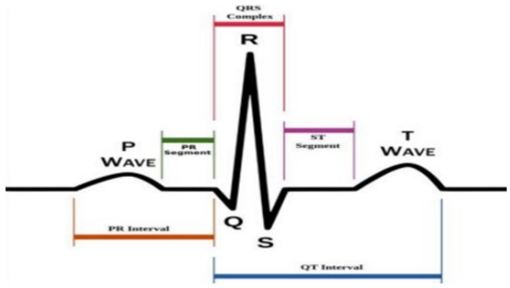

Fig. 1: Typical ECG wave [1]

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1.2 Types of noises and artefacts in ECG signals

Continuous noises: This noise is connected to signals from every lead that have identical temporal distributions but different intensities. These noises dominate multiple frequency bands. Electromyography noise is the lower component, power line interference is the medium component, and baseline wanders the higher component when we are talking frequency-wise [2]. Baseline Wander (BW) noise: The baseline wander can be brought on by changes in the impedance of the electrodes and patient movements. Power line interference noise: Background noise in ECGs and other physiological data received from the body surface is frequently caused by power line interference. Electromyography (EMG) noise: All muscles except the heart contract, which is what produces the EMG noise. Transient noise: Since it only lasts for a short duration, white Gaussian noise is the most widespread sort of transitory noise. Its spectral density is uniformly distributed since its immediate value has a Gaussian distribution and power. This noise includes instrument noise, motion artefacts from patient electrodes, and other sorts of noise. But it is impossible to divide this noise into frequency categories [2]. Patient electrode motion artefact: When the electrode equilibrium potential changes, electrode motion artefacts arise. Instrumentation noise: The electrodes, wires, amplifiers, and converters found in all pieces of equipment are the primary sources of instrumentation noise.

2. TECHNIQUES FOR ECG NOISE REMOVAL

When an ECG signal is acquired from the patient, it is usually denoised before doctors can interpret it. As shown in Fig.2, it can only go through the denoising model after adding the noise.

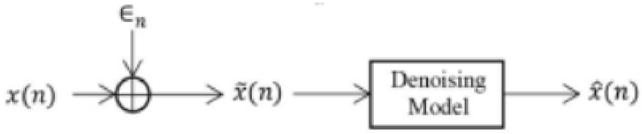

Fig. 2: A typical cardiac cycle's denoising mechanism [3].

2.1 Models for ECG signal denoising based on EMD

Each signal is separated into a few numbers of its intrinsic mode functions using an adaptive repetitive approach named Empirical Mode Decomposition (EMD). Using this repetitive signal breakdown, this empirical mode decomposition separates the entire signal into ordered components, moving from higher frequencies to lower frequencies at each intrinsic mode function level [4]. The EMD procedure's decomposition is based on the signal's local time characteristics; hence it works with nonlinear and non-stationary processes (Fig. 3) [5]. Unlike data analysis techniques like the Fourier transforms, EMD is fully data-driven and does not require any prior knowledge [6].

1. Input: noisy ECG signal $\tilde{x}(n)$
2. Sifting process
3. Repetitive application of the sifting process on proto IMF $h_k(n)$ until the stopping criterion (SD) gives the first IMF $c_1(n)$
4. Residue: $r_1(n) = \tilde{x}(n) - c_1(n)$
5. $r_1(n)$ might contain some useful signal information, hence the algorithm is run with $r_1(n)$ in place of $\tilde{x}(n)$
6. Hence, $\tilde{x}(n) = \sum_{l=1}^{L} c_l(n) + r_L(n)$
   $\tilde{x}(n)$ has L IMFs and the algorithm terminates at the L^{th} iteration, where the residue is either a constant, a monotonic slope, or a function with only one extremum
7. Thresholding or filtering or adaptive selection of IMFs $(\{c_l(n)\})$ for the purpose of signal reconstruction to get the denoised signal $\hat{x}(n)$
   $$\hat{x}(n) = \sum_{l=1}^{L} \hat{c}_l(n) + r_L(n)$$
   where $\hat{c}_l(n)$ is filtered IMF
8. Output: $\hat{x}(n)$: denoised ECG signal

Fig. 3: Algorithm 1: EMD-based denoiser's denoising algorithm [7].

Blanco-Velasco et al. concluded after analyzing both clean and noisy ECGs using EMD, using the EMD domain's temporal processing. Since noise and the QRS complex share a similar spectral signature in the high-frequency band, it is difficult to remove the noisy signal while keeping the QRS complex [6]. Lower intrinsic mode functions would have been lost, leading to 11 significant QRS complex distortions. The denoising technique invented to tackle the noisy ECG is described in Algorithm 2 (Fig. 4a), and because of applying this filter, we can see that EEMD can be an effective model to filter out the BW noise, as shown in Fig. 4b.

1. Input: noisy ECG signal $\tilde{x}(n)$
2. Delineation of the QRS complex:
   (a).Identification of R-peak in the noisy input $\tilde{x}(n)$
   (b).Use of (1) through (6) of algorithm 1 to decompose the noisy signal $\tilde{x}(n)$
   (c).$d(n) = c_1(n) + c_2(n) + c_3(n)$, the summation of first three IMFs
   (d).Two local minima in $d(n)$ on either side of the R-peak are identified
   (e).Boundary determination of the QRS complex by locating closest zero-crossings on the left-hand side of the left minimum and on the right-hand side of the right minimum
3. Windowing to preserve QRS complex:
   a typical window is tapered cosine window
4. Determination of the number of noisy IMFs by statistical test: a hypothesis testing is conducted to determine the noise order O, which is actually the number of noisy IMFs. To avoid loss of information, a limit is set on the noise order as follows:
   $O_{actual} = \min(O, \beta)$, where β is typically 5
5. Partial reconstruction of the signal:
   (a).A window function $\lambda_i(n)$ is constructed by concatenating the window functions $w_{ij}(n)$, where $w_{ij}(n)$ denotes the variable size window for the j^{th} QRS complex in the i^{th} IMF
   $$\lambda_i(n) = \sum_{j=1}^{N_q} w_{ij}(n)$$
   Where N_q is the number of QRS complexes in the i^{th} IMF
   (b).$\lambda_i(n)$ eliminates noise and retains QRS-complex information. In order to avoid abrupt changes in the QRS complex, complement of $\lambda_i(n)$ is used. The complementary function $(\bar{\lambda}_i(n))$ allows a negligible noise in lower IMFs to reduce distortion in the reconstructed signal
   $\bar{\lambda}_i(n) = 1 - \lambda_i(n) \;\; \forall n$
6. Output: the reconstructed signal:
   $$\hat{x}(n) = \sum_{i=1}^{O_{actual}} \lambda_i(n) c_i(n) + \sum_{i=1}^{O_{actual}} \bar{\lambda}_i(n) c_i(n) + \sum_{i=O_{actual}+1}^{L} c_i(n) + r_L(n)$$

Fig. 4a: Algorithm 2: EEMD-based denoiser's denoising algorithm [3].

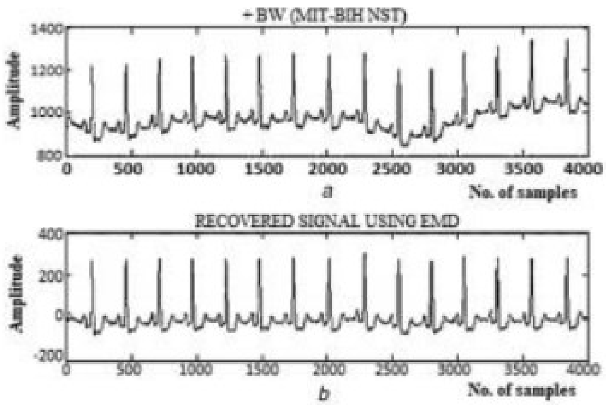

Fig. 4b: ECG signal using EEMD to denoise [3].

2.2 Models for ECG signal denoising based on Wavelet

The time and frequency range of the signal is widened by a WT when seen via the lens of a localized wavelet function. Wavelet transform can offer good time and resolution of frequency at HF and LF. Consequently, a wavelet transform is an excellent option for processing ECG information. The mother wavelet function's contractions, expansions, and translations are used to decompose a signal into a series of fundamental processes,as shown in Fig. 5 [3]. Dyadic WT (DWT) is a great option for analyzing and filtering ECG signals due to its quick computation and multiresolution capability, as shown in Fig. 6 [8].

1.	Input: $\tilde{x}(n)$ $s.t.\tilde{x}(n) = x(n) + \epsilon_n$, where $\{\epsilon_n\}$ is some noise process with variance σ^2, where n is the index of $\tilde{x}(n)$
2.	$d_l(k)$ and $a_L(k)$, detail coefficients and approximate coefficients, are obtained. The coefficients are collectively denoted as $w(k)$
3.	Shrinking is performed by thresholding to convert $w(k)$ to $w^*(k)$
4.	Finally, the inverse wavelet transform is taken on $w^*(k)$ to estimate the signal $x(n)$ in the noisy environment, using the filter bank architecture
5	Output: $\hat{x}(n)$

Fig. 5: Algorithm 3: Algorithm followed by the wavelet denoiser [3], [8].

While considering the conventional thresholding methods, researchers have developed various thresholding algorithms and techniques to denoise ECG data. One of these researchers is Smith *et al*., who discovered the polynomial coefficients [9] utilizing polynomial threshold operators, with least-squares minimization used for optimization. Alfaouri and Daqrouq have offered another denoising method for ECG data. The difference between the noisy and original detail coefficients sets the threshold for a five-level wavelet transformation using Daubechies as the mother wavelet[10].

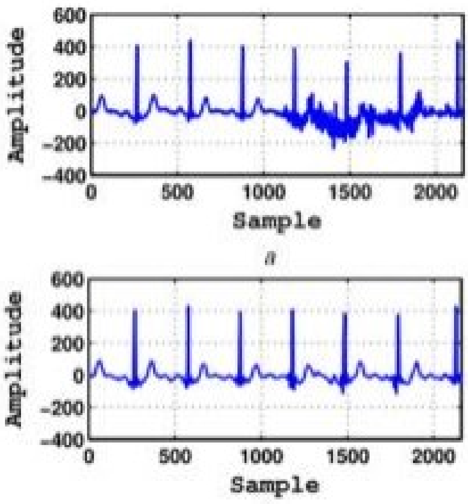

Fig 6: DWT-based ECG denoising (Sym5) [3].

2.3 Models for ECG signal denoising based on Bayesian filter

This category of denoising researches several model-based techniques for denoising ECG signals. Model-based approaches operate under the premise that hidden model states can be estimated using estimation theory. Through a series of measurements, these hidden states are seen. The Kalman filter is one such approach (KF). Although most systems are nonlinear, the fundamental KF assumes a linear model for the system dynamics and observation equations. The original Kalman filter has been improved into other forms, including EKF, EKS, and UKF.

Overviews of the enhanced versions of the standard KF and how they work are provided by Sameni *et al*., as shown in Fig. 7 [11].

1. Input: x, y, z: the state variables
2. Conversion of the non-linear dynamic ECG model from Cartesian to polar
3. Linearization of the modified model
4. Observation of s_k and ϕ_k, where $\{s_k\}$ are the noisy ECG observations and $\{\phi_k\}$ are the phase observations
5. Prediction of model parameters prior to the implementation of the filter

Fig. 7: Algorithm 4: Bayesian-filter-based denoising algorithm [11].

A marginalized particle Extended Kalman filter that addresses the drawbacks of both extended Kalman filter and particle filters has been proposed by Hesar and Mohebbi [12]. This makes use of a brand-new marginalized particle filter and EKF combo. The state model is initially changed by including angular velocity as an AR state, leading to the "marginalized particle extended Kalman filter" (MP-EKF) algorithm, which is used to convert two-state polar EDM into three-state polar EDM. ECG parameters are extracted using techniques like those in [11]. When the signal is first observed, the R-peaks of the ECG cycles are thought to be at position θ= 0. Between two consecutive R-peaks, the ECG data's phase ranges from 0 to 2π (or -π to π). The distance between the particles and the noisy readings and ECGsynth is evaluated and weighted at each time step in a particle weighting technique. A synthetic ECG 15 signal called ECGsynth is created utilizing the feature parameters that were taken from ECG(θ). Fig. 8 shows the closeness evaluation metric is the Mahalanobis distance, a statistical distance metric. For each particle, this weighting method is applied in each time step.

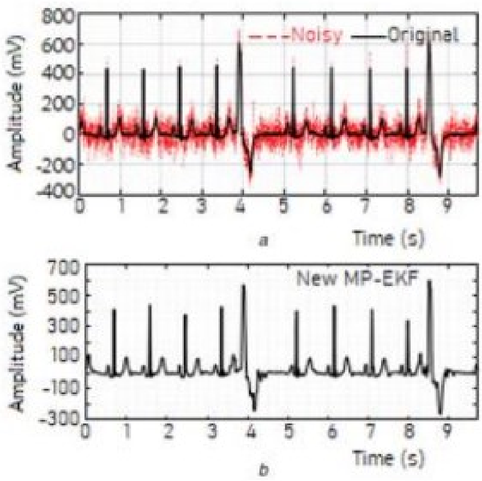

Fig. 8: Using the new MP-EKF for ECG denoising [13].

3. METHODOLOGY

The paper aims to design and implement an algorithm to filter out or remove the persistent EMG noise from the acquired ECG signal for correct reading and interpretation by doctors.

3.1 Resources and Materials.

FIR filter: Because of the strong design techniques available for them, as well as their inherent stability, FIR filters are commonly employed. The ease with which linear phase can be achieved when implemented in non-recursive form. Several methods exist for creating an FIR low pass filter, including the equiripple filter, the least square approach, and the windowing method. The Kaiser, Rectangular, Hamming, Hanning, and Blackman functions are designed using the windowing method. The main features for creating a filter include a cut-off frequency of 100Hz and a sampling frequency of 360Hz (based on the MIT/BIH database). In FIR window filters, the cut-off frequency at the 3 dB point is approximately 91.8333 Hz. The window length for rectangular, Hanning, and Hamming is 18 and 16, respectively. For Bartlett and Blackman, the filter order is 37 and 19, respectively. The Kaiser window has a filter length of 14 with a phase delay of 0.1047 rad/Hz and a cut-off frequency at 3dB of 89.60449Hz. MATLAB: A strong, complete, and user-friendly platform for technical computations in MATLAB. One of its significant advantages is the ability to create one's own reusable tools with MATLAB. The ECG database extraction process takes place in Matlab and is stored at www.physiobank.org. The workspace of Matlab can be used to call the stored ECG signal in the Simulink model. Real-time EMG noise is imported into the workspace and combined with pure ECG in Simulink model after 22 being retrieved from the MIT-BIH noise stress database as an a.mat file. Utilized in the design of the FIR low pass filter is FDATool from Matlab. Various FIR digital filter types are used to cut out high-frequency EMG noise. MIT-BIH: In this study, the data used was sourced from the MIT-BIH Arrhythmia Database on Physio Bank. The recordings were digitized at a high frequency and stored in a specific format**,** including a header file with patient information, a binary file containing the ECG signal, and a binary file with annotations. Additionally, half of the database was made available for free use. The EMG data used was taken from the MIT-BIH Noise Stress Database, also found on Physio bank, which includes recordings of both ECG and noise specific to ambulatory settings. These recordings were collected from physically active volunteers and recorded using standard equipment. Distributed Arithmetic (DA) FIR filter: Digital FIR filters can be efficiently implemented in FPGA structures using distributed arithmetic. The DA approach is frequently utilized to calculate sums of products with constant coefficients. In this scenario, the partial product term is multiplied by a constant (i.e., scaling). The Look-up Table (LUT), Shift Registers, and Scaling Accumulator components of the DA method replace the general-purpose multipliers and considerably improve the performance of the implemented filter. These blocks must be effectively mapped onto the logic cells of an FPGA. Compared to current designs for FIR Filters, the suggested architecture offers an effective area-time-power implementation that entails much-reduced latency and area-delay complexity. The equations for the DA FIR filter for calculating SNR and MSE are as follows:

$$\mathrm{SNR} = 10\log_{10}\frac{\sum_{i=0}^{N}(\mathrm{ECG_{raw}})^2}{\sum_{i=0}^{N}(\mathrm{ECG_{raw}} - \mathrm{ECG_{filtered}})^2}$$

$$\mathrm{MSE} = 10\log_{10}\frac{\sum_{i=0}^{N}(\mathrm{ECG_{raw}} - \mathrm{ECG_{filtered}})^2}{N}$$

4. CONCLUSION

This literature review aimed to evaluate the effectiveness of various ECG denoising methods in medical applications. Three key aspects of ECG denoising were investigated to support patient diagnosis and treatment: noise acquisition, eradication of prevailing noises, and contrasting the methods in use today. The results showed that the modified polar extended Kalman filter outperformed conventional denoising approaches for MA, while GAN1 was found to be effective in removing BW and EM noise. Additionally, EWT was determined to be the most appropriate method for removing PLI noise, but promising results were also obtained for CN reduction using DWT (Sym6) and MABWT (Soft).

The paper involves designing an algorithm to remove high-frequency EMG noise from ECG signals. The methodology is clearly defined, and the process includes designing and testing the algorithm on a corrupted ECG signal in MATLAB to produce a filtered pure ECG signal. The effectiveness of the designed algorithm in removing EMG noise from the ECG signal will be analyzed and discussed based on the results obtained. Overall, the study provides valuable insights into ECG denoising techniques and highlights the importance of selecting appropriate methods to ensure accurate diagnosis and treatment in medical applications.

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