DENOISING ECG BY ADAPTIVE FILTER WITH EMPIRICAL MODE DECOMPOSITION

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Abstract— Electrocardiogram (ECG) signal is an important physiological signal which contains cardiac information and is the basis to diagnosis cardiac related diseases. In this paper, several innovative and efficient methods based on adaptive filter and empirical mode decomposition (EMD) to denoise ECG signal contaminated by various kinds of noise, including baseline wander (BW), power line interference (PLI), electrode motion artifact (EM) and muscle artifact (MA), are proposed. We first present a novel method based on EMD and adaptive filter for the removal of BW and PLI in ECG signal. We then extend the method to the complex scenario where four most common noises, PLI, BW, EM and MA are present. The proposed Parallel EMD adaptive filter structure yields the best SNR improvement on the MIT-BIH arrhythmia database, corrupted by the four types of noises.

I. INTRODUCTION

Cardiovascular disease is one of the main threats to human life, taking an estimated 17.9 million lives each year which attributes about one third of the deaths all over the world [1]. Electrocardiogram (ECG) signal is an important basis for the diagnosis of cardiovascular disease and is used to extract information related to physiology of the heart. In practice, the ECG signals are often corrupted by several noise sources [2] such as electrode motion artifact (EM), muscle artifact (MA), power line interference (PLI), and baseline wander (BW). These noises could affect the doctor’s ability to provide accurate diagnosis of cardiac function. Therefore, denoising ECG signal becomes an important task in medical and engineering fields [3]. Some traditional operations such as FIR and IIR filters [4, 5], filter bank [6], modeling [7], singular value decomposition [8] and independent component analysis [9] are used to denoise PLI, BW and white Gaussian noise. The works in [10-12] used adaptive filters to eliminate one type of noise at a time. Thakor et al [13] and Wang et al [14] used adaptive filter-based methods and obtained promising results. There are also methods based on wavelet decomposition with various thresholding methods [15-21], extended Kalman filter [22, 23] and neural networks [24, 25] to remove the specific noise sources on ECG.

Empirical mode decomposition (EMD) [26] has been widely applied to analyze various signals, such as radar signal, vibration signal and biomedical signals including ECG. The denoising techniques based on EMD are investigated in [27-30]. EMD is also a very useful tool that can be applied with other methods. Xing et al [31] applied PCA with EMD, Singh et al [32] used method of Non-local Means and Modified EMD to denoise BW and PLI on ECG.

Although many methods have been proposed for ECG denoising, the type of noises considered are limited. In this paper, we investigate denoising algorithm for ECG signal corrupted by four types of noise: BW, PLI, EM and MA. This paper has two contributions on the denoising method. First, a novel algorithm to denoise ECG signal corrupted by PLI and BW using adaptive filter and EMD is presented. We then extend the algorithm to consider all four types of noises and propose four denoising algorithms. The algorithms are Staged Direct Adaptive Filter (SDAF), Parallel Direct Adaptive Filter (PDAF), Staged EMD Adaptive Filter (SEAF) and Parallel EMD Adaptive Filter (PEAF). The proposed algorithms are experimented on ECG signals from MIT-BIH Arrhythmia Database [33] with added noises from MIT-BIH Noise Stress Test Database [34], both databases are provided by Goldberger. A. et al [35]. The proposed methods are compared with other state-of-the-art algorithms.

The experiment result shows that the proposed EMD with adaptive filter-based method performs better to remove PLI and BW on ECG, and the proposed PEAF algorithm is the best algorithm to denoise ECG signal contaminated by BW, PLI, EM and MA. The paper is organized as follows: Section 2 provides a brief review of EMD and adaptive filter algorithms. Section 3 describes the proposed algorithm architecture designed for complex noising scenarios. The performance for each method is studied, compared and discussed with experimental results in Section 4. Section 5 concludes the paper and discusses ideas for future work.

II. BACKGROUND

EMD algorithm is proposed by Huang et al. [26] in 1998. The basic idea is to decompose the fluctuation of different scales present in the signal step by step to produce several sequences with different characteristic scales after smoothing the signal. Each sequence generated after decomposing is called an Intrinsic Mode Function (IMF). IMF is used to indicate a simple oscillator mode embedded in the data. EMD is an adaptive method that can extract IMFs of a signal according to the characteristics of each signal without any prior knowledge and the IMFs are the new bases that can represent the signal. EMD is especially well suited for analyzing nonlinear and nonstationary signals. EMD has made significant contributions in many areas including mechanical fault diagnosis, biomedical signal analysis and so on.

Adaptive filter is a digital filter that can automatically adjust the transfer function according to the input signal [36]. There are many types of adaptive filters including Least Mean Squares (LMS) filter, Recursive Least Squares (RLS) filter.
Each method has its own algorithm and criteria to obtain the optimal adaptive filter parameters. To denoise a signal using adaptive filter, other than the noisy signal, a reference signal input which is either the signal correlated to clean signal or the signal correlated to noise is needed. Since the clean ECG is unknown, we can obtain the correlated noise signals by applying electrodes on human body and the power line. Here we use noises as reference signal. The adaptive filter structure used in the following algorithms is shown as Fig. 1. The desired signal is the noise and by subtracting it from noisy signal, denoised ECG signal is obtained.

\[ Y(t) = X(t) - e(t) \]

![Fig. 1. Applied adaptive filter structure](image)

### III. PROPOSED METHODS

#### A. Selection of IMF’s for Denoising Each Noise

The basic idea of proposed methods is based on the property that EMD can decompose signals into stationary IMFs. Furthermore, different types of noise have their own spectrum. BW and PLI are a single frequency noise, PW’s frequency is concentrated on 0-3Hz, EM is a high frequency noise and MA occupies similar frequency range as ECG. Consequently, different noises hold different spectrum concentration which can be represent by the sum of some IMFs. Although adaptive filters are capable of coping with both stationary and non-stationary signals, the performance on stationary signals is typically better. The basic simplified structure to denoise each noise is shown in Fig. 2.

In Fig. 2, \( e(t) \) denotes the estimated noise and the output \( y(t) \) denotes the denoised ECG signal, which is equal to \( x(t) - e(t) \). The noise from MIT-BIH Noise Stress Test Database is added to the ECG signal from the MIT-BIH Arrhythmia Database. Here, clean signal plus noise \( S(t) + N(t) \) is the original target signal we want to denoise. The selection is based on applying adaptive filters on IMFs’ combinations. We adopt the noise related signals as the reference input signal of the adaptive filter to obtain estimated noise. The denoised combination of IMFs is obtained by subtracting the estimated noise. The denoised ECG signal is the sum of the denoised combination and other unused IMFs and residue.

By comparing the performance, which is directed by SNR improvement, \( SNR_{imp} \), of using the sum of different IMFs in the adaptive filter, the best combination can be recognized. Results show that for PLI, applying the adaptive filter on the first-order IMF yields the best result whereas applying the adaptive filter on the sum of IMF5–IMF8 yields the best result for BW. For EM, IMF3–IMF8 is the best pre-denoised input summation, for MA, applying adaptive filter directly to the noisy signal without EMD yields the best performance.

#### B. Methods to Denoise Different Combination of Noises

In this section, we consider the denoising problem when both BW and PLI noises corrupts the ECG signal. The proposed algorithm structure is shown in Fig. 3. Using \( IMF_1 \) and \( IMF_{58} \) respectively to denote the IMF1 and IMF5–8 after adaptive filtering, the reconstructed denoised ECG signal is shown in (1):

\[ Y(t) = X'(t) = IMF_1 + \sum_{k=2}^{4} IMF_k(t) + IMF_{58} + r(t) \]

![Fig. 3. Proposed algorithm structure to eliminate BW and PLI noise](image)

For PEAF algorithm, \( Y(t) \), the denoised ECG, is the result of removing MA from \( X'(t) \) using direct adaptive filter. \( X'(t) \) is the signal after denoising PLI, BW and EM calculated as (2), where \( r \) denotes the residue after EMD.

\[ X'(t) = IMF_1 + \sum_{k=2}^{4} IMF_k(t) + IMF_{58} \]

\[ X(t) = IMF_1 + \sum_{k=2}^{4} IMF_k(t) + IMF_{58} + r(t) \]
\[ X'(t) = IMF_1' + IMF_2' + IMF_{3b}' + IMF_{5b}' + r - \sum_{k=5}^{8} IMF_k \] (2)

For SEAF algorithm, the input signal for adaptive filter to denoise EM is the sum of \( IMF_3, IMF_4 \) and denoised IMF5–8 \( (IMF_{5b}') \). We use \( IMF_{3b}' \) to indicate the denoised IMF3-8 after EM adaptive filter in the SEAF. \( X'(t) \) is used as the input signal of adaptive filter to denoise MA in (3).

\[ X'(t) = IMF_1' + IMF_2' + IMF_{5b}' + r \] (3)

To test if the EMD with adaptive filter based model has a better performance, we proposed two denoising methods based on only adaptive filter as comparison. We proposed two methods: SDAF algorithm and PDAF algorithm. SDAF refers to the method proposed by N.V. Thakor et al [13]. We add two methods: SDAF algorithm and PDAF algorithm. SDAF refers to the method proposed by N.V. Thakor et al [13]. We add one adaptive filter layer for MA. For PDAF algorithm, we consider all types of the noises as one noise and directly use adaptive filter to denoise ECG which is the same as shown in Fig. 1. SDAF architecture is shown in Fig. 5.

IV. EXPERIMENT RESULT

In experiments, the ECG signals and BW, EM, MA added on ECG are from the MIT-BIH Database [33, 34] and PLI is a 60 Hz sinusoid. While adding the BW, EM and MA on ECG, the noises all have been shifted and passed through different filters to get noises that are not equal but correlated to the adaptive filters’ reference noises. To evaluate the performance of the proposed methods, we compare them with other SOA algorithms [21,22,28]. For the first condition where ECG signals are corrupted by BW and PLI, we used SNR and MSE for evaluation. For ECG signals are contaminated by BW, PLI, EM and MA, SNRimp is proposed to evaluate the performance. In (4-6), \( x_i \) denotes the clean signal, \( x_n \) is the noisy signal and \( x_d \) is the denoised signal.

\[
\text{SNR} = 10 \log_{10} \left( \frac{\sum_{i=1}^{N} |x_i(i)|^2}{\sum_{i=1}^{N} |x_n(i) - x_c(i)|^2} \right) \tag{4}
\]

\[
\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} (x_d(i) - x_c(i))^2}{N}} \tag{5}
\]

\[
\text{SNR}_\text{imp} = \frac{\text{SNR}_\text{output} - \text{SNR}_\text{input}}{\text{SNR}_\text{input}} = 10 \log_{10} \left( \frac{\sum_{i=1}^{N} |x_n(i) - x_c(i)|^2}{\sum_{i=1}^{N} |x_d(i) - x_c(i)|^2} \right) \tag{6}
\]

A. BW and PLI Denoising Result

The ground truth ECG signals are randomly selected from MIT-BIH Arrhythmia Database [33]. The selected ECG signals are corrupted by BW noise from MIT-BIH Noise Stress Test Database [34] and 60Hz PLI. The corrupted ECG signals are fed into the proposed EMD and adaptive filter-based algorithm. The comparison of clean ECG, corrupted ECG and denoised ECG is shown in Fig. 6. Fig. 6(a) and (b) show the time domain signals and their frequency spectra, respectively. In Fig. 6, the first line in each group is the original clean signal, the second line is ECG signal corrupted by BW and PLI, the third line shows the denoised ECG by our method.

We can clearly see the corrupted ECG blurred lots of details in the original signal. The denoised signal is very similar to the original ECG except at the beginning because adaptive filter needs time to converge.

![Fig. 7. Comparison of LMS NLMS and RLS under different SNRinput](a) SNR\text{output} Comparison
(b) RMSE Comparison

Fig. 7. Comparison of LMS NLMS and RLS under different SNRinput

![Fig. 8. Comparison with methods from Article [28,21,22]](a) Time domain comparison
(b) Frequency domain comparison

Fig. 6. Result of denoising ECG corrupted by BW+PLI

As mentioned, there are multiple algorithms for adaptive filter. Here we briefly compare LMS, NLMS and RLS using default parameters in MATLAB under same conditions to find which one is more suitable for our method. In practice, the performance of denoising is better with higher SNR and lower RMSE.

From Fig. 7 we find that LMS has a better and more stable performance at different SNRinput. As a result, we use LMS as our adaptive filter algorithm for all other methods we proposed. We compared the results of the SNRoutput under SNRinput = 10 (dB) which is commonly used in other papers. Fig. 8 compares the performance of the proposed method with other algorithms [21, 22, 28]. As evidence from the result, the proposed method has the best performance.

![Fig. 8. Comparison with methods from Article [28,21,22]](a) SNR\text{output} Comparison
(b) RMSE Comparison

Fig. 8. Comparison with methods from Article [28,21,22]
B. Result of Cancelling BW+PLI+EM+MA Noises

An example of ECG signal corrupted by BW, PLI, MA and EM simultaneously is shown in Fig. 9. The second line includes its time domain and spectrum, the third line shows the denoised ECG signal’s time domain and spectrum. We compared four algorithms which are SDAF, PDAF, SEAF and PEAF introduced before.

We evaluated the four algorithms using different ECG signals and studied the performance of each algorithm under different SNR\_input. The measurement is SNR\_imp, the improvement of SNR, which is the SNR difference between pre-denoise and after-denoise. By this way, we can compare the performance more directly especially under different SNR input. In Fig. 10, the four proposed methods are compared using different ECG signals and the SNR\_imp values are shown. In this case, the SNR\_input is fixed at 10dB. We found that among the four proposed methods, PEAF algorithm is observed to have the best performance in terms of SNR\_imp.

In future research, we can combine different adaptive filtering algorithms with the proposed architecture in this article and study the corresponding performance more precisely. We can also consider using the proposed approach with other decomposition algorithms such as VMD [37] or EEMD [38] with adaptive filtering.

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REFERENCES

[1] World Health Organization. Cardiovascular diseases. https://www.who.int/health-topics/cardiovascular-diseases/#tab=tab_1. Accessed May 29, 2020.
[2] Rakshit, M., Panigrahy, D. & Sahu, P.K. An improved method for R-peak detection by using Shannon energy envelope. Sādhanā 41, 469–477, 2016.
[3] S. Cuomo, G. [De Pietro], R. Farina, A. Galletti, and G. Sannino. A revised scheme for real time ECG signal denoising based on recursive filtering. Biomedical Signal Processing and Control, 27:134 – 144, 2016.
[4] Mahesh S. Chavan, R. A. Agarwala, and M. D. Uplane. Suppression of noise in the ECG signal using digital IIR filter. In Proceedings of the 8th WSEAS International Conference on Multimedia systems and signal processing (MUSP’08). World Scientific and Engineering Academy and Society (WSEAS), Stevens Point, Wisconsin, USA, 335–343, 2008.
[5] K. S. Kumar, B. Yazdanpanah, and P. R. Kumar. Removal of noise from electrocardiogram using digital FIR and IIR filters with various methods. 2015 International Conference on Communications and Signal Processing (ICCCSP), pages 0157–0162, 2015.
[6] Jacek M. Leski and Norbert Henzel. ECG baseline wander and powerline
interference reduction using nonlinear filter bank. Signal Processing, 85(4):781 – 793, 2005.

[7] Miroslav Zivanovic and Miriam Gonzalez-Izal. Simultaneous neurosystoidal modeling. Medical Engineering Physics, 35(10):1431 – 1441, 2013.

[8] Joseph S. Paul, M.R.S. Reddy, and V. Jagadeesh Kumar. Data processing of stress ECGs using discrete cosine transform. Computers in Biology and Medicine, 28(6):639 – 658, 1998.

[9] Allan Karde, C. & Kowar, Manoj. Denoising ECG signals using adaptive Bayesian wavelet shrinkage. In Computers in Cardiology 1998. Vol. 25 (Cat. No.98CH36292), pages 401–404, 1998.

[10] Chandrakar, C. & Kowar, Manoj. Denoising ECG signals using adaptive filter algorithm. International Journal of Soft Computing and Engineering (IJSCCE). 2. 120-123, 2012.

[11] U. Biswas and M. Maniruzzaman. Removing artifacts from electrocardiographic signals using independent components analysis. Neurocomputing, 22(1):173–186, 1998.

[12] Chandrakar, C. & Kowar, Manoj. Denoising ECG signals using adaptive filter algorithm. International Journal of Soft Computing and Engineering (IJSCCE). 2. 120-123, 2012.

[13] U. Biswas and M. Maniruzzaman. Removing power line interference from ECG signal using adaptive filter and notch filter. 2014 International Conference on Electrical Engineering and Information Communication Technology, pages 1–4, 2014.

[14] Mohammad Zia Ur Rahman, Rafi Ahmed Shaik, and D V Rama Koti Reddy. Adaptive noise removal in the ECG using the block LMS algorithm. 2009 2nd International Conference on Adaptive Science Technology (ICAST), pages 380–383, 2009.

[15] N. V. Thakor and Y. Zhu. Applications of adaptive filtering to ECG analysis: noise cancellation and arrhythmia detection. IEEE Transactions on Biomedical Engineering, 38(8):785–794, 1991.

[16] Z. Wang, C. M. Wong, J. N. da Cruz, F. Wan, P. Mak, P. U. Mak, and M. I. Vai. Muscle and electrode motion artifacts reduction in ECG using adaptive Fourier decomposition. In 2014 IEEE International Conference on Systems, Man, and Cybernetics (SMC), pages 1456–1461, 2014.

[17] R. F. von Borries, J. H. Pielruiissi, and H. Nazeran. Wavelet transform-based ECG baseline drift removal for body surface potential mapping. In 2005 IEEE Engineering in Medicine and Biology 27th Annual Conference, pages 3891–3894, 2005.

[18] Wissam Jamolk, Rachid Latif, Ahmed Toumanani, Azzedine Dliou, Oussama [El B’charr], and Fadel M.R. Maoulainine. An efficient algorithm of ECG signal denoising using the adaptive dual threshold filter and the discrete wavelet transform. Bioinformatics and Biomedical Engineering, 36(3):499–508, 2016.

[19] H. A. Kestler, M. Haschka, W. Kratz, F. Schwenker, G. Palm, V. Hombach, and M. Hoher. De-noising of high-resolution ECG signals by combining the discrete wavelet transform with the wiener filter. In Computers in Cardiology 1998. Vol. 25 (Cat. No.98CH36292), pages 233–236, 1998.

[20] M. Popescu, P. Cristea, and A. Bezerianos. High resolution ECG filtering using adaptive Bayesian wavelet shrinkage. In Computers in Cardiology 1998. Vol. 25 (Cat. No.98CH36292), pages 401–404, 1998.

[21] P. M. Agante and J.P. Marques de Sa. ECG noise filtering using wavelets with soft-thresholding methods. In Computers in Cardiology. Vol.26 (Cat.No.99CH37004), pages 535–538, 1999.

[22] Alfiouar Mihkled and Khaled Daqrouq. ECG signal denoising by wavelet transform thresholding. American Journal of Applied Sciences, 5, 03 2008.

[23] Zheng Minmin, Gao Xiaorang, and Xie Haiie. Research on an improved algorithm for wavelet denoising of ECG. Chinese Journal of Biomedical Engineering, 36(1):114, 2017.

[24] H. D. Hesar and M. Mohebbi. ECG denoising using marginalized particle extended Kalman filter with an automatic particle weighting strategy. IEEE Journal of Biomedical and Health Informatics, 21(3):635–644, 2017.

[25] M. B. Shamsollahi. ECG denoising and compression using a modified extended Kalman filter structure. IEEE Transactions on Biomedical Engineering, 55(9):2240–2248, 2008.

[26] Suranai Poungponsi and Xiao-Hua Yu. An adaptive filtering approach for electrocardiogram (ECG) signal noise reduction using neural networks. Neurocomputing, 117:206 – 213, 2013.

[27] Rui Rodrigues and Paula Couto. A neural network approach to ECG denoising, ArXiv, abs/1212.5217, 2012.

[28] Norden Huang, Z Shen, S.R. Long, M.L.C. Wu, H.H. Shih, Quanan Zheng, N.C. Yen, Chi-Chao Tung, and H.H. Liu. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. Proceedings of the Royal Society of London. Series A: Mathematical, Physical and Engineering Sciences, 454:903–995, 03 1998.

[29] G. Han, B. Lin, and Z. Xu. ECG denoising based on empirical mode decomposition: an overview. Journal of Instrumentation, 12(3):P03010, March 2017.

[30] YIN Li, CHEN Fumin, ZHANG Qi, and CHEN Xin. ECG adaptive denoising method based on EEMD and improved threshold function. Journal of Xi’an Jiaotong University, 54:101–107, 01 2020.

[31] Manuel Blanco-Velasco, Binwei Weng, and Kenneth E. Barner. ECG signal denoising and baseline wander correction based on the empirical mode decomposition. Computers in Biology and Medicine, 38(1):1 – 13, 2008.

[32] Y. Lu, J. Yan, and Y. Yam. Model-based ECG denoising using empirical mode decomposition. 2009 IEEE International Conference on Bioinformatics and Biomedicine, pages 191–196, 2009.

[33] H.-Y Xing and J.-Y Hou. Electrocardiogram noise removal based on empirical mode decomposition and independent component analysis. Journal of Clinical Rehabilitation Tissue Engineering Research, 13:651–654, 01 2009.

[34] Pratik Singh, Syed Shahnawazuddin, and Gayadhar Pradhan. An efficient ECG denoising technique based on non-local means estimation and modified empirical mode decomposition. Circuits, Systems, and Signal Processing, 37, 02 2018.

[35] GB Moody and RG Mark. The impact of the MIT-BIH arrhythmia database. IEEE engineering in medicine and biology magazine: the quarterly magazine of the Engineering in Medicine Biology Society, 20(3):45–50, 2001.

[36] Wissam Jamolk, Rachid Latif, Ahmed Toumanani, Azzedine Dliou, Oussama [El B’charr], and Fadel M.R. Maoulainine. An efficient algorithm of ECG signal denoising using the adaptive dual threshold filter and the discrete wavelet transform. Bioinformatics and Biomedical Engineering, 36(3):499–508, 2016.

[37] H. A. Kestler, M. Haschka, W. Kratz, F. Schwenker, G. Palm, V. Hombach, and M. Hoher. De-noising of high-resolution ECG signals by combining the discrete wavelet transform with the wiener filter. In Computers in Cardiology 1998. Vol. 25 (Cat. No.98CH36292), pages 233–236, 1998.

[38] S. Haykin. “Background and preview,” in Adaptive filter theory, 5th ed. Hamilton, Canada: Pearson, 2014, pp. 4-6.

[39] K. Dragomiretskiy and D. Zosso. Variational Mode Decomposition. IEEE Transactions on Signal Processing, vol. 62, no. 3, pp. 531-544, Feb. 1, 2014.