

PAPER • OPEN ACCESS

Improvement of electrocardiogram by empirical wavelet transform

To cite this article: Vikanda Chanchang *et al* 2017 *J. Phys.: Conf. Ser.* **901** 012028

View the [article online](#) for updates and enhancements.

You may also like

- [Particle-based temperature measurement coupled with velocity measurement](#)
Satoshi Someya
- [The design, manufacture and application of multistable mechanical metamaterials-a state-of-the-art review](#)
Rui Xu, Chuanqing Chen, Jiapeng Sun et al.
- [Modified Natural Silica Dimethylamine for Optimization of Sulfate Ion Absorption Using the Batch Method](#)
Ikke Riswinia Aulia and Budhi Oktavia



ECS
The
Electrochemical
Society
Advancing solid state &
electrochemical science & technology

DISCOVER
how sustainability
intersects with
electrochemistry & solid
state science research

Improvement of electrocardiogram by empirical wavelet transform

Vikanda Chanchang, Nakorn Kumchaiseemak, Malee Sutthiopad and Chaiya Luengviriya*

Department of Physics, Kasetsart University, 50 Phaholyothin Road, Jatujak, Bangkok 10900, Thailand.

* Email: fscicyl@ku.ac.th

Abstract. Electrocardiogram (ECG) is a crucial tool in the detection of cardiac arrhythmia. It is also often used in a routine physical exam, especially, for elderly people. This graphical representation of electrical activity of heart is obtained by a measurement of voltage at the skin; therefore, the signal is always contaminated by noise from various sources. For a proper interpretation, the quality of the ECG should be improved by a noise reduction. In this article, we present a study of a noise filtration in the ECG by using an empirical wavelet transform (EWT). Unlike the traditional wavelet method, EWT is adaptive since the frequency spectrum of the ECG is taken into account in the construction of the wavelet basis. We show that the signal-to-noise ratio increases after the noise filtration for different noise artefacts.

1. Introduction

The Electrocardiogram (ECG) shows characteristic of the electrical activity in hearts used for diagnosis of heart functions. ECG measurements possibly contain different noises such as power-line interference (PI), baseline wander (BW), muscle artefacts (MA) and electrode motion artefacts (EM). They can potentially cause ambiguous diagnosis. Normal ECG signals have low frequencies similar to BW, EM and MA so that they are difficult to be removed. Various methods of noise removal have been applied to reduce the noises e.g. wavelet transform, discrete wavelet transform (DWT), Empirical mode decomposition (EMD) [1-5].

Recently, Gilles proposed a new method called empirical wavelet transform (EWT) [3] which is an adaptive wavelet method. In this article, we present a study on removal of three different types of noises (BW, EM and MA) from the ECGs by using EWT.

2. Methods

The EWT is fully adaptive base on the design of a filter bank which consists of a low-pass filter and a high-pass filter, called scaling function and wavelet function, respectively. As proposed by Gilles [3], the scaling function and wavelet function are defined as in equations 1 and 2:

$$\hat{\phi}_n(\omega) = \begin{cases} 1 & , \text{ if } |\omega| \leq (1 - \gamma)\omega_n \\ \cos \left[\frac{\pi}{2} \beta \left(\frac{1}{2\gamma\omega_n} (|\omega| - (1 - \gamma)\omega_n) \right) \right] & , \text{ if } (1 - \gamma)\omega_n \leq |\omega| \leq (1 + \gamma)\omega_n \\ 0 & , \text{ otherwise} \end{cases} \quad (1)$$



$$\hat{\varphi}_n(\omega) = \begin{cases} 1 & , \text{ if } (1 + \gamma)\omega_n \leq |\omega| \leq (1 - \gamma)\omega_{n+1} \\ \cos \left[\frac{\pi}{2} \beta \left(\frac{1}{2\gamma\omega_{n+1}} (|\omega| - (1 - \gamma)\omega_{n+1}) \right) \right] & , \text{ if } (1 - \gamma)\omega_{n+1} \leq |\omega| \leq (1 + \gamma)\omega_{n+1} \\ \sin \left[\frac{\pi}{2} \beta \left(\frac{1}{2\gamma\omega_n} (|\omega| - (1 - \gamma)\omega_n) \right) \right] & , \text{ if } (1 - \gamma)\omega_n \leq |\omega| \leq (1 + \gamma)\omega_n \\ 0 & , \text{ otherwise} \end{cases} \quad (2)$$

which depend on boundaries selected by considering the frequency of the signal. As a result, the EWT algorithm is considered adaptive.

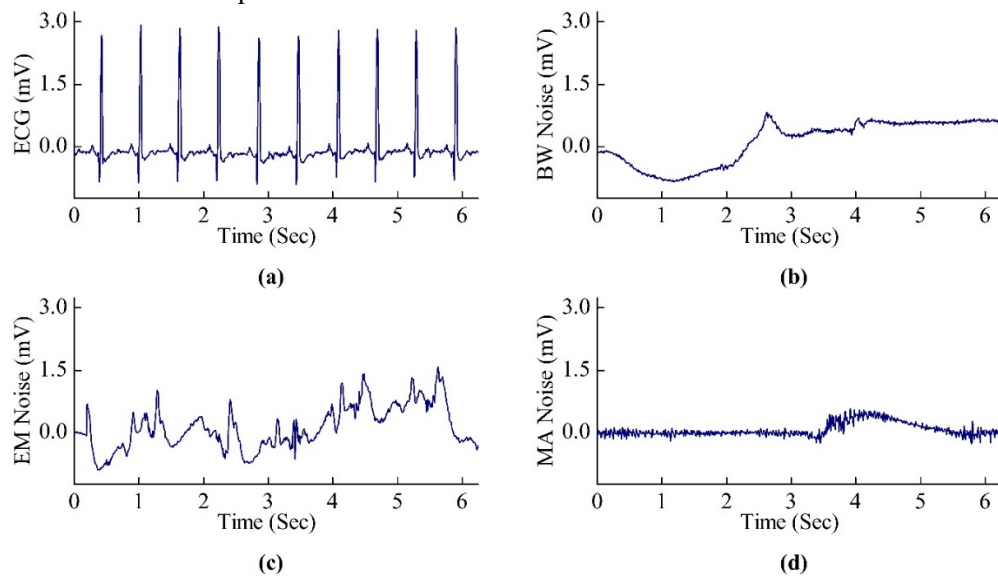


Figure 1. ECG signal and noises: (a) clean ECG (b) baseline wander (BW) (c) electrode motion artefacts (EM) and (d) muscle artefacts (MA).

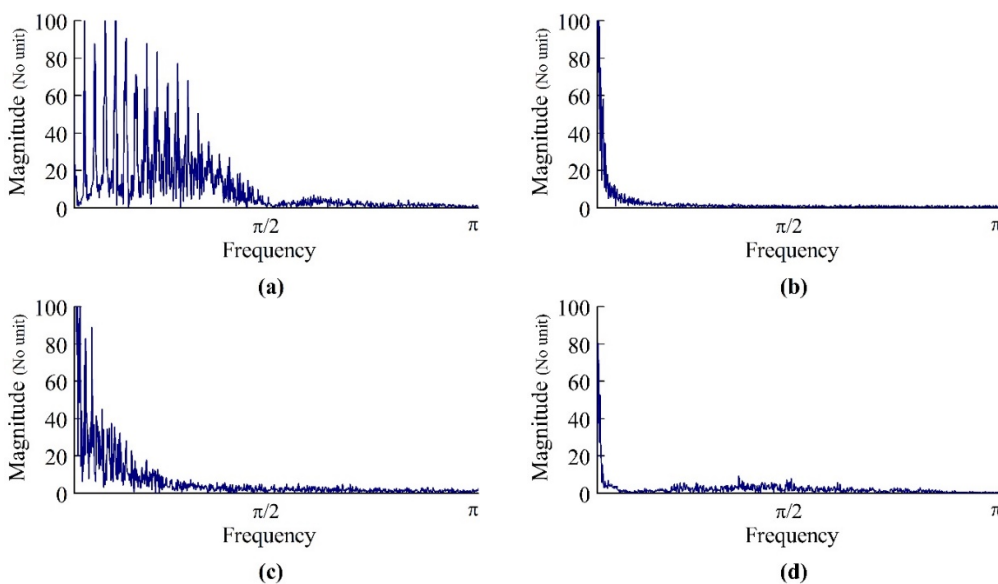


Figure 2. FFT of ECG signal and noises: (a) clean ECG (b) BW (c) EM and (d) MA.

In this article we use database from MIT-BIH Normal Sinus Rhythm Database and MIT-BIH Noise Stress Test Database [6] for testing the noise cancellation algorithm for different situations. The used ECG signal (clean ECG) and different noises: BW, EM and MA and their corresponding frequency spectra, i.e., Fast Fourier Transform (FFT), are shown in figures 1 and 2, respectively.

Figure 3 shows a construction of the scaling function and the wavelet function in the case of BW. The boundary is computed by using equation 3:

$$\omega'_n = 2\pi(1 + \gamma) \frac{f}{F_s} \quad (3)$$

where $\gamma = 0.75$, the limit of noise frequency (f) = 0.72 and the sampling rate of the signal (F_s) = 128 sample/sec so that the boundary of BW is 0.06715 [figure 3(a)]. This boundary result in the scaling function and wavelet function vs frequency as in figures 3(b) and 3(c), respectively. For EM and MA noise, the boundaries are 0.157 and 0.054, respectively, which give different scaling function and the wavelet function.

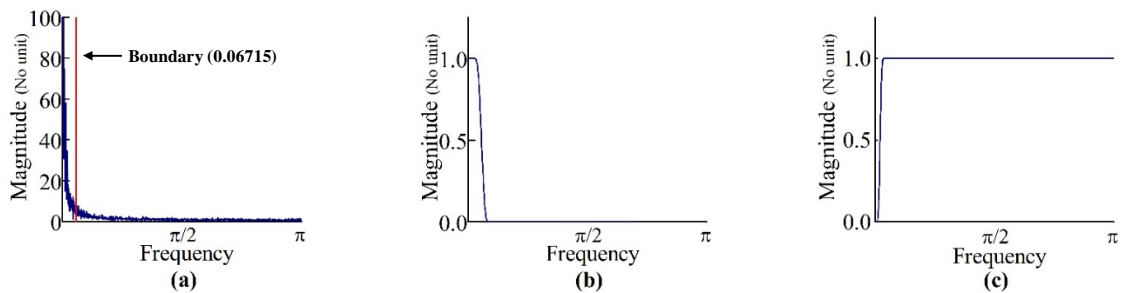


Figure 3. Empirical wavelet construction: (a) FFT of BW noise and boundaries, (b) Scaling function and (c) Wavelet function for BW noise.

To study the noise cancellation using EWT, we add a noise to the clean ECG. The noisy ECG signal is decomposed into two modes by using the EWT. Since the used noises are low frequency signals, the high frequency component of the EWT is taken as the denoised ECG.

3. Results

The three noisy ECGs, constructed by adding each noise to the clean ECG, have different forms depending on the type of noises as shown in figures 4(a)-4(c). After the noise cancellation, the denoised ECGs are improved as shown in figures 4(d)-4(f), i.e., They are looked more similar to the clean ECG [figure 1(a)] in comparison to the noisy ECG.

The detailed results of this study are shown in Table 1. We test the three types of noises for different magnitudes by multiplying a magnification ratio and the noises, i.e., the ones in figure 1(b)-1(c) have the magnification ratio of one.

While the magnification ratio is increased, the Signal-to-noise ratio (SNR) of both the noisy and the denoised ECGs decrease. For all magnification ratios, the noise cancellation causes an improvement of the SNR in all cases of noises. Note that the increment of SNR after the denoising is quite large for the case of BW but it is moderate for EM and MA.

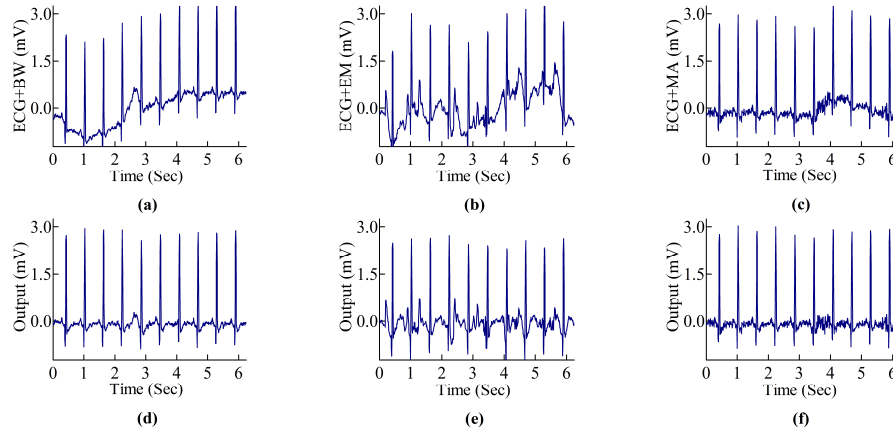


Figure 4. Removal of different noises by using EWT: ECG with different noises (a) BW, (b) EM and (c) MA. (d)-(f) denoised signals corresponding to (a)-(c), respectively.

Table 1. Signal-to-noise ratio (SNR) of noisy ECG and denoised ECG for different types of noise.

Magnification ratio	SNR of noisy ECG (dB)			SNR of denoised ECG (dB)		
	BW	EM	MA	BW	EM	MA
0.5	7.9207	6.1565	17.2073	19.1938	9.8259	18.9446
1.0	3.5818	2.4849	11.4248	17.8040	7.3305	16.4543
1.5	1.9358	1.2673	8.2747	16.1797	5.3459	14.1177
2.0	1.1778	0.7489	6.2490	14.6235	3.9450	12.1811

4. Discussion and Conclusion

We have presented an investigation on a noise cancellation using an adaptive method called empirical wavelet transform. The improvement of the signals depends on the type of noise. Similar to earlier study [1], the SNR increases very much for BW. Furthermore, our results show that EWT denosing of BW case has a better performance in comparison to EM and MA cases. This comes from the fact that the magnitude of the high-frequency components of BW noise is much lower than that of EM and MA [see figures 2(b)-2(d)] so the residue noise after the low-pass filtration is still high in the two latter cases. Therefore we suggest further studies on these two kinds of noise in ECG.

Acknowledgments

We thank the Faculty of Science, the Research and Development Institute (KURDI), the Center for Advanced Studies of Industrial Technology, and the Graduate School, Kasetsart University for financial support.

References

- [1] Kabir Md A, Shahnaz C 2012 *Biomed Signal Process Control* **7** 481-489
- [2] Huang N E, Shen Z, Long S R and Wu M C, Shih H H, Zheng Q and Yen N C 1998 *Proc. Royal Society London A*. **454** 903-995
- [3] Gilles J 2013 *IEEE Trans. Signal Process.* **61** 3999-4010
- [4] Singh O and Sunkaria R K 2016 *Australas Phys Eng Sci Med* **40** 219-229
- [5] Haritha C and Ganesan M 2016 H.C. G.M. and E.P Sumesh 2016 *International Conference on Circuit, Power and Computing Technologies* **10** 7530192
- [6] <https://physionet.org/cgi-bin/atm/ATM>