

Noise Analysis & QRS Detection in ECG Signals

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Abstract: The project has been inspired by the need to find an efficient method for ECG signal analysis which is simple and has good accuracy and less computation time. ECG signal processing in an embedded platform is a challenge which has to deal with several issues. One of the commonest problems in ECG signal processing is baseline wander removal and noise suppression, which determine posterior signal process. The initial task for efficient analysis is the removal of noise. It actually involves the extraction of the required cardiac components by rejecting the background noise with the help of filtering technique. The simulation is done in MATLAB environment. The experiments are carried out on MIT-BIH database. PSNR values are used to find the appropriate filter which gets extended with Empirical Mode Decomposition and Wavelet Decomposition to determine the stress in the ECG signal.

Keywords: ECG, Noise analysis, filters, PSNR Empirical Mode Decomposition and Wavelet Decomposition.

1. Introduction

ECG signals are the representation of heartbeat values. To obtain a distortion less, accurate & error free signals we uptake a filtering techniques by using several filters. Normally ECG signals used to get mixed with so many interferences. With these interferences we are analyzing with various filters along with the PSNR values. When these signals are analyzed the misleading happens, when it get mixed with background noise. The first aim is to remove the noise and go for analysis. In this project we have used many filters for noise removal & noise removed signal is given for analysis such as stress in the patient. Those signals are used for easy way of analysis. In this project we have taken a random noise in the addition of low frequency noise as HUM signal & high frequency noise. These noise are removed using S-Golay filter, Notch filter, Low Pass Butterworth filter, Smooth filter, Gaussian filter, Moving Average filter, Moving Weighted window, Median filter, FIR filter. The performance measures such as PSNR (Peak Signal to Noise Ratio) is calculated and determined.

2. Types Of Noise In ECG

2.1. Power line interference:

It consist of 50/60Hz pickup and harmonics, which can be modeled as sinusoids. Characteristics, which might need to be varied in a model of power line noise, of 50/60Hz component include the amplitude and frequency content of the signal. The amplitude varies up to 50 percent of peak-to-peak ECG amplitude, which is approximately equivalent to 25mv. Decomposing the power-line interfered signal into ten IMF's (Intrinsic Mode Functions), this power line information almost distributed to the 1st intrinsic mode functions.

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$$X_{rec} = 1/4 f_1 + \sum_{n=2}^N f_n$$

where f_n is the set of N intrinsic mode functions. (B.Narsimha, and et al, 2011).

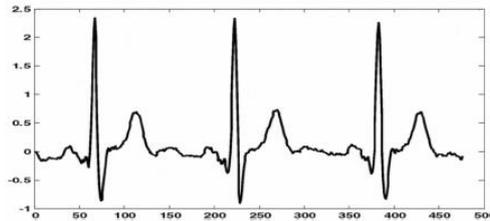


Figure 2: PLI eliminated signal (B.Narsimha and et al, 2011).

2.2. Base line drift with respiration:

The drift of the base line with respiration can be represented by a sinusoidal component at the frequency of respiration added to the ECG signal. The amplitude and frequency of the sinusoidal component should be variable. This baseline can be eliminated by decomposing the signal into 15 intrinsic mode functions reconstructing the signal with suppressing the final IMF is having the base line information. (B.Narsimha and et al, 2011).

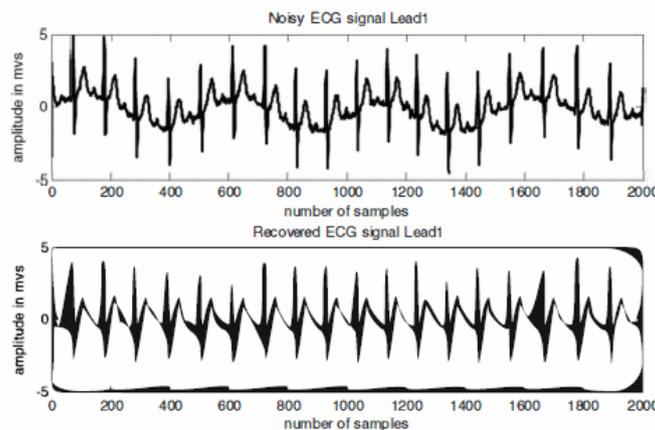


Figure 3:Base line wander effect correction (B.Narsimha and et al, 2011).

2.3. Electrode contact noise:

It is a transient interference caused by loss of contact between the electrode and the skin that effectively disconnects the measurement system from the subject. The loss of contact can be permanent, or can be intermittent as would be the case when a loose electrode is brought in and out of contact with the skin as a result of movements and vibration. (Md. Zia Ur Rahman and et al, 2009).

2.4. Muscle contraction:

The MA (Muscle Artifacts) originally had a sampling frequency of 360Hz. The original ECG signal with MA is given as input to the filter. Muscle contraction cause artifactual milli volt level potentials to be generated. The base line electromyogram is the microvolt range and therefore is usually insignificant. It is simulated by adding random noise to the ECG signal. The maximum noise level is formed by adding random single precision numbers of $\pm 50\%$ of the ECG maximum amplitude to the uncorrupted ECG. (Md. Zia Ur Rahman and et al, 2009).

2.5. Motion artifacts:

Motion artifacts are transient base line changes caused by changes in the electrode-skin impedance with electrode motion. As this impedance changes, the ECG amplifier sees a different source impedance which forms a voltage divider with the amplifier input impedance therefore the amplifier input voltage depends upon the source impedance which changes as the electrode position changes. (Md. Zia Ur Rahman and et al, 2009).

3. Empirical Mode Decomposition

A new non-linear technique, called Empirical Mode Decomposition method, has recently been developed by N.E.Huang et al for adaptively representing non-stationary signals as sums of zero mean AM-FM components. EMD is an adaptive, high efficient decomposition with which any complicated signal can be decomposed into a finite number of Intrinsic Mode functions (IMFs). The IMFs represent the oscillatory modes embedded in the signal, hence the name Intrinsic Mode Function. The starting point of EMD is to consider oscillations in signals at a very local level. It is applicable to non-linear and non-stationary signal such as ECG signal. (Huang and et al, 1998)

An Intrinsic Mode function is a function that satisfies two conditions:

- i. The number of extrema and the number of zero crossings must differ by at most 1.
- ii. At any point the mean value of the envelope defined by maxima and the envelope defined by minima must be zero.

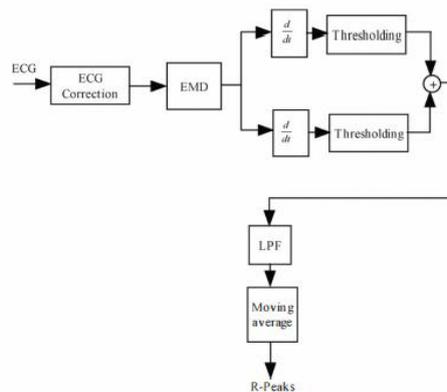


Figure 4: Block diagram for QRS detection (B.Narsimha and et al, 2011)

3.1. H. R- Peak Detection

Since the R wave is the sharpest component in the ECG signal, it is captured by the lower order IMFs which also contain high frequency noise. Past analysis using the EMD of clean and noisy ECG indicates that the QRS complex is associated with oscillatory patterns typically presented in the first three IMFs.

4. Results Notch Filter

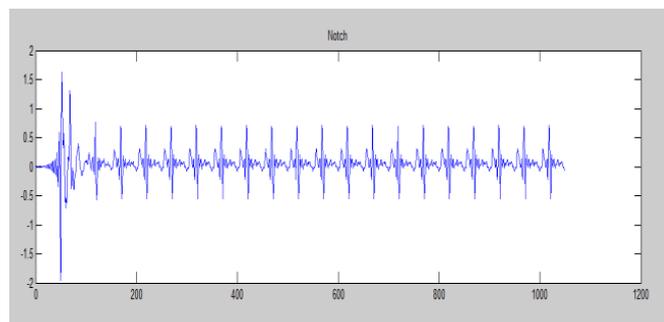
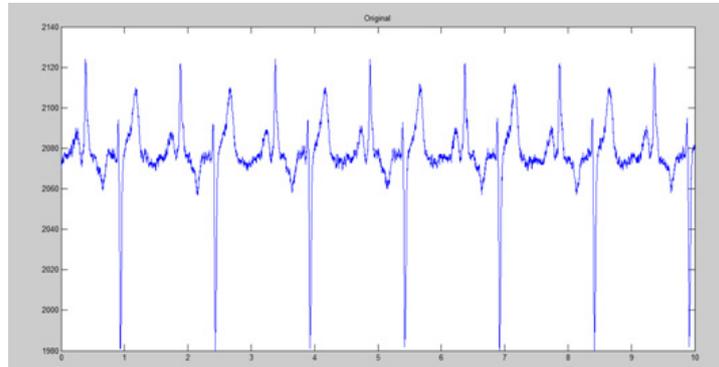


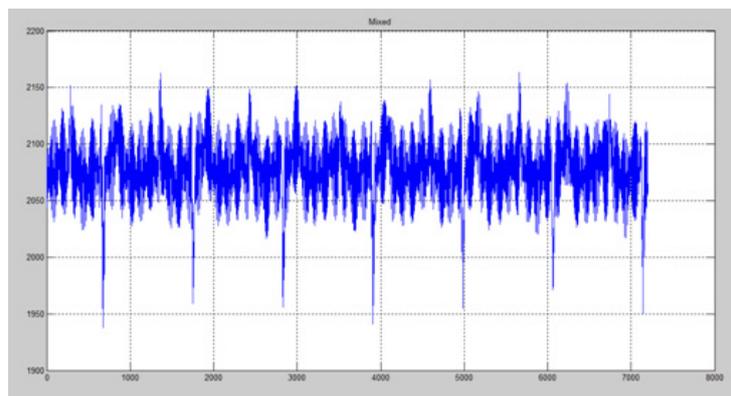
Figure 7: Denoised ECG signal using Notch filter.

In this section, we discussed on the result obtained with the experimental work done. In the proposed de-noising algorithm, the five set of ECG records of MIT/BIH database were used and sampling frequency is set to 720Hz and added with 50 Hz Power line Interference noise with different input SNR values. The effectiveness of proposed algorithm was determined by the MSE and output SNR_o values. The notch filter, Haar wavelet transform and EMD were used in proposed algorithm to obtain quality de-noised ECG signal for diagnosis and analysis. The obtained results were discussed in below sub-section.

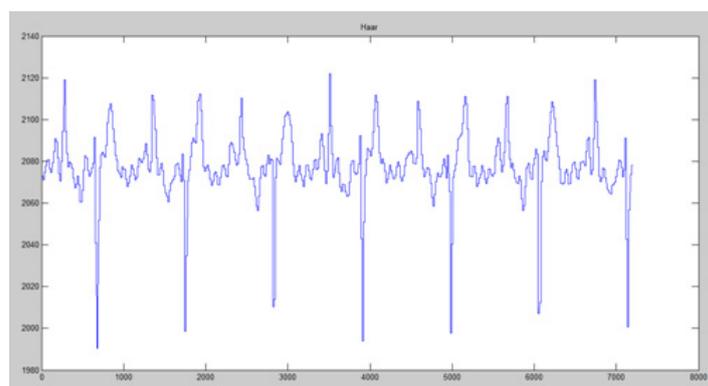
Original ECG signal



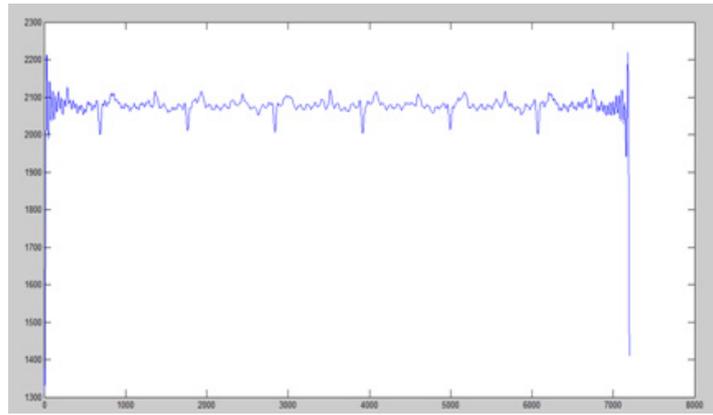
Noisy ECG signal



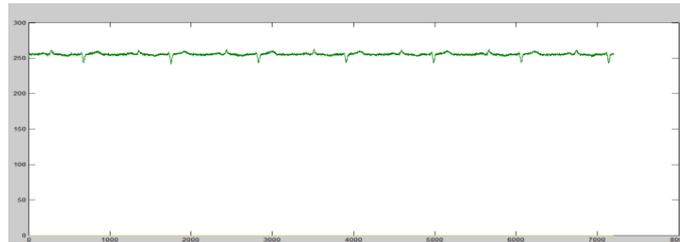
Denosed ECG signal using Haar wavelet transform



R-Peak waveform of Haar wavelet



Denoised ECG signal using EMD



R-Peak waveform of EMD

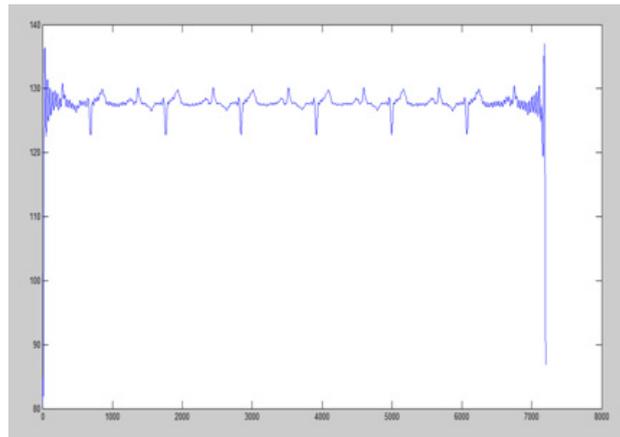


Figure 8: Output Results using EMD and Haar waveform

Table 1: The MSE and PSNR values for the de-noising algorithm using waveform transform:

Samples		1		2		3		4		5	
Wavelet	Values	3db	5db								
Haar	Psnr	14.95	16.76	28.66	28.75	28.23	28.33	25.60	25.79	29.01	28.14
	Mse	0.0119	0.0200	0.0220	0.0372	0.0220	0.0372	0.0220	0.0372	0.0618	0.1047
Sym	Psnr	10.86	11.97	28.36	28.35	28.31	28.33	23.98	24.04	29.92	31.07
	Mse	0.0149	0.0255	0.0288	0.0449	0.0122	0.0202	0.0127	0.0207	0.0392	0.0617
Db	Psnr	14.95	16.76	28.62	28.65	28.23	28.33	25.61	25.79	29.02	28.14
	Mse	0.0119	0.0200	0.0072	0.0120	0.0220	0.0372	0.0220	0.0372	0.0618	0.1047
Coif	Psnr	10.48	11.55	27.64	27.64	28.20	28.22	24.82	24.87	30.04	31.09
	Mse	0.0096	0.0161	0.0123	0.0202	0.0107	0.0130	0.0054	0.0078	0.0143	0.0209
Bior	Psnr	14.95	16.765	28.62	28.65	28.23	28.34	25.61	25.80	29.02	28.14
	Mse	0.0119	0.0200	0.0072	0.0120	0.0220	0.0372	0.0220	0.0372	0.0618	0.1047
Rbio	Psnr	14.95	16.77	28.62	28.65	28.23	28.34	25.61	25.80	29.02	28.14
	Mse	0.0119	0.0200	0.0072	0.0120	0.0220	0.0372	0.0220	0.0372	0.0618	0.1047
Dmey	Psnr	4.79	4.94	28.09	28.09	27.71	27.71	23.66	23.66	32.72	32.41
	Mse	0.0110	0.0188	0.0134	0.0182	0.0234	0.0130	0.0202	0.0350	0.0187	0.0624

Table 2: The MSE and PSNR values for the de-noising algorithm using Empirical Mode Decomposition:

Sample	1	2	3	4	5
Psnr	21.0638	14.5017	13.8271	14.4765	17.5147
Mse	0.0885	0.1883	0.2035	0.1889	0.1331

5. Conclusion

The proposed work illustrates the effect of the wavelet thresholding on the quality reconstruction of ECG signal. The notch filter applied directly to the non-stationary signal like ECG has shown more ringing effect. Haar wavelet transform is the best method to de-noise the noisy ECG signals. For 5dB input noise value, Haar wavelet transform shows the output SNRo value 95.50% with respect to other wavelet transform which is very good for de-noising signal. Finally Haar wavelet transform is compared with EMD in which we conclude that our work shows Haar wavelet transform performs better than other methods.

6. References

- [1] McManus, C.D.; Teppner, U.; Neubert, D. and Lobodzinski, S.M. 1985, "Estimation and Removal of Baseline Drift in the Electrocardiogram", *Computers and Biomedical Research*, **18**, issue 1, February, pp. 1-9.
- [2] Gradwohl, J.R.; Pottala, E.W.; Horton M.R.; Bailey, J.J. 1988, "Comparison of Two Methods for Removing Baseline Wander in the ECG", *IEEE Proceedings on Computers in Cardiology*, pp. 493-496.
- [3] Jane, R.; Laguna, P.;Thakor, and Caminal, P. 1992, "Adaptive Baseline Wander Removal in the ECG: Comparative Analysis with Cubic Spline Technique", *IEEE Proceeding Computers in Cardiology*, pp. 143 - 146.
- [4] Na Pan; Vai Mang I.; Mai Peng Un and Pun Sio Hang; 2007, "Accurate Removal of Baseline Wander in ECG Using Empirical Mode Decomposition", *IEEE International Conference on Functional Biomedical Imaging*, pp. 177-180.
- [5] Markovsky, Ivan A.; Anton, Van H. and Sabine, 2008, "Application of Filtering Methods for Removal of Resuscitation Artifacts from Human ECG Signals", *IEEE Conference of Engineering in Medicine and Biology Society*, pp. 13-16.
- [6] Arunachalam, S.P.; Brown, L.F. 2009, "Real-Time Estimation of the ECG-Derived Respiration(Edr)Signal Using A New Algorithm for Baseline Wander Noise Removal", *IEEE Conference of Engineering in Medicine and Biology Society*, pp. 5681-5684.
- [7] Dotsinsky I., Stoyanov T., "Power-Line Interference Cancellation in ECG Signals", *Biomed Instrum Technol.* 2005 Mar-Apr;39(2):155-62.
- [8] Sayadi, O.; Mohammad B.S. 2007, "ECG Baseline Correction with Adaptive Bionic Wavelet Transform", *IEEE International Symposium on Signal Processing and Its Application*. pp. 1-4.
- [9] Javaid, R.; Besar, R. and Abas, F. S. 2006, "Performance Evaluation of Percent Root Mean Square Difference for ECG Signals Compression", *Signal Processing: An International Journal*, **2**, issue 2, pp. 1-9.
- [10] Huang, N. E., Shen, Z., Long, S. R., Wu, M. C., Shih, H. H., Zheng, Q., Yen, N-C.,Tung, C. C., Liu, H. H.: Empirical Mode Decomposition Method and the Hilbert Spectrum for Non-stationary Time Series Analysis. *Proc. Roy. Soc. London*, A454,(1998), 903-995.
- [11] 11.G. Mihov and I. Dotsinsky, "Power-line interference elimination from ECG in case of non-multiplicity between the sampling rate and the powerline frequency," *Biomedical Signal Processing and Control*, vol. 3, pp. 334-340, June, 2008.
- [12] J. M. Leski and N. Henzel, "ECG baseline wander and power line interference reduction using nonlinear filter bank," *Signal Processing*, vol. 85, pp. 781-793, 2005.
- [13] V. Afonso, W. Tompkins, et al., "Filter bank-based processing of the stress ECG," *IEEE 17th Annual Conference on Engineering in Medicine and Biology Society*, 1995.
- [14] *PhysioToolkit*, open source software for biomedical science and engineering. <http://www.physionet.org/physiotools/>.