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Design Orthogonal Ramp Filter Works According NSR (1) Mendeley Fragment

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Abstract

Fourier transform provides frequency spectrum of signal for feature extraction, wavelet classifier, matching filter design, and etc. Visualization the spectrum of an indexed electrocardiogram signals from Mendeley data base coming in order to evolute mathematical form of filter. The visualized frequency spectrum is for Normal Sinus Rhythm (NSR). Filter is proposed for absolute, real, and imaginary parts to be spectrum resemblance. It is trending to ramp exponential function, the nearest approach to work as match filter for NSR signals. Scale and decay factors are set according to a programable and mathematical computations for evolution. The proposed filter is Finite Impulse Response (FIR) and it is found that, it is equivalent to second order Linear Time Invariant system (LTI). Signal purification by filter and interpolation has observed after setting the number of samples per segment length.

Keywords

Electrocardiogram, Spectrum, Filter, Denoising

1. Introduction

1.1. Revolve Around Normal Rhythm

Noise is everywhere, and for electrocardiogram artifact, noise comes from muscle contraction, breathing, etc. Essentially denoising can depend on signal processing technique when the noise came from a separated band interference, but for ecg. signal noise within the band of a week signal. Lead system and physiological points traditionally selected for clinical recording by instrumentation amplifier and a specified Common Mode Rejection Ratio (CMRR). Adaptive filter and notch filter can cancel power signal. My dream is to record ecg. signal from a float point to compact electrocardiograph with my smart phone and use sine convoluting sine (SCS) as denoiser stage, mechanism is succeeded in showing ecg. variation but even that it cannot be higher order than one because it is in resonance with human signal, and now it is looking for match filter with another direction in biomedical signal processing. Test wearable sensor by measuring signal to noise ratio (SNR) [1], study structure of sensor to reduce artifact noise [2], using three frequency detectors to remove 50 Hz and muscle breathing artifact [3], used Intrinsic Mode Functions (IMFs) and Modified Sigmoid Thresholding Function (MSTF) after Ensemble Empirical Mode Decomposition (EEMD) for reducing noise [4], propose real time accurate thresholding method to distinguish noise distribution [5].

Artificial intelligent must also works without noise for monitoring and take decision rapidly and some time it works directly for denoising by encoding bio-signal and training to eliminate noise automatically [6], using empirical mod decomposition denoising method to detect cardiac disorder [7], compare data quality to detect QRS-complex [8], propose denoising method based on deep learning to clean noisy fetal signal [9], extract feature to recognize pattern in condition of root mean square value (RMS) [10], propose integrated empirical mode decomposition adaptive threshold denoising method for processing ECGs [11].

1.2. NSR Analysis and Filter Design

Design of orthogonal filter based on matching NSR spectrum with virtual transfer function (TF). Seeking for medical and normal ECG data is required due to the diversity in situation. Mendeley repository (Mendeley, 2017) includes a suitable format of data (MAT) which makes accessing, loading, plotting, scaling, controlling appearance, analysis, and processing is flexible (MathWorks, 2023). Parts of Fast Fourier Transform (FFT) is fixed assigned to sampling rate (f_s1 = 360 Hz), 36,000 normalized samples are provided by {fft} function, to consider average as overall tacking [12] [13].

2. Filter Development and Ramp Orthogonally

2.1. Method of Formulation

During analyzing electrocardiogram signals according to MATLAB Tools, it was observed an orthogonal ramp spectrum in imaginary part of signal Fast Fourier Transform (FFT). Ramping in frequency domain can be considered as a differentiation in time domain, it is a principal concept by Fourier Transformation (FT) theory. Ramp exponential signal, starts to be a comparative spectrum form for real and imaginary parts. That is because it has similar shape for a differentiation part, in the other hand it has a ramp frequency variation due to differentiation, but its needing for a factor outcome from a derivation as it should be start, see **Figure 1**.

That means, evolution of FIR filter is desired and proposed to be matched with the spectrum of ramp-exponential-function:

$$\boldsymbol{h}(\boldsymbol{t}) = \boldsymbol{B.t.exp}^{-\boldsymbol{At}} \tag{1}$$

Differentiation for a signal in time provides orthogonal ramp spectrum equivalent to right hand in below:

$$\mathcal{F}\left(dh(t)/dt\right) = j\omega H(\omega) \tag{2}$$

Continuing in derivation, makes Fourier Transform of left side in Equation 2, as follows:

$$\mathbf{B}\frac{1}{A + j\omega} - \mathbf{A}\,\mathbf{H}(\mathbf{w}) = j\omega H(\omega) \tag{3}$$

Time multiplied exponential, provides exponential variation separated by mathematical differentiation, which lead to a transfer function (H(ω)) of filter equivalents to second order Linear Time Invariant (LTI) system, model (Butter worth):

$$H(\omega) = \frac{B}{A + j\omega} \times \frac{1}{A + j\omega} \tag{4}$$

It can see Equation 4, it is a simple form of cascade filter, cut-off frequency locates at $(\omega_{c1,2} = A)$, and it can also see Equation 1. Such kind of filter can be finite within window size (segment length) to work under digital processor consideration.

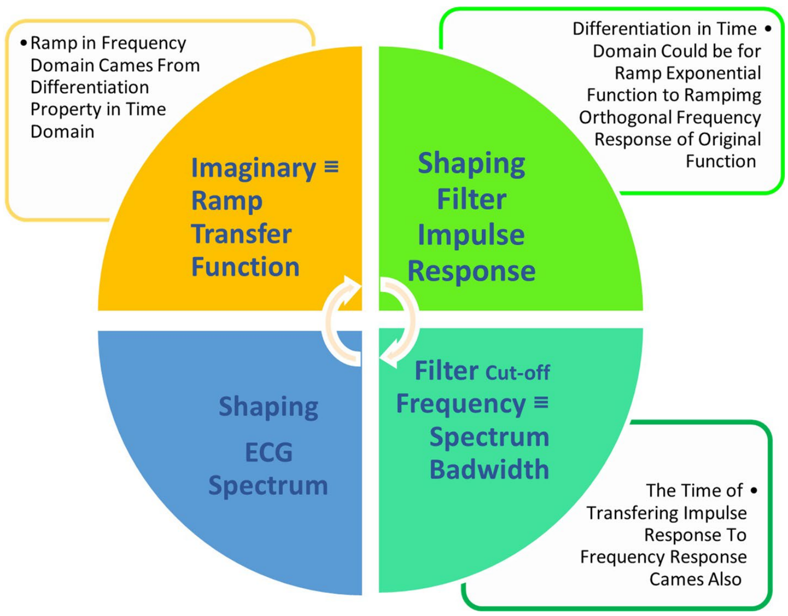

Figure 1. Cycle of providing orthogonal-ramp-FIR filter's samples.

Covering Segment Length for Formulation

Exponential function can be recovered by 11-eleven samples starting from zero and end at inverse seconds of cut-off frequency, here sampling rate can be reused but it is better to start from maximum point at time equals $\left(A^{-1}\right)$ and end at:

$$seg - length = (1 + 2 * \mathbf{pi})/\mathbf{A} \tag{5}$$

By other sense size of FIR for accumulation must be estimated, it can be 11-samples for reducing the noise or more, but let us stop at 15 digital samples (2-

bytes) to form FIR sample of the proposed filter:

$$\text{Orthogonal} - \text{Ramp} - \text{FIR} - \text{Samples} = \sum_{m=0}^{15} \delta\left(t - m/f_{s2}\right).B.t.exp^{-mA/f_{s2}} \tag{6}$$

Forming digital filter matching with NSR signal reaches final step by Equation 6. Estimation A-factor and B depend on data analysis.

2.2. Increasing Filter Order by Interpolation

Higher order filter showing more all the times. Interpolation and decimation avails to increasing filter declaration, such that even data and odd samples filtrated alone, while mixing samples is an input for the second order layer of filtration as represented by Figure 2.

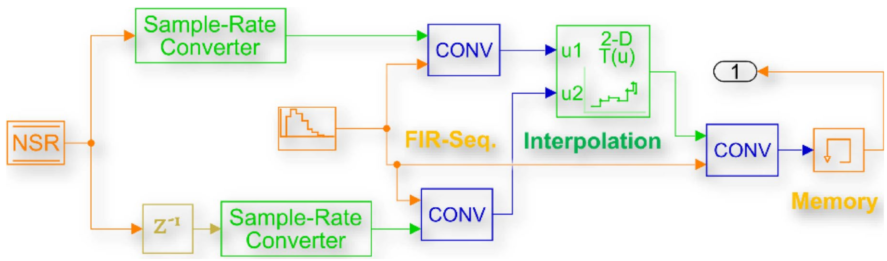

Figure 2. Interpolation procedure for higher order digital filter.

3. Results

3.1. Spectrum Results from 21 NSR (1) Sets

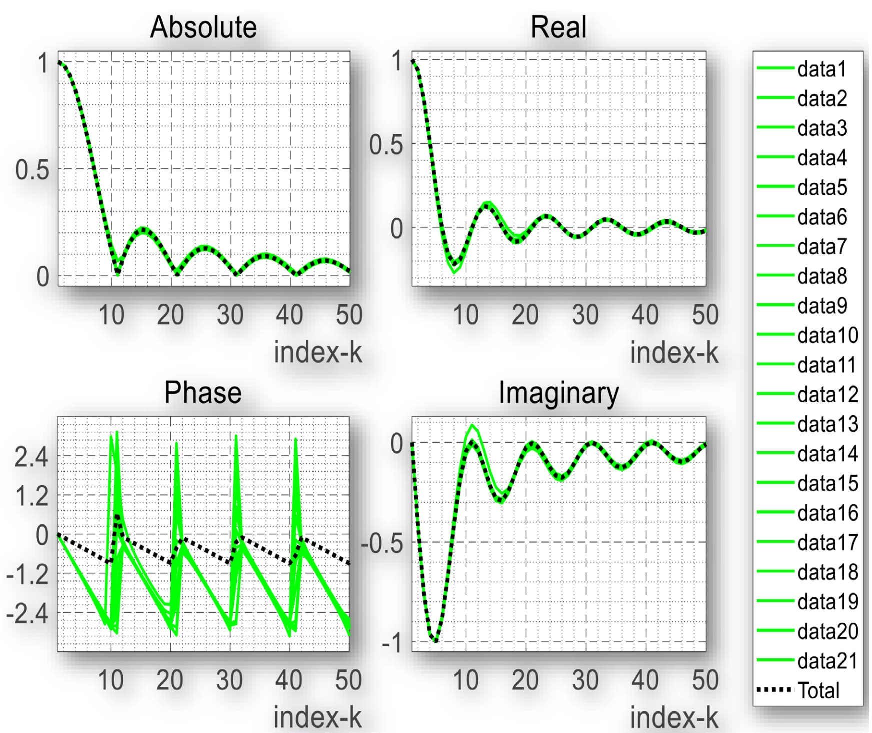

Figure 3. Frequency spectrum parts of NSR (1) data 1-21.

Normal Sinus Rhythm data from Mendeley that carry numbers 100m (1), 101m (1), 103m (1), 105m (1), 106m (1), 108m (1), 112m (1), 113m (1), 114m (1), 115m (1), 116m (1), 117m (1), 121m (1), 122m (1), 123m (1), 200m (1), 209m (1), 213m (1), 215m (1), 220m (1), 228m (1), has been loaded. These data are used for searching about spectrum form, and band limit in comparison with proposed filter with respect to sampling rate and digital unit of data (360 Hz and 200 adu/mV), soon after that 36,000 normalized samples are provided by FFT and zooming around the major 50 samples for the 21 NSR signals spectrum. The frequency spectrum of all ECG signals are likes others and average, in frequency domain as can be seen by Figure 3. It shows also ramp orthogonality of ECG spectrum.

3.2. Frequency Response of Orthogonal Ramp Filter

The factor (A) is found directly from spectrum of a higher resolution (360,000 k-index), it falls around sample number 45, which must indicate to ($2 \times \pi \times 45 \times 360/360{,}000$ rad./s), viz band limit of ECG can go on ($A = 0.2827$) equationally. Figure 4 shows comparison between FIR transfer function and NSR (1) signal spectrum. Comparison includes absolute, real, and imaginary part and it is so close to be a match filter.

3.3. Results of Filtration

Veritably Linear Time Invariant (LTI) system reduces compound noise and forward signal, test of the desired filter and interpolation procedure, is essentially done by applying convolution and removing residuals in displays. Data were explored, different styles are selected to ensure results of convolution, one of them in Figure 5.

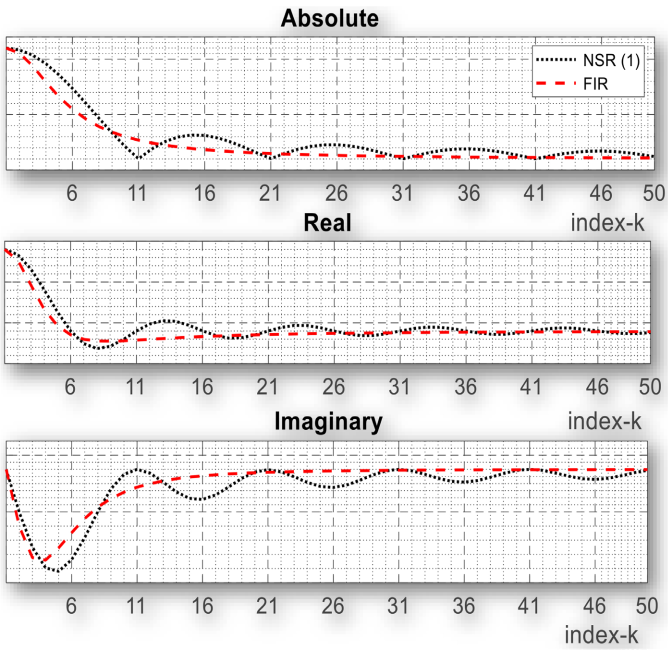

Figure 4. Frequency response of the desire FIR filter behind NSR (1) spectrum.

16-samples, 26-second segments length are selected for computation, thus residual o/p does not extend more than (3%) of the stored beat length, that prevent overlapping out of addition 16-samples, but before ongoing why the proposed filter to do that? or not, let make another look to the proposed filter alone; band of filter can be represented in time domain for 1-second segments length around the duration of one beat, (B-factor) can be set according to the mean of output tell reaching 10-[adu/mV] normally and it is around (0.0081) and from the analysis of NSR signal (A-factor) is set around (0.2827), and results show that there is a filtration for the light bouncing (**Figure 4**) of course, why that happing in spite for NSR different rates and different segments shape! Formerly it was studying spectrum of the traditional ECG signal and it was evenly for all segments, on the other hand out of filter mid band attenuation is linearly free from ripples (**Figure 4**).

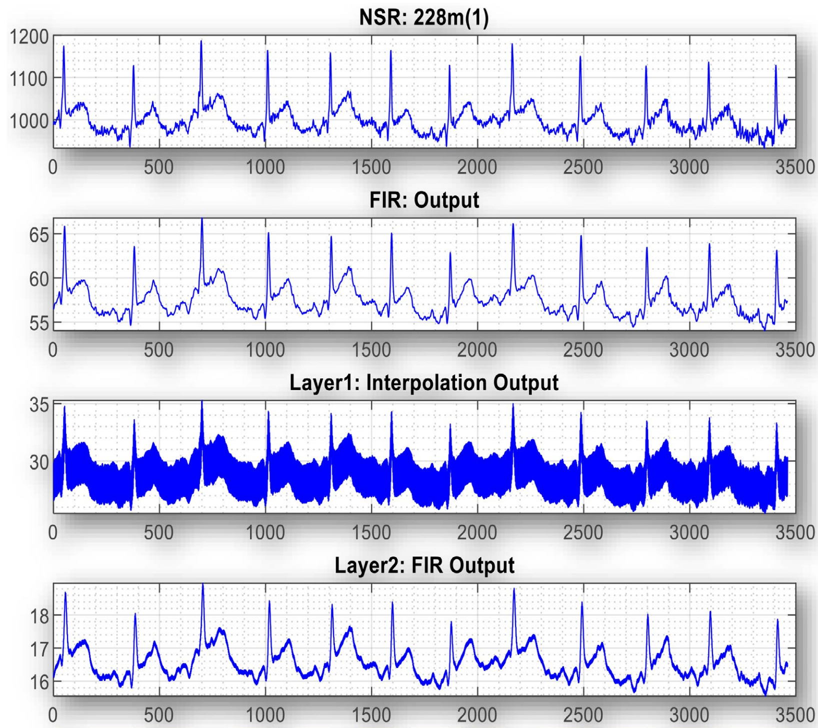

Figure 5. Orthogonal and interpolation filtrations applied by the proposed FIR filter and procedure.

4. Discussion

Denoising and frequency selective for decomposition bio signal are straight line for declaration and classification, it has depended on instrumentation amplifier, second order analog filter, adaptive filter, digital filter, wavelet transformation, qualifying, auto regression and so on. Orthogonal and Interpolation Filtrations.

In Brief, equivalent spectrum and filter model lead to reducing noise as a main objective for title and it has observed challenge in deep learning threshold and covariance, that can be better without noise, filter model can reduce effect of noise but there is another problem spectrum of noise is white and rising order of filter is required. Ideal filter is an infinite order, thus researches holed noise and class by means of neural decoding and frequency selecting. (t-variable) rises order of the proposed filter, thus it can convolute NSR within the segment for one time, (t-variable) or ramping in time and orthogonal frequency domain is the trait of proposed filter, it makes initial condition in time domain zero in the other hand the frequency response of filter {H(ω)} is Butter Worth model its cut-off frequency defined based on data, which mean that noise reduced to (-40 dB/decade) normalized after every ten cut-off frequency but (A-factor) is very low that making low frequency noise disappear rapidly also. Interpolation makes residual noise regular.

5. Conclusion

Ramp exponential variation represents the function that is close to include all frequency components of normal ECG. Sampling the function has a flexible segment length but it can be specific according to a fixed sampling rate for data and filtration process (f_{s2}) .

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Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

References

[1] Joutsen, A., Cömert, A., Kaappa, E., Vanhatalo, K., Riistama, J., Vehkaoja, A., *et al.* (2024) ECG Signal Quality in Intermittent Long-Term Dry Electrode Recordings with Controlled Motion Artifacts. *Scientific Reports*, **14**, Article No. 8882. https://doi.org/10.1038/s41598-024-56595-0

[2] Terada, T., Toyoura, M., Sato, T. and Mao, X. (2021) Noise-Reducing Fabric Electrode for ECG Measurement. *Sensors*, **21**, Article 4305. https://doi.org/10.3390/s21134305

[3] Vamsi, S., Parak, J. and Havlik, J. (2011) ECG Signal Processing and Heart Rate Frequency Detection Methods. https://www.researchgate.net/publication/266281892_ECG_Signal_Processing_and_Heart_Rate_Frequency_Detection_Methods

[4] Mohguen, O. (2023) Noise Reduction and QRS Detection in ECG Signal Using EEMD with Modified Sigmoid Thresholding. *Biomedical Engineering/Biomedizinische Technik*, **69**, 61-78. https://doi.org/10.1515/bmt-2022-0450

[5] Yu, K., Feng, L., Chen, Y., Wu, M., Zhang, Y., Zhu, P., *et al.* (2024) Accurate Wavelet Thresholding Method for ECG Signals. *Computers in Biology and Medicine*, **169**, Article ID: 107835. https://doi.org/10.1016/j.compbiomed.2023.107835

[6] Chen, M., Li, Y., Zhang, L., Liu, L., Han, B., Shi, W., *et al.* (2024) Elimination of Random Mixed Noise in ECG Using Convolutional Denoising Autoencoder with Transformer Encoder. *IEEE Journal of Biomedical and Health Informatics*, **28**, 1993-2004. https://doi.org/10.1109/jbhi.2024.3355960

[7] Hussein, A.F., Mohammed, W.R., Musa Jaber, M. and Ibrahim Khalaf, O. (2022) An Adaptive ECG Noise Removal Process Based on Empirical Mode Decomposition (EMD). *Contrast Media & Molecular Imaging*, **2022**, Article ID: 3346055. https://doi.org/10.1155/2022/3346055

[8] Bläsing, D., Buder, A., Reiser, J.E., Nisser, M., Derlien, S. and Vollmer, M. (2022) ECG Performance in Simultaneous Recordings of Five Wearable Devices Using a New Morphological Noise-To-Signal Index and Smith-Waterman-Based RR Interval Comparisons. *PLOS ONE*, **17**, e0274994. https://doi.org/10.1371/journal.pone.0274994

[9] Mvuh, F.L., Ebode Ko'a, C.O.V. and Bodo, B. (2024) Multichannel High Noise Level ECG Denoising Based on Adversarial Deep Learning. *Scientific Reports*, **14**, Article No. 801. https://doi.org/10.1038/s41598-023-50334-7

[10] Suliman, A., Farahmand, M., Galeotti, L. and Scully, C.G. (2024) Clinical Evaluation of the ECG Noise Extraction Tool as a Component of ECG Analysis Algorithms Evaluation. *IEEE Transactions on Biomedical Engineering*. https://doi.org/10.1109/tbme.2024.3386493

[11] Zhang, M. and Wei, G. (2020) An Integrated EMD Adaptive Threshold Denoising Method for Reduction of Noise in ECG. *PLOS ONE*, **15**, e0235330. https://doi.org/10.1371/journal.pone.0235330

[12] Plawiak, P. (2017) ECG Signals (1000 Fragments). Mendeley Data. https://data.mendeley.com/datasets/7dybx7wyfn/3

[13] The MathWorks (2023) Signal Processing Toolbox™. User's Guide, Inc. © COPYRIGHT 1988-2023. https://www.mathworks.com/help/signal/index.html