Enhancing ECG Readings through Adaptive Highpass Filter

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Abstract— **The presence of 0.5 Hz baseline wander stands as a significant source of interference in the precise measurement of ECG signals, inducing distortions in the original ECG recordings. In this context, we employ an adaptive high-pass filter integrated with the NLMS algorithm, featuring variable order and step size. The implementation leverages MATLAB's Signal Processing Toolbox, harnessing these algorithms for optimal signal processing. Remarkably, the NLMS algorithm yields substantial Signal-to-Noise Ratio (SNR) enhancements. Specifically, we achieve an SNR improvement of 19.83dB with a step size of 0.01 and an order of 2, 19.79dB with the same step size and an order of 4, and 19.67dB with a step size of 0.01. These results underscore the efficacy of the high-pass NLMS filter in mitigating the 0.5 Hz baseline wander noise. The NLMS algorithm assumes a pivotal role in dynamically adjusting the filter coefficients of the high-pass filter, thereby optimizing the attenuation of low-frequency components, including the troublesome baseline wander noise. This adaptive filtering process safeguards the integrity of the desired ECG signal. In sum, the NLMS algorithm serves as a linchpin in the project's high-pass filter design, endowing it with adaptability to respond to fluctuations within the ECG signal. This adaptability empowers the filter to effectively suppress baseline wander noise, thereby advancing the precision and fidelity of ECG signal measurements.**

*Keywords—**baseline wander; ECG signal; high pass NLMS; SNR***

I. INTRODUCTION

The electrocardiogram (ECG) signal holds profound significance in the diagnosis and monitoring of cardiac patients. However, the fidelity of recorded ECG signals can be compromised by an array of intrusive noises, including baseline wandering, power line interference, electrode-related artifacts, motion-induced irregularities, muscle contractions, electronic equipment-generated instrumentation noise, and electrosurgical interferences, among others. In particular, the presence of 0.5 Hz baseline wander noise poses a critical challenge during the evaluation of arrhythmia or myocardial infarction. The typical frequency range of ECG signals falls within 0.05 Hz to 100 Hz, with baseline wandering extending to 0.5 Hz, thereby overlapping with the ECG signal spectrum. Consequently, the effective removal of baseline wander noise has assumed paramount importance in the domain of ECG signal analysis. To address this issue, various digital filtering techniques, including Finite Impulse Response (FIR) and Infinite Impulse Response (IIR) filters, have been explored [1]-[5]. Nevertheless, applying fixed-coefficient filters for baseline wander reduction is complex due to the non-stationary nature of ECG signals. Recently, adaptive filtering has emerged as a powerful and widely adopted approach for ECG signal processing and analysis [6]-[8]. In particular, adaptive filters utilizing the Least Mean Squares (LMS) algorithm have demonstrated commendable performance in handling non-stationary biomedical signals [6].

The proposed system comprises a cohesive array of components working synergistically to achieve the overarching objective of baseline wander noise elimination. The process commences with the acquisition of ECG signals from patients through electrodes positioned on the body. These initial signals are typically tainted by baseline wander noise, necessitating a preprocessing stage to remove any artifacts or high-frequency disturbances that could impede subsequent filtration. This preparatory phase ensures that the signals are appropriately conditioned for further analysis.

At the heart of the system resides the Non-Stationary Normalized Least Mean Squares (NLMS) high-pass filter, renowned for its adaptability. The NLMS algorithm, an adaptive filtering technique, dynamically adjusts filter coefficients based on input signals and desired outputs. The high-pass filter is meticulously engineered to suppress the low-frequency baseline wander noise, while conserving the essential higher-frequency components intrinsic to the ECG signal. The system further incorporates a comprehensive performance evaluation framework, offering vital metrics like Signal-to-Noise Ratio (SNR) to quantify the enhancement in signal quality post baseline wander noise removal.

These metrics play a pivotal role in gauging system efficacy and facilitating comparisons with established filtering methods.

The system is complemented by a user-friendly interface, affording healthcare professionals a convenient means to input ECG signals, visualize the filtered data, and access performance evaluation metrics. This interface offers an intuitive platform for seamless interaction with the system, expediting ECG signal analysis.

This project's significance is underscored by its capacity to augment the precision and reliability of ECG analysis in clinical contexts. Through the adept elimination of baseline wander noise, healthcare practitioners can procure cleaner, more dependable ECG signals for diagnostic and monitoring purposes, potentially leading to more informed medical decisions, timely interventions, and improved patient outcomes. Moreover, this developed system holds the potential for seamless integration into existing ECG analysis frameworks and healthcare settings, thereby elevating the quality of cardiac care. The project also paves the way for future research, delving into advanced filtration techniques, the integration of machine learning algorithms, and real-time processing capabilities.

In this study, we have employed a high-pass filter in conjunction with the NLMS algorithm to effectively remove baseline wander from ECG signals. The NLMS algorithm's adaptive characteristics enable the filter to flexibly respond to fluctuations in the ECG signal, achieving remarkable attenuation of baseline wander noise. This system's performance can be rigorously assessed through SNR evaluations, with the filtered ECG signals readily available for in-depth analysis. The implications of this system are far-reaching, promising to elevate the precision and trustworthiness of ECG analysis in healthcare applications.

NLMS HIGHPASS FILTER

A. About NLMS Filter

The project incorporates the use of the Normalized Least Mean Squares (NLMS) algorithm as a central element in the development of a high-pass filter, tailored for the precise removal of baseline wander noise from ECG signals. The NLMS algorithm serves as an adaptive filtering technique, where it iteratively adjusts filter coefficients with the aim of minimizing the mean square error existing between the desired ECG signal and the resultant filtered output. Its notable attributes, including computational efficiency and ease of implementation, render it particularly suitable for real-time applications, meeting the stringent demands of such scenarios.

The operational paradigm of the NLMS algorithm revolves around the dynamic updating of filter coefficients, a process contingent on the present input frame and the intended ECG signal.The NLMS algorithm's essence lies in iteratively enhancing the filter coefficients to minimize the mean square error existing between the sought-after signal and the filtered result. The step size parameter, μ, plays a pivotal role in determining the convergence speed of the algorithm. A larger μ yields swifter convergence but may introduce instability, whereas a more modest μ ensures stability at the expense of a slower convergence rate.

Within the project's framework, the NLMS algorithm is strategically deployed to adaptively recalibrate the filter coefficients of the high-pass filter. This high-pass filter is skillfully designed to suppress low-frequency components, encompassing the baseline wander noise, while retaining the essential facets of the desired ECG signal. Through the iterative refinement of filter coefficients facilitated by the NLMS algorithm, the high-pass filter successfully adapts to the evolving characteristics of the ECG signal, effectively obviating baseline wander noise.

The NLMS algorithm confers several noteworthy advantages to the domain of ECG filtration. First and foremost, it champions adaptability, permitting the filter to adeptly respond to variations within the ECG signal and fluctuations in baseline wander noise, a crucial attribute given the dynamic nature of real-world ECG signals. Secondly, the algorithm boasts computational efficiency, rendering it particularly well-suited to the rigors of real-time applications, where processing speed stands as a paramount consideration.

In summation, the NLMS algorithm is an instrumental cornerstone in the design of the project's high-pass filter. Its innate adaptability and computational efficiency empower the filter to effectively respond to ECG signal dynamics and to accurately eliminate baseline wander noise, all within the stringent timelines and real-time constraints that define contemporary ECG signal processing applications.

B. Implementation of NLMS algorithm

1. The output of the NLMS high pass filter (desired signal) is calculated as:

$$d(n) = w(n) * x(n) \quad (1)$$

2. The error signal is calculated as the difference between the input signal and the desired signal given by

$$e(n) = x(n) - d(n) \quad (2)$$

3. The filter tap weight vectors are updated using the following equations in preparation for the next iteration:

$$w(n+1) = w(n) + \mu(n)e(n)x(n) \quad (3)$$

4. The desired signal sample will be updated according to new weights and error for next sample.

C. NLMS Highpass Model

For this project, input ECG signal is taken from the physio bank [9]. This input signal contains electrocardiogram data effected with baseline wander noise. Firstly, high pass filter is applied to the input signal to allow only the high frequency components in the signal. The output of the high pass filter is represented as x(n).

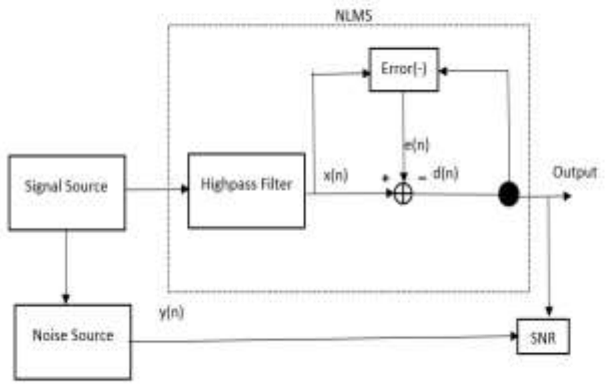

Figure 1.Block Diagram

Error signal e(n) is obtained from (1). Desired signal d(n) is represented with the weights of the filter which are continuously updated for the next iteration it is represented in (3). In this way the NLMS updates the desired signal for each sample.

For calculating signal-to-noise ratio (SNR), noise signal is obtained by applying low pass filter to the input ECG signal which allows only low frequency components. The SNR is given by;

$$SNR(dB) = 10\log_{10}\left(\frac{signal\ power}{noise\ power}\right) \qquad (4)$$

D. Experiment and result

The proposed methodology has been meticulously crafted for computer implementation through the utilization of the MATLAB environment. The ECG signal, sourced from the Physio Bank database, exhibits a sampling frequency of 1000Hz, setting the stage for rigorous evaluation and processing. The system's efficacy is rigorously evaluated through testing on a biomedical ECG signal, as illustrated in Figure 6. This specific ECG signal inherently comprises a spectrum of frequencies, rendering the denoising endeavor a formidable challenge. In situations where noise infiltrates the ECG signal, it obfuscates the distinct characteristics that are conventionally leveraged for diagnostic purposes. Notably, baseline wander noise, as depicted in Figures 2(a), 2(b), and 2(c), tends to adulterate the ECG signal's R complex. This adulteration introduces complications into the accurate measurement of a patient's heart rate. To quantify and provide empirical insight into the filtering capacity of the system, a MATLAB program has been diligently developed to calculate the Signal-to-Noise Ratio (SNR) of the noisy signal both pre- and post-filtering. This evaluation metric serves as a crucial yardstick for assessing the system's performance. Noteworthy SNR enhancements have been achieved through the application of the NLMS algorithm. Specifically, with a step size of 0.01, the algorithm yields SNR improvements of 19.83dB for an order of 2, 19.79dB for an order of 4, and 19.67dB for an order of 8, as succinctly summarized in Table I. It is worth highlighting that the NLMS algorithm, when implemented with a step size of 0.01 and an order of 2, excels in baseline wander noise reduction when compared to orders 4 and 8, with a marginal average SNR improvement difference of 0.08dB. the meticulously designed methodology, implemented in the MATLAB environment, exemplifies a proficient approach for the mitigation of baseline wander noise within ECG signals. The system's ability to markedly enhance SNR underscores its efficacy in restoring the diagnostic utility of ECG signals corrupted by noise, ultimately contributing to more accurate and reliable clinical assessments.

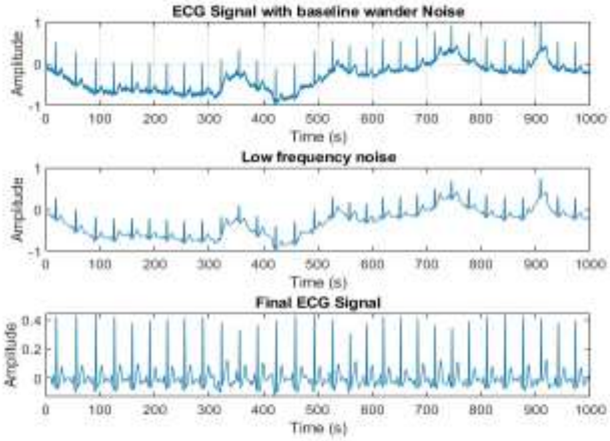

Fig. 2 (a). Output waveform of NLMS high pass filter with order 2 and step size of 0.01

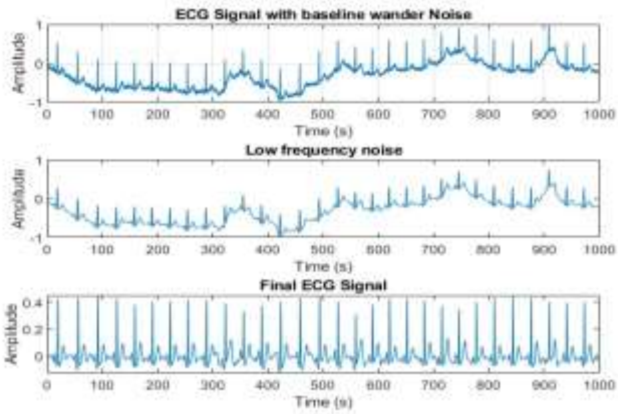

Fig. 2 (b). Output waveform of NLMS high pass filter with order 4 and step size of 0.01

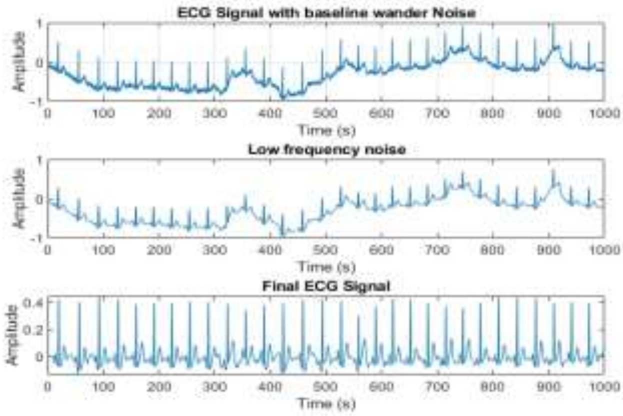

Fig. 2 (c). Output waveform of NLMS high pass filter with order 8 and step size of 0.01

To assess the filtering capability of the system in terms of signal-to-noise ratio (SNR) improvement, a MATLAB program has been developed to calculate the SNR of the noisy signal before and after filtering. This allows the reader to observe the effectiveness of the system in reducing noise and enhancing the quality of the ECG signal.

The SNR improvements achieved by the NLMS algorithm are as follows: 19.83dB for a step size of 0.01 and order 2, 19.79dB for a step size of 0.01 and order 4, and 19.67dB for a step size of 0.01 and order 8, as presented in Table I. It is noteworthy that the NLMS algorithm with a step size of 0.01 and order 2 exhibits superior performance in removing baseline wander noise from the ECG signal compared to orders 4 and 8, resulting in an average SNR improvement difference of 0.08dB.

In summary, the developed method, implemented using MATLAB, demonstrates promising results in denoising ECG signals contaminated with baseline wander noise. The evaluation of SNR improvements highlights the effectiveness of the NLMS algorithm, particularly with a step size of 0.01 and order 2, in enhancing the quality and diagnostic value of the ECG signal.

Table 1.SNR ANALYSIS OF NLMS HIGHPASS FILTER FOR ECG SIGNAL

S. No	**Filter Order**	**Step Size**	**SNR in dB**
1	2	0.005	19.72
2	2	0.01	19.83
3	2	0.09	19.75
4	4	0.005	19.75
5	4	0.01	19.79
6	4	0.09	19.70
7	8	0.005	19.62
8	8	0.01	19.67
9	8	0.09	19.65

II. CONCLUSION

In this paper, the NLMS high pass filter is developed for removing baseline wander noise from electrocardiogram (ECG) signals. The developed system has several advantages. It provides an adaptive filtering approach, allowing for effective noise removal while preserving the desired ECG signal. The NLMS high pass filter used in the system is computationally efficient, making it suitable for real-time applications.

In addition, to determine the optimal order of the filter, experiments are performed by varying the order and evaluated the performance of the filtered ECG signal. The metrics such as SNR (signal-to-noise ratio) is used to quantify the noise reduction achieved by different filter orders. By comparing the results, identified the order that provides the best balance between noise reduction and computational efficiency.

REFERENCES

[1] S. Rani, A. Kaur, and J. Ubhi, “Comparitive study of fir and iir filters for the removal of baseline noises from ecg signal, ”International Journal of Computer Science and Information Technologies, vol. 2, pp. 1105–1108, 01 2011.

[2] Lian Y, Yu JH, “The reduction of noises in ECG signal using frequency response masking based FIR filter”, IEEE international Workshop on Biomedical Circuits Systems 2004, 2(4), pp:17-20.

[3] Yin Xi, Yang Hao, Bian Yu -ping, Luo Ci-yong, “An Improved Method for Rectifying ECG Signals Baseline Drift Based on Moving Average Filter”, Journal of Computer Emulating, 2007, 24(11), pp:107-109.

[4] Lakhwani, R., Ayub, S., & Saini, J. P. (2013).” Design and Comparison of Digital Filters for Removal of Baseline Wandering from ECG Signal”. 2013 5th International Conference on Computational Intelligence and Communication Networks. doi:10.1109/cicn.2013.48.

[5] Sornmo L. “Time-varying digital filtering of ECG baseline wander”, Med Biol Eng Comput. 1993Sep; 31(5):503-8.

[6] Raj Kumar Thenua and S. K. Agrawal, “Hardware Implementation of Adaptive Algorithms for Noise Cancellation”. *International Journal of Information and Electronics Engineering, Vol. 2, No. 2, March 2012.*

[7] Mneimneh, M.A., Yaz, E.E., Johnson, M.T., Povinelli, R.J., “An adaptive kalman filter for removing baseline wandering in ECG signals”, Computers in Cardiology, 17-20 Sept. 2006, pp:253 – 256.

[8] Mateo, J., Sanchez, C., Vaya, C., Cervigon, R., Rieta, J.J.,”A new adaptive approach to remove baseline wander from ECG recordings using Madeline structure”, Computers in Cardiology, Sept. 30 2007-Oct. 3 2007, pp:533 – 536.

[9] B. Widrow, J. R. Glover, J. M. Mccool, J. Kaunitz, C. S. Williams, R.H. Hean, J. R. Zeidler, E. Dong, Jr, and R. C. Goodlin, “Adaptive Noise Cancelling: Principles and Applications,” in Proc. of the IEEE,vol. 63 , no. 12 , pp. 1692 – 1716, 1975

[10] A.S. Abutaleb, “An adaptive filter for noise cancelling,” IEEE Trans.on, Circuits and Systems, vol. 35, no.10, pp. 1201 – 1209, 1988.

[11] D. T. M. Slock, “On the convergence behavior of the LMS and the normalized LMS algorithms,” IEEE Trans. on Signal Processing, vol.41, no. 9, pp.2811-2825, 1993.

[12] P. S. R. Diniz, “Adaptive Filtering: Algorithms and Practical Implementations,” Kluwer Academic Publisher © 2008 Springer Science,Business Media, LLC, pp. 131-146.

[13] G.Saxena, S. Ganesan, and M. Das, “Real time implementation of adaptive noise cancellation,” in Proc. IEEE International conference on electro/information technology, pp. 431 – 436, 2008.

[14] G. Avalos, D. Espinobarro, J. Velazquez, and J. C. Sanchez, “Adaptive Noise Canceller using LMS algorithm with codified error in a DSP,” in Proc. 52nd IEEE International Midwest Symposium on Circuits and Systems, pp. 657 – 662, Aug-2009.

[15] G. G. Tsaneva and K. Tcheshmedjiev, “Denoising of Electrocardiogram Data with Methods of Wavelet Transform,” International Conference on Computer Systems and Technologies, pp. 9-16, 2013.

[16] A. Majkowski, M. Kołodziej, and R. Rak, “Joint timefrequency analysis: An introduction,” Metrology and Measurement Systems, vol. XXI, no. 4, pp. 741-758, 2014. [DOI: 10.2478/mms-2014-0054]

[17] D. L. Donoho, "Denoising by soft-thresholding," IEEE Transactions on Information Theory, vol. 41, no. 3, pp. 613-626, 1995. [DOI: 10.1109/18.382009]

[18] N. Verma and K. A. Verma, "Performance analysis of wavelet thresholding methods in denoising of audio signal of some Indian musical instruments," International Journal of Engineering Science and Technology, vol. 4, no. 5, pp. 2017-2052, 2012.

[19] https://archive.physionet.org/cgi-bin/atm/ATM-Signal