Noise Reduction in ECG Signals Using Adaptive Filtering with Artificial Reference Signals

Ferhat Böcek, Yahya Ekin

Abstract—An adaptive filtering method for noise reduction in electrocardiogram (ECG) signals is presented in this work. In adaptive noise filtering the importance of reference signals are crucial. In the case of having similar ECG signal to the noisy signal might not be common. To solve this issue, artificial reference signals are generated and tested. To accomplish this, different reference signals such as rectengular, triangular, sinusoidal and combination of these signals are generated. The Clean ECG sample is obtained from MIT-BIH Noise Stress Test Database. Then the LMS algorithm is used to filter the noisy signal with artificial reference signals. The error in these signals are calculated in terms of mean square error. In order to generate noisy signal, AWGN noise in different SNR values are added to Clean ECG signal. As a result, the combination of rectengular, sinusoidal and triangular signal in specified frequencies performed as good as the Clean ECG signal used as reference. The resulting MSE values are represented in various graphs and tables.

Keywords — ECG Signal Processing, Adaptive Filtering, Noise Reduction, LMS Algorithm, Digital Signal Processing

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I. INTRODUCTION

A crucial component of cardiovascular diagnostics is the signal processing of electrocardiograms (ECGs), which provide essential details about the electrical activity of the heart. Ensuring the accuracy of diagnosis and treatment planning depends heavily on the integrity of ECG signals. However, the quality of the information collected can be severely reduced because these signals are frequently tainted by noise from a variety of sources, including muscle distortions, electrode contact noise, and power line interference.

Noise in clinical settings can cause ECG readings to be misinterpreted, which may result in inaccurate diagnosis. Effective noise reduction methods are therefore necessary to improve the ECG signals' clarity. Although there are many other ways to reduce noise in ECG signals, adaptive filtering has become a very effective technique because of its dynamic adjustment to changing ECG signal properties and noise.

This work explores the design and implementation of an adaptive filtering method to lower noise in ECG data by utilizing the Least Mean Squares (LMS) algorithm. The adaptive filter's real-time parameter optimization enables it to effectively discern between the actual ECG signal and noise. This work is important because it has the potential to increase the accuracy of ECG signal analysis, which is important for cardiac anomaly diagnosis and monitoring. Healthcare providers can improve patient outcomes by making better decisions by improving the signal quality.

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II. DESCRIPTION OF THE PROPOSED ALGORITHM

The Least Mean Squares (LMS) adaptive filter, a recursive technique renowned for its resilience in signal processing, serves as the foundation for the algorithm for noise reduction in ECG signals presented in this work. The high-performance language for technical computing, MATLAB, is used to implement the algorithm. The technical specifications of the MATLAB code used to implement this technique are described in the sections that follow.

A. Signal Generation and Noise Addition

In order to assess how well the noise reduction strategy performs, the clean ECG sample from MIT-BIH Noise Stress Test Database is used. A predetermined sample frequency of 360 Hz, which is the frequency of database ECG recordings, is used to sample the clean ECG signal. Ten seconds are covered by the time vector, providing enough data for analysis. The clean ECG signal is mixed with Additive White Gaussian Noise to simulate real-world situations. This noise is implemented with different SNR values at 0 dB, 5 dB, and 10 dB, 20 dB, 30dB and 50dB Hz. To guarantee realistic noise levels, the noise's amplitude is adjusted to match the clean ECG signal's amplitude range.

B. LMS Adaptive Filtering

The LMS adaptive filtering procedure is the algorithm's core component. By iteratively modifying its coefficients, the LMS method is a kind of adaptive filter that aims to reduce the mean square error between the desired signal—the clean ECG—and the actual signal—the noisy ECG. Zero coefficients and a starting order are used to initialize the filter.

The algorithm iterates over different filter orders, starting from the initial guess and going up to a specified maximum order, in order to get the ideal filter order and coefficients. The fake reference ECG is the input signal, and the noisy ECG is the desired signal. For each filter order, the algorithm utilizes the LMS update rule to adjust the filter coefficients. The LMS step size u is deliberately selected to strike a compromise between the filter adaption process's stability and rate of convergence.

The desired output (the noisy ECG signal) and the input signal window from the artificial reference ECG are utilized to determine the anticipated output of the filter during each iteration for a given filter order. The filter coefficients are adjusted based on the error signal, which is the discrepancy between the expected and intended output. This procedure makes sure that the filter coefficients are updated in a way that takes into account noise and the dynamic character of the ECG signal during the duration of the signal.

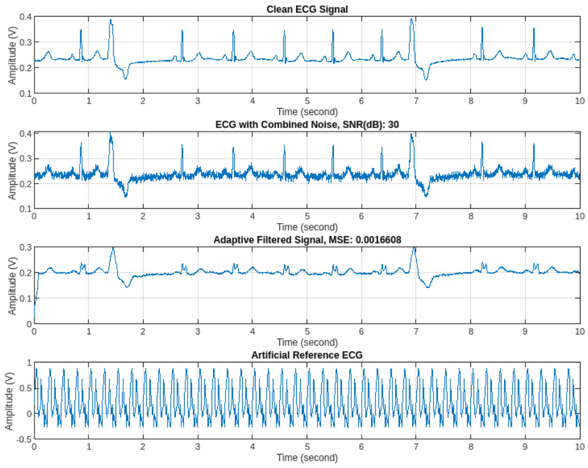
The technique finds the optimal order and coefficients by determining the configuration that yields the lowest mean squared error (MSE) after iterating through all of the filter orders. By comparing the filtered ECG signal with the synthetic reference ECG, the MSE is computed. Ultimately, the ideal filter coefficients that were discovered through the iterative approach are used to handle the complete noisy ECG data. Using the clean ECG signal, the MSE quantifies the filtering's effectiveness. The filter's ability to eliminate noise while maintaining the integrity of the original ECG signal increases with a decreasing mean square error (MSE).

C. Conclusion of Algorithm Description

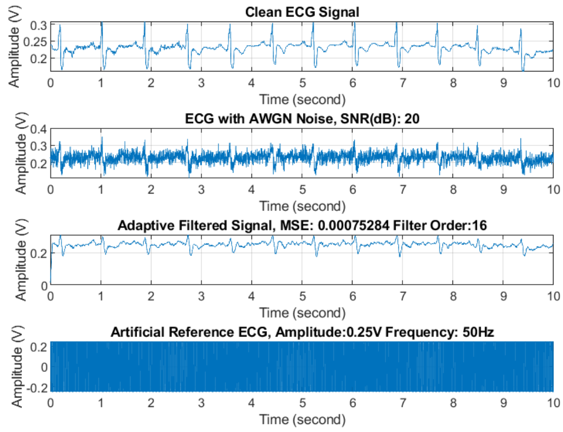
The flexibility and accuracy with which the suggested algorithm can identify and reduce undesired noise components from the ECG signal are what make it successful. The filter's coefficients are precisely adjusted to the unique characteristics of the input ECG signal by utilizing the iterative nature of the LMS algorithm to reduce the error signal. This flexibility is essential for managing the non-stationary noise seen in ECG recordings made in medical settings.

The final filtered ECG signal, the set of filter coefficients that achieve the lowest MSE, and the ideal filter order are all included in the comprehensive output that the algorithm produces at the end. These findings provide a solid foundation for additional investigation and demonstrate the algorithm's ability to improve ECG signal quality for improved patient care and diagnostic precision.

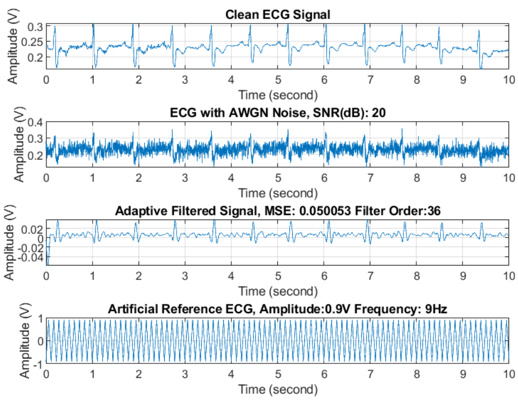
III. RESULTS AND DISCUSSION

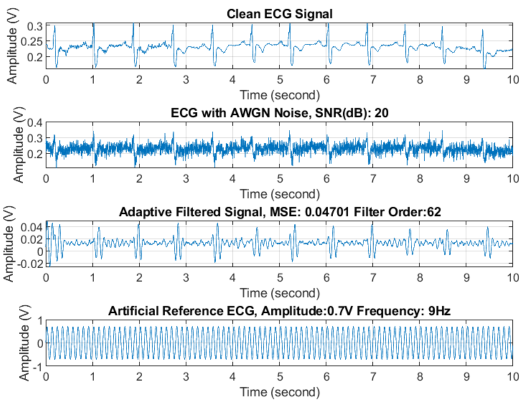


The presented graphic shows the outcomes of applying the Least Mean Squares (LMS) adaptive filtering technique to the noisy ECG signals. The clean ECG signal, the ECG with mixed noise, the adaptively filtered signal, and the artificial reference ECG that was used for filtering are the four subplots that are shown in the figure. These illustrations are essential for comprehending how the adaptive filtering mechanism operates. When comparing the adaptive filtered signal to the ECG with mixed noise, a significant noise reduction is seen. The LMS algorithm has successfully reduced the error, as seen by the Mean Squared Error (MSE) of 0.0016608 between the clean ECG signal and the adaptive filtered signal. This low MSE value indicates a high degree of similarity between the clean ECG and the filtered signal, proving that the filter can decrease noise while maintaining the important features of the ECG signal.

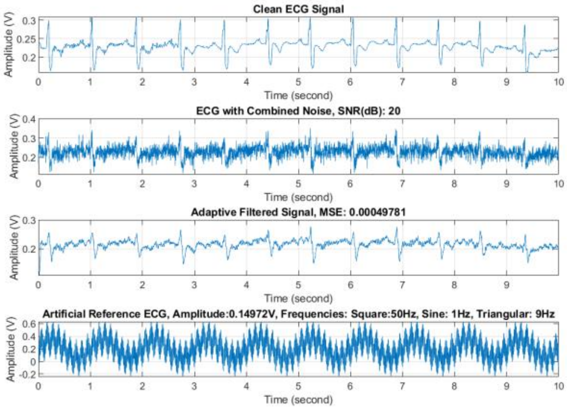


As it can be seen from the figure above, the performance of rectangular reference signal at 50Hz frequency is way better than other individual signals. Here are the figures for each individual signal when they used as reference signal. The figures are chosen for the best signal view, which means that QRS components of the signal can be seen easily. Although our adaptive filter algorithm takes lower MSE as best, in individual cases that does not mean signal is recognizable in every case.

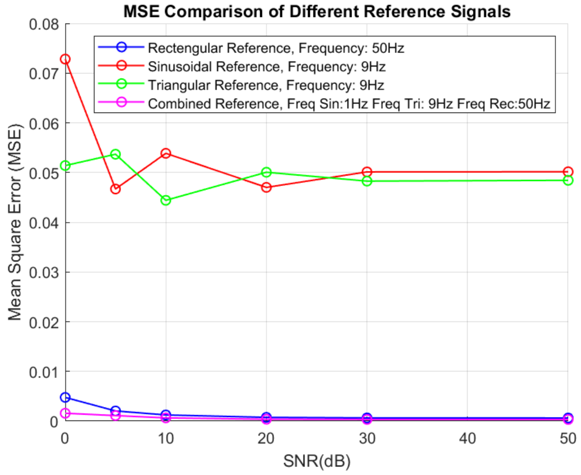




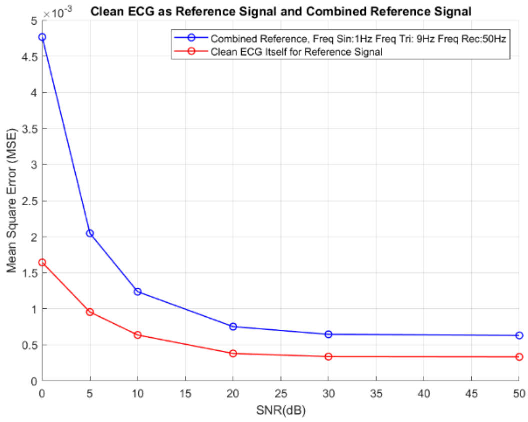
In the figure below, the performance of combined reference signal is represented. As a difference from other signals, the Q, R and S component of the ECG signal is easily to detect by another algorithm. Moreover, as the SNR increases the resulting signal is clearer and easier to detect desired ECG components.



The performance of combined reference signal with three individual signals can be seen below. The best performance is obtained by combined reference signal, and the other close signal is rectangular reference signal. However, the key factor is the frequency of rectangular signal. In the lower values of frequency, the rectangular signal does not perform well. The detailed results of MSE can be seen at table (y).



Also, for the best-case scenario which is the using reference signal as clean ECG itself, the combined signal performs as close as the original clean signal in figure(x).



The numerical result of the test cases can be seen from the table below.

To sum up, the LMS adaptive filter has shown to be a useful instrument for improving the quality of ECG signals. The signal-to-noise ratio, an important parameter in ECG signal analysis, shows a noticeable improvement, according to the data. The LMS algorithm provides a flexible approach for ECG signal processing because of its adaptive character, which bodes well for future study and advancement in biomedical engineering applications.

SNR(dB)	CLEAN_REF	COM_REF_1950	COM_REF_1912	SIN_REF_9	SIN_REF_1	TRI_REF_9	REC_REF_50
0	0.0016421	0.0015828	0.0017463	0.072813	0.14277	0.051394	0.0047658
5	0.00095514	0.0011091	0.001189	0.046682	0.15842	0.05368	0.0020459
10	0.000637	0.00064659	0.00070117	0.053859	0.14234	0.044411	0.0012371
20	0.00038091	0.00037343	0.0003636	0.04701	0.14295	0.050053	0.00075284
30	0.00033778	0.00033705	0.00034162	0.050125	0.14041	0.048272	0.00064636
50	0.00033398	0.00033502	0.0003345	0.050156	0.1404	0.048432	0.00063074

CLEAN_REF	Uses Clean ECG itself for reference signal.
COM_REF_1950	Combined Reference: Freq Sin:1Hz Freq Tri: 9Hz Freq Rec:50Hz
COM_REF_1912	Combined Reference: Freq Sin:1Hz Freq Tri: 9Hz Freq Rec:12Hz
SIN_REF_9	Sinusoidal Reference Signal: Frequency 9 Hz
SIN_REF_1	Sinusoidal Reference Signal: Frequency 1 Hz
TRI_REF_9	Triangular Reference Signal: Frequency 9 Hz
REC_REF_50	Rectengular Reference Signal: Frequency 50 Hz

IV. CONCLUSIONS

In order to reduce noise in electrocardiogram (ECG) readings, the study successfully devised an adaptive filtering strategy utilizing the Least Mean Squares (LMS) algorithm. The outcomes unequivocally show that noise is efficiently suppressed by the LMS adaptive filter with artificial reference signals and combined reference signals. The importance of using artificial reference signals are lying the similarity between artificial reference signal with the desired reference signal. This filtering technology has a lot of potential for clinical settings where detecting heart problems requires reliable ECG interpretation. This technique may lead to better patient outcomes by giving medical personnel a more lucid ECG signal, which will enable them to make more educated judgments. Additionally, the LMS algorithm's flexibility makes it appropriate for a range of ECG noise types, providing a flexible tool for biomedical signal processing. The filter's real-time coefficient adjustment capability in response to fluctuating signal and noise characteristics is especially useful in situations when signal conditions are uncertain. Even with the encouraging outcomes, there is still room for growth. Subsequent studies may investigate the application of the method in real-time processing systems, hence augmenting its usefulness in real-time clinical contexts. Furthermore, validating the algorithm's efficacy in a variety of clinical circumstances could involve testing it on a wider range of ECG data from various patient demographics. Using machine learning approaches to improve the filtering process's adaptability could be another way to develop the field. The filter could be able to learn from a sizable collection of ECG signals thanks to machine learning, which would enhance its functionality and increase its resistance to different kinds of noise. Furthermore, further research might be done to examine the effects of various step sizes and filter orders on the LMS algorithm's performance. A more precise choice of these parameters may result in even better outcomes, lowering the mean square error and delivering an ECG signal that is even more readable.

In summary, this work advances the field of biomedical signal processing by providing an efficient adaptive filtering method for electrocardiogram signals. It establishes the framework for further research into automatic and sophisticated noise reduction methods, which may result in the development of more precise and effective cardiac monitoring systems. The possibility of incorporating these algorithms into wearable and portable devices creates new opportunities for continuous, real-time cardiac health monitoring, which has the potential to revolutionize cardiac research and care.

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