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Improved PID based Adaptive Controllers for Denoising Biomedical Signals

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ABSTRACT- Biomedical signal processing is one of the most popular research domains. Very fine features in biomedical signals carry important information regarding patient's health. So, it is necessary to have noise free biomedical signals for the correct diagnosis. The major trouble for biomedical equipment is Power Line Interference (PLI) which impairs the signals. An adaptive filter can be one of the possible solutions for the removal of non-stationary noise, but maintaining the system stability along with a high convergence rate is a critical issue. The adaptive algorithm works on the principle of minimization of error for optimized coefficients updating while PID controller attempts to minimize the error over time by adjusting the control variables. In this paper, these two different approaches are combined to get an efficient solution for adaptive PLI cancellation and two new algorithms namely PID-based Response Adjustment for Reducing Error (PID-RARE) and PID-based Coefficient Adjustment for Reducing Error (PID-CARE) are proposed. The integration of NSLMS adaptive algorithm with PID controller in the proposed algorithms are found to be an effective solution to adaptive PLI cancellation and have shown quite better performance in terms of SNRout, correlation coefficient, mean square error thereby providing more cleaner signal at lesser convergence rate.

Keywords: Biomedical Signal; Power line Interference, PID, PLI Canceller, Adoptive Canceller, Denoising, ECG.

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1. INTRODUCTION

The need for biomedical signals denoising has been enormously augmented due to the requirement of fine features in biomedical signals to diagnose the exact health condition of the patient. The biomedical signals like ECG, EEG, EMG etc. are badly affected by the non-stationary interferences. So, it is difficult to get accurate result for such biomedical signals recording. Power Line Interference (PLI) is a dominant one which disturbs the spectrum of required signals [1], [2]. Most of the medical equipment are powered by the supply line of working frequency 50/60 Hz whereas the biomedical signal recorders have 3dB range of the frequencies from 0.67Hz to 150Hz. As the power line frequency lies within the frequency range of biomedical signals, captured biomedical signals are corrupted by PLI. Sometimes the PLI may totally mask the signal of interest and affects the reliability and accuracy of biomedical signals. A rigorous review on noise removal techniques in ECG signals has been provided in [3]. The most common approach proposed earlier to remove PLI is the use of a notch filter with an increased stop band, but this may lead to a change in the characteristic of the original signals. Variants of algorithms based on notch filter designed have been presented in [4-5]. Another method to remove PLI is the use of adaptive filters which can track and detect dynamic variations in the received signal. Least mean square (LMS) algorithm is commonly used in adaptive filters for noise cancellation [6-8]. The performance of various adaptive PLI cancellers based on LMS, normalized LMS (NLMS), Sign LMS (SLMS), Normalised sign LMS (NSLMS), and their modified versions are compared in [9] and it was observed that the use of sign of error term and normalization of error in NSLMS algorithm improves overall system performance. Recently, a proportionate normalised least mean square based sub-band adaptive algorithms has been presented in [10].

There are other diverse approaches used for removing unwanted interference in the biomedical signal that have been reported earlier. The neural network-based nonlinear adaptive filter proposed in [11,12] have presented a method to eliminate the baseline drift and pseudo-differential effects present in the interfering noise. A deep learning-based framework For ECG signal denoising is presented in [13,14]. In [13], the convolutional neural network is used and the correlation

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between cardiac cycles is exploited to obtain a robust ECG denoising system whereas CS-TRANS reported in [14] introduces sliding window technique into convolutional neural network to extract linear and nonlinear time-frequency features, and then use the transformer encoder to obtain deep features conducive to ECG denoising and classification. Both the methods have been evaluated for BW, MA, EM noise but their performance for PLI have not been evaluated. Large computation in neural networks limits the application of ECG analysis and real-time system implementation. Zhao Zhidong and Ma Chan [15], Suchetha *et al.* [16], and Ladrova *et al.* [17] proposed Empirical Mode Decomposition (EMD) and LMS adaptive filter PLI removal method and observed that PLI can be effectively eliminated from the ECG signal without affecting its spectrum. Combining EMD with wavelet transform is presented in [18]. Mateo *et al.* [19] and Mujahid *et al.* [20] proposed PLI canceller using radial basis function (RBF) and Wiener hybrid filter, where they make full use of the merits of both methods. An approach based on eigen value decomposition of the Hankel matrix reported in [21] inferred that PLI can be removed by eliminating the end point eigen value of the Hankel matrix formed using noisy ECG signals. In Ref [22], six different PLI removal methods: Adaptive noise canceller (ANC), wavelet transform (WT), Butterworth filter (BF), notch filter, moving average filter (MA), and empirical mode decomposition (EMD) are compared and it was observed that WT is computationally complex and cannot be included in the equipment of medical practice due to their higher cost. In other work, authors have adopted a method of Fourier decomposition method (FDM) for separating PLI and baseline wanders of EEG signals [23]. Though various efficient methodologies are proposed in the literature for biomedical signal denoising, the researchers are still being working to provide optimal solutions. In this paper, a new approach of integrating PID controller with an adaptive algorithm as a solution for PLI cancellation has been presented.

2. ADAPTIVE NOISE CANCELLER AND PID CONTROLLER

2.1. Adaptive Noise Canceller

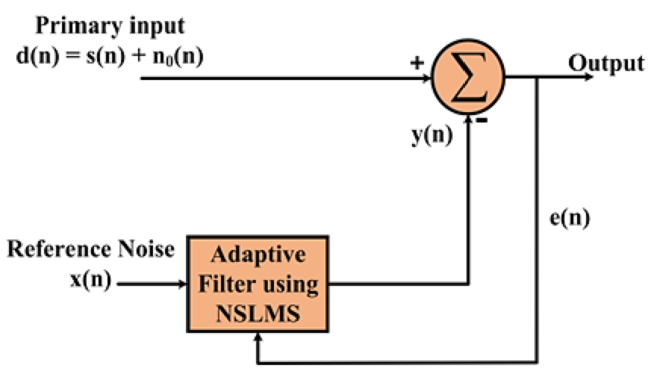

Figure 1. Generalized Adaptive Power Line Interference Canceller System

The adaptive noise canceller adjusts its coefficients vector according to variations in the noise that present in acquired signal to provide the close estimate of the noise. This estimated noise is then subtracted from the noisy input signal to provide the clean output signal. The generalized adaptive noise canceller system is shown in *figure 1*. The primary input to the system is the noisy signal *d(n)* which is sum of clean signal *s(n)* and interfered noise $n_0(n)$.

$$d(n) = s(n) + n_0(n), \tag{1}$$

Another input to the system is reference noise *x(n)* which is the initial estimation of interfered noise $n_0(n)$. The adaptive filter operates on the reference noise *x(n)* that produces the response *y(n)* which is the approximate estimate of occurred noise $n_0(n)$.

$$y(n)=w(n) * x(n) \tag{2}$$

The output response of the adaptive filter y(n) is then subtracted from the input noisy signal d(n) to get the error signal e(n) which is the desired clean signal s(n).

$$e(n)=d(n) - y(n) \tag{3}$$

Unless the value of filter output y(n) reaches the value of noise signal $n_0(n)$, the clean output signal can't be achieved. Practically, there is remarkable difference between n_0 and y which can be minimized iteratively by the process of updating filter coefficients. The Least Mean Square (LMS) algorithm is the basic adaptive algorithm. Many alterations in the coefficient updating process of adaptive filtering in order to enhance the performance of adaptive filter have been reported by researchers. Some major of them are Normalized Least Mean Square (NLMS), Sign Least Mean Square (SLMS) and Normalized Sign Least Mean Square (NSLMS) algorithms. The NSLMS algorithm is found to have better performance but has lower rate of convergence [9]. The rate of convergence of the algorithm needs to improve so as to adapt the dynamic variations in the interfered noise quickly and in turn to obtain a better trade-off between the performance parameters.

2.2. PID Controller

The adaptive noise canceller works on the principle of minimizing the error over time by updating the filter coefficients. The Proportional Integral Derivative (PID) controller also works on the similar principle of minimizing the error difference *e(t)* between desired value and actual value of the process output over time by adjusting the control variables *kp*, *ki* and *kd*. Where *kp*, *ki* and *kd* are proportional, integral, and derivative constants respectively. The coefficients of adaptive filter are updated in every iteration to near-optimal which in turn gradually reduces the error. The PID controller does the same over time by adjusting the controlled variables by taking into consideration the present, the past, and the future values of the error between output and the desired output. A PID controller is widely used in feedback control of industrial processes. *Figure 2* shows a block diagram of a PID controller.

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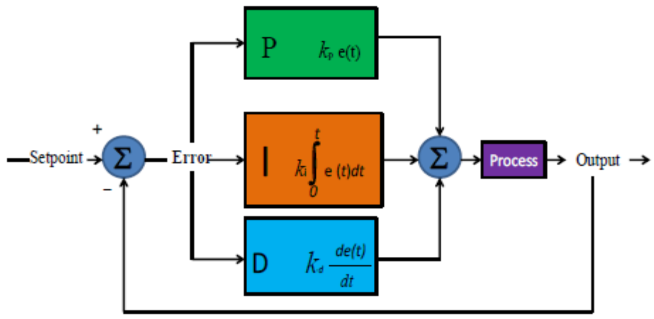

Figure 2. PID Controller

A PID controller continuously calculates an error value as the difference between a desired value and a process output variable and applies a correction based on values of proportional, integral, and derivative terms. Mathematically, the output of PID controller is expressed as

$$PID_{out}(n) = k_p P_e(n) + k_i I_i(n) + k_d D_e(n) \quad (4)$$

where,

$$P_e(n) = e(n),$$

$$I_e(n) = sum[e(n-1) + e(n)],$$

$$D_e(n) = [e(n+1) - e(n)].$$

The PID controller attempts to minimize the error over time by adjusting the control variables while adaptive algorithm works on the principle of minimization of error for optimized coefficient updating. Combining PID with an adaptive algorithm may enhance the process of optimizing the filter coefficients. The proposed algorithms in this paper combines two different approaches to get an efficient solution for adaptive PLI cancellation.

In the proposed work, PID controller is used to assist NSLMS adaptive algorithm with the aim to improvise the performance and to converge in lesser amount of time. The proposed algorithm combines NSLMS adaptive algorithm and PID controller to get an efficient solution for PLI cancellation. In this work, two versions of PID controller based adaptive filtering methods for PLI cancellation namely; Proportional Integral Derivative based Response Adjustment for Reducing Error (PID-RARE) and Proportional Integral Derivative based Coefficient Adjustment for Reducing Error (PID–CARE) are proposed.

3. PID BASED ADAPTIVE NOISE CANCELLER

3.1. PID-based Response Adjustment for Reducing Error (PID-RARE)

The block diagram of PID-RARE is shown in *figure 3*. In PID-RARE algorithm, the PID controller is used to correct the adaptive filter response y(n) to y1(n). The input to the PID controller is the difference between the corrected response y1(n) and the reference noise x(n). The PID controller functions to assist NSLMS filter to make output y1(n) close to interfered noise n_0(n). In this proposed algorithm, for every input sample, the PID controller runs multiple times till it achieves the minimum error value ϵ at its input. The corrected output y1(n) which is the close estimate of n_0(n) is then subtracted from the input noisy signal d(n) to get the signal e(n) which is a cleaner output signal. This signal e(n) acts as an error input to the NSLMS and is used to update the coefficients of NSLMS filter iteratively to provide the output y(n) that makes y1(n) close to n_0(n). In every iteration of NSLMS, the use of PID controller aids in obtaining more optimal values of filter coefficients which helps the NSLMS algorithm to converge in a lesser amount of time thereby improving its performance.

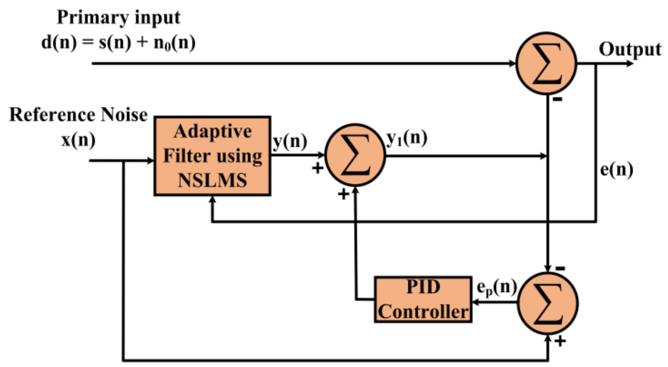

Figure 3. Adaptive PLI canceller using PID–RARE algorithm

Let x(n), as shown in *figure 3*, be the reference noise signal and s(n), n_0(n), and d(n) respectively are the clean signal, Power Line Interference (noise), and noisy signal. A generalized filter equation is expressed as

$$y(n) = w(n) \times x^T(n) \quad (5)$$

where w(n) is the filter coefficients vector in PID-RARE. The weight updating is like that for basic NSLMS algorithm which is expressed as

$$w(n) = w(n-1) + 2 \times \mu \times \frac{sign(e(n)) \times x(n)}{p} \quad (6)$$

where $e(n) = d(n) - y_1(n)$ is an error signal, μ is a step size parameter and $p = \alpha + x \times x^T$ where α is an offset. The function of PID, in general, is to minimize the difference between actual value and reference value. In PID-RARE, the PID controller is introduced to estimate the difference between NSLMS filter output *y(n)* and the actual PLI $n_0(n)$ from the input $e_p(n)$ applied to it which is the difference between $y_1(n)$ and the reference noise *x(n)*.

$$e_p(n) = x(n) - y_1(n) \quad (7)$$

In each iteration of NSLMS, the PID controller runs multiple times till it achieves an error input $e_p(n)$ to the minimum threshold value ϵ which corresponds to the correction factor generated at the output of PID controller. The corrected output in the i^{th} iteration of PID is expressed as

$$y_{1n}(i) = y(n) + PID_{out}(i) \tag{8}$$

Where $y_{1n}(i)$ represents the value of y_1 in the n^{th} iteration of NSLMS and i^{th} iteration of the PID. The input to the PID controller in the i^{th} iteration can be expressed as

$$e_{pn}(i) = x(n) - y_{1n}(i) \tag{9}$$

When the error input to PID controller reaches to minimum threshold value ϵ iteratively, it comes out of the loop. Let the value of y_{1n} at the end of PID controller loop be $y_{1n}(\epsilon)$. This value of y_{1n} will be the value of $y_1(n)$ in the n^{th} iteration of NSLMS so that $y_1(n) = y_{1n}(\epsilon)$. The error signal $e(n)$ generated in the n^{th} iteration of NSLMS is given by

$$e(n) = d(n) - y_1(n) \tag{10}$$

This error signal $e(n)$, fed back to NSLMS filter, updates the filter coefficients $w(n)$. The updated filter coefficients of the NSLMS filter obtained in association with PID are more optimal as compared to those that were in the basic NSLMS algorithm. This helps the PID-RARE algorithm to converge in a lesser amount of time.

3.1.PID-based Coefficient Adjustment for Reducing Error (PID-CARE)

PID-CARE is another variant of PID based PLI controller proposed here. The difference between the operation of PID-CARE and that of PID-RARE is that in PID-RARE, the PID controller is used to add the corrective factor to the filter response that drives the corrected output to a closer estimate of the interfering noise which, in turn, is used to update the filter coefficients. However, in PID-CARE, the PID controller is used to provide the value of the step size parameter of an adaptive filter. Thus, in contrast to the PID-RARE algorithm which uses a fixed step size parameter, the PID-CARE algorithm uses a variable step size parameter value which is obtained at the output of PID controller. The adaptation of the step size parameter, based on the error between the estimated noise and the reference noise, assists the adaptive filter in determining more optimal weights to provide closer estimates of interfering noise.

In PID-CARE shown in *figure 4*, for each iteration of NSLMS filter, the PID controller runs multiple epochs and the filter coefficients are updated as per the equation

$$w'_n(i) = w'_n(i-1) + PID_{out}(i) \times \frac{sign(e\prime(n)) \times x\prime(n)}{p} \tag{11}$$

where, $\boldsymbol{w'}_n(i)$ represents the filter coefficients of NSLMS filter in n^{th} iteration of NSLMS and i^{th} iteration of PID controller, $p = \alpha + \boldsymbol{x} \times \boldsymbol{x}^T$ and α is constant.

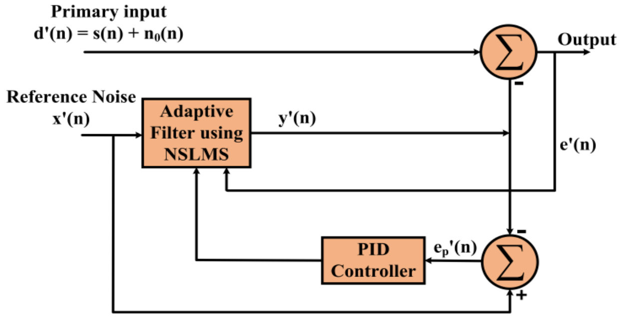

Figure 4. Adaptive PLI canceller using PID–CARE algorithm

The input to the PID controller in n^{th} iteration of NSLMS and i^{th} iteration of PID is given by

$$e'_{pn}(i) = y'_n(i) - x'(n) \tag{12}$$

The function of PID controller is to provide an adaptive step size for the NSLMS filter that assists the NSLMS filter to adapt its weights that drive the value of $y'_n(i)$ close to $n_0(n)$ of PID controller. The minimum threshold value ϵ of error input $e'_{pn}(i)$ indicates the setting of near optimal values of filter coefficients in the n^{th} iteration of NSLMS filter of PID-CARE algorithm. The error signal e'(n) generated in the n^{th} iteration of NSLMS algorithm in PID-CARE is fed back to NSLMS filter which is used for updation of filter coefficients thereby minimizing the error between $y'_n(i)$ and $n_0(n)$. In each iteration of NSLMS, PID controller runs multiple epochs till it achieves the minimum threshold value ϵ.

$$e'(n) = d'(n) - y'(n) \tag{13}$$

When the error input to PID controller reaches to minimum threshold value ϵ, iteratively, the PID controller comes out of the loop. Let the output of PID controller at the end of loop be $PID_{out}(\epsilon)$. This value of PID_{out} sets the filter coefficients of NSLMS and provides the NSLMS filter output $y'_n = y'_n(\epsilon)$ in the n^{th} iteration. The error signal $e(n)$ generated in the n^{th} iteration of NSLMS algorithm is given by

$$e'(n) = d(n) - y'_n(\epsilon) \tag{14}$$

This error output fed back to NSLMS filter is used to update the filter coefficients in $(n+1)^{th}$ iteration. In every iteration of NSLMS algorithm, the more optimal values of filter coefficients are obtained using PID controller which helps the NSLMS algorithm to converge in a lesser period thereby improving its performance.

4. RESULTS AND DISCUSSION

In this section, the performances of PID-RARE, PID-CARE and NSLMS algorithms are evaluated. The algorithms are simulated in MATLAB and analyzed for their performance comparison based on Output Signal to Noise Ratio (SNR_{out}), Correlation Coefficient (CC), Percent Root Mean Square Difference (PRD), and Mean Square Error (MSE). All the

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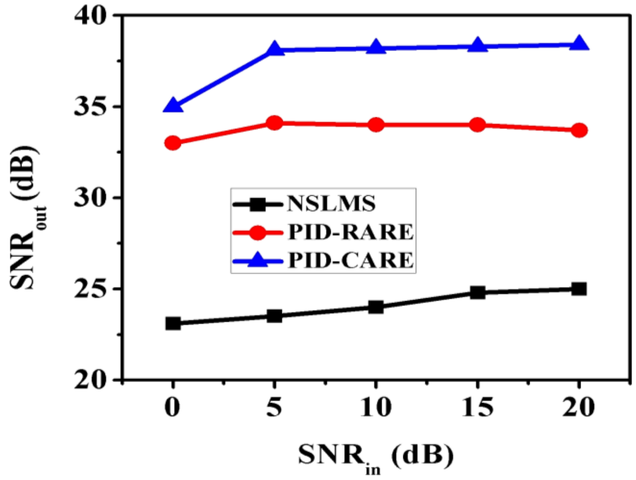
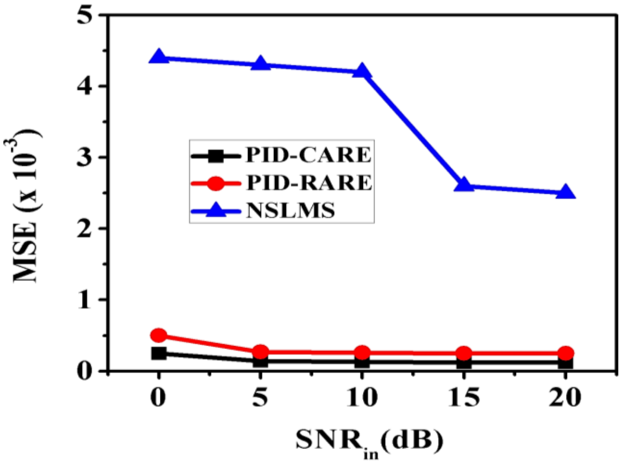
adaptive filter algorithms with four filter coefficients are considered. The ECG signal used in experimentation is taken from the Massachusetts Institute of Technology Beth Israel Hospital Arrhythmia (MIT-BIHA) database and is considered as the clean ECG signal [24-26]. The ECG signal is then contaminated with artificially generated PLI thereby generating a noisy input signal *d(n)* that is assumed to be received from the acquisition unit. This signal is assumed to be a primary input to the PLI canceller. The variation of SNR_{in} from 0 dB to 20 dB is considered. The results are obtained by averaging the readings observed from multiple runs.

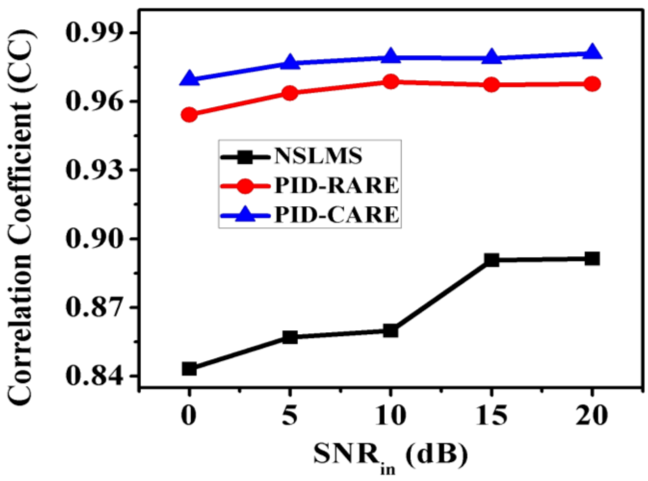
The performance comparison of PID-RARE and PID-CARE with NSLMS algorithm in terms of SNR_{out} is shown in *figure 5(a)*. It is observed from *figure 5(a)* that the PID-RARE provides an improvement of approximately 10dB in SNR_{out} over the NSLMS algorithm. Further, the PID-CARE provides superior performance as compared to NSLMS and PID-RARE with a performance improvement of approximately 15dB over NSLMS and around 4dB over PID-RARE almost over the complete range of SNR_{in}. It is to be noted that for the worst-case scenario SNR_{in} = 0dB, the values of SNRout are improved by 10dB and 12dB respectively in PID-RARE and PID-CARE over NSLMS adaptive algorithm. This proves the better reduction of noise in output ECG signal obtained by PID-RARE and PID-CARE as compared to NSLMS adaptive algorithm. The performance measure MSE which represent the mean square error between the clean input signal and the PLI canceller output signal are shown in *figure 5(b)*. It is observed that the NSLMS is performing poorly below SNR_{in}=10dB and for SNR_{in} greater than 10dB, there is a slight improvement whereas the PID-RARE and PID-CARE both are performing excellently for the full range of SNR_{in} considered. It is observed that the mean squared error values for PID-RARE and PID-CARE are significantly reduced by 10 times and 20 times respectively than NSLMS adaptive algorithm. The MSE values of 0.004323, 0.000281 and 0.00015 at SNRin = 10dB for NSLMS, PID-RARE and PID-CARE respectively, ensure that PID-RARE and PID-CARE are able to provide more cleaner signal.



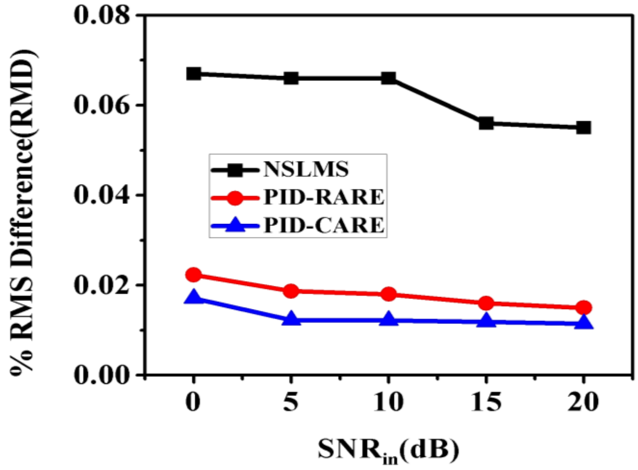
(a)



(b)



(c)



(d)

Figure 5. Performance comparison of PID-RARE, PID-CARE and NSLMS, in terms of (a) SNRout, (b) MSE, (c) CC and (d) RMD

Figure 5(c) shows that PID-RARE and PID–CARE both have shown significant improvement in value of correlation

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coefficient (CC) over NSLMS algorithm. The values of CC for NSLMS vary in the range of 0.84 to 0.89 for the value of SNRin ranging from 0dB to 20dB whereas for PID-RARE and PID-CARE they respectively vary from 0.95 to 0.96 and 0.97 to 0.98 for the range of SNRin from 0dB to 20dB. This indicates that PID-CARE and PID-RARE both provides cleaner output as compared to that of NSLMS. The Percentage Root Mean Square Difference (PRD) between the clean input and output signal are plotted with respect to SNRin ranging from 0dB to 20dB in Figure 5(d). RMSE is the root of the squared error difference between the denoised and original ECG signals. It is used for determining the variance between the output predicted by the denoising algorithm and the actual signal. PRD computes the total distortion present in the denoised signal. A lower PRD represents a better quality of the denoised signal. It is observed that the NSLMS has 6.7% PRD value at SNRin= 0dB whereas for PID-RARE and PID-CARE, the values at SNRin= 0dB are 2.2% and 1.5 % respectively. These values are decreasing with increase in SNRin and at 20dB, the values of PRD for NSLMS, PID-RARE and PID-CARE are 5.5%, 1.65% and 1.1% respectively. This indicates that the proposed algorithms are performing excellently well as compared to NSLMS in terms of PRD.

The rate of convergence which imply the number of samples required to achieve the minimum value of MSE, for various algorithms such as LMS, NLMS, SLMS, NSLMS, PID-RARE, and PID-CARE are plotted in Figure 6. The average minimum achievable values of MSE for respective algorithms are considered. It is observed that the PID-RARE and PID-CARE algorithms converge in a lesser amount of time as compared to all the other methods considered. Among the LMS, NLMS, SLMS, and NSLMS algorithms, the NSLMS algorithm takes more time to converge whereas the LMS converges much faster.

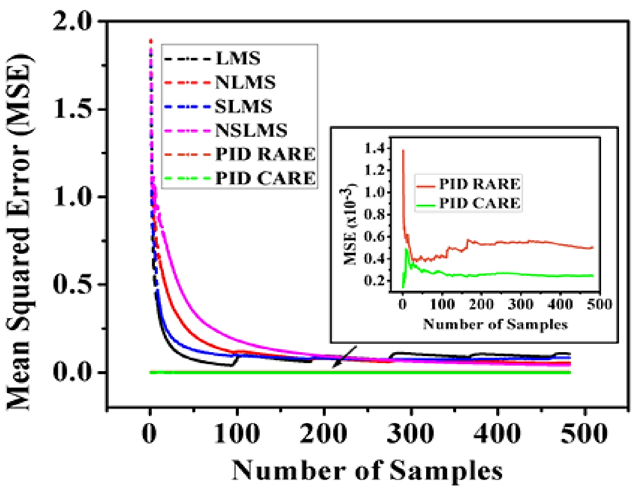

Figure 6. Convergence rate for LMS, NLMS, SLMS, NSLMS, PID-RARE and PID-CARE

Table 1. Convergence rate in terms of the number of samples required

S. No.	Algorithm	Average MSE Values	No. of samples required to converge
1.	Least Mean Square (LMS)	0.08223	44
2.	Normalized Least Mean Square (NLMS)	0.08262	167
3.	Signed Least Mean Square (SLMS)	0.08231	155
4.	Normalized Signed Least Mean Square (NSLMS)	0.08255	228
5.	PID-RARE	0.0005	02
6.	PID-CARE	0.00026	02

The MSE values to which the algorithms converge vary for different algorithms. A pop-up window in Figure 6 is plotted to give more insight to compare the convergence rate of PID-RARE and PID-CARE as the MSE values of both the algorithms are overlapping in the normal plot. From the pop-up window in Figure 6, it is observed that the PID-RARE and PID-CARE are converging within 02 number of samples to MSE values of approximately 0.0005 and 0.00026 respectively. *Table 1* depicts the average values of MSE to which the various algorithms converge and the approximate number of samples required for their convergence. From Table 1, it is observed that there is a significant difference between the convergence rate and the minimum achievable value of MSE for the proposed PID-RARE and PID-CARE algorithms as compared to the other algorithms. It is to be noted that the minimum achievable MSE value in PID-CARE is one-half of that in PID-RARE.

The algorithms are also verified for relative analysis of processing time for various algorithms as depicted in *figure 7*. The processing of 500 samples on a machine having 2.53 GHz i3 processor and 64-bit operating system is observed. The processing time mentioned here indicates the execution time required for processing 500 samples by the algorithm. The values for processing time for various algorithms; LMS, NLMS, SLMS, NSLMS, PID-RARE and PID-CARE are given in *figure 7*. Among the various algorithms, LMS has least processing time. The processing time of 0.03002 sec, 0.04972 sec and 0.3002 sec respectively are observed for NSLMS, PID-RARE and PID-CARE. It is observed that PID-RARE requires marginally more processing time as compared to that of LMS, NLMS, SLMS and NSLMS algorithms. The processing time for PID-CARE algorithm is observed to be significantly high. This is because in PID-CARE, in every iteration of NSLMS, the PID runs multiple epochs and the filter coefficients of NSLMS are updated in every iteration of PID whereas in PID-RARE, the filter coefficients of NSLMS are updated only once in each iteration of NSLMS though the PID runs multiple epochs in each iteration of NSLMS. The PID-CARE algorithm is observed to be six times slower than the PID-RARE algorithm. Owing to the overall performance results and discussion, PID-RARE algorithm is observed to have a better trade-off between the performance parameters.

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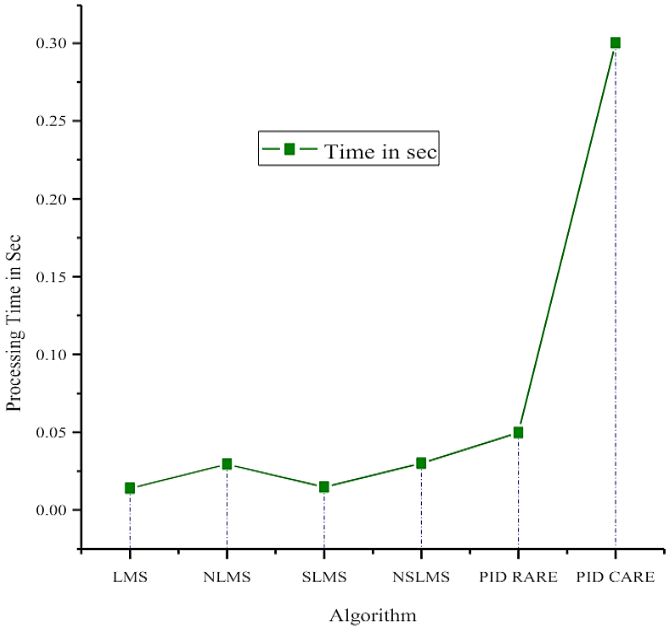

Figure 7. Processing time required by various algorithms for processing 500 samples at SNRin=0dB

To demonstrate the ability of the algorithms to adaptively track the desired biomedical signal from the noisy signal, the time domain waveform, FFT and PSD plots for NSLMS, PID-RARE and PID-CARE are plotted as shown in Figure 8 (a) to *figure 8* (e) for SNRin = 0dB. The time domain waveform of the clean signal obtained from the MIT-BIHA database with 500 numbers of samples interfered by a 50 Hz non-stationary PLI is considered as the input to the algorithms. From the time domain waveforms, it is observed that the PID-RARE and PID-CARE algorithms are providing more clean waveforms as compared to NSLMS algorithm.

Shubhojeet Chatterjee et.al. in [3] has provided a rigorous review of various noise removal techniques for ECG signals. The denoising performance on PLI for four algorithms viz. Empirical Mode Decomposition and Adaptive Switching Mean Filter (EMD-ASMF) [27], Dictionary Learning-Based Sparse Representation (DLSR) [28], Empirical Wavelet Transform (EWT) [29] and Empirical Mode Decomposition (EMD) [30] for MIT-BIHA dataset have been compared in terms of percentage-root-mean-square difference (PRD), and improvement in signal-to-noise ratio (SNRimp).

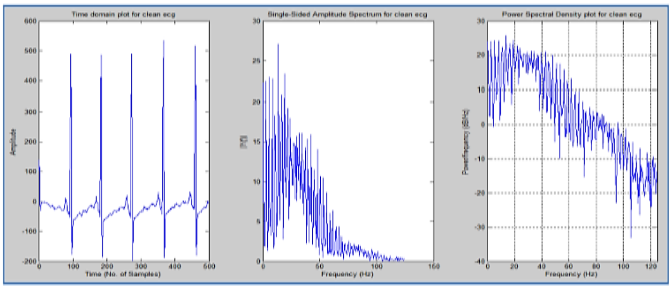

Figure 8 (a). Clean ECG in time domain, its FFT and PSD

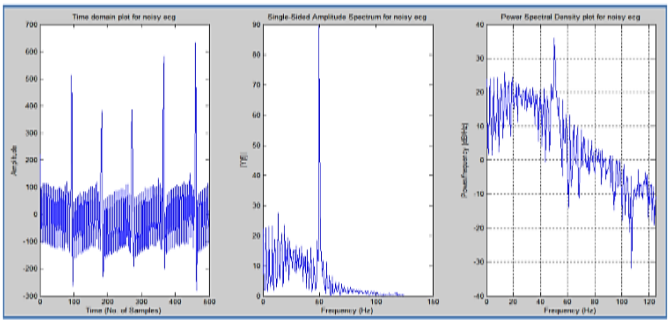

Figure 8 (b). Noisy ECG in time domain, its FFT and PSD for SNRin=0dB

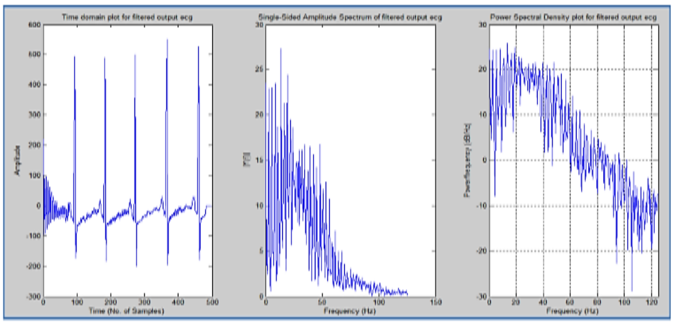

Figure 8 (c). ECG output of NSLMS Algorithm, its FFT and PSD plots for SNRin =0dB

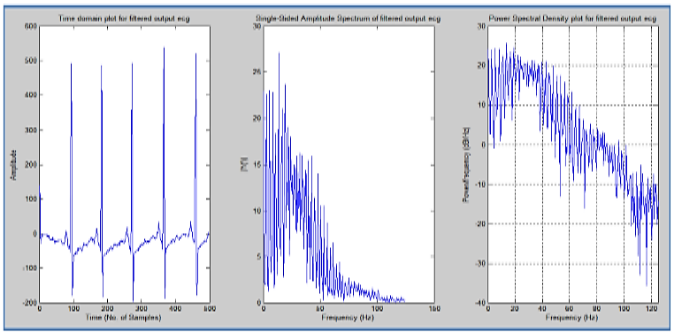

Figure 8 (d). ECG output of PID-RARE Algorithm, its FFT and PSD plots for SNRin =0dB

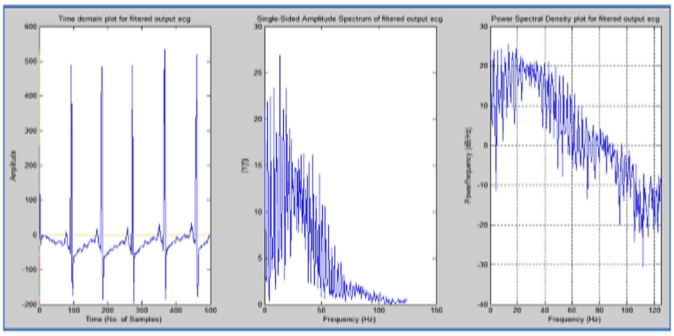

Figure 8 (e). ECG output of PID-RARE Algorithm, its FFT and PSD plots for SNRin =0dB

Table 2. Comparison of proposed algorithms with those provided in [3, 27-30] in terms of SNRimp and PRD

Sr. No.	Algorithm	SNRimp			PRD		
		SNRin = 0 dB	SNRin = 5 dB	SNRin = 10 dB	SNRin = 0 dB	SNRin = 5 dB	SNRin = 10 dB
1.	Empirical Mode Decomposition and Adaptive Switching Mean Filter (EMD-ASMF) [27]	14.50	13.5	10.5	18.84	11.88	9.44
2.	Dictionary Learning-Based Sparse Representation (DLSR) [28]	21.90	19.00	16.9	8.04	6.31	4.52
3.	Empirical Wavelet Transform (EWT) [29]	22.15	18.00	14.10	7.81	7.08	6.24
4.	Empirical Mode Decomposition (EMD) [30]	15.70	11.12	4.65	16.4	15.62	18.51
5.	Normalized Signed Least Mean Square (NSLMS)	23.26	18.46	13.9	6.7	6.6	6.6
6.	PID-RARE	33.02	29.52	24.69	2.2	1.9	1.8
7.	PID-CARE	35.33	33.06	28.22	1.7	1.2	1.2

SNRimp is the improvement in the SNR levels between the input and the output and PRD computes the total distortion present in the denoised signal. The comparison of PID-RARE and PID- CARE with those algorithms are presented in *table 2*. It is observed that both PID-RARE and PID-CARE performing excellently as compared to the other algorithms both in terms of SNRimp and PRD.

5. CONCLUSION

This paper proposed two novel techniques for adaptive PLI cancellation using PID controllers named PID-RARE and PID-CARE. The performance results of PID-RARE and PID-CARE obtained from the simulation in terms of SNRout, MSE, CC and PRD and compared with NSLMS which perform better amongst LMS, SLMS, NLMS and NSLMS. The PID-RARE and PID-CARE have shown performance improvement of approximately 10 dB and 15 dB respectively over NSLMS in terms of SNRout. The minimum value of MSE observed for NSLMS is 0.002775 whereas those for PID-RARE and PID-CARE are 0.00027 and 0.000134 which is 10 and 20 times less respectively as compared to NSLMS. Also, it is observed that PID-RARE and PID-CARE are converging within only 02 samples. These observations indicate that the PID-RARE and PID-CARE are performing excellently as compared to all the other adaptive algorithms. The performance comparison in terms of SNRimp and PRD with other algorithms viz. EMD-ASMF, DLSR, EWT and EMD shows that PID-RARE and PID-CARE are out performing over the others. However, these improvements in the performance are at the cost of higher execution time required for processing the samples. Out of the two proposed methods, PID-CARE performs relatively better in terms of all the evaluation parameters than PID-RARE however at the cost of higher execution time. Among PID-RARE and PID-CARE, the PID-RARE has lower execution time which is also comparable with that of NSLMS. Owing to the overall performance results, PID-RARE algorithm is observed to have a better trade-off between the performance parameters. The outperformance of the proposed algorithms over the others in terms of major of the parameters indicates that the proposed algorithms can be a strong contender to be used as a pre-processing step before biomedical signal processing. Though, the proposed algorithms have shown excellent performance for PLI cancellation, their effectiveness in realistic scenario is to be verified by experimenting for different types of noises that distort the biomedical signals.

REFERENCES

[1] A. K. Ziarani, Adalbert Konrad, A Nonlinear Adaptive Method of Elimination of Power Line Interference in ECG Signals, IEEE Transaction on Biomedical Engineering 2002, 49, (6), pp. 540 – 547.

[2] Ider, Y. Ziya, M. C. Saki, and H. Alper Guçer. "Removal of power line interference in signal-averaged electrocardiography systems." IEEE Transactions on Biomedical Engineering 1995, 42 (7), 731-735.

[3] Shubhojeet Chatterjee; Rini Smita Thakur; Ram Narayan Yadav; Lalita Gupta; Deepak Kumar Raghuvanshi, Review of noise removal techniques in ECG signals. IET Signal Process., 2020, Vol. 14 Issue 9, pp. 569-590.

[4] Mir, H.Y.; Singh, O., Powerline interference reduction in ECG signals using variable notch filter designed via variational mode decomposition. Analog Integr Circ Sig Process, 2024, 317–328.

[5] Chen B.; Li Y.; Cao X.; Sun W., & He W., Removal of power line interference from ECG signals using adaptive notch filters of sharp resolution. IEEE access 2019, Vol. 7, 150667–150676.

[6] Mathews, V. John. "Performance Analysis of Adaptive Filters Equipped with the Dual Sign Algorithm." IEEE Transactions on Signal Processing 1991, 39(1).

[7] Palatnik, Eugene S. "Adaptive filter for electrical supply line noise." U.S. Patent No. 5,768,166, 1998.

[8] Martinek, Radek, et al. "Adaptive noise suppression in voice communication using a neuro-fuzzy inference system, IEEE 38th International Conference on Telecommunications and Signal Processing (TSP), 2015.

[9] Shengqian, M., Guowei, X., Zhifeng, M., Shuping, W., & Manhong, F., Research on adaptive noise canceller of an improvement LMS algorithm. IEEE International Conference on Electronics, Communications and Control (ICECC) September 2011, 1611-1614.

[10] B. Bhaskara Rao; B. Prabhakara Rao, Power line interference cancellation from ECG using proportionate normalised least mean square sub-band adaptive algorithms, International Journal of Biomedical Engineering and Technology 2022 Vol.38 No.3.

[11] D. Sharma, R. Kaur, G. Singh, A Comparative Analysis of Adaptive IIR Filtering Techniques using Labview, International Journal of Hybrid Information Technology 2015, 8 (8), 289-302.

[12] Q. Xue, Y. Hu, Neural network based adaptive matched filtering for QRS detection, IEEE Trans. on Biomed. Eng. 1992, 39 (4), 317-329.

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[13] Arash Rasti-Meymandi, Aboozar Ghaffari, A deep learning-based framework For ECG signal denoising based on stacked cardiac cycle tensor, Biomedical Signal Processing and Control 2022, 71, Part B, pp.

[14] Huyang Peng, Xiaohan Chang, Zhenjie Yao, Donglin Shi, Yongrui Chen, A deep learning framework for ECG denoising and classification, Biomedical Signal Processing and Control 2024, 94, pp.

[15] Zhao Zhidong, Ma Chan, A Novel Cancellation Method of Power Line Interference in ECG Signal Based on EMD and Adaptive Filter, 11th IEEE Int. Conf. on Comm. Tech., Hangzhou, China 2008, 517-520

[16] M. Suchethaa, N. Kumaravel, Empirical mode decomposition-based filtering techniques for powerline interference reduction in electrocardiogram using various adaptive structures and subtraction methods, Elsevier journal of Biomed. Signal Processing and Control 2013, 08 (6), 575– 585.

[17] Martina Ladrova, Radek Martinek, Rene Jaros, Power Line Interference Elimination in ECG Signals, International Journal of Biomimetics, Biomaterials and Biomedical Engineering 2019, 41, 105-115.

[18] Dwivedi, A. K., Ranjan, H., Menon, A., & Periasamy, P., Noise reduction in ECG signal using combined ensemble empirical mode decomposition method with stationary wavelet transform. Circuits, Systems, and Signal Processing 2021, 40(2), 827–844.

[19] J. Mateo, E.M. Sánchez-Morla, J.L. Santos, A new method for removal of power line interference in ECG and EEG recordings, Elsevier Journal of Computers and Electrical Engineering 2015, 45, 235-248.

[20] Mohammed Mujahid, Ulla Faiz, Azzedine Zerguine, Syed Muhammad Asad, Khalid Mahmood, Tracking MSE Performance Analysis of the ϵ−NSLMS Algorithm, Proc. Int. Conf. on Comm., Sig. Proc. and their Appl., 17-19 Feb. 2015, Sharjah, United Arab Emirates.

[21] Rishi Raj Sharma, Ram Bilas Pachori, Baseline wander and power line interference removal from ECG signals using eigen value decomposition, Elsevier journal of Biomedical Signal Processing and Control 2018, 45, 33–49.

[22] Amit Singhal, Pushpendra Singh, Binish Fatimahc, Ram Bilas Pachori, An efficient removal of power-line interference and baseline wander from ECG signals by employing Fourier decomposition technique, Elsevier journal of Biomedical Signal Processing and Control 2020, 57, 101741-101741.

[23] P. Singh, S.D. Joshi, R.K. Patney, K. Saha, The Fourier decomposition method for nonlinear and non-stationary time series analysis, Proc. R. Soc. Lond. A: Math. Phys. Eng. Sci. 2017, 473 (2199), 1–27

[24] Moody GB, Mark RG. The impact of the MIT-BIH Arrhythmia Database. IEEE Eng in Med and Biol 2001, 20(3), 45-50.

[25] Goldberger, A., et al. "PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. Circulation [Online] 2000. 101 (23), e215–e220.

[26] MIT-BIH Arrhythmia Database 1.0.0. Available online: https://physionet.org/content/mitdb/1.0.0/100.atr

[27] Rakshit, M., Das, S., An efficient ECG denoising methodology using empirical mode decomposition and adaptive switching mean filter, Biomed. Signal Process. Control 2018, 40, 140–148.

[28] Rakshit, M., Das, S., Hybrid approach for ECG signal enhancement using dictionary learning-based sparse representation, IET Sci. Meas. Technol. 2019, 13 (3), 381–39.

[29] Singh, O., Sunkaria, R.K., ECG signal denoising via empirical wavelet transform, Australasian Physical & Engineering Sciences in Medicine 2017, 40 (1), 219–229.

[30] Huang, N.E., Shen, Z., Long, S.R., The empirical mode decomposition and the Hubert spectrum for nonlinear and non-stationary time series analysis, Proc. R. Soc. A, Math. Phys. Eng. Sci. 1998, 454, pp. 903–995.