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A New Fixed Point Noise Cancellation Method for Suppressing Power Line Interference in Electrocardiogram Signals

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***Abstract*—In this article, a new fixed point Leaky Sign Regressor Least Mean Mixed Norm (LSRLMMN) powered adaptive noise cancellation technique is being used for eliminating the Power Line Interference (PLI) noise embedded in the ElectroCardioGram (ECG) signal. The fixed point LSRLMMN powered noise cancellation technique used in this article has been completely quantized. The intention for the extensive quantization study and modeling approach was with a view to the physical integrated circuit implementation. All the modeling and simulation studies were carried out at the bit-level with various loss of precision schemes to ensure compliance with the set specification. The filter coefficients and all the data paths are quantized in order to establish at a high-level behavioral level of the parameters for a decreased complexity in integrated circuit implementation.**

***Keywords*—ECG, LSRLMMN, PLI.**

I. Introduction

Several methodologies are reported in the open literature for the elimination of PLI noise present in ECG signals. A new methodology, which was based on the method of Fourier decomposition was proposed to suppress both PLI and baseline wander interference simultaneously in ECG signals [1]. A novel algorithm comprising of detection, estimation, and filtering was implemented to suppress the PLI noise in ECG signals [2]. In [3], it was shown that the proposed improved variational mode decomposition technique performs better than the traditional variational mode decomposition technique for the cancellation of various artifacts including PLI noise in ECG signals.

A new technique to cancel both PLI and baseline wander interference in ECG signals utilizing a mixture of Empirical Mode Decomposition (EMD) and Empirical Wavelet Transform (EWT) techniques was presented [4]. A comparison of discrete wavelet transform, EMD, Kalman filter, and Kalman filter smoother for the removal of PLI noise in ECG signals showed that Kalman filter smoother method gives better performance than the former three methods [5]. On the other hand, the performance analysis of single stage and multistage noise cancellation techniques using a total of eight adaptive algorithms was analyzed in eliminating the 60-Hz PLI noise and three other noises embedded in the ECG signal [6].

The MSE behavior of the Leaky Least Mean Square (LLMS) adaptive algorithm has been studied [7], [8]. Additionally, the step size upper bounds of the LLMS algorithm are derived [7], [8]. The transient analysis of the Leaky Least Mean Fourth (LLMF) algorithm has been performed [9], [10]. Additionally, the step size upper bounds of the LLMF algorithm have been derived [9], [10]. The Leaky Least Mean Mixed Norm (LLMMN) algorithm is a mixture of the LLMS and LLMF algorithms. The transient analysis of the LLMMN algorithm was performed [11]. Additionally, the step size upper bounds of the LLMMN algorithm was derived [11]. A new fixed point Leaky Sign Regressor Least Mean Square (LSRLMS) powered noise cancellation technique was proposed for eliminating the 60-Hz PLI noise embedded in the ECG signal [12]. Additionally, the step size upper bound of the LSRLMS algorithm was derived [12]. In this article, a new fixed point Leaky Sign Regressor Least Mean Mixed Norm (LSRLMMN) powered noise cancellation technique is proposed for the removal of 60-Hz PLI noise present in the ECG signal. Additionally, the step size upper bound of the LSRLMMN algorithm has been obtained.

II. Stability Bound of the LSRLMMN algorithm

The proposed LSRLMMN algorithm is used in the fixed point noise cancellation technique described in [12], [13]. The LSRLMMN algorithm is a mixture of the LSRLMS and Leaky Sign Regressor Least Mean Fourth (LSRLMF) algorithms as long as the mixing variable Δ is in the range of $0 < \Delta < 1$. The LSRLMMN algorithm becomes the LSRLMF and LSRLMS algorithms as the mixing variable becomes 0 and 1, respectively. The update equation for the filter coefficients of the LSRLMMN algorithm is described by:

$$\mathbf{c}_i = (1-\epsilon\beta)\mathbf{c}_{i-1} + \epsilon \,\mathrm{sign}[\mathbf{x}_i]^{\mathrm{T}} e_i[\Delta + \bar{\Delta} e_i^2], \tag{1}$$

where $\mathbf{c}_i$ are the filter coefficients, ϵ is the filter step size, β is the leakage variable, $\mathbf{x}_i$ is the secondary input, Δ is the mixing variable, $\bar{\Delta} = 1 - \Delta$, all these variables are quantized. The ECG signal e_i, which is expected to be clean from 60-Hz PLI noise is also quantized.

Subtracting Equation (1) from $\mathbf{c}^{\mathrm{o}}$, the optimal filter coefficients vector, we have

$$\begin{aligned}\widetilde{\mathbf{c}}_i \;&=\; (1-\epsilon\beta)\widetilde{\mathbf{c}}_{i-1} - \epsilon\Delta \,\mathrm{sign}[\mathbf{x}_i]^{\mathrm{T}} e_i - \epsilon\bar{\Delta}\,\mathrm{sign}[\mathbf{x}_i]^{\mathrm{T}} e_i^3 \\ &\quad + \epsilon\beta\mathbf{c}^{\mathrm{o}},\end{aligned} \tag{2}$$

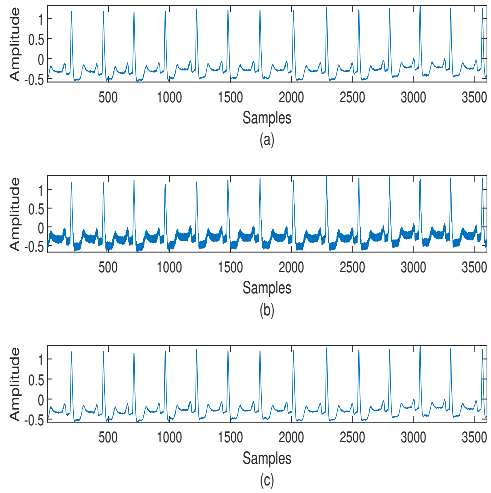

Fig. 1. (a) Clean ECG signal, (b) ECG signal contaminated with 60-Hz PLI noise, and (c) ECG signal from floating point filtering technique using the LSRLMMN algorithm.

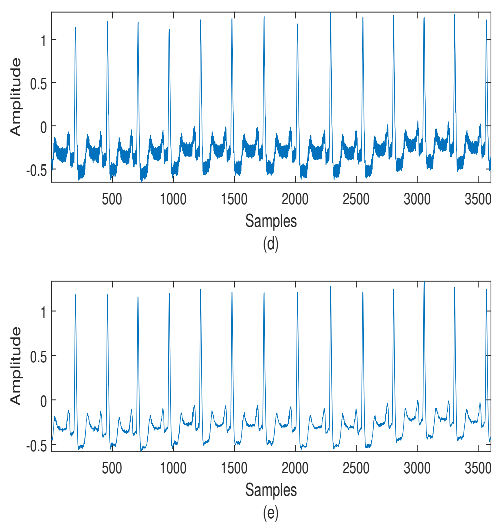

Fig. 2. (d) ECG signal from truncate quantization method using the LSRLMMN algorithm and (e) ECG signal from round quantization method using the LSRLMMN algorithm.

where the filter coefficients error vector $\widetilde{\mathbf{c}}_i = \mathbf{c}^{\mathrm{o}} - \mathbf{c}_i$. By applying the expectation operator on Equation (2) we get

$$\begin{aligned} \mathrm{E}[\widetilde{\mathbf{c}}_i] &= (1-\epsilon\beta)\mathrm{E}[\widetilde{\mathbf{c}}_{i-1}] - \epsilon\Delta \mathrm{E}\left[\operatorname{sign}[\mathbf{x}_i]^{\mathrm{T}} e_i\right] \\ &\quad -\epsilon\bar{\Delta}\mathrm{E}\left[\operatorname{sign}[\mathbf{x}_i]^{\mathrm{T}} e_i^3\right] + \epsilon\beta\mathbf{c}^o. \end{aligned} \tag{3}$$

We have from [14],

$$\mathrm{E}\left[\operatorname{sign}[\mathbf{x}_i]^{\mathrm{T}} e_i\right] = \sqrt{\frac{2}{\pi\sigma_x^2}}\mathbf{R}\mathrm{E}[\widetilde{\mathbf{c}}_{i-1}], \tag{4}$$

$$\mathrm{E}\left[\operatorname{sign}[\mathbf{x}_i]^{\mathrm{T}} e_i^3\right] = 3\sqrt{\frac{2}{\pi\sigma_x^2}}\sigma_e^2\mathbf{R}\mathrm{E}[\widetilde{\mathbf{c}}_{i-1}], \tag{5}$$

where σ_x^2 is the input data variance, σ_e^2 is the variance of the estimation error, and $\mathbf{R} = \mathrm{E}[\mathbf{x}_i^{\mathrm{T}}\mathbf{x}_i]$ is the input data autocorrelation matrix. By using (4) and (5) in (3),

$$\begin{aligned} \mathrm{E}[\widetilde{\mathbf{c}}_i] &= \left[\mathrm{I} - \epsilon\beta - \epsilon\Delta\sqrt{\frac{2}{\pi\sigma_x^2}}\mathbf{R} - 3\epsilon\bar{\Delta}\sqrt{\frac{2}{\pi\sigma_x^2}}\sigma_e^2\mathbf{R}\right] \times \\ &\quad \mathrm{E}[\widetilde{\mathbf{c}}_{i-1}] + \epsilon\beta\mathbf{c}^o. \end{aligned} \tag{6}$$

From (6), it can be shown that the mean performance of the filter coefficients error vector converges to 0 for the step size upper bound given by:

$$0 < \epsilon < \frac{2\sqrt{\pi\sigma_x^2}}{\beta\sqrt{\pi\sigma_x^2} + \sqrt{2}\Delta\lambda_{\max} + 3\sqrt{2}\bar{\Delta}\sigma_e^2\lambda_{\max}}, \tag{7}$$

where $\lambda_{\max}$ is the largest eigenvalue of $\mathbf{R}$. The step size upper bounds of the LSRLMF and LSRLMS algorithms can be obtained from (7) by equating Δ as zero and one, respectively, as given here:

$$0 < \epsilon_{\mathrm{LSRLMF}} < \frac{2\sqrt{\pi\sigma_x^2}}{\beta\sqrt{\pi\sigma_x^2} + 3\sqrt{2}\sigma_e^2\lambda_{\max}}, \tag{8}$$

$$0 < \epsilon_{\mathrm{LSRLMS}} < \frac{2\sqrt{\pi\sigma_x^2}}{\beta\sqrt{\pi\sigma_x^2} + \sqrt{2}\lambda_{\max}}. \tag{9}$$

Note that the expression for the step size upper bound of the LSRLMS algorithm in (9) is exactly the same as that derived in [12].

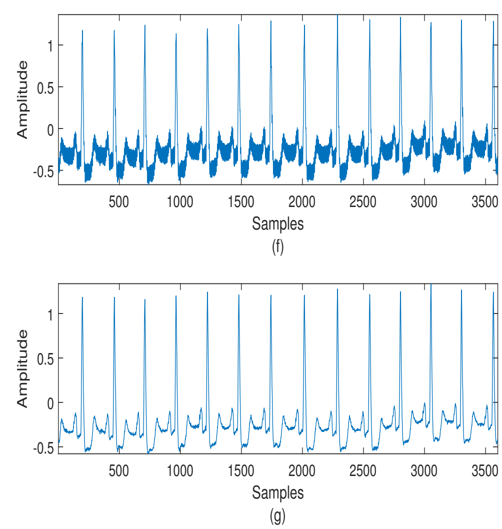

Fig. 3. (f) ECG signal from round-to-zero quantization method using the LSRLMMN algorithm and (g) ECG signal from convergent quantization method using the LSRLMMN algorithm.

III. Simulation Results

We have taken 3600 samples of the noise free ECG signal downloaded from the MIT-BIH Arrhythmia Database Recording number 105 [15], and it was contaminated using 3600 samples of artificial PLI noise having an amplitude of 100 mV, a frequency of 60-Hz, and a sampling frequency of 360-Hz. The filter length has been set at $N = 5$, the iteration count has been set at $I = 10$, the step size has been set at

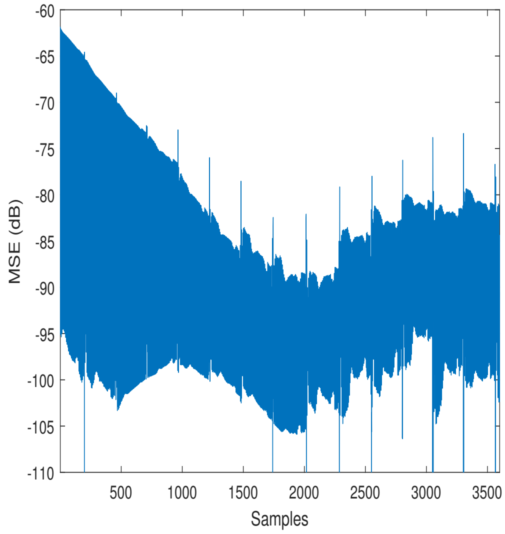

Fig. 4. MSE from floating point filtering technique using the LSRLMMN algorithm.

$\epsilon = 0.01$, the leakage variable has been set at $\beta = 0.002$, and the mixing variable has been set at $\Delta = 0.5$.

The noise free ECG signal is depicted in Figure 1(a), the ECG signal contaminated using 60-Hz PLI noise is depicted in Figure 1(b), and the ECG signal from the floating point filtering technique using the LSRLMMN algorithm is depicted in Figure 1(c). As observed in Figure 1(c), the floating point filtering technique using the LSRLMMN algorithm is found to be successful in suppressing the 60-Hz PLI noise in the contaminated ECG signal.

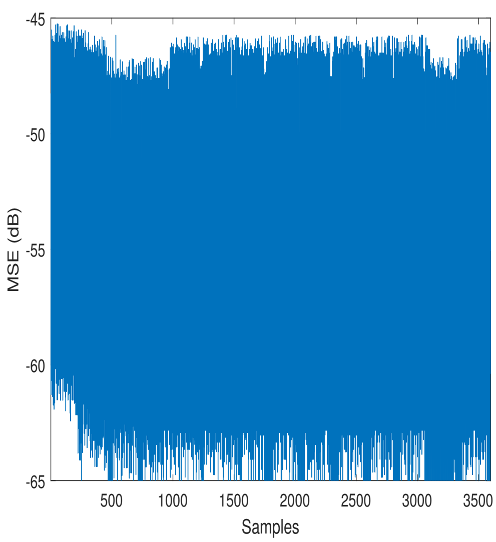

Fig. 5. MSE from truncate quantization method using the LSRLMMN algorithm.

The ECG signals from the truncate, round, round-to-zero, and convergent quantization techniques using the LSRLMMN algorithm are depicted in Figures 2(d), 2(e), 3(f), and 3(g), respectively. As observed from Figures 2(d) and 3(f), the

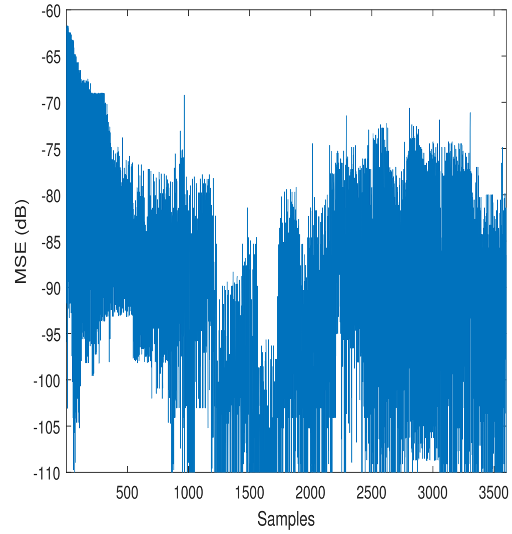

Fig. 6. MSE from round quantization method using the LSRLMMN algorithm.

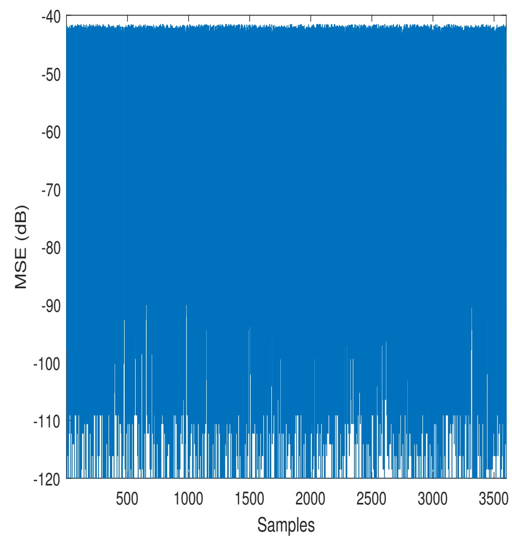

Fig. 7. MSE from round-to-zero quantization method using the LSRLMMN algorithm.

truncate and round-to-zero quantization techniques using the LSRLMMN algorithm are unsuccessful in the suppression of 60-Hz PLI noise in the contaminated ECG signal, respectively. As observed from Figures 2(e) and 3(g), the ECG signals from the round and convergent quantization techniques using the LSRLMMN algorithm are found to be similar in comparison to the ECG signal from the floating point filtering technique using the LSRLMMN algorithm as depicted in Figure 1(c). This is also evident from the SNR calculated after the floating point, round, and convergent quantization techniques, which is found to be 14.09 dB, 13.97 dB, and 13.98 dB, respectively.

As can be seen from Figure 5, the MSE behavior of the truncate filtering technique using the LSRLMMN algorithm is inferior as compared to the other three types of quantization

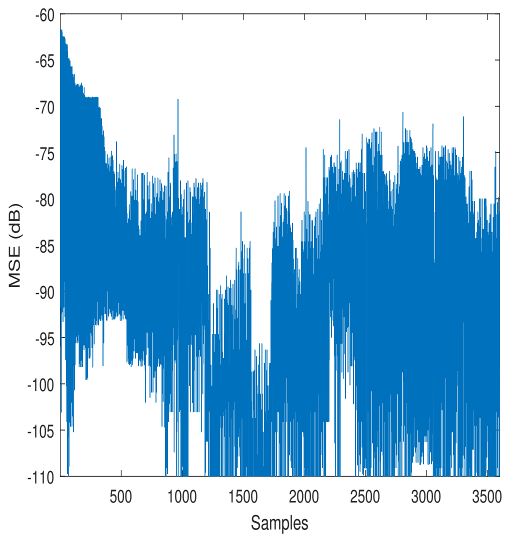

Fig. 8. MSE from convergent quantization method using the LSRLMMN algorithm.

methods, which can also be seen from the quantized ECG signal from the employment of this method as depicted in Figure 2(d). As evident from Figure 7, the MSE behavior of the round-to-zero filtering technique using the LSRLMMN algorithm is also inferior as compared to the other two types of quantization methods, viz. round and convergent, which can also be seen in the quantized ECG signal from the employment of this method as depicted in Figure 3(f). The MSE behaviors of the floating point, round, and convergent quantization techniques using the LSRLMMN algorithm are found to be similar as depicted in Figures 4, 6, and 8, which is also evident in the ECG signals from the application of these three methods as depicted in Figures 1(c), 2(e), and 3(g), respectively.

IV. Conclusions

The number of quantization bits needed for the primary input, secondary input, mixing variable, filter step size, leakage variable, adaptive filter output, filter coefficients, and purified ECG signal with respect to the fixed point LSRLMMN powered noise cancellation technique are determined to be 8-bits for the round and convergent quantization methods. Moreover, it is shown that the step size upper bound of the LSRLMMN algorithm reduces to the step size upper bounds of the LSRLMF and LSRLMS algorithms when Δ becomes zero and one, respectively.

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