A NEW APPROACH FOR REDUCTION OF BASELINE WANDER NOISE IN EMG SIGNAL

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ABSTRACT

Electromyogram (EMG) signals are usually affected by baseline wander noise in the signal acquisition stage due to movement of patient and electrode skin impedance variations. The elimination of noise in electromyogram signals is essential in medical applications for better diagnosing any neuromuscular diseases in Kinesiology. Usually, the least mean square algorithm-based adaptive noise cancellation procedure has limitations in minimizing the mean square error within the range of variation of filter coefficients. The least mean square with the firefly algorithm (LMS-FF) is suggested in designing an effective adaptive noise cancellation filter. EMG signals are taken from the Physionet database to test the performance of the proposed adaptive filter structure. The proposed LMS-FF algorithm associates the valuable properties of the two algorithms to restore the required signal time domain characteristics. The simulation results of the proposed method infer that the LMS-FF improving the signal-to-noise ratio up to 38 dB, and it is more reliable for the elimination of baseline wander noise in EMG signal than the conventional least mean square algorithm.

Keywords — Electromyogram, Kinesiology, firefly, ANC filter

I. INTRODUCTION

Electromyogram (EMG) signals are correlated with muscle events, and motor units produced bioelectrical potentials. The central nervous system controls the motor unit action potentials. The amplitude level of the EMG signal can range from 0 to 10 mV P-P, and with the dominant energy being in the range of 50 - 150 Hz. EMG signals are acquired and recorded to diagnose muscular disorders like myopathy, neuropathy in Kinesiology, and ergonomic studies in the workplace to assist in job risk analysis [5]. For research purposes, motion and gait analysis in robotics, sports-related training, and medicine, and product development, EMG signal analysis is required. Noises like baseline wandering noise, random noise, power line interference (PLI), motion artifact, electrode noise, and other biological signals (ECG,EOG) will corrupt EMG signals. In noise corrupted EMG signal, these noises occupy different frequency bands in the spectrum. One of the dominant noises in EMG signal is baseline wanders noise, and it presents at the low-frequency range. The baseline wanders noise correlates to the electromyogram signal because of the electrode movement, respiration, and skin-electrode interface. BLW noise can be observed after the electrodes are attached to the skin and represent an electrochemical imbalance at the electrode-skin interface. At the initial step of EMG signal recording to avoid baseline wanders, recommending a good electrode jelly for quick balance between skin and electrodes.

EMG signal processing is significant in the field of Electromyography and Kinesiology. Noise reduction from the collected EMG signal is the primary step in signal processing. According to the literature, many denoising techniques developed, such as high pass filter, notch filter, FIR filter, moving average filters, adaptive filters, DWT, support vector method, empirical model. Later on, due to the rapid growth in digital processors, A/D converters & digital filters, the accuracy in diagnosing disease, identifying the level of disorder, and other clinical related problems are solved. The digital filter with fixed filter coefficients is not appropriate for excision of noise in time-varying and non-stationary characterized biomedical signal processing. High pass digital filters are suitable for eliminating the wandering of EMG signal affected by respiration and are mainly observed at 0.10 Hz.
and 0.3 Hz. However, HPF is not appropriate for the preprocessing biological signals in all means[8]. From the literature to solve the difficulties related to denoising filters used in biomedical applications, adaptive filters show an excellent solution.

Moreover, many researchers suggested adaptive filters for noise reduction in electromyogram signal, signal feature extraction, and signal estimation in unknown and possibly time-varying physiological conditions. Adaptive filters are self-adjusting digital filters that can modify their filter coefficients under the error function measured by the adaptive algorithms. Adaptive noise cancellation filter shows the optimal solution at local minima but not appropriate for the global minimum requirement on multi-dimensional error surface. Usually, adaptive filter weights modify along with time-varying characteristics of input and noise signals. However, IIR adaptive structures, adaptive neural network structure, and polynomial adaptive filter structures face difficulty in global minimum and best cost function solutions. Somehow trends in gradient descent algorithms as recursive least square(RLS), normalized least mean squares(NLMS), variable step-size LMS(VSLMS), Sign-LMS, given optimal solution for adaptive noise cancellation filters in terms of convergence rate and mean square error. Unlike the gradient descent method, the performance of the bio-inspired optimization techniques provides the global minimum without performing a comprehensive search on the error surface. The combination of the least mean square algorithm and heuristic optimization algorithm aim at minimum mean square function, without depending on the filter structure, filter weights, and unknown noise signal characteristics. Therefore, these types of algorithms are capable of globally optimizing any class of adaptive filter structures [2]. Here, suggesting a firefly algorithm-based least means square algorithm (LMS-FF) reduces the low-frequency baseline wander noise in EMG signal and improves the performance of adaptive noise cancellation filters. The designed filter helpful for baseline wander noise reduction in EMG signals and enhances the diagnosis capability in neuromuscular disease; hence its time domain and frequency domain analysis performed.

II. MATERIAL & METHODS

This paper deals with the least mean square (LMS) algorithm-based adaptive noise cancellation method for denoising EMG signal related to the neuromuscular disorder called neuropathy and myopathy. Here, LMS algorithm limitations are formulated as an optimization problem for tuning filter coefficients. With the proposed method, the LMS algorithm can update its weights until error minimization using the firefly algorithm.

Least-Mean-Square algorithm

The adaptive filters with least mean square (LMS) algorithm utilized in echo cancellation in telecommunication systems, unknown signal or noise characteristics estimation, antenna beamforming, channel prediction in communication systems, elimination of foetal ECG noise from mother ECG signal, etc. Our ordered EMG signal filtering process focuses on the LMS algorithm because of its simple design, less computational complexity, and stability in the performance of an adaptive algorithm. Each iteration of adaptive algorithm entails three steps: obtain filter output(Y(n)), error estimation(e(n)), and weight adaptation(w(n))[8]. Filter Weight correction and error evaluation depicted[16] in equations (1) and (2).

\[ e(n) = D(n) - Y(n)^*w(n) \]  
\[ w(n+1) = w(n) + 2\mu e(n)D(n) \]

Wherever D(n) is the desired input signal correlated to noise. On of the tuning parameter in LMS algorithm is step size(\(\mu\)) that normalizes the convergence rate. In the noise reduction process the LMS algorithm has some limitations in selecting step size (\(\mu\)) and flexibility in the variation of filter coefficients for error minimization [5].

Firefly Algorithm

Firefly algorithm is one of the popular bio inspired swarm-based algorithm. The firefly algorithm is motivated by the fireflies, a sort of nature bug. Most of the fireflies produce brief and rhythmic flashes. The frequency of flashes is also unique for a specific form. Fireflies use their beauty of chemical light to interact, search and alarm their enemies. Inverse-square law defines the light intensity (I) at a certain distance (r) from a light source. Light intensity, therefore, decreases as compared to increases in distance. Consequently, as distance increases, the air consumes light, and its intensity falls and becomes smaller. Despite these reasons, most fireflies can be seen from a slight distance of a few hundred meters, and interacting with the fireflies is typically a sufficient distance. Thus, flashing lights can be introduced as fitness or objective functions to optimize, thus proposing a different firefly algorithm influenced by population-based nature.
A light intensity $I(r)$ at distance $r$ from a light source $(l_s)$ calculated by Eq. (3)

$$I(r) = \frac{l_s}{r^2}$$  

(3)

Light absorbed in an atmosphere with a constant light absorption coefficient $\gamma \in (0, \infty)$, it can be expressed with Gaussian by Eq. (4)

$$B(r) = B_0 e^{-\gamma r^2}$$  

(4)

Where $\gamma$ is firefly attractiveness at $r$ distance and $B_0$ is firefly attractiveness at $r = 0$.

Let $i$ and $j$ are two fireflies, and their respective locations are $X_i(x_i, y_i)$ and $X_j(x_j, y_j)$. Then the Euclidean distance ($r_{ij}$) between these two fireflies are determined by Eq. (5)

$$r_{ij} = \|X_i - X_j\| = \sqrt{(x_i - x_j)^2 - (y_i - y_j)^2}$$  

(5)

Therefore, the current location ($X_i$) of the $i^{th}$ firefly, which is less bright, moves towards brighter firefly $j$ by equation Eq. (6)

$$x_i = x_i + B_0 e^{-\gamma r_{ij}^2}(X_j - X_i) + \alpha \varepsilon_i$$

(6)

Where $\alpha, \varepsilon_i$ is random variable lie between 0 to 1.

**Proposed structure**

Many state-of-art algorithms developed to overwhelm the optimization problem in the LMS algorithm. However, all these methods offer less convergence speed because of limitations in the variation of step size ($\mu$). So we have introduced one of the bio-inspired optimization algorithms: the firefly algorithm, along with the least mean square (LMS-FF), to depreciate the mean square error.

The proposed adaptive filter's basic structure is shown in Figure 1. The importance of this method is to improve the convergence rate and searching ability of error in adaptive noise cancellation filters.

![Fig. 1 Block diagram of proposed adaptive filter structure](image)

Here the noise(S(n)) is examined as the low-frequency baseline wander noise[8]. The input EMG signal and noise signals are uncorrelated and additive. The error signal is estimated as the difference between the reference signal and output signal. As per the estimation of error in each iteration the filter weights are updated regularly until noise gets canceled.

**Data set used**

The three EMG signals used for this experiment are EMG Healthy, EMG Myopathy, and EMG Neuropathy and taken from the EMG database of Physionet. These EMG signals collected using 25 mm needle electrodes are placed at the anterior tibialis muscle of a patient and instructed that patient bend their foot gently towards the upper ankle surface then relaxed with a 4 kHz sampling rate. From 44 years old male with no background of neuromuscular disease, the EMG Healthy signal was collected. The remaining EMG Myopathy and EMG Neuropathy signals are from 57 years and 62 years age males with myopathy disease with a long history of...
polymyositis and chronic low back pain and neuropathy disease [11]. The baseline wanders noise corrupts the test signals, and that noise signal MATLAB code generated.

III. RESULTS AND DISCUSSION

If the adaptive filter perfectly works for baseline wander noise reduction, the filter response resembles the input EMG signal. An adaptive filter with LMS and LMS_FF algorithms simulation results for EMG_Myopathy signal observed in Fig. 2.

After many trial iterations, the μ value was fixed to 0.35 for the LMS algorithm. We have evaluated SNR, RMS, and MA parameters for performance analysis of adaptive filter with LMS_PSO and LMS_FF optimization algorithm [6]. Signal to noise ratio (SNR) is the ratio of raw EMG signal energy to the filtered signal energy.

![Fig. 2 Reduction of baseline wander noise in EMG signal related to myopathy disorder. i) Input EMG_Myopathy signal ii) Baseline wander noise corrupted EMG signal iii) adaptive filter LMS algorithm output iv) adaptive filter with LMS_Firefly algorithm output.](image)

The root-mean-square (RMS) value and mean absolute (MA) values measure the signal amplitude as a time-domain variable. “The RMS value represents the square root of the average power of the EMG signal whereas the MA value represents the area under the rectified EMG signal[9] [2]”. Table 1 quantitatively summarizing the parameters of baseline wander noise eliminated EMG signal using an adaptive filter with LMS, RLS, and LMS_FF algorithms.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Performance Analysis</th>
<th>Performance Analysis</th>
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<tbody>
<tr>
<td></td>
<td>SNR(dB)</td>
<td>RMS</td>
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<tr>
<td><strong>EMG _ Healthy signal</strong></td>
<td></td>
<td></td>
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<tr>
<td>LMS</td>
<td>20.2</td>
<td>6.13E-02</td>
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<tr>
<td>RLS</td>
<td>34.6</td>
<td>5.12E-02</td>
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<tr>
<td>LMS-FF</td>
<td>57.14</td>
<td>1.76E-02</td>
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<tr>
<td><strong>EMG _ Myopathy signal</strong></td>
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<td></td>
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<tr>
<td>LMS</td>
<td>22.58</td>
<td>7.19E-02</td>
</tr>
<tr>
<td>RLS</td>
<td>35.5</td>
<td>6.18E-02</td>
</tr>
<tr>
<td>LMS-FF</td>
<td>58.2</td>
<td>2.18E-02</td>
</tr>
<tr>
<td><strong>EMG _ Neuropathy signal</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LMS</td>
<td>24.8</td>
<td>8.27E-02</td>
</tr>
</tbody>
</table>

Table 1: Performance comparison adaptive filter with LMS algorithms for baseline wander noise reduction in EMG signals.
The table 1 shows the parametric analysis of LMS algorithms in signal-to-noise ratio and energy distribution under amplitude variations as RMS and MA. It infers that the adaptive filter with the LMS-FF algorithm eliminates baseline noise better than the conventional LMS and RLS algorithms.

Depending on muscle contraction the amplitude of the EMG signal varies from 0 to 10 mV. The power density spectrum of the EMG signal ranges from 0 to 500 Hz and most dominant at 50 Hz to 150 Hz for most of the muscles[7][10]. Above these frequencies, the frequency components of the EMG signal have an amplitude less than one μV and are difficult to distinguish from the noise. Fig. 3 & Fig. 4 illustrate the performance of the LMS & LMS_FF algorithms in terms of power spectral density (PSD). With the observation of power spectrum it is evident that LMS-FF algorithm removing noise and retains original signal characteristics effectively.

![Fig. 3 Amplitude spectrum of the rectified LMS output signal.](image1)

![Fig. 4Amplitude spectrum of the rectified LMSW-FF output signal.](image2)

The vital characteristic of the adaptive filter is the convergence speed that determines how fast the filter capable of eliminating the noise. From Fig. 5, the convergence speed of the LMS-FF algorithms mentions the best cost function with the number of iterations.

![Fig. 5Convergence plot of LMS-Firefly algorithm](image3)

**IV. CONCLUSION**

The outcomes of the LMS with firefly algorithm –based adaptive noise cancellation method providing error minimization, high SNR and fast convergence rate. In this problem, the LMS_FF is designed to effectively denoise the baseline wander noise in EMG signals, comparatively analyzed for healthy, myopathy, and neuropathy-related EMG signals. The proposed LMS-FF algorithm achieves 38dB improvement in SNR and RMS, MA Parameters represents this method can preserve the EMG signal characteristics effectively after filtering process.

**REFERENCES**


12. V.V.K.D.V.Prasad, P. Siddaiah and B. PrabhakaraRao, Denoising of Biological Signals using Different Wavelet Based Methods and their Comparison, Asian Journal of Information Technology, vol. 7, no. 4, pp. 146-149, April 2008 ISSN: 1682-3915


