Combination of EEMD and Morphological Filtering for Baseline Wander Correction in EMG Signals

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Abstract This paper aims at proposing an effective method for Baseline Wander removal from the EMG signals. Ensemble Empirical Mode Decomposition (EEMD) Algorithm is first applied to the baseline corrupted EMG signals to decompose them into Intrinsic Mode Functions (IMFs). After this step, morphological filtering employing octagon-shaped structuring element has been applied to filter out each IMF. Finally, the results of the proposed filtering methodology are compared with those of EMD- and EEMD-based filtering methods. Simulation results report that the methodology used in this study has eliminated the baseline wander from EMG signals with minimal distortions.

Keywords EMG · Baseline wander · EEMD · Morphological filtering

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S.C. Satapathy et al. (eds.), *Proceedings of 2nd International Conference on Micro-Electronics, Electromagnetics and Telecommunications*,
Lecture Notes in Electrical Engineering 434, DOI 10.1007/978-981-10-4280-5_38

1 Introduction

Electromyogram (EMG) signal is an electrical (biomedical) signal which is emanated whenever the muscles contract and is controlled by the nervous system. Its acquisition is done by the placement of electrodes on the surface of skin or by inserting needle deep inside the muscles [1]. EMG signal proves to be useful for diagnosis and treatment of numerous neuromuscular diseases and fatigue in muscles. For clinical applications, the EMG signal is recorded at low contraction levels so that individual (MUAPs) can be distinguished. However due to reasons such as relative shaking of electrodes, wires with respect to muscles, bad cable fixation, variations found in skin potential which is induced by needle electrodes, the electrical drifts found in equipments used for acquisition; the baseline shifts from its electrical zero which is termed as 'Baseline Wander'. These baseline fluctuations can degrade the signal quality which affects the analysis both qualitatively and quantitatively; therefore its cancelation is required for effective diagnosis [2]. Various techniques have been implemented so far for the effective removal of baseline wander from EMG signal. Carreno et al. [3] proposed a method of filter design by estimating the spectral information of the baseline fluctuation and then a high pass filter was applied to deal with baseline fluctuation. Rampp et al. [4] used Discrete Wavelet Transform (DWT) for removing baseline artifact. It has been reliable in terms of pattern preservation and effectiveness but was found to be computationally intensive. Law et al. [5] applied an approach of nonlinear error modeling for baseline wander removal. It proved to be useful especially in the case when SNR is low. However, it worked only for burst or discrete periods of signal and was not applicable across a time signal universally. Pal et al. [6] proposed baseline removal approach by estimating the spectral information of baseline fluctuation and then utilizing this for designing a high pass butterworth filter. Vergallo et al. [7–9] discussed in their work the application of EMD approach on EEG signals. Verma et al. [10, 11] used morphological filtering with non-flat structuring elements for baseline correction in ECG signals. In the proposed work, an algorithm based on Ensemble Empirical Mode Decomposition (EEMD) along with morphological filtering is used for the effective removal of baseline wander with minimum signal distortion. EEMD overcomes the scale separation problem without introducing a subjective intermittence test and decomposes the EMG signal into IMFs plus a residual signal. Morphological filters are employed on the IMFs to eliminate the baseline noise and maintain the shape of original EMG signal. Signal-to-Noise Ratio (SNR) and Percentage Root-Mean-Square Error Difference (PRD %) have been selected as the two performance metrics for the evaluation and validation of the proposed methodology. These performance metrics also helps in comparing the proposed methodology with other techniques of baseline wander removal. The organization of the rest of the paper is as follows. Section 2 gives a detailed description of the proposed methodology. Section 3 discusses the experimental results and the conclusions are provided under Sect. 4.

2 Proposed Baseline Correction Approach

The proposed methodology aims to combine the EEMD algorithm followed by morphological filtering to eliminate the baseline wander from the corrupted EMG signal. First, the EMG signal undergoes decomposition via Ensemble Empirical Mode Decomposition (EEMD) which converts the multicomponent frequency signal into mono-component frequency signal components. These mono-component frequency signal components known as Intrinsic Mode Functions (IMFs) are then filtered by morphological filters. After that, the filtered IMFs are added together to get the reconstructed baseline removed EMG signal. At the end, the signal fidelity assessment is done by performance metrics SNR and PRD % respectively.

2.1 EEMD

The Empirical Mode Decomposition (EMD), designed especially for nonlinear and nonstationary signals, is a local, data-driven technique which decomposes the signal without any precedent premise about the signal. EMD breaks down a multifrequency component signal into nonoverlapping frequency spectrums called Intrinsic Mode Functions (IMFs) and a residual signal. The IMFs are mono-frequency components that follow two conditions:

- The difference between the number of extrema (including both the local maxima and minima) and zero crossings in the time-series must be not more than one.
- The mean value of the upper envelop (defined by maxima) and lower envelop (defined by minima) is zero through the entire time-series.

EMD being such a capable decomposition technique crops some annoying problems. The fundamental problem with the original EMD is the frequent occurrence of mode mixing, i.e., the detail related to one scale can appear in two different intrinsic modes. To discard the mode mixing problem, a new noise-assisted data analysis (NADA) method introduced by Huang et al. [12], the Ensemble EMD (EEMD), defines the true IMFs as the mean of an ensemble of trials, each consisting of the signal plus a white noise of finite amplitude. The procedural steps of EEMD Algorithm are shown in Fig. 1. The resultant IMFs, namely $c_{ij}(t)$ are averaged across trials to obtain the final IMFs, $c_i(t)$ as

$$c_i(t) = \frac{1}{N}\sum_{j=1}^{N} c_{ij}(t), \tag{1}$$

where, i is the IMF order, j denotes the trial index and N is the total number of trials.

	BEGIN
Step 1:	*Input:* Baseline Corrupted EMG signal.
Step 2:	*Process:* Add a white noise series to the corrupted EMG signal.
Step 3:	*Compute:* All Local Maxima and Minima.
Step 4:	*Compute:* Upper and Lower Envelopes through Cubic Spline function.
Step 5:	*Compute:* Mean of Upper and Lower Envelopes.
Step 6:	*Compute:* Difference by subtracting mean from the noisy signal.
Step 7:	*Process:* Check if the difference is an IMF.
Step 8:	*Compute:* Residue signal by subtracting difference from the noisy signal if it is an IMF otherwise repeat steps 1-7.
Step 9:	*Process:* Check if residue signal is a monotonic function.
Step 10:	*Process:* Repeat steps 1-9 again and again with different versions of noise each time.
Step 11:	*Compute:* Mean (Ensemble) of corresponding decomposed IMFs as the final true IMFs.
	END

Fig. 1 Procedural steps for EEMD algorithm

2.2 *Morphological Filter*

Morphological filtering signifies nonlinear transformation technique mainly used for locally altering the structural features of a signal using the basic applications of set theory. In this technique, each examined signal can be viewed as a set in Euclidean space and morphological filters are set operations that modify the graph of the signal and can provide a quantitative description of its geometrical shape. An important type of morphological transforms, i.e., hat transforms can be used for detailed extraction of signal. Proper selection of structuring element is a very important step for extracting the features from the original EMG signal. Also, the size of the structuring element should be selected with proper care as its inaccurate selection may deform the adjoining wave of the EMG signal [13]. In the proposed methodology, octagon-shaped structuring element of radius 3 as shown in Fig. 2 is chosen. Baseline wander which is an artifact of low frequency is being eliminated by the help of morphological operators that constitute both high pass and low pass filter characteristics. Therefore, the proposed methodology uses top-hat filtering and bottom-hat filtering for the effective removal of baseline drift. The respective expressions of top-hat transform and bottom-hat transform is given by

$$T_h = c_i - (c_i \circ b) \tag{2}$$

$$B_h = (c_i \bullet b) - c_i, \tag{3}$$

where, T_h and B_h represent top-hat and bottom-hat transforms, c_i represents the decomposed IMFs and b is the structuring element.

Top-hat filtering and bottom-hat filtering of the IMFs decomposed from the baseline distorted EMG signal is done which generates peaks and valleys

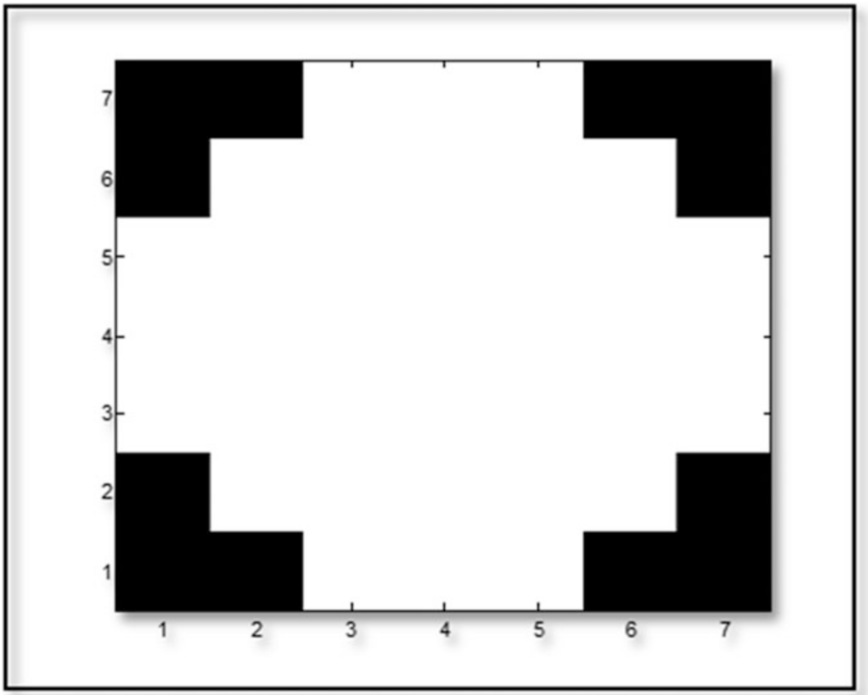

Fig. 2 Octagon structuring element of radius 3

respectively followed by subtraction of valleys from the peaks. This whole process is repeated for each IMF and after that the filtered IMFs are added to get the baseline removed EMG signal.

3 Results and Discussions

In the proposed methodology, the EMG signals are taken from The UCI Machine Learning Repository [14] including 10 normal and 10 aggressive physical actions that measure the human activity. During simulations, these EMG signals were first converted into column vector followed by the decomposition process using the EEMD Algorithm as discussed in the preceding section. After this, the decomposed IMFs were filtered using morphological filters and the filtered IMFs were reconstructed for the baseline wander removal. The decomposed IMFs using the EEMD Algorithm have been shown in Fig. 3.

The number of iterations and the noise parameter needs to be considered for applying EEMD Algorithm. Herein, ensemble number (NE) is selected 10. The noise parameter (Nstd), defined as the ratio of the standard deviation of noise to the

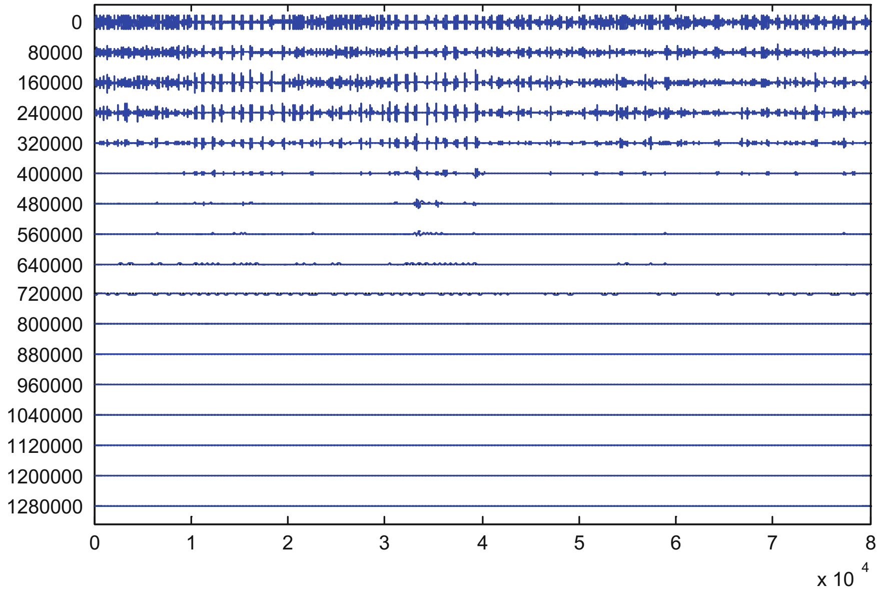

Fig. 3 IMFs obtained from EEMD algorithm

standard deviation of the signal power, is selected to be 0.2. An ‘octagon’ shaped structuring element with radius of 3 is chosen which gives the best result. The results of the baseline corrected EMG signals using the proposed methodology along with the outputs of the other techniques (EMD and EEMD) are shown in Fig. 4. Figure 4a shows an original EMG signal (Pushing4) which is already baseline drifted. It can be seen from Fig. 4b and c that the baseline corrected signals using the EMD and EEMD techniques are almost the same that is the exact replica of the original signal as the signal properties remains the same. But there is an improvement in the output of the proposed methodology over the other two methods. In this, since morphological filtering employing top-hat filtering and bottom-hat filtering is used along with the EEMD algorithm thus the baseline throughout the whole signal is brought to a zero reference which is clearly seen in Fig. 4d.

Furthermore, SNR and PRD % has been used as the two performance metrics for the evaluation and validation of the proposed methodology. The comparison of SNR and PRD % values of the baseline corrected signal using the proposed methodology with the EMD- and EEMD-based techniques has been shown in Tables 1 and 2 respectively.

Signal-to-noise ratio is a parameter which evaluates the improvement in the signal quality with respect to noise. The SNR of the proposed methodology for signal (S1) is reported to be 63.2500 dB which is much better as compared to EMD

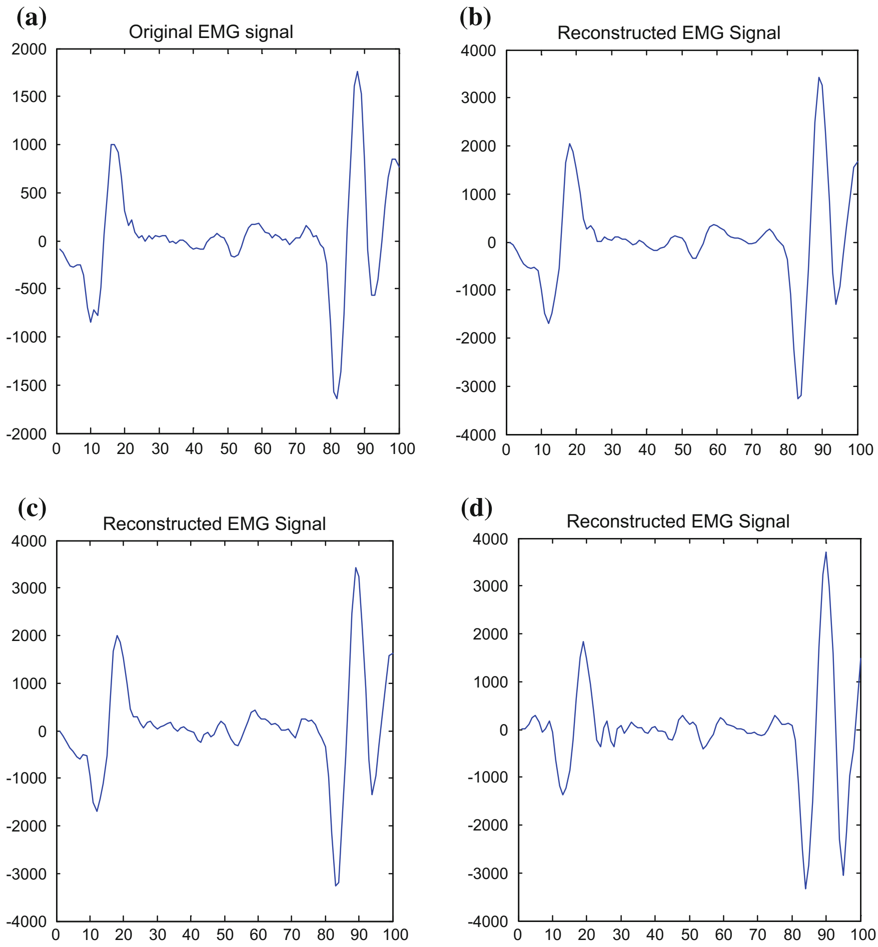

Fig. 4 **a** Original EMG signal (pushing 4), **b** EMD output signal, **c** EEMD output signal, **d** Proposed methodology output

Table 1 Comparison of SNR (in dB) of different existing methods used for baseline correction with the proposed methodology

EMG signal ref. no.	Original	EMD [15]	EEMD [15]	Proposed methodology
S1	−41.2400	−40.9150	−40.9091	62.3500
S2	−54.4346	−54.3271	−54.1080	55.0471
S3	−101.9355	−100.2435	−91.5264	−62.6738
S4	−50.3090	−50.2436	−50.1838	55.9229
S5	−65.1993	−64.9756	−64.4496	63.2815

Table 2 Comparison of PRD % values of different existing methods for baseline correction with the proposed methodology

EMG signal ref. no.	EMD [15]	EEMD [15]	Proposed methodology
S1	0.4944	0.4942	0.4752
S2	0.7506	0.7504	0.4518
S3	0.5557	0.5551	0.5298
S4	0.4074	0.4071	0.3924
S5	0.4765	0.4761	0.4731

and EEMD techniques in which the SNR is increased by only unity. Similar results are obtained for other signals also, i.e., S2–S5; wherein the proposed methodology certainly performs better with respect to the other two techniques.

4 Conclusion

This paper presented an approach for the elimination of baseline wander from EMG signals based on EEMD followed by morphological filtering. The EEMD algorithm effectively decomposes the EMG signal in time domain allowing varying frequency in time to be preserved. On the other hand, morphological filtering successfully removes the baseline wander with minimum distortion of the original EMG signal. The performance of this approach was compared with the existing EMD and EEMD algorithms [15]. This methodology achieved better results than the other two methods. The baseline drift was easily detected and removed from the decomposed IMFs. The proposed methodology outperforms the existing EMD- and EEMD-based methods in terms of both SNR and PRD % values.

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