Combination time-frequency and empirical wavelet transform methods for removal of composite noise in EMG signals

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ABSTRACT

Electromyography (EMG) is a technique used to measure the electrical activity in muscles during movement. Doctors commonly employ this method to quickly evaluate and identify conditions such as muscle problems, dystrophy, and neuropathies. The main objective of this study was to provide a reliable and effective method for preprocessing EMG signals. EMG signals are often affected by natural noise, which can make analysis challenging. To address this issue, a new method called the empirical wavelet transform (EWT) was used in this study to remove and clean the noise. Conventional methods like time domain and frequency domain analysis are limited when dealing with the non-stationary nature of EMG signals, as they do not provide sufficient information about the signals. Therefore, a time-frequency analysis tool was necessary. This research employed three time-frequency analysis techniques: periodogram, Choi-Williams, and smoothed pseudo-Wigner-Ville. The denoising and time-frequency applications demonstrated that the periodogram and EWT methods outperformed other previously published techniques regarding performance and accuracy. The results indicate the effectiveness of the periodogram and EWT methods in achieving this objective.

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1. INTRODUCTION

The electromyogram signals represent clinical tests that successively assess muscle function. The techniques for acquiring these signals are non-invasive, allowing recording by electrodes placed on the muscles. The utility of signal analysis electromyography (EMG) is to aid physicians in rapidly diagnosing major muscle and nerve abnormalities. This analysis measures the impulse velocity of the nerves in the muscles [1], [2]. Determination of the quantity of motor unit action potentials (MUAP) displayed in the EMG signal, offers useful information, such as muscular dystrophy, neuropathies, and nerve conduction status [3].

EMG signals, which are non-linear and non-stationary signals [4], require significant attention when it comes to denoising and analysis. Filtering EMG signals is a highly researched field due to the interference of natural noise during the recording and acquisition process. This natural noise obscures the valuable information present in the EMG signal, often leading to misinterpretation by experts.

In traditional methods, the first source of deviation from the baseline waveform is known as baseline wander (BW). when conventional denoising techniques are applied to correct it, there is a risk of obtaining a false representation of the waveform. The second source of noise, electrode movement (EM), is particularly troublesome as conventional filters struggle to effectively eliminate. The third type of noise, known as muscle artifact (MA), is generated by muscle contractions that coincide with the recording of muscle actions. The magnitude of this noise can overlap with the desired signals [5].

In order to effectively interpret biomedical signals, it is necessary to reduce the interference of noise with the signals. Denoising techniques are essential for obtaining accurate results. Commonly used methods, such as Finite impulse response (FIR) and infinite impulse response (IIR) filters, have been employed to eliminate noise from EMG signals [6]. While these techniques are straightforward and cost-effective, they can introduce undesired distortion to the waveform by combining the signal and the disturbance. Although the noise is removed, the useful and significant frequency components of the EMG signal may also be eliminated in the process.

Recently, there has been significant research interest in the preprocessing and analysis of EMG signals, particularly regarding their non-stationary nature and non-linearity. Adaptive analysis techniques such as empirical mode decomposition (EMD), ensemble EMD, complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN), and its variant, improved CEEMDAN (ICEEMDAN) [4], [7], [8] have gained recognition as among the most effective methods. Although these techniques have shown improvement, they still exhibit residual noise and spurious modes in the case of CEEMDAN and ICEEMDAN methods [4].

Overcoming the limitation of the variants of EMD, white noise is added during the operation to eliminate mode mixing. The noise remains in the signal after multi-mixing. Based on a filter structure closely related to wavelet theory, the empirical wavelet transform (EWT) fundamentally solves the modal mixing problem, which is a revolutionary innovation. While EMD is being researched and used in many fields, its limitations are being revealed. The effect of modal mixing is an unavoidable problem that hinders its development [9]–[11]. Gilles suggested adaptive extracting empirical modes in the frequency domain using EWT [9]. This technique has proven to be effective in several fields, such as the diagnosis of wheel bearing faults, the elimination of fog using a preliminary dark channel, hydraulic pumps, and non-stationary signals [12]–[17].

Most of the biomedical signals we encounter in our lives, in general, are non-stationary [4]. The classical methods used to analyze EMG signals are the time and frequency domain. Extracting the characteristics of the parts existing in a signal by classical processing is not necessarily straightforward, given the information provided by these components t the patient's condition [18].

The main characteristic of these signals is that their frequency information varies over time. Typically, experts and physicians process EMG signals using conventional methods like frequency domain and temporal domain analysis. Representing the signal solely as a function of time or frequency leads to incomplete information about the signal. Consequently, any decisions made based on this incomplete information might not be the most appropriate. To accurately define a non-stationary signal, it should be represented jointly in both time and frequency using a time-frequency tool [18]–[22]. This approach reveals how the spectrum of the signal evolves over time. Additionally, time-frequency methods also provide insights into the various components present in the EMG signal, including individual component durations in time and bandwidths in frequency. They also possess good noise suppression capabilities.

In this work, we applied the Choi-Williams (CW), smoothed pseudo Wigner-Ville (SPWV), and periodogram techniques [18]–[22]. These methods are well suited to analyze time-frequency information of non-stationary signals and provide higher time-frequency resolution [21], [23]. However, EMG signals are non-stationary and multi-component with high amplitude modulation, frequency modulation, and noise interference characteristics. The filtering methods used in the first part of this work to denoise EMG signals are applied before the application of time-frequency methods because the combination between these methods is complementary to accurately extract the time-frequency information and minimize the noise as much as possible. Therefore, the time-frequency resolution and anti-noise properties can be very well improved.

In addition, time-frequency methods also provide information about the number of different components existing in the signal, the durations and frequency bands of each component, as well as a good anti-noise property. Depending on the signal being analyzed, some time-frequency methods perform better than others. By objectively comparing their performances for a signal corrupted by the above-mentioned types of noise, one can find the time-frequency distribution that is the best for this signal [20], [21]. These techniques are applied to biomedical EEG and EMG signals noisy by composite noise.

This paper is structured as shown in: section 2 provides the theory of EWT; also, the time-frequency methods are proposed as SPWV, Choi-Williams distribution (CWD), and periodogram in this section. In section 3, the results of the methods are presented using real EMG signals. The last section 4 shows the conclusions of the work.

2. METHOD
2.1. Denoising methods
2.1.1. Empirical wavelet transforms

The EWT method assumes that the Fourier spectrum of the AM-FM component has good stability [9]–[11]. The bandpass filter set construction can be employed to segment and filtrate the spectra, and the signal can be decomposed adaptively via several modes. The EWT technique may be In the next three phases. Step 1: the FFT transform is applied to the signal x(t) for obtained the Fourier spectrum X(ω)(wϵ[0, π]). Locate the local maxima in the X(ω) with their associated frequencies, we denote them as local peak frequencies. Assume that X(ω) is composed of N local maxima with corresponding local peak frequencies Ωj, j = 1, 2,.........N. Order the detected maxima in descending order of frequency according to the amplitude of the local maxima [11]. Next, save the needed number of frequencies and cast off all the rest of the frequencies. The frequencies are then reorganized in ascending order. In "locmaxmin" mode, according to (1), the minimum value between successive maxima is [Ω_{n-1}, Ω_n] can be identified as the dividing boundary, and the set of limits ω = {ω_i}i=1,2,⋯, N can also be derived. Each lane can be described as follows Λn = [ω_{n-1},ω_n].

$$\omega_n = \begin{cases} 0 \rightarrow (n = 0) \\ argmin\, X\,(\omega) \rightarrow 1 \leq n \leq N-1, \Omega_{n-1} \leq \omega \leq \Omega_n \\ \pi \end{cases} \tag{1}$$

Step 2: for each frequency range, a suitable bandpass filter is created based on the definition of an empirical wavelet. In the EWT method, the basic empirical wavelet formula is based on the Meyer wavelets.
The low-pass filter is given by $\Upsilon_1(\omega)$:

$$\Upsilon_1(\omega) = \begin{cases} 1 \cdots\cdots\cdots\cdots\cdots\cdots\cdots |\omega| \leq \omega_1 - \tau_1 \\ cos\left[\frac{\pi}{2}\beta\left(\frac{1}{2\tau_1}(|\omega| - \omega_1 + \tau_1)\right)\right] \cdots\cdots\cdots\cdots \omega_1 - \tau_1 \leq |\omega|| \leq \omega_1 + \tau_1| \\ 0 \cdots\cdots\cdots\cdots\cdots\cdots\cdots others \end{cases} \tag{2}$$

And N- 1 bandpass filters $\mathrm{H}_n(\omega)$ can be designed.

$$H_n(\omega) = \begin{cases} 1 \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \omega_n + \tau_n \leq \omega \leq \omega_{n+1} - \tau_{n+1} \\ cos\left[\frac{\pi}{2}\beta\left(\frac{1}{2\tau_{n+1}}(|\omega| - \omega_{n+1} + \tau_{n+1})\right)\right] \cdots\cdots\cdots \omega_{n+1} - \tau_{n+1} \leq |\omega| \leq \omega_{n+1} + \tau_{n+1} \\ sin\left[\frac{\pi}{2}\beta\left(\frac{1}{2\tau_n}(|\omega| - \omega_n + \tau_n)\right)\right] \cdots\cdots\cdots\cdots\cdots \omega_n - \tau_n \leq |\omega| \leq \omega_n + \tau_n \\ 0 \cdots\cdots\cdots\cdots\cdots\cdots\cdots others \end{cases} \tag{3}$$

where $\tau_n = \gamma\omega_n, \gamma$ an argument must be greater than zero and small enough and the function $\beta(x)$ is given by the following equation $\beta(x) = x^4(35 - 84x + 70x^2 - 20x^2)$.
Step 3: extraction of sample components using the wavelet method and the inner product method. Internal product operations are performed to determine the estimated coefficients:

$$W_f^{\varepsilon}(0,t) = \langle f, \Upsilon \rangle = \int f(\tau)\overline{\Upsilon_1(\tau - t)}d\tau \tag{4}$$

The detail coefficients:

$$W_f^{\varepsilon}(n,t) = \langle f, H_n \rangle = \int f(\tau)\overline{H_n(\tau - t)}d\tau \tag{5}$$

The mode of operation is ultimately determined as a result of the scaling and waveform functions:

$$\begin{cases} f_0(t) = W_f^{\varepsilon}(0,t) * \Upsilon_1(t) \\ f_n(t) = W_f^{\varepsilon}(n,t) * \Psi_n(t) \end{cases} \tag{6}$$

2.1. Time-frequency methods
2.2.1. Periodogram

The parametric method employed in this work is the periodogram. The spectral estimator of this method is defined by (7):

$$PE(n,f) = Z_f^H . R_x . Z_f / ((\text{p}+1)^2) \quad (7)$$

where: $PE(n,f)$ is the output power of the filter Periodogram,

2.2.2. Non-parametric time-frequency technique SPWV

In this study, a transformation known as the SPWV transformation was applied and is defined as [20], [21]:

$$SPWV_x(t,f) = \int_{-\infty}^{+\infty} h\left|\left(\frac{\tau}{2}\right)^2\right| \int_{-\infty}^{+\infty} g(t-u) x_a\left(u+\frac{\tau}{2}\right) x_a^*\left(u-\frac{\tau}{2}\right) e^{-2i\pi f\tau} d\tau du \quad (8)$$

With: g(t) is the smoothed time window and h(t) is the smoothed frequency window.

2.2.3. Non-parametric time-frequency technique Choi-Williams

The Choi-Williams is developed as a method for finding the Wigner-Ville distribution with the least amount of intertemporal disturbance [22]–[25]. The Choi-Williams distribution is defined as (9):

$$CW_x(t,f) = \sqrt{\frac{2}{\pi}} \int \int_{-\infty}^{+\infty} \frac{\sigma}{|\tau|} exp^{-2\sigma^2(s-t)^2/\tau^2} A_x \, exp^{-j2\pi f\tau} \, d\, s d\tau \quad (9)$$

with

$$A_x = x\left(s+\frac{\tau}{2}\right) x^*\left(s-\frac{\tau}{2}\right) \quad (10)$$

2.2. EMG signals used

Electromyogram signals are used to represent the state of human muscles. The EMG signals are crucial tools commonly used in the muscles medical field to improve the treatment of patients suffering from neuropathy or myopathy muscles. By taking the difference in potential between electrodes placed at well-known locations on the patient's skin, these signals are usually obtained. The signals used in this paper are abnormal as neuropathy and myopathy. The signals in this paper are corrupted by the composite signal that gives in the work [4]. The comparative study in this work is evaluated by metrics such as root mean squared error (RMSE), percent root mean square difference (PRD), and mean squared error (MSE). The metrics are calculated as (11):

$$MSE = \frac{1}{k} \sum_{k=1}^{k} (x(n) - \overline{x}(n))^2 \quad (11)$$

The second metric is the RMSE equation obtained:

$$RMSE = \sqrt{\frac{1}{F} \sum_{f=1}^{F} (x(n) - \overline{x}(n))^2} \quad (12)$$

The third metric is PRD obtained:

$$PRD = \sqrt{\frac{\frac{1}{F} \sum_{f=1}^{F} (x(n) - \overline{x}(n))^2}{\sum_{n=1}^{N} x^2(n)}} *100 \quad (13)$$

Where: x(n) is EMG signal before adding noise and $\overline{x}(n)$ is reconstructed signal after filtering.

3. RESULTS AND DISCUSSION

3.1. Denoising methods

The denoising method employed in this study is EWT. This method is applied to EMG signals that are corrupted by composite noise. The white noise added in this composite noise varies from 0 dB to 15 dB with an increment of 5 dB. The effectiveness of this method is evaluated using the famous metrics: MSE and PRD. These metrics provide an idea about the power of the technique, which may be suitable for the analysis of EMG signals. Table 1 presents the results obtained by the method used in this study when applied to abnormal EMG signals.

Table 1. Results the PRD and MSE of myopathy and neuropathy signal

	Myopathy		Neuropathy	
SNR (dB)	MSE	PRD	MSE	PRD
0	0.0094	100.804	0.1924	100.6518
5	0.0031	57.6855	0.0625	57.3576
10	0.0011	34.1602	0.0214	33.5802
15	0.0004	21.9943	0.0084	21.0709

The results of the evaluation show the values of MSE and PRD for the two abnormal signals (myopathy and neuropathy). The EWT method demonstrates its effectiveness by producing the smallest values for these mentioned metrics (MSE and PRD). By aiming for the smallest values of MSE and PRD, the denoising EWT method can strive to achieve high fidelity in preserving the signal characteristics and minimizing distortions or noise introduced during the denoising process. Additionally, it shows better performance compared to other recently reported methods of interest research in the latest years 2021 [4] and 2020 [25].

3.2. Time-frequency methods

Of the well-known time-frequency methods used in this study, we have chosen the non-parametric methods smoothed pseudo Wigner-Ville (SPWV) and Choi-Williams, as well as the parametric Periodogram technique. These tools are applied to EMG signals that are corrupted by natural noises such as BW, motion artifact (MA), electromyogram (EM) noise, and white noise which is added last. The white noise varies from -5 dB to 20 dB with an increment of 5 dB. The effectiveness of these methods is assessed using known measures: RMSE and PRD. Tables 2 and 3 presents the results obtained by methods employed in this study applied to myopathy and neuropathy EMG signals.

Table 2. Results the PRD and RMSE of myopathy signal

	SPWV		CW		PER	
SNR (dB)	PRD	RMSE	PRD	RMSE	PRD	RMSE
-5	10072.7766	0.10920388	10090.4868	0.11260571	7573.54751	0.01497344
0	3582.74334	0.04180715	3580.09184	0.04433455	2653.76457	0.00546429
5	1358.6709	0.01851357	1353.88793	0.02023512	985.036234	0.0022753
10	557.853237	0.0092755	554.539434	0.01033957	393.701181	0.00108719
15	249.091946	0.00497293	247.231645	0.00559522	170.824738	0.00056848
20	119.855042	0.00274404	118.885396	0.00309948	80.1103661	0.00031021

Table 3. Results the PRD and RMSE of neuropathy signal

	SPWV		CW		PER	
SNR (dB)	PRD	RMSE	PRD	RMSE	PRD	RMSE
-5	443.596404	2.15457763	482.68679	2.21931871	41.7729275	0.28404872
0	149.646313	0.82276395	154.405528	0.87060483	26.8943677	0.09739573
5	113.416448	0.36946039	113.437411	0.40157878	25.6788988	0.03777285
10	78.7160383	0.18889792	79.6082987	0.20839438	17.9481727	0.01729794
15	49.2785744	0.10287926	50.1170895	0.11412721	11.2131453	0.00896495
20	29.3319276	0.05732094	29.9142861	0.06369228	6.66112322	0.00491513

Figures 1 to 4 show the results obtained by methods employed in this research involving the application of abnormal EMG signals. Figure 1 shows the RMSE of an abnormal EMG signal (neuropathy), the RMSE measured is obtained by the application of the time-frequency SPWV, CW, and PERIOD on this signal. Figure 2 shows the PRD of an abnormal EMG signal (neuropathy), the PRD measured is obtained by the application of the time-frequency SPWV, CW, and PERIOD on this signal. Figure 3 shows the RMSE of an abnormal EMG signal (myopathy), the RMSE measured is obtained by the application of the time-frequency SPWV, CW, and PERIOD on this signal. Figure 4 shows the PRD of an abnormal EMG signal (myopathy), the PRD measured is obtained by the application of the time-frequency SPWV, CW, and PERIOD on this signal.

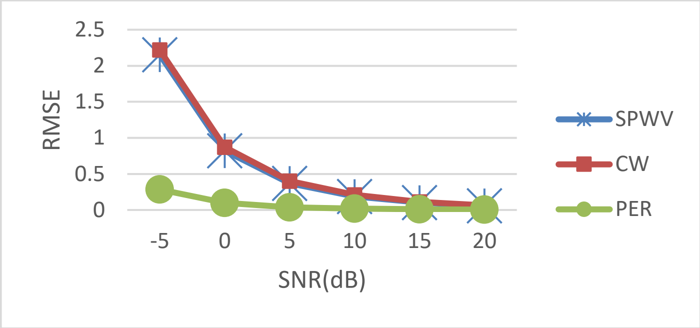

Figure 1. Obtained results of the RMSE of the neuropathy EMG

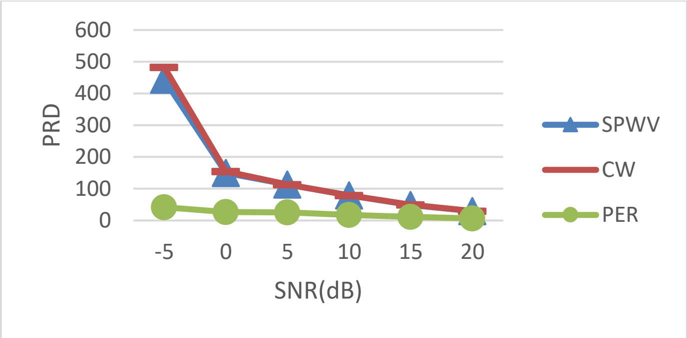

Figure 2. Obtained results of the PRD of the neuropathy EMG

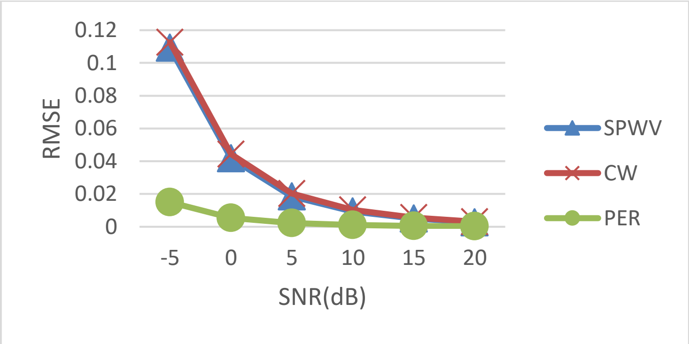

Figure 3. Obtained results of the RMSE of the myopathy signal

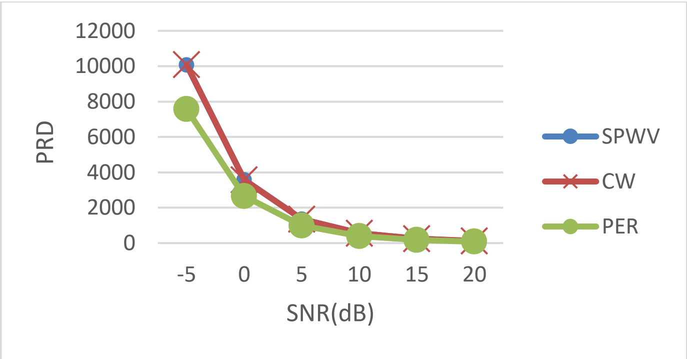

Figure 4. Obtained results of the PRD of the myopathy signal

Various metrics are used in this survey to provide comprehensive measures of the model methods involved. The RMSE and PRD can be measured in the same manner as the denoising techniques. Based on the previous evaluation presented in Tables 2 and 3 and Figures 1-4, we can indicate that the periodogram method is superior to the other methods used in this research. It demonstrates lower RMSE and PRD for the inputs of the signal-to-noise ratio (SNR) ranging from -5 dB to 20 dB compared to the other methods. The periodogram method yields good results for the preprocessing and analysis of the electric EMG biomedical signal, both in clean and noisy conditions. Furthermore, the periodogram method outperforms the methods used in a recent paper published by [25].

3. CONCLUSION

In this work, we proposed a method called EWT for eliminating composite noise in recorded EMG signals. We also presented the periodogram method for analyzing these signals. The effectiveness of the new EWT method was evaluated using a real EMG signal from the MIT-BIH database. The results showed that EWT significantly improved the MSE and PRD, outperforming the existing methods. Additionally, we examined parametric and non-parametric tools for abnormal EMG signals. The results demonstrated the effectiveness of the parametric periodogram technique, which yielded smaller RMSE and PRD values compared to the CW and SPWV methods. In conclusion, we found that both the parametric technique and EWT are superior solutions for denoising and analyzing biomedical signals such as EMG.

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