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Analysis Electroencephalogram Signals Using Denoising and Time-Frequency Techniques

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ABSTRACT
The electroencephalogram (EEG) is a test that determines brain activity. The existence of artifacts in EEG can naturally decrease the smoothness of the analysis of the biomedical signal. EEG disturbed by noises during encephalogram recordings is one of the problems that the experts have to investigate for finding solutions to remove these artifacts. To obtain an accurate EEG signal; the improved complete ensemble empirical mode decomposition with adaptive noise (ICEEMDAN) is used and compared with and its old versions. The non-stationarity and non-linearity of the EEG signal cannot provide complete information when using the traditional method (Temporal and frequency domains). Among the objectives is the comparative analysis of time-frequency distributions applied on EEG signals. The denoising and time-frequency methods used in this study are tested on healthy and abnormal EEG signals which are disturbed by natural and artificial noises. The comparative study in this work shows the effectiveness of the combination of the ICEEMDAN and Periodogram methods that are suitable for denoising and analyzing the EEG signal.

Key words: ICEEMDAN, EEG, EEMD, Time-Frequency.

1. INTRODUCTION

The brain produces the electrical activities that are recorded by electroencephalogram; this procedure is painless and safe. The measures of this activity are obtained by placing electrodes at good locations on the patient scalp [1, 2]. EEG signal has a lot of information about specific brain functions from which the experts obtain good interpretation and analyses in clinical laboratories. Generally, the signals that have low amplitudes (the amplitude order is a few microvolt) can be attacked by artefacts easily [2]. The EEG is generally obscured by the noise of physiological and non-physiological origin. The artefacts as electromyogram (EMG), electrical interference, baseline wanders (BW), ocular artefacts (OE) and motion artifact (MA) are found to be among the most significant and common during the EEG recording [3, 4]. Elimination of these artefacts is one of the obligations for processing the biomedical signals to make better diagnoses on neurological disorders and supplies a cleaner biomedical signal. In this paper, the methods as Empirical Mode Decomposition EMD and its recent versions Ensemble EMD (EEMD) and completed EEMD with adaptive noise (CEEMDAN) and the new version of these techniques have been proposed. These methods are tested in various areas as geophysical logging data, rotating machinery, changing climate and biomedical signals [5, 6, 7, 8, 9, 10, 11, 12]. The EMD technique is a suitable tool for decomposing the non-stationary signal. Despite the fact that the EMD technique presents the problem of the mode-mixing; the latter is given by the interference of discrete scales in one IMF or in different IMFs. For overcoming the limits of EMD technique the new version of EMD method is EEMD which is presented for analyzing the biomedical signals by adding the Gaussian white noise [5, 6]. The drawback of the EEMD is the apparition of the new extreme points when adding noise. This drawback appears in the modes that can give a bad interpretation of signals by the experts. To surpass this drawback, the complementary EEMD with adaptive noise (CEEMDAN) was presented in this study for giving the solution of the residual noise appearing in the methods previously cited in this section [7, 12]. The CEEMDAN tool adds the white noise with unit variance at each step of calculation of the new IMF for solving the problem of the decomposition scale deviation. The problems of spurious modes and residual noise are presented during the restoration of the original signal by the CEEMDAN method. The new technique called improved CEEMDAN technique presented by Colominas et al outperforms the other methods cited above by solving the problems that appear during the decomposition [13, 14].

The extraction of the characteristic of the component existing in the signal by traditional analysis is not always evident. These components may issue information about the health status of the brain. The classic methods used in analyzing the EEG signals are temporal and frequency domains. Despite the benefits of these traditional methods, there are some aspects that can be incomplete. The analysis of the non-stationarity and non-linearity of the EEG signals may be in the time

domain more difficult to extract good information about signals and can't give the frequency content of the signal. In the frequency domain; the analysis of the biomedical signals is not very delicate because of the disappearance of the concept of time during the appearance of the frequency contents. The time-frequency methods may be a good tool for surpassing the cited problem of the traditional methods [15, 16, 17, 18, 19]. The time-frequency methods permit extracting different characteristics of biomedical signals as EEG and have a good resolution and high anti -noise property. These methods can be the solution for the analysis, the extraction of the important frequency content and decision making. The advantages of the time-frequency methods are the capabilities to detect the behaviour of the EEG signal in the time and frequency domain synchronously. It offers an additional occasion for treatment and analyses of the EEG signal. The parametric and non-parametric techniques used in this paper are the Choi-Williams (CW), the Smoothed Pseudo Wigner-Ville (SPWV) and Periodogram (PE). These parametric and non-parametric methods have been used in several fields as an electrocardiogram (ECG), electromyogram (EMG) and acoustics signals and obtained some good results.
The research starts with an introduction, and part two presents the principles of existing techniques of the filtering and time-frequency. Part three presents the main results. The last part is a conclusion.

2. DENOISING AND TIME-FREQUENCY TECHNIQUES

2.1 Denoising Techniques

2.1.1 Empirical Mode Decomposition (EMD)

The EMD is an adaptive tool to decompose an original signal x(t) into the modes called intrinsic mode function IMFs. The Intrinsic Mode Functions can express the signal x(t) by the following expression:

$$x(t) = \sum_{j=1}^{k} d_j(t) + r(t) \tag{1}$$

Where dj is IMF_j with j=1,2…k that IMF_1 represent the component that have high frequency and k: number of the IMF_k represents represent the component that have low frequency.
With r(t) that represents the low frequency residue.
The EMD process is presented by the following steps [4, 6]:
1: Extraction all extrema of original signal.
2: computes the local average m(t):

$$m(t) = (e_{\max}(t) + e_{\min}(t))/2 \tag{2}$$

With $e_{max}(t)$ is upper envelope and $e_{min}(t)$) is lower envelope.
3: calculates of the mode $d_J(t)=IMF_J(t)$, a local detail by :

$$d(t) = x(t) - m(t) \tag{3}$$

4: The expression (1) gives the iteration.

2.1.2 Ensemble Empirical Mode Decomposition (EEMD)

The EEMD method decomposes each signal x(t) separately than the other and each step have to compute the residue. The EEMD process is a technique that needed applying the EMD method in each addition of white noise on the original signal x(t) and computing the mean of the corresponding IMFs from the realizations obtained for all the additions cited. The EEMD method describes the real mode and surpasses the disadvantage of the EMD method that related by mode-mixing [8]. The EEMD process is given as follows:
1: generated the original signal with white noise.
2: The obtained signal is decomposed by applying the EMD process for each addition to white noise.
3: Computes of the $\bar{c}$ (Average the corresponding (IMFs)) obtained by the decomposition results [8].
The signal x(k) is decomposed.

$$x(k) = \sum_{i=1}^{n} \bar{c} + \bar{r} \tag{4}$$

Where n define the IMFs number.

2.1.3. Complete Ensemble Empirical Mode Decomposition with adaptive noise (CEEMDAN)

The disadvantages of the EEMD technique resides in the decomposition of the signal who is not completely decomposed and the noise that added on the signal can engender a different number of modes for overcoming these; the CEEMDAN method was considered.
The first mode is obtained by using the EMD technique in each step that the noise added in original signal and calculate $\overline{IMF}_1(n)$ the by way the EEMD method.
We define the function Ej [.] that extract the j-th IMF decomposed by EMD. wi is the white noise[9, 10, 11].
The CEEMDAN algorithm is described as follows:
1: Decompose $x(n) + w_0\varepsilon^i(n)$ to obtain the first mode by using:

$$\overline{IMF}_1(n) = \frac{1}{I}\sum_{i=1}^{I} \overline{IMF_k^i}(n) \tag{5}$$

Where w_0 is the level of the added noise, and $\varepsilon(t)$ is the white noise with unit variance.
2: The first residue is obtained by following relation:

$$r_1(n) = x(n) - \overline{IMF}_1(n) \tag{6}$$

3: Decompose $r_1(n) + w_1E_1(\varepsilon^i(n))$, to obtain the first mode and define the second mode by :

$$\overline{IMF}_2(n) = \frac{1}{I}\sum_{i=1}^{I} E_1\left(r_1(n) + w_1E_1(\varepsilon^i(n))\right) \tag{7}$$

For k= 2, …, K, calculate the k-th residue and obtain the first mode. Define the (k+1)-th mode as follows:

$$\overline{IMF}_{k+1}(n) = \frac{1}{I}\sum_{i=1}^{I} E_1\left(r_k(n) + w_kE_k(\varepsilon^i(n))\right) \tag{8}$$

4: Iterate this operation until residue no longer achievable. The residue is given as follows:

$$R(n) = x(n) - \sum_{k=1}^{k} \overline{IMF}_k \tag{9}$$

Finally, the original signal is obtained by the equation as follows:

$$x(n) = R(n) + \sum_{k=1}^{k} \overline{IMF}_k \tag{10}$$

2.1.4 Improved Complete Ensemble Empirical Mode Decomposition with adaptive noise (ICEEMDAN)

The CEEMDAN method presents drawbacks that appearing in residual noise that to be present in its modes and the spurious modes that presented in the first decomposition. The IMCEEMDAN technique reduces the noise and gives more physical meaning of the intrinsic mode function (IMFs). The IMCEEMDAN method defines the new operator M(.) that calculates the local mean of the signal. The ICEEMDAN is given by the steps as follows [13, 14]:

a) The local means is obtained by applying the EMD method for I realizations on the signal : $x^i = x + \beta_0 E_1(w^{(i)})$ to get the first residue: $r_1 = \langle M_1(w^{(i)}) \rangle$
b) Computes the mode: $\tilde{d}_1 = x - r_1$
c) The second residue is obtained by the equation : $r_1 + \beta_1 E_2(w^{(i)})$; the second mode is obtained by the relation : $\tilde{d}_2 = r_1 - r_2 = r_1 - \langle M(r_1 + \beta_1 E_2(w^{(i)})) \rangle$
d) For p = 3, …, P calculate the pth residue $r_p = \langle M(r_{p-1} + \beta_{p-1} E_p(w^{(i)})) \rangle$
e) Calculates the pth mode $\tilde{d}_p = r_{p-1} - r_p$
f) Go to step 4 for next p.

These values $\beta_p = \varepsilon_p std(r_p)$ are selected to get the required SNR between the added noise and the residue to which the noise is added.

The goal of the addition of the white noise on the original signal during applying the modified version of the EMD method is to generate new extrema. This latest is compelled to take them to calculate the new local mean.

2.2 Time-frequency methods

The time-frequency methods are used for revealing the frequency components over time. Among these techniques; the Periodogram (PE), the Choi-Williams (CW) and the Smoothed Pseudo Wigner-Ville (SPWV) were chosen [15, 16, 17, 18, 19].

2.2.1 Choi-Williams distribution

The Choi-Williams method (CW) is a good tool for reducing the cross-terms and the resolution of time-frequency images [19].

$$CWD_X(t,f) = \frac{1}{4\pi^2} \int_{-\infty}^{\infty} \int \int_{-\infty}^{+\infty} \exp^{-j\theta t - j\tau\omega + j\theta u} \phi(\theta,\tau) A_u \, du \, d\tau \, d\theta \tag{11}$$

Where

$$A_u = x\left(u + \frac{\tau}{2}\right) x^*\left(u - \frac{\tau}{2}\right) \tag{12}$$

And $\phi(\theta,\tau) = e^{\frac{\theta^2 \tau^2}{\sigma}}$

The smoothing of the technique is modified by the parameter σ.

2.2.2 Periodogram technique

The Periodogram (PE) method was defined by the following equation [16, 17, 18]:

$$PE(t,f) = Z_f^H . R_X . Z_f \,/\, ((p+1)^2) \tag{13}$$

The PE method offers a good frequency resolution of time-frequency images.

2.2.3 Smoothed Pseudo Wigner-Ville technique

The SPWV tool is applied by using two smoothing windows h(t) and g(t). This technique is defined by the following equation [15, 17]:

$$SPWV_X(t,f) = \int_{-\infty}^{+\infty} \left| h\left(\frac{\tau}{2}\right) \right|^2 \int_{-\infty}^{+\infty} g(t-u) x_a\left(u + \frac{\tau}{2}\right) x_a^*\left(u - \frac{\tau}{2}\right) e^{-2i\pi f\tau} d\tau du \tag{14}$$

Where x*a(t) indicates the complex conjugate of $x_a(t)$. With $x_a(t)$ is a signal. Where h(t) and g(t) are the smoothing frequential and temporal windows.

2.3 Biomedical signals

The electroencephalogram test is non-invasive that can be permitted to detect the normal and abnormal electrical activities in the brain. The brain disorders are obtained by analyzing the EEG test; these disorders can be sleep disorders for example. In the time of the sleep, the Cyclic Alternating Pattern (CAP) appearing. The CAP is a periodic activity. The CAP can be provided the state of sleep stability and maybe correlated with several sleep-related anomalies [2, 3]. The signals existing in Database in [20]. The EEG signal presented in figure 1 is a healthy subject that has not presented any neurological disorders.

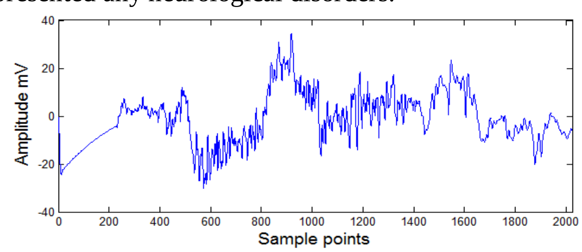

Figure 1: Normal EEG signal

The figure 2 presents the abnormal EEG signal with subject PLM.

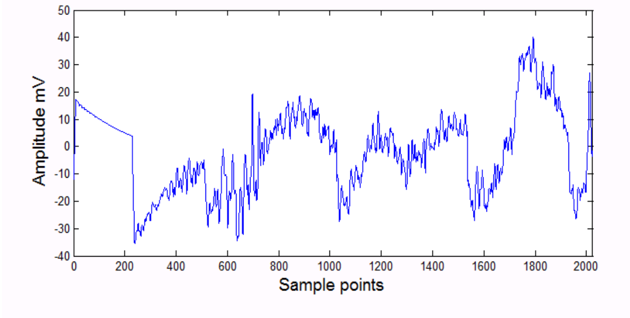

Figure 2: Abnormal EEG signal with subject PLM

The noises signals used in this research are muscle artifact (MA), Baseline wander (BW) and electrode motion (EM) [20]. The EEG signals that used in the paper are normal and abnormal with subject PLM, these signal were affected with noise CN given by the equation as follows [10]:

$$CN = \frac{qbaw*BW + qelm*EM + qmoa*MA}{qbaw + qelm + qmoa} \qquad (15)$$

The percent of the noises added the baseline wander is defined by qbaw, electromyogram noise is defined by qelm, and motion artifact noises are defined by qmoa. The values chosen are qbaw = 2, qelm = 2, and qmoa = 5. The selection of effeteness of the technique that minimizes the noise is the issue of the comparison between four de-noising techniques. The three desired metrics used in this research are Mean Square Error (MSE), Root MSE (RMSE), Percent RMS Difference (PRD) and Signal-to-noise-ratio (SNR). The SNR parameter calculates the quantity of noise in a signal. These metrics provide the quality of the information during the restoration of the components EEG signals. The metrics are calculated as follows:

The MSE equation is shown in following:

$$MSE = \frac{1}{F}\sum_{f=1}^{F}(y(n) - \bar{y}(n))^2 \qquad (16)$$

The RMSE equation is giving by the equation:

$$RMSE = \sqrt{\frac{1}{F}\sum_{f=1}^{F}(y(n) - \bar{y}(n))^2} \qquad (17)$$

The PRD is obtained by the equation:

$$PRD = \sqrt{\frac{\frac{1}{F}\sum_{f=1}^{F}(y(n) - \bar{y}(n))^2}{\sum_{n=1}^{N} y^2(n)}} * 100 \qquad (18)$$

3. RESULTS AND DISCUSSION

3.1 Results

In this part of this paper we provide the results given by the denoising methods. The denoising methods CEEMDAN and ICEEMDAN are applied to EEG signals. Figures 3 and 4 show the decompositions given by the ICEEMDAN and CEEMDAN. Figures 5 and 6 show the sifting iterations demanded by each decomposition. The filtering techniques are evaluated by their performance by being applied on normal and abnormal EEG signals. The suggested techniques are ICEEMDAN, CEEMDAN, EEMD and EMD. Before the direct application of these methods on EEG signals, we added the natural noise given by equation (15) on EEG signal and also added white noise with different values between 10dB to 35dB with a 5 dB step.

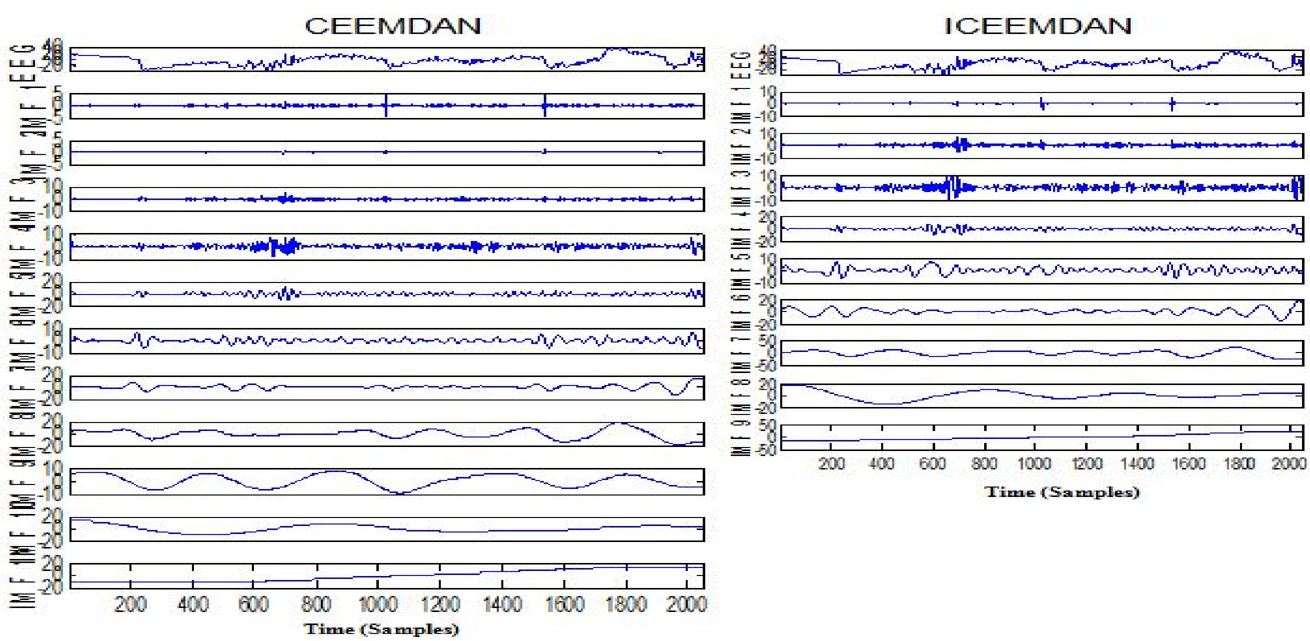

Figure 3: Decomposition of a 2048-sample abnormal EEG by: CEEMDAN; ICEEMDAN

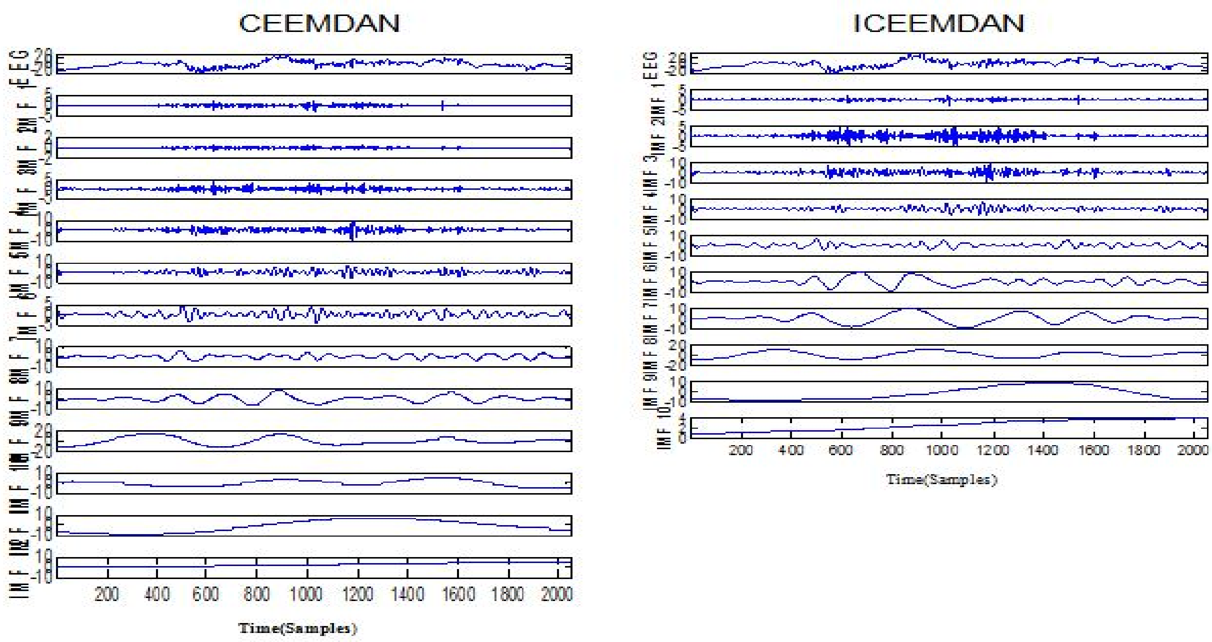

Figure 4: Decomposition of a 2048-sample normal EEG by: CEEMDAN; ICEEMDAN

The figures 5 and 6 depict the sifting iterations demanded by each decomposition.

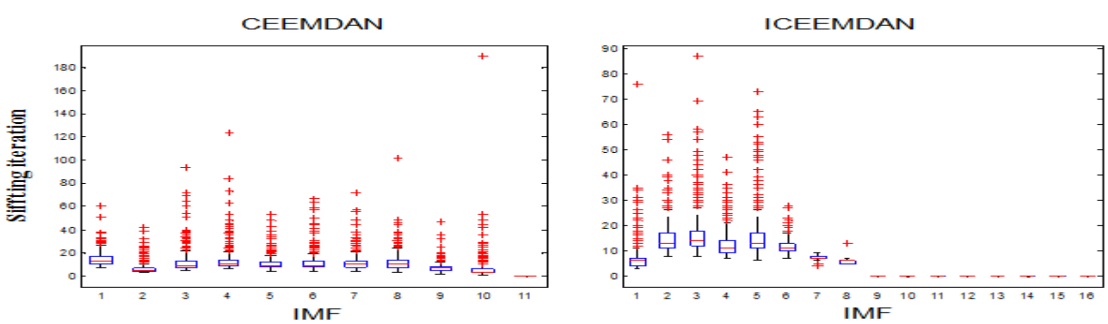

Figure 5: Sifting iterations of abnormal EEG

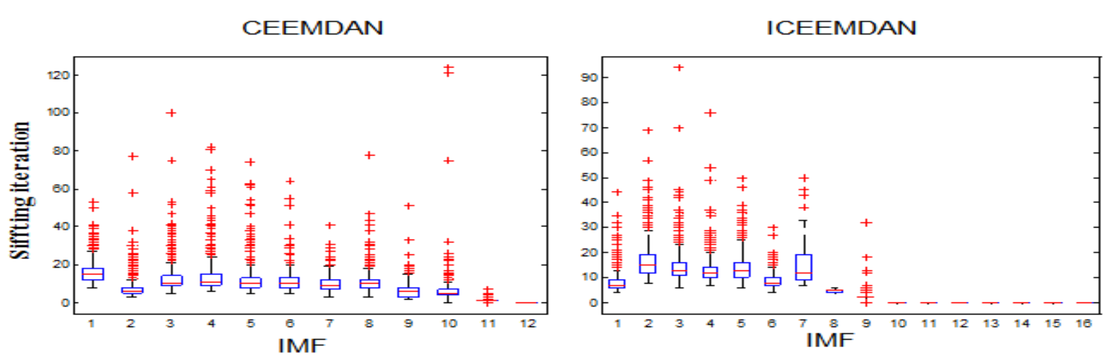

Figure 6: Sifting iterations of normal EEG

The tables 1 and 2 describe the results of the denoising techniques (ICEEMDAN, CEEMDAN, EEMD and EMD) for the EEG signal with any problem and the abnormal signal with subject Periodic limb movements in sleep (PLMS). These tables present the Mean Square Error (MSE) of these signals and give the report of the performance by comparing the results obtained by this metric. The obtained results of the MSE and PRD are shown by the figures 7 to 10. These results are given by the application of the denoising methods on normal and abnormal EEG signals with subject PLM. The results of the RMSE and PRD are given in the tables 3 and 4. These results are obtained by using the ICEEMDAN, CEEMDAN, EEMD and EMD techniques on normal and abnormal EEG signals with subject PLM.
The table 1 shows the MSE of normal EEG signal.

Table 1: MSE of the normal EEG signal

SNR	ICEEMDAN	CEEMDAN	EEMD	EMD
10	9,569	9,577	9,644	10,360
15	3,045	3,046	3,124	3,922
20	0,987	0,989	1,078	1,863
25	0,331	0,341	0,331	1,130
30	0,129	0,140	0,174	0,930
35	0,066	0,075	0,103	0,742

The table 2 shows the MSE of abnormal EEG signal.

Table 2: MSE of the Abnormal EEG signal

SNR	ICEEMDAN	CEEMDAN	EEMD	EMD
10	24,780	24,848	24,892	24,810
15	7,850	7,861	7,892	8,420
20	2,503	2,505	2,614	3,129
25	0,813	0,818	0,994	2,022
30	0,280	0,286	0,428	1,905
35	0,110	0,115	0,296	1,997

The figures 7 and 8 show the MSE of the normal and abnormal EEG signals.

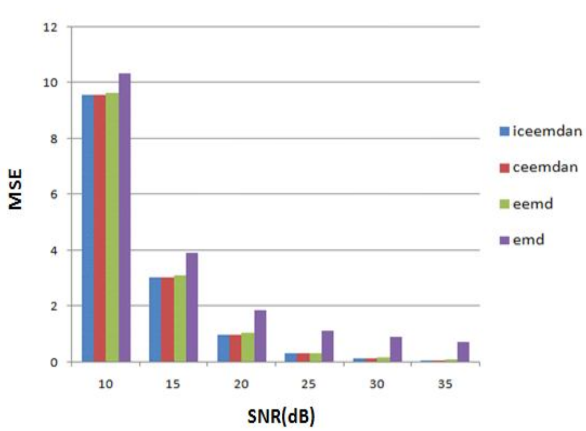

Figure 7: MSE obtained of the normal signal

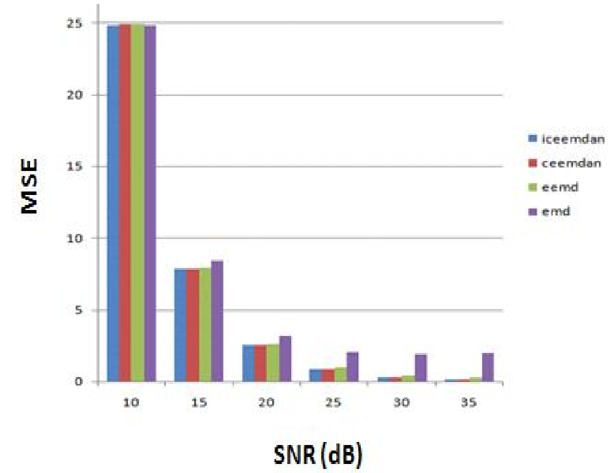

Figure 8: MSE obtained of the abnormal signal

The figures 9 and 10 show the PRD of the normal and abnormal EEG signals.

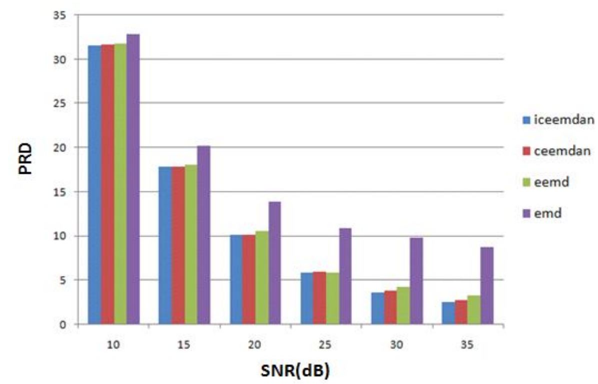

Figure 9: PRD obtained of the normal signal

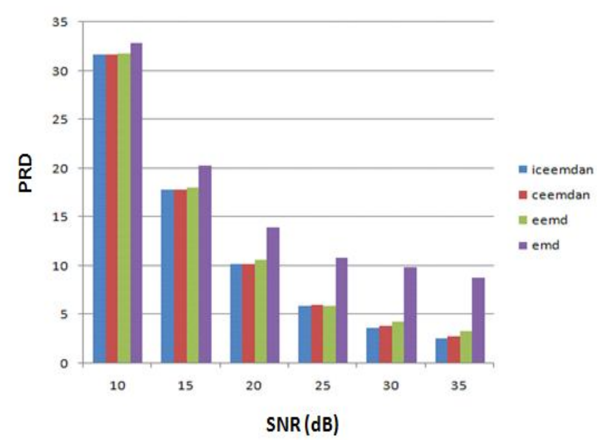

Figure 10: PRD obtained of the abnormal signal

The results of the RMSE and PRD are given in the tables 3 and 4.

Table 3: RMSE and PRD of the normal EEG signal

	RMSE				PRD			
SNR	**ICEEMDAN**	**CEEMDAN**	**EEMD**	**EMD**	**ICEEMDAN**	**CEEMDAN**	**EEMD**	**EMD**
10	**3,093**	3,095	3,105	3,219	**31,621**	31,635	31,745	32,902
15	**1,745**	1,745	1,768	1,980	**17,837**	17,841	18,069	20,244
20	**0,993**	0,995	1,038	1,365	**10,153**	10,168	10,612	13,952
25	**0,576**	0,584	0,575	1,063	**5,884**	5,968	5,882	10,865
30	**0,358**	0,374	0,417	0,964	**3,665**	3,823	4,267	9,858
35	**0,256**	0,273	0,320	0,861	**2,618**	2,796	3,275	8,803

Table 4: RMSE and PRD of the Abnormal EEG signal with subject PLM

	RMSE				PRD			
SNR	**ICEEMDAN**	**CEEMDAN**	**EEMD**	**EMD**	**ICEEMDAN**	**CEEMDAN**	**EEMD**	**EMD**
10	**4,978**	4,985	4,989	4,981	**31,587**	31,630	31,658	31,606
15	**2,802**	2,804	2,809	2,902	**17,778**	17,791	17,826	18,413
20	**1,582**	1,583	1,617	1,769	**10,038**	10,044	10,260	11,225
25	**0,902**	0,904	0,997	1,422	**5,720**	5,739	6,327	9,023
30	**0,529**	0,535	0,654	1,380	**3,358**	3,392	4,150	8,758
35	**0,332**	0,340	0,544	1,413	**2,104**	2,155	3,454	8,968

The second part of this paper presents the results of time-frequency methods. The utilization of time-frequency distributions can permit to determine and recognize the various aspects and features of EEG signals. In this part, we have applied the parametric and non-parametric methods (PE, CW and SPWL) to the EEG signal corrupted by the CN and white noises signal that vary between -5dB to 20dB with a 5dB step. The comparison of time-frequency methods is given in this part after application to The EEG signals. The figures 11 and 12 show the obtained results of the PRD by applying the parametric and non-parametric methods. The obtained results are reported in table 5 and 6 of the PRD.

The table 5 shows the PRD of the normal EEG signal.

Table 5: PRD obtained of the normal EEG signal

SNR	**PERIOD**	**CW**	**PWVL**
-5	45,578	415,395	331,081
0	23,625	204,274	164,294
5	12,653	106,129	85,680
10	6,915	57,042	46,109
15	3,826	31,269	25,284
20	2,131	17,334	14,016

The table 6 shows the PRD of the normal EEG signal.

Table 6: PRD obtained of the abnormal EEG

SNR	**PERIOD**	**CW**	**PWVL**
-5	21,473	172,235	148,512
0	15,863	88,688	74,697
5	10,482	48,153	40,181
10	6,422	26,704	22,218
15	3,783	14,930	12,413
20	2,182	8,374	6,962

The figures 11 and 12 show the PRD of the normal and abnormal EEG signals.

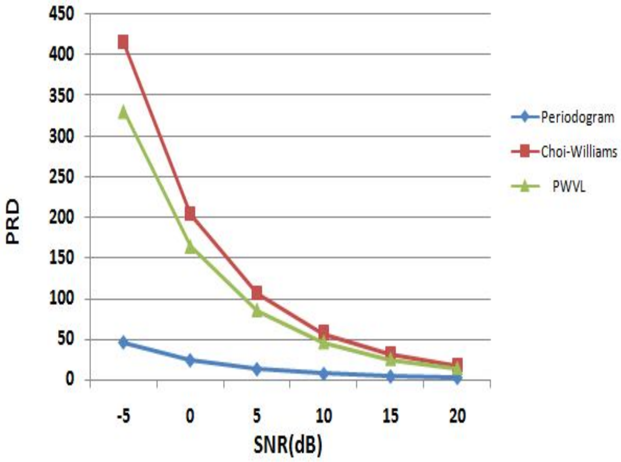

Figure 11: PRD obtained of the normal EEG

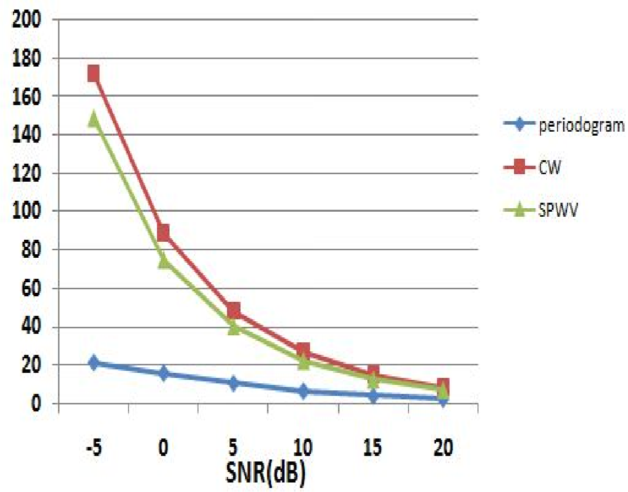

Figure 12: PRD obtained of the Abnormal EEG

3.2 Discussion

Neural information is obtained by the EEG signal; this information can be interfered with by some physiological artefacts (EM, MA, BW). These artefacts may be used as normal phenomena to deceptively drive an experimental utilization. The natural noises as BW, EM and MA are provided by noise stress and Sleep Heart Health Study PSG Database. In the first part, we present the results obtained from the discrimination among the four techniques, ICEEMDAN, CEEMDAN and the classic Methods EEMD and EMD which remove these physiological artefacts. The obtained results are explained as follows; the number of sifting iteration of CEEMDAN method is higher than ICEEMDAN method presented in figures 5 and 6. The decomposition of the abnormal EEG signal by CEEMDAN produces eleven modes, while in ICEEMDAN produces nine modes and in the normal EEG the decomposition obtained is twelve modes by CEEMDAN and ten by ICEEMDAN presented in figure 3 and 4. In these decompositions the values of the amplitudes are close in the first decompositions. In CEEMDAN method, the identification of the fundamental frequency is more difficult than using the ICEEMDAN method caused by the number of the modes in the first method (CEEMDAN). The obtained results of the metric values are shown in the figures 7, 8, 9 and 10 and tables 1, 2, 3, and 4. According to the results, the ICEEMDAN method provides the smallest values of the MSE, RMSE, and PRD for all white noise added with natural noise composite signals on healthy and PLM EEG signals used compared to CEEMDAN, EEMD, and EMD techniques. This study shows the effectiveness and the power of the ICEEMDAN method. The ICEEMDAN method is the most suitable for denoising the non-linear and non-stationary CAP signals with less noise and more physical meaning. In the second part, based on the obtained results; the Periodogram technique shows the effectiveness when it obtained low values of the PRD than other methods used (non-parametric techniques). The parametric Periodogram method is very applicable to analyze the time-frequency image on non-linearity EEG signals. The work with the Periodogram method is only sufficient for extracting the information with high resolution and precision. Among the goals of this investigation is the combination of the denoising ICEEMDAN and Periodogram methods for reducing the noise and giving a good resolution to the image time-frequency.

4. CONCLUSION

In this paper, the denoising and time-frequency methods were tested on EEG signals. The first obtained result concerning the comparative study of the denoising methods shows the power of the ICEEMDAN tool for the artifacts reduction. The second result proves the high effectiveness of the parametric time-frequency method in order to provide good analyses of the EEG signals. We deduce that the parametric time-frequency and ICEEMDAN methods are more suitable for filtering and analyzing the EEG signals.

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