Military Technical College
Kobry El-Kobbah,
Cairo, Egypt

7th International Conference
on Electrical Engineering
ICEENG 2010

Computerized EEG Abnormalities Detection

By

Ahmed Awadallah*, Mahmoud Gadallah*, Walid Foaud**, Magdy ELkafafy* and Emad ELsamahy*

Abstract:

The traditional Electroencephalogram (EEG) visual inspection suffers from the limited accuracy of the human interpretator, and the variation of different interpretator skills. In addition, the accurate investigation of the EEG requires long time and big effort. A proposed Computerized EEG Abnormalities Detection (CEAD) system is introduced to overcome the limitations of the traditional EEG visual inspection method. This system has the ability to detect the EEG abnormalities automatically and display them to the physician both numerically and graphically. Moreover, the system can show the EEG electrodes that have the abnormal events on a graphical skull map. The proposed system saves much time and effort for the interpretator, as well as providing high accuracy in detecting the EEG abnormalities.

Keywords:

EEG, Abnormalities Detection, Computerized Techniques.

---

* Egyptian Armed Forces
** EL_Azhar University

1. Introduction:

EEG signals contain huge amount of information about the function of the brain. However classification and evaluation of these signals still limited. Interpretation of EEG recordings usually done by EEG interpretators via visual inspection of the recorded EEGs various electrodes, which was found insufficient and takes a lot of time and effort. Furthermore, results of interpretation of the same EEG may differ from different interpretators depending on their experiences. Therefore, computer based methods should be used for analyzing the EEG signals [1].

Brain functioning affects the morphology of EEG. Seizure, which is kind of brain abnormality, can be detected using spikes and their firing pattern in EEG. This can be considered as the primary phase in the evaluation of brain functioning. In the context of EEG, spikes can be defined as transient signals, clearly distinguishable from the background activity with a duration ranging from 20 to 70 msec. In other words, spikes are nonstationary short–time broadband signals with high instantaneous energy. Spikes can be used in detecting many neurological disorders such as epilepsy [2,3], which is a challenging task in nonstationary signals, such as EEG. Furthermore epilepsy is characterized by sudden recurrent and transient disturbances of mental function and/or movements of the body that result from excessive discharging of groups of brain cells. Spikes that could appear in an EEG signals are shown below which include the following types: spike, sharp wave, spike and wave complex, polyspikes, polyspike and slow wave as in Figure 1.

Moreover, spikes detection with methods based on the assumption that the background signal is stationary or quasi-stationary are not appropriate for this type of signals [2].

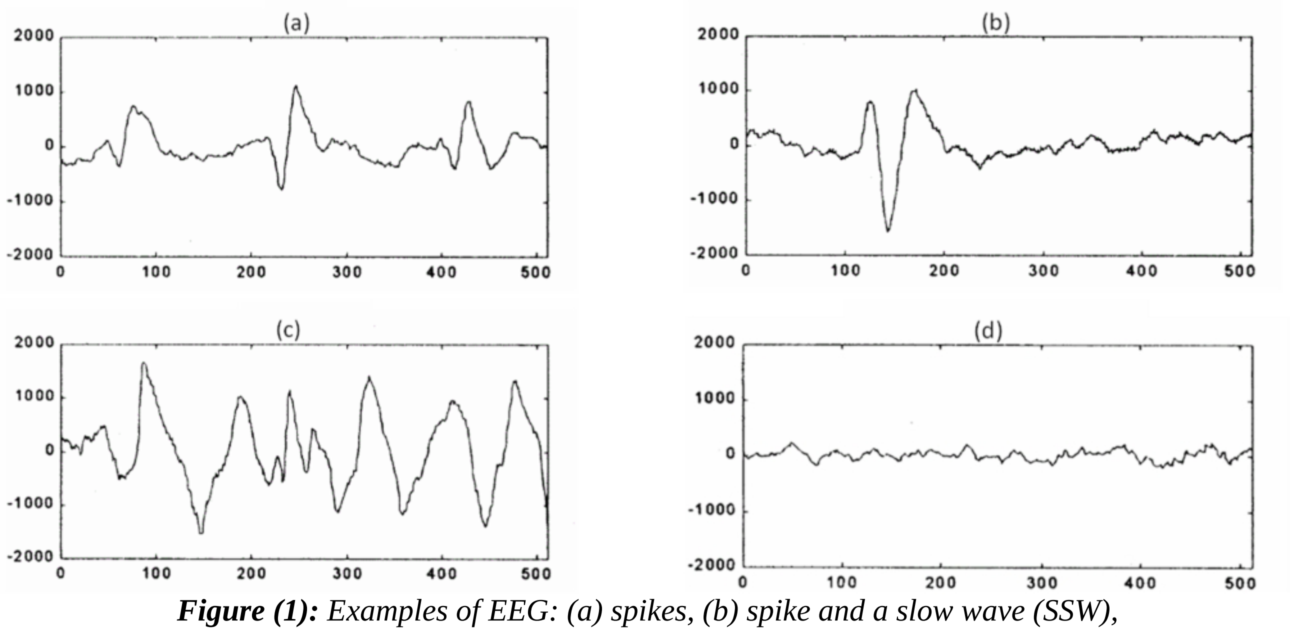

Figure (1): *Examples of EEG: (a) spikes, (b) spike and a slow wave (SSW),*

(c) polyspikes, (d) normal background EEG

Cheng-Wen Ko et al. presented an automatic spike detection algorithm for classification of multi-channel EEG signals based on artificial neural network [4]. Radial basis function (RBF) neural network was chosen for single channel recognition. Feature extraction with as few as three parameters was used as preparation for the inputs to the neural network. The computation time required for spike detection was significantly less than that needed for online display of the signals on the monitor. They believe that the algorithm proposed in this study is robust and that the simple structure of RBF neural network yields high potential for real-time implementation.

G. Calvagno et al. proposed a multiresolution approach and a nonlinear energy operator for the automatic detection of spikes in EEG [5]. The signal on each EEG channel is decomposed into three subbands using a non-decimated wavelet transform. Each sub-band is analyzed by using a non-linear energy operator. A decision rule detects the presence of spikes in the EEG, relying upon the energy of the three subbands. The effectiveness of the proposed technique was confirmed by analyzing both test signals and EEG layouts. This technique showed high accuracy in spikes detection.

Malek Adjouadi et al. evaluate the feasibility of using the Walsh transformation to detect interictal spikes in EEG data [6]. Independent sets of EEG data recorded on 18 patients with focal epilepsy were used to train and test the algorithm. Spikes were annotated independently by two EEG experts. Evaluation of the algorithm revealed an accuracy of 79%.

D. Sanshez et al. introduced a novel spike detection algorithm based on the use of Walsh Transforms [7]. The algorithm focuses on the assessment of characteristics in the EEG signal that reveal the presence of a spike feature. The algorithm showed encouraging results when applied to EEG data from seven patients.

Hamid Hassanpour et al. presented a method for detecting EEG spikes. The method is based on the time–frequency distribution of the signal [8]. The results of this technique on both the synthetic and real signals have shown that the proposed technique outperforms the original method based on time domain analysis.

Lin-Sin Pon et al. proposed that the multi-resolution wavelet transform with mathematical morphology can be used to detect and extract abnormal spike activity from epileptic EEG [9]. This method successfully separates the background activity and transient phenomenon from epileptic EEG. This approach has ability to detect both positive and negative going spikes identically.

Guanghua Xu al. introduced an automatic spike detection method in epileptic EEG based on morphological filter [10]. The proposed method is evaluated by simulated epileptic EEG data. Results show that background activity is fully restrained and spike component is well extracted. Finally, the method is applied to normal and epileptic EEG data which are actually recorded from nine testees. The average detection rate of spikes is 91.62% and no false detection for normal EEG signals.

Chenxi Shao et al. proposed an EEG spike wave detection method based on qualitative modeling of visual observation [11]. The method is based on qualitative measurement of sharpness degree of waves at spike wave frequencies. Then, constructs a qualitative description model of visual observation to discriminate spike waves from none spike waves. The result shows that this method is effective and direct to a certain extent.
Dauwels et al. explored the correlation between the EEG synchrony a Alzheimer Disease (AD) at an early stage [12]. Multiple synchrony measures are applied to two different EEG data sets: (1) EEG of pre-dementia patients and control subjects; (2) EEG of mild AD patients and control subjects. It is observed that both Granger causality and stochastic event synchrony indicate statistically significant loss of EEG synchrony, for the two data sets. Those two synchrony measures are then combined as features in linear and quadratic discriminant analysis (with crossvalidation). The classification results 83% and 88% for the pre-dementia data set and mild AD data set respectively. These results suggest that loss in EEG synchrony is indicative for early AD.

This paper is organized as follows:

- Section 2 describes the traditional EEG abnormalities extraction method.
- Section 3 introduces a theoretical background about the used algorithms.
- Section 4 describes the graphical user interface (GUI) of the proposed system.
- Section 5 discussion about the system results and its accuracy.
- Section 6 discusses the final conclusion.

2. Traditional EEG abnormalities Extraction method:

An example of a recorded EEG taken from a hospital is shown in Figure 2. This record contains a sixteen electrode measurements. much time and efforts are required by the EEG interpretators to make the patient report using the traditional EEG abnormalities extraction method. This method include the following steps:

2.1. Scan Reading

This method is started with taking a glance on the recorded EEG to give a preliminary opinion on the patient.

2.2. Determination of abnormality suspicious

The EEG interpretator focus on the intervals of abnormalities. These abnormalities are spikes, sharp waves, and slow activities.

2.3. Applying available software facilities

The interpretator uses the available software to make a manual differentiation between spikes and sharp waves by measuring the amplitude and duration using horizontal and vertical cursors.

2.4. Frequencies estimation

The interpretator estimates the background and slow activity frequencies by counting visually the EEG zero crossings per second.

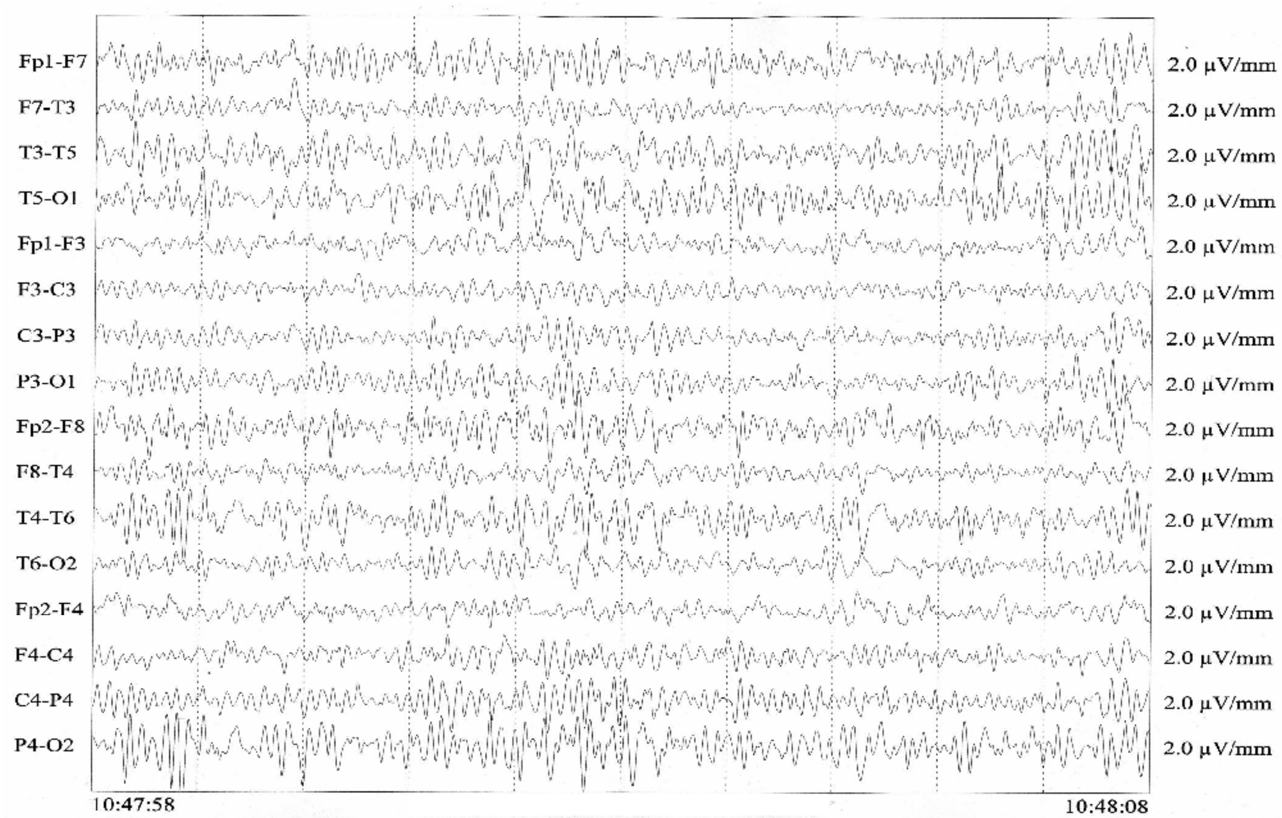

Figure (2): *A typical EEG recordings*

Although the traditional EEG abnormalities extraction method is the dominant and approved method for physician investigation, different points may be taken into consideration when using it, which are:

- Long time and huge effort are required by the interpretator to perform a complete and accurate investigation on the recorded EEG.
- The experiences and skills of the interpretator may differ from one to anther.
- The limited accuracy of the human interpretator on estimationg the EEG parameters.

Therefore, an automated method is required to save time and effort as well as increase the accuracy.

In the next section, a brief description is introduced for the EEG morphology and the algorithms used in measuring the EEG frequency in the proposed system, which are autoregressive and zero crossing.

3. Theoretical background:

First of all a discussion will be introduced about the features characterizing the spikes and sharp waves to facilitate their detection.

3.1. Important features characterizing spikes and sharp waves

With the help of medical experts short transient waveforms called spikes (or spike discharge) is simulated in Figure 3.

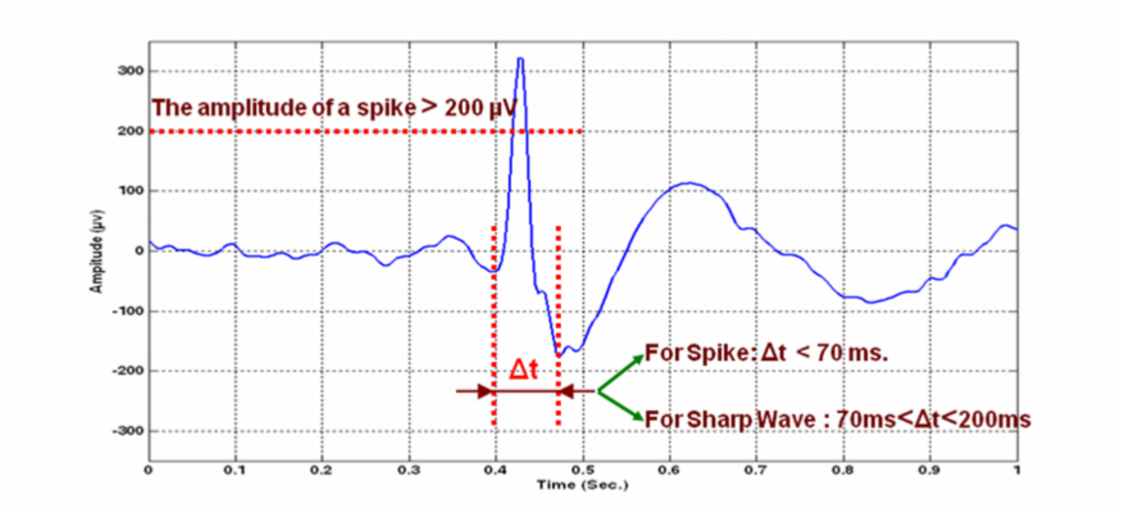

Figure (3): *Simulated spike and its morphology*

The following list of features was established as necessary to declare the existence of a spike, which are:

1. A sharp peak characterizes the spike, which is due to a sudden change in polarity of the voltage signal recorded.
2. A spike is estimated to have a total duration of 20 to 70 ms. The total duration of the spike, Δt.
3. A Sharp wave is a spike but it is estimated to have a total duration of 70 to 200 ms.
4. The amplitude of a spike is greater than 200 µV.
5. A spike is often followed by a slow wave. If they occur at rates below 3 Hz, they are called spike-and-slow wave complexes.

Now, moving to the exploration of the used algorithms in measuring EEG frequency.

3.2. Frequency measurement using Yule-Walker autoregressive (AR)

This method is also named the autocorrelation method. The prediction coefficients of the AR process can be calculated by using the estimate autocorrelation function, (ACF) [13].

The autocorrelation function parameters, $\hat{r}_{xx}(k)$, can be calculated from the input data sequence x(n) as:

$$\hat{r}_{xx}(k) = \frac{1}{N}\sum_{n=0}^{N-1-k} x(n)x(n+k) \qquad ,k = 0, 1, 2, \ldots, N-1$$

The noise power (variance) can be estimated as:

$$\sigma_e^2 = \hat{r}_{xx}(0) + \sum_{m=1}^{M} a_m \hat{r}_{xx}(m)$$

This equation is known as the Yale-Walker equation. The ACF can be used to create an autocorrelation matrix R. The prediction coefficients can then be extracted using the formula:

$$\begin{bmatrix} \hat{r}_{xx}(0) & \hat{r}_{xx}(-1) & \cdots & \hat{r}_{xx}(-M) \\ \hat{r}_{xx}(1) & \hat{r}_{xx}(0) & \cdots & \hat{r}_{xx}(1-M) \\ \vdots & \vdots & \ddots & \vdots \\ \hat{r}_{xx}(M) & \hat{r}_{xx}(M-1) & \cdots & \hat{r}_{xx}(0) \end{bmatrix} \begin{bmatrix} a(0) \\ a(1) \\ \vdots \\ a(M) \end{bmatrix} = \begin{bmatrix} \sigma_e^2 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

or

$$Ra = \sigma_e^2$$

where

R	is the autocorrelation matrix.
M	is the AR model order.
a	is the prediction coefficient vector.

The output power spectral density $S_{AR}(f)$ is given as:

$$S_{AR}(f) = \frac{\sigma_e^2}{\left|1 + \sum_{m=1}^{M} a_m e^{(-j2\pi f m \Delta t)}\right|^2} \qquad \text{where } \Delta t \text{ is the sampling interval}$$

3.3. Frequency measurement using Zero Crossing (ZC) Technique

The Zero Crossing Technique concludes that a signal in a given channel has passed through zero if it meets any of the following criteria:

- $x_i < 0$ and $x_{i-1} > 0$
- $x_i > 0$ and $x_{i-1} < 0$
- For some positive integer L, $x_i < 0$, $x_{i-l} = 0$, and $x_{i-L-1} > 0$, where $\boldsymbol{0 \le l \le L}$.
- For some positive integer L, $x_i > 0$, $x_{i-l} = 0$, and $x_{i-L-1} < 0$, where $\boldsymbol{0 \le l \le L}$.

Where x_i is the current signal value, x_{i-1} is the previous signal value, and so on [14].

4. The Proposed Computerized EEG Abnormalities Detection:

The proposed CEAD was developed under Matlab® environment. The GUI of the system, which is shown in Figure 4 enables the user to simply analyze the EEG signals. The different operations which were performed manually by the interpretator are now converted to automatic operations. Figure 4, shows the GUI for the proposed system which is outlined as follows:

1- Open the EEG recording data file.
2- Path of the opened file.
3- The selected electrode from the EEG recording.
4- Available filters (notch, high pass, and low pass) to be applied for EEG preprocessing.
5- Part of the electrode signal for certain period of time.
6- Navigation buttons (first frame, previous frame, next frame, last frame).
7- Parameters used for spike and sharp wave detection.
8- Information about the detected spikes (timing, spike duration, max spike amplitude).
9- Magnification of one of the detected spikes.
10- Navigation buttons (first spike, previous spike, next spike, last spike) for navigating between the detected spikes.
11- The total recoded time.
12- Available frequency analysis techniques (Autoregressive, Zero crossing).
13- Analysis mode (by second, by interval, slow waves).
14- Navigation buttons for frames (next, previous).
15- Coloring scheme used for EEG frequency bands identifications.
16- A brain map revealing the locations of detected spikes and slow waves on the skull.
17- Nineteen axes distributed according to the 10/20 system for displaying of the detected spikes.
18- Show the detected spikes for each electrode.
19- Number of detected spikes for each electrode according to the color scheme mentioned in No.15.

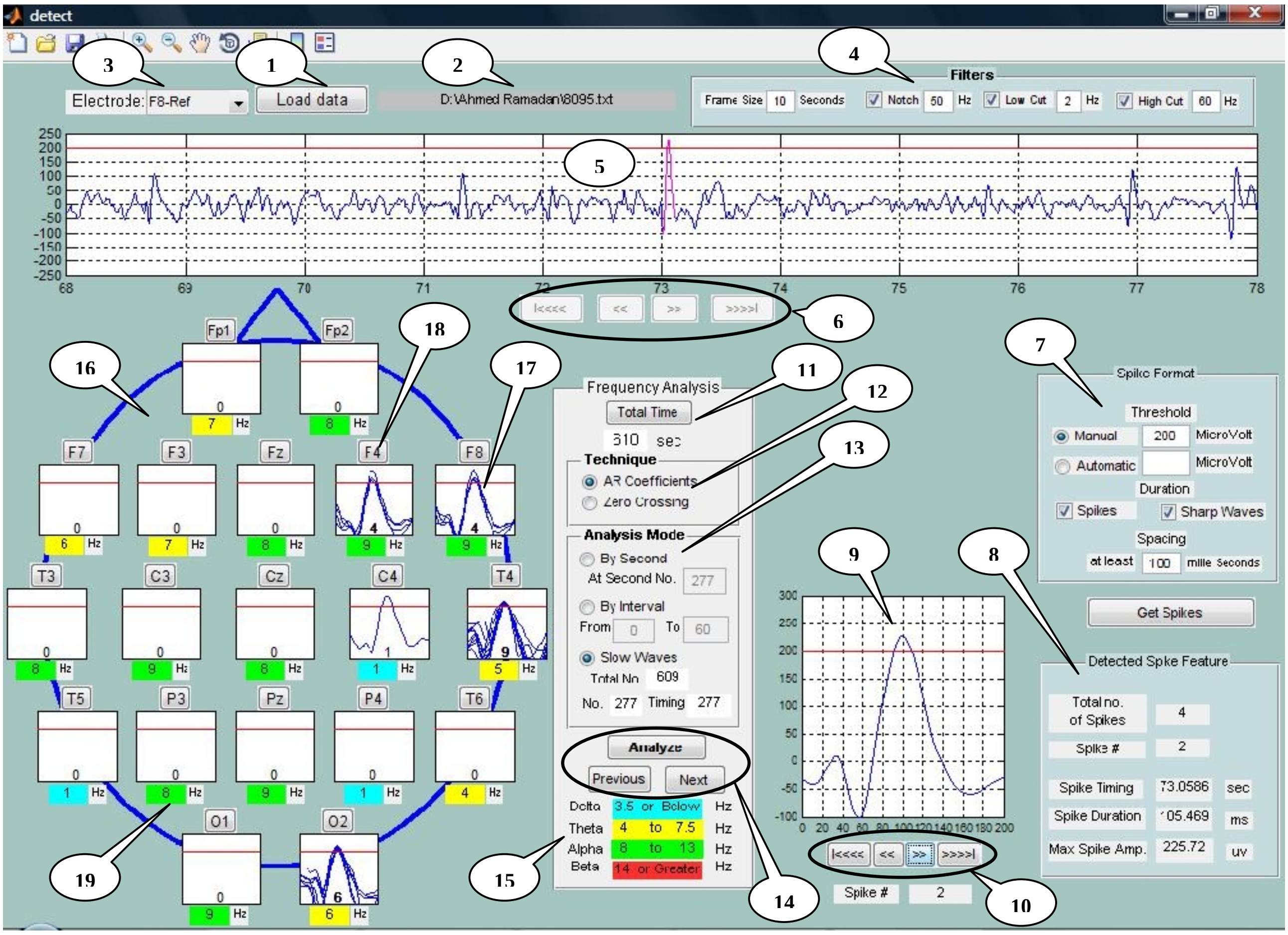

__Figure (4):__ The GUI for the proposed CEAD system

5. Experimental tests for the proposed system:

Ten abnormal EEG recordings were used to evaluate the performance of the system. The results of the CFE system for spikes and sharp waves detection were compared to the results obtained by an expert interpretator which were set as a reference, as shown in Table 1. The results show approximately a 99.38% matching between the expert interpretator and the proposed CEAD system. When other considerations were taken into account which are the consumed time and the effort required, the comparison was in favor of the proposed CEAD system.

Table (1): *Comparison between expert interpretator spike detection and the proposed CEAD system*

Patient No.	Recorded Interval (sec.)	Detected Spikes by Expert EEG Interpretator	Detected Spikes using the proposed *CEAD*	Accuracy (%)
1	620	27	27	100
2	490	35	35	100
3	630	38	37	97.4
4	690	15	15	100
5	620	2	2	100
6	610	28	27	96.4
7	600	28	28	100
8	610	0	0	100
9	600	4	4	100
10	610	4	4	100

Another evaluation was applied to check for frequency analysis, concerning the slow activities detection (Theta & Delta appearance for the adult awake).

In detecting the slow activities, the proposed algorithm behaves as a physician. In other words, it counts the number of slow waves in each second interval using ZC method.

Also, in the proposed system we added another method to find out the slow wave activities by the well known AR technique.

The results of both methods are compared by that of the expert interpretator as shown in Table 2. The results obtained by the proposed CEAD system using the zero crossing method and that of the expert interpretator are almost matched. This validates the obtained results by the proposed CEAD system.

Table: *(2) Comparison between expert interpretator frequency measurement and the proposed CEAD method at (Cz)*

Patient No.	**Recorded Interval (Sec.)**	**Slow activities detected by Expert EEG Interpretator**			**Detected Slow activities using the proposed CEAD**					
					Zero Crossing			**Spectrum Estimation**		
		total	**Theta**	**Delta**	**total**	**Theta**	**Delta**	**total**	**Theta**	**Delta**
1	620	15	15	0	15	15	0	58	43	15
2	490	390	343	47	393	345	48	455	188	267
3	630	220	170	50	222	172	50	369	192	177
4	690	698	490	178	671	493	178	687	388	299
5	620	94	94	0	95	95	0	160	143	17
6	610	285	283	2	286	284	2	487	329	158
7	600	260	250	10	261	251	10	558	501	57
8	610	83	83	0	83	83	0	188	154	34
9	600	233	229	4	235	231	4	448	412	36
10	610	270	255	15	271	256	15	556	261	295

6. Conclusions:

The proposed CEAD system was found to achieve some advantages over the usual manual method for EEG investigation. These advantages were clear after the application of different tests, which can be summarized in the following points:

- Abnormality detection is determined with high accuracy.
- Spikes and sharp waves are accurately measured and distinguished.
- Displaying all spikes on a skull map helps in foci localization.
- The proposed CEAD system produces a large amount of information for the recorded EEG in a small time, which are:
    - The total number of the detected spikes or sharp waves for every electrode.
    - The time and position of occurrence of the detected spikes or sharp waves.

- The total number of slow activities and the corresponding time and location.
- Accuate measurement for the frequency components.

The previously discussion provides us with confidence to use the proposed system even for expert to save time and effort. Moreover, this system will be of great help for non expert, physician and will behave with high accuracy.

References:

[1] Abdulhamit Subasi, M. Kemal Kiymik, Ahmet Alkan, and Etem Koklukaya, “Neural Network Classification of EEG Signals By Using AR With MLE Preprocessing for Epileptic Seizure Detection”, Mathematical and Computational Applications, Vol. 10, No. 1, pp. 57-70, (2005).

[2] Hamid Hassanpour, Luke Rankine, Mostefa Mesbah, and Boualem Boashash, “Comparative Performance of Time–Frequency Based EEG Spike Detection Techniques”, 13th European Signal Processing Conference, (2005).

[3] Clement C. C. Pang, Adrian R. M. Upton, Glenn Shine, and Markad V. Kamath, “A Comparison of Algorithms for Detection of Spikes in the Electroencephalogram”, IEEE Transactions on Biomedical Engineering, vol. 50, No. 4, April (2003).

[4] Cheng-Wen KO, Yue-Der Lin, Hsiao-Wen Chung, Gwo-Jen Jan, “An EEG Spike Detection Algorithm Using Artificial Neural Network With Multi-Channel Correlation”, Proceedings of the 20th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Vol. 20, No 4,(1998).

[5] G. Calvagno, M. Ermani, R. Rinaldo, F. Sartoretto, “A Multiresolution Approach To Spike Detection in EEG”, IEEE (2000).

[6] Malek Adjouadi*, Danmary Sanchez, Mercedes Cabrerizo, “ Interictal Spike Detection Using the Walsh Transform”, IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, VOL. 51, NO. 5, MAY (2004).

[7] D. Sanchez, M. Adjouadi, A. Barreto, P. Jayakar, I. Yaylali, “Application Of The Walsh Transform In An Integrated Algorithm for The Detection Of Interictal Spikes”, IEEE (2001).

[8] Hamid Hassanpour, Mostefa Mesbah and Boualem Boashash, “EEG Spike Detection Using Time–Frequency Signal Analysis”, IEEE (2004).

[9] Lin-Sen Pon, Mingui Sun, and Robert J. Sclabassi, “The Bi-Directional Spike Detection in EEG Using Mathematical Morphology and Wavelet Transform”, IEEE (2002).

[10] Guanghua Xu, Jing Wang, Qing Zhang, Junming Zhu, “An Automatic EEG Spike Detection Algorithm Using Morphological Filter”, Automation Science and Engineering, 2006. CASE '06. IEEE International Conference on page(s):170-175 (2006).

[11] Chenxi Shao, Shaobin Li, Jinfeng Fan, "EEG Spike Detection Based on Qualitative Modeling of Visual Observation", Fuzzy Systems and Knowledge Discovery, 2007. FSKD 2007. Fourth International Conference on Volume 2, Page(s):745 - 748 (2007).

[12] Dauwels, J.; Vialatte, F.; Latchoumane, C.; Jaeseung Jeong; Cichocki, "EEG synchrony analysis for early diagnosis of Alzheimerapos;s disease: A study with several synchrony measures and EEG data sets", Engineering in Medicine and Biology Society, 2009. EMBC 2009. Annual International Conference of the IEEE Volume , Issue , Page(s):2224 – 2227 (3-6 Sept. 2009).

[13] Metin Akay, "Biomedical Signal Processing", Academic Press, (1994).

[14] MATLAB®, "The Language of Technical Computing", Version R2009a, (2009).